Physiological Sensing for Measurement of Eating Function, and Detection of Food and Characteristics of Eating

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by

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Abstract

Eating function consists of a number of highly complex and interconnected physical and psychological processes that govern food intake, volume, satiety, and help to protect the respiratory system during eating. Disruption of these processes by a number of physiological, environmental, and social factors can effect normal eating and influence our choices of when, what and how much to consume, leading to life limiting disorders, disturbed eating habits or contribute to sustained over eating and high BMI.

In order to properly understand and formulate methods of treating high BMI, eating disorders, or functional eating impairments it is imperative that we fully understand the interaction between eating processes and various sources of stimuli. Current research is burdened by reliance upon self-report and manual monitoring, and the inherent error and bias in these techniques. This research aimed to reduce this burden through use of measurement of physiological signals of the body for automated eating function detection and monitoring. This has great potential for automated monitoring of eating and other activity, and while normally reliant upon bulky and expensive equipment and expert evaluation, recent trends in wearable sensing modalities make such sensing a viable direction of research for mobile and continuous activity tracking. To achieve the research aims this thesis sought to answer the following questions:

1. How can physiological sensing be used for the accurate sensing of chewing and swallowing?

2. How can automated eating detection be used to detect eating characteristics and food content?

3. How can sensed eating data and characteristics be applied for studying eating behaviour function and behaviour, and for motivating eating change?

This work focused on Electromyography (EMG): the measurement of signals related to muscular activity. In the first main study in this research, EMG was applied for detection and classification of swallowing, and to drive swallow training biofeedback. A threshold based swallow detection algorithm was developed, which exhibited high accuracy despite the relatively simple approach. Following this, an investigation of classifiers to distinguish between dry, liquid, and extended swallows demonstrated up to 99% accuracy for detecting extended swallows and 92% for differentiating between dry and liquid swallows. Feature importance analysis indicated that the long duration of extended swallows made these easier to classify than other types. In the final part of this study biofeedback driven by the swallow detection algorithm was evaluated in a user trial of 3 male and 3 female participants revealing response accuracy, and user acceptability of sensors and biofeedback. However, concerns regarding the robustness of the detection algorithm directed research efforts in the remainder of this thesis towards classification approaches better able to handle unexpected behaviour.

The second main study reported here focused on chew and swallow classification and food type content detection, based on detected eating in lab conditions. This resulted in algorithms, capable of robust and generalisable classification of chewing with 94% accuracy, and swallowing with 86% accuracy. Evaluation of eating characteristics and their impact upon eating classification demonstrated the importance of signal segmentation in respect to the timings of chews and swallows: long duration swallow events requiring a larger window (1.6 seconds) to capture a swallow in its entirety, and a small window (0.5 seconds) more important during chewing detection to avoid misclassification of between-chew periods. In the second part of this study models trained on an individual basis demonstrated dietary content prediction with an average of 99% accuracy for distinguishing between solids and liquids, and for differentiation between 3 solid foods. Further evaluation of the impact of eating characteristics upon food classification led to the conclusion that models trained to recognise chewing patterns of individuals help to improve classification accuracy, but was less useful for liquid swallowing differentiation which did not exhibit individual differences.

In the final study of this research, a system for driving haptic eating rate feedback and studying chewing characteristics was developed, and applied in a study of chewing rate in response to self-moderation and feedback. Measurement of 16 participants (8 male, 8

female, between 18-50), revealed a significant negative correlation between chewing rate and moderation, more pronounced in the presence of chewing rate feedback. Analysis of collected data revealed that this was the result of pauses introduced between chews, and did not impact chewing thoroughness. Participant self-reflection upon eating also demonstrated that self-moderation increased awareness of and focus upon the processes of eating, but feedback did not have any significant effect upon this. This indicates that chewing rate feedback has an influence over eating rate, without increasing perceived effort or awareness.

This thesis has demonstrated the development of a number of techniques for automated detection and sensing of eating behaviour, and for driving feedback. In the course of developing these techniques, this work has outlined a number of areas for consideration when developing classifiers for the detection of eating, classification of foods, and for extracting characteristics of chewing activity. These techniques were then applied for the study of eating, highlighting an important contribution to the understanding of eating moderation processes. This work has important implications for future study of eating and evaluation and treatment of eating, eating disorders, and BMI related conditions.

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Declaration

I declare this thesis titled: 'Physiological Sensing for Measurement of Eating Function, and Detection of Food and Characteristics of Eating' and the work presented within is, unless otherwise stated, my own. I confirm that this work was done wholly or mainly while in candidature for a research degree at the University of Kent. No part of this thesis has previously been submitted for any other academic award, at this institution or otherwise. I declare that when consulting and referring to the works of others, I have clearly attributed said works by reference. Where this thesis is based on work done by myself in collaboration with others, I have made clear below my contribution.

Author: Benjamin Nicholls

Signed: _____

Date: _____

Published work

The study reported in Chapter 3 has been published, in part, in Scientific Reports [1] and at the transactions of the 2017 IEEE International Conference on Pervasive Computing and Communications Workshops [2]. This study resulted from a collaboration between B. Nicholls (author of this thesis), C.S. Ang (supervisor), Y. Lee, W.H. Yeo, and other authors. In this study, B. Nicholls developed all software and algorithms reported, and analysed the study results, C.S. Ang helped guide this work and the study protocol, and other authors carried out data collection, conducted comparisons of sensor types used in this study, or contributed towards writing the papers. Y. Lee was lead author in writing the journal article [1], and C. Efstratiou contributed towards writing of the conference paper [2].

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Definitions and Terminology

Terminology

Within this thesis there are a number of terms and abbreviations used throughout, many of which use similar terms for distinct concepts. Many of these terms are identified and discussed within the literature (chapter 2), however some are relatively unique to this document. This section provides some brief definitions for many terms used throughout this document. In no particular order these are:

Aliasing An effect whereby two signals with differing frequencies can appear to be indistinguishable when improperly sampled [3]. Usually occurring if the signal is sampled above the Nyquist Frequency[4]

Nyquist Frequency The maximum frequency at which a signal may be sampled given the original sampling rate, beyond which aliasing will occur. The nyquist frequency is generally defined as half of the sampling rate [4].

Bioimpedance A measure of body composition based on levels of tissue impedance, or resistivity.

Mastication The act of chewing to process food with the teeth in preparation for swallowing.

Deglutition The process of swallowing of a bolus of food.

Bolus A mixture of food particles and saliva formed during mastication of food, in preparation for swallowing.

HCI Human Computer Interactions

Physiological Sensing Refers to measurement of signals related to physiological processes of the body.

Epidermal Electronics A class of electronics systems with a similar level of thickness, elasticity, and flexibility equivalent to the epidermis; the outer non-sensitive layer of the skin.

EMG Electromyography, refers to the measurement of bioelectrical activity of the muscles. This measurement technique is used extensively throughout the research reported here and is the main physiological sensing technique focused upon.

EMG Burst A period of EMG signal from the onset to termination of EMG activity related to a burst of muscle activity [5].

Chew Burst An EMG burst related to a single chew action.

Swallow Burst An EMG burst related to a single swallow action.

Chew Cycle A period of EMG signal capturing the entirety of a single chew, from the onset of EMG burst until the onset of the next burst [6].

Eating Event An eating event defined for the purpose of this document as a period of EMG activity predicted by a classification model as being part of a chew or swallow burst, and consisting of an onset and termination time-stamps. Closely correlated to EMG bursts, however they reflect the *predicted* onset and termination.

Chew Sequence Chew Sequences are defined in this document as a continuous sequence of chewing events. The onset and termination of these sequences are determined here by a significant period between the termination of a chewing event and the onset of the next.

Machine Learning Algorithm Abbreviations

A number of abbreviations are also used to refer to machine learning algorithms within this document. These algorithms are discussed in chapter 2, but this section briefly outlines some of these:

SVC Support Vector Classifier machine learning algorithm.

lSVC Support Vector Classifier algorithm using a linear kernel. Primarily for identifying linear relationships in data.

DT Decision Tree classifier algorithm.

RF Random Forest classifier algorithm.

ET Extra Trees classifier algorithm.

LDA Linear Discriminant Analysis classifier algorithm.

MLP Multi-layer Perceptron classifier algorithm.

Abbreviations are also used to refer to many features extracted for use with these algorithms, but are not defined here. A full list of features and feature equations is given in table 2.2.

Chapter 1

Introduction

Overweight and obesity is currently recognised as one of the leading health threats worldwide [7], and high BMI is widely acknowledged as contributing to a number of health risks; primarily cardiovascular disease and diabetes, but also including an increased risk of kidney disease or some cancers, amongst other conditions [1] [2]. With increasing trends in high BMI and the prevalence of obesity, it has been considered a global epidemic by the Worldwide Health Organisation since 1997 [8].

A pooled analysis 2416 population based studies by an NCD Risk Factor Collaboration [7] analysed worldwide trends in BMI between 1975-2016 amongst over 128 million children, adolescents, and adults. The findings of this analysis demonstrated a global increase in the prevalence of obesity by 4.9% in children and adolescent girls and 6.9% in boys during this time period. Although they state that the rate of increase has plateaued in high income countries, they also identified accelerated trends in increasing BMI in parts of Asia [7]. Furthermore, although the rate of BMI increase has reduced significantly in wealthier countries, it remains at a high level with the average overweight rate for European countries converging at 77% for females and 82% for males [9].

The prevalence of high BMI is considered a major problem and a risk factor for many weight related disorders, and contributed to an estimated 4 million deaths, and 125 million disability-adjusted life-years world-wide between 1980-2015 [10]. Of weight related deaths, cardiovascular disease was the leading cause, contributing to 70% of deaths, followed by diabetes related deaths, and then only 10% of deaths related to kidney disease or cancers

[1] U.S. Department of Health and Human Services, Health Risks of Being Overweight: `https://www.niddk.nih.gov/health-information/weight-management/health-risks-overweight`

[2] NHS overview of obesity: `https://www.nhs.uk/conditions/obesity/`

[10].

The proportional increase in weight gain compared to height in western culture is reported to have begun during the 20th century due to the incline in available dietary sugars and fats introduced to working class populations in order to improve industrial productivity [8]. However, eating function and behaviour is driven by a number of interconnected physiological and psychological processes driving the intake of food and influencing eating choices, and it is important to understand how these interact and are effected by external influences in order to understand the factors contributing to increased or sustained high levels of BMI or other health conditions.

Physiologically, eating is driven by a number of highly complex sequences of muscular activity controlling food ingestion. This includes the simultaneous activity of masseter muscles and other masticatory muscles involved in mastication, driving cycles of mandibular motion involved in breaking food into particles; movement of the tongue involved controlling food positioning and manoeuvring; and contraction of muscles to opening the oesophageal sphincter and a peristaltic wave through the oesophageal muscles to facilitate swallowing (otherwise known as deglutition) [11]. Meanwhile, the simultaneous modification of breathing patterns, and movement of the larynx and other muscles are vital during these processes to help protect the airway during eating, with many of these processes occurring in the shared Pharyngeal space, which is used for both eating and by the repository system [12, 13].

Disruption of this delicate sequence of processes can lead to severe repercussions, resulting in food retention in the oral cavity, "nasal regurgitation" [14, 13], and putting patients at risk of aspiration pneumonia, the bacterial infection of the lungs resulting from aspiration (inhalation of food) [13, 12]. Swallowing disorders, such as dysphagia, are one of the main conditions leading to such disruption, estimated to effect approximately 8% of the worlds population, with the elderly at particular risk [15]. As well as leading to aspiration pneumonia, these conditions also result in difficult or painful swallowing, "nasal regurgitation" or retention of food in the pharynx [14, 13], and resulting in patient social withdrawal and reduced self-esteem [16, 17, 14]. Furthermore, in extreme cases the disruption of these processes can result in the inability to voluntarily consume enough food to sustain life [16, 17, 14].

Although the muscular activity and other physiological processes involved in mastica-

tion and deglutition have been quite extensively studied and mapped out, the mechanisms involved in the control of eating patterns, speed, intake volume, satiation, and dietary choices are more complex and there are many possible factors that have been identified as influential. Many theories suggest that these are reciprocal and automated processes influenced by environmental conditions [18, 19, 20], such as atmospherics, music, noise, and lighting which can impact comfort and disinhibition, meal duration, and consumption volume [21].

Wansink [21] also emphasises the effect of social eating, which can influence perceived consumption norms, effect meal duration, and thus intake volume, and can be a major contributor to overeating or the development and maintenance of eating patterns associated with eating disorders [22]. The contribution of these environmental and social factors have upon intake volume and overeating is also thought to be partly related to oral exposure time [23, 24], and eating rate and thoroughness has been identified as a factor contributing to obesity [25, 26, 27, 28], diabetes [29], or even as an important component in stress management [30].

These are just some of the influences of over eating function and behaviour, and this topic is discussed in more detail in the next chapter (chapter 2). To understand and help manage unhealthy BMI or weight related or eating disorders, it is important to understand these eating processes and influencing factors fully, however, many researchers agree that further detailed research is necessary to fully understand these and their impact on eating disorders, intake volume, and BMI [22, 25, 26, 31, 28]. A principle limitation of research into eating behaviour is a reliance upon self-reported measures of weight, height, or intake [25, 26, 31, 28]. Such measures are widely considered biased and inaccurate [32, 33], for instance, a number of researchers analysing the accuracy of self-report for logging physical parameters found participants reported biased estimates of weight and height [33, 34, 35, 36], or misreported intake due to social desirability [32]. This inhibits confidence in the results of such studies and provide only limited insight into eating activity, and it is suggested here contributes to the lack of definitive conclusions regarding influences upon eating behaviour, and misdiagnosis of eating disorders or difficulty assessing patient treatment progress.

As well as a necessary tool for analysing and studying eating function and intake choices, self-report is also one of the main techniques employed in monitoring and treat-

ment of eating disorders [20] and as a part of weight loss and management programs [22]. The accuracy and reliability of tracked meals is an important part of weight management programs and treatment of weight related disorders and as such the limitations of self-reporting make clinicians reluctant to rely solely upon such a measure [37]. In addition to monitoring accuracy, behavioural therapies also rely upon adherence to monitoring, and patient self-efficacy and engagement with treatment [20]. These are areas which are difficult to ensure using traditional self-monitoring, and although there has been an increase in portable self-logging tools over recent years [38, 39, 40, 41, 42, 43], and these have been found to help ensure adherence to calorie tracking [44] and exercise logging [45], these are still reliant upon user logging and findings are conflicted, indicating for further research into methods for improving adherence and engagement.

In order to help combat the increased prevalence of obesity, there are two significant areas to resolve. Firstly it is important to gain a better understanding of the functional and behavioural processes involved in eating, and determine how to apply this understanding to the support of behaviour change for adoption of healthier eating patterns and dietary choices. Furthermore, the inherent bias and error of self-report is of particular detriment to the reliable monitoring of eating and diet, impacting studies involved in expanding our knowledge of eating [25, 26, 31, 28], or clinical weight management [22, 46].

The overarching goals of this research is to support weight management and eating behaviour change in a clinical setting, however this is far outside the current work at present. This thesis instead takes the first steps towards this goal, through investigating the use of automated sensing to aid in monitoring eating, overcoming the burden of error associated with self-report, and the application of such sensing for understanding eating function and disorders.

1.1 Related Work and Challenges

Wearable sensors and physiological sensing of eating processes is a promising research area ideally suited to the development of technology for reducing the inherent limitations of typical monitoring techniques which limit treatment of abnormal eating and hold back research into the complexities of eating function.

Physiological sensing refers to the measurement of signals from the human body that

capture patterns that reflect physiological responses and has applications within many fields of research or clinical study. These often involve measurement of bio-electrical activity related to the function of the heart (Electrocardiography), targeted muscle activity (Electromyography), or of neural activity related to processes of the brain (Electroencephalography). Applications using these techniques are principally medical in nature, involving the diagnosis, evaluation, and monitoring of heart conditions, neuromuscular diseases, or neurological conditions such as epilepsy, or strokes [47]. However, there is also a trend towards the use of physiological signals for the purpose of a human-computer interaction. In particular, Electroencephalography and Electromyography signals are used for the control of wheelchairs [48, 49], mobile devices [50, 51], for other assistive technologies [52], or for rehabilitation support [53, 54]. Computer games using commercial physiological sensors are also becoming more popular for the enhancement of user experience by varying game difficulty implicitly or via explicit control of game mechanics [55, 56].

Electromyography (EMG), in particular, has been used in the research and evaluation of eating function and processes. For instance, considerable research has been carried out using EMG to assess the muscles involved in mastication and deglutition [57] and the development of characteristic eating patterns in early life [5]. EMG has also been used to asses textural differences between food [58, 59]. Most significantly however, EMG has been researched for use in the evaluation of dental performance and its impact upon mastication and intake [6, 60], and has been suggested as an inexpensive and easy alternative for the evaluation and monitoring of swallowing disorders; permitting fast initial screening and eliminating the need for further evaluation where unnecessary [61, 62]. EMG has also been demonstrated for the purpose of supporting rehabilitation exercise through the use of biofeedback [63, 64].

While Electromyography has a proven background for the study and evaluation of eating, there is a lack of research into the development of complete electromyographic systems for monitoring of eating. However, it is suggested here that sensing techniques such as EMG are ideal for automated logging of eating behaviour and related information, and are be useful for studying influences upon eating behaviour, or for clinical monitoring and treatment of eating disorders. However, EMG systems used in eating related research or eating disorder evaluation typically consist of immobile or obtrusive equipment which make them unsuited to long term monitoring or monitoring outside of clinical or research

environments without the use of alternative wearable sensing modalities [62].

A number of wearable sensing solutions have also been proposed as an alternative to traditional monitoring, involving a range of different sensing technologies. These include the use of gyroscopes and accelerometers to detect hand and head motions related to eating [65, 66], in ear or throat worn microphones for the detection of food sounds for the detection of eating or assessment of food texture [67, 68], through use of strain sensors to detect surface skin motion related to chewing [69], or through multi-sensor combinations of these [70, 71, 72].

While these systems all attempt to resolve the error inherent in self-reporting and overcome the limitations of bulky and immobile sensing equipment, they still require use of specialist equipment, and do not offer solutions for assessment of signals from small, exposed, and flexible areas of the body. Areas which are vital for assessing eating function [73]. However, these demonstrate the potential of wearable solutions for mobile monitoring of eating parameters. Furthermore, new sensing modalities, such as the ultra-light, robust and flexible "Epidermal Electronics" [74], make wearable solutions using proven sensing techniques such as EMG more viable for mobile and continuous sensing. In conjunction with automated processing techniques, such modalities make such sensing ideal for the study of eating function or as an adjunct for clinical behaviour change or disorder treatment. However there are a number of questions that still require addressing before this end goal can be made a reality.

1.2 Research Questions and Aims

The motivations and background given thus far highlight the limitations of traditional clinical and research techniques for monitoring of eating function, dietary intake, and the relationships between eating and obesity. As well as indicating the potential of automated sensing solutions as a viable alternative to traditional monitoring methods. As such, the research aims of the work carried out within this thesis can be defined: *To sense and measure eating function to remove burden and error inherent in self-report, and to demonstrate how this can be applied to improve our understanding of the processes of eating.*

1.2.1 Research Questions

In outlining the background and motivations of this work a number of research questions became apparent that must be answered in order to work towards the overall goals of this research and meet the specific aims of this thesis. These are:

1. How can physiological sensing be used for the accurate sensing of chewing and swallowing?

Firstly, in the background in this chapter physiological sensing and wearable sensors are proposed as a viable and potentially accurate alternative to self-monitoring of eating information. However, while this chapter outlines a number of such approaches, these technologies and the associated research all have their own limitations, discussed in detail in chapter 2, which prompts further research regarding the best approach and alternative techniques for accurate sensing and processing techniques for the detection of chewing and swallowing. This question is answered throughout this thesis, with chapter 2 discussing the limitations of current research and potential areas to pursue, and chapter 3, chapter 4, and chapter 5 investigating new techniques for the detection of chewing and swallowing using Electromyography and classification.

2. How can automated eating detection be used to detect eating characteristics and food content?

As described in the motivation section, there are a number of complex inter-connected processes and external influences associated which control and impact eating function and decisions. In order to understand these and properly leverage them to support weight management or influence eating, it is important to detect as much additional information relating to eating beyond just chewing and swallowing. For instance dietary content and eating patterns are considered important components contributing to high BMI or obesity [22, 25, 26, 27, 28]. A detailed discussion of these factors is given in chapter 2, while chapter 4 and chapter 5 begin to investigate methods for detecting such information: specifically the detection of food types and eating speed, respectively.

3. How can sensed eating data and characteristics be applied for studying eating behaviour function and behaviour, and for motivating eating change?

Continuing on from research question 2, the detection of eating, eating patterns, and ingested food type are all important parts of improving our understanding of the complexities of eating function, and have potential for manipulating eating and affecting behaviour change towards healthier eating behaviour. The final research question seeks to answer how detected eating information might be applied in this way. In answering this question chapter 2 details many measurable parameters of eating identified in the literature and how they influence intake and BMI, then chapter 3 presents the use of swallow biofeedback for encouraging swallow training, and chapter 5 presents a means for monitoring and studying eating moderation in response to feedback.

1.3 Scope

The work within this thesis focuses upon the use of physiological sensing for the purpose of automated eating activity detection, extraction of other information regarding eating and dietary content, and the provision of health related biofeedback. Physiological sensing refers to the measurement of signals relating to any physiological process within the body, for the work carried out here, bioelectrical signals related to the neuromuscular activity of skeletal muscles are targeted via Electromyography. Electromyography of face and neck muscles may provide information regarding facial expressions, or eating behaviour such as food mastication (chewing) or deglutition (swallowing), which can be classified for the purpose of driving biofeedback. Biofeedback involves the provision of feedback (often visual or auditory) regarding a biological process, for the purpose of improving voluntary control over the process.

1.4 Contributions

In meeting the aims of this thesis and answering the research question a number of major and minor contributions have been made to the state of the research surrounding eating detection technology and for the study of eating function. A full discussion of these contributions is given in chapter 6, but in brief the contributions of this work were as follows.

The two main contributions of this thesis can be outlined as:

1. The development of techniques for chew and swallow sensing and more accurate detection of eating

2. Improving the understanding of eating processes moderation in response to feedback

In addition to these, a number of minor contributions were also made as part of the major contributions, or in their own right:

- The development of more accurate classifier techniques for chew and swallow detection
- Improving the understanding of classifier techniques for chew and swallow classification
- Development of techniques for more accurate classification of food type
- Improving the understanding of techniques to classify food type
- The design and evaluation of prototype systems for the study and investigation of eating function
- Summary and discussion of the literature surrounding the physiological parameters and clinical applications of sensing of muscles related to eating, for clinical and research purposes.
- The collection of proprietary data sets that are retained and available for use in research on request

1.5 Thesis Structure

Excluding this introduction, there are 5 major chapters within this thesis. These consist of the Literature chapter, chapters reporting the findings of three major studies involved in this research, and a chapter discussing the findings of the research and conclusions. A summary of each chapter follows:

Chapter 2 provides a review of the literature surrounding this research, within three major topics of discussion. Firstly, eating behaviour and physiological function is discussed, and limitations of current monitoring approaches and treatment of disorders identified. The use of physiological sensing and EMG in the literature, for

eating evaluation and detection, is then considered. Finally, possible consideration regarding EMG measurement of muscles related to eating, and signal processing and classification, are discussed. This includes a review of the literature surrounding the use of Electromyography for sensing of muscle activity involved in chewing, swallowing, and other facial motion, in the context of eating and clinical research, summarised in table 2.1.

Chapter 3 presents findings of the first major study in this research, using Electromyography for the detection and classification of swallowing, and to drive game-based feedback. The first part of this study involves the development and evaluation of a swallow detection algorithm. Classification algorithms and feature selection are then investigated for classification of swallow types. Finally, game-based feedback was developed for the purpose of engaging users in swallowing practice exercises and a user-evaluation conducted. The findings of this chapter demonstrate the viability of discreet modalities of EMG for physiological sensing of eating and the potential of physiological sensing for driving feedback towards swallow exercise.

Chapter 4 builds upon prior work to investigate the use of classification algorithms for the purpose of eating detection and the detection of food. The chapter demonstrates a classification technique for the detection of chewing and swallowing using Electromyography and support vector algorithms, capable of detecting chewing with an accuracy of 94% and swallowing with an accuracy of 87%. A new approach for the detection of food content is then proposed, based on EMG and sensed chewing and swallowing and a new feature set, amalgamating data relating to chewing and swallowing derived through EMG sensing. An evaluation of these different techniques is then carried out. This evaluation provides enriched understanding of the processes involved in food classification, and the findings demonstrated superior accuracy for the newly proposed technique, with an accuracy of 99.1% accuracy when distinguishing between 3 solid foods types.

Chapter 5 presents the findings of the final major study in this research. The classification techniques developed thus far are adapted for the purpose of real-time chewing detection, to study and understand eating behaviour. In this chapter, a prototype system is presented for in depth monitoring of chewing function using Electromyo-

graphy and automated chew detection. This system is used to study the processes involved in eating moderation in response to haptic feedback regarding eating speed. The findings of this study reveal a positive correlation between the use of feedback and chewing rate moderation along with details of the processes of eating and their response to moderation, and highlight the potential of EMG driven feedback for encouraging eating behaviour change.

Chapter 6 is the final major chapter of the thesis. This chapter consists of a review of the three major studies conducted as part of this research, and discusses the findings in the context of this thesis and the overarching research goals. The conclusion chapter also details the major contributions of this work along with implications and directions for future research for research, improving our understanding of eating processes, and potential for clinical application.

The overall structure of this thesis may be seen in figure 1.1. Excluding the Introduction and Conclusion chapters, there are 5 major chapters within this thesis. The chapters reporting major studies involved in this research are highlighted, and the contribution of each of these chapters to answering the three main research questions (summarised in the diagram)

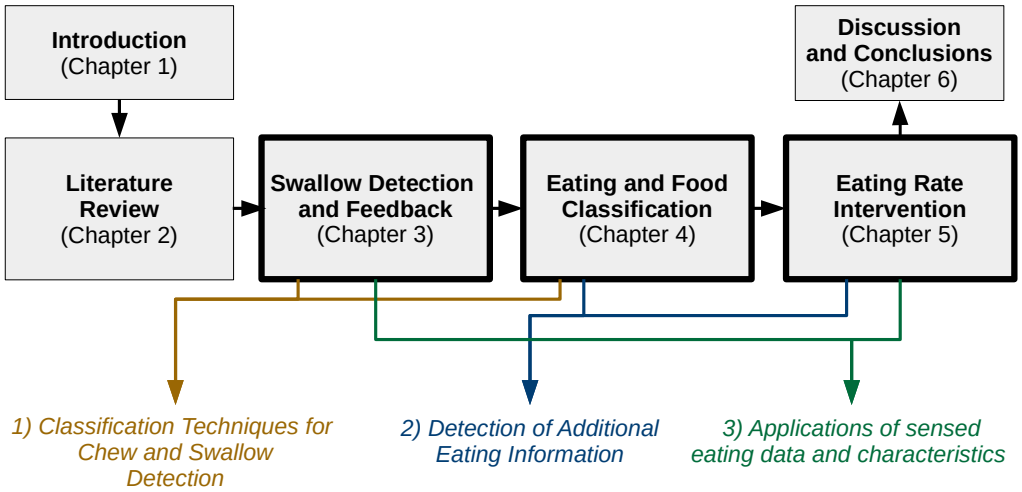

Figure 1.1: Summary of thesis structure. Main chapters are highlighted, and chapters answering respective research questions are indicated, with a summarised form of each of these questions.

1.6 Collaborations and Publications

Some of the work reported in this thesis was partially the result of collaboration with the Yeo Research Group [75] working out of Virginia Commonwealth University. Specifically, the study reported in chapter 3 was conducted as a part of this collaboration permitting use of the "epidermal" electrode sensors reported in chapter 3, which is the main focus of the collaborating researchers. Due to proprietary restrictions with this technology, the members of the collaborating research group conducted initial data collection and provided the data for use by myself. I was solely responsible for the development of the swallow detection algorithm and feedback interface involved in this study, although due to equipment restrictions the collaborating researchers also aided in testing the feedback. The user study was also conducted, in part, by members of this group. During this analysis, the data collection protocol and interview questions were formulated by myself, but the protocols and interviews were conducted by members of the group. Video footage of these sessions was recorded, and all analysis of the user analysis and interviews carried out by myself.

In addition to the work reported in this thesis, this study resulted in a number of publications. A list of the publications and description of author contributions follows:

1. Yongkuk Lee, Benjamin Nicholls, Dong Sup Lee, Yanfei Chen, Youngjae Chun, Chee Siang Ang, and Woon-Hong Yeo. "Soft Electronics Enabled Ergonomic Human-Computer Interaction for Swallowing Training". In: *Scientific Reports* 7 (Apr. 2017), p. 46697

2. B. Nicholls, C. S. Ang, C. Efstratiou, Yongkuk Lee, and W. H. Yeo. "Swallowing Detection for Game Control: Using Skin-like Electronics to Support People with Dysphagia". In: *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. Mar. 2017, pp. 413–418. DOI: 10.1109/PERCOMW.2017.7917598

Publication **1.** [1] reported the results of the study detailed in chapter 3, as well as additional comparison of the functional performance of the epidermal sensors used in chapter 3 with standard rigid surface electrodes. In this paper the reported swallow classification algorithm and the feedback interface were developed by myself, *B. Nicholls*,

as described above, with the aid of research collaborators *Y. Lee*, *D. Sup Lee*, *Y. Chen*, and *Y Chun*, under the supervision of *W.H. Yeo*, for the collection of data and to conduct a user study. These authors were also responsible for carrying out and reporting the findings of functional comparison of sensor types. Finally, *C.S Ang* helped guide the development of the user study protocol, and analysis of data by myself, and contributed to the paper. The paper was written jointly by all involved, with authors responsible for providing detail regarding their respective responsibilities in the research.

Publication **2.** [2] similarly reported the development of the swallowing classification algorithm and user study results reported in chapter 3, with an emphasis on these components of the research and without the comparison of sensor types reported Publication **1.**. The work involved in the study was distributed as described above. For the contribution to this publication, *B. Nicholls* was the lead author for the paper, guided by *C.S Ang*, and with a significant contribution in review and rewriting by *C. Efstratiou*. In this publication *W.H. Yeo* and *Y. Lee* also contributed to the review of the paper, providing context regarding the epidermal sensors used in the study.

Chapter 2

Literature Review

The main aim of this thesis is to explore the use of physiological sensing for monitoring of eating behaviour and to drive health related feedback. This chapter provides a review of relevant literature to reinforce the motivations of this research and provide a theoretical and practical background regarding the behavioural, functional, and physiological processes involved in feeding and potential abnormalities, human-physiological sensing, and its application for the automated tracking of eating. To this end, this chapter is divided into three main sections: Feeding Anatomy and Physiological Processes, Physiological Sensing and Technology for Automated Feeding Detection, Support of Rehabilitation and Health-Related Change, and Considerations for EMG Measurement and Intake Classification.

Figure 2.1 shows an overview of the internal structure of, and connections between, these sections. Section 2.1 discusses the anatomy and physiological processes of feeding, influences upon our eating behaviour, the causes of potential physiological, functional, or behavioural abnormalities, and limitations of typical treatment approaches. In addition to the use of biofeedback for rehabilitation of physical disorders, or mobile technology for the support of behaviour change type interventions. Section 2.2 then discusses physiological sensing for detection of eating behaviour, wearable sensing solutions, Electromyography for the evaluation of eating and physiological abnormalities and detection of eating and other information related to eating, and health-related and game applications of such eating technology. Finally, section 2.3 brings together many of these topics and introduces new literature to provide an overview of areas which should be considered for EMG measurement and classification.

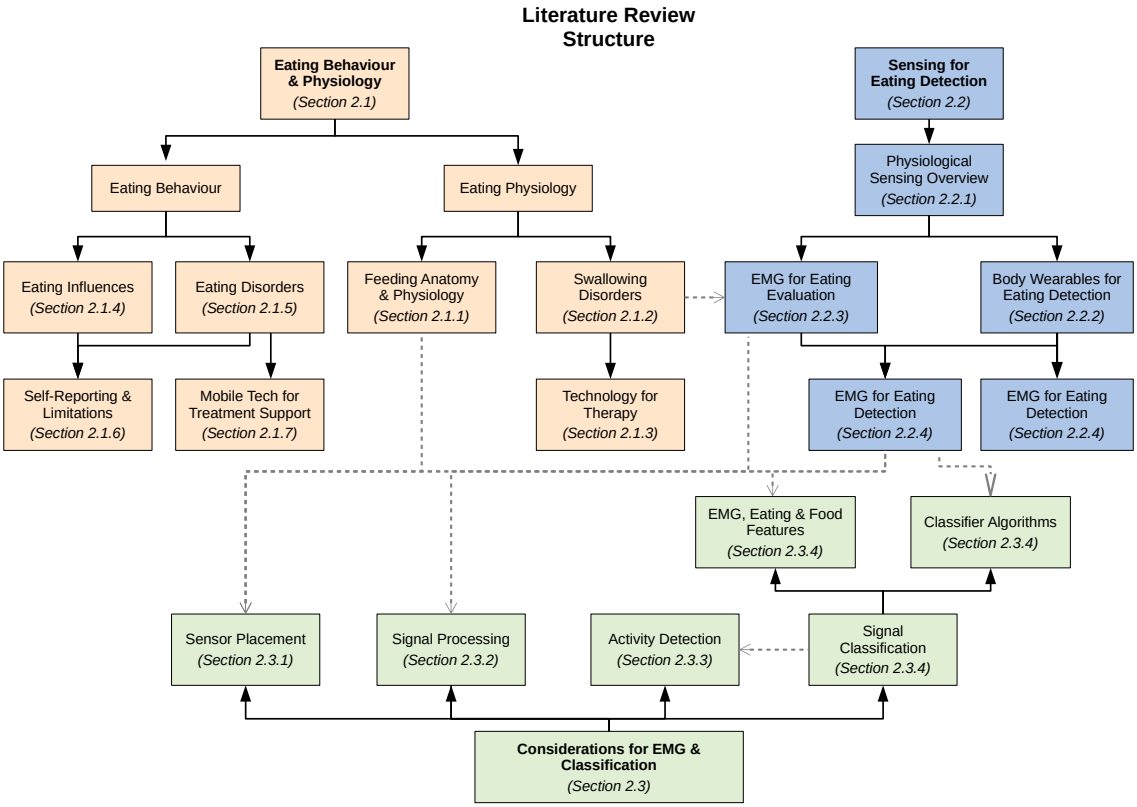

Figure 2.1: Overview of the literature review structure. Indicates the three main section, coloured separately: Feeding Anatomy and Physiological Processes, Physiological Sensing and Technology for Automated Feeding Detection, Support of Rehabilitation and Health-Related Change, and Considerations for EMG Measurement and Intake Classification. Shown are the internal structure of the main sections and the inter-connections between these topics.

2.1 Behaviour and Physiology of Feeding

In this section eating physiology and behaviour are discussed, with an emphasis upon the current understanding of eating and influencing factors, and the monitoring and treatment of behavioural and physiological disorders. In this section, the anatomy and physiological processes involved in feeding are described in Section 2.1.1, before discussing swallowing impairments, including typical techniques and limitations of swallow disorder treatment, in section 2.1.2. Finally, section 2.1.3 provides a discussion of feedback type technology in support rehabilitation of physical disorders such as these.

The behaviour of eating and possible behavioural or functional abnormalities are then discussed. Section 2.1.4 describes the development of eating disorders and typical treatment approaches and associated limitations, followed by a review of potential influences upon eating behaviour and the effect on health, in section 2.1.5. Section 2.1.6 discusses

limitations of self-reporting, a technique used in numerous studies of eating behaviour or disorders, discussed throughout this section. Finally, section 2.1.7 discusses the use of technology and mobile devices for overcoming these issues, and their use in interventions of healthcare.

2.1.1 Feeding Anatomy and Physiological Processes

Human feeding relates to the mastication (chewing) of food to break it into a consumable bolus, followed by the deglutition (swallowing) of the bolus. While eating is a predominantly voluntary behaviour, many of the physiological processes involved in ingestion of food are automatic. Below, the anatomy and physiological processes of different eating stages and airway protection are discussed. Figure 2.2, adapted from [76], gives an anatomical overview of the face and neck, indicating muscles related to mastication and swallowing.

Overview of Feeding Processes

The two main models of feeding, as described by Matsuo and Palmer [13], are the Four Stage model and the Process Model of Feeding. In the four stage model feeding is separated into the oral preparatory and propulsive, pharyngeal, and esophageal stages of feeding. The oral preparatory stage refers to holding of liquid bolus within the floor of the mouth or upon the tongue, with the oral cavity sealed to contain the bolus and prevent leakage into the oropharynx. During the oral propulsive stage, the tongue moves upwards removing the seal and transporting the bolus into the pharynx. However, this does not accurately represent the consumption of solids, as there is considerable overlap between these two stages and the pharyngeal stage of swallowing [13]. Instead, the Process Model described for human feeding processes by [11], is considered a better representation.

In this model, the processes involved in processing and consuming food is known as the "masticatory sequence" [11]. In the oral stages of eating, "Stage I" transport occurs on food entry into the mouth and involves tongue transporting food into the posterior oral cavity and placement onto the teeth for processing. The food is broken down into smaller particles and softened by saliva via mastication: rapid and regular cycles of mandibular motion, during which the masseter muscles (and temporalis to some extent) are active, contracting to close the mandible and relaxing to permit suprahyoid muscle contraction

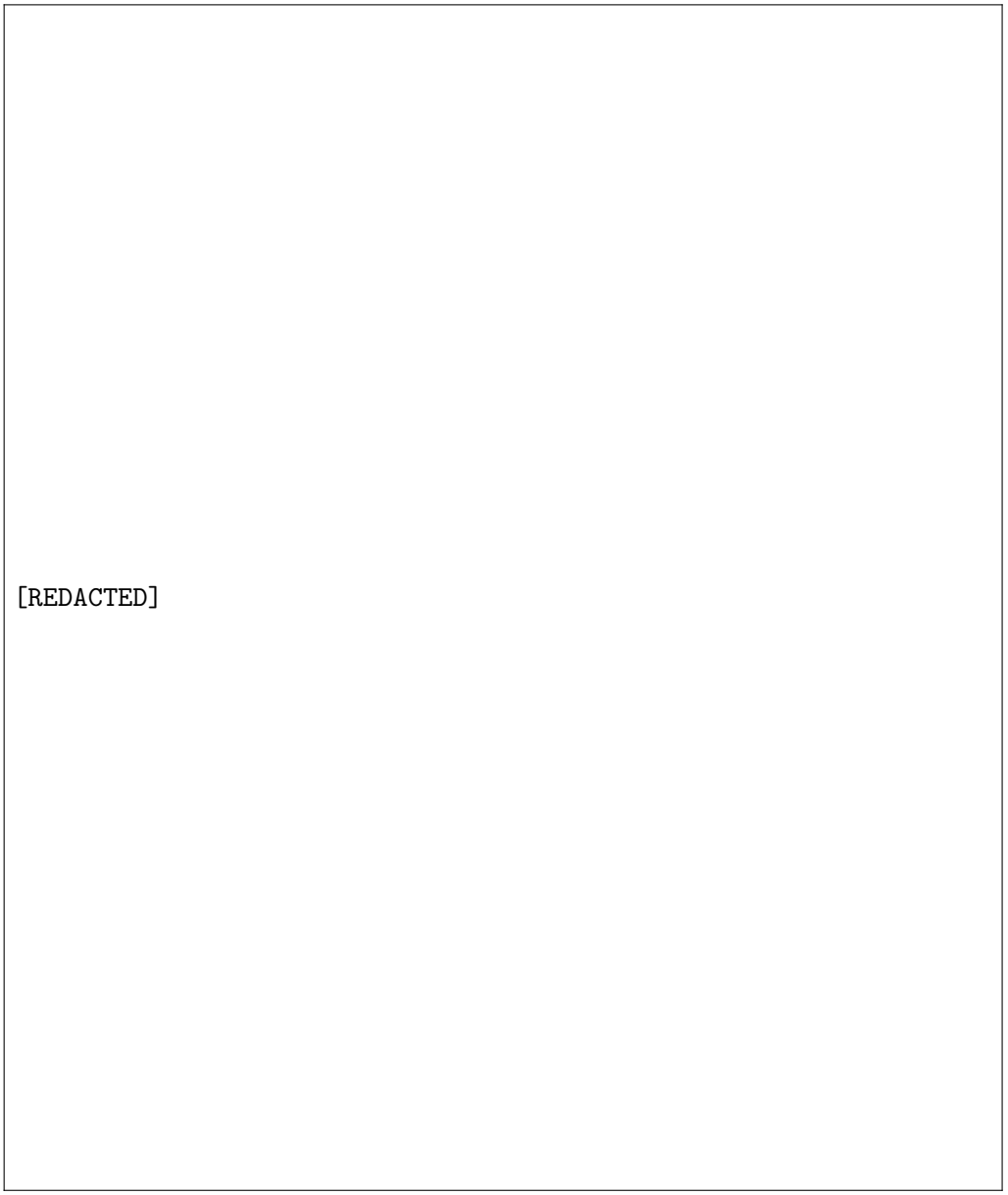

Figure 2.2: Overview of the muscles related to the processes of chewing and swallowing. Muscles related to mastication include the masseter, temporalis, and other adductor muscles of the jaw and face (upper cross-section). Muscles related to swallowing include the submental triangle (digastric and mylohyoid) and the sternohyoid muscle. Adapted from Ref. [76].

to open the jaw [11]. There are also regular motions of the tongue during mastication, helping control the position of food [13]. Mastication is followed by "Stage II" transport, during which the mandible closes and tongue moves back and increases contact with the palate to move prepared food backwards to the oropharynx ready for swallowing. This transport action can occur across multiple food processing cycles, moving more food back during each cycle of processing [13, 11]. When ingesting liquids transport occurs without separate cycles, with only a brief pause in the oral cavity [11, 13].

The masticatory sequence culminates with the Pharyngeal and Oesophageal stages of swallowing. The pharyngeal stage usually begins during the oral transport phase, and involves propulsion of the bolus through the pharynx to the oesophagus while preventing food from entering the airway [13]. During this stage the tongue retracts and the pharyngeal constrictor muscles contract to move the bolus to the upper oesophageal sphincter, which is opened to permit bolus entry via the relaxation of cricopharyngeus muscles, which normally hold the sphincter closed, and contraction of the suprahyoid and thyrohyoid muscles to open the sphincter [13]. Finally, the Oesophageal stage of swallowing involves a peristaltic wave, relaxing and tensing the oesophageal muscles to propel the bolus downwards, followed by relaxation of the lower oesophageal sphincter, normally at tension to prevent regurgitation, to allow the bolus to enter the stomach [13].

Airway Protection Mechanisms

During mastication and transport stages, the pharynx is exposed to the oral cavity and a bolus is formed on the orophyrangeal surface of the tongue, and there is potential for inhalation of food particles (known as aspiration) through the pharyngeal airway. Matsuo and Palmer [12] suggest that nasal breathing during mastication, closure of vocal folds, and bolus cohesion during transport are all important for preventing inhalation of food particles. During swallowing, the soft palate elevates to close the nasopharynx and prevent bolus regurgitation into the nasal cavity [13], and to prevent aspiration the hyoid and thyroid muscles contract to move the larynx under the base of the tongue to help protect the larynx [13]. Matsuo and Palmer [12] also suggest that a pause in respiratory cycle during swallowing, typically followed by exhalation following swallowing, also aids in airway protection.

Monitoring of these processes is of vital importance for evaluating functional per-

formance and potential impairments which lead to impairment of airway protection, or inability to consume food. The next section discusses such impairments (swallowing disorders), and their treatment.

2.1.2 Swallowing Disorders

Swallowing disorders, such as Dysphagia and Odynphagia, are associated with difficulty swallowing, painful swallowing, or other disruption of normal function, and are estimated to effect approximately 8% of the global population [15]. They can be the result of structural or functional impairment of oral and pharyngeal stages of swallowing [13, 14], and may develop following the onset of Parkinson's Disease [77, 78], other neurological conditions [79], following a stroke [80, 81, 82], as a result of treatment for cancer [83, 84, 85], or due to gastroesophageal reflux disease [86].

Symptoms and Complications

Difficulty chewing, drooling, leakage of food bolus into the pharynx due to insufficient tongue pressure, or food retention in the oral cavity are all symptoms characteristic of Oral phase abnormalities. In pharyngeal phase disorders, impaired transport of food the pharynx or incomplete transfer of food to the oesophagus, can instead result in food retention within the pharynx or "nasal regurgitation" [14, 13]. Such conditions are also reported to reduce quality of life, with patients feeling embarrassed to eat during social meals, withdrawing socially, or suffering from reduced self-esteem due to difficulty eating and help required during eating [16, 17, 14]. Moreover, impairment of swallowing or regurgitation of food can occur to the extent that patients are incapable of voluntarily consuming enough food to sustain life[16, 17, 14].

The main danger of swallowing disorders is impaired airway protection. This can lead to two main complications: laryngeal penetration and aspiration [13]. Laryngeal penetration refers to the passage of food from the mouth or regurgitated from the oesophagus into the larynx above the vocal cords, while aspiration is the inhalation of food which then passes through the vocal cords themselves [13]. Figure 2.3, reproduced from [13], shows Videoflouroscopy capturing the flow of Barium laced food entering the airway during aspiration and laryngeal penetration. Section 2.1.1 describes the airway protection mechanisms involved during eating, and impairments characteristic of swallowing disorder

patients, resulting in increased chance of food particle inhalation (aspiration) or laryngeal penetration. These usually result in coughing and choking, and aspiration can also lead to airway obstruction or aspiration pneumonia [13, 12].

Swallow Evaluation and Disorder Screening

The development of swallowing disorders can vary over time, patients developing problems up to 6 month following a stroke or other causal factor [87], making then difficult to recognise and diagnose. Screening, diagnosis and clinical assessment techniques are also reported to vary highly [82], leading to imprecise diagnosis [87].

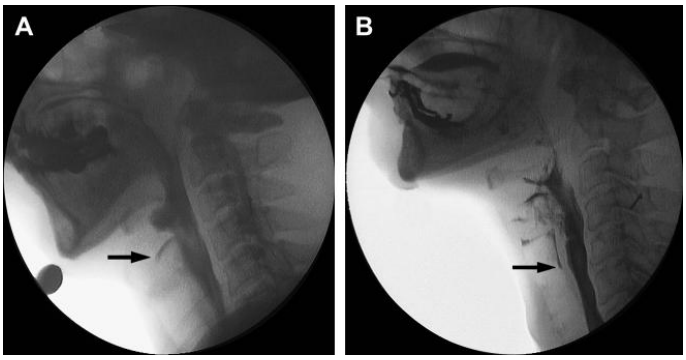

Figure 2.3: Example of Videoflouroscopy during swallowing, showing laryngeal penetration (**A**) and aspiration (**B**) in dysphagic individuals. Arrows show Barium flow in the airway. Reproduced from [13]

Currently however, Videoflouroscopy is recognised as the "gold-standard" for assessment of swallowing function during the assessment of swallowing and diagnosis of swallowing disorders or aspiration [14, 82, 87, 88]. Videoflouroscopy is an imagine procedure involving the consumption of Barium laced food and x-ray recording swallowing, permitting the evaluation of swallowing functionality (see figure 2.3) [14]. Although this technique is important for such assessment, its complex procedure, equipment expense, and the necessity of a radiological suite and multiple specialist personnel make it unsuited to non-clinical evaluation, or when patients are unconscious or immobile [89]. The procedure is also unsuited for evaluation of patients who are bed-bound, or who are unable to consume food [90]. Repeated exposure to radiation during assessment of ongoing conditions has also been highlighted as a potential danger [90, 89].

Alternative procedures for evaluating swallow function include Endoscopy and surface Electromyography. Endoscopy involves passing a fiberoptic endoscope through the nasal cavity and through the nasal floor, to permit observation and evaluation of swallowing

[89]. Endoscopy is a fast and cheap alternative, suited for patients who are bed-bound or unable to eat [90], and has been reported as a safer procedure [91], which is potentially more sensitive for aspiration detection [91, 92]. However, it still requires specialist interpretation, is invasive, and has been reported as less useful for assessing oral and oesophageal phases of swallowing [92]. Surface Electromyography (EMG), on the other hand, involves the measurement of bioelectrical signals related to activity of the muscles [47]. EMG has been recommended as a fast an inexpensive technique for swallow assessment [61], although from the review of the literature it does not appear widely used, and current solutions still requires bulky equipment and indiscreet sensor placement as can be seen in figure 2.12, later in this chapter, reproduced from [62]. A more detailed discussion of EMG for the evaluation of swallowing and swallowing function is given in section 2.2.3.

Swallow Disorder Treatment

Treatment following diagnosis also varies considerably, and is specific to the underlying causes [14, 93]. Reviews of medical treatment, such as non-oral feeding and medication, warn that they are not ideal for long term recovery [81], and behavioural therapies are instead recommended when possible [14]. Alongside these, personalised dietary modification diets, such as specific food consistencies, are prescribed depending on the underlying cause of the disorder [14].

Swallowing therapies involve compensatory manoeuvres, or indirect and direct swallowing exercises [14]. Compensatory techniques are designed to help swallow food [94, 14], and include the "chin-tuck" and "double swallow", to help patients with mild cases to continue oral feeding, or "chin-down" and "rotated-head" positions to help overcome tongue weakness [95]. Swallow exercises instead focus on improving the performance of swallowing function or increasing swallow strength and include direct exercises such as the effortful swallow [63], extended swallow ("Mendelsohn Manoeuvre") [96], or the tongue hold manoeuvre [97]. Of these techniques, the effortful swallow involves swallowing with maximal effort, the extended swallow involves the patient holding the larynx at the peak of a swallow for a given time, and the tongue-hold involves swallowing while the tongue is held between the teeth [97]. Indirect exercises, such as expiratory muscle strength training [98], or head lift exercises [99], have also been described as useful for strengthening related muscles [97].

A study by Carnaby *et al.* [100] evaluated the benefit of behavioural therapies through a comparison of high intensity (daily strength training and dietary modification) and low intensity (dietary modification, advice, and compensatory strategies) behaviour interventions. They found favourable outcomes across 306 patients, with high-intensity therapy associated with a return to normal diet and swallowing functionality within 6 months. These findings were supported by a review of 59 behaviour intervention studies by Speyer *et al.* [93], who reported that the majority of studies found positive results for these types of treatments.

On the other hand, DePippo *et al.* [80] conducted a similar study evaluating different intervention intensities over a three year trial of 115 patients, and reported finding no significant difference between interventions of differing intensity levels. The findings of this study demonstrated that patients were able to manage their own conditions with minimal guidance and instruction, or daily swallowing practice. A recent review of the literature by Foley *et al.* [81], also report a lack of evidence for behavioural therapies and a need for further research investigating their effectiveness.

Evaluation and Treatment Limitations

Quality of life and health care questionnaire based studies by Ekberg *et al.* [17] and McHorney *et al.* [16] have reported the impact of swallowing disorder on patient quality of life, along with a concerning degree of under-diagnosis or lack of treatment. This is in part due to a lack of standardised swallowing disorder screening conformity, agreed by many to be an issue [82, 88, 14, 81]. However, these authors also found that patients believed that their symptoms were untreatable and they felt embarrassment discussing them. To combat this, Ekberg *et al.* recommend efforts be made to increase recognition of swallowing disorders, symptoms, and treatment options amongst clinicians and patients. Smithard *et al.* [87] similarly highlights a need for more precise assessment and monitoring techniques over the long term. These limitations extend to the treatment of swallowing disorders through behavioural therapies.

There is a clear need for more in depth studies to better understand swallowing disorders, the benefits of different treatments and how the conditions evolve over time. However, this is difficult with current equipment which is not suited to ongoing evaluation due to expense, obtrusiveness, or repeated exposure to radiation. EMG instead provides

an easy to use and unobtrusive solution to these issues, but further research is needed to evaluate the effectiveness of its, develop systems using equipment that is more portable and discreet (discussed further in section 2.2.3).

2.1.3 Feedback Supported Rehabilitation Therapy

Rehabilitation therapy involved in regaining voluntary control of muscles and other functions is a process which varies considerably depending on the underlying cause and severity of impairment. Many patients undergoing rehabilitation therapy lack motivation, engagement, or have difficulty identifying progress and establishing self-efficacy [101]. Technology may be useful for health related feedback and assistive systems (discussed further in section 2.2), and two approaches which have particular significance for rehabilitation therapy, and for exercises related to swallowing rehabilitation in particular, are discussed here. These include biofeedback, and the use of simulated virtual and game environments to enhance such biofeedback therapy. The benefits of biofeedback and game environments for improving patient skill, motivation and self-efficacy are discussed below.

Biofeedback Therapy

Human-computer Interactive technology has a history of use in physical therapy, through Biofeedback. Biofeedback for therapy has basis within the Control Theory of behaviour [102], which proposes that human behaviour is based upon feedback loops, and this is modified to minimise discrepancies between an individuals goal state against and their current state [103]. In this way biofeedback provides some form of feedback regarding an individuals ability to achieve a physiological function goal, allowing them to modify their efforts accordingly, regaining function of impaired capacity, or relieving symptoms of related illnesses [102].

Applications of biofeedback include obtaining control over the symptoms of headaches, asthma, epilepsy, gastrointestinal disorders or even cardiovascular disorders [102]. There has also been research demonstrating the beneficial qualities of biofeedback for rehabilitation following a stroke [104, 105, 106, 107].

Biofeedback Therapy for Swallowing Disorder Treatment

More closely related to the work presented thus far, however, is the use of biofeedback therapy to support swallow training and rehabilitation as part of dysphagia treatment. Huckabee and Cannito [63] evaluated the change in swallowing performance and diet level tolerance of 10 patients suffering from dysphagia following a stroke, after completing 1 week of biofeedback sessions. A similar study was conducted by Crary *et al.* [64], and they reported similar findings for a retrospective analysis of 45 dysphagia patients. Other studies have also evaluated the use of accelerometry based biofeedback therapy for patients with poor laryngeal elevation [108] and surface EMG based biofeedback as an adjunct to normal swallowing disorder therapy [109]. The authors of all these papers reported a functional improvement in oral intake over the course of the therapy and conclude that biofeedback is a useful method for supporting swallow rehabilitation. However, these all involved case studies of a relatively small number of patients and did not compare biofeedback therapy with traditional therapies.

A more recent study by Carnaby-Mann and Crary [110] attempted to resolve procedural issues of previous research, proposing a new standardised biofeedback based therapy and reporting its effectiveness through the comparison of case studies from 24 patients; 16 of whom took part in traditional therapy with biofeedback and 8 who received the new standardised treatment protocol. All patients suffered from chronic dysphagia, and biofeedback therapy patients all failed to respond to traditional therapy prior to biofeedback. Traditional biofeedback therapy focused upon using the Mendelsohn Manoeuvre and exceeding an EMG activity threshold, encouraged home practice, and assessed progress based on their capacity to meet the EMG threshold; while the new standardised approach did not encourage home practice, and assessed improvement based upon clinical signs of aspiration. The authors reported that patients in the standardised group demonstrated significant physiological and functional swallow performance, and were much more likely to demonstrate improvement than the traditional therapy. They conclude that the standardised approach of biofeedback was superior to traditional treatment, however they also note that further controlled trials would be necessary to support their findings.

Virtual Environments and Gameplay to Support Rehabilitation

When relating to physical activity of behaviour, game and virtual environments can be used as an extension of biofeedback type techniques; the interaction between user and a virtual environment providing feedback regarding user activity. Biddiss and Irwin [111] reviewed 12 studies examining the use of activity encouraging video games, and concluded that games are an engaging medium for encouraging light to moderate intensity activity, although they highlighted a need for long term study. The benefits of video games have also been discussed by Baranowski *et al.* [112], who described them as skill development through modelling and feedback theory, and that they encourage engagement and improve user self-efficacy regarding specific goals; key components of behaviour change theories. As such, game technology is a promising approach for ensuring engagement in the treatment of conditions which normally make use of biofeedback.

Burke *et al.* [101] discusses these factors from the perspective of stroke rehabilitation using video capture technology, virtual worlds and games. They describe the limitations of traditional stroke rehabilitation: exercises that can be difficult to focus upon, potential errors in traditional therapy, the need for one-on-one sessions to guide patients through exercises, and the need to travel for these sessions. They instead suggest webcam games as a platform for rehabilitation which provides long term motivation, and is challenging but achievable, ensuring self-efficacy and engagement (an example of a webcam game proposed by Burke *et al.* [101] is shown in figure 2.4). Supporting these results, a review by Saposnik *et al.* [113] reported that amongst 12 rehabilitation studies, all unanimously demonstrated improvement of motor function in rehabilitation using immersive and non-immersive virtual environments. A similar review of 72 therapy trials involving interaction with virtual environments by Laver *et al.* [53] supported these findings, suggesting that therapy supported by such technology in addition to usual care resulted in significant motor function improvement.

There is a clear benefit of video games from the perspective of therapy: for long-term motivation to achieve behavioural goals and as a means to track progress, increase skill, and to engage subjects and improve self-efficacy. While video games and rehabilitation are considered effective extensions of well established biofeedback techniques, the literature highlights a need for further evidence regarding their use for physical rehabilitation and

Figure 2.4: Example webcam game for supportingstroke rehabilitation exercise, developed by Burke *et al.* [101]. Reproduced from [101].

investigating their effects within this domain.

2.1.4 Eating Disorders

In addition to functional impairments resulting in abnormal swallowing function, psychological conditions can result in eating disorders. These are associated with a range of negative physical symptoms, in addition to increased mortality rate, usually due to medical complications or suicide [114]. While there has been an incline in reported cases over recent decades, Fairburn and Harrison [114] suggests that this is the result of increased awareness, more people seeking help, and a historic difficulty classifying such conditions.

All eating disorders are defined by a disturbance of eating habits or weight-control behaviour, resulting in impaired physical health or psychosocial functioning [115]. These can include Anorexia Nervosa (AN), Bulimia Nervosa (BN), Binge-Eating Disorder, and other atypical eating disorders. AN and BN are both associated with over-evaluation of body shape or weight and extreme weight-control measures, and both BN and some forms of AN are associated with compensatory behaviour (excessive exercise, fasting, or purging) [115, 116, 22]. Due to similarity between BN and AN, some suggest the only significant difference of Anorexia Nervosa is a body weight less than 85% normal weight, and amenorrhoea maintained for at least 3 months [116]. Binge Eating Disorder is similar to BN, involving binge-eating without compensatory behaviours [117], and other atypical disorders are described as disturbed eating of clinical severity, but which do not meet the

criteria of anorexia or bulimia [115].

Influences and Risk Factors

From the review of the literature, it appears that the causes or processes of eating disorders are not entirely understood, and contributing risk factors are a matter of significant debate within behavioural psychology. However, there are patterns in the distribution of these conditions which are discussed in the article by Fairburn and Harrison [114]. Of particular note, eating disorders occur predominantly amongst women in western societies, with Anorexia Nervosa mostly occurring amongst adolescents and Bulimia Nervosa in young adults. Fairburn and Harrison [114] suggests that typical onset of Anorexia Nervosa occcurs during mid-teens as a result of dietary restriction, resulting in its prevalence amongst adolescents, and suggest that such cases are short lived and only require brief interventions to treat.

General risk factors for eating disorders include gender, youth, and western culture. Socioculturally, the idealisation of thinness, and exposure to media is regarded as a principle cause of eating disorders [22]. There are a number of other factors which have been proposed in relation to the onset and maintenance of eating disorder, however Polivy and Herman [116] suggests that the most likely contributors towards eating disorders are body dissatisfaction, negative emotions, low-self esteem, and individual personality features. However, they also conclude that there is not yet enough evidence to identify any particular factors which are closely related to eating disorders, and that identifying potential factors does not help to understand the underlying mechanisms. Instead they suggest that effective treatment does not require a full understanding, but only an awareness of these contributing risk factors.

Treatment and Behavioural Therapy

Treatment of eating disorders typically includes both medicinal treatment and behavioural therapy. Reviews of treatment trials demonstrate some benefits of medication for decreasing symptoms of Bulimia Nervosa or Binge Eating disorders, but report that the findings were tentative [118, 117]. On the other hand, Cognitive Behavioural Therapy based interventions are reported as effective in treating contributing behavioural and psychological

factors associated with BN [118], and effective at reducing the number of binge days or reported binging episode, in addition to psychological symptoms [117].

Cognitive Behavioural Therapy (CBT) is considered the "gold standard" technique for treating eating disorders [20], and has been found effective for treating a range of other behavioural disorders such as depression, anger management, panic, and anxiety disorders [119]. However, Fairburn *et al.* [120] highlighted that CBT has limitations for eating disorder treatment, and that in certain patients, perfectionism, low self-esteem, mood intolerance, or interpersonal difficulties interact with eating disorder mechanisms, acting as barrier to eating behaviour change.

The principle of CBT based therapies in the treatment of eating disorders is a cooperative effort between patient and therapist to identify, evaluate, and address mechanisms related to maintaining patient eating disorders [20]. Murphy *et al.* [20] describes the stages of this form of therapy. The first stage involving engaging with patients, jointly identifying negative behaviours and behavioural goals, and introducing self-monitoring techniques. Stage two consists of reviewing progress, giving praise, and making adjustments. Stage three involves addressing processes and mechanisms maintaining patient eating disorder. The final stage involves continuing progress through follow up appointments and discontinuation of self-monitoring.

For eating disorder therapies Murphy *et al.* highlight the importance of participant engagement, understanding and self-efficacy. Self efficacy is considered a core component of Behaviour Change theories [103], and was introduced by Bandura [121] who proposed that an individuals belief in their capacity to change contributed to the progress of behaviour change. Engagement and understanding refer to participants feeling involved and in control of learning about their disorder and the behaviour change process. Self-monitoring is indicated as an important part of these factors; helping patients to track progress, encouraging self-awareness of their eating behaviour, and helping to establish conscious thought regarding behaviour that seems automatic, while establishing self-efficacy [20].

Although the act of self-reporting itself is considered an important part of behavioural therapy [20], the reliability and accuracy of self-reported measures is important for the purpose of reliable tracking and monitoring of treatment progress. However, the nature of self-reported measures mean that there is the possibility of error, or bias, particularly in the case of reporting sensitive or 'embarrassing' details. This is discussed further in

section 2.1.6.

2.1.5 Factors Influencing Eating Behaviour and Implications for Health

The processes of eating behaviour and factors influencing our decisions regarding when to eat, choice of food, and quantity of food to ingest are have been substantially researched. However, these are various difficulties related to evaluating such factors and there are numerous theories describing eating processes. As such, despite substantial research, eating behaviour is still not well understood. This section discusses some theories of eating behaviour and factors which influence the various parameters of eating choice and functional activity.

Automatic Eating and Factors Effecting Eating Behaviour and Function

Many theories of eating, such as the automatic eating theory [18] or frameworks related to Social Cognitive Theory [19], focus on the impulsive nature of feeding behaviour and function, suggesting that food intake is a highly automated, or that it involves reciprocal systems influenced by environmental factors, and that the development and perpetuation of eating disorders can be related to these. Behavioural therapies support this view, emphasising reflection upon behaviour to disrupt self-perpetuating negative thoughts and feelings [20]. Wansink [21] also supports these theories, suggesting that the eating and food environments can disrupt self-monitoring of food quantity, extend meal duration, or influence perceived consumption norms (summarised in figure 2.5, reproduced from [21]).

Wansink [21] also demonstrates how ambient environmental factors can influence disinhibition, meal duration, and overall consumption volume (see Figure 2.6, reproduced from [21]). One such ambient influence is music, which can have a significant effect on meal size and duration, demonstrated by Stroebele and Castro [122], or can influence eating rate based on tempo, as demonstrated in the study by Bajic [123]. Finally, social factors are considered to have considerable influence upon eating behaviour and food intake, and Figure 2.7, reproduced from [21], shows an example of how social eating effects meal duration and perceived consumption norms. A review of 69 studies related to social influences upon eating by Cruwys *et al.* [124], support such theories, and the authors concluded that there was strong evidence that food choice and intake were influenced by social norms.

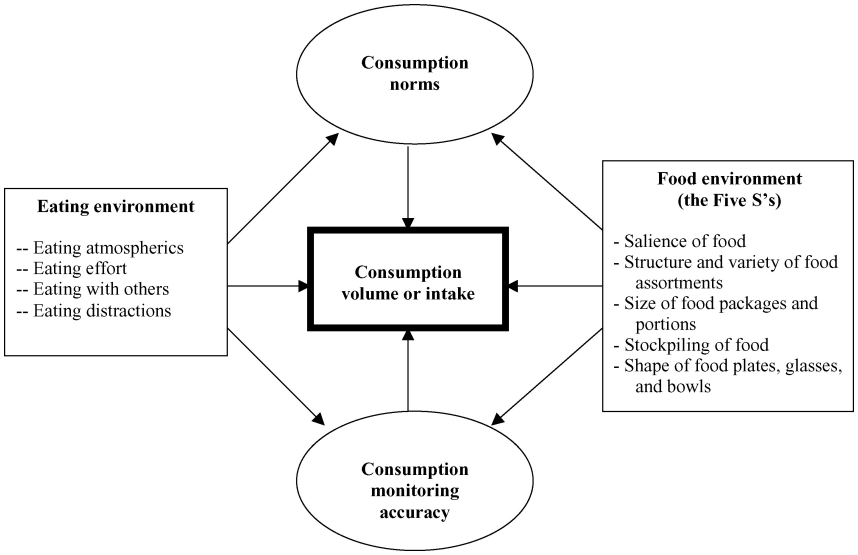

Figure 2.5: An overview of environmental factors described by Wansink [21] and how they effect perceived consumption norm, intake monitoring, and intake volume. Reproduced from [21].

