A Study of the Effects of Ageing on the Characteristics of Handwriting and Signatures.

A Thesis Submitted to the University of Kent
For the Degree of Doctor of Philosophy
In Electronic Engineering

By

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May, 2008

Abstract

The work presented in this thesis is focused on the understanding of factors that are unique to the elderly and their use of biometric systems. In particular, an investigation is carried out with a focus on the handwritten signature as the biometric modality of choice. This followed on from an in-depth analysis of various biometric modalities such as voice, fingerprint and face. This analysis aimed at investigating the inclusivity of and the policy guiding the use of biometrics by the elderly.

Knowledge gained from extracted features of the handwritten signatures of the elderly shed more light on and exposed the uniqueness of some of these features in their ability to separate the elderly from the young. Consideration is also given to a comparative analysis of another handwriting task, that of copying text both in cursive and block capitals. It was discovered that there are features that are unique to each task.

Insight into the human perceptual capability in inspecting signatures, in assessing complexity and in judging imitations was gained by analysing responses to practical scenarios that applied human perceptual judgement. Features extracted from a newly created database containing handwritten signatures donated by elderly subjects allowed the possibility of analysing the intra-class variations that exist within the elderly population.

Acknowledgments

As I reach this stage in the pursuit of academic endeavour, I look back at the past three and half years which have been the most challenging ever and appreciate the importance of the most valuable outcome – the PhD. It obviously has been filled with highs and lows but indeed worth every second. It has changed my attitude to research and life in general. There are no quick fixes and answers are never known at the onset, but answers must always come, maybe not the ones you hoped but indeed they must come. Patience is a virtue!!! For this I am indeed indebted to a number of people who have helped make this thesis a reality.

First of all, I express my profound gratitude and appreciation to Prof. M. C. Fairhurst, you most kindly accepted to supervise me, to teach me and to change my life forever. Your expertise is unrivalled and the lessons learned would guide me through life. Your friendly disposition and encouragement when things were looking bad would never be forgotten. I am indeed grateful.

Further, I would like to thank the staff in the department of electronics especially the following members of the Image and Computer Vision Group: Dr. Sanaul Hoque, Dr. Sam Chindaro, Dr. Julia Chapran, Dr. Kostas Sirlantzis, Dr. Richard Guest and Dr. Farzin Deravi, for encouraging conversations and sharing their own experiences which indeed was helpful. To my colleagues, to all the people who participated in my experiments and the Staff and residents of Knowles House, Elderly Care Home, London. Thanks.

I would also like to thank my friends especially Ejike, Ann, Olu, Nazo and the Oti's for encouraging me to pursue my dreams. To my family the most important people in my life. My Parents Chief Dr. and Engr. Mrs Ujam, thanks for your love, for making sure I rise at ungodly hours everyday to study and the continuous encouragement. To my siblings: My twin and closest, Dr Chukwugozie Ujam, Engr Uwa Ujam, Miss Nnenna Ujam, Miss Ebere Ujam and Miss Chisom Ujam thanks for being there for me. My sisters in-law and to my Father in-law (RIP) and Mother in-law thanks.

To my darling Wife, Mrs Nonyelum Ujam your love, support and encouragement has made this a reality and would never be forgotten. Thanks for allowing me embark on this study despite being newly weds. To the most beautiful girls I have ever seen: my daughters Ifunanya and Chetachi thanks for understanding that Daddy also goes to school, I love you all.

Finally and importantly, to the Lord God Almighty: I serve you with all my heart and the favour you have given me I am eternally grateful for.

Chukwuemeka Ujam

May 2008

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- **Promoting Inclusively in Security through Biometrics - State of the Art Report**
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Chapter 1
Introduction and Review

This thesis reports on a study which aims to investigate how an understanding of population characteristics can help to promote and optimise the deployment of biometric systems for person identification or the verification of individual claimed identity. In particular, we are concerned with the variability of relevant characteristics as a function of the age of individual system users and, specifically, with factors which are relevant in understanding the biometrics in relation to the elderly. Although we shall consider some issues which may be seen as generic, and independent of any particular method of obtaining identity information, we will focus particularly on handwriting and the handwritten signature as the biometric modality of interest, especially in relation to the experimental work reported. The reasons for this choice are discussed later.

Here, we therefore set out to explore some fundamental issues that face the ever increasing elderly population with respect to this type of technology. This chapter defines the general framework of our study by first of all introducing the basic concepts underlying biometric technologies, and stresses the importance of the handwritten signature in this context. A detailed examination of the current literature relating to the work investigated is presented and a critical review and analysis carried out. Several concepts are of particular interest in relation to later chapters. These include issues concerning the concept of perceived "complexity" of the handwritten signature, the intra-class variations that exist within samples taken from an elderly population of signers, and the "forgeability" (susceptibility to imitation) of handwritten signatures. Finally, the overall structure of the thesis is shown, emphasising a focus on measures that should be taken to secure, protect and improve the way in which biometric systems can be effectively used by the elderly, especially in the light of their potentially higher vulnerability.

1.1 Biometrics

Biometrics is a term widely used to refer to the personal attributes that uniquely characterize any particular individual. The term biometrics and the attributes are associated with security, identification and verification of a person's identity. Biometrics are usually characterised according to a modality or a combination of modalities. Virtually any measurable biological or behavioural characteristic can be a biometric modality [1]. Some of these include:

- Face
- Fingerprint
- Gait
- Hand Geometry
- Iris
- Signature

They can equally be classified as either

Physiological biometrics or

Behavioural biometrics

The physiological biometrics, which are unique physical characteristics of a person, involve technologies such as the following: fingerprint verification [2], hand geometry verification

[3], iris [4], face [5], ear [6] recognition etc. The behavioural biometrics, which are based on behavioural traits of individuals, are signified by the following: handwritten signature verification [7], speaker verification [8], gait recognition [9], etc.

1.2 A Brief History

Handwritten signatures have been used for centuries as a means of authenticating and recognising an individual.

The use of signatures is recorded in the Talmud (fourth century), complete with security procedures to prevent the alteration of documents after they are signed. The Talmud even describes the use of a form of "signature card" by witnesses to deeds. The practice of authenticating documents by affixing handwritten signatures began to be used within the Roman Empire in the year AD 439, during the rule of Valentinian III. The *subscripto* - a short handwritten sentence at the end of a document stating that the signer "subscribed" to the document - was first used for authenticating wills. The practice of affixing signatures to documents spread rapidly from this initial usage, and the form of signatures (a hand-written representation of one's own name) remained essentially unchanged for over 1,400 years. It is from this Roman usage of signatures that the practice obtained its significance in Western legal tradition. [10]

The use of the signature today in authenticating and verifying identity is varied and wide reaching, with the financial services sector offering perhaps the most obvious and prevalent example of everyday applications. With increasing interest in biometrics as a means of automating the identification process, the signature has been acknowledged as a true biometric modality, and this has given rise to an unprecedented increase in interest in this area.

1.3 Handwritten Signature Verification

Handwritten Signature Verification (the verification of authenticity of a handwritten signature) can be undertaken either by human inspection or by means of an automated process. Automatic handwritten signature verification can be viewed as a pattern recognition problem as well as an image processing task. Fairhurst, [11] introduces and explains these concepts in great detail. In this thesis, emphasis is laid on the verification of handwritten signatures in relation to the elderly, amongst other issues that influence usage of biometric systems by the elderly. The reason for this is that this is where least research effort seems to have been focused, despite the fact that our population is an increasingly ageing one. Additionally, work in the human processing of signatures is scarce despite its widespread use.

Signature verification is generally accepted as a non-intrusive method of biometric identification, in contrast to some other modalities, for example, finger print, face (facial recognition), iris, and voice. The handwritten signature indeed has a number of advantages over other biometrics in that it has long been established as a common means for providing proof of identity, as related to bank transactions, wills, etc. It also has higher acceptability from the public. The other biometric modalities listed are generally perceived to be more intrusive – for example, the fingerprint still carries some criminal connotation.

Generally speaking, handwritten signature verification can be approached in two ways: through a static analysis of the signature images acquired after the signature was written, or through an analysis of the signature data captured dynamically during the signing process. The static (off-line) verification of signatures is generally seen to be weaker than the dynamic (on-line) verification, since the latter evaluates kinematic information, which is well hidden from potential forgers. On the other hand, static signature verification is essential for particular applications where only the image of the signatures is available as in the case of cheque processing or document processing.

Despite this broad classification both approaches pass through typically the same phases and pose the same design problem: Collection/acquisition, pre-processing, feature selection and extraction, classification and performance evaluation.

There is an important distinction between static signature comparisons and dynamic signature verification. Both can be computerised, but a static comparison only takes into account what the signature looks like. Dynamic signature verification takes into account how the signature was executed. With dynamic signature verification it is not the shape or look of the signature that is meaningful; it is the changes in speed, pressure and timing that occur during the act of signing. Only the original signer can recreate the changes in timing and X, Y, and Z (pressure).

It has to be noted from the outset that direct comparison of different research results can be dangerous. We will see that many different techniques have been used in a range of research studies: different types of pre-processing have been applied, features extracted or classification methods used. Moreover, each study makes use of its own algorithmic implementation and database, some of which may include random or simple forgeries while others may use skilled forgeries (definitions of these forgeries are discussed later). Therefore it is obvious that a comparison between the verification performances of different systems is not possible in any meaningful way. For this reason, a report on the attained error rates achieved in different studies will be included here only as an attempt to give the range of attainable performance in the verification of signatures.

We can investigate quantitatively the performance of a signature verification system by testing it with a set of genuine and forged signatures and then obtaining the various error estimations. The construction of a signature database is usually a first requirement and its size and quality are major factors that affect the design and the performance of a system.

Some work carried out by Kalera et al [12] made use of 2 databases one at CEDAR (Centre of Excellence for Document Analysis and Recognition) and a publicly available database at Caltech [13]. Interestingly, not a lot of these publicly held signature databases exist.

It is possible to categorise forgeries in different ways. For example, the works in [14] identifies the following categories -

- Simple: where the forger makes no attempt to simulate or trace a genuine signature as only information about the name of the original author is available to the potential imitator.
- Random: where the forger uses his/her own signature instead of the signature to be tested. Here there is no attempt to any degree to produce an imitation that resembles the original signature image.
- Skilled: where the forger tries and practices imitating as closely as possible the static and dynamic information of a signature.

The performance of a system is usually assessed in terms of the attained error rates. When the error estimations are obtained they are generally referred to [15] as either Type I or Type II.
Type I or false rejection rate (FRR) is the percentage of genuine signatures falsely rejected by the system as attempted forgeries and
Type II or false acceptance rate (FAR) is the percentage of forgeries falsely accepted as genuine. Alternatively, the equal error rate (EER) is often used, which corresponds to the point where the two error curves intersect (see Figure 1.1) and hence, it is defined by an equality of the two types of error. These error estimations are of great significance when validating the various systems.

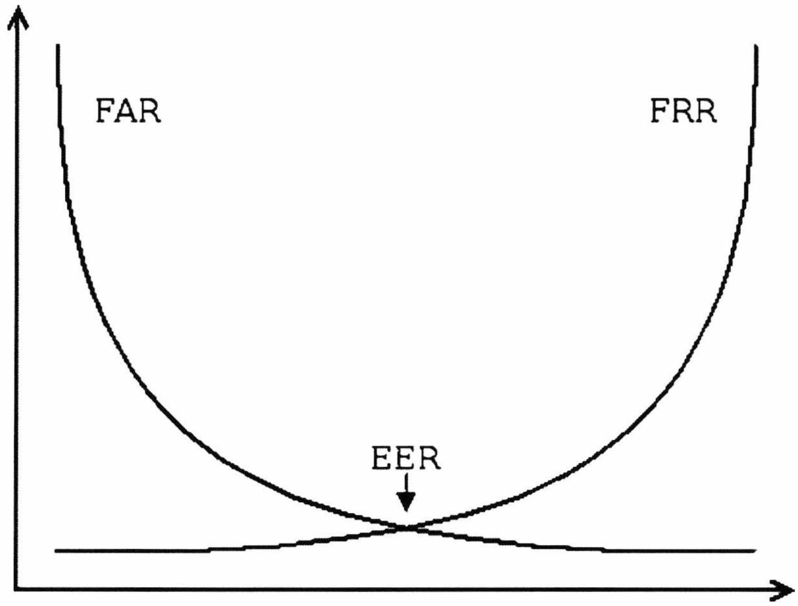


Figure 1.1: Type I/Type II (FRR and FAR) curves and the point of EER.

1.3.1 Static or Off-Line Verification

The static verification of signatures involves an analysis of the 2-D signature image.

Collection/Acquisition

Scanning and camera capture are just a few of the methods used to capture any static signature image in question. Plamondon et al [16] suggest the use of a graphic-tablet digitiser to acquire X, Y coordinate pairs without considering time information thereby simulating an off-line data entry system. Various acquisition devices are available and common ones are the Vidicon tube TV camera, CCD camera and scanners from NUMEDIA and APP-DAVOS.

Pre-processing

This stage involves performing operations on the obtained image. These could include non-uniformity correction for sensor elements, localization of the signature in the picture, extraction of the signature from the background, slicing, thresholding and filtering problems, segmentation and data reduction [16].

The pre-processing stage may involve several or all of the following procedures: separation of the signature from the background, noise reduction, data area cropping, size normalization, thinning /skeletonization, and segmentation of the signature. The precise requirements depend on the signature acquisition method (camera-based acquisition requires binarization and filtering, while an image obtained with a scanner is automatically thresholded [17]), the background pattern (a signature written on a bank cheque would require the extraction of the background as opposed to a signature written on white paper), and the type of features implemented (some particular features may require the segmentation of the signature).

Other techniques proposed in [18] include noise removal, thresholding, line segmentation and character segmentation. Binarization, slant cancellation and background elimination are a few other pre-processing techniques proposed in the literature. Dimauro et al [19] list pre-processing steps as signature localization in the image, signature extraction, width/size normalization, skeletonization and smoothing, though, they also state that this is more time consuming than in the on-line case.

Kalera, Srihari and Xu [12] in their work first converted the pen co-ordinates into the x-y co-ordinate space, followed by interpolation and then making the signature rotation invariant. They then applied the rotation normalization techniques.

