Early Prediction of Future Hand Movements Using sEMG Data

Philipp Koch, Huy Phan, Marco Maass, Fabrice Katzberg, and Alfred Mertins

***Abstract*— We study in this work the feasibility of early prediction of hand movement based on sEMG signals to overcome the time delay issue of the conventional classification. Opposed to the classification task, the objective of the early prediction task is to predict a hand movement that is going to occur in the future given the information up to the current time point. The ability of early prediction may allow a hand prosthesis control system to compensate for the time delay and, as a result, improve the usability. Experimental results on the Ninapro database show that we can predict up to 300 ms ahead in the future while the prediction accuracy remains very close to that of the standard classification, i.e. it is just marginally lower. Furthermore, historical data prior the current time window is shown very important to improve performance, not only for the prediction but also the classification task.**

I. INTRODUCTION

Surface electromyogram (sEMG) based hand movement recognition is a key element in upper limb prostheses [1], [2], [3]. The main goal of those prostheses is to restore most of the functionalities of a human hand as well as to simplify daily routine for an amputee. Consequently, a variety of hand motions as well as an intuitive usage of the prostheses have to be enabled.

Most of previous works in the field of control systems of prostheses focused on classifying hand movements during data acquisition [4], [5], [6], [7]. They shared the common approach to perform the classification task. Features are first extracted for a segment of the sEMG signal around the current time point. The corresponding movement is then determined by a pre-trained classifier given the extracted features. The classification task has been widely adopted due to its simplicity. However, we argue that this scheme causes a significant problem, i.e. time delay, which results in reduced responsiveness of the control system, and subsequently, downgrades the naturalness of the hand movements. There are two factors contributing to this time delay. First, in order to extract the features, a context window around the current time point of the sEMG signal is required. That is, the system needs to wait for a duration corresponding to half of this window for feature extraction. The second factor is the time needed for data acquisition, feature extraction, and classification. Furthermore, considering the classification task, one also is confronted with the unavoidable trade-off problem between the window length and the classification. As shown by Smith et al. [8], a larger window size will lead to a better classification accuracy. Therefore, to guarantee a good classification performance for reliable control, the window length needs to be sufficiently large. This makes the problem of time delay even worse.

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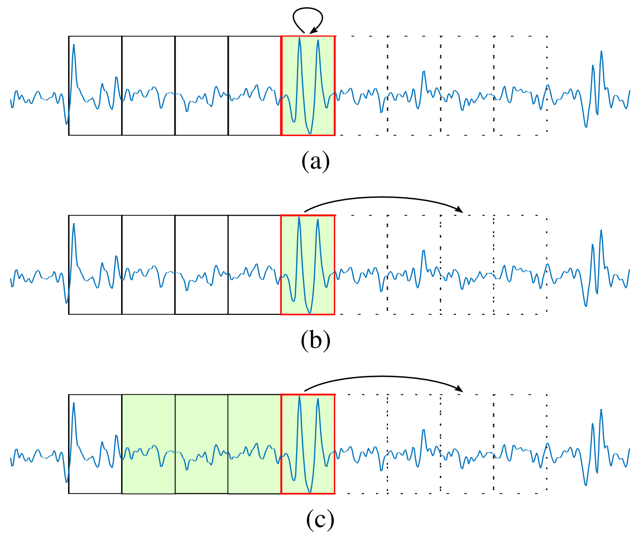

Fig. 1. Illustration of (a) the hand movement classification, (b) early prediction, and (c) early prediction with history data. Windows with shaded background are those used for classification/detection while arrows denote the time points of the target windows.

In this work, instead of classification, we study the early prediction of hand movements. By early prediction, we aim at determining the label for a segment in the future using information of the sEMG signal up to the current time as shown in Fig. 1. The ability of early prediction will overcome the time delay problem caused by the classification task since it allows the control system to foresee the hand movements and actively plan for controlling responses. Furthermore, with the time delays having been compensated, it is possible for one to enlarge the window size to extract more reliable and complex features as well as utilize more advanced classifiers to enhance the prediction accuracy. There is a strong reason that makes early prediction of hand movements feasible. Firstly, the sEMG signal is sequential by nature. That is, there are strong dependencies between consecutive windows, and a certain window should convey information about the future and, therefore, should be able to tell about their labels. Apart from the current window, earlier ones in the past, called history in the following, can also be leveraged to improve the accuracy of the prediction task. While the majority of prior works focused on the classification task, to the best of the authors knowledge, this is the first work studying early prediction of sEMG-based hand movements.