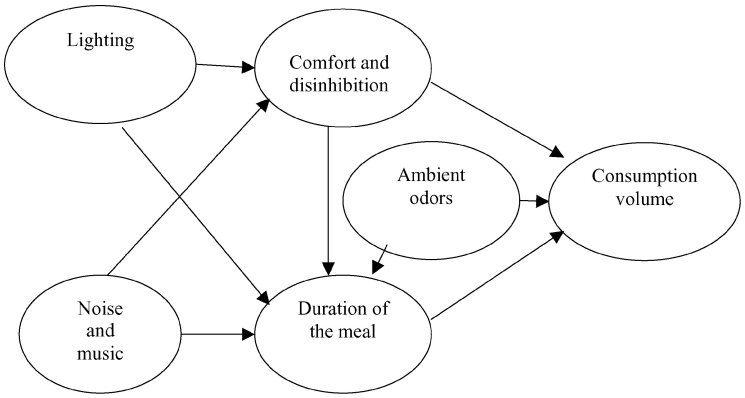

Figure 2.6: An overview of ambient environmental factors described by Wansink [21] and how they influence consumption volume through disinhibition and meal duration. Reproduced from [21].

These studies indicate that eating behaviour, particularly negative behaviours such as overeating, or attributed to eating disorders, are heavily influenced by environmental factors; with ambient distractions disrupting internal self-monitoring, or social and environmental cues influencing normal consumption norms. As such, it these factors can be appropriated to correct eating, and influence behaviour change through encouraging reflection upon eating behaviour, or to disrupt automatic eating, which is possible in the short term according to Cohen and Farley [18]. Eating disorder treatments enact such techniques, and are discussed in Section 2.1.4, as do some mobile based behaviour change interventions, discussed in Section 2.1.7.

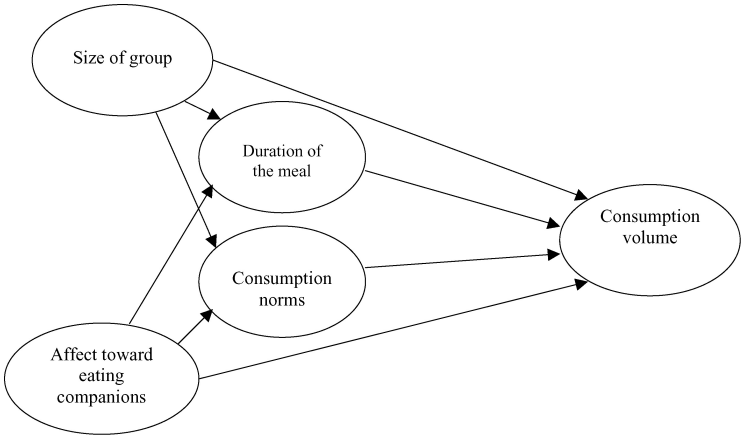

Figure 2.7: An overview of social environmental factors described by Wansink [21] and how they influence consumption volume through consumption norms and meal duration. Reproduced from [21].

Food Parameters and Their Effects Upon Eating and Satiation

Textural and taste properties of foods are also potential influences of eating behaviour. Increased viscosity of food is known to reduce intake and rate of eating [125], and in a study of 5 male (aged 29.6 ± 3.6) and 10 female (aged 25.1 ± 3.6) subjects, Forde *et al.* [24] found that oral exposure time was highly correlated to the number of bites and chews, concluding that reduced transit time in the oral cavity leads to less sensory stimulation and reduced satiation cues. A similar study into the effect of food viscosity on hunger related hormones by amongst 15 male subjects (between 18-40 years of age), conducted by Zhu *et al.* [23], found that increased food viscosity reduced hunger while increasing satiation and satiety hormones. These studies demonstrate that food texture can effect bite size and increased oral exposure, which in turn can be associated with satiation and potential intake volume; slower eating leading to higher satiation levels, and faster eating reducing satiation.

Control of Eating Rate and Effect Upon Satiation and Intake

A number of studies have explicitly investigated the effects of oral exposure on intake through manipulation of functional parameters such as eating rate. For instance, Kokkinos *et al.* [126] conducted a study on 17 male subjects (aged 29.7 ± 1.2 years) using timed eating period and a set food quantity to manipulate eating speed, and measured hunger stimulating and inhibiting hormone levels in the blood. They reported higher concentration hunger reducing hormones after a slower meal, and hypothesised that this indicates

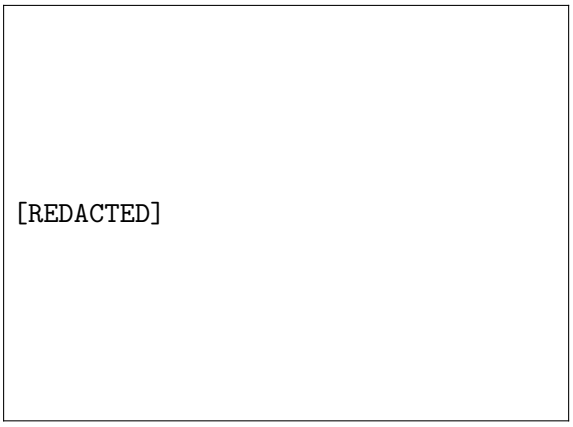

Figure 2.8: Mandometer®device used by Ioakimidis *et al.* [129] and Zandian *et al.* [128]. Shows a food weight scale and feedback device included as part of the system. Device image reproduced from [130].

eating rate as influencing factor related to overconsumption of calories. Similarly, a study by Zhu and Hollis [127], investigated the effect of controlled chewing thoroughness (chew count) amongst 18 subject, finding that increased chewing thoroughness was associated with reduced eating rate and food palatability.

A number of studies have also investigated the effect of eating rate upon food intake quantity using a "mandometer" as an automated means for analysing food intake and providing feedback based on food weight change over time (see figure 2.8). In the study by Zandian *et al.* [128], 30 linear eaters (eating at a constant rate) and 17 decelerated eaters (slowing down during the meal) took part in a number of eating sessions with intake speeds manipulated by feedback. They found that decelerated subjects demonstrated difficulty maintaining set eating speeds, and that linear eater rated satiation as higher during reduced intake rate. Ioakimidis *et al.* [129] conducted a similar study, evaluating the effect of feedback upon the eating rate of 29 linear eaters, compared with 28 eating disorder patients. They found that manipulating the eating rate of linear eaters resulted in modelling of consumption patterns identified in disorder patients. This indicates that susceptibility to external influences puts linear eaters at risk of eating disorders, but that feedback is a useful intervention tool to help model desired eating patterns [129].

Other more mobile techniques of measuring eating rate have been proposed. For instance, Jasper *et al.* [131] implemented an automated system for monitoring bite rate based upon hand motion captured by a wrist worn gyroscope, and evaluated it in lab conditions on 94 participants (62 women and 32 men, aged 19.0 ± 1.6, with a BMI of 23.04 ± 3.6) and during a "free-living" study of 99 participants (56 women and 43 men,

aged 18.5 ± 3.6). They reported that feedback reduced number of bites, but that this resulted in compensatory behaviour permitting increased intake. The authors indicate that although feedback reduces intake, further research was needed for understand the interaction of feedback, goal setting, and the effect of "real-life" eating [132].

Eating Rate and Thoroughness as an Influencing Factor of Obesity

A number of population studies have been carried out evaluating the association between eating rate, or speed of eating, and obesity, based mostly upon self-reported surveys. For example, Takayama *et al.* [25] collected data about eating habits, rate of eating, and BMI of 422 diabetes patients, and reported a significant positive correlation between fast eating rate and high BMI in male diabetes patients. A number of other studies have also reported a strong correlation between self-reported eating speed and BMI. For instance, Sasaki *et al.* [26] recorded data from 1695 18 year old Japanese women, along with a 1-month diet history recall survey, revealing a correlation between eating rate and BMI. A study of 3737 middle aged Japanese men and 1005 women, by Otsuka *et al.* [31], found a similar correlation, and also collected self-reported recall of BMI at age 20, which revealed an increase in BMI over time. Finally, Leong *et al.* [27] evaluated results of a nationwide survey of 1601 middle age New Zealand women, again report a strong positive correlation between self-reported speed of eating and higher BMI.

Such studies are not limited to population surveys of adults. Llewellyn *et al.* [28] conducted a study investigating eating rate in 254 twin children. This involved recording height and weight of children and parents, and manual extraction of eating characteristics from video footage of the children. As in other studies, the researchers found a correlation between BMI and eating speed, and reported a high degree of heritability for eating rate. Concluding that it is an example of appetitive heritability.

Although the functional effects of eating rate upon food intake and subsequent impact upon BMI and health related issues is debated, the majority of these studies suggest a positive correlation between BMI and self-reported eating rate. However, a number of these studies emphasise the need for further research to investigate the impact of eating rate upon body mass [26] or the effect weight gain and eating speed [28]. Additionally, the majority of these studies highlight their reliance upon self-reporting as a significant limitation [25, 26, 31, 28]. Issues which are discussed in section 2.1.6.

Eating Rate and Influence on Other Health Factors

There are a number of other other health factors related to chewing rate, directly or indirectly. For instance, the study by Yamazaki *et al.* [29] attempted to identify and clarify any direct correlation between masticatory performance and diabetes amongst 2283 male and 4544 female subjects (aged 40-74), concluding that based on their findings masticatory performance and eating rate should be considered a potential risk factor for identifying patients with diabetes.

There have even been studies suggesting a link between eating rate and 'stress-eating'. The research by Adam and Epel [133] and Epel *et al.* [134] attempt to identify the relationship between hunger and stress mechanisms, and they found that amongst 59 women, those who release a large amount of cortisol in response to stress consumed more calories following application of high stress tests. The study by Tasaka *et al.* [30] builds on these hypotheses, relating salivary cortisol levels to chewing rate amongst 16 male participants (aged 20-33) after study sessions involving stress loading and chewing at different rates, reporting reduced cortisol levels after fast chewing. These studies both conclude that there is an association between psychopathological stress responses and eating behaviour, and that chewing faster contributes to stress relief.

2.1.6 Techniques for Monitoring Eating, Diet, and Physical Parameters

Tracking eating behaviour, diet, or various other parameters related to eating or physical characteristics, is an important part of studies focusing on improving understanding of eating behaviour (as discussed in section 2.1.5), or as a part of screening for, or monitoring of, eating disorders (discussed in section 2.1.4). The main two techniques for this are subject self-legging such information, or through manual observation (usually confined to eating studies). However, there are considerable limitations of these two techniques which can severely reduce the extent of information which can be recorded, or impact the reliability of such data.

Self-reported measures are one of the main methods for collecting information related to eating behaviour, dietary intake, or physical parameters. Such measures offer easy logging of diet for tracking eating disorders or weight management [20], or for large scale

population studies of eating behaviour [31]. However, such measures are considered to be unreliable or prone to bias. For instance, in a large study of 1870 male (age 37-74) and 2938 female (age 35-76), participants were asked to compare self-reported and clinically measured height and weight, Spencer *et al.* [33] reported overestimated height, and underestimated weight, which increased with BMI. These results were supported by a number of other studies [34, 35, 36], and was similarly observed during reliability assessments of eating disorder screening questionnaires, conducted by Luce and Crowther [135] and Fairburn and Beglin [115]. Finally, in an evaluation of the reliability of dietary self-report, Hebert *et al.* [32] found a bias in reported intake due to social desirability amongst 41 subjects.

The main limitation of observation based studies is one of time and resource demands, which restrict the amount of data it is possible to analyse. In any large scale study, detailed analysis of data from such studies can demand a considerable amount of time or human-resources as well as requiring lab conditions for recording video footage. For instance, Llewellyn *et al.* [28] conducted a study of 254 children to investigate the correlation between eating speed and BMI, and Bajic [123] conducted a study of the effects of music on eating amongst 103 subjects. Both cases required considerable human and time resources, with the latter study reporting manual analysis of approximately 52 hours of footage, which involved detailed evaluation to determine chewing rate. Other studies overcome such issues through strict experimental protocols to simplifying recorded data [127], or with a limited number of participants [24]. While such approaches eliminate the time demands of analyses, they sacrifice detail in the collected data.

There are considerable limitations of all the approaches described above. In the case of self-reported measures, they are considered a necessary tool for population scale studies or for treatment of swallowing disorders [32, 35], but are liable to inaccuracy or bias. While studies involving manual observation restricted to lab conditions and smaller in scale, limited by demands on time and human resources. Some solutions, such as “mandometer” for measurement of rate of intake, offer automated systems of eating study, but these are relatively restricted in purpose, immobile, and limited to experimental conditions. However, technology may provide solutions for improving manual logging of eating behaviour, or automated alternatives. Mobile technologies and their use for self-logging information are discussed in the next section, while automated systems are discussed further in section 2.2.

2.1.7 Technology Support for Health Related Monitoring, Treatment, and Behaviour Change

Treatment and monitoring of health conditions, particularly those which typically involve self-reported behaviour tracking or requiring behavioural therapy, is difficult to deliver consistently and effectively. The use of readily available commercial technology systems and mobile platforms is one approach to resolve the various issues normally involved in treatments involving self-reporting. For instance, Glasgow *et al.* [136] discusses the potential of technology support to alleviate non-specialist tasks associated with behavioural counselling: to arrange appointments, monitor adherence to treatment, establishing topics of concern, amongst other areas.

Another conceptual method for healthcare support using technology is through Quantified Self-Tracking. Proposed by Swan [137], Quantified Self is a philosophy involving self-tracking of information relating to an individuals biology, behaviour, or environment, with an emphasis on acting upon such information. This can include monitoring of physical activities, diet, psychological, or other mental states and traits. Swan [138] suggests a new form of technologically enhanced healthcare models, whereby patients are an active participant in their own care, enabled by technology to research and self-monitor conditions, symptoms, and treatment progress. The emergence of technology interconnectivity through the 'internet of things', mobile devices, and new technology or sensing modalities, provides an alternative approach for enhancing self-tracking for healthcare purposes or patient or clinician feedback [139, 137].

Mobile Health Technology

The popularity, prevalence, mobility, and technological capabilities of mobile devices make them an perfect platform for health-related support, and ideal for delivering interventions. In a review of 75 intervention trials, Free *et al.* [140] identified a range of mobile based applications supporting behaviour change interventions for smoking cessation, physical activity, reduced calorie intake, and for various disease management purposes. These were found to be delivered mainly through personalised feedback, goal setting, information, and other relevant messages.

Particularly prevalent uses of mobile applications include self-monitoring of diet or

exercise, for interventions, weight loss and management programs, or within the purview of Quantified Self-tracking [140, 137]. In the commercial domain, there is also a growing popularity for mobile based self-reporting of dietary content or fitness tracking using applications and wearable sensors [38, 39, 40, 41, 42, 43].

To evaluate the use of such systems for weight loss Burke *et al.* [44] describe the trial of a mobile health based system for enhancing self-monitoring of diet in weight-loss interventions of 210 overweight subjects (78.1% male and 84.8% female, average age 46.8) over a 24 month period; comparing self-monitoring using paper diaries, Personal Digital Assistant devices, and Personal Digital Assistant devices with daily feedback. The authors concluded that daily feedback messages increased adherence to self-monitoring of intake and aided weight loss. However, a similar study by Turner-McGrievy *et al.* [45] evaluating mobile applications for diet tracking amongst 78 subjects (18 male and 60 female) and exercise logging amongst 85 subject (21 male and 64 female), did not corroborate these findings. They reported mobile usage increasing exercise logging adherence, but no difference for dietary recording. Comparatively, a meta-analysis of 12 similar trials, by Flores Mateo *et al.* [141], reported a correlation between mobile based interventions and reduced body weight and BMI, but no significant improvement in physical activity.

All these studies indicate that mobile based intervention applications are useful tools for supporting weight loss and adherence to dietary logging. However, the findings of these studies are variable, suggesting that further research is needed to determine the extent of these effects.

2.2 Physiological Sensing and Technology for Automated Feeding Detection, Support of Rehabilitation and Health-Related Change

With ongoing research into wearable systems and small and discreet sensing modalities, physiological sensing has significant potential as a continuous and mobile alternative for monitoring of physiological processes. Furthermore, through the use of machine learning based approaches there is potential to automate such monitoring for the purpose of ongoing assessment or for driving assistive systems. Machine learning algorithms, specifically classification algorithms, may be trained to isolate patterns in data which may be used to

identify given classes of data [142], and are used extensively in conjunction with physiological signals in order to recognise patterns which would not otherwise be easily detectable [143]. These algorithms have been used in conjunction with physiological sensing for the purpose improvement of control over prosthesis [144, 145, 146], for assistive technology such as wheelchairs [147, 148, 149, 49], and for improving Human-Computer Interfaces through emotion based affect recognition [150, 151].

This section discusses physiological sensing for purpose of evaluating and detecting eating, and extracting information related to eating; focusing on the use of typical signal processing and machine learning based classification. Firstly, section 2.2.1 provides an overview of physiological and its use for Human-Computer Interaction. Section 2.2.2 then provides a review of some wearable solutions and discreet modalities for mobile detection of feeding, food intake, and monitoring of other health factors. The remaining sections in this chapter focus on the use of EMG for the study of eating processes and evaluation of swallowing impairments (section 2.2.3), and the use of EMG for the detection of eating and classification of food content (section 2.2.4).

2.2.1 Physiological Sensing and Electromyography

An integral component of computer aided evaluation of eating function and behaviour is physiological sensing. Physiological sensing refers to any method for capturing information regarding physiological processes, or related to the physical state or biological function of a living organism.

Biomedical Signals and Physiological Sensing Overview

Physiological signals useful for the evaluation of health are known as "biomedical signals", the most common of which are bioelectrical signals used as a vital part of healthcare [47]. These signals are based upon the principle of action potential change of single cells in response to external stimuli. Such action potential changes are observed within muscle cells and in neurons, and can be used to evaluate the state of muscles and the central nervous system. Some well known bioelectrical signals described by Rangayyan [47] include:

Electrocardiography Electrocardiography (ECG) is probably the most well known application of biomedical signals, related to heart function. Beating of the heart is perpetuated by the self-sustained action potential triggering of the sinoatrial node,

resulting in rhythmic contraction. The firing of this node is normally a very rhythmic event and can be monitored to identify any health conditions such as arrhythmia (irregular firing), or abnormal function such as tachycardia (high heart rate).

Electroencephalography Electroencephalography (EEG) is the monitoring of the electrical activity of the brain, via measurement of excitation across cortical surface (beneath the scalp) related to physiological control, thought processes, or external stimuli. The strength of different frequency bands (rhythms) permit measurement of different neural activities and evaluation of sleep function, seizures, physical activity, or used for control systems, virtual world interaction, or feedback.

Electromyography Electromyography (EMG) is the detection of the activity of skeletal muscle fibres based upon change in action potentials during firing of motor units (motor neuron, related cells, and muscle fibres). Firing of motor units is triggered by physical activity, and the shape of measured "single-motor-unit action potential" (SMUAP) is influenced by force and functionality, or various sources of interference. They are also affected by conditions such as swallowing disorders, which were discussed in section 2.1.2 and later in this chapter (section 2.2.3).

Bioelectrical signals also include electroneurogram (action potentials propagating across the a nerve) or electrogastrogram (electrical activity of the stomach), or galvanic skin response (electrical resistance of the skin in response to stimuli). Other biomedical signals include any other useful information obtainable regarding the physiology of the body, such as Phonocardiogram (sound signals resulting from heart contraction) which provides a similar function as ECG, Vibromyogram (vibration as a mechanical manifestation of muscle contraction) often used in conjunction with EMG, or Vibroarthogram for assessment of joint function [47]. In this section and within the rest of this thesis, Electromyography is considered the main physiological signal of interest.

Physiological Sensing and Human-Computer Interaction

Human-Computer Interaction (HCI) research has attempted to pave a more direct communication pathway between human and external devices for various applications, including the use of physiological sensing for innovative health technology. For instance, for health related purposes, Pantelopoulos and Bourbakis [152] outline a number of wearable solu-

tions for health monitoring and prognosis, including wrist-worn devices for the detecting cardiac-respiratory events, sensing jackets for monitoring activity of elderly patients, or for other health monitoring and motor rehabilitation purposes. These systems include Electrocardiogram, blood pressure, respiration, temperature, posture, galvanic skin response, electromyography, or accelerometers and gyroscopes. Alternatively, EMG and EEG are are more commonly being used for assistive technology interaction, such as the control wheelchairs for those unable to operate conventional devices [149, 49], and have been demonstrated for the purpose of mobile phone interaction [50, 51].

Along with assessment of health and direct control of hardware and software, the use of physiological sensing has been reported as a means of enhancing interaction with technology. Pantic and Rothkrantz [151] argue that future devices should be able to enhance engagement by responding to emotional cues as an additional form of interaction, in gameplay for instance. Nacke *et al.* [153] determined that, to enhance game interaction, EMG, body temperature, galvanic skin response (GSR), or heart rate can be used for direct game manipulation (through voluntary signal responses) or to indirectly adapt the game environment (through involuntary reactions). Chanel *et al.* [154] similarly studied the use of EEG to monitor various emotional states, and found that these could be used to adapt difficulty in order to maintain engagement. Such applications have particular relevance within biofeedback and game-based rehabilitation environments, which, as discussed previously (section 2.1.3), have been shown to engage patients, ensuring treatment adherence, maintaining motivation, and increasing self-efficacy.

Rezwanul Ahsan *et al.* [52] discuss the limitations of current biosignal approaches for the control of assistive technology, outlining a range of increasingly commonly available assistive technology solutions for disabled people, such as tongue controlled joysticks, head-worn motion sensors, and eye tracking for mouse cursor manipulation. They highlight a lack of fine control, or specific disabilities as particular limitations of such devices. They suggest biosignal systems based upon Electrooculogram (EOG), Electroencephalogram (EEG), or Electromyogram (EMG), as a viable alternatives. In particular, Rezwanul Ahsan *et al.* highlight the benefits of EMG for computer interaction interfaces, as a technique capable of detecting subtle muscle activation without the complex calibration, learning procedures, and training required for EOG and EEG interfaces. While Rezwanul Ahsan *et al.* mention physiological differences which can affect EMG along with an inherent sig-

nal instability, there are established methods within the literature for processing EMG and dealing with such issues (described further in section 2.3).

As newer sensing technologies have become more accessible and affordable, the use of sensing devices has also become more mainstream and common in day-to-day situations. Body wearable sensors are becoming prevalent for commercial fitness monitoring [43], and as technology progresses there is increased potential for Quantified Self-Tracking for healthcare improvement (discussed in section 2.1.7). The use of automated monitoring technology via body wearable to support such tracking has been described as an inevitable outcome and predicted as part of a new form of patient contribution towards their own healthcare [138, 139, 137].

2.2.2 Body Wearable Sensors for Evaluation and Detection of Food Intake

Although physiological sensing has considerable potential within health and computer interfacing, the modality of current mainstream solutions make them unsuited for many applications. For instance the use of biosignals for evaluation of physiological function (such as swallowing functionality), or for therapy purposes (such as biofeedback or other approaches discussed in section 2.1.7), involve bulky expensive equipment (for instance, in the case of EMG. See figure 2.12), or require specialist interpretation.

Discreet Modalities for Physiological Sensing

Patel *et al.* [155] and Majumder *et al.* [156] discuss body-wearable sensors as an alternative for monitoring of eating function and other health parameters, proposing a range of components as part of a complete sensing system, as can be seen in figure 2.9. Other systems described by Sazonov *et al.* [157] use a combination of sensing approaches for the detection of food, such as the use of in-ear or throat mounted microphones for chew or swallow sound measurement and piezoelectric strain sensors for the detection of jaw motions associated with eating and talking. Amft and Troster [65] expanded upon this, describing the use of wrist worn gyroscopes to detect food intake gestures, ear worn microphones for chew detection, and EMG, microphone, or strain sensors mounted on the neck via a collar for swallow detection. As well suggesting the detection of gastric activity, thermic effects, body weight, cardiac responses, and body composition as other parame-

ters of intake. However, they reported that these were prone to interference from other behaviour or external noise, or uncomfortable [65].

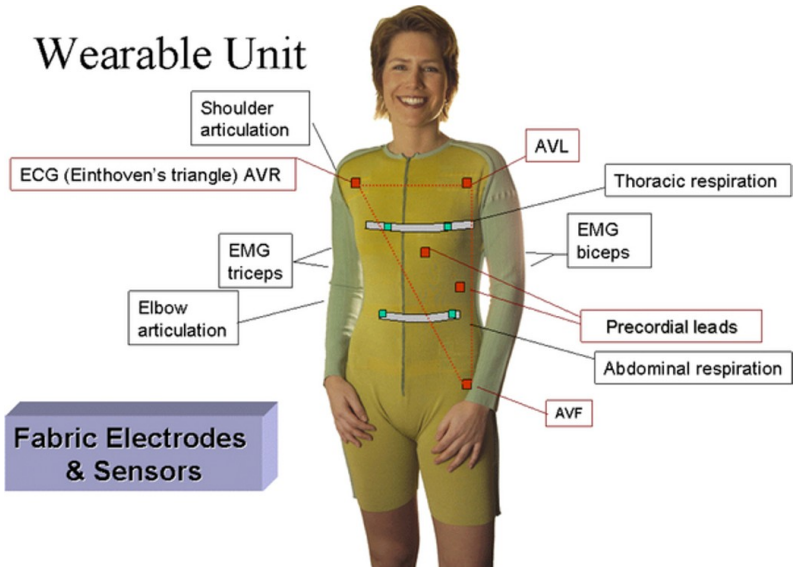

Figure 2.9: Example of a body wearable sensor system given by Patel *et al.* [155]. This system demonstrates Electrocardiogram measurement from a number of different locations (highlighted red), Electromyography of the biceps, and respiration or movement data based on stretching of the fabric. Reproduced from [155].

Amft and Troster reported results of initial prototypes for some of these systems, tested using 3 male subjects. Results included 94% accuracy for the differentiation between 4 feeding hand motions, using a motion capture jacket, and 73% accuracy for differentiation between high and low volume swallowing, using collar mounted microphone and EMG. For in ear microphone based chewing detection, Amft *et al.* [158] proposed two classification algorithms. One for the differentiation between periods of chewing and speech using a C4.5 decision tree trained using signal fluctuation and frequency features over a rolling window; reporting 99% accuracy. A second algorithm was developed to discriminate between food products, using an amplitude threshold based algorithm to isolate chews (with 90% accuracy) and decision tree algorithm was first employed to isolate individual chews, for which the authors reported accuracies ranging between 87.2% and 100%.

A later study building upon the results of this work attempted to classify 19 food types based upon food textural sound properties: “wet, loud”, “dry, loud”, “soft, quiet” [67]. During this study, 232 frequency spectral features were extracted from a total of 375 chewing sequences, using Fisher discriminant filter for feature reduction. A Naive Bayes classifier was trained for classification of food types, and an average accuracy of 86.6%

was reported. Although the results appear promising in these studies, they do not fully evaluate the robustness of their system within noisy environments, or the capacity of their classifiers to generalise to data from entirely unknown subjects, nor do they attempt to address issues of discomfort or impaired hearing which can result from ongoing usage of in ear worn microphones.

Sazonov *et al.* [68] demonstrated a similar system for measuring intake, investigating the use of acoustical data from a mic mounted on the throat for the detection of swallowing. Using acoustic swallowing signals collected from 21 subjects (12 male and 9 female, BMI 28.98 ± 6.42) during their initial study [157], they implemented a Support Vector Machine classifier for the classification of swallowing events and demonstrated an average intra-visit classification accuracy of 84.7%.

In an alternative approach, Sazonov and Fontana [69] evaluated the use of piezoelectric strain gauge mounted along the jaw for detection of chewing based on jaw motion. They developed a linear kernel Support Vector Machine based classification model for the detection of chewing, trained to be subject-independent using 20-fold cross validation. They reported an accuracy of 80.98% for this technique.

More recent research into the use of body wearables for monitoring food intake have focused on a multi-sensor approach, combining different sensor readings to attempt to improve eating detection and reduce misclassification. For example, Rahman *et al.* presented the use of Google Glass wearable device, collecting sensor data simultaneously from integrated accelerometer, gyroscope, and magnetometer to assess the motion of the head during eating [66]. They collected data from 21 male and 17 female participants between 18 and 21 years of age and evaluated the performance of Gaussian Naive Bayes, k-nearest neighbor, and random forest classifiers trained to detect eating. They made use of a variety of strategies for training and evaluating their classifiers, but only achieved an F-Score accuracy of 67.55%. They also suggest the use of photographs taken using the Google Glass to estimate food type and portion size.

Another study by Fontana *et al.* [70] demonstrated a complete system for the detection of food intake, combining a jaw motion sensor (piezoelectric strain sensor) with a watch worn gyroscope for hand to mouth gesture detection, and an accelerometer for identifying body motion. This was a "free living" type study, with 6 male and 6 female participants (aged 26.7 ± 3.7) wearing the system for a 24 hour period, using a push button to indicate

eating periods and an self-reported diary to corroborate ground truth. The proposed system also used combined sensor data to eliminate jaw motion resulting from walking or non feeding periods. An Artificial Neural Network was trained for subject-independent classification using features extracted from the sensors, and an accuracy 89.8% was reported for the detection of food intake. However, in addition to the limitations of self-reported ground truth, the authors highlighted an inability to detect liquid consumption through jaw motion detection, and the need to investigate this further.

Other recent multi-sensor approaches have demonstrated a significant improvement in accuracy of detected eating classifiers. Bi *et al.* [71] evaluated the combined use of EMG and microphone for simultaneous collection of behind eat acoustic and EMG signals during eating, conducting studies on 8 female and 12 ale participants (aged 21-30). They trained a logistic regression classifier using a Leave-One-Person-Out strategy using the first 10 participants to compare EMG and microphone data for detecting eating. While they reported accuracies greater than 90% for both combined EMG and microphone sensors, and for microphone sensor data alone, they concluded that acoustic signals were better suited to eating detection and repeated the experiment with a further 10 participants, just collecting acoustic data. They reported a final accuracy of 90.9% for the classification of chewing using a logistic regression classifier.

Another paper by Bedri *et al.* [72] presented the "EarBit", a wearable system consisting of a behind ear worn inertial sensor and optical proximity sensor, a back worn inertial sensor, and a neck worn microphone. However, in their final system they used only behind ear inertial sensors for the detection of eating and the back worn sensor for eliminating significant body motions. They trained a Random Forest classifier using a leave-one-out strategy for two scenarios: a lab study and an "in the wild" study. In the lab study they collected data from 9 female and 7 male subjects (age: 19-25), and used data from 10 subjects to produce a classifier capable of detecting chewing with an accuracy of 90.9%. In the "in the wild" study they collected data from 10 participants (3 female, 7 male, age: 18-51), and resulted in a classifier with an accuracy of 80.1%.

The systems review here seek to eliminate some of the limitations associated with traditional sensory systems, but they do not offer solutions for assessment of parameters from small, exposed, and flexible areas of the body. EMG is an approach that may be better suited monitoring of eating, but electrodes are typically affixed to the skin

of the face and neck using adhesive tape, which is indiscreet and not suited to long-term monitoring. Some wearable solutions, such as collar mounted electrodes, permit more permanent sensing, but have been described as uncomfortable [65]. One additional wearable modality of note is that of "skin-like", or epidermal, sensors. Proposed by Kim *et al.* [74], these are lightweight, flexible, conforming robustly and unobtrusively to the skin surface, and offering intimate integration without causing motion constraints [159]. Chapter 3 explores in more detail the biomedical applications of such sensors for mobile and long-term sensing, and for overcoming many issues of wearable sensors for detecting eating.

Differentiating Between Food and Predicting Intake Volume

Although approaches for the detection of intake differ in the studies discussed thus far, they all have similar goals in mind: the elimination of inaccurate self-monitoring techniques. The majority of the studies here have focused upon the premise of detecting bites, chews, swallows, or other eating gestures that signify food intake. In addition to identifying intake, a possibly important factor to monitor is the content and volume of ingested food. For food volume estimation, image recognition has been proposed as a means of estimating food quantity on a plate. For instance, Liu *et al.* [160] developed a system for monitoring intake and producing an automated visual intake volume log, using an ear worn microphone and camera. They developed a feed-forward neural network for classification of eating based on acoustic signal data captured from 6 participants within a university staff restaurant, manually annotated with ground truth. They trained the neural network using 60% of the collected data and tested using 40%, and reported an accuracy of approximately 82% for eating detection. For food volume logging, they presented a key frame detection method, a normalised colour histogram used to determine intake volume. The authors reported difficult quantifying the accuracy of this approach, but reported a high degree of correlation between estimate intake volume over time and ground truth.

A similar technique was employed by Okamoto and Yanai [161], using a smartphone camera to capture food images for calorie estimation. Their system estimated food region and dish localisation to isolate food in images and determine food quantity, and then employed a Convolutional Neural Network trained using the ILSVRC 2012 data set of food images and categories to detect food type. Calorie content was estimated based

on a quadratic curve estimate of the estimated food size from food images compared to calorie content, the model trained using 60 food images. They tested this approach using a further 60 test food images, and reported an error of 21.3% for calorie estimation.

Although image based food content and calorie estimation is an interesting approach for streamlining dietary intake monitoring, it still relies upon user adherence to self-logging in order to capture intake accurately. The use of wearable sensors to capture eating function, as discussed previously in this section, helps to alleviate some of these issues and track eating in an automated way. The article by Sazonov *et al.* [162] builds upon this premise, using data collected in previous work [157] to predict intake volume based upon detected chews and swallows.

For the detection of eating, their algorithms assumed that a high frequency of swallowing or presence of chewing was an indication of solid food ingestion, while a high frequency of swallowing and lack of chewing indicated liquid ingestion. Their algorithm was capable of 93.3% accuracy for intake detection, and 95.5% for the differentiation between solids and liquids. For determining the mass of food and liquid, the authors describe mathematical models resulting in an accuracy of 91.8% for estimating the mass of solid food, and an accuracy of 83.8% for the prediction of liquid mass.

The equation proposed by Sazonov *et al.* for the estimation of solid food mass was given as:

$$M_S = 0.5(\bar{M}^S_{SW} \times N_{SW} + M_{CHEW} \tag{2.1}$$

where $\bar{M}^S_{SW}$ was the average mass of a solid food swallow, N_{SW} was the number of swallows during food intake, M_{CHEW} was the average mass per chew and N_{CHEW} was the total chews. The equation for predicted mass of liquid consumed was based upon average mass per swallow ($barM^L_{SW}$) and number of swallows (N_{SW}):

$$M_L = \bar{M}^L_{SW} \times N_{SW} \tag{2.2}$$

A similar approach was proposed by Amft *et al.* [163], for the detection of food type using the pattern of drinking and eating events, based on perceived detection using gesture, chewing, and swallowing sensing. In this approach they modelled eating events as probabilistic grammars, and their models resulted in an accuracy of approximately 80% for the classification of 8 food types for an individual subject.

The studies examined here have a number of limitations. The majority of them propose initial prototype systems, making use of a relatively small subject pool and data sets to develop detection algorithms and evaluate the sensing systems. Furthermore, they vary considerably in approach, technology, and classification techniques, and rely on technology which is unsuited for long term, comfortable, or unobtrusive monitoring without further research. The study of different wearable devices and usage adherence amongst 13 participants (6 considered obese, 8 female, and 5 male, with an average age of 32.8 ± 12.5) by Alharbi *et al.* [164] highlights some potential issues of such wearables. Their study involved the use of and eating detection suite consisting of cameras worn on the upper torso, and wrist and neck worn sensors, conducting interviews and evaluating camera footage to determine how participants managed usage of the suite and privacy concerns. They found that participants disabled or obscured cameras to maintain privacy and determined that the size, attachment, ease of use, aesthetics, and perceived stigma of using the device were all factors that impact adherence.

Although the techniques presented in these studies exhibit some possible limitations they all demonstrate the potential for automated monitoring eating. In particular, the models presented by Sazonov *et al.* [162] and Amft *et al.* [163] present techniques by which the volume and type of food content can be predicted, based solely on eating function. This has significant implications for all approaches of feeding detection which measure chewing and swallowing.

2.2.3 Physiological Sensing and EMG Evaluation of Chewing and Swallowing Function

While attempts to produce a complete automated system for eating detection have included a variety of different approaches, few of them make use of Electromyography and muscle activity as the sole means of detecting chewing or swallowing. Instead these rely on different sensing modalities for the measurement of chewing and swallowing parameters, arm motion, or a combination of these. However, Electromyography has a long history for the analysis of muscle activity related to eating function, in addition to the assessment of abnormal swallowing functionality (as described in section 2.1.2). This technique however, is also widely considered insufficient for reasons of aesthetics and comfort. For instance, collar mounted EMG has been reported uncomfortable and unsuited to long

term monitoring by Amft and Troster [65].

Despite this, with the emergence of epidermal electronics [74] and other less obtrusive modalities for surface electromyography (as described in section 2.2.2) lend themselves to automated monitoring of eating information. This includes tracking of dietary intake, eating patterns, or monitoring of information useful for assessment of feeding impairments. The evaluation of these parameters and potential application described in the literature are reviewed here.

EMG Characteristics During Chewing and Swallowing

The relationship between muscle activity and mastication or facial expressions has been investigated using Electromyography for a substantial period of time. An early study by Ingervall and Thilander [57] evaluated the muscular activity of 25 boys and 27 girls aged 9-11 years. During this study EMG measurement was recorded from the anterior and posterior temporalis, masseter (mastication muscles), and orbicularis oris (upper lip), during chewing, swallowing and maximal contraction. They demonstrated a significant correlation between the masseter and temporalis during all exercises, but more significant during chewing and application of maximal force. This demonstrated the temporalis and masseter as some of the primary muscles of mastication.

Green *et al.* [5] also studied the association between EMG measurement and eating, presenting the development of chewing in 4 children between 12-48 months old. For each subject they recorded EMG of the masseter, temporalis, and anterior belly of the digastric during eating, and used a threshold derived from the standard deviation of the muscle at rest as a reference for determining onset of muscle activity bursts. The authors determined that the basic chewing patterns were established by 12 months of age, and observed that chewing efficiency improved and muscle activation strengthened throughout the study period. They also highlight the reciprocal nature of muscle activity patterns associated with chewing, which became more synchronous and defined during subject development (as demonstrated in figure 2.10, reproduced from [5])). Along with this, a decrease in duration and variability of EMG bursts over this period were considered by the authors to be indicators of an increase in chewing efficiency.

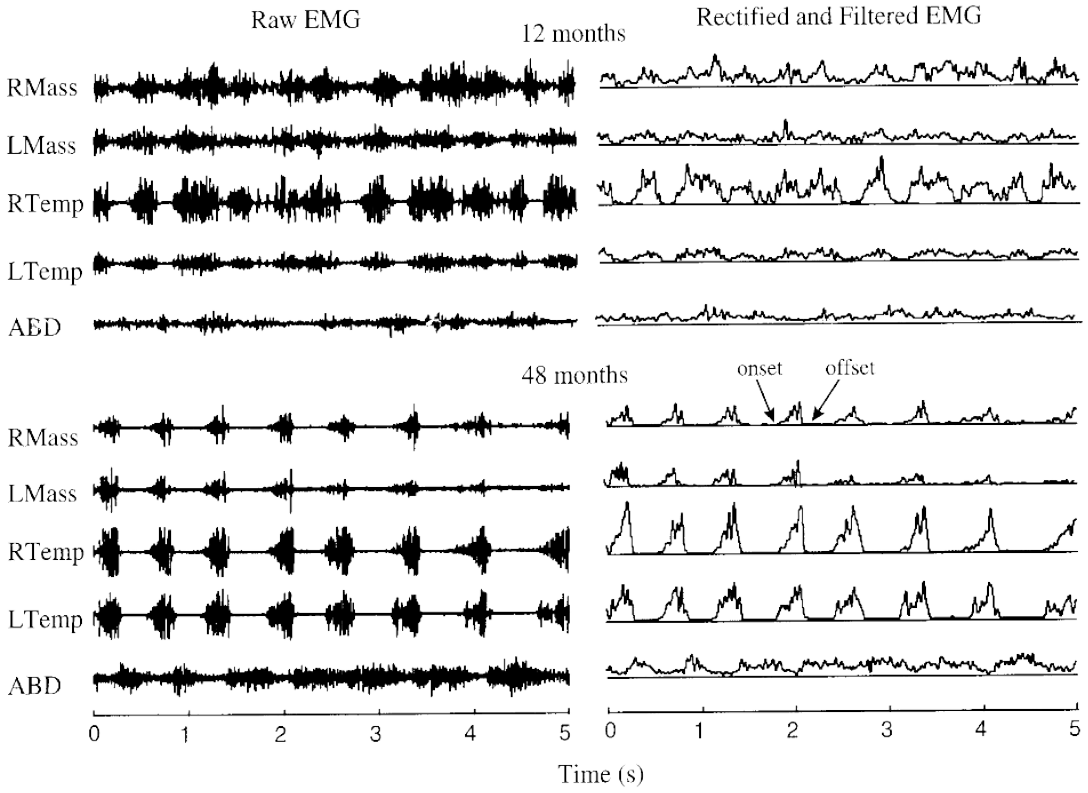

Figure 2.10: Plots showing the raw and rectified EMG signal of a subject at 12 month old and 24 month old. Shown are EMG measurements from the masseter muscles (RMass and LMass), the temporalis muscles (RTemp and LTemp) and the anterior belly of the digastric muscle (ABD). 48 months (below) demonstrates a characteristic pattern of EMG activity bursts for chewing sequences, and the rectified signal (bottom right) demonstrates onset and termination points of EMG burst associated with a single chew. Example reproduced from [5].

Evaluation of Chewing and Swallowing Function

A more in depth evaluation of mastication using EMG was conducted by Kohyama *et al.* [6] who studied the effects of age and dental status upon mastication amongst 19 elderly subjects (13 female and 6 male, aged 58-72 years), using EMG recorded from the masseter and anterior temporalis muscles during consumption of 6 food types. They determined that chewing time parameters increased and total EMG energy per chew decreased in correlation with reduced dental capacity with reduced dental capacity and increased age. Similarly, Moreno *et al.* [60] evaluated clenching, chewing and swallowing from 45 subjects (12 male and 33 female, age 22-29) with varying dental capacity during drinking, chewing of food and clenching of the jaw. They determined a high amplitude of the digastric during swallowing, and high amplitude from the masseter and temporalis during chewing and clenching, along with differences in muscular activity during mastication and

contraction, correlating with dental capacity. These masticatory studies demonstrate the possibility for isolating individual chewing cycles using EMG of the masseter and temporalis muscles. Furthermore, the differences in recorded activity demonstrate potential application of EMG for evaluation of dental status based on chewing and assessment of muscle contraction.

Electromyography has also been used fairly extensively to study the physiological processes involved in swallowing functionality. This includes a number of studies comparing normal and abnormal swallowing [165, 166, 167, 168], but of note was an evaluation of 300 adults with normal swallowing function, conducted by [62], Vaiman *et al.* [169] to determine typical characteristics of swallowing from various muscles of the face and neck. Measurements were obtained during dry (saliva) swallow, liquid swallowing, and stress test liquid swallowing (large quantities of liquid). The authors tentatively concluded that the initial oral stage of swallowing is associated with the masseter muscle and orbicularis oris; the final oral stage with the masseter and submental muscles; the pharyngeal stage with the masseter, submental, and laryngeal strap muscles; and oesophageal stage with submental and laryngeal strap muscles. Figure 2.11 shows an example given by Vaiman *et al.* [169] showing typical pattern of swallowing and the different stages, from the different muscles. Vaiman *et al.* [169] concluded that timings of swallows, signal amplitude, and pattern of activity are parameters important for swallowing evaluation.

A study by Schultheiss *et al.* [170] also attempted to evaluate swallowing function, using combined EMG and bioimpedance measurement. They conducted an evaluation of speech, head motion, and swallowing of different solid and semi-solid foods, as well as different volumes of water amongst 31 participants (15 male and 16 female, aged 32.5 ± 7.8) using both surface and subcutaneous (needle) electrodes for EMG and bioimpedance measurement. They found significant differences between head motion, speech and swallowing. Differences were also identified between liquid swallowing and other consistencies, based on the duration of preparatory stages of swallowing, maximum laryngeal elevation, and peak EMG amplitude during swallowing. They also identified differences between swallow volume (saliva swallowing and different water volumes), based on duration and speed of laryngeal elevation, duration of swallow, and integrated EMG (defined in table 2.2) over the swallow. The authors conclude that the combined system may be used to identify differences between head motion and swallowing of different food consistencies and vol-

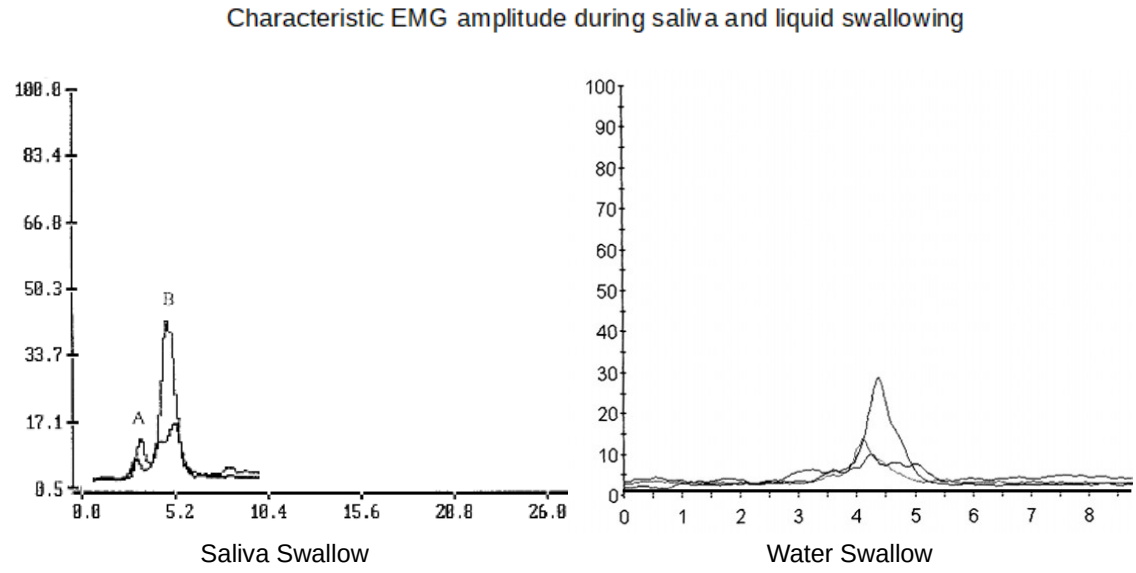

Figure 2.11: Example of typical rectified EMG signal pattern during the swallowing of saliva (left) and liquid (right). Shown *left*: Reproduced from [169] - upper peak represent the masseter muscle signal, lower peak represents the submental muscle activity during saliva swallow. Shown *right*: Reproduced from [61] - upper peak represents activity of the submental muscles, middle peak represents activity of the masseter, and lower peak represents the activity of the infrahyoid muscles during a water swallow.

umes. Together these studies demonstrate potential for the identification and evaluation of swallowing from recorded EMG signals, and indicate a number of muscles which are useful for measurement.

EMG for Dysphagia Screening and Monitoring

A natural extension of the study of normal swallowing physiological processes using EMG is its application towards the assessment of abnormal swallowing. As discussed in section 2.1.2, Surface Electromyography has been investigated as an alternative tool for the evaluation of swallowing physiology and treatment of swallowing disorders. One which is non-invasive and with potential as an initial screening technique and support for ongoing monitoring [61].

Crary and Baldwin [165] described an early attempt to fully evaluate and compare swallowing characteristics using surface electromyography amongst dysphagia sufferers and healthy subjects. Comparing the swallowing performance of 6 patients with dysphagia and 6 without, while holding water in the mouth, and during dry (saliva), low volume, and high volume water swallowing. Compared with normal subjects, they found that dysphagia patients demonstrated greater amplitude and more variable signal patterns in

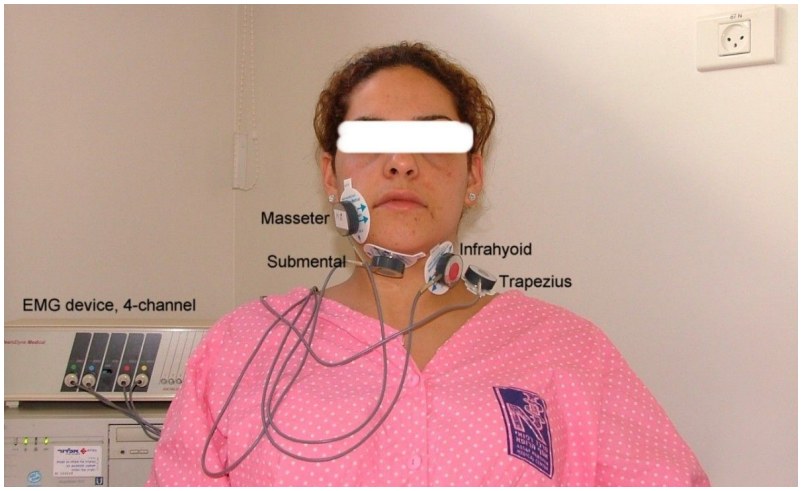

Figure 2.12: Example of EMG equipment and electrode placement for assessing various muscles related to food swallowing and dysphagia. Reproduced from [62].

the infrahyoid and perioral muscles, as well as reduced swallow duration.

Ertekin *et al.* [166] similarly made use of EMG to assess swallowing function, describing development of the "dysphagia limit", a method for evaluating swallowing function and screening for dysphagia based on the lower limit of water volume at which piecemeal deglutition was observed. They found that the "dysphagia limit" amongst 30 normal subjects was 20ml, while 66 dysphagia patients had a lower limit of between 1ml and 20 ml of water. A follow up study by Ertekin *et al.* [167] used this approach to evaluate 58 Parkinson's patients, 31 of whom were determined to be dysphagic. They reported a significantly greater duration of muscle activity amongst patients with dysphagia than those without, and a significant delay in swallow triggering time between normal and Parkinsons patients. Another study, by Potulska *et al.* [168], also found a significant difference in dysphagia limit between 18 Parkinson's dysphagia patients (12 female and 6 male) and 22 healthy subjects (12 female and 10 male), using EMG characteristics of the submental muscles to determine dysphagia limit [168].

More recent articles by Vaiman, Vaiman and Eviatar [61, 62] discuss the benefits of surface electromyography as a screening technique for dysphagia, and the need for standardised procedures; through a review of common practices and observations of surface EMG amongst 740 normal subject in previous studies. Figure 2.12 demonstrates recommended electrode placement, given by Vaiman, for evaluation of muscles involved in oral, pharyngeal, and oesophageal phases of swallowing. Vaiman also suggests dry swallowing, voluntary swallowing of a small quantity of water, swallowing a substantial quantity of

water, and continuous drinking of 100ml of water as screening tests. Identification of abnormal swallowing is also described, based on evaluation of swallow timing, amplitude of the surface EMG measurement, and shape of the signal during swallowing. Vaiman concludes that surface electromyography is an inexpensive, fast, and non-invasive screening technique. However, the current state of EMG as a solution still requires bulky equipment and indiscreet sensor placement, as can be seen in figure 2.12.

EMG for Evaluation of Foods with Different Textural Properties

As discussed in section 2.1.5, food volume, texture, and other properties are known to have an effect upon eating behaviour, function, sense of satiation, and are also connected with the physiology of feeding. There has also been a significant amount of research attempting to evaluate the association between food texture or viscosities and characteristics of chewing or swallowing using EMG, particularly in the case of mastication [171, 172]. The article by Horio and Kawamura [172] reported EMG measurement of the masseter muscles in 29 subjects during consumption of 5 foods with differing hardness qualities, and the impact of food hardness upon EMG amplitude and chewing characteristics. They found that signal amplitude increased in correlation with food hardness, along with an increase in the number of chewing strokes and duration of chewing sequence prior to swallowing. Based upon this, they concluded that chewing force and thoroughness is related to food hardness.

Later studies by Lassauzay *et al.* [58] and Peyron *et al.* [59] similarly used EMG to analyse the consumption of four gelatine based foods varying in hardness. 15 male subjects (aged 22.6 ± 1.3 years) underwent simultaneous EMG measurement of the temporalis. EMG activity bursts were determined using an algorithm based on the premise of signal activity exceeding amplitude of 10% above the average baseline amplitude, and a required interval of 0.2-1 seconds between chewing bursts to differentiate between different cycles. Their findings demonstrated a number significant parameters which increased in correlation with food hardness, including masticatory time (duration), work across a chewing cycle (the sum of EMG signal during a chewing sequence divided by number of bursts).

Beyond food hardness, some studies have attempted to quantify the effect of food textures upon chewing using Electromyography. Mioche *et al.* [173] evaluated EMG measurement of the masseter and temporalis muscles of 36 dental students (19 male and 17

female, aged between 19-22) during the consumption of 5 foods with differing textural properties. The findings of this study demonstrated total muscle work and chewing sequence duration increasing steadily with food hardness, and an increase in activity of the non-active masseter and temporalis during chewing of firmer, less elastic food items. They describe the temporalis muscle as more significantly influenced by food texture than the masseter muscle, but concluded that further research is needed to evaluate possible sources of variation in mastication of different food items. Similar findings were described by Foster *et al.* [174] who evaluated mastication of plastic (chewy caramel confections) and elastic (gelatine based confections) food types with differing hardnesses, based on EMG recordings from 15 male dental students (aged 24.1 ± 1.9 years). Foster *et al.* concluded that an increase in food hardness or plasticity resulted in masticatory adaptation via an increase in muscular activity and frequency of chewing cycles.

Papers by Miyaoka Yozo *et al.* [175] and Miyaoka Y. *et al.* [176] extend the findings of previous research, proposing the "T_P" value as a new measurement feature for the evaluation of EMG properties of different foods. This was calculated by finding the cumulative sum of the signal amplitude across a cycle of EMG activity and mapping it onto the normalised duration of the same cycle. As such, T_P is defined as the normalised time point across an EMG cycle at which point P percent of the total cumulative EMG has occurred; so T_P when $P = 50$ correlates with the time at which 50% of the total cumulative EMG has occurred during the cycle. Miyaoka Y. *et al.* [176] made use of this parameter to evaluate EMG of the masseter muscles of 10 subjects (7 male and 3 female, average age 20 years) during chewing of 6 foods with varying hardness and fracturability [176]. The authors reported a positive correlation between T_P and food hardness, and a negative correlation with fracturability. They also reported a reduction in chewing cycles associated with increased food fracturability and increase in adhesiveness.

Another study by Miyaoka Yozo *et al.* [175] attempted to evaluate 5 taste qualities of structurally identical (semi-solid) foods using this parameter. EMG of the suprahyoid muscles was recorded and T_P values calculated for each swallow cycle, with 9 T_P between 10-90% of the cumulative EMG. The authors reported a significant difference in T_P values between differing taste qualities during the first data collection, but not the second. Miyaoka Yozo *et al.* suggest that the initial differences could result from taste novelty, indicating that physiological differences associated with taste qualities are not necessarily

permanent. However, based on the findings of their other study, it can be concluded that textural properties are more consistent due to necessary physiological function of chewing activity related to the breakdown of foods with different hardness and fracturability.

2.2.4 EMG for the Detection of Chewing, Swallowing, and Related Parameters

Although there has been considerable research into evaluating eating function using EMG and the effects of food and other parameters on muscle activity, there have been fewer reported attempts to use EMG for automated detection of such activity. One system, reported by Nahrstaedt *et al.* [177], proposed the use of the combined EMG and bioimpedance system for the automated detection of swallowing activity. The algorithm consisted of two parts: segmentation of the recorded signals and detection of swallow onset and termination, followed by feature extraction and classification. Signal segmentation consisted of signal valley detection, using a piecewise linear approximation of the bioimpedance signal and detection of amplitude decline followed by an incline. Features extracted from signal segments included time and energy parameters of the EMG and bioimpedance signals. A Support Vector Classifier (SVC) algorithm using a Gaussian radial kernel was trained using data from 9 subjects (2 female and 7 male, mean age 27.4 years) and tested using 4. The authors reported 93% accurately detected swallows using the signal segmentation algorithm, but a very high degree of false positives. Inclusion of the classifier model resulted in a higher degree of accuracy with sensitively of 96.1% and specificity of 97.1%.

Alternative systems have been developed which rely entirely upon EMG measurements. For instance, a number of recent studies have reported the development of complete eating detection and intake evaluation systems based upon the use of "smart glasses" [178, 179, 180]. Conceptually, these consist of glasses equipped with electrodes within the arms, for measurement of EMG from the temporalis muscles (an example can be seen in figure 2.13), thereby eliminating many limitations of traditional adhesive EMG electrodes. Using this modality, these studies attempted to detect chewing from EMG recordings, and also to evaluate dietary content based upon characteristics of chewing sequences and other parameters.

The first of these system is described in the article by R. Zhang *et al.* [178]. They collected EMG measurement from 8 participants (4 male and 4 female, aged 20-56 and

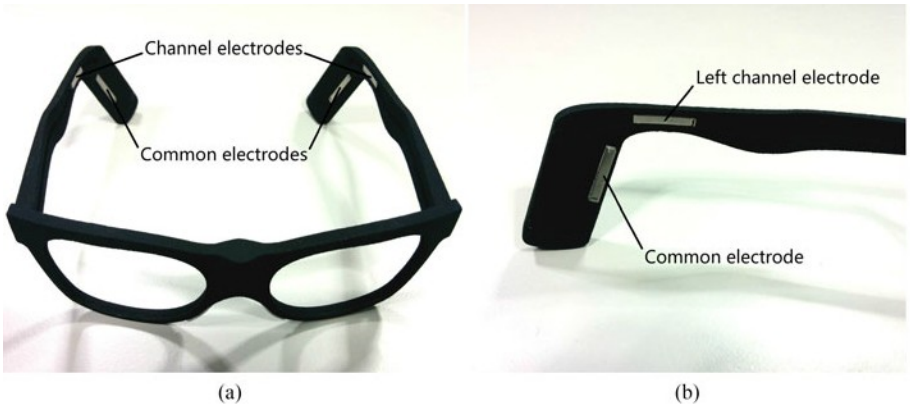

Figure 2.13: Example of Smart Eyeglasses for EMG measurement of the trapezius muscles, developed by R. Zhang and O. Amft [180]. **(a)** Overview of the glasses. **(b)** Close up of the electrodes embedded within the glasses frame. Reproduced from [178], © [2018] IEEE.

without dental problems) during eating of 5 foods under controlled lab conditions, to develop an evaluate the performance of their classifier algorithms. The study compared two chewing detection algorithms: a threshold based algorithm, detecting periods of activity where the filtered and rectified signal exceeded a given threshold for duration of 0.4-1s; and the "transition index" onset detection technique described by Abbink *et al.* [181] (discussed further in section 2.3.3). For the transition index algorithm they reported recall and precision of approximately 50%, compared with an approximate recall and precision of 80% for the threshold algorithm. They attribute the difference in performance between results reported by Abbink *et al.* [181] and their own implementation differing electrode placement.

For detection of food types, they selected 20 unspecified features extracted from "pre-onset, onset-to-offset, and post-offset" [178] segments of the signal. Random Forest (RF) and Linear Discriminant Analysis (LDA) classification algorithms were trained using 10-fold cross validation of all subject data. They obtained an accuracy of 57.2% for the RF classifier, and 46.8% for the LDA. Applying a voting filter across chewing cycles within a single chewing sequence resulted in an improved average accuracy of 74.8% for RF and 56.2% for LDA. They concluded that the low accuracy was the result of confusion between foods with similar hardness textural properties.

A similar system was proposed in the paper by Q. Huang *et al.* [179]. In this study, evaluation of the chewing algorithm was conducted using EMG of 4 participants (aged

between 20-30, BMI between 19-32) during seated consumption of food over a 40 minute period. The chewing detection algorithm reported in this paper was based on two stages of detection: the use of data variance analysis to determine periods of potential eating activity, where variance exceeded a predefined threshold; followed by chewing detection based upon given thresholds for peak-to-baseline amplitude, chewing cycle duration, and a number of chewing cycles in a chewing sequence. The authors report an overall accuracy of 96% during evaluation of this algorithm, however they also reported false positive chew detection during speech, laughter, or other activities relating to jaw motion. The authors conclude that the real time nature of this algorithm would permit the provision of feedback regarding eating, making it useful for encouraging behaviour change related to eating rate.

For food classification, Q. Huang *et al.* [179] extracted peak-to-baseline amplitude, chewing cycle duration, and T_P values (as described in previous work by Miyaoka Yozo *et al.* [175]), per chew cycle. The number of chewing cycles per sequence was also included. One fifth of all data was randomly extracted for testing purposes and the remaining data used to train a J48 decision tree, which resulted in accuracies between 69.2%–94.8% reported across the different foods.

As follow up to their previous study, R. Zhang and O. Amft [180] presented another algorithm for the detection of chewing activity, and report attempts to classify food based on hardness parameters. The developed algorithms were evaluated using data captured from EMG measurement of 10 participants (6 male and 4 male, aged 25.1 ± 2.1, BMI 23.8 ± 2.1) during a lab session involving the consumption of 3 different foods, and "free-living" monitoring sessions involving participants wearing the glasses (shown in figure 2.13) over the course of a normal day, clenching their teeth repeatedly to indicate the start or end of a meal, and self-logging activity using a diary.

The chewing detection algorithm reported by R. Zhang and O. Amft was adapted from the transition index detection method (see section 2.3.3), and resulted in a chewing detection accuracy of approximately 94% across all participants under experimental conditions. However, during a "free-living" study, involving normal daily activities, this accuracy of this algorithm was found to drop to approximately 78%. In addition to this, chewing detection accuracy was reported to be determined by comparison of smart glasses signals with those collected from reference electrodes. As such, this might instead be considered a measure of correlation between reference and test electrodes, rather than a true

accuracy metric. Furthermore, ground truth in the "free-living" scenario was confirmed using self-logging; which has been reported as unreliable or prone to bias in this paper [180] and other literature (as discussed in section 2.1.6). For in lab food classification, features were extracted from the lab recorded EMG for each chewing cycle and averaged across each chewing sequence. The authors reported 94.7% accuracy for food classification using a Linear Discriminant Analysis classifier model.

A high degree of accuracy was reported for chewing detection and food classification in all of these smart glasses based systems. However, these studies only evaluated accuracy based upon a small number of subjects, and mostly under controlled conditions. In addition to this, for food classification no attempts were made to evaluate classifiers ability to classify food on a subject-independent basis, making it difficult to determine the ability of classifiers to generalise to truly unknown subjects. Food classification was also based purely on detected chews. Swallowing information has been demonstrated as useful for evaluating foods (section 2.2.3), and reported as important for the prediction of intake volume by Sazonov *et al.* [162]. The exclusion of such information in these proposed systems results in the potential loss of important information for intake assessment.

The systems reviewed here demonstrate the potential of EMG and related approaches for the evaluation and detection of chewing, swallowing, and even for identifying food content. However, the approaches reported above are primarily prototypes and are developed and evaluated using relatively limited protocols. There is a clear need for further investigation into such systems and their impact upon research and within clinical applications.

2.2.5 Eating Technology and Wearables for Support of Rehabilitation and Health Related Behaviour Change

The previous section (section 2.1.6) outlined issues of existing techniques for monitoring and feeding and dietary intake, focusing particularly on the inherent error of self reporting. Thus far in this section, the state of the art of physiological sensing and wearable sensor modalities have been discussed. These technologies are reaching a stage in which they can be leveraged in a mobile and continuous manner for ubiquitous monitoring of feeding, thereby overcoming many issues related to monitoring eating function and behaviour. Such automated monitoring systems also help to resolve other limitations involved in the treatment of eating disorders and abnormalities; specifically the lack of motivation,

engagement and self-efficacy, and problems ensuring adherence to treatment [101].

In particular there is scope for the use of these technologies alongside persuasive and feedback systems to support adherence to treatment, encourage positive behavioural and functional change, and motivate and engage users. In their paper discussing persuasive technology for human well-being, IJsselsteijn *et al.* [182] describes it as a "class of technologies that are intentionally designed to change a person's attitude or behaviour," in a voluntary manner. Improvements in sensing and mobile technology (such as that discussed previously) mean that context specific persuasive feedback is becoming possible for a range of potential health related applications.

IJsselsteijn *et al.* suggests that these technologies can be utilized to encourage and reward healthy behaviours and learning experiences through the "engaging interactivity and subtle reward structure of computer games". However, they also highlight challenges related to sensor and classification algorithm quality, a shortage of long term studies into their effects and benefits, and a need for ethical debate around persuasive technology. While there has since been significant research into sensors and detection algorithms, the discussion of the literature thus far in this chapter still highlights these as challenges in current research.

Persuasive Technology for Healthy Behaviour Change

A particular health-related use of persuasive technology is for dietary and fitness behaviour change. As discussed in section 2.1.7 technology, particularly mobile platforms, is becoming an increasingly common tool for the logging intake and exercise in research [140, 45, 141], and in the commercial domain [38, 39, 40, 41, 42, 43]. Research into this area suggests that the use of mobile based applications improve adherence to diet and exercise self-logging [101, 45], and indicates a correlation between mobile based interventions and body weight change [141].

In addition to logging fitness activity, persuasive approaches can be used in conjunction with wearable sensors to encourage attitude change in regards to fitness. Miller and Mynatt [183] describe the use of a fitness support approach involving wearable pedometers, weekly social meetings, and a social website displaying daily step counts from users and hosting a game to which access was granted as a reward to achieving daily activity targets. They conducted a 4 week deployment of the system, monitoring usage and collecting

survey data from 42 school students (45% male, 55% female, with a minimum age of 13 years). They found that the combination of wearable sensor, website for socialising and posting encouraging commentary, and regular socialising meetings improved user attitudes about fitness and increased sense of social support, and conclude that such social computing systems can positively influence healthy behaviours.

Games for Persuasive Behaviour Change

As discussed by IJsselsteijn *et al.* [182], game environments are also useful for persuasive technology systems. The paper by Erhel and Jamet [184] discusses the benefit of digital game-based environments for motivation and learning effectiveness using am instructional and quiz based health related game. They conducted two experiments to determine the ideal instruction conditions for learning games, and to evaluate the effect of game feedback upon learning. The first study involved 46 participants (22 male and 24 female, between 18-26 years of age), during which they evaluated two forms of learning game instructions: instructional and entertaining. In the second study they then evaluated the effect of correct response feedback upon 44 participants (16 male and 28 female, between 18-26 years old). From the results of the studies the researchers determined that game based environments can promote learning, and improve motivation and engagement. However, they determined that learning only improved through use of educational instruction, or feedback to encourage active processing information.