In [16], the fact that finding a static image is not difficult is noted, and suggests the use of a window operator. This paper proposes the use of a Laplacian or the Sobel operator to detect borders. Here the threshold is fixed to select pixels above the 85% value in the cumulative Laplacian distribution. In another study Ammar et al [20] propose a four-step operation (background equalization and reduction, noise reduction by averaging, automatic thresholding and image extraction). They found it successful in removing the overlapping in a signature as well as in the signing line, at the cost of eliminating some parts of the signature in about 2% of the samples used.

Signature segmentation is highlighted as a very difficult task in [19]. Since different signatures of one writer can differ from each other by local stretching, compression, omission or additional parts. Having mentioned the above they state that the simplest approach in off-line signature segmentation is based on the identification of connected components by a contour following some algorithm.

In [21] a digitised image (IM) is physically rotated and the image position adjusted using a method based on vertical and horizontal projection profiles. The position adjustment algorithm is as follows.

Step 1: Obtain the vertical profile of IM(x,y) and locate the first horizontal baseline as a reference for both rotation and vertical adjustment.
Step 2: Rotate the image IM(x,y) little by little until the sharpest horizontal reference base line is detected.
Step 3: shift vertically the image IM(x,y) until the reference baseline in IM(x,y) coincides with that in the generated image.
Step 4: Shift horizontally the image IM(x,y) until the maximum match occurs between IM(x,y) and the generated sample image.

Wan et al [22] in their work in a bid to eliminate homogenous background produced in the scanning process, first employed local contrast enhancement and then performed local binarization. Because it is thought that a binarized signature shrinks along the edges, a dilation morphological operator was used to make the stroke wider. Then a bridge operator used to connect the areas that are one pixel apart. The resulting image was then taken as a mask to extract the gray-level signature trace from the scanned image.

Of particular interest is the work carried out by Sabourin et al [23]. Here the authors try to produce a labeled signature image where each pixel from the gray level image has a label specifying whether the pixel at a particular location is a background or a signal picture element. They use the Sobel operator for the gradient evaluation. (Recall that [16] used a Sobel operator also). They justify the use of this operator because of its ability to detect edges localized in low signal-to-noise areas. This computation is carried out on the entire gray-level image and produces a gradient image made up of various planes. The orientation follows the signature line and the resulting orientation serves as a guide in the centroidal region-growing-with-merging process. They further described the background elimination process. Furthermore a two-stage extraction process is carried out. The region-growing-with-merging process followed by the high-level merging process. In the first stage, the process grows the signal pixels into atomic regions characterized by the homogeneity of their gradient vectors. The second stage then is responsible for generating the primitive set that is related to the high level representation of the signature. Finally, Herbst and Coetzer [24] show a Radon transform Continuous model, which consists of projections (shadows) of a given function obtained at different angles.

Feature selection and extraction

The feature extraction procedure for the off-line representation and verification of signatures in the various research studies involves the use of some of the following feature types: global geometric features, local shape features, moment-based features, envelope features, wavelet features, grid features, texture features, etc.

After successfully obtaining a "purer" image or images, the next step is to extract and select unique features that could aid the identification of a particular signature and differentiate it from another. In the static verification process there are three types as proposed in [12], Global, Statistical and Geometrical/Topological. Here Kalera and co. describes global features as those that are extracted from every pixel that lies within a rectangle circumscribing the signature. It is reckoned that these features are easily extractable and insensitive to noise but are dependant on position alignment and are equally highly sensitive to distortion and style variations. The statistical features are those derived from the distribution of pixels of a signature. They include the ratio of signature width to short or long stroke height. They can tolerate minor distortions and style variations because they take into account some topological and dynamic information (pseudo-dynamic). While the Geometrical and Topological features describe the characteristic geometry and topology of a signature, thereby preserving the local and global properties. These features have a high tolerance to distortion and style variations and can tolerate a certain degree of translation and rotation variations. They finally describe a system that combines the three feature types, known as GSC features (Gradient, Structural and Concavity). This system measures the image characteristics at local, intermediate and large scales and then approximates a 'heterogeneous multi-resolution paradigm' to feature extraction. Srinivasan et al [25] also makes use of this GSC in their work.

Dimauro et al [19] state that two features can be used for signature verification: Parameters or Functions. Because dynamic information is not available in the off-line technique, they suggest or propose parameters that can be extracted from the geometric analysis of signatures. These include: signature image area, the signature height and width, the length to width ratio, number of loops, the ratio between the middle zone width and signature width and the number of elements in the signature. Their projection-based features included the number of vertical/horizontal projection peaks and the maximum value of vertical/horizontal projections. Grid based features which is exciting were quoted. This involved the signature image being divided into rectangular regions and the ink distribution in each region evaluated.

Lee et al [21] carried out work on bank cheque digit recognition. However, it is viewed that their feature extraction stage is worth mentioning and has relevance in our handwritten signature verification. They list features as number of central holes, number of right holes, number of left holes, number of intersections with the principal axis, crossing sequences, number of intersections with the secondary axis, relative location of each hole and intersection in the image and the individual digit distinctive features.

Plamondon and Lorette [14], criticise the division of feature extraction methods into text sensitive and text insensitive. They cite the fact that since the number of symbols or characters within a signature specimen is limited and often irrelevant, one cannot apply the division strictly. Also, that since the time information is not available from the signature image, the function approach to feature extraction wasn't a very good distinction for static techniques. They propose that feature selection should be based on the global or local approach. In their study, the global approach highlights the processing of the entire grey level signature image or the binary image. While the local attributes are computed from the same grey level or binary image, but are seen to be more stable. Further mention is made of the fact that most studies dealing with a set of local features also incorporate some global ones. You would see that this is shown in [22]. Here they extracted four groups of features. The pure width, image area, centres of the signature, maximum vertical and horizontal projection, vertical and horizontal projection peaks, local slant angle, number of edge points and number of cross points were listed as global features. Grid coordinates were determined adaptively by dividing pixel projection histograms into successive parts with almost equal pixel counts. This was used to define a group of average grey values in each grid overlapped on the pre-processed image as a local shape characteristic. Another widely used approach to texture analysis is the co-occurrence matrix. Each element in the matrix represents the probability of the combination of grey values at pairs of points separated by a vector. Further measurements are evaluated for each matrix, namely matrix energy, difference matrix energy, difference matrix mean and relevance variance. Guest [26] in his study extracted eight static features: pixel centroid X and Y, number of pixels within loop, loop pixel centroid X and Y, pen travel distance, signature height/width, width/height ratio, vertical centre crossing and invariant moments.

Similar to the work carried out by Kalera et al [12], Madasu, Lovell and Kubik [27], partitioned the pre-processed image into eight portions using the equal horizontal density method. Here the binarized image is scanned horizontally from left to right and then from right to left and the total number of dark pixels is obtained over the entire image. The pixels are then clustered into eight regions such that approximately equal numbers of dark pixels fall in each region. Their idea came from a need to collect the local information held in each box. It evolved from a ring and sector technique, which had the problem of revolving centroid. For each box the angle distribution was obtained and that formed a feature database.

Finally, it is worthy of note that an interesting method—The Arc Pattern Method is proposed in [28]. This work highlights the drawback of applying popular techniques. They explain the non-suitability when trying to extract features from the Japanese handwritten signature.

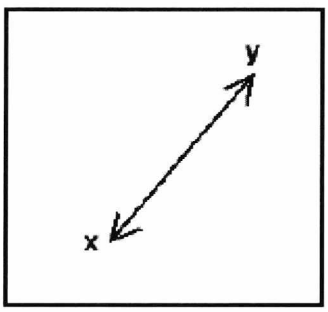
Classification

In an ideal world or environment, one would expect that an author of a signature would be able to accurately replicate it all the time. However several factors make this unattainable. These include age, emotion at time of signing, fatigue, weather, natural muscular pattern changes and other physiological conditions. For these reasons we can safely categorically say that no two signatures are exactly the same even under similar conditions. Furthermore we would also wish that signatures were unique to each individual. We will deal with that issue as it relates to "GOATS"— people or signers with inherently atypically high variability in their signature models in Chapter 5.

Signature verification is therefore represented by a two-class problem, described by the 'genuine' and the 'forgery' class. The aim of classification therefore is to separate the features and hope that the variations between two different signatures (between-class variance) are sufficiently larger than that of the same writer (in-class variance).

In practice, the choice of a classifier is a difficult problem and it is often based on which classifier(s) happen to be available, or best known, to the user. The most popular method used to classify and in other words separate two classes of signatures (Genuine and Forgery) is to measure the distance between a test sample and a known or reference sample. The Euclidean distance measure is generally used to achieve this. Its basic form is given by equation (1), where the x_i of the ith feature of the test sample is compared to the mean y_i of the ith feature computed on the genuine reference set, for a number of n features selected to represent the signature.

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (1)$$



Euclidean

Parker [29] describes an effort to determine whether simple, relatively obvious distances can yield good results. He describes three distance measures, *the temporal distance, the global relative distance and the multiple signature masks.* For the off-line method, one would only consider the global relative distance. Here, he states that "*While any two instances of a signature will differ from each other, they should be nearer to each other in some sense than to instances of different signatures*". His idea is based on finding the distance from one black pixel in one signature to the nearest black pixel in the other. While in [12] their classification technique incorporates the use of the Bayes classifier to form same writer and different writer probability distributions, using the mean and variance to classify a new instance. For the identification model they used the weighted *k*-nearest neighbour classification, which is a refinement to the *k*- nearest neighbour algorithm. In this model the inverse square of a distance from the query signature has a weight attached to it. Dimauro et al [19] propose two different approaches to building knowledge base. The first approach proposed was based on building a single template of a genuine signature; the problem with this being the development of a prototype of genuine signature. The second approach is based on using a set of genuine signatures as a reference. The issue with this was highlighted as the choice of an optimal number of reference signatures and the selection of the optimal set of genuine signatures to be used for reference. They bring up the use of matching techniques or strategies to compare test signature against reference. Multiple regional, regional and holistic matching techniques are proposed and applied.

For [21], two kinds of classifiers were considered and tested for the signature verification. These were the Euclidean distance classifier and the multilayer perceptron. The latter one ventures into the field of neural networks.

In [30] two types of classifiers were used: a *Nearest Neighbour (NN) classifier with vote* and a *minimum distance classifier*. The former allows the evaluation of the discriminant power of a shape factor (signature representation R(γ)): This can be related to a lower limit of the total error rate when all the available information is stored in memory. The latter is a more realistic solution to the verification problem, but requires the evaluation of a comparison threshold $t(i)$ for each writer enrolled in the verification system. Both classifiers and training procedures were fully described with examples. They then implement classifier combination with the notion that the feature vectors have a high dimension; the number of reference signatures already available for training is normally very low (three to six in practice); and the genuine signature shape is characterized by high intra-class variability over time. As we know, the design of a signature verification system based on a single shape factor or a single shape representation is not a trivial task. One solution was to design a class of shape factor and to build an integrated classifier permitting the cooperation of several classifiers. Combining classifiers is not new in the field of pattern recognition and has been investigated by several authors working in the field of character recognition (for example [11],[31] and [22]). Several methods have been proposed and evaluated, but the *voting principle* seems more appropriate for the signature verification problem because one integrated classifier has to be designed for each writer. In character recognition, the design of complex methods for classifier cooperation is justified because only one integrated classifier is required for the implementation of recognition systems. As an example, the implementation of integrated classifiers based on the Bayesian or on Dempster-Shafer theory leads to the proper weighting of individual classifiers and enhances the global reliability of the recognition system. These approaches require a learning procedure for each individual classifier, and a second learning phase for implementing the combining stage of the integrated classifier or for evaluating the performance in generalization of individual classifiers. So, these approaches are intractable in the case of the signature verification problem because the cardinality of the datasets available for training is always small. Here, the K individual classifiers are all of the same type: *NN* or *minimum distance* classifiers based on a transformation $\Psi(.)$ related to the positive pecstrum, the pseudopecstrum or the augmented pseudopecstrum using SE in the set {|, --, /, \}. In the case of integrated classifiers $E(x)$ based on $K = 4$ individual classifiers, a value of $a = 0$ 75 corresponds to the simple majority rule and a value of $a = 10$ states that a decision made by an integrated classifier $E(x)$ requires the unanimity of all individual classifiers.

To conclude this section, according to Srinivasan et al [25], the one class classification tasks answers the question whether or not a given questioned sample belongs to the ensemble of known samples. They employ a two-step strategy i.e.

- Obtaining questioned vs known distribution and
- Comparison of questioned vs known distribution and within class distribution.

This is further buttressed by the excellent review carried out by Jain et al [31] which emphasises that the simplest and the most intuitive approach to classifier design is based on the concept of similarity: patterns that are similar should be assigned to the same class.

Performance Evaluation

It had been stated earlier that due to the non-standardization in handwritten signature verification, a direct comparison of systems is largely to be avoided. However, the works referred to in this review all make mention of their own error rates. They will be highlighted for completeness, but not as a means of preferring one over the other. This is because, as mentioned, various databases, techniques and methods are used.

Plamondon et al [16] obtained and prepared a table of results of error rates of various research groups. They observe that the Type I and Type II errors of the order of a few percent can actually be obtained for systems working with simple and random forgeries. In [20], they introduce the AMT (Ammar Matching Technique).This is based on knowledge drawn from reference signature images, and on AMT, which enables similarity measurement. They report that with this technique they eliminate skilled forgeries with a very low rate of false rejections, with a mean error of 2% using a database of 200 genuine signatures from 20 writers and 200 skilled forgeries from 20 forgers. Also in [16], they report work introducing an algorithm to detect tracing forgeries by suggesting the ink dispersion along the pen tip trace of someone who is forging by tracing is different from that of someone who is signing naturally. They achieve an 85% rejection of forgeries when testing with 120 signatures from 12 subjects and 15 different forgers who produced 7 tracing imitations for the 12 subjects. Looking at the database used in [28], it is indeed interesting to note the results obtained from the static methods applied to the signatures used (which were provided by Japanese participants). This is interesting because of the inherent visual similarities seen in Japanese signatures. Here, they used twenty authentic signatures, ten genuine counter signatures and ten forged signatures (Eight hundred in total). With this they obtained an error rate of 14.13%- they took an average of both Type I and Type II, so precise rates are unknown from the work.