Experiments on the Non-Invasive Adaptive Prosthetics (NinaPro) dataset [9] show that we are able to obtain very good accuracy with prediction up to 300 ms ahead in the future. Furthermore, the early prediction accuracy, even with 300 ms in advance, is just marginally lower than that of classification. On the other hand, they also show that history plays an important role in the prediction task. Significant improvements are seen on the prediction accuracy when history windows are combined with the current window.

II. EARLY PREDICTION VS CLASSIFICATION OF HAND MOVEMENTS

A. Typical Classification System

Let us assume the sEMG signal is acquired by a hand prosthesis control system sequentially window by window. Let $\mathbf{x} \in \mathbb{R}^D$ denote the D-dimension feature vector representing an sEMG window and $y \in \mathbb{L}$ with $\mathbb{L} = \{1, \ldots, C\}$ represent a label of all possible C hand movements. Furthermore, it is assumed that a segment-wise classifier $\mathcal{F}$ has been learned beforehand using the training data. The goal of the typical system that considers the classification task is to determine the latest hand movement as soon as a new windowed signal is available. Formally, the classifier will perform the following mapping:

$$\mathcal{F} : \mathbf{x}_n \in \mathbb{R}^D \longmapsto y_n \in \mathbb{L}, \tag{1}$$

where n denotes the current time index.

When the current hand movement is determined, the system will respond correspondingly to control the hand prosthesis. The classification accuracy is therefore very important for reliable control. However, in order to improve the classification, a large window size is required [8], resulting in an increased time delay until the subsequent steps can take place. The additional delay induced by other steps, e.g. signal acquisition, feature extraction, and classification, needs to be taken into account as well. In general, more complex features and more advanced classification algorithms will offer better accuracy at the cost of increased computational overhead which is especially critical for this application at hand where computational resources are scarce. Concretely, there exist various factors deteriorating responsiveness of the classification-based control system and one needs to compromise in practical applications.

B. Early prediction system

Instead of determining the hand movement given the current signal window as in the classification task, the objective of the early prediction is to predict the hand movement of an unseen signal window in the future. Formally, the mapping of the prediction reads

$$\mathcal{Q} : \mathbf{x}_n \in \mathbb{R}^D \longmapsto y_{n+L} \in \mathbb{L}, \tag{2}$$

where $L > 0$ denotes the window offset between the current window to the target window in the future. The prediction is accomplished by the predictor $\mathcal{Q}$ which can be trained in the same manner as the classifier $\mathcal{F}$ in Section II-A except that the training data needs to be constructed properly for prediction rather than classification. Via the predictor $\mathcal{Q}$, we produce a duration so that the system knows in advance the hand movement that is going to take place and can actively prepare the control plan for it. As a result, we are able to get rid of the time delay experienced with the classification task and have a chance to make the hand movements more responsive and natural.

In addition to the current window, we also make use of previous windows to improve the prediction accuracy. The feature vectors of consecutive windows are simply concatenated to form the overall feature vector for prediction. Due to the sequential nature of the sEMG signal, the history windows prior to the current one should also carry information about the future one and, therefore, be useful for the prediction task although the dependency becomes weaker with a longer offset. When $H > 0$ history windows prior to the current one are taken into account, the mapping of the prediction task becomes

$$\mathcal{Q} : (\mathbf{x}_{n-H} \oplus \ldots \oplus \mathbf{x}_n) \in \mathbb{R}^{D(H+1)} \longmapsto y_{n+L} \in \mathbb{L}. \tag{3}$$

In (3), $\oplus$ denotes the concatenation operation. As alternative, one can employ a single large window which covers both the current and H history windows. The larger window is expected to bring up the prediction accuracy as it does in the classification task [8]. However, we argue that the concatenation strategy offers several advantages over the large window strategy. First of all, since the feature vectors have been computed for the history windows, we can avoid the computational cost induced by feature extraction over the long window except for the small current one. More importantly, by concatenation we are able to encode the temporal development of the signal which are ignored with the global feature vector of the large window. Furthermore, the concatenation results in higher-dimensional feature space which enriches the signal representation.

III. EXPERIMENTS

In the experiments, we will evaluate the performance of the early prediction of hand movements and compare it with that of the standard classification. We also study how the prediction performance varies with different prediction time offsets and the influence of history data on the prediction performance.