A number of studies have presented persuasive games for promoting healthy dietary or exercise behaviour. For example the paper by Grimes *et al.* [185] presents a learning game to investigate the use of mobile games to teach adults healthy eating behaviours. The proposed game was a role-playing game in which players took the role of a server with the goal of recommending the most healthy meal as quickly as possible; characters losing health based on how unhealthy the chosen food is, and players presented with "stoplight" feedback about the selected foods healthiness. They deployed the game in a "in the wild" environment, providing 12 participants (10 women and 2 men, between 31-55 years old) with a phone pre-installed with the game. Participants were asked to play at least once a week over a 3 week period and fill out short diary entries related to their use of the game. Based on their findings, the authors concluded that the game helped participants engage in the process of behaviour change.

Another example of a persuasive game for dietary behaviour change is the mobile based "LunchTime" game developed by Orji *et al.* [186]. Intended to affect long term dietary behaviour and attitude changes, this game employs a combination of goal-based, feedback, social influence, and reward mechanism techniques. Similar to other designs, players are presented with a role playing scenario, visiting a restaurant, and tasked with selecting food choices. Players are rewarded with points based on how well their food selection matches different health goals, are sent daily "challenges" and performance feedback, and their scores are presented on a publicly visible leaderboard alongside a custom social account details. The researchers evaluated this game design using 3 male and 3 female participants (between 19-40 years of age), all of whom had at least a high school diploma, and all of whom owned and used mobile devices, computers, and internet on a daily basis. Each participant made use of the game over a 10 day period and engaged in pre and post evaluation surveys regarding eating habits and attitudes, and nutritional knowledge. The researchers found that the game led to a positive attitude change related to eating and an increase in nutritional knowledge, attributing the positive change to the "slow" nature of the game permitting players to reflect on their choices. However, they also indicate that the slow approach of the game is less effective for increasing motivation or engagement, and acknowledge a need for a long term study of the effects of the game.

Persuasive games has also been demonstrated for motivating physical activity. For instance, Berkovsky *et al.* [187] presented a system for encouraging physical activity through two motivators: the chance to obtain extra time to complete the level by performing physical activity, and a virtual opponent who could be impeded through physical activity. A wearable sensor was used to capture player physical activity (jumping). The design was evaluated using 180 primary school participants between 9-12 years old (88 male and 92 female), and none of whom had prior experience with the game or limitations which would prevent physical activity. The researchers concluded that engagement with games can motivate physical activity and that physical activity did not negatively effect game enjoyment. They also reported that direct game motivators (activity to gain more game time) encouraged more activity than indirect motivators (activity to impede virtual opponent), and that higher skill level reduced activity.

As well as for encouraging general physical activity, the motivating and engaging attributes of games have also been leveraged for the support of physical rehabilitation,

discussed in more detail in section 2.1.3. The paper by Biddiss and Irwin [111] reviews a number of studies, supporting the findings of the activity motivating game described by Berkovsky *et al.*, and suggesting that games are an engaging medium for encouraing light physical activity, while Baranowski *et al.* [112] proposed that they are useful for developing news skills through modelling and feedback theory. As described in this previous section, a number of papers have explored these beneficial properties for rehabilitation, such as the study by Burke *et al.* [101] and reviews by Saposnik *et al.* [113] and Laver *et al.* [53] both concluded that game based therapies were effective for motor function improvement as an adjunct to traditional therapy.

Influencing Dietary Choices and Behaviour

The examples so far in this section have demonstrated the use of technology has been demonstrated to support self-logging of activity and dietary intake, or for encouraging reflection and an attitude change towards intake and exercise. The wearable technologies and intelligent sensing solutions described earlier in section 2.2.2 and section 2.2 are also useful for encouraging context specific eating change. A number of existing studies have employed forms of eating monitoring technology along with creative persuasive technology to encourage dietary choice consideration, manipulate satiety, or to encourage adjustment of eating function via eating rate.

For example, Kadomura *et al.* proposed a sensing fork system for the detection of eating behaviours, in combination with a persuasive game for addressing eating problems in children [188]. The reported system consisted of a sensor fork equipped with accelerometer and gyroscopes to detect eating hand motions, photocell sensors in the prongs of the fork for estimation of food type based on color, and electrodes in the fork prongs and handle, to help determine fork to mouth contact and for measuring food type based on food resistivity. Using the combination of sensors, the device can detect "at-rest" and "held" states based on accelerometer and gyroscope motion data, "poking states" based on photosensor and resistance electrode measurement of food color and resistance, and "biting state" when a complete circuit is formed between hand and mouth and the fork orientation and motion are consistent with eating gestures. The authors report 62.5% accuracy for a food detection support vector machine classifier, based on food color and resistance data of 12 food types captured through fork tongs.

In a later paper Kadomura *et al.* [189] assessed the accuracy of eating action detection using this same device, on 3 male and 3 female participants aged between 21-28, reporting an accuracy of 77% for the detection of biting actions. For food type classification they expanded on their previous work and trained a support vector machine using 850 samples of 17 food types (stabbed by the fork prongs) trained and tested using 10 fold cross-validation, reporting an overall F-Score of 87.5%, and an improved accuracy of between approximately 93%-96% when dividing foods into "Japanese, Chinese, and Western cuisines".

They also conducted a user study of a mobile based eating game, called "Hungry Panda", driven by the fork sensor device, which was designed to address picky or distracted eating amongst children by presenting entertaining interaction with a panda character which responded to food consumption and color of food, presented virtual rewards, and prompted continuation when the fork was put down. A real-life study was conducted with 5 mother-child pairs (4 female and 1 male children between 2-8 years old), all of whom exhibited picky eating and two who were reported to be distracted eaters, over 9 days. Mothers photographed food and recorded meals, took notes of eating behaviours, and took part in a post-meal survey and interview. The researchers findings indicated that the game helped improve picky eating and reduce distractions, but they also found poor accuracy of the system when the parent fed the child, as the device relied upon a complete circuit between hand, fork and mouth to detect biting.

Other proposed persuasive eating technologies make use of augmented perception of food to influence eating. For instance, Narumi *et al.* [190] investigated some theories regarding factors that influence intake quantity (such as those discussed in section 2.1.5) focusing on the concept that serving and perceived food size effects intake quantity [191]. Narumi *et al.* present the use of augmented reality head mounted display and a custom algorithm for manipulating the apparent dimensions of held snack food items and investigate the effect upon intake quantity. They evaluated the system using 8 male and 4 female subjects, between 22-36 years of age, who were healthy and had no dietary restrictions. Participants were evaluated using a within-subjects design during which participants attended 3 lab sessions (separated by at least 2 days) during which they answered pre and post meal surveys, and consumed cookies appeared under one of three different conditions randomly ordered: normal, shrunk, or enlarged. The researcher reported a significant dif-

ference between cookie apparent size and volume consumed, with participants consuming more under the shrunk condition than large, with a similar effect reported for apparent satiety.

A similar study conducted by Sakurai *et al.* [192] support these findings. In this study, the researchers instead altered perceived food quantity through manipulation of plate size, proposed as one of the techniques by which individuals estimate food volume [21]. In the research by Sakurai *et al.* they project a virtual dish around food, altering the dish to change the perceived volume of food. The authors conducted an exploratory study of 20 participants to determine the effect of projected plate size on consumed volume of cheese pieces when the available food quantity remained constant. Their results indicate that increasing the apparent size of food by reducing the ratio of projected dish size to food reduced intake volume, while reducing the apparent food size by increasing dish to food ratio resulted in increased intake.

Influencing Eating Rate Through Eating Technology and Feedback

As well as manipulating intake choice and manipulating intake volume and satiety, another line of research has sought to apply persuasive technology and feedback for altering eating rate. Studies by Zandian *et al.* [128] and Ioakimidis *et al.* [129], discussed previously in section 2.1.5 (page 31), manipulated eating speed through the use of a "mandometer" which estimated intake volume using a weight scale and provided eating rate feedback. In these studies they evaluated the effect of faster or slower eating conditions, by asking participants to eat meals with larger or smaller food portion at the same pace as during a control meal. They used this technique to evaluate the effect of eating rate (mimicking eating disorder patients) upon linear and decelerated eating patterns, and concluded that linear eaters are at risk of developing eating disorder-like eating patterns when subject to influencing stimuli.

A similar system was proposed by Kim *et al.* [193] to support patient with metabolic syndrome in portion control and eating pacing. They presented a "smart tray" equipped with weight scales and LED's in 4 sections along with an accompanying smart phone application. The application could be used to input patient physical details and activity level to estimate recommended daily calorie and sodium content, and select meal types from a list of options, as well as set desired eating pace. Calorie and sodium content was

then estimated based on the measured weight of each food, and the tray LED's used to indicate when the portion size exceeds the recommended allowance. During eating the weight of food and elapsed meal time is used to calculate eating rate, and the mobile application provides feedback if the eating rate is too fast. The system was evaluated over a 2 meal experiment with 3 male-female couples (average age = 60.1), where at least 1 member of each couple was a metabolic syndrome patient. Each session consisted of a period plating up the food, followed by the meal. The researchers reported that the LED notifications helped prevent "over-plating" food, and the eating rate feedback helped keep eating pace. However, they also noted that patients tended to keep pace with their spouse, and a need to further consider social impact upon eating rate pacing.

As well as scale based systems, other approaches have also been used to guide eating rate. For instance, kim *et al.* [46] presented a wrist-band and tabletop unit system for eating speed guidance. This system consisted of a bluetooth wristband equipped with accelerometer and gyroscope sensors for estimating eating rate from detected eating gestures (based on wrist motion rotation exceeding $\pm 70 degrees/sec$ for $200ms$) and a predefined time for a bite. Feedback is presented by a tabletop hourglass 'stoplight' (showing red, yellow, or green as they complete eating gestures), or via tactile feeedback through the wristband (a 2 second vibration when they eat faster than the predefined time for eating gestures). They evaluated the system in a pilot lab study of 22 female and 23 male participants between 17-31 years old (mean = 22.68). Participants were divided into control (no device), tactile feedback, and visual feedback groups, and each took part in a video recorded session consuming 30 grams of potato chips. The researchers reported a significant difference between the control, visual, and tactile groups, and a significant difference between control and tactile feedback for number of bites. The researchers concluded that eating rate feedback could contribute to altering eating speed, and tactile feedback leads to reduced food quantity consumed per bite.

Another approach, proposed by Kim and Bae [194], makes use of smart phone camera to track facial bite gestures (mouth opening) based on the relative position of user mouth and nose. Mouth opening gestures were used to determine hand motion from food to mouth, and the time to move from plate to mouth along with time to chew a bite identified as factors contributing to eating rate. They also proposed animated, emoji based feedback which could capture eating states and provide alerts when the eating rate

exceeded predefined levels. However, this paper presented a prototype system and did not provide details evaluating its performance, which the authors identify as a target for future work.

Eating Technology for Diet Tracking

The literature discussed above outlines a number of uses for creative eating monitoring technology for encouraging healthy eating, influencing dietary choices and eating behaviour, and guiding eating rate towards healthier eating function. Another application for such technology is for logging of dietary content in consumed meals. As discussed in section 2.1.4 logging of food intake is one of the main techniques employed in clinical and personal eating behaviour change and treatment of behavioural therapy for eating disorders. However, manual logging has an inherent error associated with it and is reliant upon patient adherence to logging. As discussed in section 2.1.7 and earlier in this section (section 2.2.5), mobile based applications are also helpful for adherence to food logging, but do not entirely solve the issue.

Ye *et al.* [195] suggested a semi-automated approach to improve upon food logging adherence, through use of hand eating gesture detection. In the proposed system they used a accelerometer equipped wrist band to detect wrist motion and transmit data via bluetooth to a smartphone application detected eating gestures using a Support Vector Machine classifier. Upon detection of eating the wrist band vibrated and displayed a message to remind the user to visually log food using an associated application, which they could accept or reject. Ye *et al.* conducted a 2 week study of 6 male and 1 female participants, aged between 20-28 with no specifically set dietary change goals. Usability of the system was estimated daily by a 12 item questionnaire, and was reported to be rated highly. They estimated precision of eating detection based on the number of reminders and negative or positive logging responses, which they reported as $31\% \pm 8\%$. Finally, the authors reported a high correlation between eating reminders and logging sessions, and concluded that it helped participants sustain logging.

Fully automated intake monitoring technology can further help to solve many of the issues involved with food logging. Section 2.2.2 (page 45) discussed some technology based approaches which have been proposed to aid in food logging, or food type estimation. For instance, Liu *et al.* [160] suggested a eating detection system (driven by acoustic

classification of eating) and camera for producing automated visual logs of consumed food, and Okamoto and Yanai [161] presented a system for estimating food calorie content based on smartphone captured images driven by a Convolution Neural Network with an error of 21.3%.

In an attempt to quantify the clinical benefits of food logging, Kim *et al.* [37] conducted a clinician based evaluation of a meal logging system. They interviewed 5 clinician during the development of their system to identify clinical requirements and determined that for lifestyle diseases clinicians need to monitor patterns in nutritional content, calorie intake, and daily distributions from food intake records. While for conditions requiring weight and food management they need to monitor maintenance of regular diet. They also determined that clinicians viewed adherence as a major issue in using logging applications. They then developed a patient mobile application for logging fullness after a meal along with other user determined food information, which was designed with an emphasis on high accessibility and low effort to increase adherence. A web interface was developed alongside the application to permit monitoring of the data by clinicians and researchers.

Kim *et al.* then conducted an 8 week study was conducted involving 6 clinicians, who recruited a combined 20 participants (10 male and 10 female between 25-71, with varying professional demographics), during which patients logged food intake and wore a fitbit to monitor activity and sleep, and took part in pre study nutritional interviews. Two checkups evaluating clinician data usage revealed a high rate of data collection and food journalling adherence, but high adherence was determined to be the result of clinician involvement and a reminder sticker attached to phone devices. From the review of clinician data usage and interviews, they determined that clinicians were interested in cross-referencing food intake data with other lifestyle data, but the lack of evidence regarding such relationships merited further research.

These findings exemplify one of the main issues involved in eating technology for behaviour change or for research. The studies discussed in this section indicate some interesting correlations between eating technology and the benefits of such devices for monitoring intake, or in conjunction with persuasive technology for motivating adherence to food journalling, or for healthy eating change. But, as in the case of the study by [37], while there are promising results the lack of evidence and difficulty in collecting data make it hard to make any final conclusions regarding the influence of these technologies over

eating, or the benefit for research and clinical treatmet.

2.3 Considerations for EMG Measurement and Intake Classification

An overview of the principles of EMG was discussed in section 2.2.1, and a more detailed discussion in section 2.2.3 reported its use for the evaluation of parameters relating to eating function and food textural properties. However, given the wide variety of techniques employed in the literature, there are a number of important factors to consider regarding EMG measurement, sensor placement, signal preprocessing and detection, feature extraction, and EMG classification. This section encompasses literature recommendation and reiterates over some previously discussed topics regarding these areas, with a focus upon implementation and techniques related to measurement, processing and classification.

The first consideration for the acquisition of surface EMG signal is sensor placement. The selected position for placement of electrodes upon the surface of the skin during Electromyography is dependent upon the targeted muscle for measurement. The muscles related to eating, of the face and neck, are relatively interconnected and section 2.3.1 discusses potential muscles of interest outlined within the literature and related positioning of sensors. EMG signals are naturally noisy due a number of factors and there are a number of recommendations for reducing such noise as part of or after acquisition, which are discussed in section 2.3.2. Section 2.3.3 then reviews a number of approaches for the detection of muscle activity onset and terminations which have been proposed within the literature. Finally, machine learning may also be useful as part of the signal processing process, for the detection of signal activity periods, or for other signal classification purposes. Machine learning, associated algorithms, and feature extraction approaches are discussed in section 2.3.4.

2.3.1 Sensor Placement

As a means for evaluation or the detection physical activity, Electromyography requires careful sensor placement to capture muscle activity related to target specific muscles which are employed in the activities of interest. In the context of this thesis, there are a number of interconnected muscles relating to chewing and swallowing [76], which are also associated

with other jaw motion, facial expressions, head motion, and speech [196, 13]. The anatomy and physiology of eating processes were discussed in section 2.1.1, and figure 2.2, adapted from [76], shows muscles related to chewing and swallowing.

For EMG placement, Criswell and Cram [73] provide details regarding specific muscles, electrode placement, and exercises which demonstrate activity from these muscles. Muscles associated with feeding processes are indicated in the figure earlier in this chapter, and figure 2.14, adapted from [73], shows many sensor placement positions detailed by Criswell and Cram [73]. They suggest wide placement of electrodes across the temporalis and masseter for the general measurement of mastication and facial muscles (figure 2.14, **a**). The Anterior Temporalis is recommended for information regarding mastication and mandible motion during jaw clenching, jaw motion, and swallowing (figure 2.14, **c**). The masseter provides similar information regarding mandible elevation, jaw closure, grinding, and mastication, and is active during teeth clenching, swallowing, and talking (figure 2.14, **b**). Finally, the muscles of the suprahyoid (or submental space) is also related to mandible motion (jaw opening), but is more heavily associated with larynx elevation during swallowing activity (figure 2.14, **d**).

For dysphagia assessment, Criswell and Cram [73] suggest monitoring the suprahyoid and buccinator muscles (figure 2.14, **e**). Stepp [196] suggests similar sites for the evaluation of dysphagia, including the buccinator, orbicularis oris and other perioral muscles as associated with cheek motion. They also suggest masseter muscles, and the digastric (of the submental space) to a lesser extent, as the primary muscles associated with mastication, and the suprahyoid or infrahyoid as potential muscles for evaluation of swallowing with EMG.

Within the literature discussed thus far, EMG has also been used to evaluate eating function, food textural properties, assess swallowing functionality related to dysphagia, and to classify chews, swallows and foods. Primarily, the targeted muscles for these sites align with those discussed here, but vary across the literature. An overview of the main targeted muscles, associated physical function, and related literature is given in table 2.1.

Table 2.1: Summary of notable observations from the literature regarding EMG placement for muscles related to eating, physiological characteristics, and notable clinical and research applications.

EMG Sensor Placement and Clinical and Research Applications for Notable Muscles Related to Eating			
Targeted Muscle	Notable Behavioural Actions	Physiological Characteristics	Clinical and Research Applications
Temporalis (Anterior)	Mastication, Maximal force (clenching jaw) [57, 5, 73]	• Reduced EMG amplitude from impaired dental status or muscle function [169, 165, 6, 60]	• Evaluation of eating [5, 58, 173, 174, 57] • Dysphagia assessment [169, 165, 62] • Chewing detection [170, 178, 197, 180] • Food classification [179, 178, 180, 58]

Masseter	Mastication, Maximal force (clenching jaw) [57, 5, 73, 171]	• Impaired dental status or muscle function reduce amplitude [169, 165, 6, 60] • Increased amplitude related to food hardness and fracturability [174, 176] • Associated with oral stages of swallowing [169]	• Evaluation of eating [57, 173, 174, 6, 60] • Dysphagia assessment [62, 169] • Dental assessment [6, 60] • Chewing and food texture evaluation [174, 176]
Suprahyoid Muscles (Digastric, Submental Triangle)	Swallowing, jaw opening, speech [73]	• Associated with final oral, pharyngeal, and oesophageal stages of swallowing [169]	• Evaluation of swallowing [5, 60, 61, 167] • Dysphagia evaluation and screening [169, 62, 166] • Swallow detection [177] • Food texture and taste classification [175]

Infrahyoid and Laryngeal Strap	Swallowing [73, 169]	• Associated with pharyngeal and oesophageal stages of swallowing [73, 169]	• Evaluation of swallowing [167, 169, 61] • Dysphagia evaluation and screening [62]
Perioral Muscles (Orbicularis Oris and Buccinator)	Mastication (assistance), cheek/mouth motion [73, 57]	• Associated with initial oral stage of swallowing [169, 57] • Dysphagia assessment [62, 196]	

2.3.2 EMG Signal Processing

EMG signal amplitude is inherently unstable due to a range of factors, including the presence of random amplitude noise related to motor neuron firing rate, noise developed due to signal propagation through the body, electrical interference from EMG equipment, ambient electromagnetic radiation, and due to movement artefacts [143]. Cross-talk is an additional source of interference, activity of nearby muscles contaminating the targeted signal [198]. Reaz *et al.* [143] emphasises the need to avoid or eliminate as many sources of noise as possible, while maximising signal information.

The article by Chowdhury *et al.* [198] suggests a number of techniques for avoiding EMG noise. For moderating cross-talk or noise related to signal propagation through various tissues, the authors suggest using smaller electrodes, minimising electrode spacing, and ensuring electrodes are positioned along the muscle fibre to reduce such noise. Chowdhury *et al.* also consider movement artefacts resulting from independent motion of muscle, skin, and electrode, or artefacts related to skin impedance. To reduce these artefacts, the authors note use of conductive gel as an intermediary and increasing skin impedance through light abrasion.

Figure 2.14: Example of sensor placement sites recommended by Criswell and Cram [73]. Shown are: (**a**) Temporal/Masseter (wide) placement for general recording of mastication, (**b.**) Masseter placement for mastication measurement, (**c.**) Anterior Temporalis placement which provides assistance in chewing, (**d.**) Suprahyoid placement for measurement of muscles involved in mouth opening and swallowing, and (**e.**) placement for measurement of the Buccinator, which assists in chewing. Adapted from [73].

Digital filtering is also a common practice used to eliminate many signal artefacts resulting from noise, however the choice of filter and cutoff values vary widely within the literature, and are partially a matter of application and researcher preference. Slow changes in signal activity resulting from movement or inherent signal instability usually appear in the 0-20 Hz range [143, 198, 196, 199], while EMG signal above 500Hz is usually associated with high frequency noise [196]. As such a number of researchers suggest the use of a high pass filter with a cutoff of 20Hz and a low pass filter with a cutoff of 500Hz, for general elimination of these noise sources from EMG signals [198, 196, 199], although Criswell and Cram [73] instead suggest a band-pass filter with a cutoff range of 100-200Hz. This would also permit the elimination of ECG contamination within the signal, which occurs within a frequency range below 100Hz [198].

The frequency selection is also a matter of debate between studies evaluating EMG related to eating. Vaiman *et al.* [169] made use of a band pass filter within a range of 25-450Hz for their evaluation of normal swallowing function using EMG, along with a 60Hz

notch filter. However, Reaz *et al.* [143] cautioned against using notch filters in case of lost signal information. In their evaluations of EMG with different food textures, Lassauzay *et al.* [58] and Kohyama *et al.* [6] instead filtered recorded signals within a pass band of 1-1000Hz, while Miyaoka Y. *et al.* [176] and Miyaoka Yozo *et al.* [175] applied a filter with a high-pass and low-pass cutoff of 10Hz and 30Hz respectively. Of the studies attempting to classify chewing and food information, R. Zhang *et al.* [178] applied a band pass filter of 10-500Hz and R. Zhang and O. Amft [180] used a high pass filter with a cutoff of 20Hz, but did not specify an upper cutoff frequency.

2.3.3 Activity detection

Another matter of debate is the choice of technique for signal onset and termination detection. Reaz *et al.* [143] discusses the common practice of threshold based detectors, with the simplest form using a "single threshold", but emphasises that its performance varies depending on the chosen threshold, signal noise, and targeted muscle. Instead they suggest the addition of a second or more thresholds and inclusion of additional parameters which help to improve detection accuracy and reduce misclassification. A typical method for defining this threshold is by selecting an amplitude several standard deviations greater than a baseline period, in the following manner:

$$thr = \mu_0 + j * \delta_0 \tag{2.3}$$

where μ_0 is the mean background noise of the signal, or a baseline period when the muscles are at rest, δ_0 is the standard deviation during that same baseline, and j is a scaler [181, 200].

The value of this scalar, j, is also a matter of debate in the literature. Hodges and Bui [201] recommend caution in the choice of threshold, which can result it Type I errors (false positives) if too low, Type II errors (false negatives) if too high. Di Fabio [202] suggest using $j = 3$ for this value, and calibrating the threshold in post-hoc processing, by adjusting the baseline selection window incrementally, until at least 25 consecutive samples were found to exceed the threshold. On the other hand, Li *et al.* [200] suggests that the value of j should instead be selected during processing of the signal. In addition to this, the duration for which the signal must exceed the threshold can also effect detection accuracy [201], with too low a duration resulting in potential misclassification of background activity

bursts as muscle onset, or too long a duration risking the failure to detect short activity bursts.

Another method recommended by Li *et al.* [200] was the application of a "Teager-Kaiser" energy operator to the EMG signal prior to threshold use. Originally proposed for computing the energy of sound, the TKE operator Ψ is defined in time, for the signal x as:

$$\Psi_d[x(n)] = x^2(n) - n(n+1)x(n-1) \tag{2.4}$$

where $x(n)$ is the EMG signal at sample n. They then suggest the use of a threshold based approach for detection of muscle activity onset, as described previously.

Alternative methods include the "transition index" proposed by Abbink *et al.* [181], which is based upon the principle of determining the approximate onset of jaw opening by applying a filter to highly smooth a the signal (low pass, cutoff point set to 3Hz) and using a high threshold. They then define a "search interval" as a period between 200ms prior to the upward threshold crossing and the next upward threshold crossing. This interval can be used to find the onset of EMG bursts by searching within this interval (across the normally smoothed signal) for a transition from amplitudes below a typical threshold to those above. From the centre of the search interval and moving towards the start of the interval, the transition index is calculated as $Trans(i) = n < (i) + n > (i)$, where $n < (i)$ is the count of n samples preceding sample i which exceed the threshold, and $n > (i)$ is the count of n samples following sample i which exceed the threshold. Burst onset can then be determined as the maximum transition index, and termination can be determined by the minimum transition index.

Amongst studies attempting to classify feeding activity (section 2.2.4), R. Zhang *et al.* [178] reported a precision and recall of 80% using a threshold based approach for chewing cycle detection. Q. Huang *et al.* [179] similarly applied a multiple threshold based detection algorithm, which resulted in a 96% accuracy during evaluation of this algorithm, however they also reported false positive chew detection during speech, laughter, or other activities relating to jaw motion. Finally, R. Zhang and O. Amft [180] implemented an algorithm based upon the technique proposed by Abbink *et al.* [181], and reported a 94% accuracy across all participants. However, as previously discussed, in this study, accuracy of this algorithm was found to be significantly lower for chewing detection in the presence of "real-world" activities.

2.3.4 Machine Learning

Machine learning encompasses a wide range of techniques used for modelling data structures, and for analysis and prediction of data, and for statistical analysis, pattern recognition, signal processing, bioinformatics and a range of other uses [142]. Such techniques are also considered particularly useful for the analysis of physiological signals such as Electromyography, capable of identifying patterns in data not easily detected by other methods [143]. As discussed previously, this makes them affective for enhancing Human-Computer Interaction, particularly in regards to the control of prosthesis [144, 145, 146] and assistive technology [147, 148, 149, 49].

Of particular interest in such tasks is the use of machine learning for classification. Classifier algorithms are used to identify unknown patterns in data, where data can be separated into one or more distinct groups. Such models can be trained using supervised learning, to recognise patterns in known data and permit future data to be divided accordingly, or through unsupervised learning, in which models attempt to identify patterns without previous examples, for exploratory analysis of data [142]. The two major areas involved in producing models for classification tasks are the extraction of information pertinent and useful for the classification goal, known as feature generation, followed by the training of a classifier [142]. There are a wide range of possible classification algorithms and features which are relevant for the classification of EMG signals, and this section discusses some of the commonly available techniques and algorithms which should be considered.

Classification Algorithms

A large range of classifier algorithms have been proposed for a range of signal analysis tasks, some of which are described in the books by Theodoridis [142] and Kuncheva [203]. The following are a number of algorithms which have been identified in the literature, and are used for signal evaluation and recognition, or for computer or device control systems:

Linear Discriminant Analysis Linear Discriminant Analysis (LDA) algorithms are used for classification purposes or for feature dimensionality reduction. They are based upon Fisher's Linear Discriminant [204] and involves a linear transformation technique, to identify linear discriminants within a feature space to separate two classes

[142]. For the classification of food based upon EMG measurement, R. Zhang *et al.* [178] and [180] implement models based upon LDA algorithms, reporting 56.2% and 94.7% classification accuracy respectively. [199] describes the benefits of LDA algorithms, praising their simplicity, lack of specification parameters, and ability to perform reliably well. However, they highlight that these are only capable of capturing linear classification problems.

Decision Trees Decision Tree classifiers (DT) are based upon the sequential separation of items into classes using a series of branching binary tests; each test checking if a single feature matches a condition. Training of such classification trees involves finding a structure and tests which are best able to represent a decision making process for identifying classes of interest [142]. While decision trees are simple to understand, apply, and are capable of providing insights even with small amounts of data, they are prone to instability and overfitting [142]. Random Forest classifier algorithms (RF) are a variant of decision trees proposed by Breiman [205] that use a combination of bagging to combine a number of separate trees (an ensemble of decision trees) for variants of the training data set, and random feature selection for each test node. This thereby overcomes many of the overfitting concerns of traditional decision trees [142]. Another variant of decision trees is the Extremely Randomised Decision Tree proposed by Geurts *et al.* [206], which also creates an ensemble of decision trees, but fully randomises splitting of the tree's nodes, resulting in accurate and computationally efficient classifier models.

Random Forest classifiers are poplar algorithms for classification of physiological data thanks to their ability to robustly detect both linear and non-linear relationships in data. R. Zhang *et al.* [178] report the use of a Random Forest Classifier (RF) for the classification of foods, reporting an accuracy of 74.8%. While Huang *et al.* [197] reported the use of a J48 Decision Tree for the same purpose, reporting per-food accuracies of 69.2%–94.8%.

Artificial Neural Networks Artificial Neural Networks (ANN) classifiers have their basis in understanding the functionality of the human brain, and function through the interaction of multiple simulated neurons (perceptron) layers, learning achieved through the adjustment of synaptic weights to minimise a cost function [142]. In

a review of EMG processing techniques Reaz *et al.* [143] recommends the use of Artificial Neural Networks in particular as a technique capable of finding pattern which would otherwise not be easily detected. Nazmi *et al.* [199] and Chowdhury *et al.* [198] support this conclusion, suggesting that their adaptable architecture make ANNs capable of robust classification in non-linear tasks. Chowdhury *et al.* describes these characteristics as making them a popular choice for prosthesis and assistive robotics control systems, Virtual Reality interaction systems, and rehabilitation applications. However, Nazmi *et al.* emphasises that these algorithms require very careful consideration of system architecture, and can involve long training times.

Support Vector Machine Support Vector Machines (SVM), or Support Vector Classifiers (SVC), are popular tools for classification and regression tasks, capable of solving linear or nonlinear classification problems depending on the selected kernel [199]. SVM are based upon the premise of mapping feature vectors onto a higher dimensional space and identifying a hyperplane which maximise a margin between classes within this higher dimension [207]. Chowdhury *et al.* [198] states that their reliability, robustness, accuracy, and simple implementation and training requirements makes them a popular choice, particularly for disease diagnosis and control systems. However, they also require careful parameter selection in order to obtain the best result.

While traditionally these algorithms are designed to identify a linear hyperplane, using a linear kernel function, Hsu *et al.* [207] identifies 3 other kernel functions which permit non-linear solutions for classification tasks: polynomial, radial basis function (RB), and sigmoid. A gaussian radial kernel has also been recommended for classification of swallowing using EMG and Bioimpedance by Nahrstaedt *et al.* [177]. Hsu *et al.* [207] recommend use of the RBF kernel, as it is capable of non-linear classification, with less parameter requirements than the polynomial function, and capable of non-rlinear classification comparable to the linear kernel. The authors also suggest carrying out a search for ideal parameters using cross-validation grid search, prior to training with the full training data.

Feature Extraction

Another vital component of signal classification, prior to training an algorithms, is the selection of features that accurately characterise classes of signals. Phinyomark *et al.* [208] highlighted the importance of eliminating redundant features and selecting only those best suited for the task, to maximise the performance of classifier algorithms. A range of notable features recommended within the literature, or used for the evaluation or classification of eating or food texture, along with abbreviations (used to refer to the feature here) and extraction methods, is given in table 2.2.

To recommend useful features and identify redundancies, Phinyomark *et al.* [208, 209] conducted an evaluation of 37 common time and frequency domain features, extracted from EMG of the arm from 20 subjects (10 male and female) carrying out various gestures. Phinyomark *et al.* [208] categorised time-domain features into 4 groups: amplitude features, time-frequency features, prediction model methods, and time-dependence methods. For amplitude features, they recommended the use of features as providing either energy or complexity information; recommending MAV or IEMG for obtaining energy information, and WL for complexity information. The second group consisted frequency features calculated from the time domain, and included MYOP, WAMP, SSC, and ZC. Of these features, the authors recommended WAMP for this group. However, MYOP was found to perform comparably and contains similar information. Of the final two groups, Phinyomark *et al.* recommended the use of Auto Regressive coefficients for prediction models, and they suggest the Mean Absolute Value Slope for time-dependence features. However, the authors reported significantly better performance for classification using signal amplitude features, compared to prediction models and time-dependence features, and conclude that amplitude features should be focus in signal classification. They also suggest that frequency based features are not well suited to EMG signal classification.

A later evaluation by Phinyomark *et al.* [209] assessed the relationship between anthropometric measurements and the performance of select features for the classification of arm gestures. In addition to EMG, physical measurement of the participants were made, including body mass (subject weight), standing height, BMI, and various dimensional measurements of the hand and arm. Although many such measurements were not relevant for the work in this thesis, Phinyomark *et al.* made a number of interesting ob-

servations. They determined that WAMP and ZC were particularly robust to random or electrical interference noise. Detrended Fluctuation Analysis, a fractal complexity feature, was found to be useful for the classification of weak EMG signals. To characterise strong signals, they recommended Maximum Fractal Length, and MAV or RMS. Phinyomark *et al.* found sample Entropy (quantifying the unpredictability of EMG signals over a time segment) to be robust for determining the muscle contraction variability, recommending it as reliable over long-term usage and tolerant to noise. Finally, they recommend the MNF as a feature for muscle fatigue detection.

Within other literature discussed in this chapter, a number of other EMG parameters were found to be useful for the evaluation of eating and food texture, and as such are useful for the classification of intake or food content. For instance, the synchronous pattern of EMG bursts, signal amplitude, timing of chews, and number of chews have all been reported as associated with chewing efficiency [5, 6, 60]. Signal amplitude and swallow duration are similarly considered important for swallowing assessment, as well as for dysphagia [169, 165, 61, 62]. For the evaluation of texture, a number of studies have found an association between food textural components and increased signal energy [172, 59, 58, 174, 173], as well as an increased number of chews per chewing sequence [59, 58, 174, 172, 176], or chewing duration [172, 173, 59, 58]. As discussed in section 2.2.4, Miyaoka Y. *et al.* [176, 175] also proposed the use of the "T_P" parameter (see table 2.2) to capture signal complexity information across a given EMG burst, for evaluating textural differences.

The majority of chewing or swallowing detection techniques employ threshold based detection algorithms based upon EMG energy information [143, 198, 199, 202, 200], while other techniques attempt to capture signal complexity information [181]. Of the studies implementing eating detection and food classification systems, R. Zhang and O. Amft [180] made use of primarily time-domain features relating to signal energy: MAV, SD, peak amplitude, RMS, and IEMG. While Huang *et al.* [197] extracted features characterising both individual chewing cycles and entire chewing sequences, reporting peak amplitude, chew cycle duration, and T_P values for individual cycles, and included the number of chewing cycles per sequence.

Table 2.2: Summary of notable features recommended within the literature, and equations or extraction techniques.

EMG Classification Feature Summary	
Feature Name and Usage	Method
Mean Absolute Value (MAV) [209, 208, 180, 165, 60, 6, 61, 62]	Average of the absolute EMG signal across a sample. Defined as: $$\mu = \frac{1}{L}\sum_{i=1}^{N} \mid x_i \mid \quad (2.5)$$ where x_i is the EMG signal at segment i and N is the number of segments.
Integrated EMG (IEMG) [209, 208, 178, 59, 58]	Related to EMG signal firing point [208]. Defined as the summation of the absolute EMG signal across a sample: $$IEMG = \sum_{i=1}^{L} \mid x_i \mid \quad (2.6)$$
Variance (VAR) [209, 208]	Variance of EMG signal across a sample: $$VAR = \frac{1}{N-1}\sum_{i=1}^{L}(x_i^2 - \bar{x}) \quad (2.7)$$ where $\bar{x}$ is the mean of the sample.
Root Mean Square (RMS) [209, 208, 199, 180]	Square root of the average square of EMG amplitude across a sample $$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2.8)$$
Standard Deviation (SD) [209, 208, 180]	Standard deviation (σ) of the EMG signal across a sample: $$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \quad (2.9)$$ where $\bar{x}$ is the mean of the sample.

Waveform Length (WL)
[209, 208]

Cumulative length of EMG waveform over signal segment

$$WL = \sum_{i=1}^{N-1} \mid x_{i+1} - x_i \mid \tag{2.10}$$

Peak Amplitude
[197, 60, 6, 165, 61, 62]

The peak amplitude across a given sample of the EMG signal.

Myopulse Percentage Rate (MYOP)
[209, 208]

Related to firing of Motor Unit Action Potentials. Average number of times that the absolute of the EMG signal exceeds *thr*

$$MYOP = \frac{1}{N} \sum_{i=1}^{N} [f(\mid x_i \mid] \tag{2.11}$$

$$f(x) = \begin{cases} 1, \text{ if } x \geq thr \\ 0, \text{ otherwise} \end{cases}$$

Willison Amplitude (WAMP)
[209, 208]

Sum of times the absolute EMG exceeds a given threshold *thr*:

$$MYOP = \frac{1}{N-1} \sum_{i=1}^{N} [f(\mid x_i - x_{i+1} \mid] \tag{2.12}$$

$$f(x) = \begin{cases} 1, \text{ if } x \geq thr \\ 0, \text{ otherwise} \end{cases}$$

Zero Crossing (ZC)
[209, 208]

Number of times EMG amplitude crosses zero amplitude:

$$ZC = \frac{1}{N-1} \sum_{i=1}^{N} [sgn((x_i \times x_{i+1}) \cap \mid x_i - x_{i+1} \mid \geq thr] \tag{2.13}$$

$$sgn(x) = \begin{cases} 1, \text{ if } x \geq thr \\ 0, \text{ otherwise} \end{cases}$$

Slope Sign Change (SSC)
[209, 208]

Count of the number of times the EMG signal slope changes:

$$SSC = \frac{1}{N-1}\sum_{i=1}^{N}[f((x_i - x_{i-1}) \times (x_i - x_{i+1})] \tag{2.14}$$

$$f(x) = \begin{cases} 1, \text{ if } x \geq thr \\ 0, \text{ otherwise} \end{cases}$$

Mean Frequency (MNF)
[209, 208, 199]

Average frequency calculated by:

$$MNF = \sum_{j=1}^{M} f_j P_j / \sum_{j=1}^{M} P_j \tag{2.15}$$

Where f_j is the frequency of the power spectrum at frequency bin j and Pj is EMG power spectrum at frequency bin j and M is the length of the frequency bin.

Mean Power Spectrum (MNP)
[209, 208, 199]

Average of the power spectrum of the EMG signal sample:

$$MNP = \frac{1}{M}\sum_{j=1}^{M} P_j \tag{2.16}$$

where P_j is the EMG power spectrum at frequency bin j and M is the length of the whole frequency bin.

Median Frequency (MDF)
[209, 208, 199]

Frequency at which the spectrum is divided into two regions of equal amplitude

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \tag{2.17}$$

where P_j is the EMG power spectrum at frequency bin j and M is the length of the whole frequency bin.

Median Power Frequency (MPF)
[209, 208, 199]

Band power of the median frequency calculated using Fast Fourier Transform

T_P Values [197, 176, 175]	Defined as the normalised time point across a chewing cycle at which point P percent of the total cumulative EMG has occurred [175]. Calculated using the following steps: 1. Calculate cumulative sum across sample window. 2. Normalise duration of sample. 3. T_P = the normalised time at which P percent of the cumulative sum of the signal has occurred
Cycle Duration [197, 169, 60, 6, 165, 166, 61, 62]	Duration of a chew or swallow EMG activity cycle, from onset to termination
Cycles per sequence [197, 176, 162]	Count of the number of chewing cycles within a given chewing sequence

2.4 Summary and Research Questions

This chapter has discussed and reviewed the current state of research regarding three main topics: Feeding Anatomy and Physiological Processes, Physiological Sensing and Technology for Automated Feeding Detection, Support of Rehabilitation and Health-Related Change, and Considerations for EMG Measurement and Intake Classification.

Section 2.1 highlighted the importance of individual and environmental factors, and their effect upon eating function, speed, volume, and the effect these parameters have upon health. However, there is also a need for considerably more research to understand the intricacies and interconnected influences of different factors upon feeding. A major limitation in eating studies, and monitoring or treatment of eating disorders is the use of self-reported weight, height, dietary intake, and factors. Self-reporting is a measurement technique which is prone to bias [32], and for which it is difficult to ensure accuracy. Within eating studies or disorder treatment, the main methods of ensuring accuracy is currently to implement controlled experimental conditions and manual observation of food weight to determine intake volume, speed, or dietary content [28, 123]. However, this is a

resource expensive approach in large scale studies, and may itself influence eating. There is a clear need for an automated method to continuously and discreetly monitor eating intake in situations outside of experimental conditions, or those where video recording or manual observation is not appropriate, such as while partaking of normal day-to-day activities, and without the presence of uncomfortable or intrusive equipment that can influence results..

Similarly, for the treatment and monitoring of swallowing disorders there is a great deal of debate regarding screening and treatment procedure, and a notable degree of underdiagnosis [17, 16]. While videoflouroscopy is considered the gold-standard for assessing swallowing function [14], there is a lack of agreed guidelines for these techniques [87]. Moreover, videoflouroscopy requires expensive equipment, professional assessment, and certain patient requirements which are not always feasible [89]. EMG has been recommended as an alternative technique for supporting screening and monitoring of swallowing function, which is fast and inexpensive [61, 62]. This provides a solution to the issues associated with other screening methods, however currently used methods are still reliant on specialist electrode placement and assessment, and are unsuited to long term monitoring.

The last topic discussed in this section was the use of technology to enhance treatment and monitoring. The increasing prevalence, popularity, and power of mobile devices offers a solution to many of the issues highlighted above. Mobile device based interventions have been demonstrated as useful for increasing adherence to self-monitoring, and also for promoting healthy eating behaviour and function [44, 45]. Game-based feedback interventions have also been reported as useful for increase adherence to treatments, and for encouraging physical rehabilitation [112]. Biofeedback has been used for similar purposes in regards to dysphagia rehabilitation, for support of swallowing exercises within interventions [63, 100]. However there are issues of engagement, motivation, and patient training, which can be significantly improved through the use of fun and simple to understand game-based feedback.

Section 2.2.1 explores the various approaches of assessment and detection of ingestive activity. Although there are a number of different technological approaches and sensor mediums which have been investigated for this purpose, the majority rely upon bulky equipment or wearable sensors which are inconvenient or indiscreet. While traditional forms of Electromyography face similar issues, novel modalities such as smart glasses [180]

or epidermal electronics [74] offer a discreet solution to this problem. The use of EMG for the detection of eating also has considerable support in its long history of use for evaluation of eating functionality [57], which provide strong indicators related to characteristics of EMG signals and how they relate to chewing, swallowing, impaired performance, and food types.

In addition to EMG for the detection of eating events, Sazonov *et al.* [162] and Amft *et al.* [163] have presented algorithms by which mass of solids and liquids can be predicted with a high degree of accuracy, which would be integral if automated monitoring of dietary intake by sensing of eating is to be deemed a valid alternative to self-reporting. Howevovinger, mass of food alone is relatively meaningless in many applications, such as dietary monitoring for determining nutritional value or dietary energy content consumed. In order to determine these factors, any monitoring systems must also be able to perform robust classification of a wide range of broad food types based on sensory and behavioural data, and factor in the predicted nutritional value of these foods into the models discussed here. In this way the mass and nutritional content of foods could be determined given the automated detection of eating.

The limited selection of foods evaluated in the literature discussed here, along with suggestions by authors [162], suggest that currently it is only possible to categorise broad food types using the evaluated techniques. However, the systems presented here and initial research into food classification demonstrate significant potential for future dietary tracking systems.

It is suggested here that the conjunction of mobile technology and continuous, unobtrusive, and mobile sensing devices provide a platform for accurate intake tracking, automated provision of feedback for encouraging behaviour change and feedback training, or for other Human-Computer Interfacing. With this in mind there are a number of research questions which are identified here. Already listed in chapter 1, these are:

1. How can physiological sensing be used for the accurate sensing of chewing and swallowing?

2. How can automated eating detection be used to detect eating characteristics and food content?

3. How can sensed eating data and characteristics be applied for studying eating be-

haviour function and behaviour, and for motivating eating change?

The remainder of this thesis answers these questions, and to explore the potential of Electromyography for automated detection of eating, extraction of other related information, and use for driving real-time health-related feedback.

Chapter 3

Electromyography for Swallow Detection, Classification, and to Drive Biofeedback

3.1 Introduction

This chapter reports the first main study of the overarching research of this thesis. Monitoring of swallowing is a necessary component for studying the physiology and function of swallowing, and for evaluation of swallowing for signs of swallowing impairment and for monitoring and treating swallowing disorders. However, typical techniques for the study and evaluation of swallowing make use of intrusive or expensive procedures and are not suited for long term or repeated evaluation. Electromyography has been demonstrated as a fast and inexpensive alternative for the assessment of swallowing [62], and has been used to offer biofeedback support for swallow rehabilitation therapy [64]. In conjunction with new sensing modalities, EMG provides a solution to many of the issues related to swallowing assessment and disorder treatment, providing a mobile platform for unobtrusive sensing of eating function. It is also proposed here that such sensing platforms can be used in conjunction with feedback to engage and motivate patients undertaking swallowing rehabilitation exercise.

This chapter aims to establish the first step in achieving the tracking of eating and its applications, focusing on tracking swallowing activity; for studying swallowing and assessing function, and for driving game-based feedback for rehabilitation exercise. With

this aim in mind there a number of research goals addressed in this chapter:

- Develop an algorithm for the detection of swallowing using EMG
- Determine features which cab be extracted from swallowing EMG
- Investigate the use of classifier algorithms for detecting swallowing types
- Demonstrate the use of EMG and swallow detection algorithm for driving swallow exercise biofeedback

To achieve these goals, this chapter is divided into three main sections. Firstly, section 3.2 reports the development of a swallow detection algorithm, and evaluates its performance using both conventional electrodes and a alternative sensing format. Section 3.3 then investigates the use of classification algorithms in conjunction with recorded EMG signal for differentiating between swallow exercises typical in swallow assessment and therapy. Finally, section 3.4 reports the development of game-based biofeedback for swallow exercising, and reports the findings of a user-evaluation study regarding the viability of EMG based swallow sensing and game based feedback.

Research Collaboration

The work reported in this chapter is the result of collaboration with the Yeo Research Group [75], and resulted in publication of two papers as described in the introduction chapter (section 1.6). This collaboration was pursued to investigate the use of "epidermal" sensor modalities being developed as a part of the collaborators research (discussed in the next section), for the purpose of automated swallow detection and as a part of feedback systems. As there were restrictions imposed on the use of these experimental sensors, the collaborating researchers were responsible for carrying out study protocols and for collecting data.

The author of this thesis designed all study protocols, and was responsible for analysis of the collected sensor data, development of swallow detection algorithms described in section 3.2, development of swallow classifier algorithms discussed in section 3.3, and the design and development of the biofeedback system in section 3.4. Throughout this chapter, details are provided in appropriate procedure sections where members of the Yeo research group were involved in data collection.

3.1.1 Electromyography and Epidermal Sensing

Surface EMG has been described as an fast, inexpensive, and non-intrusive alternative for the evaluation of swallowing function and diagnosis of swallowing disorders [61, 62], however conventional rigid electrodes are obtrusive and unsuited for continuous sensing of exposed or flexible areas of the body. Alternative sensor modalities such as "epidermal" electronics, proposed by Kim *et al.* [74], provide a suitable alternative to traditional sensors.

Epidermal electronics are discreet, comfortable, flexible, robust, and have high conformity to the surface of the skin, eliminating the need for electrolytic gel intermediaries that are used to reduce signal noise [210]. Prior works have demonstrated the use of such electronics for long-term (greater than 2 weeks) recording of EMG, ECG, and EEG signals [211], precise temperature mapping [212], thermal conductivity [213], hydration [197], and muscle stimulation [145]. They have also been demonstrated for EMG measurement from a number of muscle groups, including measurement of the masseter muscle [210] (see figure 3.1, **c** and **d**).

As seen if figure 3.1 (**a**), epidermal electronic circuits can include a range of components and an integrated system have the capacity for continuous sensing and wireless data acquisition. To investigate the possibility of this medium, the study reported in this chapter makes use of epidermal electrodes for the measurement of muscle activity. In section 3.2 both conventional and epidermal electrodes are used for collection of data and development of a swallowing detection algorithm, and the capacity of the algorithm to translate to both sensor types is then evaluated. In the remainder of this study, epidermal electrodes are used for the purpose of evaluating swallow-driven feedback. A full comparison of these sensors and conventional electrodes is described in an extension of the work in this chapter, reported in the paper by Lee *et al.* [1].

3.2 Development of EMG Based Swallow Detection Algorithm

The first goal in this research was the development of an algorithm for the detection of swallowing events from measured Electromyographic activity. This served as a vital step towards the classification of swallow type and for driving real-time biofeedback. This sec-

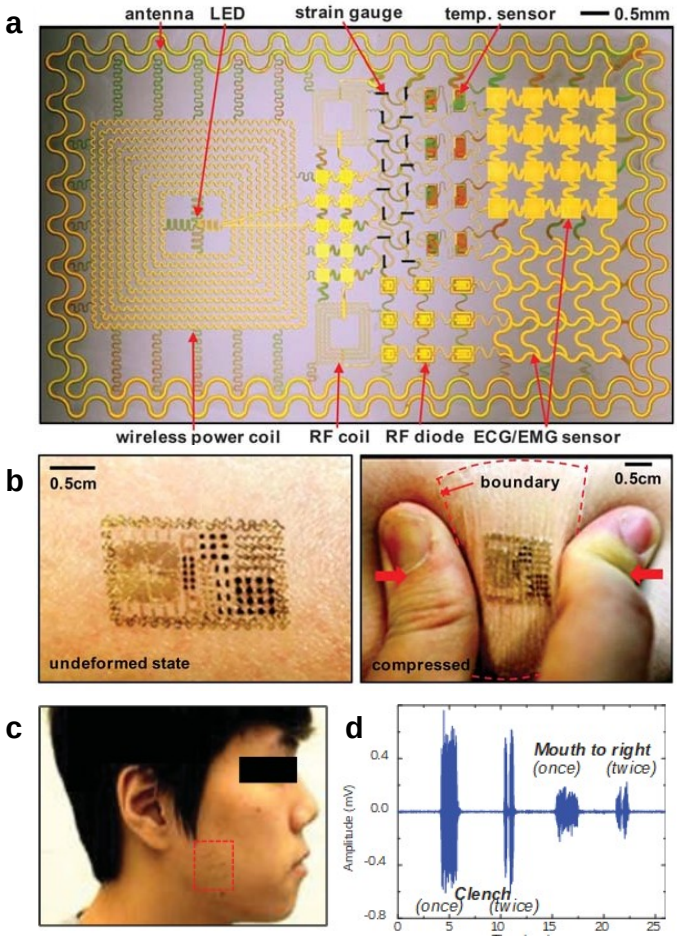

Figure 3.1: Examples of epidermal electronics for sensing purposes. Shown are (**a**) example of an epidermal circuit, including a number of components; (**b**) the epidermal circuit applied to the skin, demonstrating flexibility; (**c**) functionally invisible electrodes applied to the skin over masseter muscles; and (**d**) EMG signal recorded from the masseter electrode. **a** and **b** are adapted from Kim *et al.* [74], and **c** and **d** are adapted from [210].

tion reports the collection of data and development of a classification algorithm for the detection of swallowing. Data was collected using both conventional electrodes and epidermal electrodes. The performance of this algorithm for the detection of swallowing was then evaluated using the data collected using both conventional and epidermal electrodes to determine if algorithms developed using one form are transferable to other electrode types without significant impact.

3.2.1 Data Collection

For the development of swallow detection algorithm and subsequent investigation of swallow classification, training and test data was collected. This data consisted of EMG signal measurement and recording of video footage during a range of swallowing exercises, and

was used for both the development of a swallow detection algorithm and for training and testing of swallow classifiers.

Although the protocols outlined below were designed by the author of this thesis, it should be noted that data was collected by members of the Yeo research group [75], operating out of Virginia Commonwealth University. As such, they performed all aspects of the data collection procedure without supervision of the author. This included recruitment and screening of participants, selection of experimental conditions, setting up experimental equipment and equipping participants with sensors, and the recording of EMG and video footage.

Participants

For this stage of the study participants were recruited following the approved protocol at Virginia Commonwealth University (*approved number: HM20001454*). A total of 3 male and 3 female participants were recruited for data collection, from the staff and student body of Virginia Commonwealth University. As advanced age and swallowing difficulties are known to effect EMG signal quality [62], inclusion criteria required recruited participants to be between 21 and 40 years of age, have a BMI (between 18.5 and 25), and have no known medical disorders that would interfere with swallowing function. However, due to restrictions within the bounds of the research collaboration and recruitment protocol, it was not possible to share other details about participants. Each participant took part in EMG measurement of the submental and masseter muscles while carrying out voluntary swallowing exercises. In total EMG measurements were recorded over a total of 216 swallows each, for the two sensor types.

Materials and Sensor Placement

Each participant took part in two data collection session, following identical procedure for each. In a single data collection session participants were equipped with conventional rigid electrodes, data from which was used to develop the swallowing detection algorithm. Following this, participants took park in a second session during which they instead had epidermal sensors affixed to their skin. An example of both conventional electrodes with snap wiring and epidermal electrodes can be seen in figure 3.2, adapted from [1]. In both cases EMG data was measured using a Bluetooth enabled wireless data capture device

(BioRadio; Great Lakes NeuroTechnologies, Cleveland, OH), connected to the epidermal sensors via ribbon cables. This unit transmitted EMG measurements to a computer system for recording.

In each session the sensors were affixed across the submental muscles, an area expected to demonstrate muscle activity during deglutition [73]. The centre of the muscle group was identified by asking participants to palpate the muscles by swallowing, and the electrodes were then placed across the muscles. Full details of sensor placement procedures are detailed in appendix A.1.

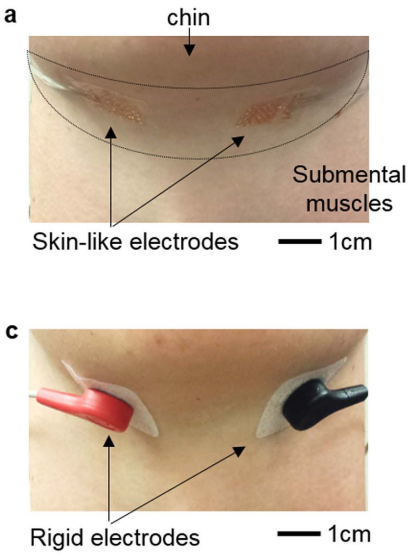

Figure 3.2: Example of traditional rigid surface electrodes with typical snap wiring (**a**) and epidermal epidermal electrodes with connected ribbon wires (**b**), affixed across the body of the submental muscles. Adapted from [1].

Data Collection Procedure

During each data collection session EMG signal measurements were recorded with a sample rate of 1024Hz. Typically, the highest frequency components of EMG signal are between 400-500Hz, thus the EMG sample rate was limited this sampling frequency to capture this range and reduce the chance of high frequency noise or aliasing, and could safely be filtered to obtain the the full EMG frequency spectrum according to Nyquist theorem [4, 196]. At the same time, synchronised video footage was also recorded to permit post-hoc annotation of ground truth regarding swallowing events.

Each participant carried out the same sequence of swallowing exercises. These included:

Dry Swallow: Participants carried out 15 repetitions of voluntary saliva swallowing, an action commonly used as a functional test for EMG activity of the suprahyoid and masseter muscles [73], and for testing and screening of dysphagia [62].

Liquid Swallow: Participants carried out 15 repetitions of voluntary liquid swallowing. Consuming a small mouthful of water.

Extended Swallow: Known as the Mendelsohn Manoeuvre [96], this involved dry swallowing while paying focusing upon the motion of the Adams apple as they do so. At the peak of the swallow participants attempted to hold the swallow action for two seconds. This is an exercise commonly used to help improve swallowing in patients with swallowing disorders, raising the larynx and opening the oesophagus [97, 214]. Participants carried out 6 voluntary repetitions of this exercise.

Data Processing

For the purpose of ground truth, video footage collected during the data collection sessions was manually reviewed and coded by the researcher, for the identification of swallowing ground truth. During this process, the onset and termination time of each swallow action was identified and recorded.

As discussed in chapter 2, EMG signals are sensitive to movement or electrical interference. To improve signal quality, band pass filtering was applied to remove noise and movement artefacts. Many suggestions have been made regarding the frequency range for optimal signal filtering, and the general consensus is that the usable EMG signal frequency range is between 20-500Hz, with the signals below this range effected by signal instability, and exceeding the upper limit resulting in increased chance of signal aliasing (as discussed in section 2.3.2). For this work, to ensure maximum signal information while eliminating noise, a Butterworth bandpass digital filter was chosen, with a pass band in the range of 20Hz to 500Hz and a filter order of 5. This was found to provide an effective compromise, removing signal noise while retaining useful signal features. The signal was filtered and rectified using following the process outlined in appendix B.1, and the Root Mean Square

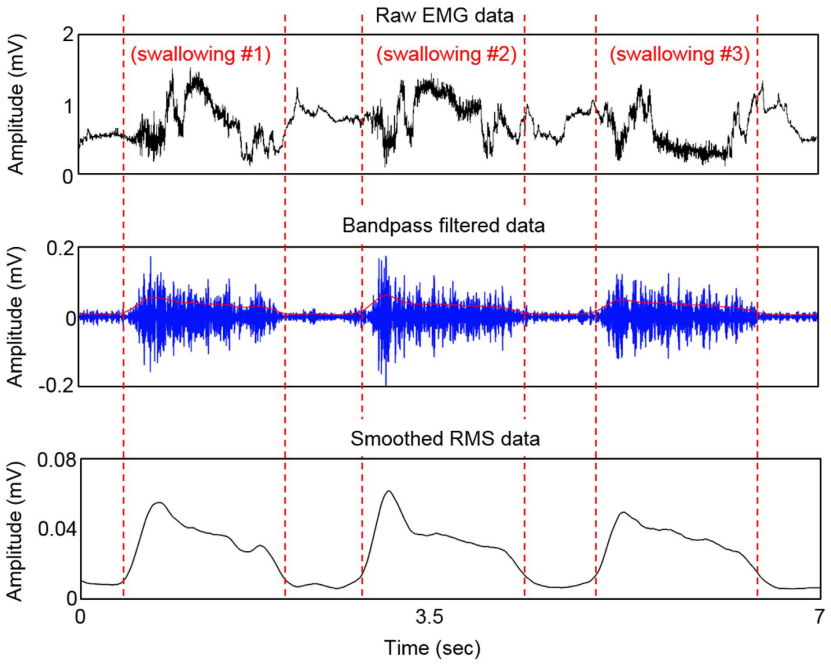

Figure 3.3: Example EMG of the submental muscles during swallowing, showing raw, filtered, and RMS envelope processing stages. Adapted from [1].

envelope of the signal was calculated. Figure 3.3 shows an example of the raw EMG, filtered signal, and RMS envelope during three separate swallows.

3.2.2 Swallow Detection algorithm and Results

Following the collection of data using conventional electrodes, the collected data was evaluated and a swallow detection algorithm developed and performance evaluated. The developed algorithm was then evaluated using data collected via epidermal sensors to test the viability of these for swallow detection with other sensor types.

Signal processing made up an important first step in the swallow detection algorithm, filtering out unwanted signal noise and movement artefacts and providing a smoothed signal envelope for further assessment. Following signal processing, a swallow detection algorithm was employed to detect EMG activity bursts pertaining to swallowing. This algorithm made use of a threshold based approach for identification of EMG bursts. Due to signal variability between participants, the thresholds were calibrated individually for each participant based upon observation of the recorded signal, and calculated as:

$$thr = \mu_0 + j * \delta_0 \qquad \text{(2.3 revisited)}$$

where μ_0 was the observed mean baseline during a period of calibration, δ_0 was the standard deviation of the signal during this period, and j indicated scaler values which were manually set for each participant. In this case j was by default set to a value of 3, as recommended in the literature [202]. However, the calibration period included ground truth swallow events, and where the threshold was found to result in false positive signal spikes the value of j, was adjusted following the recommendations of Di Fabio [202]: by identifying a value of j resulting in no EMG signal spikes exceeding the threshold apart from activity correlating with recorded calibration swallows, or a value of j resulting in the minimum non-swallow activity exceeding the threshold while ensuring that at least 25 consecutive signal samples were above the threshold for each recorded calibration swallow.

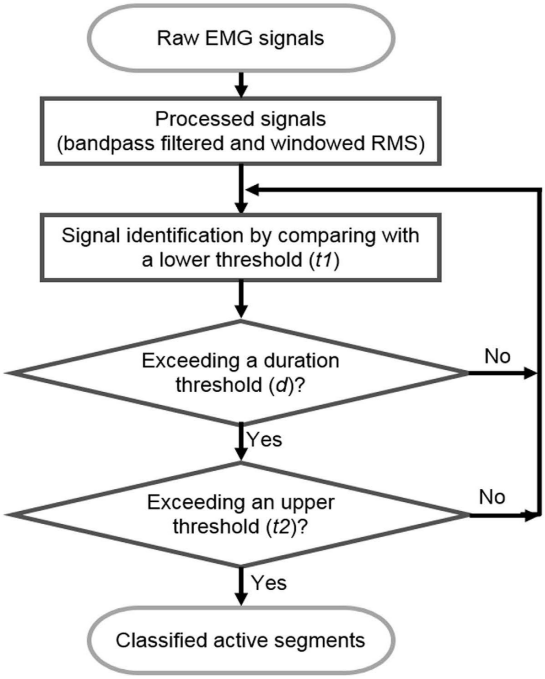

Figure 3.4: Flowchart providing an overview of the swallow detection algorithm. In the flowchart, *t1* refers to the lower threshold parameter, *t2* refers to the upper threshold parameter, and *d* refers to the minimum required activity duration.

As a single threshold is generally considered unsatisfactory for the reliable detection of EMG activity [143], the detection algorithm implemented made use of a double threshold approach, along with a minimum required activity duration for the identification of such EMG bursts, and the detection decision flow for this algorithm is described in figure 3.4. This algorithm detected periods of EMG activity which exceeded the lower threshold for a given duration and demonstrated an significant peak between onset and termination. Once

the onset of muscle activity was determined, the same technique was used to ensure that the burst was considered complete only once the magnitude dropped below the primary threshold and remained there for the given duration threshold value.

The performance of this threshold technique was evaluated based upon ground truth obtained from the manually annotated video footage. As shown in table 3.1 although the scope of the study was relatively limited in scale, the results are very promising with high accuracy for the detection swallowing during dry and liquid swallows. The detection of swallows during extended swallowing appeared to be more challenging to detect with this technique. This can possibly be attributed to difficulty with this swallow exercise, reported by some subjects; the variable success during this manoeuvre resulting in an unstable amplitude, indistinct swallows, and leading to unexpectedly low accuracy for this swallow type.

Table 3.1: Table showing performance of the threshold based swallow detection algorithm, tested using data collected from conventional electrodes. Included is the number of successfully detected swallows and false positives for each participant and different swallow type.

Swallow Detection Results - Conventional Electrodes								
Swallow Type		Participant Number 1	2	3	4	5	6	Total Accuracy
Dry	Total Attempts (Swallows)	15	15	15	15	15	15	
	Successfully Detected	15	15	14	15	13	14	92.47%
	False Positives	3	0	0	0	0	0	
Liquid	Total Attempts (Swallows)	15	15	15	15	15	15	
	Successfully Detected	15	15	15	15	15	15	96.77%
	False Positives	0	1	0	1	1	0	
Extended	Total Attempts (Swallows)	7	7	5	5	6	6	
	Successfully Detected	7	7	5	5	6	6	87.80%
	False Positives	2	2	0	0	1	0	

Reliability of the algorithm was then tested with data collected using the epidermal sensors. As can be seen in table 3.2, the algorithm demonstrated similar accuracy when used in conjunction with these sensors. Although comparable in performance, there was an anomalous increase in false positives for participant 4 during dry swallowing, and an increase in accuracy during extended swallowing. While in the previous case participants reported difficulty with extended swallows, in this case participants appear to have become used to this swallow exercise, improving their ability to achieve the desired result. The

Table 3.2: Table showing performance of the threshold based swallow detection algorithm, tested using data collected from epidermal electrodes. Included are the number of successfully detected swallows and false positives for each participant and different swallow type.

Swallow Detection Results - Epidermal Sensors								
		Participant Number						Total Accuracy
Swallow Type		1	2	3	4	5	6	
Dry	Total Attempts (Swallows)	15	15	15	15	15	15	88.54%
	Successfully Detected	15	13	15	15	12	15	
	False Positives	0	0	0	1	0	5	
Liquid	Total Attempts (Swallows)	15	15	15	15	15	15	96.77%
	Successfully Detected	15	15	15	15	15	15	
	False Positives	0	0	1	2	0	0	
Extended	Total Attempts (Swallows)	7	7	5	5	6	6	90.00%
	Successfully Detected	7	7	5	5	6	6	
	False Positives	0	0	2	0	1	1	

performance in this case indicates that the algorithm developed with conventional sensors are transferable to other sensor types.

3.3 Classification of Swallow Type

Following the detection of swallowing events, using the threshold based swallow EMG burst detection algorithm, the use of machine learning approaches was then investigated for differentiating between swallowing types. The accurate classification of different swallow types is a function that would be useful for accurately determining successful completion of tasked swallow exercises, such as extended swallows. Such classification has particular applications in areas such as swallow training as part of eating functionality rehabilitation following stroke or cancer [97].