The extensive testing carried out in [23] consisted of 800 signature images, 20 writers each produced 40 genuine specimens. This yielded a Type I error rate of 1.34% and a Type II error rate of 1.34% when tests were carried out using the leave-one-out process. In contrast, the global approach to testing showed a Type I error of 5.36% and a Type II of 1.34%. A discussion is held in [31], that for error estimates to be reliable, the test and training sets should be sufficiently large and should both be independent to which we agree. Therefore, if a classifier has a small training set, the classifier would not be robust and would have low generalization ability. So, if the test is small, then the confidence in the estimated error rate would be low. It is also worth mentioning that the error estimate of a classifier is a random variable. The authors of [25], show a test-bed of 1320 genuine signatures obtained from 55 individuals giving 24 each. They then also obtained 1320 forgeries. Here they use the probability of similarity as the signature verification technique. Test cases with probability > 50% were accepted as genuine and those below as forgeries. Those between 40% and 60% were treated as inconclusive. Here they propose 84% accuracy with a scope to increase to 89%.

The Zernike moments method is introduced in [32] which is based on a set of complex polynomials which form a complete orthogonal set. The performance reported here is 83.6% accuracy and is based on 1320 genuine and 1320 forged signatures.

Lee et al [21], performed three sets of experiments, in the first set of experiments, a database of 550 genuine signatures contributed equally from 5 subjects, 100 simple and 300 skilled forgeries were compiled. On average a 3% equal error rate was achieved by testing only random forgeries. In the case of skilled forgeries a 14.3% equal error rate was observed. In the second set of experiments, using 94 genuine signatures extracted from real bank cheques contributed by 6 subjects, they achieved 7.3% for the Type II errors. In the third set of experiments they investigated a new signature verification approach which employed one-hidden layer perceptron classifier and used the signature stroke orientation feature. A database of 300 genuine signatures acquired from 3 subjects and 180 skilled forgeries were equally divided for the training and testing of the classifier. An equal error rate of 4.7% average was then obtained.

Earlier it was mentioned that Kalera et al [12] carried out work on two databases. Database A consisted of 839 genuine signatures for training and 560 genuine signatures for testing, while for database B 991 genuine signature samples were used for training and 500 genuine samples for testing. For each database they showed a verification result and an identification result. The verification results for database A yielded a (False Acceptance Rate) FAR of 23.18% and a (False Rejection Rate) FRR of 20.62% giving an (Equal Error Rate) EER of 21.90%. Identification results showed an accuracy of 93.18%, when k=3 in the k-nearest neighbour case.

For database B, they show that as FAR decreases with increasing threshold, the FRR increases. A FAR of 34.91% was obtained and FRR of 28.33% achieved. These gave an ERR of 31.62%. In another set, FAR=33.8%, FRR=30.93% and an ERR=32.37% were reported. Identification results were declared as an optimal performance of 93.33% when k=3 and 91.6% at k=4. They finally, decided to compare their results with other offline methods, but because of reasons outlined earlier, it will not be presented here.

Finally, Plamondon et al [18] expresses the view that the tolerance levels for applications in which signature verification is required is smaller than what can be tolerated for handwriting recognition. This is for both Type I and Type II errors. Some systems impose some unrealistic and unattainable requirements. Having said that, they claim that the majority of signature verification systems, work with an error margin of about 2% to 5%, shared between the two errors. It is also acknowledged that the evaluation of signature verification algorithms, as for many pattern recognition problems, raises several difficulties. Moreover, signature verification poses a serious difficulty, which is the problem of Type II error evaluation, or the real risk of accepting forgeries. From a theoretical point of view, it is not possible to measure Type II errors, since there are no means by which to define a good forger and to prove his/her existence, or non existence.

1.3.2 Dynamic or On-line Verification

This area is generally more popular than its static counterpart. On-line verification captures details that are not necessarily visible to the signer. In other words, the on-line case deals with the spatio-temporal representation of the input. Because of this they are generally found to achieve better results than the off-line methods.

Collection/acquisition

Several methods exist to collect dynamic data, such as graphic tablets, which generate electronic signals representative of the signature trace during the writing process. For example, position-velocity, acceleration, pressure and force signals [19]. In [33], Leclerc et al, highlights the importance of the acquisition process. This is because the quality of the signals is critical to optimizing the comparison process. An instrumented pen is introduced which is capable of measuring the angle of the pen and the force exerted on it. They further state that the digitizer is without question the most widely used acquisition device. Gupta and McCabe [34] claim that early dynamic handwritten signature verification was based on using specially instrumented pens since no suitable equipment for capturing signatures was available. This they say has changed in the last several years, as graphics tablets have come into widespread use with tablets that can capture a signature as samples of coordinate pairs. Some also capture pen pressure and pen tilt, 100 to 200 times a second.

A number of capture devices are listed in the market place. They include, SignatureGem, SigLite, ClipGem and ePad-ID. There is even a mention of PDA's and pen based computers. Bell Labs introduced the BioSig in 2002. While the work carried out by Jain et al [35] used a digitized tablet called the IBM CrossPad from the A.T. Cross company. It had a sampling rate of 100-150 samples per second.

Pre-processing

Here it is generally agreed that the pre-processing involved is less expensive then the static counterpart. Kaplani [15] in her work states that this is because the signature data obtained from the digitizing tablet is much less noisy or redundant. Minimal pre-processing is required if the signal is good. This stage is sometimes omitted by many researchers. Smoothing, re-sampling, normalization, extraction of pen-up/pen-down signal, detection of gaps and segmentation were all listed as possible stages here. Lorette [36] defines this process as a term that includes all the algorithms that are carried out on raw data to produce relevant information. It is equally suggested that a lot of pre-processing is handled by software and consists of signal amplifying, filtering, conditioning and digitizing.

Jain et al [35] in their work, say that the output from a digitizing tablet or pen can be jagged because the writer's hand may become unsteady whilst holding the pen. This is due in part to space limitations. To overcome this, smoothing and resizing is done. A commonly used method to smooth the signature is based on a Gaussian filter. Qu et al [37] proposed a dynamic signature verification system. In their system, they re-sampled the dynamic signature signals and normalized to a standard length and missing data points interpolated before being sent to the feature extraction subsystem.

Dimauro et al [19], state that the pre-processing of an on-line signature generally consists of filtering, in order to remove spurious signals from the signature. A normalization procedure is used to standardize the signature in time-duration and size domain. Segmentation based on curvilinear and angular velocity signals of the pen movements during signing is also another technique.

In summary, the literature is not very clear on pre-processing in the dynamic or on-line verification process. It is assumed that near perfect signals are always obtained or imperfections can be ignored. In any case if pre-processing is carried out, it is used to reduce spurious noise. This can be done by filtering/smoothening, normalization, segmentation, pen-up and pen-down detection and slant correction.

Feature Selection and Extraction

The procedure for feature selection and extraction in the on-line/dynamic verification of signatures varies from one system to another. The features include duration, speed, centripetal and tangential acceleration, velocity, pressure, tilt, force and other time related functions. They generally can be divided into Functional or Parametric. In the Functional approach you encounter little or non-existent feature extraction, Signature velocity v(t), Signature accelerations a(t), Actual trajectories x(t), y(t), Pressure p(t) and other time functions. While the Parametric or Summary information, entails complex feature extraction, can be local or global. Global: Total time, Signature path length. Local: Path tangent angles and curvature.

Nelson and Kishon [38] in their study extracted the following features: signature time (T), Length (L), Root-mean-square (rms) measures: rms speed (V), rms centripetal acceleration (Ac), rms tangential acceleration, rms total acceleration (A), rms jerk (J) (jerk being the time derivative of acceleration), average horizontal speed and the integral of centripetal acceleration magnitude.

While Jain et al [35], not only extracted the usual features such as velocity, pen pressure and pen tilt but went ahead to compute local curvature, speed, total writing time, and bounding box or the number of strokes. They expand this by stating that all strokes are combined into one long stroke and computed the absolute speed and relative speed between two critical points. They finally extracted absolute speed, normalized speed, absolute speed between critical points and normalized speed between critical points.

In their work Shafiei and Rabiee [39] assumed that a signature can be described by a left-to-right Hidden Markov Model (HMM) with loop, forward and skip transitions. They state that the probability density function modelling of the HMM is the most important part in order to design the most appropriate models for the verification task. They then chose continuous HMM based on a Gaussian mixture model. Segmentation was carried out and each segment characterized by location of its most significant point in the signature i.e. average velocity, average acceleration, average pressure, pressure variance and two angles of tangent lines to curve of segment in two segment end points.

Dimauro et al [19] propose new parameters such as Fourier-Hadamard and Wavelet transforms. These are coefficients obtained from mathematical transforms. Pippin [40] in his work extracted global features (average pressure, pen tilt, average velocity, number of pen ups and number of strokes). He also performed velocity based stroke segmentation, stroke encoding and performed dynamic time warping.

As an indication of ageing, consideration is given to the work carried out, where Wirotius et al [41] introduced three new global features. They are Fractal dimension, Depth's dimension and Vector's dimension. The Fractal dimension characterises the degree of irregularity of a set. So it could be used to quantify the complexity of a line. The bigger the fractal dimension, the less the line is legible. One of the most interesting properties is that it is invariant by affine transformation. The Depth's dimension characterises the degree of vertical superposition of a curve. The bigger the Depth's dimension, the more the curve is formed with superimposed lines. As in the case of Fractal dimension, this dimension is invariant by translation. Finally, the Vector's dimension is close to the Fractal dimension in Euclidean geometry. Nevertheless, the Vector's dimension, contrary to Fractal dimension, includes the chronological order of the points and so gives a temporal aspect to this dimension.

Qu et al [37], extracted global features such as pen-up time, mean or variance of the x and y displacement signal in a number of sliding windows, number of pen ups and downs, variance of pressure signal in a number of sliding windows, number of sign changes in the x and y velocities and x and y accelerations, number of zero values in the x and y accelerations. They also captured stroke length and stroke duration time.

Attention is also drawn to the studies undertaken in [14, 25, 31, 36] where similar work is carried out.

Classification

We take a look at the various classifiers and the classification methods seen in the literature. Leclerc et al [33], performed a comparative study of three techniques that are widely used: Regional correlation, Elastic matching and Tree matching. Their findings do not show any superiority amongst them. While reading the various works, it becomes obvious that the classification schemes employed here are similar to those of their static counterparts.

Nelson et al [38] show two models for classifying signatures: One from genuine signature data only and the other from genuine and forgery data. In the former model, a feature vector probability distribution is specified. This is to aid the optimal decision rule for signature verification. They assume a Gaussian model. Classification is based on the outcome of a threshold measure. The Mahalanobis distance is chosen to measure dissimilarity. Success here depends on the genuine signatures matching the statistical models more closely than the forgeries. Another model uses a constructed classification rule applying statistical models for signatures and forgeries. Here certain assumptions are made. Firstly, they assume that the same variance standardization is good for both genuine and forged signatures. Then secondly, they assume that once adjusted, the forgeries for different signatures are exchangeable, and have a Gaussian distribution with the same mean and covariance. They state this is chosen purely for convenience sake.

In [14], they identify two parameters: Local and Global. Local parameters: maximal or minimal values of signals features extracted from specific segments like number of peaks, local curvature, starting direction, etc. Global parameters: total time, number of segments or pen lifts, means and standard deviations, number of zero crossings, number of maxima and minima for each segment, area, proportions, etc. These resemble features as dealt with in the previous section, but in this context they aid the classification process outlined here.

Pippin [40] used the *k*-nearest neighbour algorithm to sample the classification of each of the *k*-closest points to the test instance. The majority classification determines the classification of the new instance. He used many different values for *k* and acceptance thresholds. Jain et al [35], state that once features have been extracted, a method must be chosen to compare two signatures. They represent each signature as a string or sequence of feature vectors, whose size is the number of local features extracted. String matching also known as dynamic time warping is a well known method for comparing various strings. From this a threshold is set and then classification is carried out.

In [34] five different classifier approaches, linear discriminant function, Euclidean distance classifier, Dynamic programming matching technique, Synthetic discriminant function and the Majority classifier.

Performance evaluation

As previously stated, direct comparison between systems is highly discouraged. As in the case of static verification, individual work/performance is highlighted and presented. Gupta [34] claimed that any technique using statistical features is unlikely to provide a total error rate of less than 10% if a reasonably large database is used.

Qu [37] in their work had a database of 110 signatures split into 50 reference and 60 test signatures from 10 volunteers. They set a threshold to 75% and achieved an FRR of 30% and an FAR of 46.67%. Under the same experimental conditions, they state that the stroke based features can help the system achieve better FRR and FAR rates than non-stroke based systems. Thus, they suggest that their results show that the stroke based features contain robust dynamic information and offer greater accuracy. Wiritious [41], used an 11 signer database each providing 10 samples. They achieve an EER of 20%.

Shafiei [39] carried out work using HMM. Their database contained 622 genuine signatures and 1010 forgery signatures that were collected from a population of 69 subjects. They achieved an FAR of 4% and an FRR of 12%. They claim these results are because of a small number of signatures used in their training. Pippin [40] in his work, achieved an accuracy of 81% using the k-nearest set in the global filter method. This improved to 91% when *k* changed. An EER of 4% was then obtained. Using local filters, he got a 77% accuracy and an EER of 11%. This was on a database of 180 genuine signatures and 73 skilled forgeries of 10 subjects.

1.4 Aim and Structure of Thesis

This thesis describes research which aims to address some of the identity management issues surrounding the elderly when using biometric systems and technology. It elucidates issues pertaining to their neglect and vulnerability. It seeks to offer a solution to researchers and designers of biometric systems which will enable them to incorporate an awareness of the elderly's needs when developing solutions for them.

To achieve this, the analysis carried out follows an initial examination of handwritten signatures and verification systems. Consideration is given to both automatic and human approaches to examining or inspecting signatures. An in-depth examination of issues that enhance the inclusivity of the elderly is revealed. Following on from this, characteristics of signatures are presented with a bias towards the elderly. A look at the issues that surround complexity and intra-class variability of handwritten signatures of the elderly are also considered.

A brief analysis and description of each chapter in this thesis now follows:

Chapter 1 introduces and sets the scene to this thesis by discussing various biometric systems. An emphasis on the elderly is presented by way of illustrating a context for the research studies available in the field of handwritten signatures with a static and dynamic approach. Various systems found in the studies are critically examined with a view to suggesting better approaches in the implementation thereof. Finally, a look at forging or imitating signatures both by skilled forgers or unskilled forgers is examined with a particular attention to the performance of the elderly at inspecting and identifying such imitations.