A. Ninapro Dataset

For evaluation of the early prediction approach, we conducted the experiments on the second version of the database from Ninapro project [7], [9]. The database includes sEMG signals of 50 different hand movements (including rest) for 40 abled healthy subjects. The subjects performed six repetitions of each type of hand movement (except rest). For signal acquisition twelve electrodes were placed around the subjects' forearms.

To be consent to the previous works on the dataset in [9], we follow the same preparation steps and use the same data splits in our experiments. Specifically, the repetitions 2 and 5 were used for evaluation while the remaining repetitions were used as training data. The performance for both classification and early prediction was evaluated individually for each subject. The performance average over all subjects is finally reported.

B. Preprocessing and Features

The processing scheme proposed by Englehart and Hudgins [10] was employed. The steps of this scheme include preprocessing, segmenting the signal into windows followed by extracting features on window level. For preprocessing the signals were channel-wise normalized to achieve zero mean and unit standard deviation. The necessary statistics were calculated using train data exclusively. Afterwards, the signals were segmented into overlapping windows of length 200 ms with 95% overlap (equivalent to 10 ms). We also vary the overlapping degree in the experiments to study its influence to the prediction accuracy.

A feature vector then needs to be extracted to represent each window. Although different features can be used, we made use of the root mean square (RMS) for this purpose. The RMS is calculated channel-wise. For a windowed signal $s(n)$ of length N on a single channel the RMS can be computed as

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|s(n)|^2}\,. \tag{4}$$

The RMS is arguably one of the most commonly used feature for sEMG representation. Furthermore, for the Ninapro dataset, the RMS features alone were shown to achieve comparable performances compared to those obtained with combinations of different feature types (including the RMS) while being of lower dimensionality [9].

C. Classifiers and Predictors

Any classification framework can be used to train the classifiers and predictors in the experiments. However, our goal is not to seek for the best algorithm for the task at hand. Therefore, we adopted random forest classification [11], which exhibited very good performance for the classification task on the experimental dataset [9], to train both the classifiers and predictors. The number of trees was set to 100.

D. Experimental Results

We show in Fig. 2 the obtained early prediction accuracies as functions of the prediction time offset. The time offset is counted from -100 ms which is the offset from the center to the end of the current window. Furthermore, to study the influence of the history, we explore different history values $H = \{0, 5, 10, 15, 20\}$, which is equivalent to $\{200, 450, 700, 950, 1200\}$ ms of the signal. It should be noted that with $H = 0$ and the time offset of -100 ms, the setup will become the standard classification as in [9].

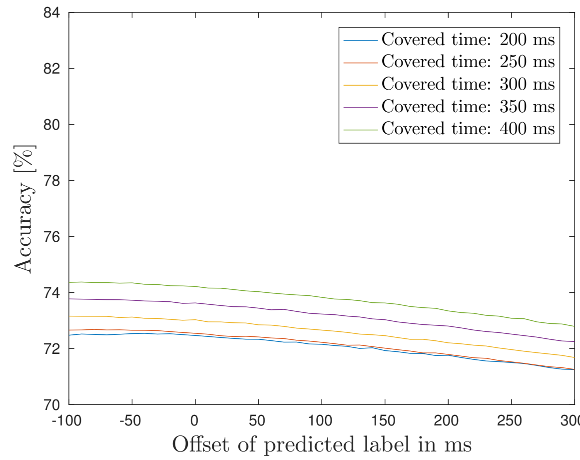

Fig. 2. Early prediction accuracy (%) as a function of the prediction time offset for different number of history windows $H = \{5, 10, 15, 20\}$ with an overlap of 95%.

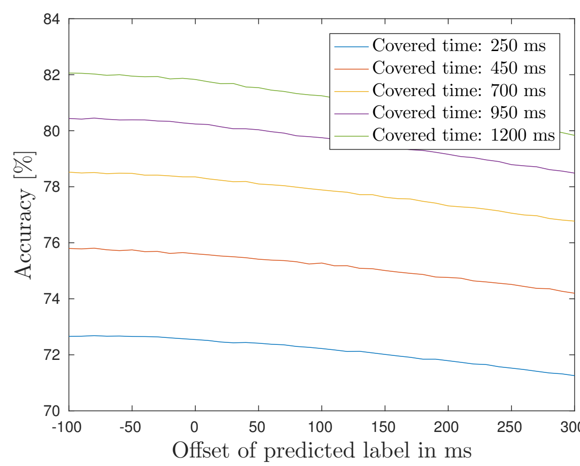

Fig. 3. Early prediction accuracy (%) with different overlapping degree of consecutive windows. The results have been obtained with the number of history windows $H = 5$.