3.3.1 Design and Training

For the purpose of this investigation, the data previously collected for development of the swallow detection algorithm (described in section 3.2.1) was used again for training and evaluation of classifier algorithms for differentiation between swallow types. While the swallow detection algorithm demonstrated a high degree of accuracy, to ensure maximum fidelity the data was segmented according to the swallow ground truth, assuming previous

and accurate swallow detection. Swallows were labelled according to ground truth as Dry Swallows (DS), Liquid Swallows (LS), or Extended Swallows (ES). As discussed before, in this case dry swallowing referred to voluntary saliva swallowing, while liquid swallowing was associated with swallowing a sip of water, and extended swallowing ("Mendelsohn Manoeuvre" [96]) was the act of attempting to hold the peak of a normal dry swallow for a given duration.

Feature Extraction and Classification Algorithms

For the classification of EMG functionality a wide range of signal features have been investigated. However, in order to maximise the performance of any produced classification algorithms, it is important to eliminate redundant features and select a range best suited to the task. A discussion of the importance of feature selection and extraction and review of literature describing useful features was provided in the literature chapter (Section 2.3.4). It is recommended, by Phinyomark *et al.*, that selected features should include those providing signal energy information, complexity information, and frequency information [208, 209]. The features investigated in this study were selected based on these recommendations and are listed in table 3.3. The span (duration) of each swallow was also determined here to be useful for identifying extended swallows, based on observation of swallowing and signal characteristics, and was included in the set of investigated features. In addition to these the full frequency domain was included, extracted using the Fast Fourier Transform function in 10Hz bins. This was included to investigate the importance of individual frequency band and its importance is evaluated in section 3.3.3.

All features were extracted from submental EMG for each swallow event separately, and all features in the feature array were standardised. A summary of included features is given in table 3.3 and details of these features was given in chapter 2.

In addition to investigating the selection of features, a number of different classification algorithms were also evaluated to determine their capacity to accurately classify different types of swallows. Of these, Linear Discriminant Analysis (LDA) and linear kernel Support Vector Classifier (lSVC) algorithms were selected for their capacity to classify linear distributions, radial basis function kernel Support Vector Classifier (SVC) and Multi-Layer Perceptron (MLP) algorithms were selected for their capacity to classify more complex and non-linear problems. Three decision tree based algorithms were also selected for their

Table 3.3: List of features investigated for swallow classification. A discussion and details of these features is given in chapter 2, table 2.2

Swallow Classification Features	
MAV	Mean Absolute Value
IEMG	Integrated EMG
RMS	Root Mean Square
SD	Standard Deviation
WL	Waveform Length
MYOP	Myopulse Percentage Rate
WAMP	Willison Amplitude
MNF	Mean Frequency
MNP	Mean Power Spectrum
MDF	Median Frequency
MPF	Median Power Frequency
freq_bins	Frequency Domain Bins
Span	Swallow event duration

capacity to perform well in the classification of both linear and non-linear distributions: a basic decision tree classifier (DT), a Random Forest algorithm (RF), and an Extremely Randomised decision tree classifier (ET). Decision tree algorithms, in addition to offering flexible classification and good performance, also permitted the exposure of metrics regarding the contribution and importance of features for classification. During training, decision trees are grown with the aim of improving the homogeneity of data in child nodes, using function to determine the ideal split to make.

A common choice of splitting function is the "gini impurity measure" [215, 216], which is an impurity function effectively measuring the probability p_j of sample j being incorrectly classified, and is defined as:

$$\phi(p) = \sum_j P_j = (1 - p_j) \tag{3.1}$$

At each node split this gini impurity value is less in the two child nodes than in the parent node, until such time that there is only one possible element within a node. In a Random Forest classifier the decrease in gini impurity can be used as an estimate of feature importance, by calculating the average total decrease in node impurity for a

feature, weighted by the number of samples reaching the splitting node [217, 218]. While this is useful for estimating feature importance, caution using this has been advised when using this for feature selection due a recognisable bias towards categorical features with a high number of categories [219]. Despite this, mean purity decrease is a useful technique for exploring feature importances, and is used here for evaluating feature relevance for swallow classification and as a part of feature elimination.

Classifier and Feature Evaluation and Selection Procedure

During the training and testing of classifier algorithms feature importance was assessed using Random Forest classifier feature importance, based on decrease in gini impurity, given by equation (3.1). Recursive feature elimination was employed during the training phase to iteratively eliminate the worst performing feature according to the feature importances, with the overall performance of the algorithm recorded.

To fully investigate the classification of swallow types, a nested 5-fold cross validation algorithm was employed in order to maximise use of the available data. For each fold of the outer loop a Random Forest algorithm was trained using the training data to determine feature importances and select the best performing feature combination in the available data. Overall feature importance and elimination determined by taking the average of these results across all validation loops. Within the inner cross-validation loop the training data is further divided for the purpose of parameter tuning. Each classifier algorithm was then trained using the selected features and parameters, and tested on the outer cross-validation loop test set. The predictions for each cross-validation test fold were recorded and a final evaluation of predictive performance carried out upon the combined predictions.

Three different classification cases were evaluated. Firstly, classifier models were investigated for the multi-class classification (ES-LS-DS) of all three swallowing classes: Liquid Swallow (LS), Dry Swallows (DS), and Extended Swallow (ES). Following this, Liquid and Dry swallows were reclassified as Normal Swallows (S) and a model was trained to differentiate between Extended Swallows and normal swallows (ES-S). Finally, Extended swallow classes were entirely removed from the sample pool and a model was trained to differentiate between Dry and Liquid Swallows (LS-DS). This made it possible to evaluate the trained models for their capacity to perform binary predictions of extended swallowing

from other types of swallows, or to differentiate between normal swallowing of saliva or liquid.

3.3.2 Feature Evaluation and Classifier Performance

Feature Evaluation

During training of the models, the contribution of features to the classification of different classes was evaluated using Random Forest feature importances. This permitted feature reduction and evaluation of the validity of frequency domain features, which have been concluded to be redundant for EMG classification in the literature [208].

This technique was used for training of both models making use of frequency domain features, in addition to models making use of only features giving a summary of the frequency domain. Both model types made use of other time-domain features, prior to feature reduction. Feature importances for each classification task are summarised in figure 3.5.

In this figure a similar trend in feature contribution can be observed for each classification task. The span or duration of swallowing event was found to be the most significant feature for all three classification tasks. Following span the Integrated EMG and Waveform Length values were found to be the next most important features for each classification case, reflecting signal energy and complexity respectively. For the Extended Swallow classifier case the other features demonstrated very little significance when compared with these three. Comparatively, for the liquid and dry swallow classification case there is a less significant drop in feature importance after these highest ranking features, particularly when not including frequency features.

The significance of these three features was not unexpected for the multi-class classification task (ES-DS-LS) and the Extended swallow vs normal swallow classification task (ES-S). Extended swallows are, by their own definition, characterised by an extended duration, and were expected to demonstrate a significantly greater span of EMG burst than other swallowing types. IEMG and Waveform Length both capture functionally related temporal characteristic across the sample span: IEMG defined as the sum of the absolute signal across the sample, and Waveform Length as the sum of the change in amplitude across the sample. As such, this explains their high degree of importance.

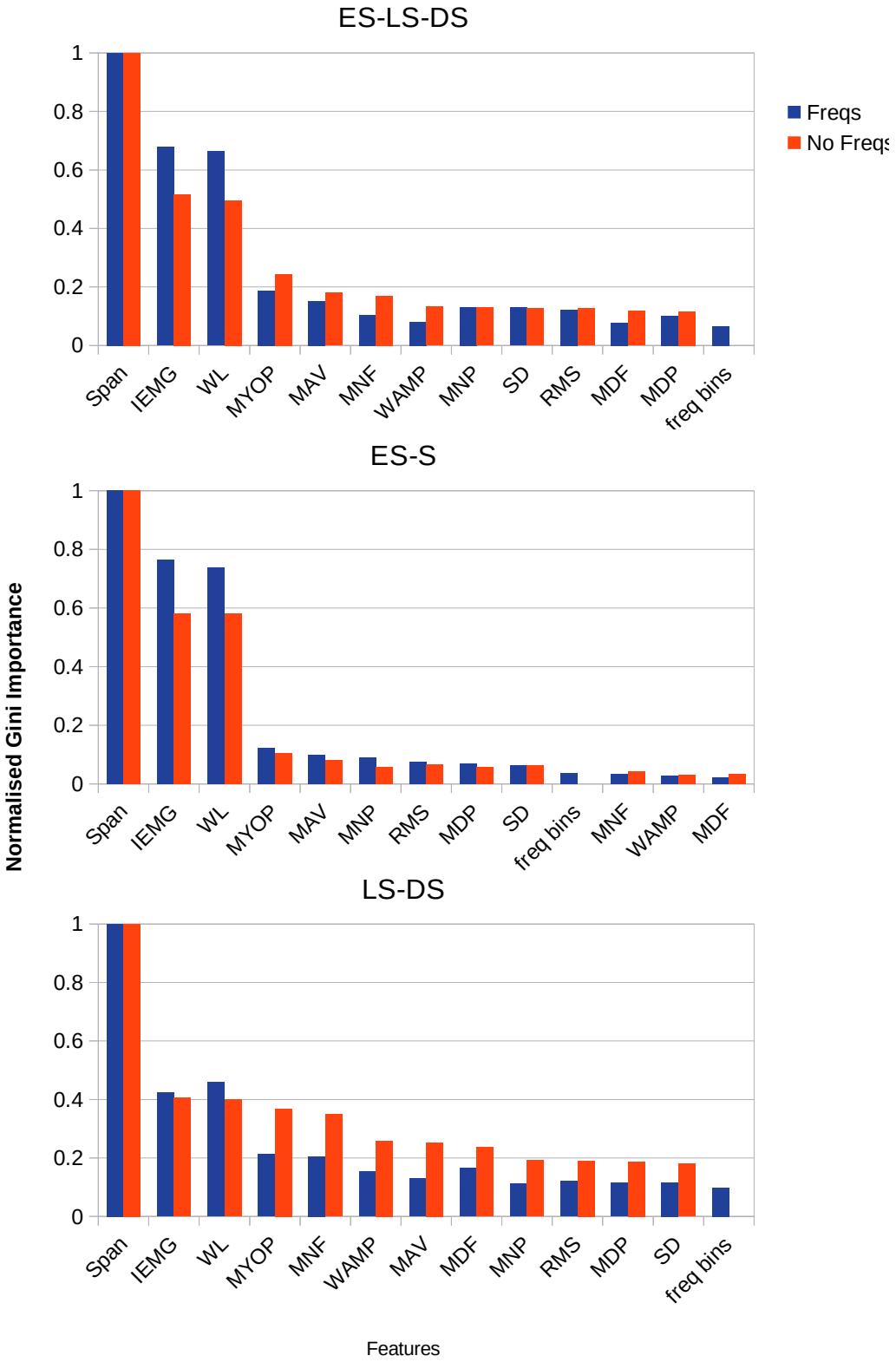

Figure 3.5: Relative importances of each feature used in the classification of swallows, using different models. Importance estimated from normalised gini importance [205], defined by equation (3.1). Shown here: **ES-LS-DS** shows the importances of features in 3 way classification of all classes, **ES-S** shows importances for Extended Swallow classification, and **LS-DS** shows the importances for distinguishing between Liquid Swallows and Dry Swallows.

In the Dry and Liquid Swallow classification case the frequency based features, Myopulse and Mean Frequency, demonstrates a similar degree of importance in the model not including other frequency components. Other signal energy and frequency components show a lesser degree of contribution, as a result of correlation with similar more contributing features.

In all classification models including individual frequency ranges, these bins demonstrated a similar or lesser degree of contribution to classification than the average representations of the frequency features. Moreover, frequency based features are only found to be significant in the case of dry and liquid swallow differentiation, having very little contribution to extended swallow detection. This supports reports of the redundancy of frequency based features, as described by Phinyomark *et al.* [208]. It also indicates that the removal of these features has little bearing upon the classification of swallow type.

Feature Reduction

During model training, recursive feature elimination was performed as described in the previous section. A summary of feature elimination performance results can be found in figure 3.6. From these, it can be observed that multi-class model (ES-LS-DS) performance peaks when using approximately 6 features for both the models using frequency bins and those not. The addition of extra features demonstrated no score improvement beyond this point, while the inclusion of 12 or more features resulted in an accuracy loss. Cross-examining the feature importances evaluation, it can be seen that the only frequency content included in these top features were the myopulse and mean frequency features.

As can be seen in figure 3.6, for Extended swallow detection there was very little functional difference in F-Score for any number of features, although use of 7 features was found to give the optimal result with a score of 0.995 (SD=0.001). This was approximately the same in both the model trained with and the model without full frequency domain. In both cases, random forest classifier models demonstrated approximate score of 0.99 when just using span to differentiate between model types. As discussed previously, this was to be expected with extended swallows being characterised by a significant difference in swallow duration.

Neither the multi-class, or extended swallow classification cases demonstrated any improvement through the inclusion of detailed frequency bins. Comparatively, the dry and

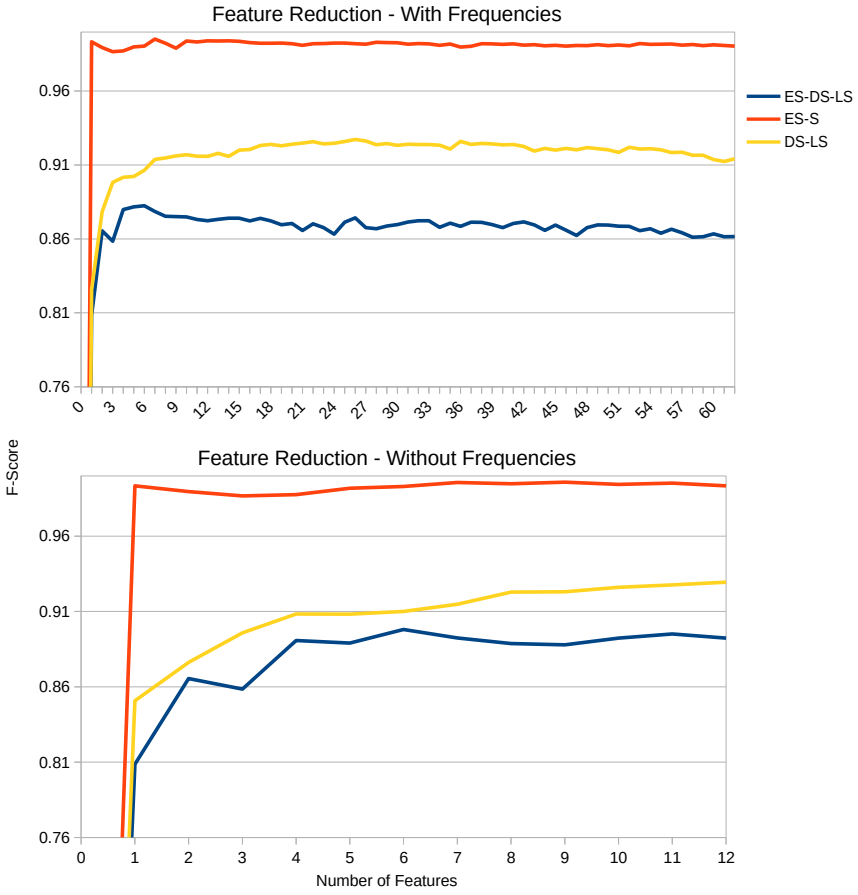

Figure 3.6: Results of feature reduction, using Random Forest Classifier, to identify the optimal number of features to be used in swallow classification. Plotted is F-Score prediction accuracy against number of features used for classification. The top plot shows feature reduction including full frequency domain features, while the bottom plot shows feature reduction without full frequency domain. Included are plot lines for: **ES-DS-LS** model trained for 3 way classification of all classes, **ES-S** model trained for classification of Extended swallows, and **DS-LS** model for distinguishing between Dry and Liquid swallows.

liquid classification task models showed some benefit from the inclusion of these features. Results of recursive feature reduction demonstrate improved classification performance in correlation with the inclusion of additional features. This trend appears to continue with the inclusion of specific frequency content bins; peak performance found using 26 features, with a mean F-Score of 0.927. This demonstrates that classifiers capable of differentiating between liquid and dry swallows benefit more substantially from the increased complexity of features representing frequency content.

3.3.3 Classification Performance

Models were trained, tuned, and tested for each classification algorithm. In addition to this they were trained and tested for both feature sets: those solely using summarised frequency content information and those including detailed frequency content. Although the feature importance evaluation demonstrated negligible importance of frequency content for the multi-class classification case and the Extended swallow case, there was some indication that the full frequency content is of use in the dry and liquid swallow classification case. In order to make a final evaluation regarding the relevance of these features upon classification performance, models were trained for both feature sets permitting comparison during final model selection. Figure 3.7 provides a summary of the classifier performance (based on F-Score) using each classification algorithm, for models using frequency domain features and models without.

Multi-class classification models for distinguishing between extended swallows, liquid swallows, and dry swallows were first evaluated using each classification algorithm. Models trained based on the tree based classifier algorithms demonstrated superior classification accuracy over the other models, with the high score identified for the Random Forest based model trained using feature sets excluding frequency domain bin features. Final results for the model based on a Random Forest algorithm can be seen in table 3.5.

Examining these results for each class (see table 3.4), it was clear that there was a bias t the extended swallow class over the dry and liquid swallow classes. The high performance for classification of extended swallows with a low number of features indicates that this is a substantially simpler classification task on its own, compared to the differentiation between dry and liquid normal duration swallows. In the dry swallow vs liquid swallow case, the results follow a trend similar to that demonstrated during the multi-class case. For extended swallow classification case the performance of all models excluding frequency bins was very high supporting the conclusion that this was an easy classification task.

The evaluation of feature importances showed that the frequency bin based features had little contribution to classification, which was supported by the results of the final model (table 3.5). As can be seen in figure 3.7, for the majority of classification algorithms the models based upon features excluding detailed frequency bin content demonstrated a comparable or improved degree of classification accuracy.

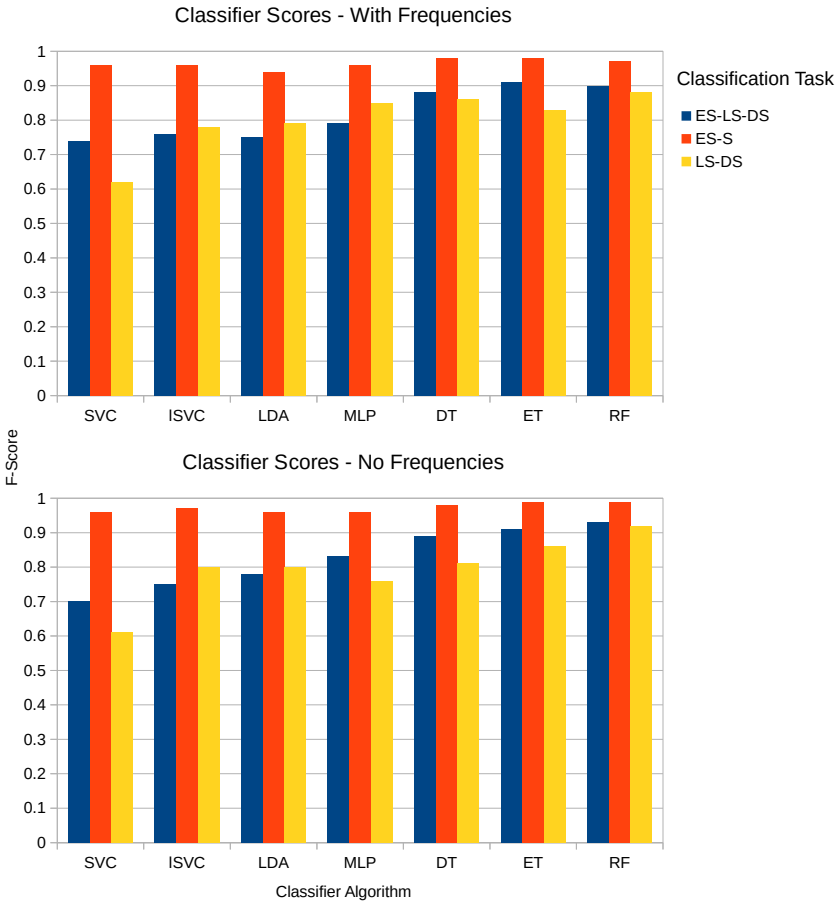

Figure 3.7: Classification performance (F-Score) for classifier models, each based on one of the investigated classifier algorithms. Top: accuracy of models including full frequency domain features. Bottom: accuracy without full frequency domain. Included are bars depicting accuracy of: **ES-DS-LS** model trained for 3 way classification of all classes, **ES-S** model for classification of Extended swallows, and **DS-LS** model for distinguishing between Dry and Liquid swallows.

3.4 Biofeedback and User Evaluation

Viability for the detection of EMG activity bursts during deglutition and classification of swallowing types based upon these detected bursts was evaluated during the first part of this research (section 3.2 and section 3.3). The next stage in this research was the application of EMG measurement and swallow detection for driving feedback designed to support swallow exercise. As discussed in the literature section (section 2.1.3), biofeedback is a useful tool for supporting rehabilitation for swallowing disorder patients [64, 109], but suffers from a lack of standardisation [110], require clinical supervision and interpretation, and have difficulty maintaining patient engagement and motivation [112]. To overcome

Table 3.4: F-Score per class accuracy for swallow classification models. Includes results for: **ES-LS-DS** multi-class classifier model for prediction between all swallow classes, **ES-S** binary classifier for determining Extended swallows from other swallow types, and **LS-DS** binary classifier model for determining between Dry and Liquid Swallows

Random Forest F-Score Per Class			
Class	ES-LS-DS	ES-S	LS-DS
S*		0.99	
ES	0.99	0.98	
DS	0.9		0.92
LS	0.89		0.92
Average	0.93	0.99	0.92

** Combined Dry and Liquid swallows, for classification of Extended swallow*

Table 3.5: Average F-Scores for Random Forest based classifier model. Includes results for each classification case: **ES-LS-DS** multi-class classifier model for prediction between all swallow classes, **ES-S** binary classifier for determining Extended swallows from other swallow types, and **LS-DS** binary classifier model for determining between Dry and Liquid Swallows

Random Forest Average F-Scores		
Classification Case	No Frequencies	Frequencies
DS-LS-ES	0.93	0.9
ES-S	0.99	0.97
DS-LS	0.92	0.88

these issues, this section demonstrates the application of the swallow detection algorithm developed here to drive a prototype form of biofeedback intended to support swallow training. As such, the objectives of this third stage of this research were:

- To design and implement swallow driven feedback to engage and motivate participants in swallow training
- To conduct a pilot study of the prototype to gauge the effectiveness and appropriateness of the sensors and feasability and usefulness of the feedback

3.4.1 Data Acquisition and Biofeedback

Biofeedback Requirements and Design

To achieve the objectives of this stage of research, the swallow detection, monitoring and feedback system was required to meet a number of specific requirements. Firstly, the system should make use of the automated swallowing detection algorithm outlined in section 3.2, in order to drive swallowing feedback and to record EMG data related to

swallowing along with detected swallows. As well as permitting continuous user interaction with feedback, this also allows post-experimental review of swallowing related EMG activity and analysis of feedback response performance. The system was required to processes EMG and detect and respond to swallowing with minimal possible delay to permit users to react to feedback in a responsive way.

The detection of swallowing and provision of swallowing biofeedback has particular implication for rehabilitation and strength training regimes intended for patients with difficulty swallowing or swallowing disorders. As existing forms of swallow biofeedback suffer from difficulty maintaining user engagement and motivation, and important requirement of the biofeedback design was to consider ways to overcome these limitations. Furthermore, with the long-term vision of providing alternative platforms to support such rehabilitation, it was also important to consider swallw training exercises typical of rehabilitation regimes as well as other principles of swallow rehabilitation training.

To help motivate and engage participants, a game-based feedback design was selected. In many forms of biofeedback and behavioural therapies, such as Cognitive Behavioural Therapy [103], it is considered essential to encourage patients to set goals and to reflect on progress in order to engage patients and motivate them to pursue improvement, and to develop self-efficacy [20, 119, 114]. These elements of cognitive therapies are closely related to mechanisms of modelling and feedback theory involved in biofeedback and game based learning Baranowski *et al.* [112]. Games have been demonstrated as useful for motivating users, which [112] attributes to "meaningful play" and "challenge" of game design. To achieve these outcomes Baranowski *et al.* recommends achievable game goals and providing users with the means to measure success. In addition to this, although the objectives should be achievable, the authors also emphasise a need to maintain sufficient difficulty to maintain user interest, as well as providing ongoing success targets and varying the challenge.

To meet these requirements, a continuous platform type gameplay was selected, involving a rolling ball which could be controlled to 'jump' over gaps between moving platforms by swallowing to trigger jumps. A continuous score was kept based on the duration of unbroken gameplay, and displayed at the top of the screen to provide users with feedback on achievement. A game over screen, displayed upon the game avatar falling between a platform gap, was also designed to show the players achieved score, along with the mes-

sage: 'Game over. Now try to beat your previous score!'. The score display and game over message were designed to allowed players to reflect on progress, while providing them with an ongoing goal and motivating them to keep playing. Finally two elements were introduced to vary the gameplay and difficult and maintain engagement and focus. Firstly, within the game, the speed of movement was varied based on color coordinated platforms: where purple platforms resulted in normal speed, yellow platforms reduced speed by 50%, and red increased speed by 50%. Secondly, the size of gaps between platforms was varied randomly, to present further challenge and reduce game predictability. This final element was also important for encouraging certain principles of swallow training, discussed below.

Introducing principles of swallow training was the second main requirement of the biofeedback. As has been discussed previously in this chapter and in the literature chapter (chapter 2), swallow exercises involved in rehabilitation for swallow disorder patients include repetition of swallowing to train muscle strength as well as practising key swallowing manoeuvres such as the extended swallow (the swallow maintained at the height of laryngeal elevation) and effortful swallow (with maximal force applied to a swallow) [63, 96, 97]. These three components were all considered and included in the game design. Repeated swallowing was designed to be a necessity within the gameplay, with continuous moving platforms bypassed via swallow controlled jumping. To encourage effortful swallowing, the strength of the avatars jump was designed to scale with the magnitude of the EMG signal measured from the user: increasing swallow magnitude resulting in continuous increase in jump height. As well as responding to swallow effort, the jump control was also designed to maintain the elevation of the avatar for the full duration of the EMG activity associated with a detected swallow. As well as varying user experience, the varying gap size between platforms was also designed to work in tandem with this avatar control feature: the ability to maintain jumps helping to overcome the maximal platform gaps and thus encouraging extended swallowing.

System Specifications

The implemented system for data capture and provision of feedback included a hardware system for the acquisition of EMG measurements, and a software solution for the real time monitoring and capture of physiological data and for driving training feedback. An overview of the full system can and the roles of respective components can be found in

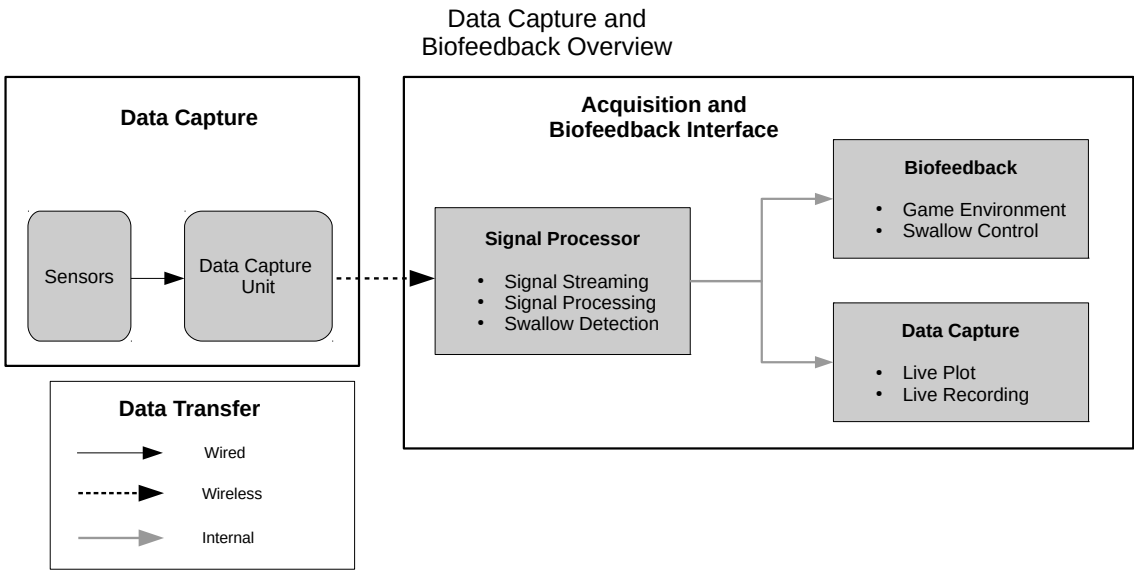

Figure 3.8: Overview of data capture and biofeedback interface system components, developed as a part of the study reported in this chapter. Demonstrates the capture of data, transfer to a system running the interface software, and the major tasks of each interface component.

figure 3.8, and figure 3.9 demonstrates the data capture interface and equipment. This involved the same materials as described in the data acquisition section (section 3.2.1. In this case, the epidermal electronic sensor type [210] was selected to permit user evaluation of this sensor format and the feasibility and acceptance of the sensors in comparison with the other components of the system, which consisted of traditional electronic devices. The electrodes were mounted upon the surface of the skin over the muscles of the submental triangle (under the chin) and connected via a flexible ribbon like cable to a Bluetooth enabled data capture device and wireless transmitter. Data was then distributed wirelessly to a custom computer interface.

The custom software implemented for this system consisted of three principle components: a data acquisition interface for the detection and collection of EMG measurements from the submental muscles, an integrated swallow detection algorithm for the detection of EMG bursts associated with swallowing, and a real-time feedback control system for driving game-based swallow training feedback. All components were integrated into a single control interface, developed using C# [220] and Microsoft .NET Framework 4.5 [221]. This platform was selected in part because the data capture hardware (BioRadio, GreatLakes Neurotechnologies[1]) is provided with a native Microsoft .NET Framework for

[1] https://glneurotech.com/bioradio/bioradio-specifications/

application development[2], making this a convenient framework for development. In addition to this, the framework integrates easily with the Unity based games, which was chosen as the game development environment for this work (described below). Consistency across the software platform was decided upon in an attempt to reduce the latency of inter-process communication and maintain response timeliness.

The feedback control system monitored the status of connected data acquisition devices and permitted control and monitoring recorded data. As is indicated in figure 3.9, summarising interface components, this also permitted the control of parameters for streaming settings (channel selection, and sampling window size), and filter settings (band-pass frequency range and filter order). It could also be used to control the calibration of baseline measurement and parameters.

During data acquisition, this system could be used to detect swallowing activity using the same algorithm developed during part one of this research, adapted and integrated into the custom software. The procedure used by the algorithm for detecting swallowing activity was the same as that described in section 3.3, and figure 3.4 provides details of this algorithm functionality. The integrated algorithm resulted in binary detection of swallowing activity, triggering a flag to indicate a real time change from inactivity to swallowing activity. For the purpose of real-time monitoring and provision of feedback, this algorithm had the benefit of providing fast and easily calculated detection with only negligible processing delays.

The final component of this system was real-time feedback provided for swallow training, the design of which was discussed previously. The game-based feedback was developed using Unity Software [222], selected as a flexible game development environment that is easily extendible to work with external devices and works efficiently with the .NET framework. During use, the swallow detection algorithm results to the game-based feedback. During swallowing a positive swallow detection resulted in the ball 'jumping', where the elevation scaled based on swallow magnitude, and staying elevated while the swallow is held, for instance in the case of an extended swallow. Gameplay was continuous with an updating score relating to the duration the user manages to continue playing without falling through a platform gap. On this event the player is faced with a game-over screen and invitation to beat their previous score. Figure 3.10 shows a screenshot of the game-

[2]http://glneurotech.com/BioRadioSDKDocumentation/html/ffb032ba-5944-4d52-ab89-448553765c01.htm

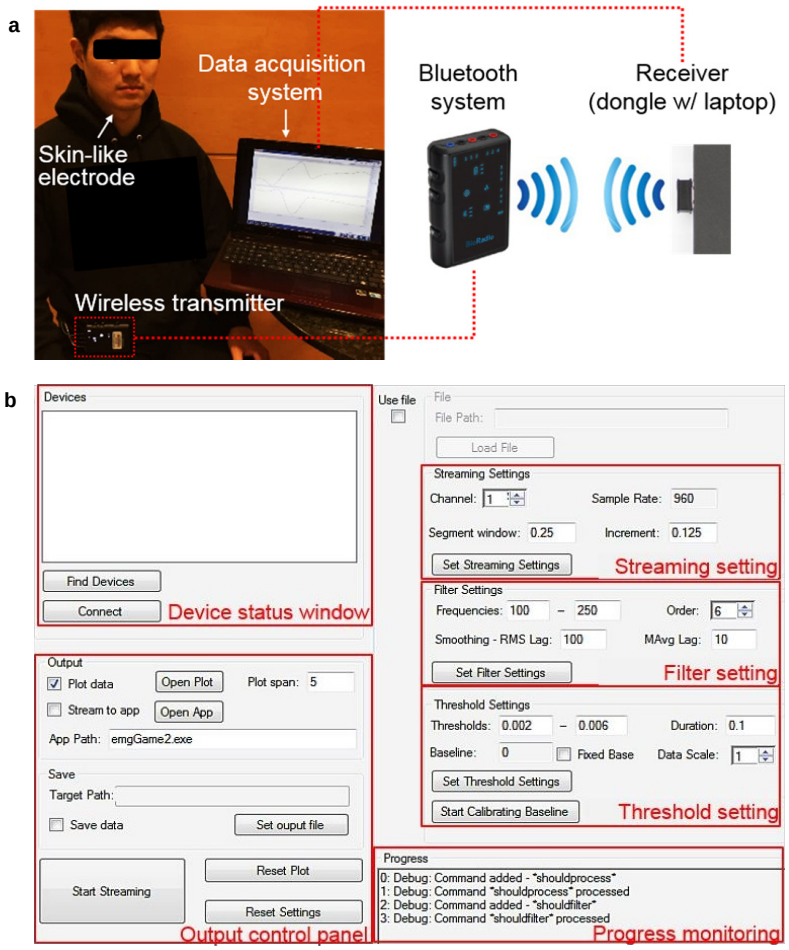

Figure 3.9: Overview of the hardware setup and software system associated with the swallow monitoring and biofeedback interface. **(a)** Overview of the data capture hardware; EMG measurements captured and transmitted to data acquisition system via Bluetooth enabled transmitter. **(b)** Screenshot of the data capture, swallow monitor and biofeedback control interface, showing the different components of the interface

based feedback, demonstrating an example of a ball jump in correspondence with a period of positively detected swallowing activity.

3.4.2 User Evaluation Procedures

In this stage of the research, collaboration with the Yeo research group [75] was continues to permit use and evaluate the feasibility of "epidermal" sensors with the biofeedback system. Once again, collaborating researchers, operating out of Virginia Commonwealth University, were responsible for recruitment and screening of participants, setting up experimental materials and sensors, and were also responsible for ensuring participant adherence to instructions and for carrying out user interviews. Interview footage was recorded

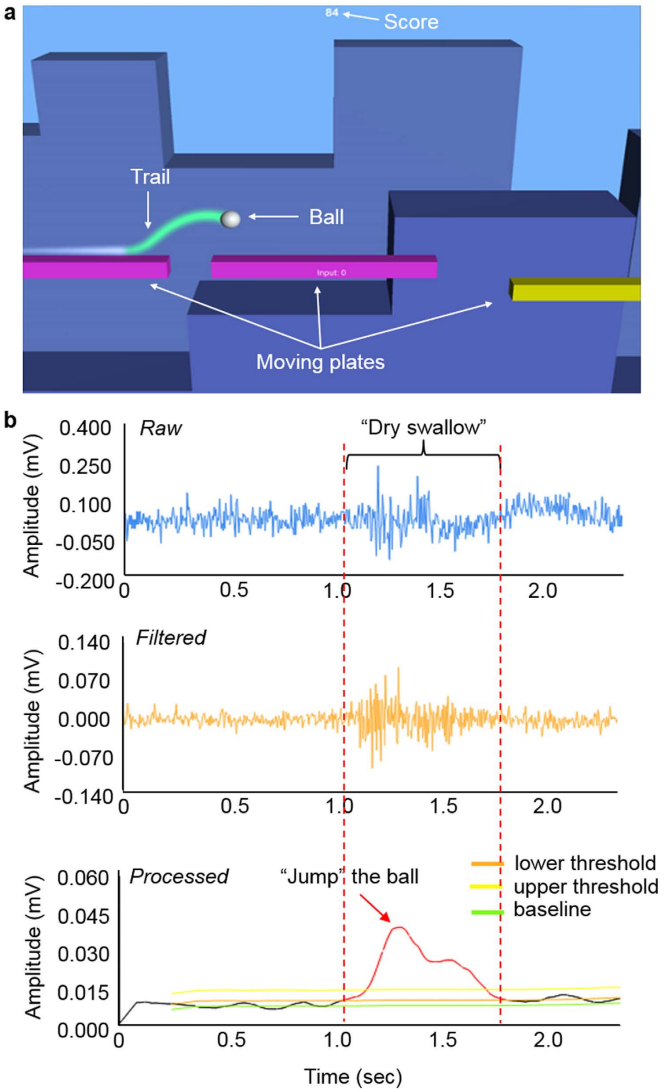

Figure 3.10: Screenshot of the game-based feedback environment (**a**) and example of game control via swallowing EMG signal detection (**b**).

for post-hoc analysis by the author of this thesis at a later date.

A small trial user study was conducted using the developed feedback and monitoring system, the purpose of which was threefold. Firstly, to determine the accuracy and performance of swallow detection beyond the initial testing conditions; in this case when applied for the purpose of driving eating feedback. It was also intended to establish amongst participants the acceptability of the epidermal sensor modality in comparison with the other components during the study, and to gauge participant opinion regarding continuous use or use in different environments. Finally, the study was intended to determine the user impression of the feedback itself, and gain an initial idea of its feasibility and effectiveness for engaging users in swallow training.

This trial consisted of two parts. Firstly, a user trial, using the epidermal sensors to control the feedback system. This was then followed by a user evaluation, consisting of a survey and short follow-up interview to gauge user experience and impression of the system components.

During this user study, the six participants recruited for the first part of this research were asked to take part in the evaluation. As such this study involved a small sample of healthy participants. This was partly due to recruitment restrictions for the collaborators at the Virginia Commonwealth University. However, in addition to this, although the long term vision for the developed swallow detection algorithm and feedback was to apply these to clinical behaviour change and support of rehabilitation, this was an early prototype and it was important to gauge the acceptance and perceived feasibility of the sensors and feedback before any further studies involving swallow detection or feedback.

Participants and Equipment Set-Up

The six participants recruited for the first part of this study were asked to take part in the evaluation. The use of the same participants was in part due to recruitment restrictions of the collaborating researchers at the Virginia Commonwealth University. However, as the swallow detection algorithm was developed based on these same participants, it also permitted a degree of certainty regarding the accuracy of the algorithm for the selected subjects and permitted evaluation of the continued accuracy of the algorithm during a separate session, and following repeated calibration.

Participants were briefed in full about the evaluation and were equipped with electrodes following the same placement and equipment setup procedure as carried out in the previous stage of the study (section 3.2.1). The supervising researcher then carried out a period of reference measurement during periods of inactivity and swallowing to ensure signal fidelity and permit calibration of baseline, filtering, and threshold parameters, as necessary.

User Trial Procedure

The user trial of the system was conducted over a single session per participant. The use of the feedback was described in full to each participant, and participants were provided with a short training period, with the researcher demonstrating the control of the feedback via swallowing.

Participants were then asked to attempt to control the game-based feedback, and permitted unlimited time to guide the ball through the game environment, traversing platforms by swallowing to control 'jumping'. They were instructed to continue for as long as possible, but to avoid user discomfort participants were permitted to cease when they could no longer comfortably dry swallow; allowing the game to end.

To collect a comprehensive amount of data, and to provide an opportunity to challenge participants to improve and beat their previous scores, participants were asked to repeat this process 5 times. However, during repeated swallowing there was a risk of muscle fatigue and it was important to provide a recovery period between each attempt, to avoid impacting user performance or effecting the EMG measurements and to prevent compromising swallow detection accuracy and feedback control. Once the ball had fallen into a gap the game ended and the participants were provided with a drink of water and given two minutes to rest. At this point the participants were challenged to beat their previous score, the game restarted and the process repeated. During each session, video footage of the participants and game-play feedback was recorded, allowing information to be extracted regarding the game response and participant control accuracy.

Follow-Up Interview

Following the user-trail, each participant was asked to the fill out a short survey and take part in a follow-up interview. These were designed to investigate user impression of a number of factors relating to the sensors and feedback. These included user impression of:

1. The comfort of the sensors and other components of the system
2. How suitable the users felt the sensors would be for use in different environments (at home amongst family, or in the office with peers)
3. How suitable the users felt the sensors would be for long term and continuous use
4. The users impression of the game-based feedback itself

The users were first asked to rate each topic and their experience with the system from 'poor' to 'excellent' using a seven-point scale. The use of scales, such as the Likert-Scale, for user experience assessment is an approach which is deemed reliable, robust

and recommended as the standard for user experience studies [223]. Typically, a 5-point scale is considered sufficient for moderate sample sizes, with more questions resulting in diminishing returns in terms of the granularity of context of user experience [223]. However, in the case of small sample sizes, the use of a 5-point scale has been found to have insufficient sensitivity to data variation, only able to partially capture the attitude range of participants responses [224], and contributing to data loss [225]. A larger number of user response choices on the other hand has been found to provide increased sensitivity, with a 7-point scale in particular recommended to provide a better reflection of the true response of user evaluations [225, 226]. As this study involved a small sample size, a 7-point scale was selected to provide increased granularity of detail and a better impression of user opinion regarding the topics of interest.

Following the survey, users took part in a short discussion during which the researchers asked users to vocalise their thoughts regarding each of these same topics. Researchers were also instructed to direct their questions to aspects of the sensors and feedback based on the survey responses, to identify any particular concerns or thoughts about these aspects. This stage was carried out to provide qualitative insight into the users experience. Audio of all interviews was also recorded, for post-hoc response transcription and analysis by the thesis author.

3.4.3 Results and Discussion

Feedback Performance

Following the user evaluation trials video footage was reviewed and data regarding user swallowing function and feedback response manually extracted to permit assessment of swallow detection algorithm and game-based feedback response accuracy in real-time, less experimentally controlled conditions. Extracted data included the total number of attempts to control the game (observed voluntary swallows), the number of successful responses, and the number of false positives. The number of successful responses was defined here as the number of game-based feedback responses following an observed swallow, while false positives were defined as the number of feedback responses without any related swallowing activity observable. Details of the total recorded successful responses and false positives across all five gameplay attempts for each participant can be found in table 3.6.

Table 3.6: Table demonstrating attempts to control real-time feedback by way of swallowing detection, successful responses, and false positives.

Feedback Control Results			
Participant Number	Attempts (Swallows)	Successful Responses	False Positives
1	27	27	17
2	14	11	2
3	20	18	4
4	20	20	0
5	27	26	6
6	52	48	10

The total successful response rate, calculated as the sum of all successful game responses divided by the sum of all observed attempts to control feedback (by swallowing), was found to be 93.8%. This shows a very low false negative rate and high feedback response across all participants. A false positive rate (total number of false positives divided by the total number of attempts) of 24.4% was found across all participants and gameplay trials. This corresponded to a mean of 1.3 false positives per gameplay trial. As shown in the results, the distribution of false positives was mostly biased to participant 1 and 6. Exaggerated motions were observed during the trails for these participants, in attempting to increase their success rate. This added unexpected activity from the tongue, neck, and head motion, and resulted in an increase in false positives. It is theorised here that this is an indication that the use of a simple threshold technique is not very robust to minor fluctuations on the EMG signal. In addition to this, some of the failed responses are also considered to have resulted from impeded swallowing activity due to participant difficulty with the repeated swallowing activity, which was reported by some participants.

Evaluation of response time between swallow and feedback response was conducted across all participants and gameplay trials. This revealed a population average response delay of 1.033 ± 0.039 ($SD = 0.479$). However, it should be noted that this delay was estimated as the period between the earliest time of observed swallow function (from video footage) and the equivalent feedback response onset, and as such there is potential for error between observed timestamps and response time. The observed delay is considered the sum of signal transmission delay, processing time, the period between participant application of effort (to swallow) and muscle response, and the period between the onset of EMG response and EMG signal exceeding the threshold. The implications of this delay are discussed further in the discussion section (section 3.5.3).

User Evaluation

Following the gameplay trials each participant took part in the user evaluation type interview. Each participant provided rating on a 7-point scale regarding a number of factors relating to the comfort of sensors, participant perceived psychological comfort using the sensors in different environments (at home or in the office) and over a long term period, and their impression of the game-based feedback they were presented with. Follow up interview questions were asked based upon these scores regarding any particular positive or negative impressions participants had.

The mean of the numerically coded scores for each of the Likert-scale measured factors can be found in table 3.7. As can be seen, comfort of the sensors was rated very highly along with the perceived comfort in different environments. Follow up interviews emphasised these results, indicating that this was due to the discreet and flexible nature of the sensors. However, four participants stated that they were still "aware" of the sensors, and they felt like they were wearing a "band-aid". All participants also praised the system mobility, and all but one stated that they thought the wireless system would permit interesting continuous monitoring of eating activity. On the other hand, the long term use of such sensors was rated lower, and follow up interviews highlighted concerns regarding system robustness and restricted motion, although this was limited to the less discreet and more bulky components of the system such as the wiring and data capture device.

The feedback system was rated above average, and during post-hoc interviews three participants reported that they found the system "fun" to use, while two stated that it made repeated swallowing easier, or improved their focus upon the task. However, three also reported that repeated swallowing was a difficult task to maintain without more significant recovery periods.

Although the results of this biofeedback control evaluation indicated a high accuracy, the relatively limited subject pool and difficulty accurately measuring the false negative rate made it problematic to draw any final conclusions regarding the accuracy of this system. In addition to this, some negative comments were highlighted, with a bias against the system hardware. However, it was determined during the interview sessions that these concerns were primarily focused upon the bulkier, more traditional components of the system, such as the wiring and wireless transmitter. As such, replacement of these

Table 3.7: Average numberically coded user-evaluation ratings measured on a 7-point likert scale, for factors of sensor comfort, perceived psychological comfort wearing the sensor in varying environments, or for long-term usage, and opinion of the game-based feedback

Average Interview Rating (Likert 7-point Scale)				
	Sensor Comfort	Different Environment	Long-Term Use	Game Feedback
Mean	6	5.83	4.5	5.16
SD	0.81	0.89	1.38	1.06

components with less obtrusive and more robust components would alleviate these issues.

3.5 Discussion and Limitations

It was proposed in this chapter that Electromyography is an unobtrusive approach for tracking swallowing, and a useful alternative to current procedures for assessing swallowing performance. Furthermore it was considered possible that EMG would be useful for the purpose of rehabilitative feedback applications, with an emphasis on feedback for swallow exercise. To explore this, the goals of this study were to develop a swallow detection algorithm, investigate feature extraction and the use of classifier algorithms to differentiate between swallow types, demonstrate the use of swallow detection for driving swallowing feedback, and to investigate the viability of EMG for unobtrusive sensing of swallowing and for driving feedback.

3.5.1 Swallow Detection Algorithm

Section 3.2 described data collection and development of a swallow detection algorithm, using a threshold based activity onset detection approach. This algorithm demonstrated a high accuracy of approximately 90% or more for two types of sensors, suggesting that the algorithm developed with conventional sensors was transferable to other sensor types. A number of other approaches for swallowing detection, discussed in the literature (in section 2.2.2 and section 2.2.4), reported variable success for the detection of swallowing. For instance, the use acoustic signals from throat mounted mic and classifier algorithms have been proposed for the detection of swallowing, with accuracies of up to 85% [68, 158, 65]. Alternatively, Nahrstaedt *et al.* [177] used combined EMG and bioimpedance in conjunction with valley detection and a Support Vector Machine, resulting in an high detection accuracy. While the approach presented in this chapter did not exceed the results

of this combined approach, it demonstrated that EMG alone is still a reliable technique for swallowing detection, outperforming alternative sensing approaches even with simple threshold based algorithms.

However, the procedure involved for collection of the EMG data used for the development and evaluation of the swallow detection algorithm involved strict lab conditions limiting participant movement or other none-swallowing activity. As such, it was difficult to assess the robustness of the developed algorithm in the face of such unexpected activity. Furthermore, unexpected movements enacted by participants during the biofeedback evaluation resulted in observed anomalous activity and increased false positives further highlighted the issue of non-robust swallow detection. With the relatively simple algorithm employed in this stage of the research, it is difficult to account for such unexpected muscle activity, and it is suggesting that a threshold technique is not the best approach for swallow detection. The following chapters investigate alternatives using classifier algorithms and training with more varied data sets to improve classifier robustness.

3.5.2 Swallow Classification

Expanding upon swallowing detection, section 3.3 explored the identification of features which are useful for identifying swallow types, and the use of classifier algorithms for differentiating between these. As shown in table 3.3, 12 main features were investigated along with detailed frequency domain. Features relevance was evaluated using feature importances and through conducting feature elimination, and swallow span (duration) was determined to be the most useful feature for swallow classification, followed by Integrated EMG and Waveform Length. These features represent signal amplitude and complexity information, which has been recommneded as the most informative content for EMG analysis [208].

Detailed frequency content was demonstrated to be fairly redundant for swallow classification, with 12 features found to be the optimum number for classification of all swallow types or liquid swallows (see figure 3.6) and only mean frequency and myopulse representing frequency content in these 12 (as can be seen in figure 3.5). For extended swallow detection, swallow span (duration) was found to be the most relevant features, and there was no significant improvement with the addition of more features. This supported observations that extended swallowing resulted in a predictably increased swallow duration

than other swallow exercises. A Random Forest classifier algorithm resulted in an accuracy of 0.93 for liquid and dry swallow differentiation, and 0.99 for extended swallow detection.

3.5.3 Feedback System and User Evaluation

In the final main section of this chapter (section 3.4), use of the swallow detection algorithm for feedback interaction was demonstrated. A system for detecting and monitoring swallowing was developed (seen in figure 3.9), and demonstrated for the purpose of driving game-based biofeedback designed to motivate and engage users during swallow exercise (seen in figure 3.10). A user evaluation was then carried out to test game feedback responsiveness and to determine viability of the used sensors for monitoring of swallowing and the feedback for supporting swallow practice. A successful response rate of 93.8% was demonstrated by the game system, despite repeated swallowing and the chance of this resulting in difficulty achieving successful swallows.

A post evaluation interview revealed that users felt the sensors were comfortable and that they would be happy to wear the sensors continuously and in social environments thanks to their discreet format. However, there were issues highlighted regarding the combination of epidermal electrodes with more conventional components. Participants noted concerns regarding robustness of the sensors, but on investigation these concerns were found to focus on the traditional components of the system. Subjects expressed concern that wires might become pulled loose or that they were overly aware the data capture unit. It is considered likely in the discussion that replacing these components with less obtrusive alternatives would alleviate these concerns, but it is hard to draw any conclusions without further investigation.

Although the feedback demonstrated a high response accuracy, there was also a notable response delay of approximately 1 second. The presence of the feedback delay highlights some significant concerns regarding the system design in itself. As the feedback was, in part, designed to encourage extended and effortful swallowing to jump between the platform gaps through varying platform spacing and movement speed, fine control of the game 'avatar' and jump timing was important to enable participants to sufficiently achieve their goals; detrimentally effected by response delay. Furthermore, this implied some uncertainty in the results of the performance evaluation which was based upon the

number of successful responses, leading to positive bias in accuracy due to failed game responses leading directly to user avatars falling through platform gaps and cessation of the game trial. However, the feedback response accuracy was similar to that obtained in section 3.2 for the swallow detection algorithm, lending support to the response accuracy found.

In addition to interaction consideration, feedback delay is known to have significant implications for user engagement with feedback systems and educational games. For instance, in a discussion of promoting learning through game environments, Charles *et al.* [227] emphasises that there delays should be minimised between point acquisition and feedback to maintain engagement. Likewise, feedback delay minimisation one of the most significant challenges involved in the design of responsive feedback systems for sports purposes, which can lead to user dissatisfaction if not successfully minimised [228]. However, while response delay is known to be a significant issue for both functional interaction and user engagement, during the user evaluation (reported in section 3.4.3), participants did not highlight any of these issue. Instead users emphasised the engaging aspects of the feedback and that it aided concentration upon swallowing.

The game-based feedback presented as part of the biofeedback system also demonstrated promising outcomes during this evaluation, with users reporting that they found the game entertaining and helpful for focusing on repeated swallowing, although the act of repeated swallowing itself was viewed negatively. While biofeedback has been previously used for treatment of swallowing disorders, these usually rely upon forms of feedback which are unintuitive and thus require therapist supervision or significant patient training [64]. Traditional biofeedback has also been reported to suffer from issues related to patient motivation and engagement, and game based environments have been recommended a useful approach for resolving these issues [101]. An early concept for game-based swallow biofeedback was proposed by Stepp *et al.* [229], mapping EMG amplitude of the submental muscles directly to vertical position of a game avatar, to control the avatar and hit targets. However, performance of their system was determined based on number of targets hit, which they reported as a limitation, and they found a low success rate and high degree of variance.

Comparatively, the system presented in this chapter made use of a swallow detection algorithm to govern when the game would respond. As reported above, this resulted

in high response accuracy and participants reported that it helped them focus on the repeated swallowing task. Furthermore, this system presented encouraged participants to perform extended swallow exercises and swallow repetition with minimal training, through use of an intuitive platform navigation game environment, and randomly varying platform sizes. Based of the review of the literature, the use of game environments for feedback in conjunction with discreet "epidermal" sensors [74] can be concluded to be a mobile and unobtrusive approach for swallow exercise.

However, there were a number of limitations involved in the evaluation of the performance and usability and feedback of this system, as well as involving the user evaluation design. Firstly, the user evaluation made use of a 7-point scale survey for rating points relating to the participant experience, followed by an interview, to obtain detailed insight into the user responses. However, although this approach was chosen to obtain as much detail as possible regarding experience, the limited selection of survey topics limited the insight that was possible in this case, particularly with a small participant sample. In order to fully understand user experience and impression, surveys should provide a range of questions (rated areas) and response options, so as not to limit user responses and provide sufficient response details [223]. Future research should take this into account and include a more in depth analysis of user experience as well as a larger sample pool, to improve insight and increase response certainty.

There were also a number of question remaining regarding the impact of the response delay, and whether it has an adverse impact upon evaluation of feedback performance, usability, or user experience. As well as pursuing further work to improve the performance of the feedback system and reduce delay, further research is necessary to determine the extent of the impact of the delay on functional interaction and user interaction. Furthermore, alternative feedback designs approaches should be considered that would be better able to integrate feedback delay with negligible impact.

3.5.4 Data Collection Limitations

The main limitations of this chapter were related to the relatively limited scope the experimental protocols used in this study. Data collection and the user evaluation was conducted in this study with 6 participants, and under experimental conditions during which the participants were asked to limit non swallowing motion. As such the data used

for developing and testing of the swallow detection algorithm did not include significant muscle activity related to non-swallowing actions, meaning that robustness of the algorithm could not be determined here and suggesting that this would not perform well in response to unexpected noise or head motion.

The design of the user evaluation also presented some limitations for the evaluation of the feedback and user reception. A single session was conducted for each user, with repeated trials of the feedback system and rest periods introduced between trials to alleviate muscle fatigue which can impact user performance and result in unusual EMG activity impacting the performance of the system. However, participants still indicated that repeated swallowing was difficult, which was expected while using feedback designed to focus on swallow exercise, and there was a danger of this having other unknown influences over results. In the future, a repeated measurement design over separate sessions would be better suited for collecting data over multiple trials per participant. This would also offer the opportunity to study the impact of the game upon user performance over time. The inclusion of a larger subject sample size would also provide further details regarding these effects and strengthen the findings.

3.5.5 Implications

The work reported in this chapter has some significant implications for both research and clinical treatment. The study and evaluation of swallowing function is limited by expensive or intrusive procedures which are not suited to continuous or repeated assessment. Unobtrusive EMG and activity detection methods such as those described in section 3.2 are useful during continuous studies, permitting continuous monitoring and automated isolation of swallows for evaluation. Furthermore, section 3.3 has demonstrated the classification of particular swallow exercises used as part of rehabilitation. This has particular implications for the treatment of swallowing disorders, permitting easier detection patient success or failure when attempting specific swallowing exercises. The features extracted as part of this work is also of particular use as parameters of importance for the identification of impaired swallowing, as discussed by Vaiman and Eviatar [62].

In addition to swallow detection and classification, this chapter has demonstrated the use of EMG for driving biofeedback. Biofeedback is a technique which has been used as part of therapy for swallowing rehabilitation [64], however such biofeedback requires

patient training, and provides only simple feedback or requires supervision and interpretation of feedback and achievement of goals by a clinician. The game-based feedback presented in section 3.4 is a step in overcoming these issues, designed to make use of the motivational and engaging properties of games for therapy [101, 112]. Based on the findings of this research, it is concluded here that this form of feedback can be employed to encourage users and improve self-efficacy during swallow exercise, and to guide patients in particular exercises. Combined with automated detection of swallow types this could provide detailed information regarding goal achievement, thereby reducing the need for clinician supervision.

3.6 Conclusions and Contributions

The most significant contributions of this chapter were focused around the automated detection of swallowing and classification. One of the main objectives of this research was to identify more accurate techniques for the detection of swallowing, and the results of this chapter made significant progress to achieving this objective. Firstly, the research outlined here evaluated the use of EMG in conjunction with a threshold based activity detection technique, resulting in high detection accuracy.

However, the findings of this chapter also led to doubts regarding the robustness of this approach, and led to the conclusion that alternative approaches better able to handle unexpected motion or muscular activity when detecting swallowing should be pursued. For instance, the work outlined here regarding the detection of swallowing demonstrated that some classifier algorithms, such as decision tree based algorithms, are successful in evaluating complex classification problems. Based on the findings of this chapter, it is hypothesised that the use of such algorithms along with a larger subject pool and more diverse data set would help to provide robust swallow detection, and the next chapter investigates this in more detail.

As well as outlining techniques for swallow detection outlining the direction for future research in this thesis, the findings reported here also demonstrate factors involved in differentiation between swallow types, by way of classifier algorithm. Section 3.3 evaluated the choice of classifier algorithm and feature importance for swallow type classification and indicated that, amongst evaluated features, it was important to select features representing

EMG signal complexity, as well as those providing information about the swallow itself, such as the duration of an individual swallow. For instance, swallow duration was found to be particularly important for classification of extended swallows. Interestingly, only 7 features were found to be necessary for optimal detection of extended swallows, which was found to be consistent across all classifier algorithms evaluated. These findings support the conclusion that extended swallow detection is a relatively simple classification problem.

Differentiation between dry and liquid swallows, on the other hand, was found to be a more complex task. Evaluation of features revealed that this benefited from inclusion of a wider range of information, with a peak classifier accuracy found when using 26 features. Amongst these features, those including frequency content information were found to be beneficial. When evaluating classifier algorithm choices, decision tree based algorithms were found to give superior accuracy for this problem, likely due to the capacity of decision tree models to handle non-linear classification problems. These factors highlight the greater complexity involved in differentiating between liquid and dry swallows, compared to the simple task of extended swallow detection.

The work in this chapter lays the groundwork for subsequent research discussed in this thesis, particularly that the work focusing on the detection and classification of eating function; indicating a number of important considerations for classification of swallowing information. In addition to this, the findings of this chapter suggest that physiological sensing is a viable approach for on body-sensing, and the biofeedback approach designed as part of this work is useful for helping to engage and motivate users in swallow exercise. The next chapter builds upon the results of this chapter, expanding the experimental protocols and further explores the detection of eating and food types.

Chapter 4

Classifiers for Automated Detection of Eating and Food

4.1 Introduction

This chapter reports the findings of the second study carried out during this research. This builds upon results of the previous study (chapter 3) with an expanded protocol to further develop chew and swallow detection techniques, and to begin investigating the extraction of other information from eating, such as type of food.

As discussed in chapter 2, the tracking of both eating function and dietary content is an important component of understanding the processes of eating and eating disorders (section 2.1.4). One which is reliant upon self-reporting, a measure which is prone to inaccuracy and bias [32]. Physiological sensing based eating detection offers an automated alternative to self-reporting. However, automated systems reviewed in the literature for simultaneous eating detection and estimation of food type only take into consideration chewing behaviour [178, 180, 179]. The inability of these approaches to detect and include swallowing activity in evaluation of eating significantly limits the estimation of food type and other information.

The main aims of this chapter are to build upon the findings of chapter 3 to further develop automated eating detection techniques, and begin to investigate the extraction of other information related to feeding from detected eating. The focus of this chapter was exploring machine learning based approaches to achieve this aim. As such the main goals of this chapter were to:

- Investigate the use of classifier algorithms to develop robust and accurate models for the detection of chewing and swallowing
- Adapt and compare techniques described in the literature for classification of food content

In this chapter, the first step in achieving these goals was the collection of a robust data set, including a range participants of varied age and BMI, and involving varied activity to simulate real-world behaviours in addition to eating. As such, section 4.2 describes the study methodology; including the development of tools and protocol to streamline data collection and automatically provide detailed ground truth. Following data collection, section 4.3 investigates the use of classifier algorithms, and reports their performance for the detection of eating (section 4.3.1) and for detection of food content (section 4.3.2). Section 4.3.2 also compares two food classification techniques adapted from the literature with a new approach proposed here.

4.2 Data Collection and Processing Procedures

There were two main goals of this study. Firstly, the development of models for the classification of eating, capable of generalising to unknown subjects and robust in the presence of unrelated activity. Following this, was the investigation of potential additional information that can be extracted from EMG measurements given the detection of eating events (individual chews or swallows). This section outlines the methodologies involved in achieving these outcomes, including details of data collection, processing, feature extraction, and classification.

4.2.1 Data Collection

To achieve these goals it was necessary to collect EMG measurements during the consumption of food and a range of other activities, such as head motion and speech. Moreover, it was important to collect comprehensive and informative ground truth information regarding this behaviour. The measurement of such activity and precise ground truth was carried out to ensure training and test data was available encompassing a variety of subjects and "real-world" type behaviour, for training algorithms capable of classifying targeted behaviour in a robust and generalised manner. A purpose built data collection

procedure was developed along with accompanying hardware and software for the purpose of streamlining the data acquisition process. These permitted self-reporting of chewing and swallowing activity, in addition to semi-automated labelling of ground truth for foods being consumed, head motion, and speech.

Data Collection System

The data collection system consisted of custom hardware and software paired with an physiological data capture device and a standard laptop computer. Participants are equipped with standard surface electrode sensors (#H124SG, Covidien, Ireland[1]) connected to a bluetooth enabled EMG measurement and transmitter unit (Shimmer 3, Shimmer Sensing, Ireland[2]). Two muscles are targeted during this study, with electrodes sensors placed across the masseter and submental muscle groups. Placement procedure can be found in appendix A.1. The data capture device streams the signal to a laptop client running custom software. Also connected to the laptop is a custom 'clicker' type peripheral which is used by participants to record eating events when paired with the custom software. Figure 4.1 shows details of the data collection system, and provides example images of the 'clicker' device and on screen experimental instructions.

The data collection software was developed using C# .Net platform [220], making heavy use of the Shimmer API [230] to stream data from the capture device. This software permits the researcher to view and record streamed sensor data, saving the raw EMG data streamed from the data capture device while simultaneously recording ground truth labels. Sensor data from the 2 channels, ground truth, and video footage were all recorded separately but simultaneously and synchronised. In addition to this, the software also served to guide participants through the data collection, providing textual and audio instructions (example seen in figure 4.1, c).