Chapter 2 examines the ageing or elderly in the society. It focuses on the inclusivity of the elderly in biometric system use and design. A proposal for secure authentication is put forward after considering various modalities for biometric use. Limits of these biometric technologies are shown and advances are proposed.

Chapter 3 illustrates the data collection and acquisition process and methods utilized to enable the construction of a signature database that contains both forged 'imitated' and genuine signature samples or images. It also serves as the reference point for all the experiment set-up carried out in this piece of work. The various equipment and software used to capture the data was discussed. Additionally, a collection of captured text both in upper and lower case was detailed and the various perceived complexity of signatures with verification scenarios were detailed.

Chapter 4 is engaged with the distinguishing features of the elderly. A look at the dynamic features that quite easily separate the young from the elderly is carried out. The discriminatory features that are unique especially the velocity based features are examined in greater detail. Various experimental studies are initiated and carried out to further capture the unique features that separate the two age groups.

Chapter 5 goes on to examine the stability of those features extracted from the signatures produced by the elderly. It takes a critical look at the intra-class variability of signatures within an elderly population. A look at the intrinsic variability of handwritten signatures is embarked upon from an evaluation point of view.

Chapter 6 provides a view of the perceived complexity of handwritten signatures from both a younger and an elderly subject perspective. An insight into human perception and performance in evaluating and judging forgeries by different age groups is gained. Further experiments are carried out with a view to exposing the link between perception of complexity and forgeability by way of error rates obtained during a verification exercise. Finally, some ideas are developed to express the link between error and complexity.

Chapter 7 concludes the work undertaken and reported in this thesis by providing a summary of the work done, highlighting the contributions made to the field and discusses suggestions for future work.

1.5 Conclusion and Summary

Handwritten signature verification is reviewed in this work. The breakdown of these systems into static and dynamic modes of capture is also presented. The field of Automatic Signature Verification is one in which constant work is being carried out. The survey carried out here serves as an insight into some of the important work in the literature. One cannot overstate the fact that performance results are restricted to per database or per model/system. Obvious applications are readily seen, such as within the financial services sector. Subsequent chapters provide a focus on the handwritten signature as the biometric modality of choice.

Chapter 2 follows the general review carried out in Chapter 1 above and provides a complete focus on the elderly including an in-depth look at the issues surrounding this specific group and their use of biometric systems. It focuses on the important issue of inclusivity of the elderly in relation to their interaction with biometric systems. It sets the scene for the principal theme of this thesis by focusing on this vulnerable ever growing population. Proposals for protecting the elderly are discussed and limitations in usage of the various common biometric devices are highlighted. It also concludes by presenting a detailed discussion of the various biometric modalities and the advantages they offer for adoption by elderly users.

Having extensively reviewed the various literature, we now proceed to Chapter 2 which carries on with the central theme of this thesis by looking at the inclusivity of the elderly. This is appropriate because the number of this segment of the population is ever increasing. Chapter 2 elaborates extensively on the challenges and issues that these people face with regards to biometric use.

Chapter 2

Inclusivity Issues in Relation to the Elderly and Biometrics

2.1 Introduction

As the take-up of biometric systems becomes more widespread, it is increasingly necessary to identify key issues which determine the effectiveness of the deployment of such systems in different population groupings. A user-group often overlooked to date has been the elderly, yet across Europe and, indeed, worldwide we are an ageing population, and there are real benefits to be gained by understanding the needs of elderly people in embracing biometrics technologies. With respect both to social inclusion and human dignity, and in relation to basic arguments about economic activity, it is vital that the pace of technological development in the biometrics field does not disadvantage such an important section of society. The elderly population are characterised not just by their potentially higher spending power in many cases but also their increasing dependence on social services over time, and by their generally greater demand on healthcare systems, increasing vulnerability, declining mobility and levels of physical dexterity. These latter issues are of particular concern on the one hand when considering both the potential for improving quality of life by means of improved identity management but, on the other, by the implications for effective interaction with biometric systems. There are many examples of issues and scenarios which must be addressed if the elderly are to be fully included in the developing e-society. These include:

- The increasing pervasiveness of identification technologies will place an additional burden on the elderly who, at least in the short term, may lack confidence in their ability to cope with computer-based technology.
- Despite some good research, there is still a lack of detailed understanding about how biometric data and biometric templates behave with ageing, specifically within an elderly population.
- Emerging socio-economic policies aim generally to allow the elderly to retain their independence for as long as possible, focussing on home-based care, rather than institutionalisation. This type of policy carries with it greater demands for remotely-accessed healthcare, with a consequent urgent need for reliable remote identification of (predominantly elderly) individuals.
- It generally seems to be implicitly assumed that issues concerning the design of user interfaces for biometric systems, and the way in which information at the system interface is managed and exploited, is largely independent of user age. This may be a misleading assumption, and is an area which needs careful review.
- The current drive towards appropriate biometrics standards carries the need to ensure that system design and questions of interoperability encompass the requirements of all significant user groups, including the elderly.
- The elderly have specific vulnerabilities. For example, there is much evidence of exploitation of older people in relation to signatures, handwriting and document analysis (for example, forging signatures on wills).

In this chapter the focus is on exactly these key issues, which are essential if biometric identification technologies are to be integrated into widespread use. This chapter will assess the technical and non-technical impact of biometric systems adoption in an ageing society, review the current and future position of biometric deployment and summarise usage scenarios of biometrics within an elderly population. Finally we will review the major biometric modalities with respect to physiological changes, practical issues of use within a biometric framework and evidence of trial/system implementation.

The focus of this chapter also is much more than a review of the biometric trends that affect the elderly, and aims to highlight and address the various concerns outlined in [43]. The researchers investigated thoroughly the issues that surround the use of biometrics by an elderly population, suggested policy and development directions which relevant research and policy-making communities might usefully adopt. They also analysed trends and issues which already exist with respect to biometrics within the elderly population.

Specifically, this chapter aims to provide an outline roadmap for appropriate technological research and to identify complementary social policy development issues to ensure the inclusion of all relevant factors relating to an elderly population within biometric system development. In doing so the aim is to present a summary and some ideas to underpin future work on which the research communities might usefully focus.

In order to increase user acceptance, future biometric systems have to be secure and easy to use for each potential user group. Due to the increasing numbers of elderly people in the world, their special needs, caused by ageing and/or illness, must be taken into consideration for both software and hardware, to design new biometric solutions. This chapter deals with technical and non-technical problems and their solutions for an elderly population using biometric systems for mandatory and/or convenience reasons.

2.2 Towards a Social and Technological Partnership

Principally, there seems to be a lack of focus in current work on biometric applications on the needs of the elderly. This rapidly growing section of the general population seems to be neglected in relation to support for and in research to help the design of biometric devices and in developing policies for their deployment. Key issues are highlighted, which must be addressed as a priority if biometric identification technologies are to be fully integrated into widespread use. These issues include the additional burden emerging biometric technologies place on the elderly, the unknown behaviour of biometric templates when formed using data from elderly or ageing participants, the increasing need for reliable remote monitoring of elderly individuals and the need for an examination of the design of user interfaces and requirements capture within an elderly population.

Assessing the trend shown in the proportion of the total population aged 60 years or over, it is clear that Europe is becoming older. By the year 2050 nearly 31% of the population in Europe will be over 60 years old, meaning that by this date the proportion in industrial countries will have approximately doubled compared to the year 2005. An example of the transformation of the age distribution in Germany from the year 2005 to the year 2050 is demonstrated in Figure 2.1. The median age grows from 42.1 years old to 47.4 years old [44]. This is seen by the increase in numbers of people above the age of 74 to 99 years old as shown in the Figure 2.1 (taken from [44]).

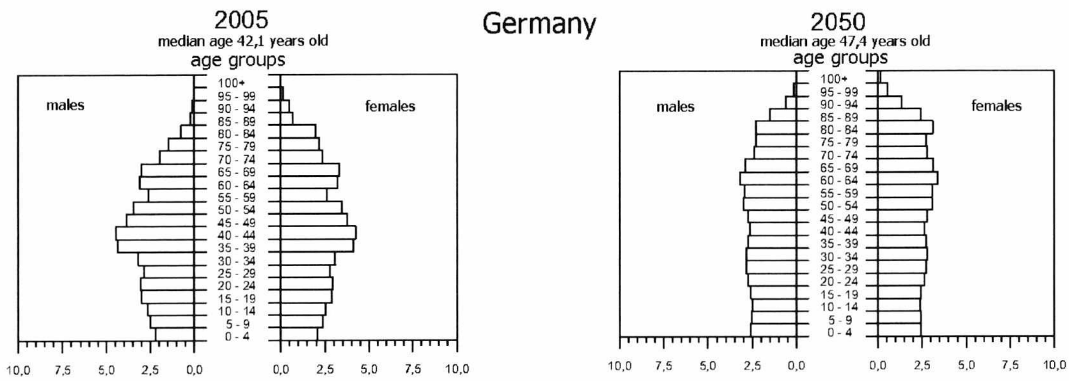


Figure 2.1: Evolution of Age Distribution in Germany from 2005 to 2050 [44]

When looking closely at the handwritten signature or handwriting in general as a biometric of choice for the elderly, we need to consider a number of merits and demerits. The ageing individual is generally associated with an increase in failing health and general frailty. With this fragility, tremor and other deteriorations in motor functions are often observed which in turn affect an individual's handwriting. The advantage of this biometric modality, however, is the fact that in the absence of dementia (which is a condition often associated with the elderly), biometric measurements can often be reproduced quite naturally albeit at a slower pace. These factors have to be considered carefully when dealing with the design of systems which the elderly would naturally use. It is stressed, however, that these factors can also easily be extrapolated to other modalities.

However, claims and counter-claims by proponents of other modalities also abound, often stressing that one particular modality is better than another. It is clear, however, that each has its own peculiar characteristics, and performance profiles will vary considerably with the choice of biometric. The general point to be made is that all biometric modalities (handwriting, face, fingerprint, iris, etc.) are associated with issues which make them increasingly difficult to embed effectively in biometric systems which target use among the elderly. This is more pronounced with failing health and increased ageing.

2.3 Biometrics within an Elderly Population: a Social Context

It is evident that there is an increased worldwide awareness of biometrics for individual identity authentication, and of the development and deployment of biometrics at various levels. The threats and realities of increasing levels of danger in modern society have pushed governments, companies and institutions to embrace the opportunities afforded by biometrics-oriented security solutions. However, the potential benefits cannot be achieved without also facing the inherent difficulties associated with new technologies, and public attitudes of scepticism, cynicism, and general lack of trust are frequently encountered.

Europe is certainly not immune to the problems of being an ageing population [43], and the elderly demand and deserve appropriate attention in this respect. Euractiv in [45] provides a useful source of information about policy issues in the EU relating to biometrics. Here, the focus is on the inclusion of biometric data in travel documents such as passports. Some particularly relevant issues include the fact that from 2005, EU member states have been introducing biometric data into newly-issued passports which include digital facial images and fingerprints. A Committee has been set up of member state representatives to decide on the details of the fingerprinting process [45]. The current technical standard on visas and residence permits is to be amended by the Commission in the light of technical difficulties. EU citizens have been required to have full biometric passports for visa-free entry into the US from 26 October 2006. Because of these visa and passport projects the growth of the biometrics market in recent years has been considerable. In Germany, for example, while, in 2004 the industry had an estimated investment of about €12m, it is predicted to be €370m by year 2009 [46].

There are many individuals and organizations that promote and argue the concept of eHealth. One of such bodies is active in Europe, promoting co-operation between member states with regard to health care delivery. The 'eHealth' concept amongst others, focuses on a key societal challenge, that of better healthcare for an ageing society mirroring activities in the US [47]. In one of their conferences Brenda Wiederhold of the Interactive Media Institute talks of Failsafe Medical Identification through biometric monitoring [48]. Here she looks at the challenges inherent in storing patient medical records in an integrated data network and the substantial problems which can be introduced through human error or deception. It is highlighted that biometric identification technology which incorporates physiometric methods may be useful to ensure that EU Personal Health System procedures reliably identify individuals in order to protect the accuracy of their medical records.

Similarly, in relation to the health care issue, most governments are aware of the implication of the rise in the number of the elderly. A report [49] discusses work commissioned by the UK Government from a health-oriented “Think Tank”, The King's Fund. They found "serious shortcomings" in care provision and funding arrangements and called for investment to treble by 2026. The report predicts that the number of elderly people with high social care needs will increase by more than a half by 2026, that to meet these needs at current service levels investment will need to be raised from £10.1bn to £24bn and for a good but financially justifiable level of person care and safety, investment would have to reach £29.5bn by 2026, representing an increase of 1.3% of GDP to 3%. As a consequence, governments may have to consider tax increases to cover the rising costs of supporting the elderly, of which biometric remote health care delivery is likely to be a part [50].

An interesting result of the ageing profile within Europe is the increase in travel and relocation of the elderly as they join their younger relatives abroad. John Davies in [51] carried out a study focusing on a targeted population –aged 50 years and more Albanian elderly individuals-and noted this trend. The consequence is therefore likely to be an increased health care burden and associated cost on younger relations.

In May 2005, the UK Government re-introduced the Identity Cards Bill with a greater focus on biometric methods. In the same month a trial was carried out by the UK Passport Service (UKPS), where it was noted that the elderly had a 22% failure to enrol rate [52]. This draws attention to a serious issue which will clearly need to be addressed as the programme is ultimately rolled out.

Also in the UK, the London Borough of Newham examined biometrics as a possible technology to regulate home access for elderly residents. Bob Lack, a security specialist working with the Newham Borough in public safety, claims that the majority of end users find biometric technology intimidating, and states "People can get very intimidated by machines recording, analyzing and storing information about their body. They are worried about what will happen when things go wrong."[53].

Again, it is helpful to use a specific exemplar modality to illustrate some important issues in relation to the usefulness and application of biometrics within everyday activities of an elderly person. The handwritten signature is widely used by the elderly in many spheres of life. For example, in health care scenarios: the elderly typically execute their signature to collect drugs and to sign out or confirm attendance of various health workers. The signature is important in relation to access to transactions such as: pensions, affidavits, business agreements, wills, separations, licences, execution of the power of attorney, banking in general (cheques, withdrawals, cards etc), letters, membership cards, certificates, mortgages, general correspondence and post office transactions. This list is by no means exhaustive but does illustrate the many and various scenarios where the elderly use signature-based authorisation and, indeed, where there could be a dispute as to authorship. Because the handwritten signature has been such a part of everyday life for so long, its acceptance by elderly people may be higher than for many other biometric modalities. On the other hand, authentication based on handwriting may not always be as effective in biometrics applications in comparison to using other modalities, for example iris or fingerprint. Here additional research is necessary to establish the practical operational characteristics of different modalities in respect of elderly users and, where necessary, to increase the authentication performance.