As can be seen from Fig. 2, the prediction accuracy gradually downgrades with the increase of the prediction time offset. This tendency is generalized for all studied values of H as well. This result is expected since the temporal dependency between the current window and the target window becomes weaker with a larger time offset. The reduction of accuracy, however, is not significant. For instance, even with the prediction offset time of 300 ms the prediction accuracies are lower than those of the standard classification only by 1.23%, 1.41%, 1.48%, 1.52%, and 1,57% with $H = \{0, 5, 10, 15, 20\}$, respectively. Practically, given that we have compensated 400 ms for the delay, these small accuracy drops should be accountable since the delay could be more important than the overall accuracy for the outstanding usability of hand prosthetic [12].

On the other hand, positive contribution of the history data can also be seen from Fig. 2 not only for the early prediction but also the standard classification. The evidence is that the accuracy curves are lifted up as long as more history windows are integrated. Average improvements of 0.08%, 0.52%, 1.11%, and 1.70% absolute are obtained for $H = \{5, 10, 15, 20\}$ compared to the case without history ($H = 0$).

In order to investigate the effects of the overlapping degree between consecutive windows, we fixed the number of history windows to $H = 5$ and repeated the experiments with the overlapping degree of 95%, 75%, 50%, 25%, and 0% (corresponding to the covered times of $250, 450, 700, 950, 1200$ ms). The early prediction accuracies obtained with different studied overlapping degrees are shown in Fig. 3. As can be seen, the overlapping degree is inversely proportional to the prediction accuracy as a lower overlapping degree leads to a better performance. More specifically, the average accuracy gains of 3.02%, 5.67%, 7.52%, 9.01% absolute are obtained with 75%, 50%, 25%, and 0% overlap compared to the original setting of 95% overlap. The possible explanations for these results are twofold. First, with less overlapping windows, we are able to cover a larger duration of the signal. As a result, different levels of temporal dependency, i.e. both long-term and short-term, are taken into account to train more reliable predictors. Second, with the same dimensionality of the feature space (5×12 in this case), highly overlapping windows more likely result in strong correlations between the features which is counter-productive for the predictor training. Reduction of overlapping degree in this experiment can be interpreted as a decorrelation procedure which is expected to improve the quality of the predictors at the end. It should be emphasized that this finding is also applied for the standard classification setting (i.e. the prediction time offset of -100 ms). For the sake of comparison, the best classification accuracy obtained with our experiments (i.e. 82.06% with $H = 5$ and 0% window overlap) outruns that reported in [9] (i.e. approximately 73%) by more than 9% absolute.

E. Discussion

In the experiments, we only focused on prediction for a single future window at the offset L from the current window n. However, as the prediction can be done for the window at $n + L$, it should be practically possible to predict contiguous hand movements for the window sequence ranging from $n + 1$ to $n + L - 1$. This prediction sequence can not only be used to prepare the control plan but also to smooth out spurious prediction labels, for example using median filtering. Furthermore, although we have investigated the prediction time offset up to 300 ms, it should be possible to extend it further. However, the prediction accuracy is expected to level off at some time point in the future when the link between the current window and the target one becomes too weak for reliable prediction. These open issues are worth further studying in the future work.

Considering the history, the character of the analysed data is probably important for the choice of history length and overlap of history windows. When the time covered by the history is disproportionately large, the further information causes no increase of the accuracy since there is no substantial dependency between the past and the current movement.

IV. CONCLUSIONS

This paper has presented a preliminary study on the early prediction of sEMG-based hand movements for hand prosthesis, which helps to compensate for time delays induced by the conventional classification approach. The experimental results on the Ninapro database revealed that while early prediction of future hand movements is practical (up to 300 ms) the prediction accuracy is nearly as good as that of the classification task. Furthermore, it was shown to be important to integrate history windows prior to the current one to leverage different degrees of temporal dependencies to further improve prediction performance. An average accuracy gain of up to 9.01% absolute was obtained for the prediction task with 5 additional nonoverlapping history windows.

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