In previous works, including that reported in chapter 3, ground truth is determined via strict protocols and instructions to perform actions at given times [60, 62], or through post-collection annotation of the data using markup software and video footage or assessment of the signal [178, 69, 30]. For some purposes this is a time consuming but acceptable method, but when identifying complex ground truth for many events occurring in rapid succession this is resource intensive and infeasible. Inspiration was instead taken from

[1]Now Medtronic: www.medtronic.com
[2]http://www.shimmersensing.com/

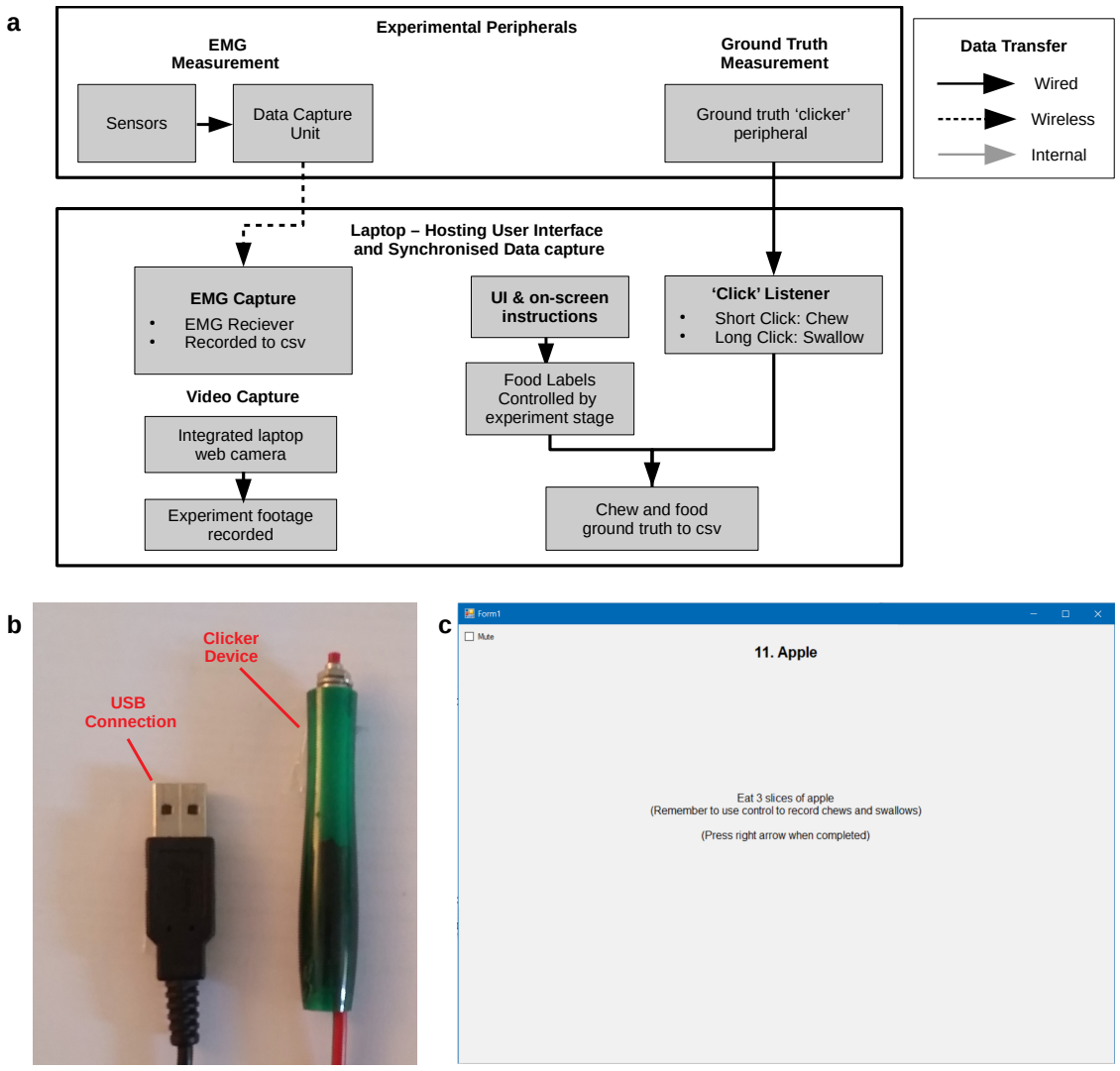

Figure 4.1: Components of the data capture system used to collect data during eating of various foods and head motion. **a.** provides a flowchart summarising experimental data collection system and interaction between hardware and software, for EMG data acquisition, video footage capture, ground truth collection, and on-screen instructions. **b.** shows the custom 'clicker' peripheral connected to a laptop via USB connection, to permit ground truth self-logging based on mouse click events on the application window. **c.** shows example of experimental application screen, displaying instructions for this stage of data collection (in conjunction with audio instructions).

studies by Nahrstaedt *et al.* [177] and Schultheiss *et al.* [170] in which participants are asked to record swallows through self reporting using a manual switch. This technique was adapted to streamline the data collection and annotation processes through participant self-reporting and automated data labelling.

During data collection, participants are able to self-report individual chews and swallows by performing a short click or long-hold of a 'clicker' device respectively (figure 4.1, b). The custom software is designed to recognise these and record ground truth labels accordingly. Ground truth labels regarding food content or activity unrelated to eating was also collected automatically, determined by experimental stage. Figure 4.1, a, provides details of this process.

Data Recording

During the data collection sessions participants were briefed in full regarding the study purpose and what would transpire during the collection session. Participants gave written consent to EMG and video footage collection procedures reported here, and to indefinite retention of anonymised data for future use beyond the scope of this study. Approval for the following experimental procedures was granted by the University of Kent Ethics Committee, on 19th July 2018[3] (approved reference number: 0721718, at the University of Kent). Participants were equipped with the sensors which were checked along with the custom software to ensure it was functioning as expected. The full system and usage was demonstrated to the participants prior to taking part in the session.

Participants were asked to follow on-screen instructions guiding them through the experimental procedure: 5 minutes of baseline measurement, 5 minutes speaking aloud, head motion, and consumption of a small meal. Head motion was also carried out at times while eating to simulate normal movement during eating. Inclusion of reading and head motion was included to permit training of classifiers which are robust to unrelated activity. Full details of the sequence can be found in appendix A.2.

Following completion, the sensors were removed from the participants, replaced, and the procedure repeated. This allowed the researches to ensure that minor changes in sensor placement did not adversely impact the quality of data recorded, demonstrating that the system is usable despite slight variations in sensor position. This also provided a

[3]University codes of research ethical conduct: https://research.kent.ac.uk/researchservices/ethics/

significant quantity of data for each participant.

Food Selection

A range of food items were selected in order to provide a variety of textures. This would provides variation to the EMG signal acquired during consumption of different food items, thus leading to a more robust classifier. Additionally this permits us to explore the classification goal of identifying food types from eating EMG.

Given the constraints of the subject pool and availability, it was not possible during this research to investigate a large number of foods. As such a selection of foods and liquids were selected to represent different textures and viscosities. For this study food items selected were: Apple, Jam Sandwich, Pizza, Yoghurt, and Water.

Participants were each asked to consume a total of 18 portions of each food item, over the two repetitions of the experimental procedure and the various meal sections. Food items were prepared prior to each study session. Each solid food item was cut into small bite-size portions, approximately 2.5cm square in the case of pizza and sandwiches, and apple slices 2cm by 2.5cm. Yoghurt was provided in a small container along with a 5 ml spoon. A portion of yoghurt was defined as a single spoonful. Unlimited water was provided and a portion was described to participants as a small mouthful.

During recruitment of participants, full information regarding the content of the food involved in the study was disclosed. Recruitment criteria required that participants find the foods involved palatable and have no allergies or dietary restrictions that prevent participants consuming the foods involved in the study.

Participants

Potential participants were recruited from the staff and student body of the University of Kent. Applicants were considered viable if they were between 18-40 years of age and had no dietary or eating disorders which would adversely impact eating during the study. Participants were selected to include a range of physical characteristics and information including gender and weight, height and BMI was recorded for each participant. This was done to maximise the range of physical differences in the subject pool in an attempt to improve robustness of the developed models to generalise to unknown subjects. Recorded physical information permitted analyses of the impact of these factors on the performance

of final classifier models and implications this would have on future research. Each participant taking part in the study received a £10 Amazon voucher as compensation.

In total, 16 participants took part in the study, 8 of whom were between the ages of 18-25, 7 between 26-35, and 1 between 36-40. Of these, 7 were male and 9 female, and 7 of the 16 were considered to be overweight, with a BMI greater than 25 and one was considered slightly underweight with a BMI of 18.1. Each participant recorded 2 data sets, however for 3 of these participants only 1 dataset was considered viable due to hardware faults, and 1 participant elected not to return take part in a second data collection session. In total, 28 data sets were collected from 16 participants, each comprising of approximately 20 minutes of EMG data recorded during a combination of activities and food consumption.

4.2.2 Data Preparation and Classification

Data Processing

Following data collection, all data was collected with a sampling frequency of 1024Hz, filtered and processed to eliminate noise or movement artefacts, and the upper envelope of each EMG channel extracted. Typically, the highest frequency components of EMG signal are between 400-500Hz, thus the EMG sample rate was limited to 1024Hz to capture this range and reduce the chance of high frequency noise or aliasing, and could safely be filtered to obtain the the full EMG frequency spectrum according to Nyquist theorem [4, 196]. As discussed in the literature (chapter 2), low frequency signal interference resulting from movement or inherent signal instability usually occurs between 0-20Hz. To eliminate these sources of noise, the signal was filtered in the same manner as described in the previous chapter (section 3.2.1), using a Butterworth band-pass filter with a cutoff frequency of 20Hz to 500Hz at an order of 5. See appendix B.1 for signal processing pseudocode.

Ground Truth Correction

Each dataset was collected with self-reported ground truth labels. While this gave a good indication of individual chew and swallow events, it was only an approximate indicator of the signal activity ground truth and did not guarantee the identification of uniform and predictable onset and termination times. To correct this, ground truth for each dataset underwent automatic and manual review to ensure fidelity. Firstly, automatic

correction of chewing event onset and termination was applied, using threshold based activity detection, using EMG of the masseter muscle. Correct ground truth timings could then be identified, where periods of potential EMG activity intersect or lay within close temporal proximity to ground truth time stamps, and used to correct ground truth. The same process was repeated for swallow ground truth correction, using submental activity. However, as these muscles also exhibited some activity during chewing, manual review of swallow EMG activity and video footage was also used to confirm swallow ground truth onset and termination.

Pseudocode demonstrating the procedure for automatic correction of ground truth can be found in appendix B.2. The threshold value (thr) for this was determined using the approach suggest by Abbink *et al.* [181] and Li *et al.* [200] for EMG detection, as discussed in section 2.3.3. Given as a point j standard deviations from the baselines mean:

$$thr = \mu_0 + j * \delta_0 \qquad \text{(2.3 revisited)}$$

where μ_0 is the mean of the baseline, δ_0 is the standard deviation of the baseline, and $j = 5$.

Eating Event Classification

In the previous chapter (chapter 3), a threshold based algorithms was designed for the purpose of swallowing detection. However, EMG of facial muscles is sensitive to inter-muscular cross-talk [196] and prone to interference from speech, head motion, or jaw clenching [73]. The previous study involved controlled experimental procedures for data involved in the development of this algorithm, but there were some indications that it was not robust to unexpected activity. In this chapter, classifier algorithms are instead investigated. These are alternative approaches widely researched in relation to EMG analysis as they are capable of identifying patterns in the available data which is not alternatively be easy to detect [143].

Three classification cases were evaluated for the detection of eating, as outlined in table 4.1. Firstly, a multi-class classification case was investigated, followed by the production of binary classification models for the detection of chewing or swallowing individually. In the binary cases no data was discarded from the training and test data, but any activity unrelated to the specific class was relabelled as inactivity.

Table 4.1: Description of the three classification cases investigated in this chapter, for detection of chewing and swallowing.

Investigated Classification Cases	
Classifier Model	Details
Multiclass	Differentiate between no activity (NA), activity during a Chew (C), and during a Swallow (S)
Binary Chew	Detect activity during a Chew (C). Inactivity, or swallow activity grouped under unrelated activity label (NA)
Binary Swallow	Detect activity during a Swallow (S). Inactivity, or chew activity grouped under unrelated activity label (NA)

After filtering and rectification of the signal, additional processing was carried out. The signal was downsampled and features extracted using a sliding, overlapping window with a non-linear hamming function applied. For each sample, features were extracted from the two signal channels and the sample was labelled according to the ground truth, as either belonging to a period of inactivity (NA), or a chew (C) or a swallow (S) event.

During the evaluation of video footage and ground truth certain differences between chewing and swallowing behaviour were observed, relating to the duration and frequency of events, which were important to consider when sampling the signal for feature extraction and classification. It was determined that the duration of swallowing events was significantly greater than that of individual chewing event: chews occurring with a duration of approximately $0.1s$ and swallowing events taking up to $2s$. Furthermore, chewing behaviour could generally be recognised as a highly periodic sequence of individual chewing events, and with significantly greater frequency than individual swallows. These observations were in line with the literature reviewed in chapter 2, both describing the physiological processes of feeding (section 2.1.1) and the characteristics of EMG during chewing and swallowing (section 2.2.3).

As such it was desirable to maximise the sampling window to capture as much of an individual EMG burst as possible, so as to avoid loss of characteristic signal activity in long duration events such as swallowing. However, a large window was considered likely to result in an over-generalisation of EMG signal during highly frequent and short duration chewing events, resulting in a loss of fidelity for the identification of onset and termination points for individual chews. Therefore, during initial training the accuracy of each model was evaluated using a range of window sizes from 0.1 seconds to 2 seconds in length to

Table 4.2: List of features investigated for chew and swallow classification. A discussion and details of these features is given in section 2.3.4, table 2.2.

Swallow Classification Features		
MAV	Mean Absolute Value, equation (2.5)	Average of the absolute EMG signal across a signal segment
IEMG	Integrated EMG, equation (2.6)	Summation of the absolute EMG signal across a signal segment, reflecting the EMG signal firing point [208]
RMS	Root Mean Square, equation (2.8)	Root mean square of a signal segment
SD	Standard Deviation, equation (2.9)	Standard deviation of a segment of the EMG signal
MYOP	Myopulse Percentage Rate, equation (2.11)	Average number of times the EMG signal in a segment exceeds a threshold, relating to EMG motor unit action potential [209]
MNF	Mean Frequency, equation (2.15)	Average signal frequency
MNP	Mean Power Spectrum, equation (2.16)	Average of the EMG signal power spectrum
Peak	Maximum Amplitude	Maximum signal amplitude in the EMG segment

determine an ideal compromise for accurate detection of both chews and swallows.

Features extracted for each sample were selected according to recommendations within the literature (section 2.3.4) and findings of the previous study (chapter 3). These features include a combination of signal energy, complexity and frequency content, as recommended by [209, 208]. A list of these features can be found in table 4.2. Across the 2 channels of EMG a total of 18 features were extracted per sample for use in the classification of eating events. The feature extracted during this work assumed a period of individual calibration for each user. As such features were normalised given the minimum and maximum values recorded for each participant.

As this study was aiming to create as robust a model as possible, in the face of head motion, speech, or unexpected and unrelated signal activity, as much of the available data was retained as possible. All samples unrelated to chewing or swallowing were labelled as periods of inactivity (NA) despite any other behaviours occurring. This resulted in class imbalances, towards the inactive class. In the training set this was compensated for by computing class weights and applying these to data during training of all models, carried out using the scikit-learn built-in functionality [231]. Class imbalances in the test sets were also liable to cause anomalous results during testing. To account for this the test data was resampled, downsampling the majority class to balance with the minority.

Food Detection Classification

The second main goal of this study was to investigate what additional information regarding eating can be determined following the detection of eating events. The detection of food type from EMG signals and eating events is presented as one such application. To fully investigate the potential for classification of food content based upon EMG and eating events, three machine learning based approaches for feature extraction were investigated to determine the ideal approach for food classification. Two were derived from the literature and adapted for use with the data collected here [179, 180, 178]. The third approach, proposed here, amalgamated and extended these other techniques to include swallowing information.

For all approaches investigated, the EMG signals were filtered and rectified as described previously (section 4.2.2). All classification approaches investigated in this stage made use of features describing the EMG signal content during eating events or the pattern of eating events themselves. As such the EMG signal was then segmented according to ground truth timestamps for each individual chewing or swallowing cycle, assuming a perfect accuracy during this stage. Eating sequences were determined given the interval between termination of chewing or swallowing cycles and onset of the proceeding cycle. An eating sequence was considered, here, to be complete when an interval of more than 1.5 seconds was identified between the termination of an eating event and the onset of another. This value was determined based on manual observation of the data and supporting ground truth and video footage.

The two techniques adapted from the literature were based upon studies by R. Zhang and O. Amft [180] and Q. Huang *et al.* [179], and are discussed in detail in the review of the literature (section 2.2.4). In both of these studies, "smart-glasses" were used with built in electrodes for EMG measurement of the temporalis muscles for the detection of chewing. Features were extracted from the EMG signal during eating, for use in classifying food content. R. Zhang and O. Amft [180] extracted a number of signal features during each chew, averaged over the first 10 chews of a chewing sequence. These features were then used to train and test an Linear Discriminant Analysis classifier model capable of classifying food types over entire chewing sequences, reporting 94.7% accuracy. Q. Huang *et al.* [179] followed a similar approach, but instead treated each individual chew as a

separate sample, including EMG signal features from individual chew bursts and a count of chews found in the associated chewing sequence. Thus, this second technique captured information regarding individual chew signal along with some information regarding the pattern of chewing. Q. Huang *et al.* reported training a J48 Decision Tree capable of classifying food with a 69.2%–94.8% accuracy.

Although both approaches reported a high, if sometimes variable, accuracy, it should be noted that neither approach reported any attempt to evaluate the capacity of their models in a subject-independent basis (capable of generalising to unknown subjects). In addition to this, they did not include the detection of swallowing in their feature sets, with the temporalis lacking significant activity during swallowing. Furthermore, they made no attempt to detect liquid intake or differentiate between solids and liquids, likely due to lack of chewing during liquid intake.

To resolve these issues a third approach was proposed here, making use of sensors placed across the masseter and submental muscles to take advantage of both chewing and swallowing detection. A new feature set was also proposed, amalgamating the beneficial features used in the studies described above while including swallowing information. In this approach, each eating event was considered a separate sample, as described by Q. Huang *et al.* However a more diverse feature set describing both individual events and the pattern of events within the sequence to which they belong is chosen. Then for each eating event the features of both the previous techniques are extracted for a total of 22 features across two channels.

Table 4.3 gives a summary of the features extracted from eating sequences or cycles, for the two techniques adapted from the literature and the newly proposed feature set. For all approaches features were normalised on an individual participant basis, assuming a period of calibration for feature extraction with each subject. For all approaches, each sample was labelled according to the ground truth based on food item being consumed at the time. Each sample was labelled appropriately as Apple, Pizza, Sandwich, Yoghurt, or Water.

Classifier Performance Evaluation Methodology

During analyses of classifier performance, all models were trained and parameters tuned using group based k-fold cross validation ($k = 3$). Final evaluation and model selection

Table 4.3: Summary of features extracted for each feature extraction technique used for food classification. Eating cycle features indicate those calculated over individual chew or swallow cycles. Eating sequence features indicate those calculated across entire eating sequences, or as an average of individual cycles across the entire sequence. More details about the extraction of features can be found in section 2.3.4, table 2.2.

Feature Extraction Technique	Eating Cycle Features	Eating Sequence Features
R. Zhang and O. Amft [180]	NA	MAV, SD, RMS, Peak, IEMG. - Average taken for each chew cycle across eating sequence
Q. Huang *et al.* [179]	Peak, eating cycle duration, T_p values (p = 25, 50, 75)	Count of chewing cycles across eating sequence – included for each eating cycle sample
Proposed technique	MAV, SD, Peak, RMS, IEMG, T_p values (p = 25, 50, 75), eating cycle duration	Chew Count, Swallow Count, IEMG, Duration - Features included for each eating cycle sample

was performed with a distinct and separate subset consisting of all data from a random selection of 25% of participants (4 participants).

Following this, further evaluation was also performed to fully evaluate the capacity of selected models to generalise to unknown subjects and identify any trends in classifier performance related to subject demographics. A leave-one-group-out selection technique was employed, retaining all data from subject p and training using the remainder. Performance of the trained model for predicting the data classes for participant p was then evaluated. This was repeated for each participant retaining the class predictions and actual labels in each case and producing a final classification report for all predictions.

For each classification task a number of models were assessed prior to final parameter tuning and selection. In each case a number of different classification algorithms were assessed, including Support Vector Classifiers (SVC), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees meta estimator (ET), which are discussed further in section 2.3.4.

For training and testing of all models, the sci-kit learn library was employed [231]. In each case, full classification reports were produced consisting of precision, recall, and F-Score accuracy metrics. These permitted evaluation of each models performance predicting each class and a weighted average of each metric provided an overall performance indicator.

The F-Score accuracy metric is mostly used here in evaluating and comparing between the produced models.

4.3 Classifier Development and Performance

Table 4.4: Number of eating events recorded - distribution of chew and swallow events for each food class.

Recorded Eating Events			
Class Label	Chew	Swallow	Total
Apple	3595	369	3964
Sandwich	4282	376	4658
Pizza	6073	395	6468
Yoghurt	230	330	560
Water	0	587	587
Total	14180	2057	16237

Reported here is the development and performance of classification models for the detection of ingestive behaviour. During data collection 384 minutes of data were collected over all participants. During this time, 5 minutes sitting still and 5 minutes of speech were collected for during each session and the remainder of the data was collected during consumption of a small meal. The total number of chews, swallows, and distribution of food labels may be found in table 4.4.

4.3.1 Eating Detection

Classification of eating events was investigated making use of various models for different classification cases, as described in table 4.1. Firstly, multi-class classification (C-S-NA) of chew (C) and swallow (S) labelled samples from periods of inactivity (NA) was investigated. Following this, binary classification models were developed for the detection of chews against unrelated activity (C-NA) and swallows against unrelated activity (S-NA).

Multi-Class Classification

Firstly, a multi-class classification model was developed and evaluation of sample window size conducted. The effect of varying window size on each class is demonstrated in figure 4.2. As can be seen a very small sample window (128 observations in length) results in a very poor result for both chew and swallow classes. The best accuracy for the chew class was found with a window 512 observations in length (*F-Score*= 0.91), and with a window

of 2048 for the swallow class (*F-Score*= 0.82), using a linear kernel SVC algorithm. Using the weighted average F-Score as a measure of classification accuracy, a sample window of 768 observations in length 0.75 seconds) was determined to be the best compromise between chewing and swallowing. Figure 4.2 demonstrates this compromise for the linear SVC based model, but this was found to be the case for all algorithms and this window size was selected for further evaluation and testing of these models.

Table 4.5 shows the predictive performance of all algorithms for identifying chews and swallows using the unseen test data, in the multi-class case. The linear SVC algorithm clearly demonstrated the greatest predictive accuracy overall and for each individual class, with an average F-Score of 0.79 using a window size of 768 observations (0.75 seconds).

Table 4.5: Summary of multi-class eating classifier model performance using different algorithms. Shows F-Score per chew (C), swallow (S), and periods of inactivity (NA), along with weighted average. Scores are shown for each classifier algorithm: Support Vector Machine (SVC), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees algorithm (ET). Sampling window for all algorithms is 768 observations.

Per-Class F-Score and Weighted Average				
Class Label	Classifier Algorithm			
	SVC	LDA	DT	ET
NA	0.78	0.71	0.69	0.69
C	0.88	0.83	0.8	0.85
S	0.70	0.60	0.46	0.42
Average	0.79	0.72	0.65	0.65

While a compromise in window length was found for classification of chew and swallow classes, a bias towards the prediction of inactive (NA) or chew (C) classes was still observable from the individual class scores. The normalised confusion matrix (figure 4.3) for the SVC based model highlights this trend, demonstrating considerable confusion between swallow (S) and inactivity (NA) labels, with approximately 36% of S labels being misclassified as NA. The results indicated that the selected window, although offering a the best possible balance between chew and swallow prediction, was not large enough to provide accurate predictions of swallowing. However, from figure 4.2 it can be seen that increasing the window size compromises accuracy of the chew class prediction. Instead, the improvement of accuracy for each class was further investigated through the use of binary classification models.

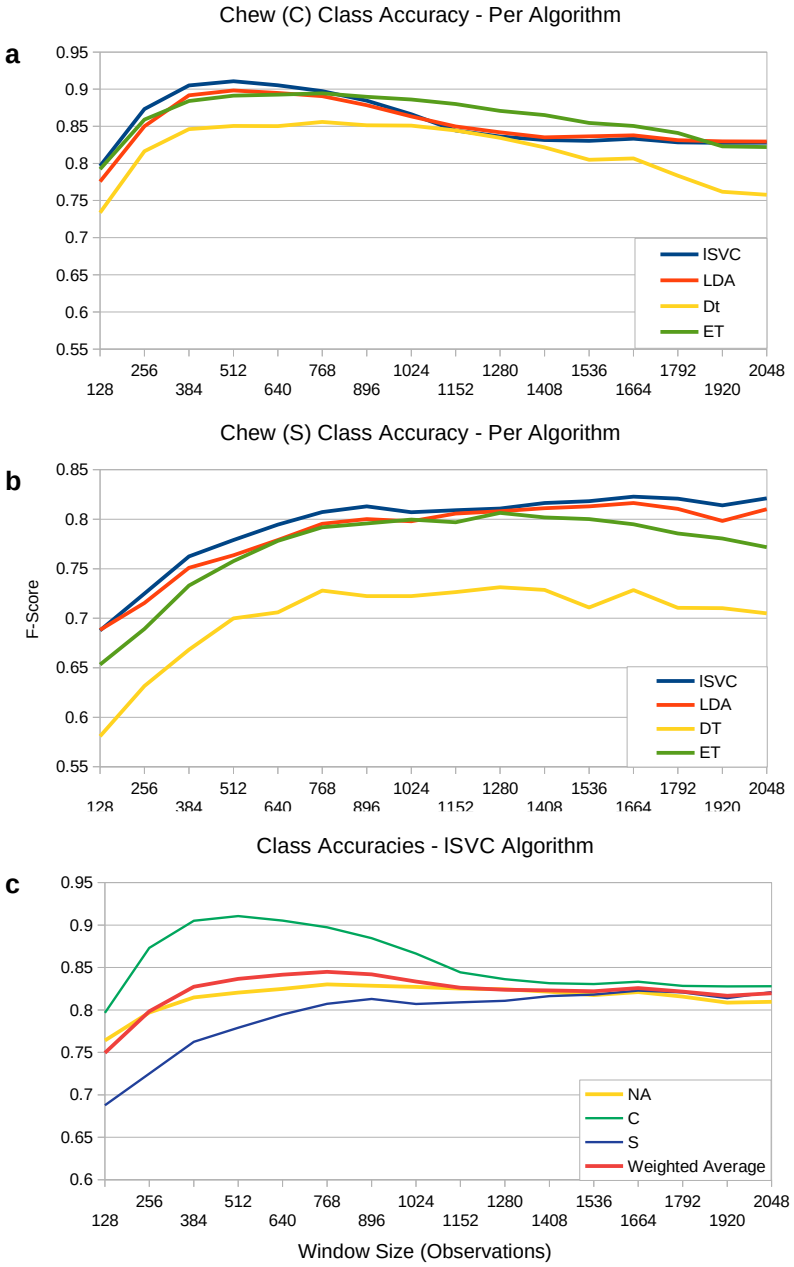

Figure 4.2: Evaluation of sample window sizes for multi-class classification of chews, swallows, or periods of inactivity (C-S-NA). Shown are the F-Score accuracies against window size for: **(a)** Chew class accuracy for each of the evaluated classifier algorithms, **(b)** swallow class accuracy for each of the evaluated algorithms, and **(c)** class accuracies and weighted average for the linear SVC based model. In **a** and **b**, *lSVC* refers to linear Support Vector Classifier, *LDA* to Linear Discriminant Analysis, *DT* to Decision Tree, and *ET* to Extended Tree algorithms. In **c**, *NA* refers to the classification score for detecting periods of inactivity or unrelated activity, *C* refers to the score for Chew detection, *S* to the score for Swallow detection, and the *Weighted Average* is the weighted average of all class scores.

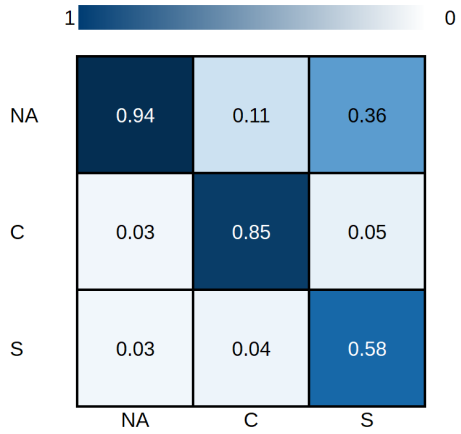

Figure 4.3: Normalised confusion matrix for the lSVC based model for multi-class classification of inactivity (NA), chews (C), and swallows (S).

Binary Classification

To investigate this and further improve classifier performance, binary classification models were then developed for the separate detection of chewing or swallowing from inactivity.

Window size evaluation was repeated as part of the training procedure for the binary chew classifier models. As expected, results of this evaluation for the binary chew classification case (figure 4.4, *a*) follow a pattern similar to that observed in the multi-class case, with rapidly increasing accuracy until 512 observations in length (0.5 second) for all algorithms, followed by a gradual decline with increasing window size. For swallowing detection, a similar pattern to that of the multi-class case was observed, with accuracy gradually increasing with much greater window sizes (figure 4.4, *b*). The optimum window size was found to be 1664 observations (1.62 seconds) for the linear kernel SVC, however the optimum window size was less uniform in this case, and varied between algorithms.

When evaluated against the test set, the models for binary classification of chews demonstrated significantly improved performance over the multi-class classification case, for all algorithms (table 4.6). It was determined that the SVC model once again resulted in the best predictive performance on the test set, showing a 0.06 improvement over the multi-class case for the chew class. Accuracy for binary swallow detection (table 4.7) was also found to improve over the multi-class case, with an improvement of 0.16 for the swallow class for the linear kernel SVC algorithm with a window size of 1664 observations (1.625 seconds). For the swallow classifier, the ideal window size for each algorithm differed

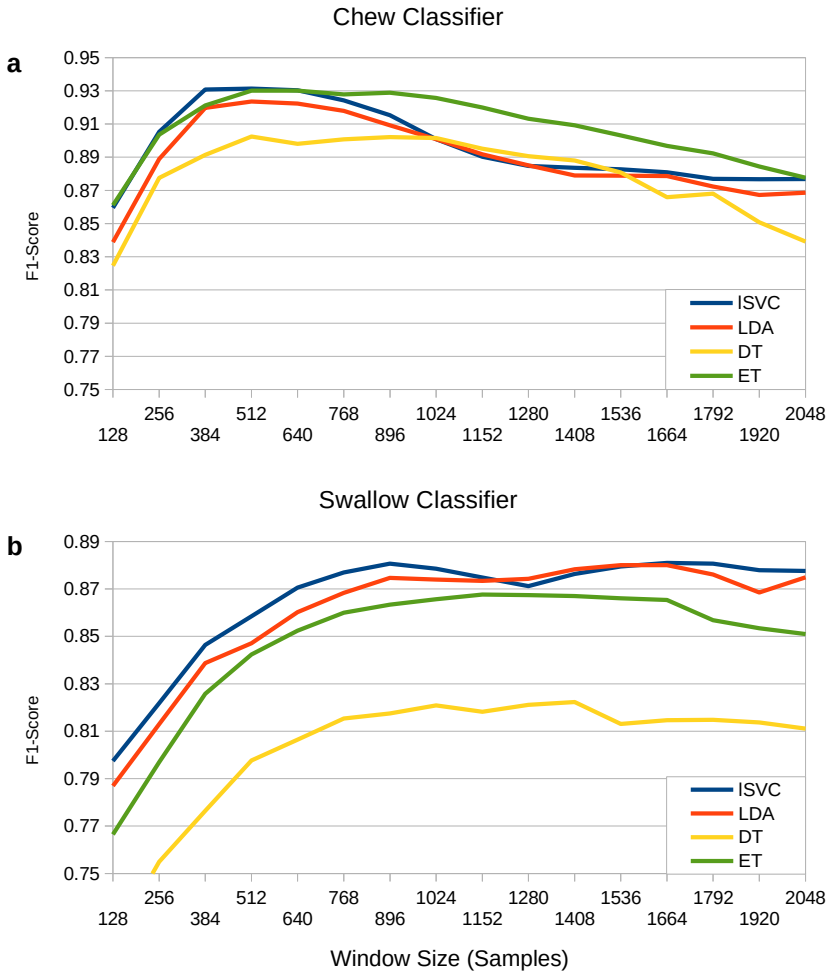

Figure 4.4: Evaluation of sample window sizes for binary chew (C-NA) and swallow (S-NA) classifier models. Shown are the weighted average F-Score accuracies against window size for: **(a)** Binary chew classifier accuracy for each of the evaluated classifier algorithms, and **(b)** binary swallow classifier accuracy for each of the evaluated algorithms.

in length, and were listed in table 4.7.

Part of the goal of this work was the production of eating classification models capable of robustly detecting eating despite the presence of unrelated activity. To help meet this goal the models developed here were trained using data which included periods of head motion and speech, labelled as periods of inactivity. The high classification accuracy achieved in this work suggests that there was little interference in predictive accuracy caused by this unwanted behaviour. The final selected models were binary classifier models based upon linear kernel SVC classification algorithms, with a sample window size of 512 observations in length for chewing prediction and 1664 observations (1.625 seconds) for swallowing prediction.

Table 4.6: Performance summary for the binary chew classifiers. Shows F-Score per class and weighted average for each algorithm: Support Vector Machine (SVC), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees algorithm (ET). Sample window size for all models = 512.

Binary Chew Classifier F-Scores				
Lbl	Classifier Algorithm			
	SVC	LDA	Decision Tree	Extra Trees
NA	0.94	0.90	0.87	0.89
C	0.94	0.88	0.84	0.86
Average	0.94	0.89	0.86	0.88

Table 4.7: Performance summary for binary swallow classifiers. Scores are shown for each classifier algorithm: Support Vector Machine (SVC), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees algorithm (ET). Sample window sizes: lSVC = 1664, LDA = 1536, DT = 1408, ET = 1152.

Binary Swallow Classifier F-Scores				
Lbl	Classifier Algorithm			
	SVC	LDA	DT	ET
NA	0.85	0.8	0.74	0.73
S	0.86	0.69	0.5	0.43
Average	0.86	0.75	0.62	0.58

Leave-One-Out Subject Evaluation

Selected models were then tested using a leave-one-participant-out selection approach to permit estimation of the models predictive consistency across different participants, and permitting the identification of any anomalous outliers. This evaluation was performed using the binary chew and swallow models based upon linear SVC algorithm, as selected in the previous section.

For each test case (participant) class predictions were recorded and merged, permitting a final evaluation of the models performance for all test cases (table 4.8). There was a slight, but not significant, improvement in F-Score for both classes, with an score of 0.95 for the chewing class and a score of 0.87 for the swallowing class. Evaluating the results for each individual test case demonstrated in a relatively consistent score for all participants (as can be seen in figure 4.5), and a low standard deviation of only 0.02 for the chewing classifier and 0.04 for the swallowing classifier. Persistence of the classification performance across all subjects and the low standard deviation of the F-Scores support the conclusion that these models generalise well to entirely unknown subjects. Furthermore, lack of variation in performance amongst participants despite differences in age, gender, and BMI value suggest that these factors have little effect upon the detection and classification of

EMG signals during eating.

Table 4.8: Performance summary for binary chew and swallow classifiers, using SVC algorithm, on a leave-one-out test case. Shows average precision, recall and F-Score metrics for individual classes. Sample window size: C = 512, S = 1664

LOO Average Classifier Accuracy Per Participant			
Class	Precision	Recall	F-Score
C	0.95	0.95	0.95
S	0.87	0.88	0.87
Average	0.91	0.91	0.91

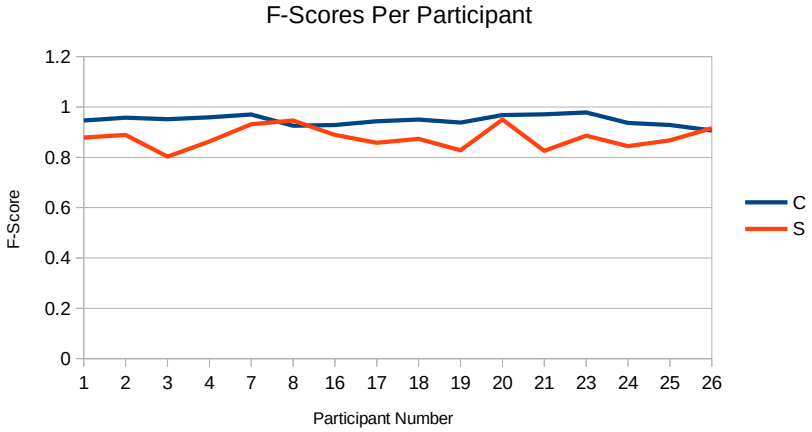

Figure 4.5: Plot of average F-Score for each test case (participant) in leave-one-out evaluation of binary chew and swallow classifiers. Shown are scores for chew (C) and swallow (S) binary classifiers, using linear kernel SVC classifier, sample window size: C=512, S=1664.

While there were no definitive correlations observed between score and demographics, it is interesting to note that for swallowing detection the high performing cases (F-Score above 0.9) all consisted of individuals with high BMI. For chewing, no test cases resulted in an F-Score of under 0.91 and the high scoring cases for chewing prediction (with F-Score above 0.96) were found to be similarly distributed between high and normal BMI. However, it should be noted that the size of the subject pool was not extensive enough to make any significant conclusions from these observations.

4.3.2 Food Classification

Following eating detection, classification of the food type of ingested items, given eating EMG activity, was then investigated, following the procedures laid out in section 4.2.2. Firstly a multi-class model was developed to investigate the differentiation between all food types. Following this the classification problem was divided into three: the classification

of foods as either solids or liquids, and then the classification of different solid foods or liquids.

Multi-Class Model

Firstly, classifiers were trained for prediction of all food types, investigating models based upon various classification algorithms, and comparing the three feature sets (table 4.2). The weighted F-Score accuracy measures for each feature extraction approach and classification algorithm may be found in table 4.9. As can be see, for all classification cases SVC based models using the newly proposed features were found to provide greater predictive accuracy than the equivalent models using the feature sets adapted from the literature, or other classifier algorithms.

On examination of the confusion between classes (see figure 4.6) for the SVC based model employing the proposed features, it can be observed that the majority of confusion is confined to solid food types and liquid food types. For all solid foods there were very few cases of class labels being misclassified as liquids, and similarly there are no cases of liquids being misclassified as solids.

Food Sub-Type Classification

Taking advantage of this, the classification problem was then subdivided into multiple cases. The observation of distinct separation between solids and liquids in the multi-class model indicated that a binary classifier model would perform well for differentiating between solids and liquids. As can be seen in table 4.9 for the Solid vs Liquid case (SVL), training models with all classes relabelled as either solids (S) or liquids (L) resulted in a very high classification performance. This was expected, with the consumption of solid and liquid food types characterised by significantly different eating patterns, as discussed in the literature section (section 2.2.3).

On the other hand, no significant improvement was found for the average F-Score performance for the Solids classification model over the average F-Score for the full food classification model (All), with similar average score for both, using and SVC model with the newly proposed feature set. Furthermore, on a per-class basis no significant difference was found between the performance of these two classifiers, as seen in table 4.10. Liquids also only demonstrated a minor improvement of 0.02 in accuracy for the water class. This

Table 4.9: Performance summary for classification of food. Shows average F-Scores for different classifier algorithms and feature sets, for classification of all foods (All), detecting solids vs liquids (SVL), differentiating between solids, and differentiating between liquids.

Food Classification F-Score Per Model and Classifier Algorithm					
Model	Feature Extraction Technique	Classifier Algorithm			
		SVC	LDA	DT	ET
All	Q. Huang *et al.* [179]	0.55	0.54	0.50	0.52
	R. Zhang and O. Amft [180]	0.48	0.53	0.45	0.50
	Proposed Features	0.66	0.62	0.55	0.60
SVL	Q. Huang *et al.* [179]	0.99	0.96	0.98	0.99
	R. Zhang and O. Amft [180]	0.84	0.86	0.76	0.85
	Proposed Features	0.99	0.97	0.99	0.99
Solids	Q. Huang *et al.* [179]	0.55	0.53	0.50	0.51
	R. Zhang and O. Amft [180]	0.43	0.44	0.38	0.41
	Proposed Features	0.65	0.63	0.56	0.58
Liquids	Q. Huang *et al.* [179]	0.70	0.73	0.62	0.70
	R. Zhang and O. Amft [180]	0.75	0.73	0.69	0.70
	Proposed Features	0.74	0.76	0.70	0.71

Table 4.10: Performance summary for food classification accuracy per food type. Shows F-Score per class label for each food type, for classification of all foods (All), detecting solids vs liquids (SVL), differentiating between solids, and differentiating between liquids. Class accuracies for individual foods are left blank where that foods was not detected by the classifier model.

Food Classification F-Score per Food Type				
Food Type	Model			
	All Food	Solids	Liquids	S Vs L
Solids				0.99
Liquids				0.94
Apple	0.52	0.54		
Sandwich	0.60	0.59		
Pizza	0.78	0.77		
Yoghurt	0.75		0.75	
Water	0.71		0.73	
Weighted Average	0.66	0.65	0.74	0.99

trend is similarly observable when comparing the class confusion for the liquid classifier (figure 4.6, *b*) with the multi-class, both indicating similar accuracies for the yoghurt and water classes.

Leave-One-Out Subject Food Classification

To further investigate the capacity of selected models to generalise to unknown participants, a leave-one-out test subject approach was again followed; systematically retaining all data pertaining to a single subject as a test case, while training on the data from all

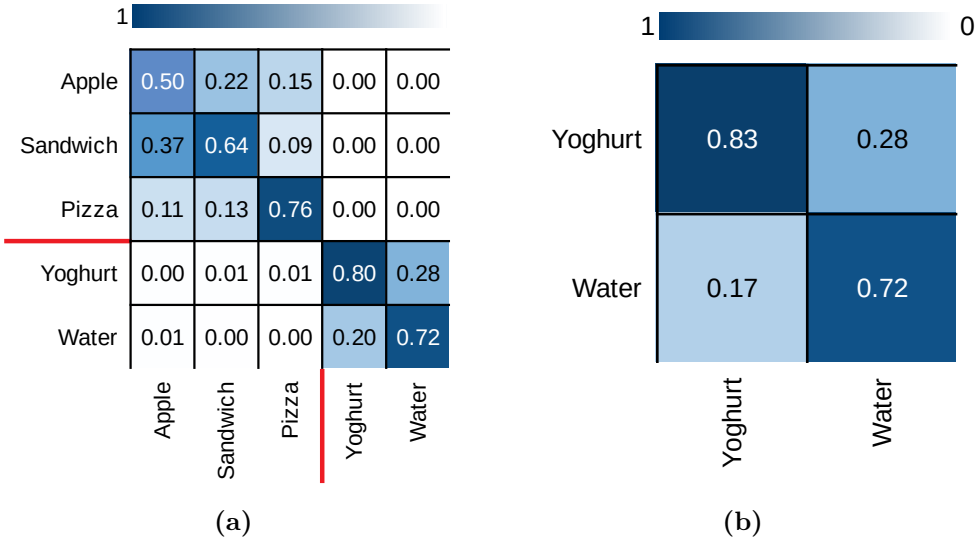

Figure 4.6: Confusion Matrices for Food Classification SVC Model. **a.** Shows the confusion scores for classification of all food using the multi-class SVC classifier; the highlighted lines emphasising the distinct separation apparent between solid and liquid classes, with little distinction between the broad food types. **b.** shows the confusion values for classification of liquids, using a binary SVC classifier.

remaining subjects. As can be seen in table 4.11, summarising the results of this evaluation, the average F-Scores for each model are similar to the previously obtained results with some improvement, confirming that these models are able to generalise effectively.

However, while the solid vs classifier resulted in a very high accuracy and uniformity (*F-Score*= 0.99, *SD*= 0.01), a number of outliers were found for the liquid and solid classifier models. While this study did not include a substantial enough subject pool to draw any significant conclusions from these outliers, there were some interesting points to note. As can be seen in figure 4.7, the majority of subjects were found to cluster within the 0.6-0.9 F-Score range for both models. However a single male participant between 18-25 and with a normal BMI was found to have a very poor predictive accuracy for liquids, but high for solids. No other participants had an accuracy of less than 0.7 for liquids. Additionally, of three participants who had a poor solid accuracy (less than 0.5), all were considered to have high BMI. While there appear to be some minor trends in the performance of these models relating to age and BMI, the subject pool was not significant or in depth enough to draw any definitive conclusions.

Table 4.11: Average F-Score and standard deviation for each classification model (based on Support Vector Classifier algorithm), evaluated on a leave-one-out subject test cases. Scores are shown for each classifier algorithm: Support Vector Machine (SVC), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees algorithm (ET).

Leave-One-Out Food Classification F-Scores				
	All	Solids	Liquids	S vs L
Average	0.682	0.689	0.721	0.993
SD	0.121	0.134	0.200	0.006

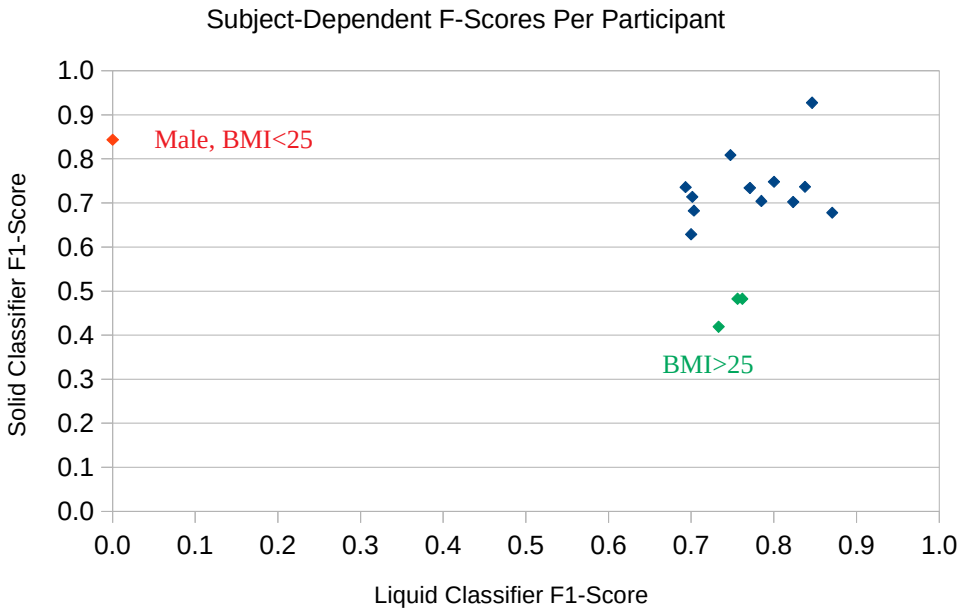

Figure 4.7: Plot of F-Scores for Solid and Liquid classifiers, per participant. Indicated are outlier participants: one male of normal BMI demonstrating low liquid prediction accuracy, and three with low solid prediction accuracy who had high BMI.

Subject Dependant Evaluation

Although the results reported here demonstrate that the models making use of the proposed features outperform those using feature sets adapted from the literature, these results do not align with those reported in the equivalent studies [180, 179]. However, neither of these original studies investigated the capacity of these models to generalise to entirely unknown subjects, with R. Zhang and O. Amft [180] reporting training and testing on individual participants and Q. Huang *et al.* [179] selecting a randomised sample of one fifth of all data. To fully compare the model developed here with the results reported in the literature a subject dependant evaluation method was employed. This

time a standard stochastic cross validation approach was used for training and validation purposes, retaining 25% of all data randomly as a test set.

Performance of the models using this approach much more closely aligned with the results reported in the literature. It can be seen in table 4.12 that, unlike in the previous evaluation, the models making use of Extra Trees algorithm mostly performed better or equally as well as the other algorithms. Comparing the per class accuracy for different feature selection approaches with Extra Trees based models, results were observed similar to the previous evaluation in distribution: the newly proposed features outperforming both the methods derived from the literature.

The impact of attempting to generalise onto unknown participants can be seen when comparing the per class accuracies of the models when evaluated with a group based test set or random sample test set. Comparing the results of the ET based model here (table 4.12) with the subject-independent SVC based model (table 4.9), no significant difference was found for the Solid vs Liquid classifier classes. As discussed previously these classes have distinctive differences which make them easy to classify and highly generalisable, and no significant difference was expected here.

For the classification of solids the subject-dependent model demonstrated an accuracy far exceeding that of the subject-independent model. The results here demonstrate that a model can classify these classes with high accuracy if it has previously been trained to recognise data from the a given participant, but will not necessarily generalise as well to entirely unknown subjects, indicating subject specific differences in eating pattern. For the liquid food classes there was a less pronounced difference between the random-sample and group-based test cases, with a 0.04 loss in F-Score for the yoghurt class and an improvement of 0.05 for the Water class. This indicated that, unlike solid foods, individual characteristics are less significant for liquid recognition

4.4 Discussion

This chapter reports the second study included in this research, with the goal of automated detection of eating and extraction of additional ingestive information. The aim of this chapter was to build upon previous findings to further develop automated chewing and swallowing detection, and to investigate the extraction of food content information based

Table 4.12: Weighted F-Scores for subject-dependent classification of all foods (All), detecting solids vs liquids (SVL), differentiating between solids, and differentiating between liquids. Shown are results for all feature set extraction technique and classifier algorithms. Tested on a random subset of 25% data retained from all subjects.

Subject Dependant F-Scores For Food Classification					
Model	Feature Set	Classification Algorithm			
		SVC	LDA	DT	ET
All	Q. Huang *et al.* [179]	0.66	0.62	0.8	0.78
	R. Zhang and O. Amft [180]	0.54	0.51	0.51	0.56
	New Features	0.76	0.74	0.95	0.89
SVL	Q. Huang *et al.* [179]	0.99	0.97	0.99	0.99
	R. Zhang and O. Amft [180]	0.87	0.86	0.82	0.89
	New Features	0.99	0.97	0.99	0.99
Solids	Q. Huang *et al.* [179]	0.66	0.63	0.8	0.78
	R. Zhang and O. Amft [180]	0.5	0.51	0.59	0.55
	New Features	0.77	0.75	0.97	0.92
Liquids	Q. Huang *et al.* [179]	0.73	0.73	0.72	0.73
	R. Zhang and O. Amft [180]	0.7	0.69	0.67	0.69
	New Features	0.72	0.71	0.7	0.74

Table 4.13: F-Score per class label and weighted average for each food classifier type trained on a subject-dependent basis. Includes scores for classification of all foods (All), detecting solids vs liquids (SVL), differentiation between solids and differentiation between liquids.

Subject-Dependent F-Scores Per Food Label				
Class Label	Classification Model			
	All	Solids	Liquids	S Vs L
Solid				1
Liquid				0.95
Apple	0.99	0.99		
Sandwich	0.99	0.99		
Pizza	0.99	0.99		
Yoghurt	0.71		0.71	
Water	0.76		0.78	
Average	0.97	0.99	0.75	0.99

on detected eating. To achieve this, the goals of this study were to investigate classifier algorithms for robust and accurate detection of eating, and determine to what extent detected eating can be used to extract information about food type, and how important swallowing is for this purpose.

4.4.1 Eating Classification Findings

For the classification of eating events, all classification was conducted using a sliding window to sample the EMG signal and extract features representing this sample for training and testing purposes. Observation of chewing and swallowing behaviour from ground truth and video footage indicated differences between the two behaviours: high frequency and periodicity of chews, and lower frequency and extended duration of swallows. An evaluation of windows size was conducted to compromise between capturing the entirety of swallowing events, while avoiding misclassification of inactive periods between chews and loss of onset and termination fidelity. This evaluation revealed an ideal window of 0.5 seconds for chewing prediction and up to 2 seconds for swallow prediction. A window of 0.75 seconds was found to give the best compromise between classes (see figure 4.2).

The multi-class case was tested against an unknown subset of data, which revealed a bias towards the chewing and inactive classes, as can be seen in the confusion matrix (figure 4.3). As such, binary classification cases were instead considered to permit optimum selection of window size for each. For the chew classification case a model was trained capable of 94% predictive accuracy, while for the swallow detection case a predictive accuracy of 86% was found. The significant increase in accuracy for both cases leads to the conclusion that window size is a vital consideration for chew and swallow detection, and while it is difficult to differentiate between chews and swallow given the same sampling window, it is possible to accurately detect both chews or swallows from periods of inactivity in a binary manner. The predictions can then be combined post classification for multi-class prediction.

As discussed in section 4.2.2, unrelated activity or increased subdermal fat results in noise, or unrelated activity interfering with detection of eating. Factors which were not considered in the previous study (chapter 3). The current study used an expanded protocol however, including unrelated activities in the training and test data, collected from participants with varied BMI and age. Furthermore, the final selected models were

evaluated with a leave-one-participant-out approach (see figure 4.5). This revealed low variance between subjects for the chewing classification accuracy, and slightly larger, but still not significant, variance for swallowing. While the limited number of participants made it difficult to draw an conclusions regarding these factors, it is interesting to note that the accuracy of these models appeared to have no correlation with participant BMI or age range. This indicates that signal processing permits elimination of excess noise sufficient to permit classifier algorithms to identify signal patterns.

This was also a limitation in related studies reviewed in the literature (section 2.2.4). Two "smart-glasses" based studies demonstrated comparable performance for chewing detection using threshold based algorithms [179, 180]. For their algorithm Q. Huang *et al.* [179] reported an accuracy of 96%, however they also indicated a high degree of false positives associated with unexpected activity. Similarly, R. Zhang and O. Amft [180] reported chewing detection accuracy of approximately 94% for their algorithm in lab conditions, but only 80% accuracy with real-world interference. Comparatively, the results of the study reported here were robust and accurate in the presence of unrelated activities.

However, the swallowing detection classifier in this chapter resulted in an accuracy of 87% (F-Score=0.87), which was significantly lower than the 90% accuracy found using a threshold based algorithm in the previous chapter (chapter 3), or an accuracy of 93% reported by Nahrstaedt *et al.* [177] using a combined bioimpedance and EMG based algorithm. As the current study made use of a subject independent design, the high accuracy reported in chapter 3 may indicate that it is more difficult to detect swallows for unknown subjects than it is for chews. Alternatively, the larger subject pool may highlight a bias in the subject selection of the previous study. However, the higher performance reported through the use of combined EMG and bioimpedance measurement techniques, proposed by Nahrstaedt *et al.* [177], is suggested here to be attributable to a number of factors: smaller sample size, limited variation between subjects, experimentally controlled bolus size swallowed, and different sensor placement, across the sternohyoid muscle rather than submental muscles. Furthermore, the inclusion of both bioimpedance and EMG adds additional processing costs to the detection of swallowing activity, while the approach used here for swallow detection relies solely upon analysis of a single EMG channel. Given the accuracy achieved for chewing detection here, higher accuracies are expected to be

achieved in future work for detection of swallowing using EMG alone, in repeated experiments permitting further evaluation of the performance of this classifier, or an analysis of the use of alternative muscles related to swallowing.

4.4.2 Food Classification Performance Discussion

For the classification of food types, a number of classifier algorithms were investigated along with three different feature extraction techniques. Outlined in table 4.1, the first two approaches were adapted from studies by R. Zhang and O. Amft [180] and Q. Huang *et al.* [179], and focused on the use of temporalis muscle EMG for detection of chewing events, while the final approach proposed here amalgamated these two approaches and included additional features taking advantage detected swallows in addition to chews.

In this investigation models were developed on a subject-independent basis to first detect all five food items, including solids and liquids. The best model found in this case resulted in an average accuracy of 66%, and there was considerable confusion between classes, but not between solid and liquids (figure 4.6). Following this, models were trained for distinguishing between solids and liquids, or for classifying specific liquids, or specific solids. While, the accuracies for liquid and solid classifiers were still low, the solid vs liquid classifier was found to demonstrate an accuracy of 99%. It is proposed here that this is due to distinct differences in the pattern of eating, with ingestion of solids involving a sequence of chews followed by a swallow, while drinking exhibits only individual swallows. The presence of outliers and relatively high variation between subjects in the leave-one-out evaluation of the solid differentiation classifier or liquid differentiation classifier, indicates that there are individual differences which effect the prediction of these classes. However, the subject pool was not significant enough in this case to make any definitive conclusions.

In all classification cases an SVC based model using the newly proposed feature set was found to give superior results compared to the other algorithms or feature extraction techniques adapted from other studies. However, the results found for the classification of solids was found to be significantly lower than those reported by Q. Huang *et al.* [179] or R. Zhang and O. Amft [180], who reported 77.2% accuracy for 5 food items and 94.7% accuracy for 3 food items respectively. However, these studies evaluated the accuracy of their models on a subject-dependent basis, and it was therefore not possible to establish the accuracy of their models with unknown subjects.

Addressing this, additional subject dependent models were trained. These models were found to have accuracies much closer to those reported in the literature (see table 4.12). In this case, the newly proposed features were once again found to outperform the alternative features for all classification cases, when using an Extra Tree algorithm based model. In the case of solid food classification the accuracy of the trained model increased dramatically, exceeding those results reported in the literature with an accuracy of 99.1%. This result demonstrates that the newly proposed feature set, including signal energy information and eating pattern information regarding both chewing and swallowing, was better able to detect food type than the equivalent approaches just making use of chewing behaviour. Although it should also be noted that in this study, different muscles were also targeted for the detection of chews (masseter) and a different food selection was used. The use of both chewing and swallowing detection also had the benefit of permitting differentiation between liquid and solid foods, and allowing estimation of type of liquid. Although there was also no significant change in the accuracy of either of these in the subject dependent case, when based on an Extra Trees algorithm.

These results suggests that, with the inclusion of newly proposed features taking advantage of both chewing and swallowing behaviour, classifier algorithms are capable of accurately differentiating between solid foods when trained on an individual. However, these results also suggest that it is much harder to generalise to entirely unknown subjects, and that individual eating characteristics are important for food classification. The pattern of chewing cycles has been reported to be an important indicator of food hardness and textural properties [176, 173, 174, 59], and it is concluded here, based on the results of this study, that not only are chewing patterns important for food classification, but that they are unique to the individual. Furthermore, swallowing on its own lacks these characteristic patterns and, as such, is less relevant for the classification of liquids, resulting in generalised and non-generalised models which demonstrate similar accuracies.

4.4.3 Limitations

This study focused on EMG of the masseter and submental muscles. However, alternative approaches in the literature have focused on alternative muscles, such as the temporalis for chewing detection [178, 180, 179], or combined bioimpedance and EMG of the sternohyoid muscle for swallow detection [177]. In latter case, reported accuracy was much higher, and

this approach should be investigated in the future and compared with the current technique to determine if the targeted muscles, or bioimpedence alongside EMG are better suited to eating detection.

For food type classification, it was found to be more difficult to detect liquids or foods with a generalised model, than other cases. This is in part due to an insufficient number of feeding events train a model capable of generalising to unknown subjects. This is a particular issue for liquid foods which involved much fewer feeding events than solids (as seen in table 4.4). Additional data collection should be investigated to determine if it improves liquid classification or ability to generalise.

The subject pool in this study was significantly extended from the previous study. However, all participants taking part in the study were considered healthy, without disorders which effect their eating. Furthermore, unrelated activity was limited to speech and head motion, and only five foods were consumed during this study. These factors all limit the capacity to generalise to unknown subjects. Furthermore, a limited food range means that the capacity of classifier models to detect a range of different foods is still relatively unknown.

4.5 Conclusions and Contributions

The main goals of this chapter was to help answer research questions 1 and 2 outlined at the start of this thesis (chapter 1), which focused on determining how to overcome the inherent error of self-report and other typical techniques for monitoring eating and related parameters which are vital for research into eating processes and clinical weight management or eating behaviour change (discussed in chapter 2). This chapter demonstrated how physiological sensing can be used for the detection of eating, and for the identification of other important information related to eating. In this case, this work investigated the use of EMG in conjunction with classifier algorithms for the detection of chewing and swallowing, and then explored EMG and eating features for the detection of food type.

The outcomes of this investigation constitute significant contributions to the state of the art. In the first part of the research, eating detection using classifiers was investigated and resulted in the development of techniques for training classifier models capable of accurate detection of both chewing and swallowing. As well as being capable of general-

ising to unknown subjects without impacting performance, the models also demonstrated an accuracy and robustness exceeding related threshold based approaches [179, 178, 180], concluded to be the result of a inclusion of data from a diverse range of subjects and non-eating activity. As part of the development of these models, this chapter also contributed an improvement to the understanding of chew and swallow duration and patterns, and the importance of window size selection when segmenting the EMG signal for chew and swallow classification. The findings demonstrated that fine segmentation was necessary for sensitive detection of individual chews, while a broad window was needed to capture the entirety of EMG patterns related to swallows. Thus it is recommended that separate models are used for detection of each eating event type.

Similar to eating classification, this chapter also reported techniques for the detection of a select sample of foods based on EMG and detected chews and swallows. This consisted of a new feature selection strategy combining individual chew and swallow EMG signal content with chewing sequence pattern information, which have otherwise only been considered separately and without inclusion of swallow information [179, 178, 180]. This approach was demonstrated to outperform compared techniques from the literature [179, 180] for classification of solid foods, with a significantly higher accuracy when trained on a subject-dependent basis. Furthermore, as a part of developing this strategy this research outlined the impact of food type and individual chewing patterns upon classification accuracy: the findings indicating that chewing patterns are indicative of food type for models trained to recognise individual variations, but that swallowing does not exhibit similar variation unique to the individual. As such, it can be concluded that chewing can be leveraged for higher accuracy in classification of solid-foods, but liquids are harder to distinguish between.

This chapter has demonstrated that eating detection can be applied for the detection of other information related to feeding, such as food type. This has significant implications in research and clinical treatment, which is discussed further in chapter 6. While food detection was investigated in this case, other useful information can be derived for the evaluation of swallowing (as demonstrated in chapter 3), as well as for researching chewing parameters. The next chapter investigates the use of chewing detection for one such purpose: the calculation and monitoring of chewing during a controlled lab study.

Chapter 5

Analysis of Eating Processes in Response to Moderation and Feedback

5.1 Introduction

The previous chapters of this thesis have explored techniques for the detection of chewing, swallowing, and for extraction of other information related to feeding, such as measurement of swallowing parameters and detection of swallow type in chapter 3, and the classification of food type based on eating function in chapter 4. This chapter further explores the measurement of eating information, focusing upon parameters of chewing, and demonstrates an application of such measurement with the aim of studying the effect of visual chewing rate feedback upon eating processes and eating moderation. This constitutes the final study reported in this thesis.

As discussed in chapter 2, eating speed is a factor determined to be a causal factor of obesity and been studied for its connection with a range of health factors such as BMI [28, 31], diabetes [25], as part of stress relief and stress eating [133, 30], or as a contributing factor for eating disorders [128, 129]. As described in previous chapters, such studies rely on participant self-monitoring or manual observation in experimental settings. Alternative approaches to studying eating speed have made use of a "Mandometer", an electronic scale measuring the weight of food over time, to estimate intake rate [128, 129], or on body worn gyroscope detecting food to mouth gestures for determining rate of bites [131]. Although

they give a more quantifiable measure of eating speed, these measurement techniques do not permit detailed evaluation of eating processes such as chewing and swallowing. Furthermore, although they made use of feedback to control eating rate, they did not evaluate the effect of feedback upon eating itself.

The connection between eating speed and health, particularly weight, suggest that eating speed is a useful feature to target in behaviour change interventions for weight management and eating disorder treatment. Traditional behaviour change focuses on self-reporting and reflection [20], to help counter automatic eating, environmental influence upon eating, and to permit self-reflection of behaviour change goals [18, 232, 233]. Mobile devices have also been used to support such treatment, providing a platform for self-reporting intake [43], and using feedback theory [173] to implement behaviour change through delivery of personalised feedback messages [44]. It is proposed here that such techniques can also be used to help influence eating speed and promote healthier eating habits.

The aim of this chapter is to continue exploring the extraction of information related to eating, and to demonstrate an application of this technique. In this case, there was a particular focus upon the study of eating speed and its relationship with eating and how this might be applied for research and behaviour change. To that end the main goals of this chapter are:

- To demonstrate the use of real-time chewing detection for monitoring of chewing rate and other parameters of chewing
- To present a system for collecting data on these parameters, and for driving real-time feedback related to chewing rate
- To investigate the application of this system for behaviour change and the study of eating

To meet these goals, this chapter first briefly reports the adaptation of chewing detection models developed in the previous chapter for use in this setting (section 5.2). Following this, section 5.3 describes the development of a system for real-time measurement of chewing and provision of chewing related feedback, including an overview of the system components, and techniques for calculation of chewing parameters and for driving

real-time haptic feedback related to chewing speed. Finally, the application of this system is presented for the study of the processes of eating and the effect of feedback

The main aim of this study was to determine the effect of self-moderated eating speed upon chewing parameters, and investigate the influence of feedback upon such self-moderation, to determine if it is a suitable adjunct to eating speed behaviour change. In meeting these aims, a repeated measure approach is taken, evaluating each participant under three conditions during a single experimental session: control (normal eating), self-moderated eating speed, and self-moderated eating with the support of haptic feedback regarding chewing speed. Section 5.4 describes the procedures and methodology for this lab study, section 5.5 evaluates the collected data to determine the effect of self-moderation and feedback, and section 5.6 discusses the study findings.

5.2 Real-time Mastication Classification

For the purpose of this controlled lab study, a continuous measurement system was developed to permit monitoring participant eating and for the provision of feedback in real-time. At the core of this system was the requirement of a classification algorithm capable of providing accurate and robust predictions for detecting chewing events in real-time. These predictions could, in turn, be used to identify live information regarding the characteristics of an individuals chewing behaviour.

The classification algorithm developed for this study was heavily based upon the findings of previous chapter, but differed slightly. The classifier was trained using the dataset previously acquired. Data consisted of two channel EMG collected from 16 participants over 28 sessions, each session involving activity recorded during head motion, reading aloud and the consumption of a meal. In the previous work masseter and submental muscles were targeted as muscles known to exhibit activity during chewing and swallowing respectively [73]. As this study chewing was the specific activity of interest, only the EMG channel corresponding to the masseter muscle was considered. Additionally, this minimised the participant exposure to unfamiliar sensors during experimental sessions, which were considered potential distractions and as such confounding variables in the feedback study.

Following the same signal processing procedure as in the previous study, the data was

sampled with a window of 0.5 seconds in length. From each sample the same features were extracted (as those indicated in table 4.2), with the exception of the Myopulse percentage rate. This was excluded due to the requirement of an additional calibration phase and potential redundancy, as it was considered to provide frequency information [208], which was already represented in these features.

As in the previous study, all available data was included for testing and training purposes no matter if there was unrelated activity present, to help produce a robust model. Each entry in the final feature array was labelled according to the ground truth as either occurring during a burst of EMG activity related to chewing behaviour (C), or as inactivity or unrelated activity (NA). A linear kernel SVC classifier was then trained using the available data. Testing was performed using the same approach as described previously, using a subset of all data from 25% of participants for evaluation of the model. For training and testing the 'scikit-learn' library was used [231] within the Python environment [234].

5.2.1 Classifier Performance Evaluation

For the binary classification of chewing activity in a real-time type scenario, from single channel EMG, the model resulted in an average recall, precision and F-Score all of 0.93 when tested on the retained test data. This result demonstrates only a minor loss in accuracy than that reported for the previously developed classifier, which reported in an average 0.94 for all three of these metrics (section 4.3.1). A full evaluation of the model performance is given in table 5.1.