2.4 An Ageing Population

In this section we examine both the technical and non-technical implications of an increasingly ageing society. In particular we assess issues of mobility, health and finance and establish attitudes towards and expectations of technology and, specifically, biometric systems in the context of an elderly population.

2.4.1 Non Technical Implications of an Ageing Population

Assessing current trends within population demographics across the EU, it is apparent that over the next 50 years, the average age of the population of Europe will increase. Figure 2.2 shows, for each member state, the percentage of adults over the age of 65 compared with those aged between 15 and 64. It can be noted that in 2005, across the 25 EU states, on average 23% of the adult population were aged over 65. This is predicted to rise to over 50% by 2050 [54]. All EU states have experienced an increase in life expectancy, gaining on average 3.4 years at age 65 between 1970 and 1989 [55]. The average life expectancy in the EU25 (The 25 EU member states at that time) in 2004 was 81.2 years for women and 75.1 years for men.

Clearly this has major implications in terms of governmental spending provision in areas such as welfare, pensions and healthcare (on average EU states spend 0.4% of GDP on healthcare provision for the over 65s – a figure that is rapidly rising). Given this increasing ageing population, there are certain characteristics and trends within this population that must be assessed. Figure 2.3 shows the interaction between major societal elements concerning the elderly. It is apparent that security plays a central role within daily activities of the elderly.

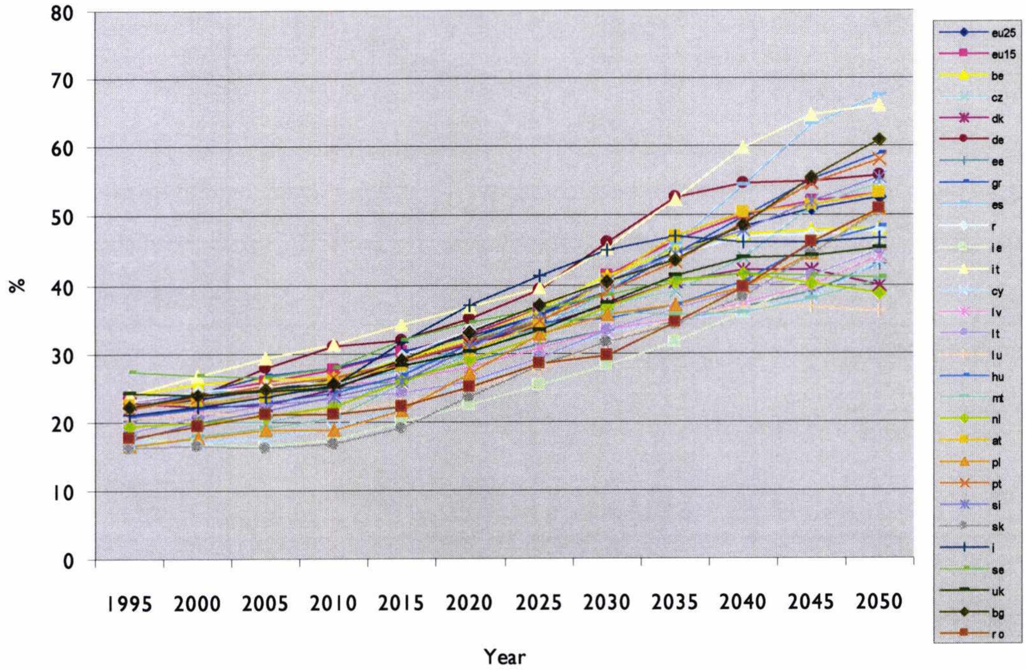


Figure 2.2: % of adults over the age of 65 in EU member states [43]

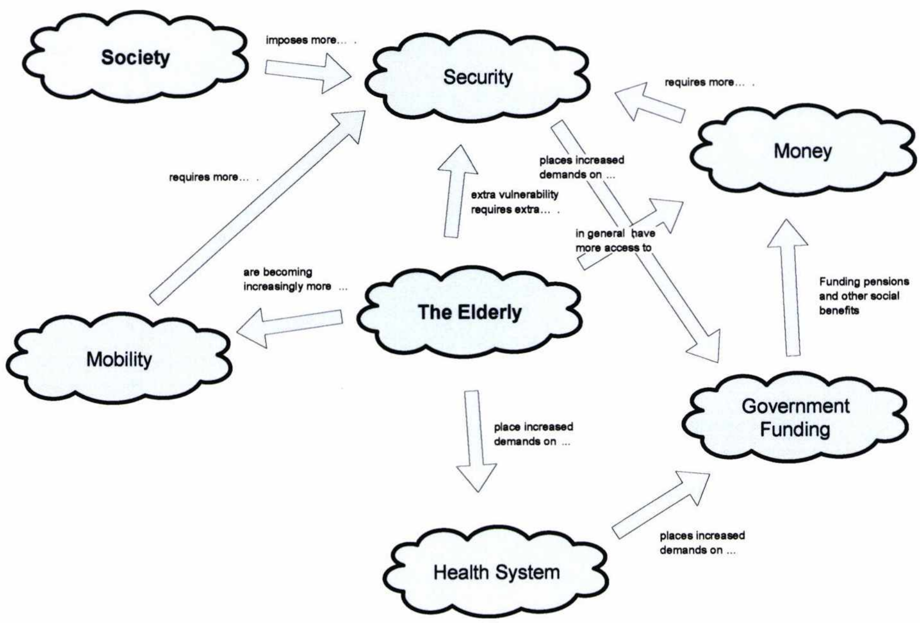


Figure 2.3: Societal Element Interactions [43]

Coughlin [56] highlights that the baby boomers of the 1940's are now the same individuals that are swelling the elderly population. He highlights the challenges that they present and face, such as increased demand on social welfare systems, suggesting the need for policies to take care of this ageing population and tasking governments on welfare. The future elderly population are predicted to be wealthier, healthier and more educated than their counterparts in the past.

2.4.2 Issues at the Technological and Social Interface

It has been highlighted [43] that there is a serious and urgent need to design systems which explicitly take into consideration the special needs of the elderly. Also, an understanding of the relevant technologies used by the elderly must be sought in relation to the possible adoption of biometric tools.

The key issues identified were as follows:

- Lack of relevant policies to protect the elderly
- Non appreciation and lack of understanding of biometrics by the elderly
- Absence of effective design strategies which are targeted solely to cater for the elderly
- A need to match each modality with its corresponding unique impact on the elderly i.e. understanding that the various modalities present differing problems
- Need for appropriate "education" and support for the elderly in this area

It is known that with regard to the use of biometric systems by the elderly, a number of unique challenges naturally occur. For example:

- Dealing with the natural resistance or assumed inability of the elderly to learn new things.

- Development of ageing aware templates and devices such that during use the elderly are not frustrated due to the inability of the system to accurately identify or verify them.

Thus, the conception of future biometric systems should take into consideration that the elderly may not want to interact with an additional technical system if they do not fully understand its function and/or operation. Biometric systems which can be entirely transparent (i.e. not directly have any influence on normal behaviour) to older people could increase their acceptance. For example, camera- based biometric systems working with only minimal interaction of the user (or preferably without any active interaction), could be an interesting alternative to systems which need additional effort and/or explicit supervision. Biometric modalities which can use camera-based capture include iris, face or even handwriting, as demonstrated in [57]. On the other hand, potential users should be fully aware of the issues surrounding biometric data acquisition and should be offered flexibility and choice where possible.

Cost is seen as a major factor, and from the reports generally available, it appears that on every occasion a biometrics system rollout takes place an associated increase in cost is seen. This is indeed surprising and reveals the fact that there seems to be a lack of success in pre-assigning a cost to any major biometric implementation. Although some of the figures reported are still a contentious subject of discussion and are often hotly disputed, the general point is still relevant. A discussion in [58] describes an example where the UK Government previously calculated the cost of introducing ID cards to be between £1.3 and £3.1 billion. However, other estimates have now increased to £5.5 billion with critics fearing it could rise higher still. Some experts claim that biometric technologies were "a lot less mature" than manufacturers would like to suggest. Test reports [59] can be found which point to a diverse range of difficulties of varying degrees of severity.

Because most biometric systems are generally trialed on a small population, there can be a significant difficulty when deploying them across a larger group. Also, because of self-evident template update issues the non-habitual elderly user of any biometric system poses a particular problem. Of course, the naturally slower pace at which the elderly tend to function raises further specific issues, as the various steps from enrolment to verification in a biometric system can consequently take considerably longer on average. Factors such as poor eyesight, arthritic hands, and deteriorating memory can all contribute to this process.

More generally, security, legal, privacy, health and safety, best and common practice and standardisation issues are just a few of the many areas where particular problems need to be addressed.

2.4.3 Towards a Roadmap for Social Development

Border crossing systems seem to be the focus of various government-led projects in applying biometrics policy. The issues surrounding this application need to be investigated thoroughly and system usage monitored adequately. Fairhurst et al [43], in fact, addressed the current trends and reported various trials and results and, indeed, made a number of recommendations. These recommendations include the inclusion of elderly aware protocols that cater for the elderly and the adoption of systems that recognize this age group especially as they are seen to be much more mobile within the European boarders.

The UK government estimates that more than 4 million disabled people will encounter problems when using biometric techniques [60], of which a large proportion includes the elderly. This creates a degree of social exclusion that is very contentious. The fact that the elderly know that they may be excluded may serve as a deterrent and create a feeling of reluctance to ever use any biometric system. Similarly, various religious groups have identified concerns over the use of biometrics. Predominantly, religious institutions that oppose the use of biometrics refer to it as the 'mark of the beast' as written in the Christian Bible [61], and this suggests that governments would be well advised to engage various religious bodies in discussions in this area.

There are also privacy concerns relating to the elderly that need to be addressed. The elderly and indeed everyone using a biometric system needs to be shown evidence that their concerns are being addressed and that no misuse of data will occur [62]. Notwithstanding reservations such as these, there appears to be a gradually increasing acceptance of biometrics in general [61].

Governments need to reassure elderly users (and the wider public in general) in relation to issues surrounding the hygiene, health risk and medical concerns that sometimes arise, in order to aid user acceptance.

There seems to be a greater focus on biometrics by government agencies but the age imbalance needs to be addressed. They need to encourage private sector bodies to adopt and embrace biometrics policies with a greater emphasis on the elderly. In some areas government-initiated trials have suggested that the biometrics of ethnic-minority, elderly and disabled people have a higher chance of being incorrectly matched against their true identity. Similarly, individuals with certain physiological problems have been said to experience issues with inaccurate identification [63].

As it is known that in the next 10 years there will be a rapid increase in the number of elderly subjects, governments need to address the role and choice of any biometric modality.

The above discussion suggests some general principles which might be used to guide future policy making in relation to biometrics and the elderly. They are as follows:

1. Design and widespread use of a secure universal database of elderly biometric features and profiles.
2. Create laws that back the inclusion of the elderly.
3. Increase the education of the elderly as to the merits of biometric technologies.

4. Introduce measures which encourage businesses to ensure a large portion of the elderly community are catered for in designs of new systems e.g. capture devices for the elderly.
5. Develop strategies to minimise the increasing prevalence of identity theft in the elderly.
6. EU should emulate the US model of elderly inclusion within the policy decision making process.

2.4.4 Towards a Roadmap for Technological Development.

In this section we consider some important technical issues for the future surrounding biometrics and link these to some considerations for the wider research community.

There are clearly significant contributions that the research community can make which may influence policy direction and focus, therefore leading to the establishment of a much more inclusive culture when considering biometric solutions. It is known that government and academia often work in isolation, but we can seek to foster greater cooperation between the two and enable parallel and directed plans which can greatly enhance quality of life for a section of the community which is increasing both in size and influence. This can be achieved by ensuring regular workshops are held that involve both government and academia with an aim to exchange ideas and set policy direction together.

There is already evidence in various EU member states (for example, the UK, Germany, and Netherlands) that there are still many recognised technical issues that need to be addressed before a successful policy for future development of biometrics can be claimed. A Dutch study [64] describes and highlights - as an example - the concerns these countries have faced solely from the roll-out of biometric passports. There has also been some apparent relaxation in the US on its rules on the Visa-Waiver programme because of the predominant technical issues. Enrolment and usability issues topped the list of technical problems encountered by the elderly. The issues emerged as they were faced with the need to press their fingers harder and longer when trying to enrol into a fingerprint recognition system. In fact, it is even reported that the Irish Government shelved plans to deploy biometric passports for similar reasons.

Another major issue can be seen in the area of standards for biometrics as it attempts to ensure vendor compatibility. This is a problem which is currently receiving much attention and where significant progress continues to be made [61]

Research carried out by the International Biometrics Group (IBG) [65], showed that in many fingerprint recognition devices, 20% of the users were wrongly identified. This was brought about by exchanging an individual's finger used for capture. The research community has to carry out more work in guarding against such incidents. Studies have also shown that 30.4% of genuine users were rejected because the system could not handle slight variations such as cuts and bruises to the finger. System ease-of-use can also be a problem. The study showed that up to 20 percent of elderly people were unable to use one of the tested biometric devices.

Thus, we can suggest a number of areas which might usefully be addressed by the research community in this area:

1. Align and agree research methodologies when exploring a particular biometric modality.
2. Grant universal access to and create a secure academic database of signatures and other templates which various academic communities would contribute to and have a moderator in charge.
3. Work in the area of standards needs to continue as rapidly as possible.
4. Ensure a proper focus on template ageing with particular reference to the characteristics of elderly users.
5. Create and encourage much more collaborative effort amongst the various research communities.
6. Enable the adoption of standardisation of enrolment procedures.

7. Ensure the commonality of features, databases, error/performance rates when designing and using biometric systems.
8. Encourage adequate data protection.
9. Design special user interfaces for different age groups.
10. Establish consultation channels with particular sub-population representation groups.