The results demonstrated only a minor loss in accuracy with the data and feature change, and was not considered to impact performance significantly. This also indicated that the myopulse percentage rate (excluded in this version of the classifier) had only a minor impact upon the classification of chewing events. Similarly, it indicated that measurement of EMG from the submental muscles was of little importance for the classification of chewing. An observation supported by Criswell and Cram [73] who describe the masseter muscle as demonstrating significant activity during chewing, but do not report their use for the detection of swallowing.

Table 5.1: Accuracy metrics for the real-time chewing classifier based upon lSVM algorithm. Accuracy scores based upon subset of data from 4 unseen participants.

Real-Time Chew Classifier Accuracy			
Class Label	Precision	Recall	F1-Score
NA	0.94	0.91	0.93
C	0.92	0.94	0.93
Average	0.93	0.93	0.93

5.3 Data Measurement and Feedback System

Having established a real-time classification algorithm capable of detecting chews from single channel EMG of the masseter muscle, the next step was the development of a real-time system built around this classification algorithm, for the detection of chewing events based upon classifier prediction, the extrapolation of chewing rate and other measures, real-time monitoring, and the provision of near real-time feedback. This system would permit the effect of feedback upon eating processes to be monitored and recorded.

5.3.1 System Overview

The system consisted of a Bluetooth enabled EMG signal capture device (Shimmer 3, Shimmer Sensing, Ireland[1]) connected to standard surface electrodes (#H124SG, Covidien, Ireland[2]) affixed across the masseter muscles on the dominant side of the user, as described in the previous chapter (chapter 4) or in appendix A.1. To demonstrate the applications capacity in a mobile context, the measured signal was streamed live via Bluetooth to a mobile device (Samsung Galaxy S6, SM-G920F, Samsung [3]) running Android version 3.0. The mobile device receives signal via a custom application and acts as a local intermediary between the signal capture device and remote classifier, and also handled user feedback regarding chewing rate.

Figure 5.1 gives an overview of the chewing detection, monitoring, and feedback system. A laptop (Dell, Inspiron 7559[4]) connected to the mobile device via Bluetooth connection acts as a remote server handling signal processing and classification. This server also calculates chewing rate information, permits live monitoring and recording of live

[1]http://www.shimmersensing.com/
[2]Now Medtronic: www.medtronic.com
[3]https://www.samsung.com/
[4]https://www.dell.com/

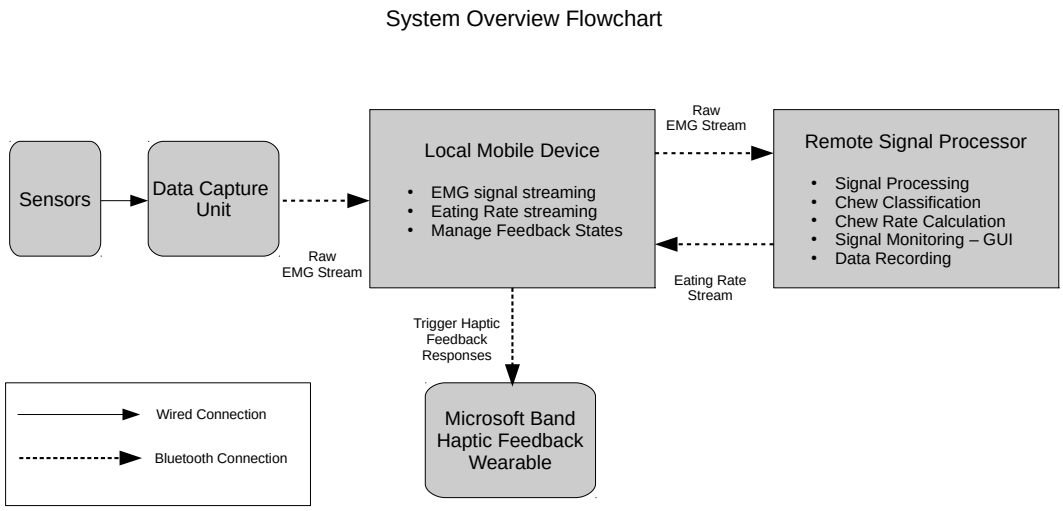

Figure 5.1: Overview chart demonstrating the flow of data throughout the chew detection, monitoring and feedback system.

data, and returns live chewing rate information to the mobile device for the purpose of driving feedback. Feedback was delivered via a Microsoft Band device (Microsoft Band 2, 4M5-00002, Microsoft [5]).

5.3.2 Signal Processing and Classification Software

A custom software application hosted on the remote server was considered the most integral part of the systems software. This application carried out all processing of the incoming data, including feature extraction and chewing prediction using the algorithm and techniques previously described. It also conducted chewing event detection based upon these predictions, calculated chewing rate for the purpose of driving feedback, and permitted remote, live, monitoring and recording of sensor reading throughout the sessions.

The software was developed using Python 2.7 [234], using TKinter [235] and matplotlib [236] for creating the graphical user interface and plotting data. The classification model implements sci-kit learn methods for performing predictions [231]. A Bluetooth connection was established with the mobile device and the EMG signal streamed. All data was stored in a fixed size first-in-first-out container (deque) of 512 elements in length, equating to a sample window of 0.5 seconds in length. This container was then periodically polled

[5] https://www.microsoft.com/en-gb

(every 0.1 seconds), filtering and feature extraction carried out upon the data contained therein. Features for each sample were used to obtain predictions from the classifier model. Finally, predictions were subject to a voting filter over a small window (of 8 samples), to reduce the chances of unexpected and individually occurring false positives.

Following the real-time prediction of EMG chew bursts, the detection of chewing event onset and termination was performed, determined by changes in prediction. The classification model was designed to return a positive prediction for all samples classified as occurring during an EMG burst, and a chewing event defined as the period occurring between the onset and termination of positive predictions, with time stamps recorded accordingly. Upon the termination of each event, the predicted label, timestamps, and duration of each event was recorded to an output file.

It was then possible to calculate chewing rate from the detected chewing event onset and termination timestamps, calculated as the number of chews in 1 second using the formula:

$$CR = \frac{1}{n}\sum_{i=0}^{L} f(chew_event_i); f(x) = \begin{cases} 1, & \text{if } x_{onset} >= t - n \text{ and } x_{term} < t \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

giving the average number of chews per second over the last n seconds, and where $chew_event_i$ is a chewing event observed during the session, L is the total number of chews observed, x_{onset} refers to the onset time of the chew event x_{term} is the termination time of the chew event x, t is the current time, and $n = 5$. The algorithm counts the number of chews which occurred over the last n seconds, to estimate the number of chews per second. Any chew events with an onset older than $t-n$ are periodically purged. As the approximate duration of chewing events has been identified as 0.5 seconds (chapter 4) and a similar gap between such events in a chewing sequence was estimated here, measuring chewing rate over the last 5 seconds permitted the timings of approximately 5 chews to be captured for calculating chewing rate. This was deemed to provide acceptable accuracy for chewing rate calculation while attempting to minimise the time error for feedback response.

For the purpose of this study adjusted chewing rate was also calculated for the purpose of driving feedback in a manner that prompted moderated chewing rate. To achieve this an offset equivalent to 1% of the maximum chewing rate recorded during a period of normal eating (recorded using the 'Calibrate Stats' function) was applied to the calculated

chewing rate. During each processing loop the normalised and adjusted chewing rate was then passed back to the local mobile client via Bluetooth, for the purpose of driving feedback.

During chewing rate calculation all chew events were recorded to an output CSV file in along with event duration, and onset and termination times. Following each processing loop the extracted features, chewing rate values, and predicted activity type for the associated data sample were similarly recorded to a separate output file. This information was only recorded when the 'Record' option was selected in the applications GUI.

For the purpose of live monitoring user progress, the GUI was also updated in to display a plot of the processed signal and the users chewing rate. The live plot was updated at every processing loop with the mean filtered signal point, with a colour change to indicate predicted chewing events. A textual display on the same plot was also updated at each loop with the calculated chewing rate values.

5.3.3 Mobile Feedback Application

The mobile device ran a custom application for streaming data from the Shimmer data capture device and passing it to the remote processor. The mobile applications was developed using the Android API [237], and made use of the Shimmer API [238] for the purpose of receiving data from the Shimmer streaming device. Feedback was provided via the Microsoft Band wearable, which was controlled using the Microsoft Band SDK [239].

Following processing the chewing rate values were then transmitted back to the mobile device via Bluetooth to drive feedback. Typically, according to feedback intervention theory, feedback permits the improvement of "task performance" through the comparison of performance feedback with some goal following completion of this task [103]. Discrepancies between performance and the goal motivates subjects to improve their capabilities [103]. Biofeedback is an application of this theory, closely correlated to the goal of the controlled lab study carried out here. In this context subjects are trained to gain voluntary control over some physiological function through the provision of feedback representing their performance and the application of reinforcement [102].

There are potential, additional, benefits to feedback provided the form selected. Eating has been previously theorised to be a form of automatic behaviour, with a human tendency to consume food without conscious consideration [18]. This automatic eating decision

making has been documented as extended beyond active eating, environmental factors having a strong influence upon choices such as food selection, quantity, or when to eat [19]. For instance, the presence of food has been found to result in a desire to eat even in spite of a lack of hunger [18, 19], while social situations result in eating conformity to peers [240], and even music has been demonstrated to increase food intake [122] or effect eating rate [123], likely due to distraction from conscious eating. As such, "mindful eating" is a technique recommended for weight loss and eating behaviour change interventions, helping subjects to maintain awareness of their eating, individually examining hunger and satiation to help override automatic eating [232, 232, 233].

The use of mobile technology based weight loss applications have been demonstrated as similarly beneficial for adhering to dietary plans or exercise routines [45, 141], and for behaviour change. Conceptually, such mobile application interventions have a similar effect to mindfulness interventions, requiring subject to give conscious thought to their eating habits and helping override automatic eating choices based on personal goals. This is particularly true in the case of applications which include regular feedback regarding performance[44], intermittently reminding subjects of their goals and performance thus far and motivating them to continue meeting these targets.

In addition to helping subjects meet active goals during eating, chewing rate feedback also helps to reduce automatic eating and focus upon behaviour change goals. While continuous feedback has the potential to reduce attention of eating or otherwise influence it, in the same way that music can distract individuals from internal intake monitoring [21] or affect eating rate based on music tempo [123], a periodic change in feedback and training relating to the meaning of feedback instead serves to attract users attention to their eating and remind them of their goals.

While biofeedback systems make use of visual or audio feedback, visual feedback was disregarded for this study as it would require specific attention when eating, while audible feedback would be overtly obvious to other individual in social scenarios; considerable limitations for mobile and discreet self monitoring in social scenarios. Haptic feedback on the other hand, was considered to provide continually present and relatively discreet feedback, that would not demand specific attention, but still act to draw users attention back to their goal. For the purpose of this study, a form of haptic feedback was selected as a simplified, abstract, and just-in-time representation of chewing rate. The feedback

application established another Bluetooth connection to a wrist-worn band capable of providing haptic responses (Microsoft Band).

Differing states of haptic responses were selected to represent magnitudes of chewing rate. These responses consisted of periodic haptic pulses of different intensities, permitted by the default notification types provided by the Microsoft Band SDK [239], and governed by simple threshold levels, using a normalised chewing rate. Four states were selected to ensure that the feedback was simple and memorable enough for users to clearly understand the meaning of each level after a short period of explanation and training. These corresponded with normalised chewing rate as follows:

1. 0.0–0.3: Low chewing rate, represented by no haptic pulses.
2. 0.3–0.6: Moderate chewing rate, represented by periodic individual haptic pulses.
3. 0.6–0.8: Fast chewing rate, represented by periodic double haptic pulses.
4. 0.8–1.0: Fastest chewing rate, represented by longer, high intensity double haptic pulses.

5.4 Lab Study Methodology

To demonstrate the application of eating classification, the live chewing detection algorithm was investigated for driving feedback as a support tool for participant self-moderation during eating. For this purpose a controlled lab study was designed to investigate the effect of real-time eating feedback upon chewing rate, as an immediate or short term influence. Approval for the following experimental procedures was granted by the University of Kent Faculty of Sciences Research Ethics Advisory Group for Human Participants, on 19th June 2018 [6] (approved reference number: 551617, at the University of Kent).

A repeated measure study design was selected to measure the effect of self-moderation of eating speed on chewing, and to compare self-moderated eating speed with and without haptic chewing rate feedback. Each participant attending in a single study session encompassing all treatment types over the course of this session, with each treatment acting as a repeated measurement factor. This permitted the effects of self-moderation upon chewing

[6] University codes of research ethical conduct: https://research.kent.ac.uk/researchservices/ethics/

rate and the difference between self-moderation with and without feedback to be investigated on an individual basis. Moreover, this also maximised the data it was possible to collect from the subject pool available. As all treatments took place in a single session, counterbalancing was implemented for the two treatment sections to offset the effect of time upon eating function due to increasing fullness, or increasing familiarity with the experimental conditions.

5.4.1 Participants

Participants were recruited from the student and staff of the University of Kent. Potential participants were screened prior to taking part in the study, and deemed eligible to take part if they were between the ages of 18-50, and had no dietary restrictions to the foods provided for the study, and no medical conditions which would interfere with their consumption of food or collection of data given the provided details. Additionally, inclusions criteria required that participants find the food provided favourable. Participants were required to sign documentation consenting to the recording of anonymised sensor data and survey responses, which would be retained beyond the scope of this study.

Demographic details were recorded for each participant taking part in the study, including age range, gender and BMI. In total, 20 participants were selected to take part in study. Of those who took part, there were equal numbers of male and female participants. The majority of participants were within the a healthy weight range according to their BMI (13 participants), while 3 were found to be sightly underweight (BMI less than 18.5), and 4 were found to be overweight (BMI greater than or equal to 25). Of selected participants, the majority (11 participants) were between 26 and 35, while 4 were under 25, and 5 were over 35.

5.4.2 Materials

The components specified in section 5.3 were used during the course of this study. Participants had adhesive electrode sensors affixed over their masseter muscles, following the placement procedure outlined in appendix A.1, and were equipped with a Microsoft Band wearable for the study duration. The mobile device and remote processing laptop, which were included as part of this system, were placed nearby, but out of line of sight of the participants.

The food selection was duplicated from previous data collection methodology involved in the development of chewing classification algorithms (chapter 4). This food was selected again to ensure optimal performance of the classification algorithm and consisted of: two thirds of a small apple, half a small pizza, one and a half jam sandwiches and unlimited water. In this case yoghurt was excluded from the selected food, as this study primarily focused upon the detection of chewing and yoghurt was found to be mostly consumed without chewing. Water was included during the course of a meal however, as a necessity for participant comfort. As in the previous study, participants were informed of foods involved in the study during the recruitment process, to ensure that food was favourable and did not conflict with dietary restrictions. In this study, participants were permitted to substitute any of the provided food items with others of the available food. Food was separated into 3 portions, each portion consisting of food measures which remained consistent across each portion.

5.4.3 Study Procedure

Each participant took part in a single study session consisting of three phases: a control phase involving unrestricted normal eating, and two treatment phases involving self-moderation of chewing rate, with and without feedback. Details of the experimental procedure for this study are given in appendix A.3.

Prior to these session participants were equipped with the sensing equipment as described in the materials section, and the custom software used to ensure the capture of a clear signal and accurate detection of chewing. Participants were then presented with food allotted to them for the session and asked if they would like to make any substitutions or reductions. Following this, the allotted food was divided into three separate portions for the different stages of the study.

Each participant then took part in the three periods of eating, completely consuming one portion of food in each period. Firstly, all participants took part in a period of uncontrolled eating, asked to eat the food normally and try to ignore the researcher. This permitted a measure of the participants normal eating performance to be assessed, along with calibration of the software parameters and measurement of reference values. Following this participants were informed about the study focus upon self-moderation of chewing rate, and asked to take part in two self-moderated eating speed treatment

sessions. The treatment phases were as follows:

Self-moderated eating During this period participants were asked to moderate their chewing rate, trying to estimate their normal eating speed and slow down while eating the provided food portion.

Self-moderated eating, with haptic feedback Prior to this period the chewing rate driven haptic feedback was demonstrated to participants, and brief training provided regarding the response levels. During this period participants were then asked to moderate chewing rate in the same manner. However, this time they were asked to try and do so while maintaining awareness of the feedback, providing an abstract representation of chewing rate.

All participants took part in both treatment sessions, and as such time and relative fullness were potential confounding variables effecting the results. To minimise their effect, counterbalancing was applied between treatments, with half of the participants (randomly selected) taking part in the self-moderation session first, and the other half taking part in the feedback session first.

Prior to the main study, a trial of these procedures was conducted with 5 participants to evaluate the methodology, determine the ideal approach for data analysis, and determine if any significant changes were required before proceeding. The trial was conducted satisfactorily and the results from these initial 5 participants were included in the data from the main study.

5.4.4 Chewing Measurement

During each meal phase of the study a range of information was recorded in regarding eating using the custom software, as described the feedback system design section (see section 5.3). Most importantly, this included the onset and termination of each individual eating event. Using this data, it was possible to extract a number of variables that were hypothesised to be effected by feedback. These included: chewing rate across the entire eating phase, repeated measures of chewing rate across an eating sequence, the duration of detected events, and the period between detected events,

During data collection the live chewing rate was calculated and recorded using equation (5.1). However, this rate was sensitive to pauses between mouthfuls of food and as

such was not used as an accurate indicator of chewing rate while eating across the entire meal phase. Instead, during data analysis substantial gaps between chewing events were considered an indication of a pause following completion of a chewing sequence, or mouthful of food. During such a pause, a participant would swallow food and take in another portion for processing. Based on this an adjusted chewing rate could be calculated to compensate for such pauses, by attenuating periods between chewing events which exceeded a given threshold. In this way, corrected values were found for chew event onset, *corr_on*, and termination, *corr_off*. Simultaneously, this process could be used to identify the onset of chewing sequences, *seq_on*, and termination times of chewing sequences, *seq_off*. Full pseudocode outlining this process is available in appendix B.2.1.

Once these corrected times were found, the chewing rate over the whole session, $CR_overall$, could be defined as the number of detected chew events, L, divided by the time, in seconds, between the onset of the first chew event and termination of the last. Calculated as follows:

$$CR_overall = \frac{1}{L}(corr_off_L - corr_on_0) \tag{5.2}$$

In addition to chewing rate, equation (5.2), additional measures of eating were derived from the detected eating events. These measures included: average duration of chewing events, average period between chewing events, average duration of chewing sequences, average period between chewing sequences, and average number of chews per chewing sequence.

Average duration of chewing events, *chew_dur*, was determined by the following equation:

$$chew_dur = \frac{1}{L}\sum_{i=0}^{L}(chew_off_i - chew_on_i) \tag{5.3}$$

The average period between chewing events, *chew_gap*, was determined by the following equation:

$$chew_gap = \frac{1}{L}\sum_{i=1}^{L}(corr_on_i - corr_off_{i-1}) \tag{5.4}$$

Following identification of chewing sequences based on a threshold for identifying significant gaps between chewing events, as discussed previously, the duration of and period between chewing sequences could also be calculated. For instance, given the identification

of chewing sequence onset (*seq_on*) and chewing sequence termination (*seq_off*), achieved using the process outlined in appendix B.2.1, the average duration of eating sequences, *seq_dur*, and average period between chewing sequences, *seq_gap*, per meal could be calculated. This was done using the following equations:

$$seq_dur = \frac{1}{L}\sum_{i=0}^{L}(seq_off_i - seq_on_i) \tag{5.5}$$

$$seq_gap = \frac{1}{L}\sum_{i=1}^{L}(seq_on_i - seq_off_{i-1}) \tag{5.6}$$

5.4.5 Eating Awareness Survey

In an attempt to capture this information a short survey was administered after each phase of the study to encourage participants to reflect on their eating and gauge their level of self-awareness of their eating activity and food consumed during that phase. In order to measure such effects, previous studies [128, 233] have employed questionnaires to encourage self-reflection, such as the "Kentucky Inventory of Mindfulness" to capture participants degree of mindfulness in day-to-day life [241], and the "Three Factor Eating Questionnaire" to identify participants dietary restraint, disinhibition and hunger in a general context [242]. While these give a general context of participant mindfulness and eating, they do not provide details regarding participant insights of a particular task such as eating.

For this specific study a custom questionnaire was instead designed. Based upon other eating questionnaires [242, 241], this consisting of 23 statements asking participants to reflect on different aspects of eating. Statements were selected that encompassed 4 different categories or topics, selected to provide insight into these areas of interest:

- **Awareness of eating environment:** The eating environment and various contributing elements, along with social influences has been isolated as one of the main influences eating disinhibition, meal duration, and overall consumption volume [21] and as such understanding how eating moderation and feedback effects participant perceptions of their eating environment was a key area to investigate. In addition to this, the experimental setting and presence of the researcher in the room were potential confounding variables, and asking participants to reflect on the environment provided insight into the effect of the setting.

- **Food:** Like the eating environment, properties of consumed food, such as salience and texture, are considered to impact eating rate and intake volume [24, 23]. As such, it is important to better understand if and how moderation or feedback effect participant self-reflected impression of food: if it changes their impression of the food consumed, distracts from enjoying the food, or enriches the experience.

- **Eating function:** Self-awareness of eating is an area considered to be one of the key processes involved in self-moderation or eating related behaviour change, with "mindful eating" [18, 232, 233] and cognitive behavioural therapy [114, 20] both involving reflection upon the act of eating, during or following meal consumption. As such, determining the impact of self-moderation and feedback upon participant reflection on eating processes themselves has particular repercussions for eating related behaviour change treatments.

- **Eating speed:** Finally, the focus of the study was the impact of feedback and self-moderation upon eating speed, which as discussed previously has particular links to intake volume, BMI, and other health factors. As such it was considered interesting to evaluate the impact on participants self-reflected impression of their eating speed and thoroughness, and how this differs to quantitatively measured parameters of eating.

In addition to providing insight into each of these areas, the variety of questions ensured that the participants would not lead the participants to focus overly upon a single research goal or outcome. All questions were formulated to correspond to one of these categories by the author of this Thesis, in collaboration with the PhD supervisor, Dr. C.S. Ang. A full list of the questions and their respective categories can be found in appendix A.3.2.

Following each study phase this questionnaire was immediately presented. Participants were asked to consider a normal eating scenario and compare their experience with recently completed eating phase, then score each statement on a 5 point scale from 'strongly disagree' to 'strongly agree'. The responses were numerically coded, between 1 for 'strongly disagree' and 5 for 'strongly agree'. During analysis each question was considered individually, but categorical groupings permitted wider observations and conclusions to be made about the effect of the different treatments on these aspects of participant awareness of eating.

5.5 Study Evaluation and Results

Study session were carried out for 20 participants using the data collection and feedback system described in section 5.3, and implementing the experimental protocol and procedures described in the previous section. Each participant took part in three experimental conditions over a single session. These consisted of a control eating period (normal eating), an eating speed moderation period, and a moderation period with the support of chewing rate feedback. Data was recorded regarding a range of chewing parameters during each period, along with questionnaire responses regarding participant self-awareness, which was collected immediately following each treatment period. For the evaluation this data and comparison between treatment periods, all results were statistically analysed using SPSS statistical analysis software (Version 25.0) [243].

5.5.1 Measures of Eating

Eating measures for each participant were calculated and statistical tests applied to determine the differences between treatments. Descriptive statistics regarding these along with full SPSS statistical test results are available in appendix C.1. Bar charts comparing the average of each of these measures between treatment sessions can be found in figure 5.2, figure 5.3, figure 5.4, figure 5.5, figure 5.6, and figure 5.7.

Repeated Measure Analysis of Variance was computed to determine statistical significances between treatments. Prior to conducting ANOVA, normality was tested using the Shapiro-Wilk test of normality [244], and sphericity was tested using Mauchly's Test of sphericity [245]. Where sphericity was violated, the Greenhouse-Geisser correction for violations of sphericity [246] was used to measure significance, otherwise sphericity was assumed. Post-hoc tests were conducted using the Bonferroni correction for multiple comparisons [246] to determine the difference and significance between the control (normal) and moderated eating, and more importantly between the two eating moderation treatments.

During normality testing, some variables were found to not follow a normal distribution, despite the application of log transforms (results of normality tests available in table C.2). As such, non-parametric tests and post-hoc analysis were also applied (reported in table C.5 and table C.6). However, the results of ANOVA and the non-parametric alter-

native resulted in very similar findings despite variable normality, or lack thereof. Thus, only the Analysis of Variance results are reported in this chapter, for eating measures. Full results of the Analysis of Variance and post-hoc tests are reported in appendix C.1.1.

Chewing Rate

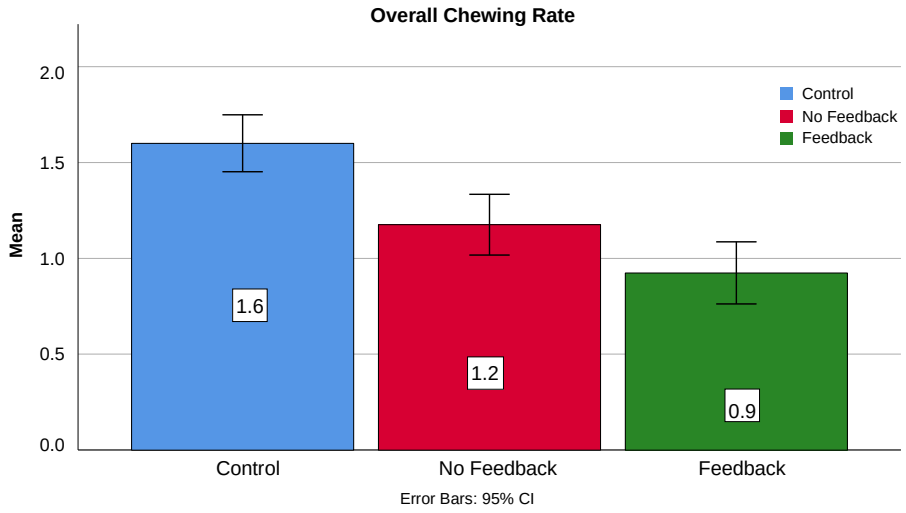

Figure 5.2: Average overall chewing rate across eating period, for each treatment. With 95% confidence interval.

Overall chewing rate for all subjects was calculated using equation (5.2) for each participant, and population averages for each treatment compared. As can be seen in figure 5.2, there was a significant difference between the control (normal) eating and treatment (moderated) eating periods ($F[2, 38] = 58.243$, $p = 0.000$). Post-hoc pair-wise comparison demonstrated that the control (normal) eating period exhibited a much higher overall chewing rate than both the non-feedback treatment period and the feedback treatment period ($p = 0.000$). Furthermore, comparing the two moderation eating periods, the non-feedback period exhibited a higher overall chewing rate ($p = 0.001$).

Period Between Chewing Event and Chewing Sequence

The average period between chews was calculated for each participant using equation (5.4), along with the average period between chewing sequences, using equation (5.6). Tests of significance also revealed a significant difference between treatments across all participants for both the period between chewing events ($F[2, 38] = 66.01$, $p = 0.000$), and for period between chewing sequences ($F[1.30, 24.77] = 16.65$, $p = 0.000$). As can be seen in the bar chart for periods between chew events (figure 5.3) the period between chewing events were

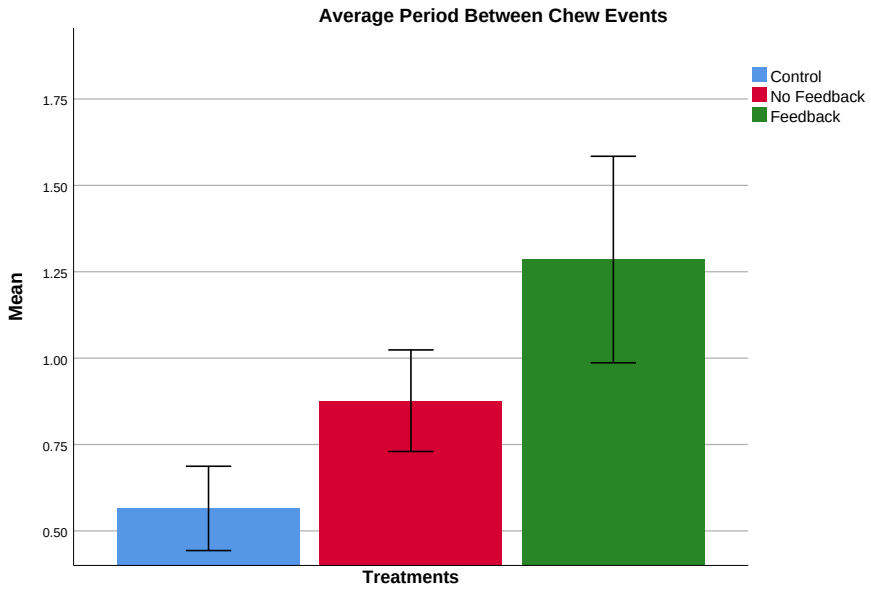

Figure 5.3: Average period between chewing events, with 95% confidence interval

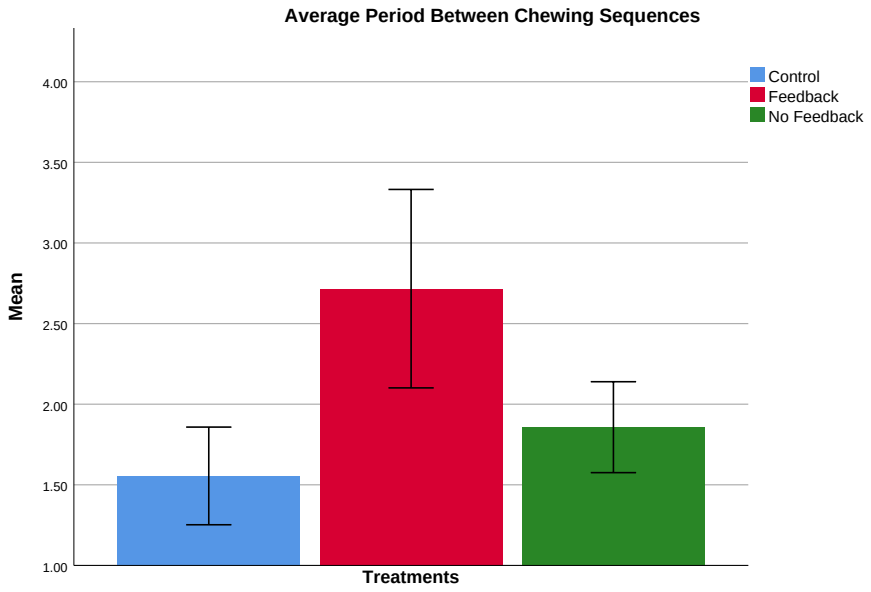

Figure 5.4: Average period between chewing sequences (time from termination of one sequence or event to onset of the next), with 95% confidence interval

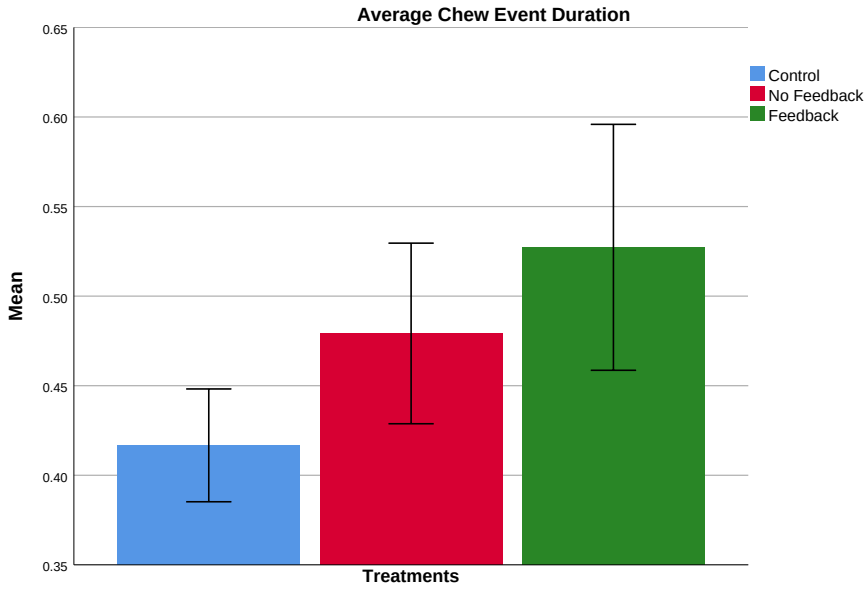

Figure 5.5: Average duration of individual chewing events, with 95% confidence interval

significantly higher in the non-feedback ($p = 0.000$) and feedback ($p = 0.000$) treatments than during the control period. Similarly, the period between chewing events for the Feedback treatment was found to be significantly higher than the non-feedback treatment ($p = 0.038$). For the period between chewing sequences (figure 5.4), no difference was found between the control and non-feedback treatment ($p = 0.073$), but the feedback treatment was found to have a significantly greater period between chewing events than both the control and non-feedback periods ($p = 0.004$).

Chew Event Duration and Chew Sequence Duration

For each participant, the average duration of chewing events for each was calculated, equation (5.3), along with the average duration of chewing sequence, equation (5.5). Figure 5.5 shows the population averages for duration of individual chews, while figure 5.6 shows the average duration of chewing sequences (between first and last chew of chewing sequence), during the control and treatment periods. Analysis of Variance indicated a significant difference between treatments for both chewing sequence duration ($F[2, 38] = 31.70$, $p = 0.000$) and chew event duration ($F[2, 38] = 5.84$, $p = 0.006$) measures. Post-hoc testing indicated that the average duration for chewing sequences was significantly shorter for the control period than both the non-feedback treatment ($p = 0.024$) and the feed-

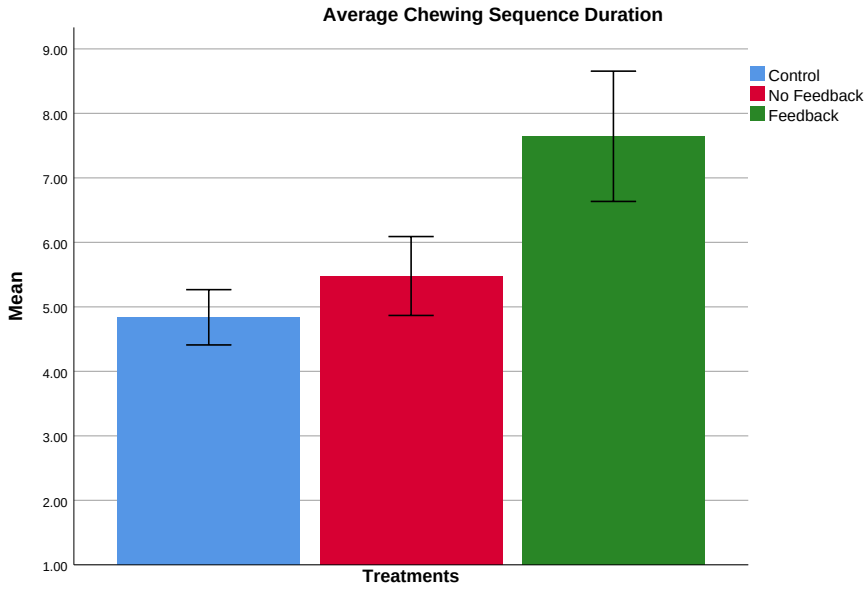

Figure 5.6: Average duration of chewing sequences (time between onset and termination), with 95% confidence interval

back treatment ($p = 0.000$), and was significantly higher for the feedback treatment than the non-feedback treatment ($p = 0.000$). On the other hand, post-hoc analysis did not indicate a significant difference for the chewing event duration between the control and non-feedback treatment ($p = 0.160$), or between the feedback and non-feedback treatments ($p = 0.390$). Only the feedback treatment demonstrated a significantly higher chew event duration than the control period ($p = 0.012$).

Number of Chews Per Chewing Sequence

The final eating measure recorded was the average number of chew events per chewing sequence, for each treatment (see figure 5.7). ANOVA tests indicated a significant difference between the three periods ($F[2, 28.98] = 9.76$, $p = 0.001$). However, while post-hoc tests found that the non-feedback treatment resulted in a reduced number of chew events per chewing sequence ($p = 0.000$), no significant differences were identified between the feedback treatment and the control ($p = 0.207$) or non-feedback treatment ($p = 0.193$).

5.5.2 Measures of Awareness

As described previously, participants were required reflect on their eating following each treatment and rate a number of statements relating to several factors of subject self-

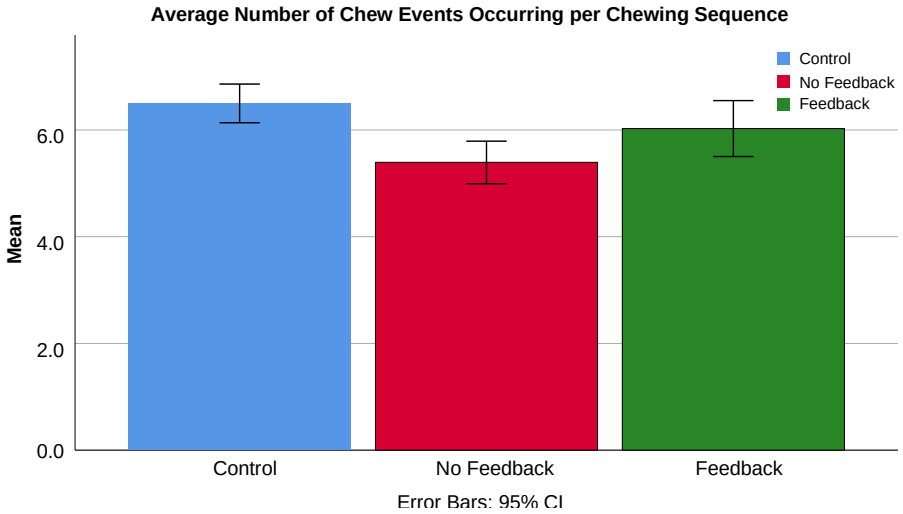

Figure 5.7: Average number of chews occurring per chewing sequence, with 95% confidence interval. For control and eating moderation treatments.

awareness of their environment, food, eating, and speed of eating. The results from each of these statements were numerically coded. Each statement was analysed separately, but grouping into categories permitted some conclusions regarding these factors of awareness to be made.

Descriptive statistics, tests or normality, and comparison evaluation of differences between the treatments for each statement are reported in appendix C.2. For each statement, Shapiro-Wilk test of normality was applied and all statements were found to violate the assumption of normality (table C.8). As such, a Friedman test was applied for non-parametric comparison of means to identify differences between treatments (reported in full in table C.9), followed by a Wilcoxon signed rank test for post-hoc analysis of pairwise differences between the treatments (reported in table C.10).

Analysis of Different Factors of Awareness

Analysing the different categorical groupings of statements separately, a number of interesting observations could be made. The first category of questions related to the environment in which participants were consuming food. From visual assessment of the average scores for these statements (which can be seen in figure 5.8) it can be seen that all of these scores are approximately centred around an average score of 3, and for statement 1, 3, and 4 the average score for the moderated eating periods were less than the control period. However, this difference was only significant in the case of statement 4 relating to how formally the participants felt they were sitting ($X^2(2) = 6.837$, $p = 0.033$), and post-hoc

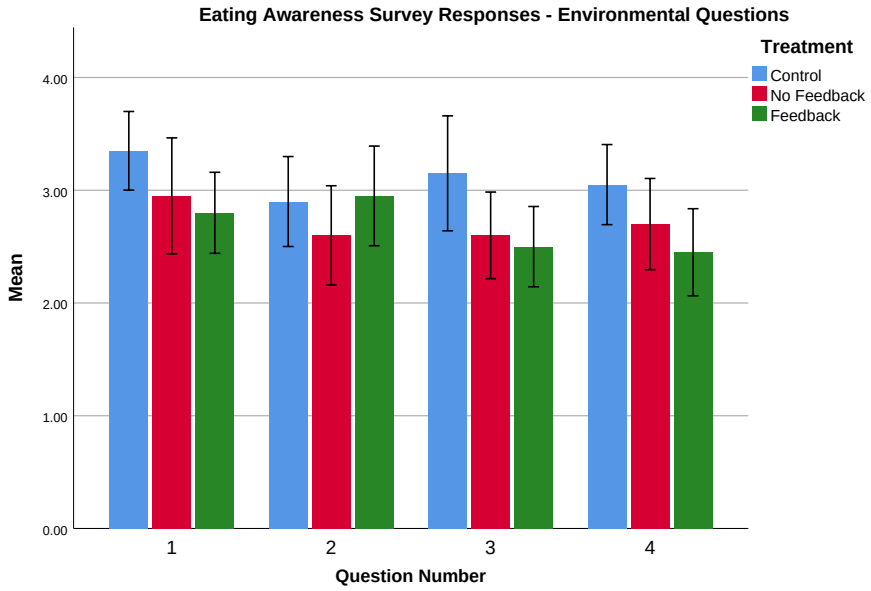

Figure 5.8: Average scores for eating awareness survey statements 1-4, with 95% confidence interval. Statements are those relating to the eating environment.

analysis revealed that the no-feedback moderation period resulted in a significantly lower score for this statement ($z = -2.053$, $p = 0.047$).

The difference found between treatments statement 4 was the only significant difference found between treatments for statements related to the environment, eating, and food awareness. However, there were a number of other interesting observations to be made about these groups.

The second category of statements considered were those related to eating itself, and population averages of scores for these statements can be see in figure 5.9. None of these statements exhibited notable difference between treatment periods, but compared to the eating environment statements most demonstrated scores consistently below 3, suggesting that participants were not overly focused on the volume or with their mouths open. This was with the exception of statements 5 and 9 which both had average scores exceeding 3 and were related to self-conciousness about swallowing and chewing respectively.

Like the statements relating to eating awareness, those related to the participant focus on the food itself also demonstrated average scores that were relatively consistent and did not differ significantly between treatments (as can be seen in figure 5.10). Unlike the eating related category however, these were all scored consistently above 3.

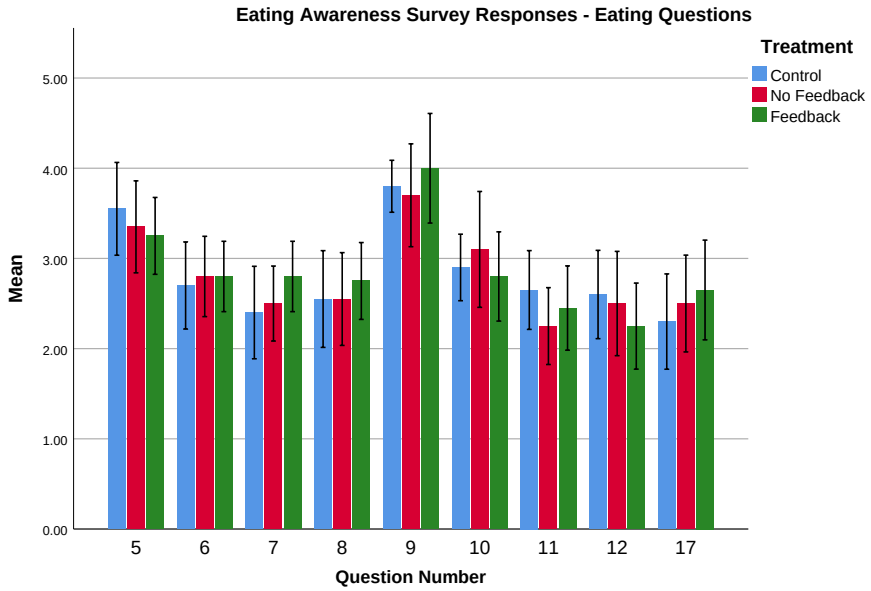

Figure 5.9: Average scores for eating awareness survey statements 5-12 and 17, with 95% confidence interval. Statements are those relating to the awareness of eating itself, excluding those related to eating speed and thoroughness.

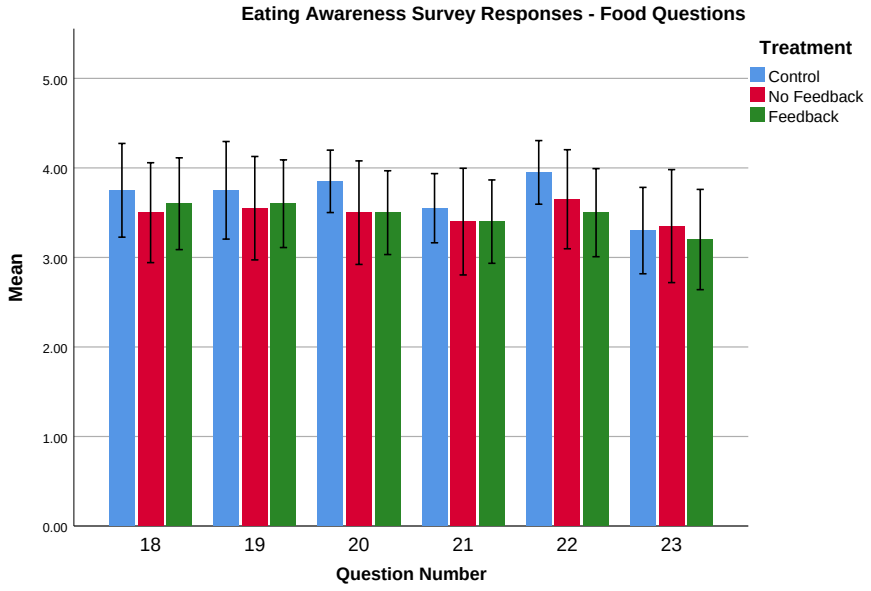

Figure 5.10: Average scores for eating awareness survey statements 18-23, with 95% confidence interval. Statements are those relating to the awareness of food during eating.

5.5.3 Awareness of Eating Speed and Thoroughness

When comparing difference between treatment periods statements 13-16, related to eating speed and thoroughness were more more significant than the results discussed above. Like the other statements, non-parametric tests of significance and post-hoc pairwise comparison were performed on these (appendix C.2). The specific statements involved in this category can be found in table 5.2, and a comparison of the population averages for each treatment group visualised in figure 5.11.

Table 5.2: Excerpt from the Full Eating Survey statements Table (table A.1) showing statements 13-16, relating to chewing speed and thoroughness of chewing

Excerpt from Survey statement Table	
Statement Number	Statement
13	I was trying to chew my food thoroughly
14	I felt self-conscious about how quickly I ate
15	I felt I was eating too quickly
16	I was trying to eat slowly

In the case of the statements in this category of awareness, the responses demonstrated a more obvious variation between experiment periods, for all of the related questions. These differences were found to be significant between experiment periods for all of these statements (seen in table C.9. For question 13, relating to impression of chewing thoroughness, post-hoc analysis revealed that scores for the no feedback period were significantly greater than the control period ($Z = -3.346$, $p = 0.000$), as were the scores of the feedback period ($Z = -2.018$, $p = 0.044$). Additionally, participants reported less focus on chewing thoroughness during the feedback period, although this was *not* found to be significant ($Z = -1.308$, $p = 0.254$).

For question 14, relating to participant self-conciousness regarding their speed of eating, the scores for both the feedback and non-feedback treatment periods were found to be significantly greater than the control period, but not significantly different from one another ($Z = -0.045$, $p = 0.995$). Similarly for statement 15, participants appeared to feel they ate too quickly following both the no-feedback ($z = -2.206$, $p = 0.034$) and feedback ($z = -2.789$, $p = 0.004$) treatment sessions compared to the control period, but pairwise comparison did not demonstrate a significant difference between treatments ($z = -1.222$, $p = 0.292$). Finally, this trend continues for the final statement, with participants attempts to slow their eating scored significantly higher in the non-feedback ($Z = -3.566$,

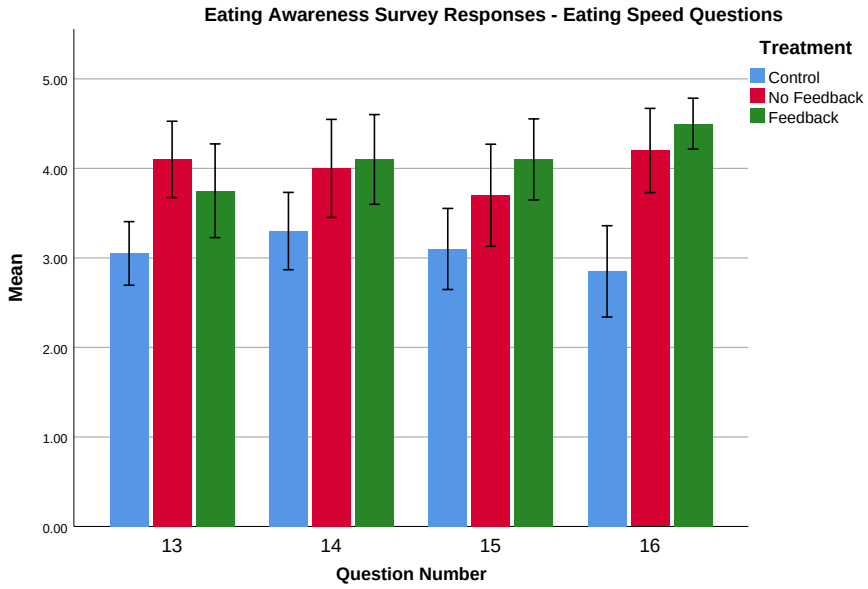

Figure 5.11: Average scores for eating awareness survey statements 13-16, with 95% confidence interval. Statements are those relating to chewing speed, reported after control and eating moderation treatments.

$p = 0.000$) and feedback ($Z = -3.559, p = 0.000$) treatment periods than during the control, and once again, while there was some minor difference in the treatments scores in this case it was not found to be significant ($Z = -1.265$, $p = 0.180$).

5.6 Study Findings and Discussion

The main goal of the controlled lab study reported in this chapter was to identify the effects of feedback upon subject eating parameters and the degree of eating self-awareness. It was predicted here that there self-moderation would have a significant impact upon such parameters, particularly the reduction of chewing rate. Furthermore, it was hypothesised that feedback during self-moderation of eating would result in a more pronounced change in chewing parameters and self-awareness reports. In this section, measured changes in chewing activity are discussed, followed by measures of awareness.

5.6.1 Measures of Chewing Activity

Eating speed and chewing thoroughness are considered factors which impact various aspects of human health, including effecting satiation [127], increasing possibility of high BMI [26], or even increasing risk of developing eating disorders [128]. As such, this lab

study aimed to investigate the effect of eating rate self-moderation upon eating activity, specifically chewing, and the use of feedback as an adjunct to such moderation. The main prediction for changes in chewing activity was a reduction during eating moderation, more significant with the support of feedback to help participants moderate. However, other measures were also explored to investigate what, if any, difference was observed.

As predicted, participants exhibiting a lower rate of chewing during self-moderation of eating than during normal eating, and were also found to further reduce chewing rate during feedback supported moderation. Correlating directly with this was a significant increase found for the period between chews during treatment periods compared with the control, which was again larger during the feedback treatment. This implies that implementing a pause between chews or mouthfuls of food was a technique employed as a means to control feedback.

Given the reduction in chewing rate and increase in period between chews, a reasonable assumption could be made regarding chewing sequence duration (time between onset of chewing and termination). Namely, that this duration would increase as chewing rate reduced and the period between chews increased, due to the greater time to required complete a set number of chewing events. This prediction was confirmed by the test of significance results. Comparatively, no significant difference was found in the duration of chewing events between the two eating moderation treatment periods. This suggests that although participants spent longer chewing each mouthful during moderation, particularly when supported by feedback, the duration of individual chews remained relatively constant.

Related to the chewing sequence duration, was the average number of chewing events occurring during each chewing sequence, which was considered to indicate chewing thoroughness. Like the chewing event duration, for this measure there was no significant difference identified between the eating moderation treatments. The average number of chews per chewing sequence instead remained relatively constant, suggesting that a change in chewing rate does not result in an increase or reduction in the thoroughness of chewing for experiment participants. Furthermore, the lack of change in number of chews or duration of chewing events implies that the increase in average duration of chewing sequences, and chewing rate in general, are primarily a function of the time between individual chews rather than other factors.

5.6.2 Measures of Awareness

In addition to quantitative measures of eating being recorded during each session, participants were asked to reflect their awareness of their environment, food, eating itself, and on eating thoroughness and speed. Participants rated a number of statements in these categories using a 5 point scale, to estimate overall levels of eating awareness. Self-reflection is an important part of eating related behaviour change [114, 20], and awareness of eating, known as "mindful" eating, has similarly been theorised as a component of such behaviour change[232, 233, 241]. It was hypothesised here that self-moderation and feedback would have an impact upon participants self-awareness regarding eating.

The results reported here partially supported this hypothesis. There was a low level of variation between treatments for the categories related to the eating environment, food, and eating itself. However, there was a significant difference found for all statements related to eating speed and thoroughness (specific statements found in table 5.2). For statement 14 (participant self-consciousness regarding their eating speed) and statement 15 (participant sense that they were eating too quickly), a similar increase in score was observed for the two treatment periods compared with the control period indicating that task awareness increased self-consciousness and impression of eating speed, but feedback had no impact.

Statements 13 and 16, related to effort affected for thorough and slow eating respectively, similarly demonstrated significant increases during eating moderation, but no difference between treatments. Comparing these results with the reduced chewing rate suggests that although both feedback and non-feedback moderation increase effort applied to moderation, feedback improves chewing rate reduction task performance without increasing perceived effort. Interestingly, although moderation increased perceived effort applied to chewing thoroughness, no difference was found between treatments for number of chews, this further suggests that applied effort does not necessarily correlate with a functional difference in this case.

Although the other categories showed no significant differences between treatments, from the general differences observed between categories (section 5.5.2) it can be tentatively concluded that participant focus on food took precedence over environment or eating itself. The eating environment was also seemingly of greater concern than of the processes

of eating itself, with the exception of participant self-conciousness about how they were eating which was of higher concern to participants than the environment or even the food. While most statements relating to eating were scored low, suggesting little concern regarding the act of eating itself, the statements related to eating speed and thoroughness, which could also be considered a part of this category, were rated at approximately 3 or greater during eating moderation. This suggests that participants were more aware of how they were eating while attempting to moderate eating speed, particularly focusing on those particular aspects of eating.

Although participants appeared to be more aware of their eating environment during the control period that during moderation periods, it should be noted that, due to all meal periods occurring during a single session, the control period was always carried out prior to the two treatment periods. While counterbalancing was applied between the two treatment periods to attempt to moderate any temporal effects, the control was always carried out prior to these. This was done to permit calibration of the system and for baseline measurement. As such, there is potential that differences between control and treatment periods was the result of participants becoming familiar with the setting, and less self-aware regarding their environment.

5.7 General Discussion

This chapter reports the final study carried out as a part of this thesis. The main aims of this chapter were to continue exploring eating information extraction and to demonstrate its application for research and behaviour change. To achieve these aims, this chapter presented a system for monitoring chewing parameters, as a new method for data collection in eating studies and for provision of behaviour change related feedback. The application of this system was then demonstrated in a study of eating function.

5.7.1 Findings and Implications

The main component of the chewing monitoring system was a model for the automated detection of chewing behaviour. The model used as part of this system was adapted directly from the work carried out in the previous chapter (chapter 4), with minor changes in signal processing technique to ensure real-time processing and the removal of a feature

(myopulse percentage rate) to reduce calibration requirement. This resulted in a model with predictive accuracy for chewing comparable to that found in the previous chapter (93% accuracy), indicating that myopulse percentage rate had only a minor contribution to the classification of chewing, or was a redundant feature for this task.

As in the previous study (reported in chapter 4), the accuracy of this technique was similar to that reported in the literature by R. Zhang and O. Amft [180] and Q. Huang *et al.* [179]. However, these studies reported significant false positives or reduction in accuracy with the presence of real-world type activity. The classifier models in this and the previous study were trained and tested using data including a range of activity alongside eating to help improve robustness, and still demonstrated a high degree of accuracy and ability to generalise to unknown subjects.

This chewing detection technique and classifier model was then used within a complete chewing monitoring and feedback provision system. Prior studies have used feedback based systems for the study and control of eating speed, measuring changes in food weight over time [129, 128], or rate of bites based on hand to mouth food gestures [132]. However, these solutions permitted the study of intake speed, they did not provide details regarding eating processes, such as characteristics of chewing.

Comparatively, the lab study carried out in this chapter evaluated chewing behaviour in detail to study the effect of self moderated eating speed upon chewing behaviour, and the effect of haptic feedback as an adjunct to this. This demonstrated that chewing rate feedback significantly reduced chewing speed, achieved through introduction of pauses between individual chews, but did not effect thoroughness of chewing. These findings have significant implications on other research, for instance, Zhu and Hollis [127] investigated the effect of experimentally adjusted chewing thoroughness, reporting that increased thoroughness did not effect meal size, but did reduce eating rate. On the other hand, the finding here indicate that while self-moderation of eating speed has an impact on chewing rate, chewing rate did not impact thoroughness. To fully determine the impact of these findings on such research, these studies should be repeated using the methodologies used here to fully investigate the relationships between intake rate, chewing rate, and the effects of moderation.

While there has not been extensive research into the application of feedback as a means to support chewing rate moderation, a number of researchers are working towards similar

goals; using rate of intake feedback to manipulate eating speed [128, 129], but without studying the effect of such feedback upon the mechanics of eating. The system described in this chapter would also permit estimation of change in chewing parameters over the course of a single session, and thus allow comparison with "linear" or "decelerated" eating patterns [128, 129].

In addition to developing systems for chew detection using smart glasses, the papers by R. Zhang and O. Amft [180] and Q. Huang *et al.* [179] highlight the development of a system of chewing evaluation and monitoring as a key direction of their research, with the goal of oral intake assessment and provision of feedback to support behaviour change, particularly of chewing rate. Such goals are closely related to those pursuant in the research reported here, and the system developed was demonstrated for these goals through the study reported in this chapter. Further implications of the data measurement and feedback methodology presented here, and potential application, are discussed further in the next chapter (chapter 6).

5.7.2 Model of Functional Eating Moderation

Based on the findings of this study a model can be formulated representing the effect of eating moderation and eating feedback. This model can be seen in figure 5.12, and represents the functional differences in eating resulting from the different treatments, and the factors that were determined to have influenced these changed. As discussed in section 5.6.1, changes in chewing rate was concluded to result from the introduction of pauses between individual chews (the period between chews). These pauses were also confirmed to influence chewing sequence duration thanks to consistent chewing thoroughness, which can be seen in figure 5.12 is not effected by any other factors. It was seen in the eating study results that eating moderation had a significant effect upon chewing rate, more-so with the presence of feedback. As chewing rate was demonstrated to be the result of period between chews it can be concluded that moderation and feedback are primarily influencers over the duration of this inter-chew period.

In addition to these functional parameters, this model also demonstrates the reciprocal nature of chewing rate and participant reflection upon chewing. The results of the participant eating reflection survey (discussed in section 5.6.2) indicated a significant increase in focus upon eating speed while focusing upon moderating eating. It was concluded

that task awareness of eating moderation resulted in participants reflecting upon eating rate (particularly chewing rate in this case) as well as thoroughness. In particular the significant difference in the statement related to the effort applied to eating slowly during moderation indicates that reflection upon eating speed contributed to chewing rate reduction, forming a feedback loop as demonstrated in figure 5.12.

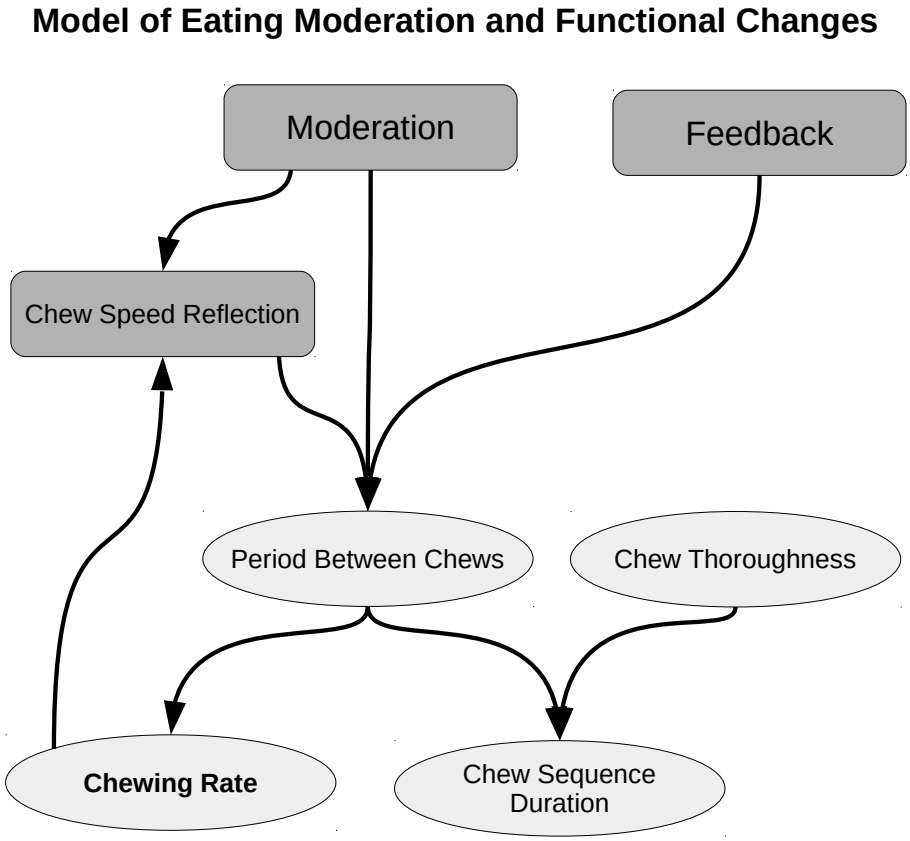

Figure 5.12: Model of the functional effects of eating moderation and feedback. Shown here are Moderation (the act of eating rate moderation), Feedback (eating rate feedback) as primary influencers. These have an impact upon the period between chews, which in turn effects chewing rate and chewing sequence duration. This also demonstrates the reciprocal processes of chewing rate and chewing speed reflection.

5.7.3 Limitations

There were three main limitations associated with this research. The chewing monitoring system used here relied solely upon chewing as a means of measuring eating parameters, estimating chew sequence termination through significant pauses between chews. This did not account for unexpected pauses in chewing, and had the potential to effect the accuracy of calculated parameters, although such occurrences were not observed to occur frequently enough to do so. In future research the inclusion of swallowing detection in

this system may not only help to confirm termination of chewing sequences, but would permit observation of the relationship between moderated eating speed and swallowing.

In addition to eating rate, some related studies also focus upon the effect of eating rate upon intake volume [132, 131, 127], or rate of intake [128, 129]. Such variables would provide interesting insight in conjunction with measured chewing parameters, but were not measured during the study reported in this chapter. The repeated measure approach to this study meant that meals were consumed across three treatment in a single session and were tailored to a participants particular appetite to prevent overeating and premature session conclusion. As such, assessment of intake volume was not possible.

This repeated measure protocol also meant that increasing familiarity with the experimental conditions, or reduced appetite throughout the course of a session might impact the results. Counterbalancing was applied between self-moderation treatment periods to help reduce this, but the control period always occurred prior to both treatment to permit calibration and baseline measurement. As such there was potential uncertainty regarding observed differences between treatment periods and the control period. In future studies, separate session should be considered for repeated measures to reduce the impact of time and consumed food upon appetite and study familiarity, and to permit evaluation of intake volume in relation to self-moderation and feedback.

5.8 Conclusions and Contributions

The work and findings reported in this chapter was the final significant stage of this research and answering the research questions outlined in the beginning of this thesis (section 1.2.1). Firstly, the work in this chapter extended the use of sensing in conjunction with machine learning techniques (the focus of chapter 4) for detection of chewing in controlled lab situations, and applying these techniques for monitoring chewing during a controlled lab study. This helped to answer research question 3, related to how physiological sensing can be used to detect eating; confirming findings of the previous chapter and demonstrate once again that these techniques were useful for automated and accurate detection of eating, thus overcoming the inherent error or bias of self-reporting and other manual monitoring techniques.

However, more heavily focused on in this chapter was answering Research Questions

2 and 3, which asked what other information related to eating can also be derived from detected eating events and how this information can be applied in research respectively. This chapter described how detected chews can be used to derive statistics regarding characteristics of chewing, including chewing rate and thoroughness, the duration of individual chews and period between chews, and the duration of chewing sequences (per mouthful of food) and period between chewing sequences. This information was used to drive a system for monitoring chewing characteristics and driving feedback.

This chapter also demonstrated a minor and major contribution of this research. Firstly, the system developed here for monitoring chewing and studying the effects of feedback upon eating moderation is a significant contribution for overcoming a limitation of many eating studies: the inherent bias an error of self-report, or inaccuracies and resource demand of manual observation (as discussed in chapter 2). This system instead permits accurate and automatic monitoring of detailed chewing characteristics, and was applied for the purpose of studying the effect of feedback upon chewing and the processes of moderation in a controlled lab study, resulting in valuable insights and demonstrating the systems value as a research tool.

The findings of this study encompassed one of the major contributions of this thesis, constituting an improvement of the understanding of the processes of eating speed moderation in response to feedback. By monitoring characteristics of chewing and performing surveys regarding participant reflection upon eating, during a control (normal eating) period and eating moderation with and without feedback, it was possible to make conclusions regarding the processes of moderation. The results demonstrated an decrease in chewing rate and period between chews, but no change in thoroughness, implying that chewing rate is a function of the time introduced between chews rather than other factors. The results also demonstrated a more significant reduction in chewing rate with the influence of feedback, but survey results found no difference between participant reflection regarding eating speed compared to moderation without feedback. This indicates that while task awareness increases reflection upon eating speed, feedback does not increase perceived awareness while remaining an effective influence over chewing rate.

The findings of this study along with the monitoring techniques and system used to research these processes have considerable implication for future eating research, or even clinical applications. The following chapter discusses these further, focusing particularly

on areas for further research which the findings of this chapter in conjunction with the findings highlighted in previous chapters.

Chapter 6

Discussion and Conclusions

Human eating consists of a number of highly complex, inter-connected and synchronised processes involved in efficiently managing the intake of food necessary for survival [11, 12, 13]. These processes are essential to proper food ingestion and airway protection [13], and are closely related to the processes involved in regulating intake volume and satiety [127, 22]. The disruption of these physiological or behaviour processes of eating can have a major impact on food intake and lead to functional and behavioural eating disorders, such as swallowing disorders [13, 14, 15], eating disorders and obesity [114, 22]. As such it is vital to properly understand these processes, their interaction, and the impact of abnormalities or other influences. However, typical monitoring approaches such as self-reporting intake are burdened by inherent human error and bias [32, 33, 33, 34, 35, 36, 32], thereby inhibiting our ability to fully understand the complex processes involved in eating and treatment of eating related disorders.

The broader ongoing target of this research is to improve the state of the research surrounding understanding eating function and behaviour and supporting treatment behavioural modification for weight management and eating disorders. Specifically, the work in this thesis focused on overcoming the burden and error inherent in self-report for eating monitoring. This chapter discusses the findings and outcomes of this research (section 6.1), provides an overview of the significant research contributions (section 6.2), and finally highlights areas for further research (section 6.3).

6.1 Discussion

Health informatics and research into health related technology covers a wide range of fields including the use of technology, information sharing and management, and data to support and enhance patient care: from bioinformatics studying the molecular processes of the body, to public informatics studying diseases and health using large scale population data [247]. Although varied, these fields all share a similar data processing pipeline, as outlined by Fang *et al.* [248], consisting of the acquisition, storage, processing and analysis, sharing, and search of information for utilisation for medical purposes. This pipeline can be seen summarised in figure 6.1, with a summary of the focus of health technology in two key stages of interest: Data acquisition and utilisation. The focus of the literature outlined in chapter 2, and of the work in this thesis, was upon methods of acquisition, processing, and use of data for eating related research and clinical applications and sensing. While data management, sharing, and search of data are expansive fields in themselves, this was outside of the scope of this research, which instead sought to answer questions relating to the research aim of overcoming the burden inherent in typical data collection techniques and how to go about applying collected data.

The focus of the work reported in this thesis was upon achieving these aims through the development and application of automated eating detection techniques, making use of physiological sensing, particularly Electromyography. EMG of muscles related to eating has used extensively to evaluate eating function and research the development of eating characteristics [57, 5, 58, 59, 6, 60]. Although traditional applications of this technology have been reliant upon specialist equipment and assessment, recent trends in research towards wearable sensing and electronics systems such as 'epidermal' sensing systems [74] make wearable solutions using proven sensing techniques such as EMG more viable for mobile and continuous sensing. In researching this technology and techniques for achieving the research aims, this work has investigated data collection and processing for eating detection, and the use of this data for studying eating and to provide feedback, as outlined in figure 6.1. In researching these areas, this thesis answered the following research questions:

1. How can physiological sensing be used for the accurate sensing of chewing and swallowing?

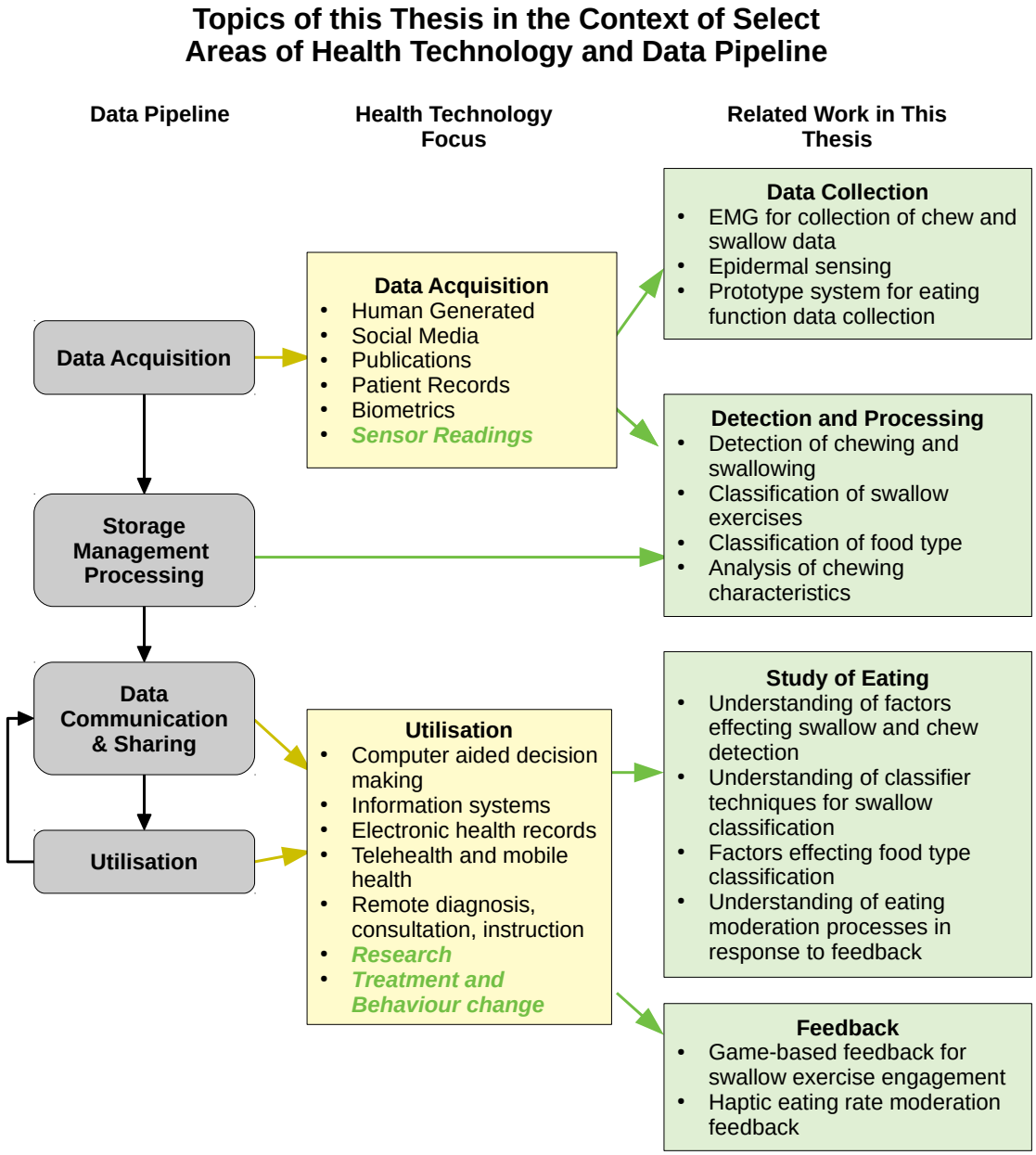

Figure 6.1: The Data Pipeline (*left*) summarises the general data pipeline for health technology and informatics as described by [248]. The health technology focus (*middle*) outlines two areas of interest in relation to this work and provides some context in relation to health informatics and technology. Data Acquisition outlines some general sources of data for health related technology, while Utilisation summarises some applications of this data, as described by Fang *et al.* [248] and Hersh [247]. Related Work in this Thesis (*right*) then outlines the general topics involved in this work and shows where these are situated along the pipeline.

2. How can automated eating detection be used to detect eating characteristics and food content?

3. How can sensed eating data and characteristics be applied for studying eating behaviour function and behaviour, and for motivating eating change?

These questions are discussed below in the context of the findings of this thesis.

6.1.1 How can physiological sensing be used for the accurate sensing of chewing and swallowing?

The first question to be answered in this research was how physiological sensing can be leveraged to accurately and automatically sense eating function, with an emphasis on chewing and swallowing. Currently available techniques for automated eating detection have a number of restriction, specifically oriented around limitations of available hardware and insufficient research to conclusively determine the viability of such approaches (as discussed in chapter 2 and chapter 4). Through Research Question 1, this thesis attempted to resolve these issues by exploring the use of EMG for automated eating detection, and the viability of new modalities for unobtrusive and comfortable sensing of muscle activity related to eating.

Chapter 3 reported the first stages of answering this research question, through the development of a threshold based algorithm for detecting swallows based on EMG signals, which demonstrated a promising accuracy of approximately 90%. This algorithm demonstrated the reliability of Electromyography for swallow detection, even with a simple detection algorithm and small sample size, compared with alternative sensor types such as acoustic signals which may be prone to interference from external noise [68, 65].

The subsequent study, reported in chapter 4, expanded on this research with a larger subject pool, and varied subject BMI and behaviours; with the aim of improving the robustness of resulting detection models. This chapter investigated the use of classifier algorithms for the detection of eating behaviour from EMG of the masseter and submental muscles, demonstrating a model with an accuracy of 87%, and chewing, with an accuracy of 94%. Previous literature has reported similar research detecting periods of chewing using EMG of the temporalis captured using "smart-glasses" [178, 180, 179], but not using simultaneous detection of both chewing and swallowing. While the studies by R.

Zhang and O. Amft [180] and Q. Huang *et al.* [179] reported comparable accuracy to that of the models developed here, they also reported false positives in the presence of unrelated behaviour and did investigate the performance of their algorithms on a subject-independent basis. Comparatively, the models developed in chapter 4 were demonstrated to be robust and able to generalise to unknown subjects; achieved through use a larger and more diverse dataset to help improve robustness.

From these findings, it can be concluded that machine learning techniques can be applied alongside physiological sensing technology for the accurate detection of chewing and swallowing. Such models are also able to generalise to unknown subjects for this task, and are robust to non-targeted activities when such activities are included in the training data and labelled as inactivity.

6.1.2 How can automated eating detection be used to detect eating characteristics and food content?

Although the detection of chewing and swallowing is an important step towards overcoming the limitations of self-report in research or clinical applications, it is important to be able to derive more details regarding eating processes and performance, eating habits, patterns, and food content. Thus this research question was posed to determine what important information can be derived. Three main types of information were investigated in this research: 1) dietary content, 2) types of swallow, and 3) characteristics of chewing sequences.

Dietary content is an area of particular interest for eating behaviour studies, as part of clinical weight management [22, 116], or for treatment of eating disorders [114, 20]. While evaluation of the relationship between EMG and food content has been studied extensively, few attempts have been made to automatically detect dietary content from eating behaviour and EMG [178, 180, 197]. Chapter 4 investigated and compared an alternative classification approach which demonstrated an accuracy of 99% for differentiating between 3 solid foods when trained on a subject-dependant basis, 99% for the differentiation between solids and liquids, and 74% for differentiation between liquid and viscous liquid (yoghurt). The accuracy of this technique was found to be significantly higher than the literature based techniques for solid food classification, which only reported between 69-95% accuracy [179]. Superior accuracy was concluded to be the result of the a

newly proposed feature set, which included signal content and eating pattern features for both chewing and swallowing, whereas the literature adapted approaches only made use of chewing information. The high accuracy for distinguishing between solids and liquids was also of note, and was concluded to be the result of distinct behavioural differences observed between solids, which involved chewing sequences, and swallows, which did not.

Other characteristics of eating such as muscular effort involved, duration and timings, and sequentiality of processes, are also considered important for understanding eating processes [5, 57, 11, 13]. For instance, swallow effort and duration, as well as successful completion of specific swallowing exercises[97, 63, 96] are important for swallow performance evaluation [170, 165], or for swallow disorder monitoring and treatment [168, 61, 62, 93, 81, 80]. Chapter 3 investigates classification of three swallow types involved in swallow rehabilitation therapy: dry, liquid, and extended swallows. Trained models demonstrated an accuracy of 92% for for distinguishing between dry and liquid swallows, and 99% for identifying extended swallows. Analysis of feature importance revealed that span (duration) of swallows is important for the relatively simple task of extended swallow classification, while other signal information is more important for the more complex classification of liquid and dry swallows. It can be concluded from these results that machine learning techniques are capable of differentiating between limited swallow types, although the performance of this for other types of swallow exercises has yet to be determined.

Characteristics of chewing, particularly the sequentiality of chewing and individual chewing patterns, are also of interest to the research community for their association with satiety [24, 23, 125, 126, 127], intake volume [128, 129, 131, 132], and links to high BMI and obesity [25, 26, 31, 27, 28]. To understand the exact nature of these relationships and if they can be targeted clinical behaviour change interventions it is important to monitor all the intricacies of these parameters. Chapter 5, outlined the use of chewing detection to capture chewing rate, chew duration, chew periodicity, muscular effort, chewing duration per mouthful, time between mouthfuls, and meal duration. These were calculate to investigate the effect of feedback upon self-moderation of eating speed, and revealed a number of interesting findings (discussed in the next section, section 6.1.3). This demonstrated that a range of information can be derived from detected chews, permitting identification of inter-relationships which otherwise might not be possible, and the study of influencing factors.

6.1.3 What are the clinical and research applications of sensed eating data?

As has been discussed at length, there are a number of shortcomings of typical approaches for monitoring eating function and intake behaviour in the study of eating or for clinical applications. Answering research questions 1 and 2 outlined the use of sensing and automated detection methods for overcoming these limitations, while this final research question relates to how these techniques can be applied in research of for clinical purposes.

One of the main applications explored in this thesis is use of eating sensing for monitoring of eating and related parameters, as outlined in answering research question 2. The implications of this monitoring for research was explored in chapter 5, which investigated the moderation of eating processes in response to eating rate feedback. A platform was developed to detect and monitor various parameters of chewing and compare these in detail with and without feedback. Using this monitoring platform, a statistically significant reduction in chewing rate was observed during eating speed moderation with the presence of feedback, and it was concluded that this was a result of the introduction of pauses between individual chews and did not effect chewing thoroughness (section 5.6.2). While other research has used feedback to manipulate eating rate [128, 129], or studied the effects of artificial eating rates upon chewing throughness [127], there has been little research specifically examining the effects of feedback upon eating processes. This area of research has particular implications for the study investigation of eating rate and its association with appetite and satiety [127], intake volume [132], or high BMI [27], offering a means to study the exact nature of eating rate and its relation to such factors. These implications and areas for future work are discussed in more detail in section 6.3.4.

As well as exploring the application of sensed eating for monitoring eating parameters and the study of eating, this thesis has also examined its application for driving feedback. As discussed in the literature (chapter 2), feedback regarding physiological processes has been used to help gain control over life-limiting disorders, support rehabilitation, or as part of implementing behaviour change to encourage healthier eating habits. As part of the study reported in chapter 5 haptic chewing rate feedback was delivered to participants, hypothesised to aid self-moderation of eating speed. This study demonstrated that, across 20 participants, feedback had a significant affect in supporting voluntary eat-

ing rate reduction; resulting in a significant difference in eating rate between treatment groups ($F[2, 38] = 66.01$, $p = 0.000$. $\eta 2 = 0.78$), with an average chewing rate during feedback based moderation 46.9% slower than with no feedback. As discussed in the literature, eating speed is considered correlated to a number of health factors, and these results indicate that the use of such feedback is potentially beneficial for ensuring users adhere to self-moderation of eating rate.

Feedback can also be used to support swallow rehabilitation or training in cases of swallowing disorders, and while biofeedback has been applied in the past towards this aim [63, 64], feedback has been limited to auditory or visual cues without considering techniques for improving motivation or engagement. Chapter 3 instead presented game-based feedback intended to motivate and engage participants in swallowing practice. Results of a user-evaluation of the system highlighted a positive impression of the feedback system, with users reporting that they felt it was fun to use and helped them focus on swallowing goals. Although clinical applications are beyond the scope of the research in this thesis (as discussed in section 6.3.1), it is suggested here that this continuous gameplay could be used to apply key exercise principles: encouraging swallow repetition and varying gap size to encourage extended swallowing [97]. Furthermore, challenging subjects to surpass previous scores may motivate users and result in skill improvement, leading to an increase in self-efficacy [112, 101].

It is the opinion of the author that the monitoring and feedback systems discussed in this thesis have considerable implications for the research of eating processes and clinical treatment, far beyond those that were explored as part of this work. Some of these applications are areas for future work are discussed in more detail in section 6.3.4.

6.2 Contributions

This thesis and the work it reports provide a number of significant contributions. These can be separated into major and minor contributions to the literature. The following sections outline these contributions and provide some details.

6.2.1 Major Contributions

This research has made two major contributions:

1. **The development of techniques for chew and swallow sensing and more accurate detection of eating**

The first major contribution of this research was the development of techniques for the more accurate detection of chewing and swallowing, provided as a part of Research Question 1. Models for the detection of swallowing and chewing were developed and reported in chapter 3, chapter 4, chapter 5, but the focus of the work making up this contribution was reported in chapter 4. There are a range of techniques which may be used for the detection of muscle activity using EMG, as outlined in chapter 2, many reliant upon variations of signal thresholds. However, use of these approaches for automated sensing of eating has been reported to result in low accuracy or false positives when exposed to "real-world" activities [178, 180, 179]. The work in chapter 3 instead demonstrated the use of classification techniques for the production and training of models capable of robust detection of chewing and swallowing, and able to generalise successfully to entirely unknown subjects. As discussed in section 6.1.1, this was the result of using data from 16 participants and including a range of behaviour other than chewing or swallowing in the training datasets along with use of classifiers and careful selection of signal features and signal segment selection window (discussed in as part of minor contribution 1). This resulted in models capable of more accurate and robust detection in comparison to threshold based approaches discussed in the literature [179, 178, 180].

2. **Improving the understanding of eating processes moderation in response to feedback**

This research also demonstrated a significant contribution towards understanding of the moderation of eating processes in response to feedback. As part of answering research question 3, regarding the possible research applications of eating detection, a study was conducted (reported in chapter 5) using chewing detection to investigate the effect of feedback upon eating moderation. By examining a number of parameters derived from detected chews, as discussed in section 6.1.2, it was demonstrated that eating rate reduced during eating moderation, and did so more significantly when the participants were presented with feedback. The analysis of these results also highlighted an increase in pauses between individual chews during moderation, and an increase in chewing sequence duration. On the other hand, these results demonstrated no significant change in duration

of individual chews, or any significant changes in number of chews per chewing sequence. This lead to the conclusion that chewing rate is reduced by chewing speed moderation, and results from the introduction of pauses between individual chews, but that this process does not effect chew duration or thoroughness. These results constitute a contribution to the the understanding of eating moderation, as well as highlighting a number of areas for follow up research into the processes of eating moderation, or other studies of eating processes that might benefit from automated monitoring of chewing or swallowing.

6.2.2 Minor Contributions

As part of answering the research questions put forth at the start of the thesis, a number of minor contributions were also made. These included:

1. **Improving the understanding of classifier techniques for chew and swallow classification**

A significant part of the development of new eating detection techniques (major contribution 1) was an investigation into EMG classification techniques, and best practices for classification of chewing and swallowing activity. Chapter 2 (section 2.3), provides a critical review of EMG classification for detecting muscle activity, feature selection, and choice of classification algorithms. This research contributes to the understanding of classification techniques by explicitly examining some of these parameters for the purpose of chew and swallow classification. For instance, chapter 3 (section 3.3) reported analysis of algorithm selection and feature importance swallow type classification, and revealed that it is important to select features representing the swallow itself along with EMG signal complexity, in particular the span (duration) of swallows. Comparison of selected features also revealed that only 7 features were needed to optimally classify the extended swallow type due to a clear increased swallow span, but that for the differentiating between dry and liquid swallows, increased complexity of the problem benefited from additional features incorporating frequency content. For this problem it was found that tree based classifiers performed best, particularly for liquid and dry swallow types.

Chapter 4 then explored classifier for detection of chewing and swallowing. It was hypothesised that, due to distinct differences in the duration and frequency of chewing cycles and individual swallow events, the size of the signal segmentation window would have a

significant impact upon classification accuracy. Analysis of window sizes demonstrated that, due to the cyclical and periodic nature of chewing cycles, chewing detection requires a small window in order to isolate individual chews and prevent misclassification of periods between chews (optimal window of 0.5 seconds), while a longer window was necessary to correctly capture the entirety of signal segments pertaining to swallows (optimal window of 1.625 seconds). Thus separate classifiers were recommended to optimally detect chewing and swallowing. An analysis of classification algorithms also revealed that, for this problem, a Support Vector Classifier with a linear kernel was optimal for the classification of chews and swallows, and was able to perform generalised classification using data from unknown individuals.

2. **Development of techniques for more accurate classification of food type**

Also related to major contribution 1, as part off the development of eating detection classifiers this thesis also explored the classification of food types and presented a new classification technique, comparing this approach against two comparable studies selected from the literature, which classified foods using EMG of individual chews [180] or features reflecting chewing sequence patterns [179]. These studies presented models capable of 94.7% [180] and 69.2%-94.8% accuracy respectively, but only considered developed subject-dependent classifier models and made no attempt to classify liquids. As described in the discussion of research question 2, chapter 4 instead presented an alternative classification technique combining features consisting of information about individual chew EMG signals and about the pattern of chewing segments themselves, which resulted in a subject-dependent classification accuracy for solid foods that was significantly greater than the compared approaches (99%). The capacity of this techniques for accurate differentiation between liquids and solids, or for differentiation between two liquids was also demonstrated.

3. **Improving the understanding of techniques to classify food type**

As part of the development of the food classification technique outlined in chapter 4 (minor contribution 2), an evaluation of the optimal approach for classification of food types was conducted, contributing to the understanding of the relationship between food type and eating processes and its impact upon food classification. Furthermore, the accuracy

of classifiers trained to generalise to unknown individuals was compared to that of models trained to recognise individual subjects. Together these results lead to some interesting observations on eating patterns and the impact on food classification. Firstly, a significantly greater predictive accuracy was found for models trained on an individual basis rather than those attempting to generalise to unknown subjects. However, no such improvement was found for models trained on an individual basis compared to generalisable modes, when differentiating between solids and liquids, or between different liquids. Chewing patterns are considered important for distinguishing between foods based on texture, and from these results it can also be concluded that these patterns vary uniquely between individuals, and making classification of solid foods from unknown subjects a challenging task. Swallowing on its own, on the other hand, does not exhibit such patterns and so classification of liquids, without chewing, is reliant upon EMG signal energy information and does not benefit as significantly from training of models to recognise individual patterns.

4. **The design and evaluation of prototype systems for the study and investigation of eating function**

Related to research question 3, one particular contributions of this research applications was the development of a prototype system for monitoring and study of eating function. As has been discussed at length (chapter 2), existing techniques for the study of eating processes are burdened by inherent error and bias, or (it is suggested in this work) do not provide as much information about the detail of eating function as automated approaches are capable. The system developed in chapter 5, as discussed for research question 3, permitted study of eating moderation in response to feedback. As well as leading to a major contribution (major contribution 2), the system constitutes a contribution in itself, as a means to study such processes and phenomena with a detail and accuracy that would not otherwise be possible. The implications for this system in research, along with applications and recommendations for future research are outlined further in section 6.3.4.

5. **Summary and discussion of the literature surrounding the physiological parameters and clinical applications of sensing of muscles related to eating, for clinical and research purposes**

There is a substantial amount of literature surrounding the collection of EMG signals, their processing and transformation, and potential applications including the study of

various physiological characteristics of clinical application for assessment and treatment of conditions. Some of this literature, specifically those studies focusing on the use of EMG for targeting muscles specifically involved in eating, is reviewed in the literature (chapter 2). The literature around this area can be difficult to review due to its varied and distributed nature, with research tending to focus on muscles only for a single avenue of research depending on the research area and discipline. This is particularly problematic when researching techniques involved in sensor placement, signal processing, physiological characteristics that impact the collected EMG signals, and potential applications. For instance, muscles of the face and neck, are involved in performing facial expressions, movement of the head, eye motion, speech, and breathing, in addition to eating, and are important to consider for the assessment of speech [196], swallowing [169], respiration and airway protection [13], and other facial activity.

To help overcome this challenge, figure 2.14 presents an overview of the reviewed literature inn the context of EMG and its use in association with the muscles of the face and neck, with an emphasis on eating processes. This includes a summary of some of the major muscles of interest (particularly relating to eating), notable behavioural activities that exhibit muscular activity, some physiological characteristics of those muscles or effecting those muscles may in turn impact EMG signals, and a brief summary of research and clinical applications for which EMG of these muscles has been used. This provides researchers in this area with a single point of reference for looking up these muscles in context of these points.

6. **The collection of proprietary data sets that are retained and available for use in research on request**

Finally, the research in chapter 4 has involved the collection of a substantial data set as part of the development of classifiers for the detection of chewing and swallowing, and for classification of foods. This data consisted of 384 minutes of EMG data collected from the submental and masseter muscles of 16 participants during the consumption of a small meal, while reading aloud, and during head motion. Of the participants, 8 were between the ages of 18-25, 7 between 26-35, and 1 between 36-40. Of these, 7 were male and 9 female, and 7 of the 16 were considered to be overweight, with a BMI greater than 25 and one was considered slightly underweight with a BMI of 18.1. This data consisted of

EMG from 14180 separate chews and 2057 swallows in total, and includes ground truth indicating: the type of event (chew or swallow), the food being consume at the time of the event, and labelled speech or head motion when these events were occurring. This data was retained beyond the scope of this research by signed consent of participants, and will be made available to other researchers on request and all aid possible offered to help with interpretation and use of the data and ground truth.

6.3 Future Research Directions

This section reflects on the research reported in this thesis, the scope of the work, and discusses potential limitations of the three main studies which were carried out (reported in chapter 3, chapter 4, and chapter 5) along with areas for improvement. Following this, potential implications of the findings of this research are discussed along with areas for further development and directions for future research which have been highlighted by these findings.

6.3.1 Research Scope and Limitations

The research discussed thus far has significant implications within the clinical domain for weight management and the support of treatment of obesity related conditions, eating disorders, or swallowing disorders, particularly in respects to encouraging health related behaviour change using feedback. In the initial stages of this research a particular emphasis was given to the potential impact of sensing technology for swallow disorder treatment and for monitoring and feedback for swallow rehabilitation. This was a focus of chapter 3, and was advised upon by Dr. David Smithard[1], a clinician specialising in swallowing disorders and a leading member of the Dysphagia Research Society[2]. Dr Smithard was involved in an advisory capacity during the initial research into this area, and while setting long term research goals and research questions for this work. However, while the long-term goal of this research is to target clinical applications of eating sensing, this is far beyond the scope of the research reported in this thesis, which focuses on sensing and feedback techniques to better enable research in this area. A vital part of any work going forwards

[1]Dr Smithard, Research Gate Profile: `https://www.researchgate.net/profile/David_Smithard/info`
Dr Smithard, British Laryngological Association Page: `http://www.britishlaryngological.org/dr-david-smithard-0`

[2]`https://dysphagiaresearch.site-ym.com/`

must be the involvement of clinicians to help design the structure of future research and studies, and assist in studying the clinical benefits of eating sensing.

Moreover, it is vital to investigate the impact of eating monitoring for treatment of eating eating disorders, swallowing disorders or other conditions. As such, the experimental procedures employed in this research have some limitations. This was most notable in the swallow detection, classification, and feedback research reported in chapter 3. As part of this work, data was collected from 6 healthy subjects under experimental conditions limiting their movement to those necessary for swallowing. The controlled conditions made difficult to reliably determine robustness of developed swallow detection algorithm under different conditions or with different BMI measurements. The following chapter (chapter 4) attempted to resolve this for the development of eating classifiers, with an expanded data pool including 16 participants with varying BMI and involving eating and non-eating behaviour, thereby helping to train a more robust detection model. However, this was still limited to subjects without reported health conditions which might impact eating, and was restricted to experimental conditions. It is recommended that future development of eating detection algorithms partially focus upon the effect of real world conditions upon eating detection using EMG, to ensure the developed techniques are robust in the face of day-to-day activities. Furthermore, it is important to investigate if these sensing techniques are effective for monitoring swallowing disorder patients.

There are additional data collection considerations for expansion in the future to better validate and improve the value of the monitoring and eating detection techniques outlined in this thesis. Firstly, Chapter 3 examined the classification of three different swallow types commonly used in swallow exercises [97]. However, other exercises are often used in the evaluation and rehabilitation of swallow functionality, such as the "effortful swallow" [97], and must be researched and included in future classifier models before such techniques can be fully considered for deployment in clinical scenarios. Similarly, the detection of food types (reported in chapter 4) requires the enrichment of the data and further work to fully realise the potential of the classification techniques. The models developed as part of this work demonstrated accuracy of up to 99% for food classification, and provided valuable insights regarding the classification of solids, liquids, and differentiation between individual foods. However, this was only for five food types and is insufficient for scenarios with a wider food selection. Further research should be pursued to study the impact of

other foods on eating detection and to investigate the classification of a broader range of foods, and particularly focusing on distinguishing between different liquids. While it should be the future goal of any food classification research to distinguish between a wide range of food types, this is not feasible in the near future due to the thousands of possible foods, as well as eating patterns unique to the individual, as demonstrated in this thesis. However, differentiation between a set selection of foods would be of particular interest for clinical applications that involve setting of specific diet plans, such as weight management or for the treatment of eating disorders [22].

6.3.2 Development of Sensing Technology and Inclusion of Additional Sensors

There are many levels of wearable devices and other technologies in the literature that have been discussed in this thesis (chapter 2) for the purpose of monitoring eating or supporting eating related treatment. This section discusses some of these components in the context of the techniques developed in this thesis, and their potential use alongside these techniques and recommends directions for future research investigating these.

The work in this research focuses on the use of EMG for sensing of eating. As has been discussed, traditional EMG sensing relies upon bulky sensors and immobile sensing equipment [169] which are unsuited to monitoring eating. However, the emergence of new sensor modalities make EMG better suited to portable sensing. For instance, epidermal sensors [74], were used as part of the work reported inchapter 3. The findings of chapter 3 indicated that these were comfortable and considered acceptable by the users for continuous use. User evaluation also highlighted concerns regarding the traditional components of the sensing system in comparison with the epidermal components. Ongoing research into the miniaturisation of data capture, wiring, power source, and wireless transmission components using "epidermal" electronic modality [74, 159] provides a potential solution for these concerns. However, this modality of component was not used in the remaining studies reported in this thesis, and it is recommended here that future research should include a detailed evaluation of the long-term acceptability of epidermal systems for eating monitoring.

As well as the use of more suitable sensing modalities, the inclusion of additional sensing regarding other physiological parameters is suggested here as a potentially beneficial

direction for future research. The work in this thesis focused upon the detection of eating through measurement of masseter and submental muscle activity for the detection of eating, however there are a number of muscles related to the various physiological processes of eating, which are considerably inter-related and demonstrate activity during facial expressions and head motion, alongside eating. In particular, related work has investigated the use of the EMG of temporalis muscles for detection of chewing [178, 180, 179], or the use of Bioimpedance in conjunction with EMG of the sternohyoid muscle (one of the infrahyoid muscles[3]), for detection of swallowing [177]. Targeting other muscle sites instead of, or in addition to, those focused on in the research reported here may help to clarify eating detection, provide more detailed information, or permit detection of other behaviours.

Additionally, in the eating moderation study reported in chapter 5, only chewing information was considered for evaluating eating processes, and it was hypothesised that swallowing might provide additional insight to help accurately determine the swallow of food following chewing, as well as offering a chance to evaluate swallowing as part of eating moderation processes. As such, it is recommended that future work include a comparison of different muscle sites for eating detection, as well as including swallowing information for the study of eating processes involved in moderation.

In addition to this, other sensor types would provide a wider perspective for the study of eating or assessment of eating related health. The inclusion of alternative sensing approaches for the detection of food, such as sound based food texture recognition [67], or food type and quantity logging using image recognition [161] potentially offer a means to confirm EMG based recognition, while food volume estimation algorithms such as that described by [157] provide a means for monitoring intake volume in addition to food type. While the techniques in this thesis provide a means for detecting chewing and swallowing, they cannot fully evaluate dietary intake at the current time and techniques such as these must be considered in future work to offer intake estimation in order to provide a means to completely monitor all aspects of eating.

A particular focus of future development of the techniques outlined in this work should be on improving performance and investigating their use in conjunction with one another and with other sensing. Areas of development include refinement of the algorithms and

[3]see figure 2.2 for the position of the sternohyoid muscle and table 2.1 for a description of the physiological characteristics of the infrahyoid muscles

techniques, as described above, and research to determine the best approach towards hosting signal processing and classification models for continuous mobile detection. This should be carried out in parallel to the development of novel sensing hardware, such as ongoing development of "epidermal" on body sensing platforms by the Yeo Research Group [75]. With the combination of these components further research can be carried out for the use of these systems for a range of research and clinical applications, which are discussed in the remainder of this chapter.

6.3.3 Clinical Application Research

As described in section 6.3.1, there are a number of possible clinical areas for which eating sensing has implications and potential applications, which should be explored further in future work. In addition to necessary research to determine the accuracy and use of the techniques described in this thesis for use with swallowing or eating disorder patients (discussed in section 6.3.1), some clinical applications of note for future research include: weight management, eating disorders, and physiological abnormalities.

As outlined in the thesis introduction, the ongoing epidemic of obesity and prevalence of high BMI is considered a major health risk [7, 10]. Understanding and tackling the issue of obesity is the area with the potential to be most significantly impacted by this research. This thesis has demonstrated techniques for determining chewing speed (chapter 5), detecting food types (chapter 4), and the use of chewing rate feedback to encourage a change in eating behaviour (chapter 5). These have significant implications for weight change interventions, as a means for providing of feedback encouraging the adoption of eating patterns and styles which have been associated with increased satiation and reduced intake [127, 24], or for detecting adherence to a set diet plan, using a model trained to detect specific foods.

Combining such detection with mobile applications would permit goal setting and progress review, and delivery of targeted feedback messages areas that have been demonstrated as vital for weight change therapy [20, 44]. These are all practical applications for for consideration for future research into the use of these techniques to tackle the obesity problem. In addition to this, future research with these techniques includes improving understanding of the nature of influences over food intake and obesity.

Related to weight management, there are also considerable implications and scope for

further research related to eating disorders. Traditionally, screening of eating disorders is carried out through clinical interviews, questionnaires, and clinical assessment, and it can be hard to identify many disorders without obvious physical symptoms (see section 2.1.4). Many disorder sufferers exhibit characteristic eating patterns [129, 128] or compensatory behaviours [115, 22], and the techniques and technology demonstrated in this thesis should be researched further to determine if sensing can be used to detect such patterns and determine their applicability for studying such processes. As with weight management, eating disorder treatment also involves self-logging, goal setting, and review of progress [20], and the eating monitoring techniques developed here should likewise be researched to determine their use as an automated alternative to self-logging, and as a means to identify patients in need of further treatment.

Finally, a similar area of research is the use of these techniques as part of monitoring, evaluating, and providing rehabilitation for patients with abnormal eating function, such as swallowing disorders. EMG has been suggested as a means of assessing swallowing function and screening for disorders [61], and a number of EMG parameters have been described for the evaluation of swallowing disorders [62] or dental performance [6, 60]. Techniques are described in this thesis for the detection of swallow type (often used to assess swallowing performance [97]) and chewing parameters, in chapter 3 and chapter 5 respectively. It is recommended here that further research is also conducted to investigate the use of classifier algorithms to detect disorder characteristics, potential deviations from normal healthy function, or for recognition of known life threatening symptoms associated with swallowing disorders such as nasal leakage or aspiration.

Treatment of swallowing disorders often also involves behavioural therapy, including swallow exercises or practice of compensatory manoeuvres designed to help consume food [97, 14, 94], but lacks a standardised treatment approach [87], requires professional supervision, and suffers from low patient motivation and engagement. The use of biofeedback and goal setting potentially reduces the need for in-person assessment and improves motivation [101, 102, 103], and chapter 3 presents the design of feedback meant take advantage of this. However, this work is in its preliminary stages and it is recommended here that further research be carried out into the development of such feedback systems and the impact they might have on treatment of swallowing disorders.

6.3.4 Researching Eating Processes and Influences

This research also have major implications for studying eating and improving our understanding of eating behaviour and the various influences upon eating choices of when to eat, food selection, intake volume, and intake speed. One such research application was the study outlined in chapter 5. This study examined chewing rate feedback and its effect upon the processes of eating moderation, using the prototype monitoring and feedback system developed as a part of the research. This demonstrated a considerable impact of feedback upon moderation and provided a number of interesting insights into the processes of chewing, described in section 6.1.3 and section 6.2, but did not study the impact of moderation upon other eating processes such as swallowing. As was discussed in section 6.3.2, the inclusion of swallowing information may aid in confirmation of chewing sequence termination, or provide additional insight into the processes of eating and their relationship with voluntary eating moderation, and should be another area for consideration when continuing this line of research.

The focus of this study upon haptic feedback and the impact upon moderation processes. Other related work investigating eating rate, or clinical applications of biofeedback have instead focused on the use of visual or auditory feedback [64, 109, 126, 127]. Although the findings of the work in chapter 5 demonstrated a significant effect resulting from haptic feedback, another direction for further research should be to extend this study to investigate the effect other forms of feedback upon eating processes (audio, visual, and haptic). Studying alternative feedback types and considering potential implications upon eating is particularly important for determining the ideal approaches for behaviour change research and interventions, as discussed in section 6.3.3.

There are a range of factors that influence eating processes, and a number of publications in the literature emphasise that various external and internal influences can effect out choices of when to eat, food selection, intake volume, and intake speed (described in chapter 2). In particular, distractions from food and social meals have been suggested as disrupting internal moderation cues and impacting meal duration and intake volume [19, 21]. Another suggested direction for future eating research is to adapt the monitoring techniques of chapter 5 to investigate some of these factors, and study the impact of different distractions from eating (television, music, or other stimuli), social meals, and

portions sizes upon eating processes during normal eating or while applying voluntary eating moderation.

Finally, specific eating patterns have also been connected to high BMI and obesity [28, 31], diabetes [29], and even stress-levels [30]. It has been suggested that these are related to the impact of eating patterns, particularly slower eating and increased oral exposure time, upon hunger and satiety controlling hormones [127, 126]. Eating rate and other parameters have also been linked to specific eating disorders [129, 128]. With these factors all potentially effected by eating patterns, it is important to research these areas further to better understand the relationship between these and eating processes. As described in section 6.3.3, a better understanding of these processes is also important when considering the use of automated monitoring and feedback systems clinical applications related to weight management or the treatment of eating disorders.

Equipping participants with mobile enables sensing and the monitoring system developed as a part of chapter 5 (with appropriate adaptations) permits the study of some of these factors and their relationships to the processes of eating, moderation, intake, other influences, and the relationship of these factors to health risks such as obesity. Furthermore, it provides a platform for collecting continuous information in an unconstrained manner, and with an greater level of detail and potentially reduced impact of necessary experimental constraints that would otherwise be required when making use of other monitoring techniques such as video recordings, manual observation, or participant self-reporting.

Appendix A

Participant Study Procedures

A.1 Surface Electrode Placement Procedure

EMG signals were collected targeting chewing and swallowing activity. For the purpose of mastication, the two primary masticatory muscles groups are the Masseter muscles and the Temporalis muscles used predominantly to control the elevation of the mandible [76, 249]. In the context of Electromyography Criswell and Cram [73] demonstrate the similarity of the signals from the two sites during chewing; describing mastication as the predominant action identifiable from the masseter muscles, and "assistance in chewing" as an important action of the Temporalis. The masseter has also been described as easy to identify and reliable, which is a useful consideration for the purpose of reproducibility of this work [196].

The act of swallowing is a complex procedure carried out over oral, Pharyngeal and Esophageal stages, and as such involves a number of muscle groups. Of particular import during the oral and Pharyngeal stages are the muscles connecting to the hyoid (suprahyoid and infrahyoid) [24, 97, 76]. The the suprahyoid and submental muscle group are considered particularly important for the purpose of EMG evaluation during swallowing action [196, 62], and for the purpose of assessment and treatment of swallowing disorders [62, 64, 169].

The masseter muscle was targeted for measurement of EMG associated with mastication. For the masseter muscle group the voltage input and measurement electrodes were placed approximately 2cm along the direction of the fibres of the masseter muscle belly. The approximate position of electrode placement is indicated in figure A.1, **a**. The belly

Figure A.1: Surface electrode placement positions for EMG measurement of the Masseter muscles (**a**) and Suprahyoid muscles (**b**). Adapted from [73]

was found by asking the participant to palpate the muscle through clenching the teeth [73, 62]. The paper by Jeong *et al.* [210] also demonstrates this position for placement of electrodes for this group. This sensor placement methodology was used for the studies reported in chapter 4 and chapter 5.

The submental muscles were targeted for measurement of EMG associated with deglutition. For the detection of the submental muscle group activation electrodes were placed under the chin on one side of the midline in an anterior to posterior direction. The approximate position of electrode placement is indicated in figure A.1, **b**. The area was chosen by palpating the muscle group by swallowing a few times, and the electrodes placed across the mass [73, 62]. This sensor placement methodology was used for the studies reported in chapter 3 and chapter 4.

A.2 Eating Classification Data Collection Procedure

The following procedure was used in the collection of data for use in the development of classifiers for the detection of eating behaviour and food content, reported in chapter 4.

Participants were guided through the data collection meal sequence by the custom software application. Participants were asked to carry out the following phases of data collection, after which the sensors were removed and replaced before repeating this se-

quence. The actions were carried out in the following sequence:

1. 5 minutes resting – keeping still
2. 5 minutes speech - reading out loud from a provided article [1]
3. Moving the head - rocking the head "back and forth" and "side to side". 10 full motions of each were carried out.
4. Consumption of a small meal of 5 food and liquid items. This was further divided into the following sequence:
    - 3 eating phases (bite-chewing-swallow), or a single sip-swallow phase (head stationary).
    - 3 eating phases (bite-chewing-swallow), or a single sip-swallow phase (head moving side to side).
    - 3 eating phases (bite-chewing-swallow), or a single sip-swallow phase (head moving up and down).

    Water was consumed between each of stages of the meal sequence.

A.3 Eating Moderation Intervention Procedure

The following procedures and materials listed were used for the feedback based eating speed moderation intervention type study reported in chapter 5.

A.3.1 Experimental Procedure

Participants are equipped with standard surface electrode sensors (#H124SG, Covidien, Ireland[2]) connected to a bluetooth enabled EMG measurement and transmitter unit (Shimmer 3, Shimmer Sensing, Ireland[3]). Participants are also equipped with a Microsoft Band device (Microsoft Band 2, 4M5-00002, Microsoft [4]), for delivering feedback.

Once the electrodes have been placed and connected, the emg unit may be used to acquire chewing and swallowing data from the two sites. The data is streamed to a mobile

[1] https://en.wikipedia.org/wiki/Google
[2] Now Medtronic: www.medtronic.com
[3] http://www.shimmersensing.com/
[4] https://www.microsoft.com/en-gb

device used to govern feedback, which communicates securely with a laptop which acts as a remote classification and monitoring service.

The participants take part in three different study phases. Following each phase, participants immediately filled out a short questionnaire (question for which are given in appendix A.3.2). The three sessions are carried out in a single sitting. Participants are instructed to consume all food items they are presented with in each session, but that they are within their rights to refuse to finish a portion at any time if they feel they have eaten to much. Similarly, it is explained that they may withdraw from the experiment at any time without giving a reason.

Participants are shown food portions allotted for each session and asked to confirm the portion sizes. Participants may request more or less food, or substitution of one food type for more of another. The food items consisted of: an apple, a slice of pizza, low-fat yogurt, jam sandwich and water.

Prior to each study phase the participants carry out a short period of calibration involving maximum voluntary contractions – clenching and releasing the jaw, and dry swallowing. The first phase consists of the participants simply consuming the first food portion normally. They are given unrestricted time to eat the allotted food. During this period eating rate is recorded and used to tune feedback parameters.

During the second phase, participants are asked to repeat the previous study phase, but this time attempt to self-moderate eating rate. Such that they eat half as fast as they believe they normally would. During the final phase, participants are also asked to self-moderate eating speed, but are also presented with a form of feedback and asked to stay mindful of this feedback. However, they are given no specific instructions on how to interact with it. Eating rate is normalised and offset slightly based on parameters (tuned during the first phase), which is expected to encourage participants towards a change in eating behaviour. Participants are given the same quantity of food in each session and asked to eat it in full. Counterbalancing is carried out between the second and third study phase for each participant, to randomise their order such that half of the participants took part in the non-feedback self-moderation phase first, and the other half took part in feedback self-moderation first.

Prior to the second phase, participants are given a short period of training in the nature of the chewing rate. Haptic feedback consists of periodic haptic pulses of different

intensities, related to the chewing rate of the participant, relative to the recorded chewing rate in the control period. Participants are instructed in full about the nature of the feedback and what it represents. The feedback levels are as follows:

1. 0.0–0.3: Low chewing rate, represented by no haptic pulses.
2. 0.3–0.6: Moderate chewing rate, represented by periodic individual haptic pulses.
3. 0.6–0.8: Fast chewing rate, represented by periodic double haptic pulses.
4. 0.8–1.0: Fastest chewing rate, represented by longer, high intensity double haptic pulses.

A.3.2 Eating Awareness Survey and List of Associated Awareness Statements

The following table lists the eating intervention survey statements used in the study reported in chapter 5. All statements used are listed in full, along with 'awareness factors' with which they were associated. In each study session, participants took part in three meal periods, following the procedures outlined in appendix A.3.1. Immediately following each of these, participants were then asked to fill out a survey, rating each of the statements in table A.1 on a 5 point Likert-scale, from "strongly disagree" to "strongly agree".

Table A.1: Survey questions for measuring subject awareness regarding a number of different factors. Table shows the specific questions, question numbers and related factors of awareness. Used in the eating moderation intervention in chapter 5

Survey Questions and Their Related Factors		
Question Number	Question	Awareness Factors
1	I found myself more aware of the other person in the room	Environmental, Total
2	I felt uncomfortable	
3	I felt self-conscious about the way I was sitting	
4	I found myself sitting more formally	
5	I felt self-conscious about the way I was swallowing	Eating, Total
6	I felt self-conscious about how loudly I was swallowing	
7	I felt i was swallowing too loudly	
8	I was trying to swallow quietly	
9	I felt self-conscious about the way I was chewing	
10	I felt self-conscious about how loudly I was chewing	
11	I felt i was chewing too loudly	
12	I was trying to chew quietly	
13	I was trying to chew my food thoroughly	Speed, Eating, Total
14	I felt self-conscious about how quickly I ate	
15	I felt I was eating too quickly	
16	I was trying to eat slowly	
17	I felt self-conscious about whether I was eating with my mouth open	Eating, Total
18	I felt I was focused on the food I was eating	Food, Total
19	I was trying to pay attention to the food	
20	I was aware of the flavour of the food	
21	I was trying to pay attention to the flavour of the food	
22	I was aware of the texture of the food	
23	I was trying to pay attention to the texture of the food	

Appendix B

Signal Processing Techniques

B.1 EMG Filtering and Rectification

EMG signal is filtered using a uni-directional Butterworth bandpass filter. The filter pass band is within the frequency range of 20-500Hz and filtered to an order of 5. It is then rectified to extract the signal envelope.

```
def FilterAndRectify(signal):
        #Filter the signal
        FILTER signal with bandpass Butterworth filter; frequency
        ↪  range = 20-500Hz, order = 5
        Let signalm = the mean of signal
        for each point t in signal:
            Let signal(t) = |signal(t) - signalm|
        return signal
```

B.2 Ground Truth Correction

During the development of chew and swallow classifier models (chapter 4), EMG ground truth was recorded using a hand held 'clicker' type device. Participants were asked to click the device once for each individual chew action, briefly, and to depress and hold the button for the duration of each swallow event. Each 'click' was recorded as EMG data ground truth with onset and termination time-stamps, with short depressions of the button being recorded as chew events, and long depressions recorded as swallows. This

gave an approximation of the EMG signal time-point correlating to each chew and swallow.

As this technique only provided an approximation of the event onset and termination and was liable to user error or delay, automatic correction of the ground truth was then carried out. Correction was based upon the detection of potential periods of EMG activity using a given threshold for signal amplitude. Periods of potential EMG activity and approximate ground truth are compared and checked for near-simultaneous entries, given a permissible *time_error*. Appropriate ground truth entries time-stamps are then updated with the onset and termination times of their EMG burst counterparts. Psuedocode describing this procedure follows:

```
def CorrectGT(mass_emg, ground_truth, uJ = 5, time_error  = 64,
↪  target_class):
        # mass_emg = 1D array containing EMG signal from masseter
        ↪  muscle group
        # ground truth = 2D array containing ground truth label
        ↪  and onset, termination, and mid_point timestamps
        # uJ = threshold scalar
        # time_error = maximum time between period of EMG activity
        ↪  and ground truth for the activity to be considered as
        ↪  associated with the ground truth
        # target_class = the ground truth class of interest, for
        ↪  timestamp correction

        baseline = the period of signal indicated by the
        ↪  ground_truth timestamps for the baseline label
        base_mean = MEAN of baseline
        base_sd = STANDARD DEVIATION of baseline
        threshold = base_mean + base_sd * uJ
        onsets, offsets, mid_points = APPLY THRESHOLD to identify
        ↪  onsets, terminations, and mid points of signal
        ↪  activity
        for each ground_truth.label:
                if ground_truth.label is not target_class:
```

```
                continue

                  activity_midpoint = ABSOLUTE of
                  ↪  mid_points-ground_truth-mid_point
                  activity_onset = closest_activity onset
                  activity_offset = closest_activity termination

                  if (activity_onset to activity_offset intersects
                  ↪  with ground_truth.onset to
                  ↪  ground_truth_offset) or (activity_midpoint <
                  ↪  time_error):
                        ground_truth.onset = activity_onset
                        ground_truth.offset = activity_offset

            return ground_truth
```

B.2.1 Chew Event and Sequence Identification

During the chewing rate intervention type study reported in chapter 5, the developed monitoring system recorded the onset and termination of individual chewing events to permit calculation of a number of parameters related to chewing, including average chewing rate over an entire eating meal. However, this was not considered an accurate indication of average chewing rate while eating, due to the effect of significant pauses associated with the completion of chewing sequences (mouthfuls of food). As such, it was desirable to identify the onset and termination times for chewing sequences, and eliminate significant pauses between these for the purpose of calculating average chewing rate.

To achieve this, the pseudocode below outlines the process used to identify chewing sequence onset and termination times, and to find chewing onset and termination times corrected to attenuate the effect of significant pauses between chewing sequences. This function accepts an array of chew event onset times, $chew_on$, and termination times, $chew_off$, and returns corrected onset times, $corr_on$, and termination times, $corr_off$, where the time stamps have been adjusted such that periods between events exceeding a threshold are replaced by the mean period between all gaps. At the same time, the function

below also identifies and returns chewing sequence onset, seq_on, and termination times, seq_off, based on the same significant periods.

```
def find_chewsequences(chew_on, chew_off, uJ):
        # chew_on = onset times for each chew event
        # chew_off = offset times for each chew event
        # uJ = threshold scalar for calculating significant
        ↪ periods between event
        # corr_on = corrected onset with significant periods
        ↪ between chews eliminated
        # corr_off = corrected onset with significant periods
        ↪ between chews eliminated
        # seq_on = onset times of identified chewing sequences
        # seq_off = termination times of identified chewing
        ↪ sequences

        #Find mean and standard deviation for periods between chew
        ↪ events
        mn_gap = MEAN of (chew_off-chew_on)
        sd_gap = STANDARD DEVIATION of (chew_off-chew_on)

        # Calculate threshold for identifying significant gaps
        ↪ between chew events
        thr = mn_gap + (sd_gap*uJ)

        j = 1
        corr_on[0] = chew_on[0]
        corr_off[0] = coff_off[0]
        seq_on[0] = chew_on[0]

        # Loop over all chew event onsets
        for i = 1 to LENGTH of chew_on by 1 do
```

```
                #Identify significant gaps between offset of
                ↪  previous chewing event and onset of current
                if chew_on[i] - chew_off[i-1] < thr do
                        # If no significant period found, update
                        ↪  the relative chew onset
                        corr_on[i] = chew_off[i-1] + (chew_on[i] -
                        ↪  chew_off[i])
                else
                        #If a significant period is found, set the
                        ↪  gap to the mean the period between all
                        ↪  chews, and update the relative chew
                        ↪  onset
                        corr_on[i] = corr_off[i-1] + mn_gap

                        #Also, at this time update the termination
                        ↪  of the last chewing sequence, and
                        ↪  onset of new sequence
                        if n > 2 do
                                seq_off[j-1] = chew_off[i-1]
                                seq_on[j] = chew_on[i]
                                j = j+1

                # Set the relative termination of the current chew
                ↪  event
                corr_off[i] = corr_on[i] + (chew_off[i] -
                ↪  chew_on[i])

        return corr_on, corr_off, seq_on, seq_off
```

Appendix C

Chewing Rate Study Results Analysis

This appendices provides the SPSS [243] statistical results for the analysis of measures obtained during the study reported in chapter 5. This includes descriptive statistics, tests of normality, tests of significance between repeated measures, and post-hoc pairwise comparison. Appendix C.1 reports these results for measures of chewing recorded during this study. Appendix C.2 reports results for measures of self-reflection and awareness, as well as statistical tests, for scores calculated from numerically coded responses to survey questions provided in appendix A.3.2.

C.1 Chewing Measure Statistical Tests

Table C.1: Descriptive statistics for the measures of chewing.

Chewing Measures: Descriptive Statistics

Treatment	Measure	Mean		Std. Deviation
		Statistic	Std. Error	Statistic
Control	Chewing Rate	1.60	0.07	0.32
	Chewing Sequence Duration	4.84	0.20	0.92
	Chewing Event Duration	0.42	0.02	0.07
	Time Between Chew Events	0.34	0.04	0.16
	Time Between Chewing Sequence	1.56	0.14	0.65
	Chew Events per Chewing Sequence	6.50	0.17	0.77
No feedback	Chewing Rate	1.18	0.08	0.34
	Chewing Sequence Duration	5.48	0.29	1.31
	Chewing Cycle Duration	0.48	0.02	0.11
	Time Between Chew Cycles	0.59	0.05	0.23
	Time Between Chewing Sequence	1.86	0.13	0.60
	Chew Cycle per Chewing Sequence	5.39	0.19	0.85
Feedback	Chewing Rate	0.92	0.08	0.35
	Chewing Sequence Duration	7.64	0.48	2.16
	Chewing Cycle Duration	0.53	0.03	0.15
	Time Between Chew Cycles	0.86	0.10	0.45
	Time Between Chewing Sequence	2.72	0.29	1.31
	Chew Cycle per Chewing Sequence	6.03	0.25	1.12

Table C.2: Shapiro-Wilk normality test for measures of chewing.

Eating Measures: Normality Test				
Treatment	Measure	Shapiro-Wilk		
		Statistic	df	Sig.
Control	Chewing Rate	0.986	20	0.987
	Chewing Sequence Duration	0.823	20	0.002
	Chewing Event Duration	0.888	20	0.025
	Time Between Chew Events	0.868	20	0.011
	Time Between Chewing Sequence	0.954	20	0.424
	Chew Cycle per Chewing Sequence	0.963	20	0.600
No feedback	Chewing Rate	0.927	20	0.136
	Chewing Sequence Duration	0.904	20	0.049
	Chewing Event Duration	0.813	20	0.001
	Time Between Chew Events	0.962	20	0.594
	Time Between Chewing Sequence	0.978	20	0.900
	Chew Cycle per Chewing Sequence	0.954	20	0.428
Feedback	Chewing Rate	0.891	20	0.028
	Chewing Sequence Duration	0.909	20	0.061
	Chewing Event Duration	0.851	20	0.006
	Time Between Chew Events	0.896	20	0.035
	Time Between Chewing Sequence	0.937	20	0.211
	Chew Cycle per Chewing Sequence	0.871	20	0.012

C.1.1 Eating Measure Repeated Measure Analysis of Variance

Table C.3: Results of repeated measure Analysis of Variance to determine significance of differences between treatments, for each chewing measure

Chewing Measure: Repeated Measure ANOVA Test						
		df	Mean Square	F	Sig.	Partial Eta Squared
Treatment	Total Chew Rate	2	0.330	58.243	0.000	0.754
	Chew Sequence Duration	2	0.188	31.696	0.000	0.625
	Chew Event Duration	2	0.045	5.843	0.006	0.235
	Period Between Chew Sequences*	1.304	0.400	16.645	0.000	0.467
	Period Between Chew Cycles	2	0.786	66.007	0.000	0.776
	Chew Events per Chew Sequence*	1.525	0.046	9.775	0.001	0.340
Error (Treatment)	Total Chew Rate	38	0.006			
	Chew Sequence Duration	38	0.006			
	Chew Event Duration	38	0.008			
	Period Between Chew Sequences*	24.777	0.024			
	Period Between Chew Cycles	38	0.012			
	Chew Events per Chew Sequence*	28.981	0.005			

*. Sphericity Violated Greenhouse-Geisser determines significance

Table C.4: Analysis of Variance post-hoc comparison of treatments for each measure of chewing. Bonferroni adjustments applied to significance measures.

Chewing Measure: Post-Hoc Pairwise Comparisons

Measure			Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Total Chewing Rate	Control	No Feedback	0.425*	0.051	0.000	0.292	0.558
		Feedback	0.676*	0.063	0.000	0.510	0.842
	'No Feedback	Feedback	0.251*	0.054	0.001	0.109	0.393
Duration of Chew Sequence	Control	No Feedback	-0.641*	0.216	0.024	-1.207	-0.074
		Feedback	-2.807*	0.465	0.000	-4.027	-1.586
	'No Feedback	Feedback	-2.166*	0.401	0.000	-3.219	-1.114
Duration of Chew Event	Control	No Feedback	-0.062	0.030	0.160	-0.142	0.017
		Feedback	-0.111*	0.034	0.012	-0.199	-0.022
	'No Feedback	Feedback	-0.048	0.030	0.390	-0.128	0.032
Period Between Chew Sequence	Control	No Feedback	-0.302	0.123	0.073	-0.626	0.022
		Feedback	-1.161*	0.306	0.004	-1.965	-0.358
	'No Feedback	Feedback	-0.859*	0.231	0.004	-1.465	-0.253
Period Between Chew Event	Control	No Feedback	-0.249*	0.038	0.000	-0.349	-0.149
		Feedback	-0.521*	0.089	0.000	-0.754	-0.288
	'No Feedback	Feedback	-0.272*	0.080	0.009	-0.482	-0.062
Chew Events per Sequence	Control	No Feedback	1.107*	0.207	0.000	0.563	1.651
		Feedback	0.473	0.245	0.207	-0.171	1.117
	'No Feedback	Feedback	-0.634	0.323	0.193	-1.482	0.213

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

[b]. Adjustment for multiple comparisons: Bonferroni.

C.1.2 Chewing Measure Non-Parametric Tests

Table C.5: Results of Friedman test of significance between treatment periods, for chewing measures.

Chewing Measures: Friedman Test of Difference				
	N	Chi-Square	df	Sig.
Total Chewing Rate	20	32.7	2	0.000
Average Duration of Chew Sequence	20	21.7	2	0.000
Average Duration of Chew Cycle	20	8.4	2	0.014
Average Time Between Chew Sequence	20	24.1	2	0.000
Average Time Between Chew Cycles	20	33.6	2	0.000
Average Chew Cycles per Chew Sequence	20	16.3	2	0.000

Table C.6: Chewing Measure Wilcoxon Pairwise Comparison

Chewing Measure: Post-Hoc Pairwise Comparison[a]				
Measure			Z	Sig
Total Chewing Rate	Control	No Feedback	-3.883[b]	0.000
		Feedback	-3.920b	0.000
	No Feedback	Feedback	-3.509[b]	0.000
Average Duration of Chew Sequence	Control	No Feedback	-2.427[b]	0.014
		Feedback	-3.808b	0.000
	No Feedback	Feedback	-3.472[b]	0.000
Average Duration of Chew Cycle	Control	No Feedback	-1.792[b]	0.076
		Feedback	-3.173[b]	0.001
	No Feedback	Feedback	-1.045[b]	0.312
Average Time Between Chew Sequence	Control	No Feedback	-2.725[b]	0.005
		Feedback	-3.584[b]	0.000
	No Feedback	Feedback	-3.509[b]	0.000
Average Time Between Chew Cycles	Control	No Feedback	-3.920[b]	0.000
		Feedback	-3.920[b]	0.000
	No Feedback	Feedback	-3.211[b]	0.001
Average Chew Cycles per Chew Sequence	Control	No Feedback	-3.733[b]	0.000
		Feedback	-1.904[b]	0.058
	No Feedback	Feedback	-1.643[c]	0.105

[a]. Wilcoxon Signed Ranks Test

[b]. Based on positive ranks.

[c]. Based on negative ranks.

C.2 Question of Awareness Statistical Tests

Table C.7: Descriptive statistics for awareness related questions

Awareness Questions: Descriptive Statistics				
Treatment	**Question Number***	**Mean**	**Std. Deviation**	**Std. Error of Mean**
	1	3.350	0.745	0.167
	2	2.900	0.852	0.191
	3	3.150	1.089	0.244
	4	3.050	0.759	0.170
	5	3.550	1.099	0.246
	6	2.700	1.031	0.231
	7	2.400	1.095	0.245
	8	2.550	1.146	0.256
	9	3.800	0.616	0.138

Control

	10	2.900	0.788	0.176
	11	2.650	0.933	0.209
	12	2.600	1.046	0.234
	13	3.050	0.759	0.170
	14	3.300	0.923	0.206
	15	3.100	0.968	0.216
	16	2.850	1.089	0.244
	17	2.300	1.129	0.252
	18	3.750	1.118	0.250
	19	3.750	1.164	0.260
	20	3.850	0.745	0.167
	21	3.550	0.826	0.185
	22	3.950	0.759	0.170
	23	3.300	1.031	0.231
	Total	72.350	9.449	2.113
Feedback	1	2.800	0.768	0.172
	2	2.950	0.945	0.211
	3	2.500	0.761	0.170
	4	2.450	0.826	0.185
	5	3.250	0.910	0.204
	6	2.800	0.834	0.186
	7	2.800	0.834	0.186
	8	2.750	0.910	0.204
	9	4.000	1.298	0.290
	10	2.800	1.056	0.236
	11	2.450	0.999	0.223
	12	2.250	1.020	0.228
	13	3.750	1.118	0.250
	14	4.100	1.071	0.240
	15	4.100	0.968	0.216
	16	4.500	0.607	0.136
	17	2.650	1.182	0.264
	18	3.600	1.095	0.245
	19	3.600	1.046	0.234
	20	3.500	1.000	0.224
	21	3.400	0.995	0.222
	22	3.500	1.051	0.235
	23	3.200	1.196	0.268
	Total	73.700	9.863	2.205
	1	2.950	1.099	0.246

2	2.600	0.940	0.210
3	2.600	0.821	0.184
4	2.700	0.865	0.193
5	3.350	1.089	0.244
6	2.800	0.951	0.213
7	2.500	0.889	0.199
8	2.550	1.099	0.246
9	3.700	1.218	0.272
10	3.100	1.373	0.307
11	2.250	0.910	0.204
12	2.500	1.235	0.276
13	4.100	0.912	0.204
14	4.000	1.170	0.262
15	3.700	1.218	0.272
16	4.200	1.005	0.225
17	2.500	1.147	0.256
18	3.500	1.192	0.267
19	3.550	1.234	0.276
20	3.500	1.235	0.276
21	3.400	1.273	0.285
22	3.650	1.182	0.264
23	3.350	1.348	0.302
Total	73.050	14.500	3.242

*. Related questions may be found in Table A.1

Table C.8: Shapiro-Wilk test of normality for questions of awareness

Awareness Questions: Tests of Normality				
Question Number*	**Treatment**	**Statistic**	**df**	**Sig.**
1	Control	0.765	20	0.000
	Feedback	0.800	20	0.001
	No Feedback	0.908	20	0.047
2	Control	0.869	20	0.011
	Feedback	0.851	20	0.006
	No Feedback	0.876	20	0.015
3	Control	0.887	20	0.024
	Feedback	0.843	20	0.004
	No Feedback	0.863	20	0.009
4	Control	0.816	20	0.002
	Feedback	0.875	20	0.015

	No Feedback	0.867	20	0.010
5	Control	0.872	20	0.013
	Feedback	0.859	20	0.007
	No Feedback	0.887	20	0.024
6	Control	0.878	20	0.017
	Feedback	0.804	20	0.001
	No Feedback	0.902	20	0.046
7	Control	0.845	20	0.004
	Feedback	0.804	20	0.001
	No Feedback	0.875	20	0.014
8	Control	0.860	20	0.008
	Feedback	0.877	20	0.016
	No Feedback	0.906	20	0.043
9	Control	0.771	20	0.000
	Feedback	0.890	20	0.026
	No Feedback	0.871	20	0.012
10	Control	0.809	20	0.001
	Feedback	0.874	20	0.014
	No Feedback	0.939	20	0.493
11	Control	0.887	20	0.023
	Feedback	0.885	20	0.022
	No Feedback	0.859	20	0.007
12	Control	0.869	20	0.011
	Feedback	0.865	20	0.010
	No Feedback	0.884	20	0.021
13	Control	0.816	20	0.002
	Feedback	0.858	20	0.007
	No Feedback	0.836	20	0.003
14	Control	0.857	20	0.007
	Feedback	0.790	20	0.001
	No Feedback	0.785	20	0.001
15	Control	0.916	20	0.082
	Feedback	0.753	20	0.000
	No Feedback	0.829	20	0.002
16	Control	0.849	20	0.005
	Feedback	0.723	20	0.000
	No Feedback	0.742	20	0.000
17	Control	0.877	20	0.015
	Feedback	0.882	20	0.019
	No Feedback	0.894	20	0.032

18	Control	0.858	20	0.007
	Feedback	0.874	20	0.014
	No Feedback	0.908	20	0.048
19	Control	0.934	20	0.048
	Feedback	0.876	20	0.015
	No Feedback	0.881	20	0.018
20	Control	0.809	20	0.001
	Feedback	0.879	20	0.017
	No Feedback	0.886	20	0.023
21	Control	0.875	20	0.015
	Feedback	0.839	20	0.004
	No Feedback	0.898	20	0.037
22	Control	0.816	20	0.002
	Feedback	0.845	20	0.004
	No Feedback	0.890	20	0.027
23	Control	0.878	20	0.017
	Feedback	0.796	20	0.001
	No Feedback	0.881	20	0.019

*. Related questions may be found in Table A.1

Table C.9: Results of Friedman test of significance for differences between treatment periods, for eating awareness questions

Awareness Questions: Significance		
Question*	Chi-Squared	sig
1	3.652	0.161
2	3.040	0.219
3	4.955	0.084
4	6.837	0.033
5	2.351	0.309
6	0.146	0.929
7	3.950	0.139
8	1.800	0.407
9	1.500	0.472
10	0.150	0.928
11	2.286	0.319
12	0.828	0.661
13	15.600	0.000
14	11.444	0.003
15	14.182	0.001
16	26.339	0.000
17	3.000	0.223
18	0.167	0.920
19	0.122	0.941
20	0.500	0.779
21	1.018	0.601
22	0.824	0.662
23	0.129	0.938

*. Related questions may be found in Table A.1

Table C.10: Results of Wilcoxon Signed-Rank test for pairwise differences between treatment periods, for questions of awareness

Awareness Questions: Pairwise Comparisona				
Question*	**Treatment**		**Z**	**Sig. (2-tailed)**
1	Control	NoFeedback	-1.198b	0.255
		Feedback	-1.964b	0.070
	NoFeedback	Feedback	-.363b	0.746
2	Control	NoFeedback	-1.255b	0.285
		Feedback	-.225c	0.960
	NoFeedback	Feedback	-1.146c	0.277
3	Control	NoFeedback	-1.854b	0.072
		Feedback	-2.356b	0.023
	NoFeedback	Feedback	-.302b	1.000
4	Control	NoFeedback	-1.461b	0.195
		Feedback	-2.053b	0.047
	NoFeedback	Feedback	-1.311b	0.258
5	Control	NoFeedback	-.677b	0.553
		Feedback	-.868b	0.438
	NoFeedback	Feedback	-.550b	0.620
6	Control	NoFeedback	-.060c	1.000
		Feedback	-.364c	0.811
	NoFeedback	Feedback	-.061c	1.000
7	Control	NoFeedback	-.513c	0.789
		Feedback	-1.270c	0.237
	NoFeedback	Feedback	-1.732c	0.148
8	Control	NoFeedback	-.214b	0.852
		Feedback	-.676c	0.590
	NoFeedback	Feedback	-.777c	0.512
9	Control	NoFeedback	-.292b	0.826
		Feedback	-.936c	0.353
	NoFeedback	Feedback	-.777c	0.502
10	Control	NoFeedback	-.811c	0.531
		Feedback	-.312b	0.836
	NoFeedback	Feedback	-.984b	0.379
11	Control	NoFeedback	-1.725b	0.125
		Feedback	-.794b	0.410
	NoFeedback	Feedback	-.559c	0.616
12	Control	NoFeedback	-.333b	1.000
		Feedback	-1.382b	0.250

	NoFeedback	Feedback	-.905b	0.563
13	Control	NoFeedback	-3.346c	0.000
		Feedback	-2.018c	0.044
	NoFeedback	Feedback	-1.308b	0.254
14	Control	Feedback	-2.405c	0.013
		NoFeedback	-2.725c	0.007
	NoFeedback	Feedback	-.045c	0.995
15	Control	NoFeedback	-2.206c	0.034
		Feedback	-2.789c	0.004
	NoFeedback	Feedback	-1.222c	0.292
16	Control	NoFeedback	-3.566c	0.000
		Feedback	-3.559c	0.000
	NoFeedback	Feedback	-1.265c	0.180
17	Control	NoFeedback	-.710c	0.531
		Feedback	-1.160c	0.344
	NoFeedback	Feedback	-.497c	0.633
18	Control	NoFeedback	-.726b	0.502
		Feedback	-.465b	0.745
	NoFeedback	Feedback	-.241c	0.914
19	Control	NoFeedback	-.539b	0.631
		Feedback	-.640b	0.619
	NoFeedback	Feedback	-.104b	0.941
20	Control	NoFeedback	-1.038b	0.336
		Feedback	-1.412b	0.166
	NoFeedback	Feedback	.000d	1.000
21	Control	NoFeedback	-.546b	0.597
		Feedback	-.882b	0.489
	NoFeedback	Feedback	-.121b	0.938
22	Control	NoFeedback	-1.127b	0.255
		Feedback	-1.656b	0.100
	NoFeedback	Feedback	-.620b	0.584
23	Control	NoFeedback	-.144c	0.896
		Feedback	-.233b	0.868
	NoFeedback	Feedback	-.540b	0.642

*. Related Questions can be found in Table A.1

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

c. Based on negative ranks.

d. The sum of negative ranks equals the sum of positive ranks.