A number of specific solutions are now examined in more detail:

2.5 Attitudes, Technological Concerns and Expectations

The ageing population present a series of issues in terms of mobility and wellbeing balanced against disability coupled with technological apprehension. This, in turn, presents a new challenge to the design and implementation of technological solutions. Elderly people will eventually become a significant part of a customer base for existing, as well as, future products. Designers need to be able to implement future tools and products that older people will find both practical and easy to use. This section looks at a series of recent studies that have examined the attitudes and expectations of an elderly population towards technology and in particular biometric implementations.

The Codeworks Accessible Technology Lab [66] has conducted a project to find out how to design technologies to fit the capabilities of older people. They found that only subsets of the changes that occur with ageing undermine engagement with technology. Detrimental factors include deterioration in visual acuity and contrast sensitivity, a decline in cognitive performance, specifically memory and attention, and those activities which involve fine motor control. They also recommended that appropriately designed technology that can facilitate daily life through the maintenance of independence, social relationships, health and ability is given priority in a needs-analysis. Mobile phones, e-mail and the internet can be seen as facilitators to maintaining communication and receiving up to date information regarding health and finances.

The elderly have a tendency to find it hard remembering or, as it were, reacting to or implementing new instructions at a fast pace. They are usually slower at performing general tasks and are equally slow to pick up new skills. The elderly are used to and often prefer human assistance to using self-service terminals but this can be overcome with suitable user interfaces and appropriate training. Many elderly people use gadgets such as the telephone or video cassette recorder even though they may not be familiar with all of its facilities [67].

Renaud [68] proposes a technique for matching the risk levels of a web site to the security rating of an authentication mechanism and presents an authentication mechanism that is tailored to the needs of elderly users for protecting sites with a low risk rating. As is suggested, the web can be a valuable resource for the aged but the elderly user can often encounter difficulties either due to diminished vision or general frailty. This work, however, focuses on the security aspects which have an unlimited application and help to the elderly.

Table 2.1 summarises the areas/scenarios where technology will be used by the elderly population for identity management and security.

Application Area	**Examples**
Travel	Border Control, Passport, Driving Licence, National Identity
Banking	Pension, Social Security/Welfare, Banking Account Access/Payment
Healthcare	Health Records, Prescription.

Table 2.1: Security and Identity Scenarios

2.5.1 Biometrics

Biometric technology is entering a much more mature phase in its development. However, there is still apparently a limited amount of information available when it comes to dealing with the elderly. In the next few years, biometric systems will be more widely used by the general public for applications such as passports. For some people, biometric systems are likely to be much easier to use than the conventional identification systems, but it is important that significant sections of the community are not unnecessarily excluded from using such systems.

Qazi [69] carried out a survey of biometric authentication systems and in his review highlights the advantages and disadvantages of the various biometric modalities but is silent on the specific issue of the elderly, which is seemingly the case with most work reported in the literature.

Medically, we know that as age increases one's vision deteriorates. For instance, in a sixty year old, only about one third of the light reaches the retina compared to when they were twenty. Also a reduction in one's ability to focus appropriately whether far or near, resulting in a reduction in the speed of adapting to changes in illumination, becomes more apparent. In addition to visual problems, many older people have a combination of impairments (cognitive impairments such as dementia, physical impairments such as arthritis and Parkinson's disease etc). Also multi-tasking becomes less easy. The resultant effect of all these problems is that the elderly may have problems in using a biometric terminal at the same speed as their younger counterparts [70]. This speed issue is one example of where the biometric devices need to be adapted to cater for the elderly. As elaborated on in Chapter 4 we see that this can also have an impact on intra-class variability.

Biometric identity verification systems usually exhibit higher failure rates with the very old [71]. As people get older, ageing processes tend to degrade biometric characteristics. For instance, the ridges of fingerprints wear down and cataracts are more prevalent.

The UK Passport Service (UKPS) Biometrics Enrolment Trial set out to test the processes and record customer experience and attitudes during the capturing and verification of facial, iris and fingerprint biometrics, rather than test or develop the biometric technology itself. One of the three sample groups recruited included a disabled participant sample comprising of 750 individuals. According to the UKPS [72], the trial results highlighted several issues that require further investigation. Among other issues, further trials are needed to specifically target those disabled groups that have experienced enrolment difficulties due to environment design, biometric device design, or to specific group problems - for example, black participants and participants aged over 59 had lower iris enrolment success rates. This is down to a combination of factors- apprehension, lack of inclusion of this group in pre-design trials, etc.

Gill [70] emphasises issues relating to the visual capacity of the elderly, building on the observation that there is increasing interest in systems which help confirm a person's identity. Others have observed that the elderly are more open to biometric technology than many would suspect because they prefer not having to remember a PIN number and want to take extra steps to protect their finances [73]. Other studies have assessed the impact of biometrics on society including the elderly [74] within the EU. Given the increasing number of elderly people in the EU a major finding is that the costs incurred by re-enrolment or updating passports could be considerable.

From a legal perspective, Roethenbaugh [75] stresses that the use of biometrics is, so far, permitted by law and that most democracies have incorporated laws to prevent abuses of privilege. This generally safeguards ordinary citizens from unreasonable activities by governments, businesses and other organizations. It has also been noted that there have been a number of instances in the US where individuals have used the law to challenge the introduction of biometrics. In each case the use of the biometric system was upheld.

Until the implementation of a biometric system goes beyond the boundaries of fundamental human rights, it is likely that the law will generally find in favour of biometric implementers and vendors. However, a number of legal and policy concerns must be addressed to help guarantee public acceptance of biometrics; in particular the security of the biometric system, the biometric data and the rights of access to the system. As biometric applications diversify, more areas of legal challenge may become apparent. Preventing unauthorized disclosures about the biometric system itself is the first step to resist any such challenge.

2.6 Biometrics Deployment Overview: Identification Technologies – Global Position

In this section, potential areas for adoption by elderly people of biometric systems are discussed. These can be divided broadly into *mandatory applications* and *convenience applications*. Mandatory applications are, for example, border control systems using biometric ID documents and other (often Government-initiated) biometric security solutions, which cannot be avoided by a customer. Convenience applications are systems which may make daily life more comfortable, convenient or safe for the user, but where he or she has the choice whether or not to use it.

2.6.1 The Current Position

On 13 December 2004 the council of the European Union decided to use machine-readable biometric data of the owner in the passports of the member states [76]. Thus, citizens of many countries will consequently be obliged to possess and use such documents of identification. Under this legislation the elderly, therefore, cannot refuse the use of biometric systems if the documents use biometric characteristics. In Table 3.2 the dates of first issuing biometric passports of some European countries are presented.

Country	Date
Austria	June 2006
Denmark	August 2006
Finland	August 2006
France	April 2006
Germany	November 2005
Greece	August 2006
Iceland	May 2006
Lithuania	August 2006
Netherlands	August 2006
Poland	August 2006
Portugal	July 2006
Slovenia	August 2006
Sweden	October 2005

Table 2.2: First-time Dates of Issuing Biometric Passports [43]

2.7 General Biometric Usage Issues

In this section we examine the general requirements for the use of biometric systems within an elderly population. Specifically we address issues of user interface design and usage scenarios.

2.7.1 User Interface Issues

The requirements of elderly people are not often explicitly considered in the design of computer systems and software, and as a result older people can often find them difficult to use. Human-computer interface (HCI) issues span across various disciplines related to computer science and are also an important aspect of general biometric system usage. In this section we consider some HCI and biometric design requirements related to the usability of systems in both a general and an elderly population, in order to be able to develop some design recommendations for the future.

The Scottish Higher Education Funding Council (SHEFC) has funded the UTOPIA (Usable Technology for Older People: Inclusive and Appropriate [77]) project to research the relationship between older people and technology in three ways:

- Developing a methodological approach to design for older people.
- Exploring relevant application areas.
- Influencing industry to recognize the issues involved in designing for older people and the necessity to do so.

In developing systems sympathetic to the needs of an elderly population it is important to utilise effective methodologies which incorporate the views, opinions and experiences of this population in all stages of the design. Therefore the essential parts of the methodology of the UTOPIA project are:

- Building a diverse user-base,
- Forming a long-lasting partnership with older people and
- Developing approaches for effective interaction with this target user group.

In [78] a methodology is described to interact with elderly people intended to facilitate the development of improved system design. Some of the difficulties encountered when working with an elderly population are described and the concept of 'mutual inspiration' is introduced. The concept of 'mutual inspiration' is deduced from interaction between software developers and designers and can be applied to the interaction between technology developers and elderly subjects. This concept stems from design and feedback where the target user of a system is actively involved in its design. Mutual inspiration can provide a way to make interactions with elderly subjects more effective and could lead towards a more active involvement in the development process and therefore more innovative (and useful) results. Between researchers/developers and elderly people there often exists a cultural and experiential gap - many elderly people have little exposure to certain technologies (e.g. computers) and may not appreciate the possibilities of new technologies, being accustomed to traditional/conventional methods of task execution. Over the last few decades enormous changes have taken place in development of technologies, and therefore participants and developers may have very different experiences. This can make communication between the researcher and user difficult. In addition, words may have different meanings for different age groups, and technical terms (e.g. words 'monitor' and 'windows') can be very confusing for an elderly population.

Eisma et al. describe in [79] how the elderly can be included most effectively in the development process. Techniques were suggested for eliciting information from the target user group and strategies developed for involving older users throughout the development process. One important point is the recruitment of potential users. An appropriate group of elderly people ensure diversity in aspects such as demographics (age, gender, and class), experience with technology or inclusion of specific groups (individuals who have specific difficulties, for example mobility or speech problems). To get a diverse and representative sample one should include people from many different backgrounds, with various life experiences and people living in their own home or in care homes.

Eliciting information from older people is particularly difficult because many different aspects have to be considered. Challenges can be caused by decreasing abilities in sight, hearing and short term memory. Age-related cognitive deficits can make self reporting inaccurate (for example, in a standard questionnaire) and older people tend to tire more quickly. Specially designed formats can be used for interaction between a researcher/developer and elderly subjects: specially adapted questionnaires can be used to obtain quantitative or qualitative data using multiple choice or open ended questions with space for remarks. In focus groups the participants must be encouraged to value their own opinions, express themselves honestly, and enjoy their experience. In workshops, participants must be able to examine and experience new technology. Interviews can also be utilised, especially for older people who are disabled or frail and spend more time in their homes. An application of this is actually reported in Chapter 6.

Goodman et al. [80] carried out an interview and questionnaire survey containing questions about computer use and ownership of older people. More than 350 persons who were over the age of 50 took part in this survey. In the report the authors point out that many older people have problems with computers which are caused by software applications and complicated documentation. User documentation and other support material may use incomprehensible terms which do not really help the elderly user.

2.7.2 Usage Scenarios and Applications

In [81] a study of public perception of biometric devices revealed that there is a growing acceptance of these devices in our society which, while not total, was nevertheless encouraging in the present context. Use of these devices in a variety of locations ranging from schools to hospitals and many other organizations, is highlighted in this study. Various modalities are explored, from the fingerprint to the iris and then to remote monitoring/tracking of individuals. This work further suggests that an organization that uses biometrics instead of passwords would reduce the number of calls to a help desk, thereby generating a cost saving of up to $100 (USD) per call to a traditional help desk. They compare this to the actual cost of the biometric device itself and show that a cost-based analysis indicates the potential value of the uptake of biometrics. With the potential financial benefits and other benefits that these biometric devices offer individuals and organizations, they predicted a growth in the industry from $93.4 million in 2001 to $4 billion in 2007 a figure yet to be determined if met because of prevailing economic conditions.

Despite this huge financial involvement, it is reported that the general acceptance is still slow. Reasons cited for hesitancy to use biometric devices include lack of confidence in the reliability, difficulties integrating with other systems, and getting people to change their work patterns. However, the most often cited obstacle is user apprehension [82, 83]. Therefore, in order to gain public confidence and acceptability of biometric devices the various concerns raised need to be identified and addressed.

The changing demographics in the EU have made it imperative that biometric solutions and applications for the elderly are seriously pursued. A few scenarios are highlighted below (see [84-86] for details):

Pensions: In the EU, the pension scheme is a highly regulated activity. Current legislation in countries such as the UK [87] applies to schemes where the scheme itself underwrites liability to cover against biometric risk.

Passports: The forced renewal of passports from non-biometric types which are held mostly by the elderly.

Healthcare: A method of understanding the health technology needs of the ageing population is described in [88]. Here a list of selected various technologies that were accepted by the elderly is mentioned. These include traditional tele-monitors with peripheral biometric attachments, videophones, in-home messaging devices, instamatic cameras, and personal computers with internet connectivity. Such systems are also highlighted in [89, 90]. Interestingly, it was noted that when it came to younger patients they preferred to have their health needs met by simpler, 'non-computer' devices.

With these systems a valuable resource - time - is saved when it comes to emergencies. Questions need not be asked as the patients' data is already on file and can be retrieved from anywhere securely by any of the medical personnel that needs to attend to an elderly patient. Many medical systems are built to cater for this ever increasing need of the elderly. Camarinha-Matos et al [91] address this issue by proposing a virtual elderly support community. Here biometric solutions are employed to offer greater security and to implement safer user identification. They implement a TeleCARE project which integrates their infrastructure with traditional home appliances such as televisions.

Banking: Recent applications in this area include the ability to withdraw cash from cash dispensers (ATMs) using fingerprints and also secure verification of identity using electronic signatures.

2.8 Specific Biometric Modality Issues

Each biometric modality presents a unique set of issues when used within an elderly population. In this section we outline the major modalities in terms of issues of use, implementation and then research physiological effects due to ageing and evidence of biometric trials using these modalities within an elderly population.

2.8.1 Face

Facial recognition systems extract key points within an image of a person's face and directly map these against a reference template. Capture is through the use of a standard video camera and is therefore non-invasive.

2.8.1.1 Physiological Effects of Ageing

The face is one of the first human physiological features in which ageing is readily apparent. Various studies [92-94] have assessed the physiological effects of facial ageing. In younger years there is a high association with changes in the cranium's shape. Growth is non linear – rates of growth within different regions of the face are non-linear across different races and genders. The biggest changes are seen in infancy up to age 7 and at adolescence with full facial maturity reached at age 13. In the older years wrinkles and other skin defects become more pronounced.

Many attempts have been made to model ageing within facial images for use in forensic and other applications. Berg et al [95] tried to simulate facial ageing by using flaccidity deformation criteria. Ricanek et al [96] undertook a study of the effect of normal adult ageing on standard PCA face recognition accuracy rates. In this study they state the well-known concern that the issue of face ageing has not been explicitly explored in research on Facial Recognition (FR) systems. In their work, they address the impact of age-progression which includes both structural and texture changes and assess performance issues using the Facial Recognition Technology (FERET) database [97]. Their work examines why the Principal Component Analysis (PCA) FR system, and possibly other appearance based FR systems, has diminished recognition rates.

A different approach is examined in both [98, 99] where the authors try to simulate facial ageing to produce improved recognition results. As highlighted in this work the process of facial ageing is such that the appearance of an individual is greatly changed. This change has a bearing on the accuracy of biometric systems. Results show that recognition rates are improved by considering external factors such as the lifestyle of the individuals. If age normalization is carried out before the training and classification of the images, recognition rates are seen to improve.

A brief survey of results obtained from various face recognition algorithms is presented by Barrett [100], where two general approaches to the problem of automated face recognition are described and their effectiveness and robustness with respect to several possible applications discussed.

Finally, [101, 102] present various ageing techniques that cater for facial ageing. The reported work considers skin texture and presents a database of longitudinal facial images that span more than 20 years. Additionally, characteristics of the face are exploited. Face recognition and face modelling are amongst the areas of facial ageing that are investigated. An assessment of the impact which ageing has on various recognition systems is observed and the error rates recorded including age, gender and race.

The ageing of the face is still a challenge amongst researchers today because the various changes that occur to the face happen differently to different people, for instance various races have different facial bone structures, as also do the different genders.

2.8.1.2 Biometrics Trial Review

There have been many biometric trials carried out using facial images. Two age groups ("young" and "old") were investigated by Givens [103]. The analysis was performed on the FERET database using principal component-based face recognition algorithms. They observed that older persons are recognized better than younger persons, using the hypothesis that the face becomes increasingly characteristic with increasing age, and therefore easier to recognize automatically (with the implication that younger children ought to look more alike than older children). Their findings are further confirmed by [104, 105] where tests were carried out on adults aged 18 and above. A total of 37,437 individuals and 121,589 images were collected. The aim was to observe the effect of gender, age and time delay on recognition. They found that males were easier to recognise than females and that for every ten year increase in age a resultant increase of 5% was seen in performance. It also showed a 74% average identification rate for people aged 38-42 while a 62% average identification rate for ages 18-22 was seen. A slightly different average performance rate was seen in [106] where a 2-3% increase is noted for every ten year increase in age. However, the same general findings are observed with regard to ease of identification with respect to age.

The UK Passport Service carried out a biometrics enrolment trial with more than 10,000 participants. They observed a 99.85% success rate of enrolment with 96.5% succeeding at a first attempt. Rates were different between races and age, with a decrease in success with an increase in age observed. It was concluded that face verification is less likely to succeed where participants are aged 60 years and over [107].

A similar trial was carried out in the Netherlands [108]. Here, 14,700 people and 14,504 biometric documents were registered. It is noted that the trial participants were relatively old, compared to the age structure of the Dutch population. A 97.7% verification rate was achieved. They noted that, as might be expected, the over-60's took longer to record their biometric data. Also it took longer to verify individuals that were at the extreme age brackets of the elderly and the younger.

2.8.1.3 Template Ageing and Update Issues

There is general agreement that the greater the time elapsed between enrolment and verification, the higher the error rates. Work reported in [109-111] shows various trials conducted and, irrespective of the reference set or number of people involved, the results confirmed this finding. Studies reported in [104, 105, 107] involved 1199 individuals who were photographed over a two year period. This study found that photographs that were taken more than two years apart significantly reduced recognition. The authors report a 50% reduction in error rates.

2.9 Speaker Recognition

Speaker recognition uses features within an individual's speech to identify a person. Features may relate to the pattern of speech or the anatomical individuality of a speaker. Data is generally captured using a conventional microphone.

2.9.1 Physiological Effects of Ageing

At a basic level there are naturally observed differences in younger and older voices including obvious gender-related issues. A loss of elasticity of tissue and weakening of muscles are reasons for age-related changes and these are manifest through voice change in terms of pitch, stability of voice and audibility [112-115].

The study reported in [116] highlights a relationship between the natural ageing of the body, illness and vocal changes. A sample of 48 men representing three chronological age groupings (25–35, 45–55 and 65–75) and two levels of physical condition (good and poor) were used. A frequency analysis program was used to measure mean fundamental frequency, jitter, shimmer and phonation range from samples of connected speech and sustained vowel production. The two 'illness' groups produced significantly different results. Subjects in good physical condition produced maximum duration vowel phonation with significantly less jitter and shimmer and had larger phonation ranges than did subjects of similar chronological ages who were in poor physical condition.

Changes in vocal amplitude characteristics were studied from sustained vowel production in healthy adult women in [117]. The authors wanted to establish beyond doubt if there were any changes in the production of speech that exist and occur as an individual ages. Sixty female volunteers were grouped in 10 six age groups of 20-, 30-, 40-, 50-, 60-, and 70-year-olds. Their findings provided some interesting information. Amongst the measures used (peak, alternating, and minimum glottal airflow) no significant variation was seen for any of these variables when comparing the ages of 20 to 70. However significant variability change occurs when the below 20 year olds were compared to the 70 year olds. The implication of the authors' findings is such that it is likely that in healthy females, vocal changes are not significant. They state that either the assumed anatomical changes produce less significant phonatory change in the healthy individual or the healthy individual is more capable of using strategies to counteract degenerative laryngeal changes.

A pilot study reported in [118] aimed to:

(i) Make accurate measurements of age-related changes in female speakers' vocal tract configurations with acoustic reflection technique (ART);
(ii) Obtain acoustic information of vowel formant frequency changes as a function of ageing; and

(iii) Test the hypothesis that there are age-related vocal tract dimensional changes and concomitant decreases in all the vowel formant frequencies as people age.

These findings seem consistent with the rest of the literature considered in this thesis; – the authors study does show that we should consider changes in vocal output as people age as being a significant interest. Generally, as people age their vocal capabilities change and as such are significant.

2.9.2 Biometrics Trial Review

Lloyds Bank in conjunction with Nortel Networks and Nuance has trialed a voice recognition system that identifies its customers, reduces fraud and aids customer satisfaction across a wide range of customer interaction tasks. The results showed an increase in overall customer satisfaction alongside considerable cost savings to the bank in terms of staff overheads at their major call centres and a reduction in fraud [119].

2.9.3 Template Ageing and Update Issues

The reliability of voice systems is seen to decrease as one ages [120, 121]. The significant variations in one's vocal output from younger ages to the elderly are seen as a significant deterrent to a better system. As is shown also, some systems cannot cope with differences in gender voices. So the operation of such voice systems must take into account these naturally occurring variations, for example puberty and variations due to ill health, either temporary or permanent (due to cough, cold or accident).

2.10 Fingerprint

There are a variety of fingerprint matching pattern based algorithms used for biometric purposes but most rely on the assessment of ridge patterns from finger images. Traditionally, fingerprint samples are collected using an ink pad and paper. However, modern biometric systems use technologies such as imaging, capacitance and thermal sensing. Fingerprints have a long history especially within the forensic profession (due to their stability and uniqueness) but to some this may bring connotations of criminality to their adoption within routine biometric identification applications.

2.10.1 Physiological Effects of Ageing

The fingerprint generally stabilises within the first year of life, maintaining its structure throughout a person's lifetime [122, 123]. Deformation issues can arise through wear (usually a function of a person's occupation) and illness/wounds. In the latter case, if the wound is not too deep papillary lines will reform.

2.10.2 Biometrics Trial Review

The BioFinger project [122] set out to investigate the ageing of fingerprints with regard to their characteristics. The project examined the influence of the ageing process on the performance of a biometric recognition algorithm. Data was provided by the German Federal Office of Criminal Investigation (BKA) and examination was carried out with all fingers images except those from the small finger. Investigations showed that results were affected by the choice of assessment components and sensors. It was seen that the best sensor achieved an error rate that was ten times lower than the worst one while the optical sensors operating with the method of frustrated internal reflection achieved the best results. The results did not indicate clearly whether any age group shows a significant degradation of the values compared to other age groups. The low number of fingerprints tested per person, which were taken at time intervals of 10, 20, and 30 years, is the reason for the limited number of comparisons in these examinations. The results did not indicate clearly whether any age group shows a significant degradation and therefore no reliable conclusions were reached.

Image quality does produce differences within age groups [124, 125]. Using two different devices, specifically capacitance and optical fingerprint sensors, it has been observed that age has an effect on image quality of each index finger, regardless of device used. This was tested on two population age groups: the elderly (62+) and a younger (18-25 years) group. A possible reason for this is the ability of an elderly person to use the device accurately and with stability. Issues of user interface as mentioned in [124] may affect performance.

Fingerprint usability trials have been carried out in the UK, The Netherlands and Germany [94, 107, 111]. In [94] a finger scanner was used to capture two fingerprints (left and right index finger), and the fingerprint quality was assessed in relation to the participant's age. The quality of the fingerprints recorded was analysed using the NIST Fingerprint Image Software 2 (NFIS2) and a 5 category rating used from 1(excellent) to 5(poor). A 96.8% success in acquisition of two fingerprints was seen. In 1.3% one fingerprint was successfully taken while in 1.9% of the cases it was impossible to take a fingerprint. One or two fingerprints were successfully verified in 97% of the participants.

Fingerprint quality in relation to the participant's age was assessed finding that the quality of the fingerprints diminishes with age. Also in the over 65's the probability of fingerprint quality being higher than 3 on the NIST scale steadily increases, and therefore the probability of verification failure is reasonably high. Further tests were carried out to find out whether it was possible to obtain record biometric identifiers from children under 14. In 161 children, it was observed that it is virtually impossible to obtain fingerprints from children aged 3 or 4. Where it was possible to obtain one fingerprint from children aged 3 or 4 this was generally of the thumb (larger surface area than the other fingers). This was due to the fact that the skin of the finger is locally very soft (children who suck their thumbs a lot usually have the skin of the finger very soft) and the fingers are often moist. Likewise, when the baby has a strong fist, this can make it very difficult to open.

2.10.3 Template Ageing and Update Issues

In [122] template ageing was noted as an influencing factor in the fingerprint biometric performance. The wider the time frame between enrolment and verification the worse the FRR, which doubles if the time period reaches ten years. Analysis of template ageing performance according to age groups was carried out in relation to degradation of the FRR. It was found that it degrades equally in all age groups.

2.11 Signature

Since the signature has been used for authentication purposes in the social and juristic spheres for centuries, handwriting is an intuitive modality for authentication. Handwriting biometrics can be divided in dynamic methods and static methods. The static approaches are only based on the result of a completed writing process, while dynamic methods use time dependent signals of the entire writing process. In general some of these signals are:

- Pen position,
- Pen tip pressure and
- Pen orientation angles (azimuth and altitude).

The rest have been fully reviewed in Chapter 1.

In general the dynamic modality of handwriting is associated with signature verification in the context of biometric user authentication systems. Vielhauer [126] shows that additional types of handwriting samples (e.g. pass phrase, personal identification number) may be used for this purpose too. The author calls these kinds of alternative handwriting samples semantics. Sensors for dynamic handwriting acquisition can be Tablet PCs, PDAs or graphical tablets.

2.11.1 Physiological Effects of Ageing

The individualization of handwriting starts remarkable early [127]. Differences in handwriting have already developed by the first year of school. Changes in handwriting continue to diversify throughout childhood and teenage years until consolidation in the mid-twenties. Throughout adulthood, writing styles change to a lesser extent. However once old age reached, muscular and cognitive deterioration is seen to have a large effect on an individual's writing style, possibly exacerbated through illness or injury (for example arthritis and Parkinson's disease) or visual impairments.

Parkinson's disease is a chronic, progressive neurodegenerative movement disorder with characteristic primary symptoms of tremors, rigidity, slow movement, difficulties in balancing and walking. Since writing is based on complicated fine motor manipulations it can be a difficult task for Parkinson patients [128]. For these individuals it is typical that the first letters of a word or signature are written in "normal" size, but with the further writing process they become smaller and smaller. Together with trembling the writing becomes then illegible and not repeatable.

Fogarol reports in [129], from the forensic document examination perspective, on the change of the handwriting of old and ill humans. The handwriting of elderly or ill persons can be similar to each other, since similarly disturbances are involved at their creation: hesitations, tremors, slowing down and fragmentation. This leads to a consequent simplification of the letter shapes and inter-letter connections.

There are many problems relating to the comparability of different studies of biometric systems. The first is the problem of different test environments. Almost every evaluation scenario uses its own database including different user groups, size of test sets, sensors, algorithms and so on. Another problem is the analysis and presentation of the test results, which can adopt different performance indicators which make direct comparisons difficult.

2.11.2 Biometrics Trial Review

A number of studies have investigated handwriting/drawing performance in elderly subjects using both *on-line* and *off-line* performance features. The authors in [130, 131] investigated the ageing effects of on-line handwriting and drawing, finding that there were differences in normal writing production with younger subjects writing with higher velocity and with more fluidity in their writing process (less changes in pen velocity). Other studies [132] have supported these findings in relation to target location and shape drawing respectively.

In the context of using signatures as a biometric, it is important to assess if these reported variations amongst a population affect the performance of a biometric system. As biometric systems rely on accurately matching a template and a test (donated) signature it is also important to establish if variations occur between both multiple samples and multiple signature sessions for an individual as a function of age. In designing a system any differences in standard features values across a range of ages should be accounted for.

2.11.3 Template Ageing and Update Issues

In [126] Vielhauer and Croce Ferri present a method to monitor the ageing process of the biometric handwriting features used. The approach allows updating obsolete data, without the usual unnecessary cost and time effort spent on the conventional update of the entire database. According to the presented protocol it can be determined whether a failed verification is caused by manipulation of data or by ageing. In the case of ageing, a re-enrolment of the user is suggested by the protocol.

2.12 Iris

Iris recognition is based on images of the human eye where patterns of texture, striations and so on in the iris are used for recognition. The iris is the colored area that surrounds the pupil and controls the light dependent contractions. Iris patterns are unique and are obtained by using a video or image based acquisition system (usually small, high-quality cameras to capture a black and white high-resolution photograph of the iris). This biometric characteristic remains stable over a lifetime and is independent of different environments such as the weather or occupational differences. Liveliness detection as is present in other modalities (e.g. the fingerprint) is possible by observing iris contractions or eye movements.