Bibliography

[1] Yongkuk Lee *et al.* "Soft Electronics Enabled Ergonomic Human-Computer Interaction for Swallowing Training". In: *Scientific Reports* 7 (Apr. 2017), p. 46697.

[2] B. Nicholls *et al.* "Swallowing Detection for Game Control: Using Skin-like Electronics to Support People with Dysphagia". In: *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. Mar. 2017, pp. 413–418. DOI: 10.1109/PERCOMW.2017.7917598.

[3] D.S. Wilks. "Chapter 9 - Time Series". In: *Statistical Methods in the Atmospheric Sciences*. Ed. by Daniel S. Wilks. Vol. 100. International Geophysics. Academic Press, 2011, pp. 395–456. DOI: https://doi.org/10.1016/B978-0-12-385022-5.00009-9.

[4] Enwenode Onajite. "Chapter 8 - Understanding Sample Data". In: *Seismic Data Analysis Techniques in Hydrocarbon Exploration*. Ed. by Enwenode Onajite. Oxford: Elsevier, 2014, pp. 105–115. ISBN: 978-0-12-420023-4. DOI: https://doi.org/10.1016/B978-0-12-420023-4.00008-3.

[5] Jordan R. Green *et al.* "Development of Chewing in Children From 12 to 48 Months: Longitudinal Study of EMG Patterns". In: *Journal of Neurophysiology* 77.5 (1997). PMID: 9163386, pp. 2704–2716. DOI: 10.1152/jn.1997.77.5.2704.

[6] K. Kohyama, L. Mioche, and P. Bourdio3. "Influence of age and dental status on chewing behaviour studied by EMG recordings during consumption of various food samples". In: *Gerodontology* 20.1 (2003), pp. 15–23. DOI: 10.1111/j.1741-2358.2003.00015.x.

[7] Leandra Abarca-Gómez *et al.* "Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128.9 million children, adolescents, and adults". In:

The Lancet 390.10113 (2017), pp. 2627–2642. ISSN: 0140-6736. DOI: https://doi.org/10.1016/S0140-6736(17)32129-3.

[8] World Health Organization *et al. Obesity: preventing and managing the global epidemic: report of a WHO consultation on obesity, Geneva, 3-5 June 1997*. Tech. rep. Geneva: World Health Organization, 1998.

[9] Roberto Duncan and Patricia Toledo. "Do overweight and obesity prevalence rates converge in Europe?" In: *Research in Economics* 72.4 (2018), pp. 482–493. ISSN: 1090-9443. DOI: https://doi.org/10.1016/j.rie.2018.09.002.

[10] GBD 2015 Obesity Collaborators. "Health effects of overweight and obesity in 195 countries over 25 years". In: *New England Journal of Medicine* 377.1 (2017), pp. 13–27.

[11] Jeffrey B. Palmer *et al.* "Coordination of Mastication and Swallowing". In: *Dysphagia* 7.4 (Dec. 1992), pp. 187–200. ISSN: 1432-0460. DOI: 10.1007/BF02493469.

[12] Koichiro Matsuo and Jeffrey B. Palmer. "Coordination of Mastication, Swallowing and Breathing". In: *Japanese Dental Science Review* 45.1 (2009), pp. 31–40. ISSN: 1882-7616. DOI: https://doi.org/10.1016/j.jdsr.2009.03.004.

[13] Koichiro Matsuo and Jeffrey B. Palmer. "Anatomy and Physiology of Feeding and Swallowing – Normal and Abnormal". In: *Physical Medicine and Rehabilitation Clinics of North America* 19.4 (2008), pp. 691–707.

[14] Jeffrey B. Palmer, Jennifer C. Drennan, and Mikoto Baba. "Evaluation and treatment of swallowing impairments". English (US). In: *American Family Physician* 61.8 (Apr. 2000), pp. 2453–2462. ISSN: 0002-838X.

[15] Carol Marie McGinnis *et al.* "Dysphagia: Interprofessional Management, Impact, and Patient-Centered Care". In: *Nutrition in Clinical Practice* 34.1 (2018), pp. 80–95. DOI: 10.1002/ncp.10239.

[16] Colleen A. McHorney *et al.* "The SWAL–QOL and SWAL–CARE Outcomes Tool for Oropharyngeal Dysphagia in Adults: III. Documentation of Reliability and Validity". In: *Dysphagia* 17.2 (Apr. 2002), pp. 97–114. ISSN: 1432-0460. DOI: 10.1007/s00455-001-0109-1.

[17] Olle Ekberg *et al.* "Social and Psychological Burden of Dysphagia: Its Impact on Diagnosis and Treatment". In: *Dysphagia* 17.2 (), pp. 139–146.

[18] Deborah Cohen and Thomas A Farley. "Eating as an Automatic Behavior". In: *Preventing Chronic Disease* 5.1 (Jan. 2008), A23. ISSN: 1545-1151.

[19] Mary Story, Dianne Neumark-Sztainer, and Simone French. "Individual and Environmental Influences on Adolescent Eating Behaviors". In: *Journal of the American Dietetic Association* 102.3, Supplement (2002), S40.

[20] Rebecca Murphy *et al.* "Cognitive Behavioral Therapy for Eating Disorders". In: *Psychiatric Clinics* 33.3 (Sept. 2010), pp. 611–627. ISSN: 0193-953X. DOI: 10.1016/j.psc.2010.04.004.

[21] Brian Wansink. "Environmental Factors That Increase The Food Intake and Consumption Volume of Unknowing Consumers". In: *Annual Review of Nutrition* 24.Journal Article (2004), pp. 455–479.

[22] Thomas A Wadden and George A Bray. *Handbook of obesity treatment.* Guilford Publications, 2018.

[23] Yong Zhu, Walter H. Hsu, and James H. Hollis. "The Impact of Food Viscosity on Eating Rate, Subjective Appetite, Glycemic Response and Gastric Emptying Rate". In: *PLoS ONE* 8.6 (2013), e67482.

[24] C.G. Forde *et al.* "Oral Processing Characteristics of Solid Savoury Meal Components, and Relationship with Food Composition, Sensory Attributes and Expected Satiation". In: *Appetite* 60 (Jan. 2013), pp. 208–219. ISSN: 0195-6663. DOI: 10.1016/j.appet.2012.09.015.

[25] S. Takayama *et al.* "Rate of Eating and Body Weight in Patients with Type 2 Diabetes or Hyperlipidaemia". In: *Journal of International Medical Research* 30.4 (2002), pp. 442–444.

[26] S Sasaki *et al.* "Self-Reported Rate of Eating Correlates with Body Mass Index in 18-y-Old Japanese Women". In: *International Journal Of Obesity* 27 (Oct. 2003), p. 1405.

[27] Sook Ling Leong *et al.* "Faster Self-Reported Speed of Eating Is Related to Higher Body Mass Index in a Nationwide Survey of Middle-Aged Women". In: *Journal of the American Dietetic Association* 111.8 (2011), pp. 1192–1197.

[28] Clare H. Llewellyn *et al.* "Eating Rate Is a Heritable Phenotype Related to Weight in Children". In: *The American Journal of Clinical Nutrition*} 88.6 (2008), pp. 1560–1566.

[29] Toru Yamazaki *et al.* "Mastication and Risk for Diabetes in a Japanese Population: A Cross-Sectional Study". In: *PLoS ONE* 8.6 (2013), e64113.

[30] Akinori Tasaka *et al.* "Influence of Chewing Rate on Salivary Stress Hormone Levels". In: *Nihon Hotetsu Shika Gakkai Zasshi* 52.4 (2008), pp. 482–487.

[31] Rei Otsuka *et al.* "Eating Fast Leads to Obesity: Findings Based on Self-Administered Questionnaires among Middle-Aged Japanese Men and Women". In: *Journal of Epidemiology* 16.3 (2006), pp. 117–124.

[32] James R Hebert *et al.* "Social Desirability Bias in Dietary Self-Report May Compromise the Validity of Dietary Intake Measures". In: *International Journal of Epidemiology* 24.2 (Apr. 1995), pp. 389–398. ISSN: 0300-5771. DOI: 10.1093/ije/24.2.389.

[33] Elizabeth A Spencer *et al.* "Validity of Self-Reported Height and Weight in 4808 EPIC–Oxford Participants". In: *Public Health Nutrition* 5.4 (2002), pp. 561–565. DOI: 10.1079/PHN2001322.

[34] Dale A Schoeller *et al.* "Self-Report–Based Estimates of Energy Intake Offer an Inadequate Basis for Scientific Conclusions". In: *The American Journal of Clinical Nutrition* 97.6 (June 2013), pp. 1413–1415. ISSN: 0002-9165. DOI: 10.3945/ajcn.113.062125.

[35] Randi E. McCabe *et al.* "Eating Disorders, Dieting, and the Accuracy of Self-Reported Weight". In: *International Journal of Eating Disorders* 29.1 (Dec. 2000), pp. 59–64. ISSN: 0276-3478. DOI: 10.1002/1098-108X(200101)29:1<59::AID-EAT9>3.0.CO;2-\#.

[36] Frank J. Elgar *et al.* "Validity of Self-Reported Height and Weight and Predictors of Bias in Adolescents". In: *Journal of Adolescent Health* 37.5 (2005), pp. 371–375. ISSN: 1054-139X. DOI: https://doi.org/10.1016/j.jadohealth.2004.07.014.

[37] Yoojung Kim *et al.* ""My Doctor Is Keeping an Eye on Me!": Exploring the Clinical Applicability of a Mobile Food Logger". In: *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA). CHI '16. ACM, 2016, pp. 5620–5631. ISBN: 978-1-4503-3362-7. DOI: 10.1145/2858036.2858145.

[38] *MapMyRide*. en. https://www.mapmyride.com/.

[39] *MapMyRun*. en. https://www.mapmyrun.com/.

[40] *Nike+ Training App for iPhone & Android*. en. https://www.nike.com/gb/en_gb/c/nike-plus/training-app.

[41] *Strava — Run and Cycling Tracking on the Social Network for Athletes*. https://www.strava.com

[42] *Free Calorie Counter, Diet & Exercise Journal — MyFitnessPal.Com*. en. https://www.myfitnes

[43] FitBit. *FitBit*. https://www.fitbit.com.

[44] Lora E. Burke *et al.* "Using mHealth Technology to Enhance Self-Monitoring for Weight Loss: A Randomized Trial". In: *American Journal of Preventive Medicine* 43.1 (2012), p. 20.

[45] Gabrielle M. Turner-McGrievy *et al.* "Comparison of Traditional versus Mobile App Self-Monitoring of Physical Activity and Dietary Intake among Overweight Adults Participating in an mHealth Weight Loss Program". In: *Journal of the American Medical Informatics Association* 20.3 (2013), pp. 513–518.

[46] Joohee kim *et al.* "An Eating Speed Guide System Using a Wristband and Table-top Unit". In: *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (Heidelberg, Germany). UbiComp '16. ACM, 2016, pp. 121–124. ISBN: 978-1-4503-4462-3. DOI: 10.1145/2968219.2971460.

[47] Rangaraj M. Rangayyan. "Introduction to Biomedical Signals". In: *Biomedical Signal Analysis*. IEEE, 2015. ISBN: 9781119068129. DOI: 10.1002/9781119068129.ch1.

[48] Inhyuk Moon *et al.* "Wearable EMG-Based HCI for Electric-Powered Wheelchair Users with Motor Disabilities". In: *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference On*. 2005, pp. 2649–2654.

[49] K. Tanaka, K. Matsunaga, and H. O. Wang. "Electroencephalogram-Based Control of an Electric Wheelchair". In: *Robotics, IEEE Transactions on* 21.4 (2005), pp. 762–766.

[50] Enrico Costanza, Samuel A. Inverso, and Rebecca Allen. "Toward Subtle Intimate Interfaces for Mobile Devices Using an EMG Controller". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Portland, Oregon, USA: ACM, 2005, pp. 481–489.

[51] Andrew Campbell *et al.* "NeuroPhone: Brain-Mobile Phone Interface Using a Wireless EEG Headset". In: *Proceedings of the Second ACM SIGCOMM Workshop on Networking, Systems, and Applications on Mobile Handhelds*. New Delhi, India: ACM, 2010, pp. 3–8.

[52] Rezwanul Ahsan, Muhammad Ibrahimy, and Othman O. Khalifa. "EMG Signal Classification for Human Computer Interaction A Review". In: *European Journal of Scientific Research* (Jan. 2009).

[53] KE Laver *et al.* "Virtual reality for stroke rehabilitation". In: *Cochrane Database of Systematic Reviews* 11 (2017). ISSN: 1465-1858. DOI: 10.1002/14651858.CD008349.pub4.

[54] Gustavo Saposnik *et al.* "Effectiveness of Virtual Reality Using Wii Gaming Technology in Stroke Rehabilitation: A Pilot Randomized Clinical Trial and Proof of Principle". In: *Stroke* 41.7 (2010), pp. 1477–1484.

[55] Kai Kuikkaniemi *et al.* "The Influence of Implicit and Explicit Biofeedback in First-Person Shooter Games". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. CHI '10. Atlanta, Georgia, USA New York, NY, USA: ACM, 2010, pp. 859–868. ISBN: 978-1-60558-929-9.

[56] Erin Reynolds. "Nevermind: Creating an Entertaining Biofeedback-Enhanced Game Experience to Train Users in Stress Management". In: *ACM SIGGRAPH 2013 Posters*. Anaheim, California: ACM, 2013, pp. 1–1.

[57] Bengt Ingervall and Birgit Thilander. "Relation between facial morphology and activity of the masticatory muscles". In: *Journal of Oral Rehabilitation* 1.2 (1974), pp. 131–147. DOI: 10.1111/j.1365-2842.1974.tb00771.x.

[58] Claire Lassauzay *et al.* "Variability of the masticatory process during chewing of elastic model foods". In: *European Journal of Oral Sciences* 108.6 (), pp. 484–492. DOI: 10.1034/j.1600-0722.2000.00866.x.

[59] M. Peyron, C. Lassauzay, and A. Woda. "Effects of Increased Hardness on Jaw Movement and Muscle Activity during Chewing of Visco-Elastic Model Foods". In: *Experimental Brain Research* 142.1 (2002), pp. 41–51.

[60] Isabel Moreno *et al.* "Electromyographic Comparisons between Clenching, Swallowing and Chewing in Jaw Muscles with Varying Occlusal Parameters." eng. In: *Med Oral Patol Oral Cir Bucal* 13.3 (Mar. 2008), E207–213. ISSN: 1698-6946 1698-4447.

[61] Michael Vaiman. "Standardization of Surface Electromyography Utilized to Evaluate Patients with Dysphagia". In: *Head & Face Medicine* 3.1 (2007), p. 26.

[62] Michael Vaiman and Ephraim Eviatar. "Surface Electromyography as a Screening Method for Evaluation of Dysphagia and Odynophagia". In: *Head & Face Medicine* 5.1 (2009), p. 9.

[63] Maggie Lee Huckabee and Michael P. Cannito. "Outcomes of Swallowing Rehabilitation in Chronic Brainstem Dysphagia: A Retrospective Evaluation". In: *Dysphagia* 14.2 (Feb. 1999), pp. 93–109. ISSN: 1432-0460. DOI: 10.1007/PL00009593.

[64] MichaelA Crary *et al.* "Functional Benefits of Dysphagia Therapy Using Adjunctive sEMG Biofeedback". In: *Dysphagia* 19.3 (2004), pp. 160–164.

[65] O. Amft and G. Troster. "On-Body Sensing Solutions for Automatic Dietary Monitoring". In: *Pervasive Computing, IEEE* 8.2 (2009), pp. 62–70.

[66] Shah Atiqur Rahman *et al.* "Unintrusive Eating Recognition Using Google Glass". In: *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare* (Istanbul, Turkey). PervasiveHealth '15. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2015, pp. 108–111. ISBN: 978-1-63190-045-7.

[67] O. Amft. "A Wearable Earpad Sensor for Chewing Monitoring". In: *Sensors, 2010 IEEE*. 2010, pp. 222–227. ISBN: 1930-0395.

[68] E. S. Sazonov *et al.* "Automatic Detection of Swallowing Events by Acoustical Means for Applications of Monitoring of Ingestive Behavior". In: *IEEE Transactions on Biomedical Engineering* 57.3 (Mar. 2010), pp. 626–633. ISSN: 0018-9294. DOI: 10.1109/TBME.2009.2033037.

[69] E. S. Sazonov and J. M. Fontana. "A Sensor System for Automatic Detection of Food Intake Through Non-Invasive Monitoring of Chewing". In: *Sensors Journal, IEEE* 12.5 (2012), pp. 1340–1348.

[70] J. M. Fontana, M. Farooq, and E. Sazonov. "Automatic Ingestion Monitor: A Novel Wearable Device for Monitoring of Ingestive Behavior". In: *IEEE Transactions on Biomedical Engineering* 61.6 (June 2014), pp. 1772–1779. ISSN: 0018-9294. DOI: 10.1109/TBME.2014.2306773.

[71] Shengjie Bi *et al.* "Toward a Wearable Sensor for Eating Detection". In: *Proceedings of the 2017 Workshop on Wearable Systems and Applications* (Niagara Falls, New York, USA). WearSys '17. ACM, 2017, pp. 17–22. ISBN: 978-1-4503-4959-8. DOI: 10.1145/3089351.3089355.

[72] Abdelkareem Bedri *et al.* "EarBit: Using Wearable Sensors to Detect Eating Episodes in Unconstrained Environments". In: *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1.3 (Sept. 2017), 37:1–37:20. ISSN: 2474-9567. DOI: 10.1145/3130902.

[73] Eleanor Criswell and Jeffrey R. Cram. *Cram's Introduction to Surface Electromyography.* 2nd Edition. Sudbury, MA : Jones and Bartlett, 2011.

[74] Dae-Hyeong Kim *et al.* "Epidermal Electronics". In: *Science* 333.6044 (2011), pp. 838–843.

[75] *Yeo Research Group.* URL: https://sites.google.com/view/yeogroup/home.

[76] Norton Neil S. *Netter's Head and Neck Anatomy for Dentistry.* 3rd. 1600 John F. Kennedy Blvd, Philadelphia: Elsevier, 2017.

[77] Nick Miller *et al.* "Hard to swallow: dysphagia in Parkinson's disease". In: *Age and Ageing* 35.6 (2006), pp. 614–618. DOI: 10.1093/ageing/afl105.

[78] Kris Tjaden. "Speech and Swallowing in Parkinson's Disease". In: *Topics in geriatric rehabilitation* 24.2 (2008), pp. 115–126. ISSN: 0882-7524. DOI: 10.1097/01.TGR.0000318899.87690.44.

[79] DW Buchholz. "Dysphagia Associated with Neurological Disorders". In: *Acta oto-rhino-laryngologica Belgica* 48.2 (1994), pp. 143–155. ISSN: 0001-6497.

[80] K. L. DePippo *et al.* "Dysphagia Therapy Following Stroke". In: *Neurology* 44.9 (1994), pp. 1655–1655. ISSN: 0028-3878. DOI: 10.1212/WNL.44.9.1655.

[81] Norine Foley *et al.* "Dysphagia Treatment Post Stroke: A Systematic Review of Randomised Controlled Trials". In: *Age and Ageing* 37.3 (2008), pp. 258–264.

[82] Rosemary Martino *et al.* "Dysphagia after stroke: incidence, diagnosis, and pulmonary complications." In: *Stroke* 36 12 (2005), pp. 2756–63.

[83] Donald G. Sessions, Roberta Zill, and Sandra L. Schwartz. "Deglutition After Conservation Surgery for Cancer of the Larynx and Hypopharynx". In: *Otolaryngology–Head and Neck Surgery* 87.6 (1979). PMID: 119201, pp. 779–796. DOI: 10.1177/019459987908700613.

[84] Cathy L. Lazarus *et al.* "Swallowing Disorders in Head and Neck Cancer Patients Treated With Radiotherapy and Adjuvant Chemotherapy". In: *The Laryngoscope* 106.9 (1996), pp. 1157–1166. DOI: 10.1097/00005537-199609000-00021.

[85] Barbara R. Pauloski. "Rehabilitation of Dysphagia Following Head and Neck Cancer". In: *Physical Medicine and Rehabilitation Clinics of North America* 19.4 (2008). Dysphagia, pp. 889–928. ISSN: 1047-9651. DOI: https://doi.org/10.1016/j.pmr.2008.05.010.

[86] Gerold J Wetscher *et al.* "The Effect of Medical Therapy and Antireflux Surgery on Dysphagia in Patients with Gastroesophageal Reflux Disease without Esophageal Stricture". In: *The American Journal of Surgery* 177.3 (1999), pp. 189–192. ISSN: 0002-9610. DOI: https://doi.org/10.1016/S0002-9610(99)00011-2.

[87] G. David Smithard *et al.* "The Natural History of Dysphagia Following a Stroke". In: *Dysphagia* 12.4 (), pp. 188–193.

[88] Tai Ryoon Han, Nam-Jong Paik, and Jin Woo Park. "Quantifying Swallowing Function after Stroke: A Functional Dysphagia Scale Based on Videofluoroscopic Studies". In: *Archives of Physical Medicine and Rehabilitation* 82.5 (May 2001), pp. 677–682. ISSN: 0003-9993. DOI: 10.1053/apmr.2001.21939.

[89] Robert W. Bastian. "Videoendoscopic Evaluation of Patients with Dysphagia: An Adjunct to the Modified Barium Swallow". In: *Otolaryngology–Head and Neck Surgery* 104.3 (Mar. 1991), pp. 339–350. ISSN: 0194-5998. DOI: 10.1177/019459989110400309.

[90] Thomas M. Kidder, Susan E. Langmore, and Bonnie J. W. Martin. "Indications and Techniques of Endoscopy in Evaluation of Cervical Dysphagia: Comparison with Radiographic Techniques". In: *Dysphagia* 9.4 (Sept. 1994), pp. 256–261. ISSN: 1432-0460. DOI: 10.1007/BF00301919.

[91] Wu Chih-Hsiu *et al.* "Evaluation of Swallowing Safety With Fiberoptic Endoscope: Comparison With Videofluoroscopic Technique". In: *The Laryngoscope* 107.3 (1997), pp. 396–401. DOI: 10.1097/00005537-199703000-00023.

[92] C. Madden *et al.* "Comparison between videofluoroscopy and milk-swallow endoscopy in the assessment of swallowing function". In: *Clinical Otolaryngology & Allied Sciences* 25.6 (2000), pp. 504–506. DOI: 10.1046/j.1365-2273.2000.00385.x.

[93] Renée Speyer *et al.* "Effects of Therapy in Oropharyngeal Dysphagia by Speech and Language Therapists: A Systematic Review". In: *Dysphagia* 25.1 (2010), pp. 40–65.

[94] Jeri A. Logemann. "The Evaluation and Treatment of Swallowing Disorders". In: *Current Opinion in Otolaryngology & Head and Neck Surgery* 6.6 (1998). ISSN: 1068-9508.

[95] Joshua S. Schindler and James H. Kelly. "Swallowing Disorders in the Elderly". In: *The Laryngoscope* 112.4 (2002), pp. 589–602. DOI: 10.1097/00005537-200204000-00001.

[96] Martyn S. Mendelsohn and Fred M. S. McConnel. "Function in the pharyngoesophageal segment". In: *The Laryngoscope* 97.4 (1987), pp. 483–489. DOI: 10.1288/00005537-198704000-00014.

[97] LoriM Burkhead, ChristineM Sapienza, and JohnC Rosenbek. "Strength-Training Exercise in Dysphagia Rehabilitation: Principles, Procedures, and Directions for Future Research". In: *Dysphagia* 22.3 (2007), pp. 251–265.

[98] Jaeock Kim and Christine M Sapienza. "Implications of expiratory muscle strength training for rehabilitation of the elderly: Tutorial". In: *Journal of rehabilitation research and development* 42.2 (2005), pp. 211–224. ISSN: 0748-7711.

[99] Reza Shaker *et al.* "Rehabilitation of Swallowing by Exercise in Tube-Fed Patients with Pharyngeal Dysphagia Secondary to Abnormal UES Opening". In: *Gastroenterology* 122.5 (May 2002), pp. 1314–1321. ISSN: 0016-5085. DOI: 10.1053/gast.2002.32999.

[100] Giselle Carnaby, Graeme J. Hankey, and Julia Pizzi. "Behavioural Intervention for Dysphagia in Acute Stroke: A Randomised Controlled Trial". In: *The Lancet Neurology* 5.1 (2006), p. 31.

[101] J. W. Burke *et al.* "Optimising Engagement for Stroke Rehabilitation Using Serious Games". In: *The Visual Computer* 25.12 (2009), pp. 1085–1099.

[102] David S. Olton; Aaron R. Noonberg. *Biofeedback: Clinical Applications in Behavioral Medicine.* Prentice-Hall International, Inc., London: Englewood Cliffs, N.J. : Prentice-Hall, 1980.

[103] SF Michie *et al. ABC of Behaviour Change Theories.* Silverback Publishing, 2014.

[104] Yinpeng Chen *et al.* "The Design of a Real-Time, Multimodal Biofeedback System for Stroke Patient Rehabilitation". In: *Proceedings of the 14th Annual ACM International Conference on Multimedia.* Multimedia '06. Santa Barbara, CA, USA New York, NY, USA: ACM, 2006, pp. 763–772. ISBN: 1-59593-447-2.

[105] Yinpeng Chen *et al.* "Media Adaptation Framework in Biofeedback System for Stroke Patient Rehabilitation". In: *Proceedings of the 15th International Conference on Multimedia.* Multimedia '07. Augsburg, Germany New York, NY, USA: ACM, 2007, pp. 47–57. ISBN: 978-1-59593-702-5.

[106] Huang He *et al.* "Interactive Multimodal Biofeedback for Task-Oriented Neural Rehabilitation". In: *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of The.* 2005, pp. 2547–2550.

[107] Julie D. Moreland, Mary Ann Thomson, and Angela R. Fuoco. "Electromyographic Biofeedback to Improve Lower Extremity Function after Stroke: A Meta-Analysis". In: *Archives of Physical Medicine and Rehabilitation* 79.2 (1998), pp. 134–140.

[108] Narender P. Reddy *et al.* "Biofeedback therapy using accelerometry for treating dysphagic patients with poor laryngeal elevation: case studies." In: *Journal of Rehabilitation Research and Development* 37.3 (2000), p. 361. ISSN: 07487711.

[109] H.C.A. Bogaardt, W. Grolman, and W.J. Fokkens. "The Use of Biofeedback in the Treatment of Chronic Dysphagia in Stroke Patients". In: *Folia Phoniatrica et Logopaedica* 61.4 (2009), pp. 200–205. ISSN: 1021-7762. DOI: 10.1159/000227997.

[110] Giselle D. Carnaby-Mann and Michael A. Crary. "McNeill Dysphagia Therapy Program: A Case-Control Study". In: *Archives of Physical Medicine and Rehabilitation* 91.5 (2010), pp. 743–749. ISSN: 0003-9993. DOI: https://doi.org/10.1016/j.apmr.2010.01.013.

[111] E Biddiss and J Irwin. "Active Video Games to Promote Physical Activity in Children and Youth: A Systematic Review". In: *Archives of Pediatrics & Adolescent Medicine* 164.7 (2010), pp. 664–672. DOI: 10.1001/archpediatrics.2010.104.

[112] Tom Baranowski *et al.* "Playing for Real: Video Games and Stories for Health-Related Behavior Change". In: *American Journal of Preventive Medicine* 34.1 (2008), 74–82.e10. ISSN: 0749-3797. DOI: https://doi.org/10.1016/j.amepre.2007.09.027.

[113] Gustavo Saposnik, Mindy Levin, and for the Stroke Outcome Research Canada Working Group. "Virtual Reality in Stroke Rehabilitation: A Meta-Analysis and Implications for Clinicians". In: *Stroke* 42.5 (2011), pp. 1380–1386.

[114] Christopher G Fairburn and Paul J Harrison. "Eating Disorders". In: *The Lancet* 361.9355 (2003), pp. 407–416. ISSN: 0140-6736. DOI: https://doi.org/10.1016/S0140-6736(03)12378-1.

[115] Christopher G. Fairburn and Sarah J. Beglin. "Assessment of Eating Disorders: Interview or Self-Report Questionnaire?" In: *International Journal of Eating Disorders* 16.4 (Dec. 1994), pp. 363–370. ISSN: 0276-3478. DOI: 10.1002/1098-108X(199412)16:4<363::AID-EAT2260160405>3.0.CO;2-\#.

[116] Janet Polivy and C. Peter Herman. "Causes of Eating Disorders". In: *Annual Review of Psychology* 53.1 (2002). PMID: 11752484, pp. 187–213. DOI: 10.1146/annurev.psych.53.100901.135103.

[117] Kimberly A. Brownley *et al.* "Binge Eating Disorder Treatment: A Systematic Review of Randomized Controlled Trials". In: *International Journal of Eating Disorders* 40.4 (2007), pp. 337–348.

[118] Jennifer R. Shapiro *et al.* "Bulimia Nervosa Treatment: A Systematic Review of Randomized Controlled Trials". In: *International Journal of Eating Disorders* 40.4 (2007), pp. 321–336.

[119] Andrew C. Butler *et al.* "The Empirical Status of Cognitive-Behavioral Therapy: A Review of Meta-Analyses". In: *Clinical Psychology Review* 26.1 (2006), pp. 17–31. ISSN: 0272-7358. DOI: https://doi.org/10.1016/j.cpr.2005.07.003.

[120] Christopher G Fairburn, Zafra Cooper, and Roz Shafran. "Cognitive Behaviour Therapy for Eating Disorders: A "Transdiagnostic" Theory and Treatment". In: *Behaviour Research and Therapy* 41.5 (2003), pp. 509–528. ISSN: 0005-7967. DOI: https://doi.org/10.1016/S0005-7967(02)00088-8.

[121] Albert Bandura. "Self-Efficacy: Toward a Unifying Theory of Behavioral Change." In: *Psychological Review* 84.2 (1977), pp. 191–215. ISSN: 1939-1471(Electronic),0033-295X(Print). DOI: 10.1037/0033-295X.84.2.191.

[122] Nanette Stroebele and John M. de Castro. "Listening to Music While Eating Is Related to Increases in People's Food Intake and Meal Duration". In: *Appetite* 47.3 (2006), p. 285.

[123] Vladislava Bajic. "The Experience of Eating: The effects of music on food-taste, food-pleasantness, and the rate of mastication". PhD thesis. University of Kent, Apr. 2018.

[124] Tegan Cruwys, Kirsten E. Bevelander, and Roel C. J. Hermans. "Social Modeling of Eating: A Review of When and Why Social Influence Affects Food Intake and Choice". In: *Appetite* 86.0 (2015), p. 3.

[125] N. Zijlstra *et al.* "The Effect of Viscosity on Ad Libitum Food Intake". In: *International journal of obesity* 32.4 (2007), pp. 676–683.

[126] Alexander Kokkinos *et al.* "Eating Slowly Increases the Postprandial Response of the Anorexigenic Gut Hormones, Peptide YY and Glucagon-Like Peptide-1". In: *The Journal of Clinical Endocrinology & Metabolism* 95.1 (2010), pp. 333–337.

[127] Yong Zhu and James H. Hollis. "Chewing Thoroughly Reduces Eating Rate and Postprandial Food Palatability but Does Not Influence Meal Size in Older Adults". In: *Physiology & Behavior* 123.0 (2014), p. 62.

[128] Modjtaba Zandian *et al.* "Decelerated and Linear Eaters: Effect of Eating Rate on Food Intake and Satiety". In: *Physiology & Behavior* 96.2 (Feb. 2009), pp. 270–275. ISSN: 0031-9384. DOI: 10.1016/j.physbeh.2008.10.011.

[129] Ioannis Ioakimidis *et al.* "A Method for the Control of Eating Rate: A Potential Intervention in Eating Disorders". In: *Behavior Research Methods* 41.3 (Aug. 2009), pp. 755–760. ISSN: 1554-3528. DOI: 10.3758/BRM.41.3.755.

[130] *The Mandometer Clinics — Treatment for Eating Disorders*. https://mando.se/en/.

[131] Phillip W. Jasper *et al.* "Effects of Bite Count Feedback from a Wearable Device and Goal Setting on Consumption in Young Adults". In: *Journal of the Academy of Nutrition and Dietetics* 116.11 (2016), pp. 1785–1793. ISSN: 2212-2672. DOI: https://doi.org/10.1016/j.jand.2016.05.004.

[132] Jenna L. Scisco *et al.* "Slowing Bite-Rate Reduces Energy Intake: An Application of the Bite Counter Device". In: *Journal of the American Dietetic Association* 111.8 (Aug. 2011), pp. 1231–1235. ISSN: 0002-8223. DOI: 10.1016/j.jada.2011.05.005.

[133] Tanja C. Adam and Elissa S. Epel. "Stress, Eating and the Reward System". In: *Physiology & Behavior* 91.4 (2007). Proceedings from the 2006 Meeting of the Society for the Study of Ingestive Behavior, pp. 449–458. ISSN: 0031-9384. DOI: https://doi.org/10.1016/j.physbeh.2007.04.011.

[134] Elissa Epel *et al.* "Stress May Add Bite to Appetite in Women: A Laboratory Study of Stress-Induced Cortisol and Eating Behavior". In: *Psychoneuroendocrinology* 26.1 (2001), pp. 37–49. ISSN: 0306-4530. DOI: https://doi.org/10.1016/S0306-4530(00)00035-4.

[135] Kristine H. Luce and Janis H. Crowther. "The Reliability of the Eating Disorder Examination—Self-Report Questionnaire Version (EDE-Q)". In: *International Journal of Eating Disorders* 25.3 (Mar. 1999), pp. 349–351. ISSN: 0276-3478. DOI: 10.1002/(SICI)1098-108X(199904)25:3<349::AID-EAT15>3.0.CO;2-M.

[136] Russell E. Glasgow *et al.* "Interactive Behavior Change Technology: A Partial Solution to the Competing Demands of Primary Care". In: *American Journal of Preventive Medicine* 27.2, Supplement (2004), p. 80.

[137] Melanie Swan. "The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery". In: *Big Data* 1.2 (2013). PMID: 27442063, pp. 85–99. DOI: 10.1089/big.2012.0002.

[138] Melanie Swan. "Emerging Patient-Driven Health Care Models: An Examination of Health Social Networks, Consumer Personalized Medicine and Quantified Self-Tracking". In: *International Journal of Environmental Research and Public Health* 6.2 (2009), p. 492.

[139] Melanie Swan. "Sensor Mania! The Internet of Things, Wearable Computing, Objective Metrics, and the Quantified Self 2.0". In: *Journal of Sensor and Actuator Networks* 1.3 (2012), p. 217.

[140] Caroline Free *et al.* "The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review". In: *PLoS Med* 10.1 (2013), e1001362.

[141] Gemma Flores Mateo *et al.* "Mobile Phone Apps to Promote Weight Loss and Increase Physical Activity: A Systematic Review and Meta-Analysis". In: *Journal of Medical Internet Research* 17.11 (Nov. 2015). Ed. by Panagiotis Bamidis, e253. ISSN: 1439-4456. DOI: 10.2196/jmir.4836.

[142] Sergios Theodoridis. *Machine Learning : A Signal and Information Processing and Analysis Perspective*. Kent, United Kingdom: Elsevier Science & Technology, 2015. ISBN: 978-0-12-801722-7.

[143] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin. "Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications". In: *Biological Procedures Online* 8.1 (Dec. 2006), pp. 11–35. ISSN: 1480-9222. DOI: 10.1251/bpo115.

[144] Claudio Castellini and Patrick van der Smagt. "Surface EMG in Advanced Hand Prosthetics". In: *Biological Cybernetics* 100.1 (Jan. 2009), pp. 35–47. ISSN: 1432-0770. DOI: 10.1007/s00422-008-0278-1.

[145] Baoxing Xu *et al.* "An Epidermal Stimulation and Sensing Platform for Sensorimotor Prosthetic Control, Management of Lower Back Exertion, and Electrical Muscle Activation". eng. In: *Advanced materials (Deerfield Beach, Fla.)* (2015).

[146] Gernot R. Müller-Putz *et al.* "EEG-Based Neuroprosthesis Control: A Step towards Clinical Practice". In: *Neuroscience Letters* 382.1–2 (), pp. 169–174.

[147] Moon Inhyuk *et al.* "Wearable EMG-Based HCI for Electric-Powered Wheelchair Users with Motor Disabilities". In: *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference On*. 2005, pp. 2649–2654.

[148] B. Rebsamen *et al.* "Controlling a Wheelchair Indoors Using Thought". In: *IEEE Intelligent Systems* 22.2 (Mar. 2007), pp. 18–24. ISSN: 1541-1672. DOI: 10.1109/MIS.2007.26.

[149] Torsten Felzer and Bernd Freisleben. "HaWCoS: The "Hands-Free" Wheelchair Control System". In: *Proceedings of the Fifth International ACM Conference on Assistive Technologies*. Edinburgh, Scotland: ACM, 2002, pp. 127–134.

[150] Pramila Rani *et al.* "An Empirical Study of Machine Learning Techniques for Affect Recognition in Human–Robot Interaction". In: *Pattern Analysis and Applications* 9.1 (May 2006), pp. 58–69. ISSN: 1433-755X. DOI: 10.1007/s10044-006-0025-y.

[151] M. Pantic and L. J. M. Rothkrantz. "Toward an Affect-Sensitive Multimodal Human-Computer Interaction". In: *Proceedings of the IEEE* 91.9 (2003), pp. 1370–1390.

[152] A. Pantelopoulos and N. G. Bourbakis. "A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis". In: *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* 40.1 (2010), pp. 1–12.

[153] Lennart Erik Nacke *et al.* "Biofeedback Game Design: Using Direct and Indirect Physiological Control to Enhance Game Interaction". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Vancouver, BC, Canada: ACM, 2011, pp. 103–112.

[154] G. Chanel *et al.* "Emotion Assessment From Physiological Signals for Adaptation of Game Difficulty". In: *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on* 41.6 (2011), pp. 1052–1063.

[155] Shyamal Patel *et al.* "A Review of Wearable Sensors and Systems with Application in Rehabilitation". In: *Journal of NeuroEngineering and Rehabilitation* 9.1 (Apr. 2012), p. 21. ISSN: 1743-0003. DOI: 10.1186/1743-0003-9-21.

[156] Sumit Majumder, Tapas Mondal, and M. Jamal Deen. "Wearable Sensors for Remote Health Monitoring". In: *Sensors* 17.1 (2017). ISSN: 1424-8220. DOI: 10.3390/s17010130.

[157] Edward Sazonov *et al.* "Non-Invasive Monitoring of Chewing and Swallowing for Objective Quantification of Ingestive Behavior". In: *Physiological Measurement* 29.5 (2008), pp. 525–541.

[158] Oliver Amft *et al.* "Analysis of Chewing Sounds for Dietary Monitoring". In: *UbiComp 2005: Ubiquitous Computing* 3660.Journal Article (2005), pp. 56–72.

[159] Woon-Hong Yeo *et al.* "Multifunctional Epidermal Electronics Printed Directly Onto the Skin". In: *Advanced Materials* 25.20 (2013), pp. 2773–2778.

[160] J. Liu *et al.* "An Intelligent Food-Intake Monitoring System Using Wearable Sensors". In: *2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks*. May 2012, pp. 154–160. DOI: 10.1109/BSN.2012.11.

[161] Koichi Okamoto and Keiji Yanai. "An Automatic Calorie Estimation System of Food Images on a Smartphone". In: *Proceedings of the 2Nd International Workshop on Multimedia Assisted Dietary Management* (Amsterdam, The Netherlands). MADiMa '16. ACM, 2016, pp. 63–70. ISBN: 978-1-4503-4520-0. DOI: 10.1145/2986035.2986040.

[162] Edward S. Sazonov *et al.* "Toward Objective Monitoring of Ingestive Behavior in Free-living Population". In: *Obesity* 17.10 (2009), pp. 1971–1975. DOI: 10.1038/oby.2009.153.

[163] Oliver Amft, Martin Kusserow, and Gerhard Tröster. "Probabilistic Parsing of Dietary Activity Events". In: *4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)*. Ed. by Steffen Leonhardt, Thomas Falck, and Petri Mähönen. Springer Berlin Heidelberg, 2007, pp. 242–247. ISBN: 978-3-540-70994-7.

[164] Rawan Alharbi *et al.* "WillSense: Adherence Barriers for Passive Sensing Systems That Track Eating Behavior". In: *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (Denver, Colorado, USA). CHI EA '17. ACM, 2017, pp. 2329–2336. ISBN: 978-1-4503-4656-6. DOI: 10.1145/3027063.3053271.

[165] Michael A. Crary and Brent O. Baldwin. "Surface Electromyographic Characteristics of Swallowing in Dysphagia Secondary to Brainstem Stroke". In: *Dysphagia* 12.4 (Aug. 1997), pp. 180–187. ISSN: 1432-0460. DOI: 10.1007/PL00009534.

[166] C Ertekin, I Aydoğdu, and N Yüceyar. "Piecemeal Deglutition and Dysphagia Limit in Normal Subjects and in Patients with Swallowing Disorders." In: *Journal of Neurology, Neurosurgery & Psychiatry* 61.5 (1996), pp. 491–496. ISSN: 0022-3050. DOI: 10.1136/jnnp.61.5.491.

[167] Cumhur Ertekin *et al.* "Electrophysiological Evaluation of Pharyngeal Phase of Swallowing in Patients with Parkinson's Disease". In: *Movement Disorders* 17.5 (Apr. 2002), pp. 942–949. ISSN: 0885-3185. DOI: 10.1002/mds.10240.

[168] Anna Potulska *et al.* "Swallowing Disorders in Parkinson's Disease". In: *Parkinsonism & Related Disorders* 9.6 (2003), pp. 349–353. ISSN: 1353-8020. DOI: https://doi.org/10.1016/S1353-8020(03)00045-2.

[169] Michael Vaiman, Ephraim Eviatar, and Samuel Segal. "Evaluation of Normal Deglutition with the Help of Rectified Surface Electromyography Records". In: *Dysphagia* 19.2 (2004), pp. 125–132.

[170] Corinna Schultheiss *et al.* "Evaluation of an EMG Bioimpedance Measurement System for Recording and Analysing the Pharyngeal Phase of Swallowing". In: *European Archives of Oto-Rhino-Laryngology* 270.7 (2013), pp. 2149–2156.

[171] A. van der Bilt *et al.* "Oral Physiology and Mastication". In: *Physiology & Behavior* 89.1 (Aug. 2006), pp. 22–27. ISSN: 0031-9384. DOI: 10.1016/j.physbeh.2006.01.025.

[172] T. Horio and Y. Kawamura. "Effects of texture of food on chewing patterns in the human subject". In: *Journal of Oral Rehabilitation* 16.2 (), pp. 177–183. DOI: 10.1111/j.1365-2842.1989.tb01331.x.

[173] Laurence Mioche *et al.* "Variations in Human Masseter and Temporalis Muscle Activity Related to Food Texture during Free and Side-Imposed Mastication". In: *Archives of Oral Biology* 44.12 (Dec. 1999), pp. 1005–1012. ISSN: 0003-9969. DOI: 10.1016/S0003-9969(99)00103-X.

[174] K. D. Foster, A. Woda, and M. A. Peyron. "Effect of Texture of Plastic and Elastic Model Foods on the Parameters of Mastication". In: *Journal of Neurophysiology* 95.6 (June 2006), pp. 3469–3479. ISSN: 0022-3077. DOI: 10.1152/jn.01003.2005.

[175] Miyaoka Yozo *et al.* "Differentiation Of Activity Patterns In the Suprahyoid Muscles During Swallowing of Foods With Five Taste Qualities". In: *Journal of Sensory Studies* 20.6 (2006), pp. 473–483. ISSN: 0887-8250. DOI: 10.1111/j.1745-459X.2005.00041.x.

[176] Miyaoka Y. *et al.* "Analysis of Masseter Activity Patterns Using TP Values during Chewing of Foods with Different Shapes and Textural Properties". In: *Journal of Texture Studies* 44.3 (Jan. 2013), pp. 196–204. ISSN: 0022-4901. DOI: 10.1111/jtxs.12012.

[177] H. Nahrstaedt *et al.* "Swallow Detection Algorithm Based on Bioimpedance and EMG Measurements". In: *IFAC Proceedings Volumes* 45.18 (Jan. 2012), pp. 91–96. ISSN: 1474-6670. DOI: 10.3182/20120829-3-HU-2029.00067.

[178] R. Zhang, S. Bernhart, and O. Amft. "Diet Eyeglasses: Recognising Food Chewing Using EMG and Smart Eyeglasses". In: *2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*. June 2016, pp. 7–12. DOI: 10.1109/BSN.2016.7516224.

[179] Q. Huang, W. Wang, and Q. Zhang. "Your Glasses Know Your Diet: Dietary Monitoring Using Electromyography Sensors". In: *IEEE Internet of Things Journal* 4.3 (June 2017), pp. 705–712. ISSN: 2327-4662. DOI: 10.1109/JIOT.2017.2656151.

[180] R. Zhang and O. Amft. "Monitoring Chewing and Eating in Free-Living Using Smart Eyeglasses". In: *IEEE Journal of Biomedical and Health Informatics* 22.1 (Jan. 2018), pp. 23–32. ISSN: 2168-2194. DOI: 10.1109/JBHI.2017.2698523.

[181] Abbink, Van Der Bilt, and Van Der Glas. "Detection of Onset and Termination of Muscle Activity in Surface Electromyograms". In: *Journal of Oral Rehabilitation* 25.5 (Jan. 2002), pp. 365–369. ISSN: 0305-182X. DOI: 10.1046/j.1365-2842.1998.00242.x.

[182] Wijnand IJsselsteijn *et al.* "Persuasive Technology for Human Well-Being: Setting the Scene". In: *Persuasive Technology* (Berlin, Heidelberg). Ed. by Wijnand A.

IJsselsteijn *et al.* Springer Berlin Heidelberg, 2006, pp. 1–5. ISBN: 978-3-540-34293-9.

[183] Andrew D. Miller and Elizabeth D. Mynatt. "StepStream: A School-Based Pervasive Social Fitness System for Everyday Adolescent Health". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada). CHI '14. ACM, 2014, pp. 2823–2832. ISBN: 978-1-4503-2473-1. DOI: 10.1145/2556288.2557190.

[184] S. Erhel and E. Jamet. "Digital Game-Based Learning: Impact of Instructions and Feedback on Motivation and Learning Effectiveness". In: *Computers & Education* 67 (2013), pp. 156–167. ISSN: 0360-1315. DOI: https://doi.org/10.1016/j.compedu.2013.02.019.

[185] Andrea Grimes, Vasudhara Kantroo, and Rebecca E. Grinter. "Let's Play!: Mobile Health Games for Adults". In: *Proceedings of the 12th ACM International Conference on Ubiquitous Computing* (Copenhagen, Denmark). UbiComp '10. ACM, 2010, pp. 241–250. ISBN: 978-1-60558-843-8. DOI: 10.1145/1864349.1864370.

[186] Rita Orji, Julita Vassileva, and Regan L. Mandryk. "LunchTime: A Slow-Casual Game for Long-Term Dietary Behavior Change". In: *Personal Ubiquitous Comput.* 17.6 (Aug. 2013), pp. 1211–1221. ISSN: 1617-4909. DOI: 10.1007/s00779-012-0590-6.

[187] Shlomo Berkovsky *et al.* "Physical Activity Motivating Games: Virtual Rewards for Real Activity". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA). CHI '10. ACM, 2010, pp. 243–252. ISBN: 978-1-60558-929-9. DOI: 10.1145/1753326.1753362.

[188] Azusa Kadomura *et al.* "Sensing Fork: Eating Behavior Detection Utensil and Mobile Persuasive Game". In: *CHI '13 Extended Abstracts on Human Factors in Computing Systems* (Paris, France). CHI EA '13. ACM, 2013, pp. 1551–1556. ISBN: 978-1-4503-1952-2. DOI: 10.1145/2468356.2468634.

[189] Azusa Kadomura *et al.* "Persuasive Technology to Improve Eating Behavior Using a Sensor-Embedded Fork". In: *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Seattle, Washington). UbiComp

'14. ACM, 2014, pp. 319–329. ISBN: 978-1-4503-2968-2. DOI: 10.1145/2632048.2632093.

[190] Takuji Narumi *et al.* "Augmented Perception of Satiety: Controlling Food Consumption by Changing Apparent Size of Food with Augmented Reality". In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Austin, Texas, USA). CHI '12. ACM, 2012, pp. 109–118. ISBN: 978-1-4503-1015-4. DOI: 10.1145/2207676.2207693.

[191] Barbara J Rolls, Erin L Morris, and Liane S Roe. "Portion size of food affects energy intake in normal-weight and overweight men and women". In: *The American Journal of Clinical Nutrition* 76.6 (Dec. 2002), pp. 1207–1213. ISSN: 0002-9165. DOI: 10.1093/ajcn/76.6.1207.

[192] Sho Sakurai *et al.* "CalibraTable: Tabletop System for Influencing Eating Behavior". In: *SIGGRAPH Asia 2015 Emerging Technologies* (Kobe, Japan). SA '15. ACM, 2015, 4:1–4:3. ISBN: 978-1-4503-3925-4. DOI: 10.1145/2818466.2818483.

[193] Jaejeung Kim, Joonyoung Park, and Uichin Lee. "EcoMeal: A Smart Tray for Promoting Healthy Dietary Habits". In: *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA). CHI EA '16. ACM, 2016, pp. 2165–2170. ISBN: 978-1-4503-4082-3. DOI: 10.1145/2851581.2892310.

[194] Joohee Kim and Byung-Chull Bae. "An Animated Emoji Feedback System for Eating Rate Guidance". In: *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers* (Singapore, Singapore). UbiComp '18. ACM, 2018, pp. 388–391. ISBN: 978-1-4503-5966-5. DOI: 10.1145/3267305.3267577.

[195] Xu Ye *et al.* "Assisting Food Journaling with Automatic Eating Detection". In: *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA). CHI EA '16. ACM, 2016, pp. 3255–3262. ISBN: 978-1-4503-4082-3. DOI: 10.1145/2851581.2892426.

[196] Cara E. Stepp. "Surface Electromyography for Speech and Swallowing Systems: Measurement, Analysis, and Interpretation". In: *Journal of Speech, Language, and Hearing Research* 55.4 (2012), pp. 1232–1246.

[197] Xian Huang *et al.* "Epidermal Differential Impedance Sensor for Conformal Skin Hydration Monitoring". In: *Biointerphases* 7.1 (2012), p. 52.

[198] Rubana H. Chowdhury *et al.* "Surface Electromyography Signal Processing and Classification Techniques". In: *Sensors* 13.9 (2013), pp. 12431–12466. ISSN: 1424-8220. DOI: 10.3390/s130912431.

[199] Nurhazimah Nazmi *et al.* "A Review of Classification Techniques of EMG Signals during Isotonic and Isometric Contractions". In: *Sensors* 16.8 (2016). ISSN: 1424-8220. DOI: 10.3390/s16081304.

[200] Xiaoyan Li, Ping Zhou, and Alexander S. Aruin. "Teager–Kaiser Energy Operation of Surface EMG Improves Muscle Activity Onset Detection". In: *Annals of Biomedical Engineering* 35.9 (Sept. 2007), pp. 1532–1538. ISSN: 1573-9686. DOI: 10.1007/s10439-007-9320-z.

[201] Paul W. Hodges and Bang H. Bui. "A Comparison of Computer-Based Methods for the Determination of Onset of Muscle Contraction Using Electromyography". In: *Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control* 101.6 (Dec. 1996), pp. 511–519. ISSN: 0924-980X. DOI: 10.1016/S0921-884X(96)95190-5.

[202] RP Di Fabio. "Reliability of Computerized Surface Electromyography for Determining the Onset of Muscle Activity". eng. In: *Physical therapy* 67.1 (Jan. 1987), pp. 43–48. ISSN: 0031-9023.

[203] L. I. Kuncheva. *Combining pattern classifiers methods and algorithms; EBL (Ebook library)*. English. 2004. ISBN: 9780471210788; 9780471660255.

[204] R. A. Fisher. "THE USE OF MULTIPLE MEASUREMENTS IN TAXONOMIC PROBLEMS". In: *Annals of Eugenics* 7.2 (1936), pp. 179–188. DOI: 10.1111/j.1469-1809.1936.tb02137.x.

[205] Leo Breiman. "Random Forests". In: *Machine Learning* 45.1 (Oct. 2001), pp. 5–32. ISSN: 1573-0565. DOI: 10.1023/A:1010933404324.

[206] Pierre Geurts, Damien Ernst, and Louis Wehenkel. "Extremely Randomized Trees". In: *Machine Learning* 63.1 (Apr. 2006), pp. 3–42. ISSN: 1573-0565. DOI: 10.1007/s10994-006-6226-1.

[207] Chih-Wei Hsu, Chih-Chung Chang, Chih-Jen Lin, *et al.* "A practical guide to support vector classification". In: (2003).

[208] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. "Feature Reduction and Selection for EMG Signal Classification". In: *Expert Systems with Applications* 39.8 (June 2012), pp. 7420–7431. ISSN: 0957-4174. DOI: 10.1016/j.eswa.2012.01.102.

[209] Angkoon Phinyomark, Franck Quaine, and Yann Laurillau. "The Relationship between Anthropometric Variables and Features of Electromyography Signal for Human–Computer Interface". In: ed. by Ganesh R. Naik. Applications, Challenges, and Advancements in Electromyography Signal Processing. ID: 110770. Hershey, PA, USA: IGI Global, 2014, pp. 321–353. ISBN: 978-1-4666-6090-8. DOI: 10.4018/978-1-4666-6090-8.ch015.

[210] Jae-Woong Jeong *et al.* "Materials and Optimized Designs for Human-Machine Interfaces Via Epidermal Electronics". In: *Advanced Materials* 25.47 (2013), pp. 6839–6846.

[211] James J. S. Norton *et al.* "Soft, Curved Electrode Systems Capable of Integration on the Auricle as a Persistent Brain–Computer Interface". In: *Proceedings of the National Academy of Sciences* 112.13 (2015), pp. 3920–3925.

[212] R. C. Webb *et al.* "Ultrathin Conformal Devices for Precise and Continuous Thermal Characterization of Human Skin". In: *Nature materials* 12.11 (2013), 10.1038/nmat3779.

[213] Yoshiaki Hattori *et al.* "Multifunctional Skin-Like Electronics for Quantitative, Clinical Monitoring of Cutaneous Wound Healing". In: *Advanced Healthcare Materials* 3.10 (2014), pp. 1597–1607.

[214] Heather M. Clark and Natalia Shelton. "Training Effects of the Effortful Swallow Under Three Exercise Conditions". In: *Dysphagia* 29.5 (Oct. 2014), pp. 553–563. ISSN: 1432-0460. DOI: 10.1007/s00455-014-9544-7.

[215] Leo Breiman. *Classification and regression trees*. Belmont, Calif: Wadsworth International Group, 1984, p. 358. ISBN: 0412048418.

[216] Leo Breiman. "Technical Note: Some Properties of Splitting Criteria". In: *Machine Learning* 24.1 (July 1996), pp. 41–47. ISSN: 1573-0565. DOI: 10.1023/A:1018094028462.

[217] Leo Breiman and Adele Cutler. *Random Forests - Classification Description*. https://www.stat.b

[218] Gilles Louppe *et al.* "Understanding Variable Importances in Forests of Randomized Trees". In: *Advances in Neural Information Processing Systems 26*. Ed. by C. J. C. Burges *et al.* Curran Associates, Inc., 2013, pp. 431–439.

[219] Carolin Strobl *et al.* "Bias in Random Forest Variable Importance Measures: Illustrations, Sources and a Solution". In: *BMC Bioinformatics* 8.1 (Jan. 2007), p. 25. ISSN: 1471-2105. DOI: 10.1186/1471-2105-8-25.

[220] Microsoft Corporation. *C# Language Specification*. Version Version 5.0. URL: https://www.%20microsoft.com/en-us/download/details.aspx?id=7029.

[221] Microsoft Corporation. *.Net Framework*. Version Version 4.5. URL: https://www.microsoft.com/en-gb/download/details.aspx?id=30653.

[222] *Unity Software*. Unity Technologies.

[223] John Brooke *et al.* "SUS-A quick and dirty usability scale". In: *Usability evaluation in industry* 189.194 (1996), pp. 4–7.

[224] Shing-On Leung. "A Comparison of Psychometric Properties and Normality in 4-, 5-, 6-, and 11-Point Likert Scales". In: *Journal of Social Service Research* 37.4 (2011), pp. 412–421. DOI: 10.1080/01488376.2011.580697.

[225] Kraig Finstad. "Response Interpolation and Scale Sensitivity: Evidence Against 5-point Scales". In: *J. Usability Studies* 5.3 (May 2010), pp. 104–110. ISSN: 1931-3357.

[226] ROBERT PETERSON. "A Quantitative Analysis of Rating-Scale Response Variability". In: *Marketing Letters* 8.1 (Jan. 1997), pp. 9–21. ISSN: 1573-059X. DOI: 10.1023/A:1007909424993.

[227] Therese Charles, David Bustard, and Michaela Black. "Experiences of Promoting Student Engagement Through Game-Enhanced Learning". In: *Serious Games and Edutainment Applications*. Ed. by Minhua Ma, Andreas Oikonomou, and Lakhmi

C. Jain. London: Springer London, 2011, pp. 425–445. ISBN: 978-1-4471-2161-9. DOI: 10.1007/978-1-4471-2161-9_21.

[228] Anton Umek and Anton Kos. "The Role of High Performance Computing and Communication for Real-Time Biofeedback in Sport". In: *Mathematical Problems in Engineering* 2016 (2016), p. 11.

[229] C. E. Stepp *et al.* "Feasibility of game-based electromyographic biofeedback for dysphagia rehabilitation". In: *2011 5th International IEEE/EMBS Conference on Neural Engineering*. Apr. 2011, pp. 233–236. DOI: 10.1109/NER.2011.5910530.

[230] ShimmerEngineering. *Shimmer API C*. May 2018.

[231] F. Pedregosa *et al.* "Scikit-learn: Machine Learning in Python". In: *Journal of Machine Learning Research* 12 (2011), pp. 2825–2830.

[232] Jeanne Dalen *et al.* "Pilot Study: Mindful Eating and Living (MEAL): Weight, Eating Behavior, and Psychological Outcomes Associated with a Mindfulness-Based Intervention for People with Obesity". In: *Complementary Therapies in Medicine* 18.6 (Dec. 2010), pp. 260–264. ISSN: 0965-2299. DOI: 10.1016/j.ctim.2010.09.008.

[233] G. A. O'Reilly *et al.* "Mindfulness-Based Interventions for Obesity-Related Eating Behaviours: A Literature Review". In: *Obesity Reviews* 15.6 (Mar. 2014), pp. 453–461. ISSN: 1467-7881. DOI: 10.1111/obr.12156.

[234] Python Software Foundation. *Python*. Version Version 2.7.15. URL: http://www.python.org.

[235] *TkInter*. URL: https://wiki.python.org/moin/TkInter.

[236] J. D. Hunter. "Matplotlib: A 2D Graphics Environment". In: *Computing in Science Engineering* 9.3 (May 2007), pp. 90–95. ISSN: 1521-9615. DOI: 10.1109/MCSE.2007.55.

[237] Google. *Android Developer Guides*. May 2018. URL: https://developer.android.com/guide/.

[238] ShimmerEngineering. *Shimmer API Android*. May 2018. URL: https://github.com/ShimmerEngineering/ShimmerAndroidAPI.

[239] Microsoft Corporation. *Microsoft Band SDK*. Version Version 1.3.20628. URL: https://www.nuget.org/packages/Microsoft.Band/.

[240] Marion M. Hetherington *et al.* "Situational Effects on Meal Intake: A Comparison of Eating Alone and Eating with Others". In: *Physiology & Behavior* 88.4–5 (2006), p. 498.

[241] Ruth A. Baer, Gregory T. Smith, and Kristin B. Allen. "Assessment of Mindfulness by Self-Report: The Kentucky Inventory of Mindfulness Skills". In: *Assessment* 11.3 (Sept. 2004), pp. 191–206. ISSN: 1073-1911. DOI: 10.1177/1073191104268029.

[242] Albert J. Stunkard and Samuel Messick. "The Three-Factor Eating Questionnaire to Measure Dietary Restraint, Disinhibition and Hunger". In: *Journal of Psychosomatic Research* 29.1 (Jan. 1985), pp. 71–83. ISSN: 0022-3999. DOI: 10.1016/0022-3999(85)90010-8.

[243] IBM Corp. *IBM SPSS Statistics for Windows*. Version Version 25.0. Released 2013.

[244] S. S. Shapiro and M. B. Wilk. "An Analysis of Variance Test for Normality (Complete Samples)". In: *Biometrika* 52.3/4 (1965), pp. 591–611. ISSN: 00063444. DOI: 10.2307/2333709.

[245] John W. Mauchly. "Significance Test for Sphericity of a Normal N-Variate Distribution". In: *The Annals of Mathematical Statistics* 11.2 (1940), pp. 204–209. ISSN: 00034851.

[246] Kathrynn Ann Adams author. and Eva K. Lawrence author. *Research methods, statistics, and applications*. English. 2015.

[247] William R. Hersh. "Medical InformaticsImproving Health Care Through Information". In: *JAMA* 288.16 (Oct. 2002), pp. 1955–1958. ISSN: 0098-7484. DOI: 10.1001/jama.288.16.1955.

[248] Ruogu Fang *et al.* "Computational Health Informatics in the Big Data Age: A Survey". In: *ACM Comput. Surv.* 49.1 (June 2016), 12:1–12:36. ISSN: 0360-0300. DOI: 10.1145/2932707.

[249] Koichiro Matsuo and Jeffrey B Palmer. "Anatomy and Physiology of Feeding and Swallowing – Normal and Abnormal". In: *Physical medicine and rehabilitation*

clinics of North America 19.4 (Nov. 2008), pp. 691–707. ISSN: 1047-9651. DOI: 10.1016/j.pmr.2008.06.001.