2.12.1 Physiological Effects of Ageing

The iris pattern and colour is formed before birth and does not naturally change over the course of a lifetime [133]. That means the iris pattern is stable with age. The general structure of the iris is genetically determined with certain parts of the iris (e.g. the vasculature) largely in place at birth. Other areas (e.g. the musculature) mature around two years of age. The healthy iris varies little with age, but the pigmentation patterning continues until adolescence.

Various diseases of the eye can drastically alter the appearance of the iris, but most diseases only alter the pigmentation and not the iris pattern [133]. For recognition the iris is analysed in greyscale and, for that reason, the change of pigmentation is not important.

Park and Lee in [134] raise the issue that eyelids, eyebrows and glint can cause performance deterioration within an iris recognition system. The characteristics of these parts of the face can vary with increasing age or by cosmetic changes.

2.12.2 Biometric Trial Review

The authors in [107] report on a biometric enrolment trial carried out by the UK Passport Service. The study has focused on testing the use of biometrics (face, iris, and fingerprint) through a simulation of an application process, inclusion of exceptional cases (e.g. difficulties in enrolment), measurement of process time, assessment of customer perceptions and reactions and evaluation of identification using fingerprint and iris biometrics and/or verification using facial, iris and fingerprint biometrics. Their enrolment and verification tests were carried out using a Panasonic BM-ET 300 iris camera.

Three sample groups were recruited: The first group contained 2,000 persons representative of the national population; the second group (7,266 subjects) was a sample with mixed demographic factors. The third group of 750 persons comprised disabled participants. During the iris trial, a reduction of the enrolment success rate with increasing participant age could be observed. Persons aged up to 60 had higher enrolment success rates than persons that were aged over 60.

Assessing the verification success rates, test subjects aged 55 or over were less likely to verify successfully than people aged less than 55. Based on the sample groups it is possible to conclude that the verification success rate for the first group (app. 98%) and for second group (app. 96.5%) were significantly higher than that for the group of disabled participants (91%). The average duration of the verification process was found to be 58 seconds for first group, 59 seconds for second group and 78 seconds for the third (disabled) group. The study also highlights problems through wearing glasses caused by different strength of lens, reflected light and vari-focal and bi-focal lenses.

The BioP II study [111] deals also with biometric systems based on face, fingerprint and iris. The goals here were the comparison of recognition performance, usability and acceptance, system security and the possibility of storing data on an (Radio Frequency token) RF token- data updates/storage by RF. Altogether, 2081 persons were enrolled and 2025 persons gave demographic data such as gender, age or educational background. For the iris recognition process the report points out that the recognition performance of persons with an age under 20 and over 50 is lower than the recognition performance of the people of the in-between age groups. In addition, the authors of the study identified that a higher proportion of the test subjects over 50 wear glasses, which leads to reflections during the capturing phase. Other difficulties that were observed were problems of an elderly population coping with the 'user interface' of the system.

In [135], Daugman points out some problems of today's iris recognition systems. The user has to bring the head into the right position in front of the camera and has to be optically on-axis (i.e. looking at the camera) and he or she has to "stop and stare". The author proposes possibilities to make the iris capturing process more intuitive, natural and fluid, such as: motion-compensated imaging and faster strobe times, use of multi-mega pixel cameras to compensate changing distances, provision of clearer feedback to users to help them present a quality image, the development of better methods to avoid reflections from cornea or glasses.

2.12.3 Template Ageing and Update Issues

As stated in Section 2.12.1, from the current point of view there are known restrictions caused by ageing or illness which affect the iris recognition. On the other hand, specific illnesses of the eyes should be investigated to assess performance levels within biometric systems.

2.13 Conclusion

This chapter has examined many issues concerning the use of biometrics within an elderly population. It is evident that these finding are of significant importance as instances of biometric technology deployment increases allied to the evidence that the proportion of elderly citizens within the EU is also increasing. Given that biometric technology is being mandated for many national security and identity projects, the applicability of the technology within an elderly population must be balanced against the specific needs of this population group.

It is clear that each of the major biometric technologies have their own advantages and disadvantages for use within an elderly population, many related to the physiological changes that naturally occur, others to the usability issues of the sensors and capture technology.

It is encouraging to note that the needs, opinions and performance of the elderly have been considered within many of the recent biometric system trials. What is interesting is that these trials have identified performance issues which need further research in order to ensure universal access within national systems.

In addressing the needs of an elderly population using biometric systems, this chapter has presented an outline roadmap of possible directions for research in the social and technological domains. It has served as a means to highlight the challenges that exist in the use and acceptance of biometrics amongst the ever growing 'ageing' population and has raised various issues that need to be addressed as a matter of urgency. Policy and strategic directions are suggested and the integration of biometrics research carried out by academic and governmental bodies is strongly encouraged.

The focus and direction of this research has been geared towards assessing the problems encountered by the elderly in embracing biometric technology, the pitfalls apparent in the roll-out of such technologies and the need to look at this issue both from a social and a technical perspective.

To this end future work should address the concerns raised in here and future research planning should seek ways to realise the aspirations noted here. In the next chapter, Chapter 3, the procedure used in collection and the formation of a signature database is explained. The data collected forms the basis and source of the input data for experiments to be carried out in subsequent chapters.

As we have looked at the technical and social challenges that the elderly face when embracing biometrics, we seek to demonstrate our argument with the data collected as an exemplar of the kind of practical issues that can be found when dealing with the elderly. Firstly, in Chapter 3 the mechanisms for acquiring data are introduced. This data collected serves as a rich source of information and is invaluable during the experimental process of understanding reaction and factors that affect the elderly. Results seen will help serve as an input when considering the various recommendations that we have made to aid the inclusivity of the elderly in biometrics.

Chapter 3

Experimental Infrastructure and Data Collection

The methods used to collect and construct the database of handwritten signatures used in the experiments we will report is described in this Chapter. The data collection exercise was carried out using human subjects. These participants provided all the signatures acquired for the experimentation, both the genuine samples and the imitated samples constituting “forgeries”. The collection method used a digitising tablet for the capture of the signature data and therefore allowed the extraction of both static and dynamic features of the signature samples. The procedures adopted will be documented in the following sections.

3.1 Introduction

Acquisition of handwritten signatures can be performed broadly either by online or offline methods. Typical offline methods include camera capture, scanning, tracing and copying. These methods ultimately provide a static or 2D image as an outcome. The static versus dynamic data has been discussed in Chapter 1. Conversely, online methods include digital tablet capture, digital pen capture and some hybrid methods such as the ones used in [136] where the subjects were asked to sign over a piece of marked paper placed over a tablet. The literature [36] shows that the use of data input devices date back to the 1970's. These input devices include instrumented pens and digitising tablets.

Currently, systems have moved further in the development process. Nowadays, we are met with systems that are highly sensitive, user friendly, highly accurate and error tolerant. In relation to errors, it has been shown (see, for example, [137]) that digitisers are typically prone to introduce a number of inherent errors. These errors are classified as:

a) Intrinsic Errors
b) Spatial Errors and
c) Temporal Errors

These refer respectively to, change in pen tilt, inaccurate firmware processing, position coordinates and sampling or non-simultaneous sampling. The spatial errors relate to errors caused by issues with position coordinates whilst the temporal errors relate to irregularities in the sampling period.

Digitiser technology has since developed further, providing higher accuracy, reliability, and user-friendly interfaces. It also introduces the measurement of parameters in addition to the standard x- and y – coordinates, with high sensitivity in the pen-tip pressure captured, and other characteristics such as pen altitude, azimuth, etc. A great number of parameters can be further extracted from the ones directly captured by the tablet, such as the pen-tip velocity, acceleration. The digital tablet used employed latest digitiser technology therefore the errors mentioned above were redundant and subsequently were not observed. The only errors observed were user errors due to the mistyping of file names which were easily corrected.

3.2 Data Acquisition

The data obtained in this study consist of genuine and forged (imitated) handwritten signature samples, and other samples of (non-signature) handwritten text. These data were collected dynamically by a digitising tablet, a bespoke pen and a computer. These elements are described in the following sections.

3.2.1 Digitising Tablet

The tablet used was a WACOM ArtPad Intuos II tablet (Model: KT-0405-R) used in conjunction with a WACOM UltraPen Ink (Model: UP-401), a 3 axes force sensitive pen with either blue or black ink.

Figure3.1: Example of Digitising tablet and Pen in use.

The specifications of the tablet used are as follows:

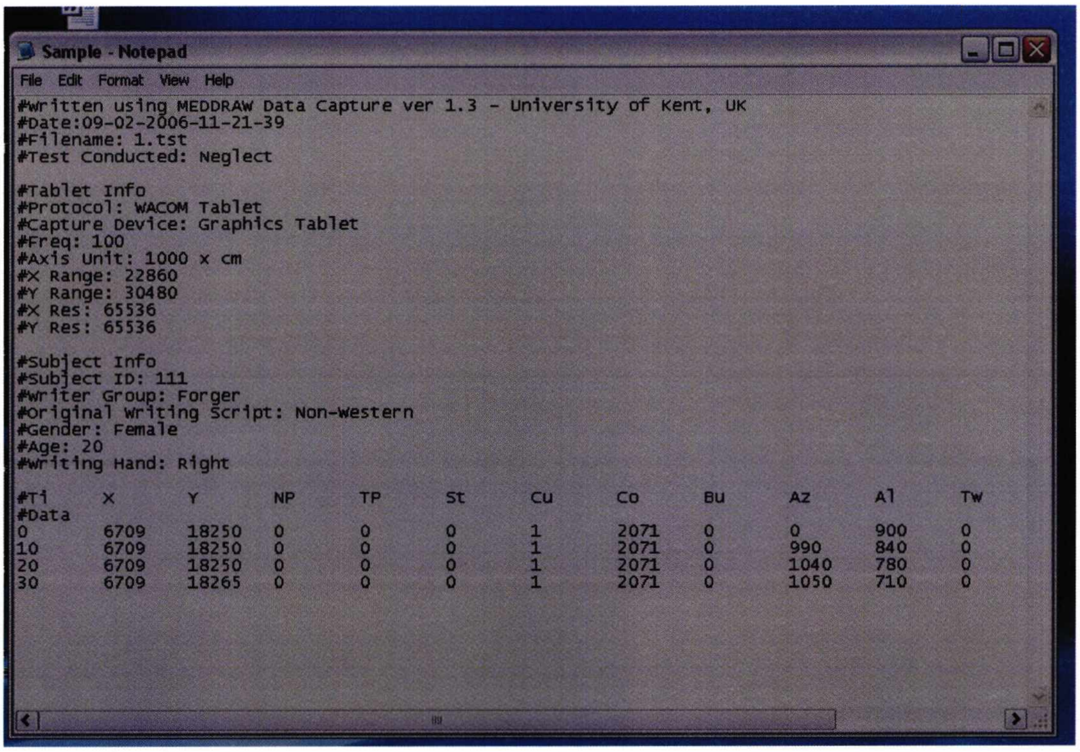
- Area of capture: (128X96) mm
- Resolution: 2540 lpi
- Overall Accuracy +/- 0.5mm
- Pressure levels: 256 levels
- Maximum reading height: 5mm or less (This refers to the maximum height at which writing movements above the tablet would be recorded)
- Maximum report rate: 205 points per second (The number of simultaneous recorded points)

- Origin position: upper left

These devices were connected to the serial port of an Intel® Pentium® 4 CPU 3.00 GHz computer which had 512 MB of RAM. Its operating system was Microsoft Windows XP Professional Version 2002 Service Pack 2. Communication between the Pen and the tablet is achieved through the use of electro-magnetic (Radio) waves. The tablet transmits an electromagnetic signal to the pen, which in turn modifies it and sends it back to the tablet for position and pressure analysis. A grid of wires below the tablet's screen alternates approximately every 20 micro-seconds to accommodate the transmission and reception of the information. The tablet sends the information to the computer via its serial port.

3.2.2 Format

Figure 3.1 shows a sample raw (unprocessed) signature file. The program used to capture the data was written using in-house data capture software developed in the Department of Electronics at the University of Kent. This software has been used in past projects and shown to be useful and robust.



Sample - Notepad

File Edit Format View Help

```
#Written using MEDDRAW Data Capture ver 1.3 - University of Kent, UK
#Date:09-02-2006-11-21-39
#Filename: 1.tst
#Test Conducted: Neglect

#Tablet Info
#Protocol: WACOM Tablet
#Capture Device: Graphics Tablet
#Freq: 100
#Axis Unit: 1000 x cm
#X Range: 22860
#Y Range: 30480
#X Res: 65536
#Y Res: 65536

#Subject Info
#Subject ID: 111
#Writer Group: Forger
#Original Writing Script: Non-Western
#Gender: Female
#Age: 20
#Writing Hand: Right

#Ti     X       Y       NP    TP    St    Cu    Co      BU    AZ      Al    Tw
#Data
0       6709    18250   0     0     0     1     2071    0     0       900   0
10      6709    18250   0     0     0     1     2071    0     990     840   0
20      6709    18250   0     0     0     1     2071    0     1040    780   0
30      6709    18265   0     0     0     1     2071    0     1050    710   0
```

Figure 3.2: Sample Signature File

As illustrated in the Figure 3.2 the software captures the x-coordinate, y-coordinate, Azimuth (AZ), Pressure and Altitude (Al) amongst other parameters. The file is written and time-stamped for each new entry. This therefore makes the entry sequential and reporting, calculation and analysis are all made easier. This is because one just has to subtract the values on one line from the preceding or succeeding line to obtain a Delta (Difference) value. The time stamp recorded specifies the system time at which an event occurs. Note that the maximum sampling frequency of the tablet is 205Hz, which equates to a sampling interval of 4.878msec (max). Furthermore, the position coordinates that the tablet captures is in 1000 x cm, the pressure ranges from 0 to 256 levels and the resolution of the x and y directions is set at a constant value.

This file can be reconstructed in a digitised format using the format and variables defined by the capture software. Both figure 3.3a and b show the reconstruction of the file originally shown in Figure 3.2. The first figure shows the dots that represent pen position that it is filled and rotated in this case as an example of the processes that take place when capturing the signatures. The rotation happens only when other pre-processing takes place. Here it is just an illustration.

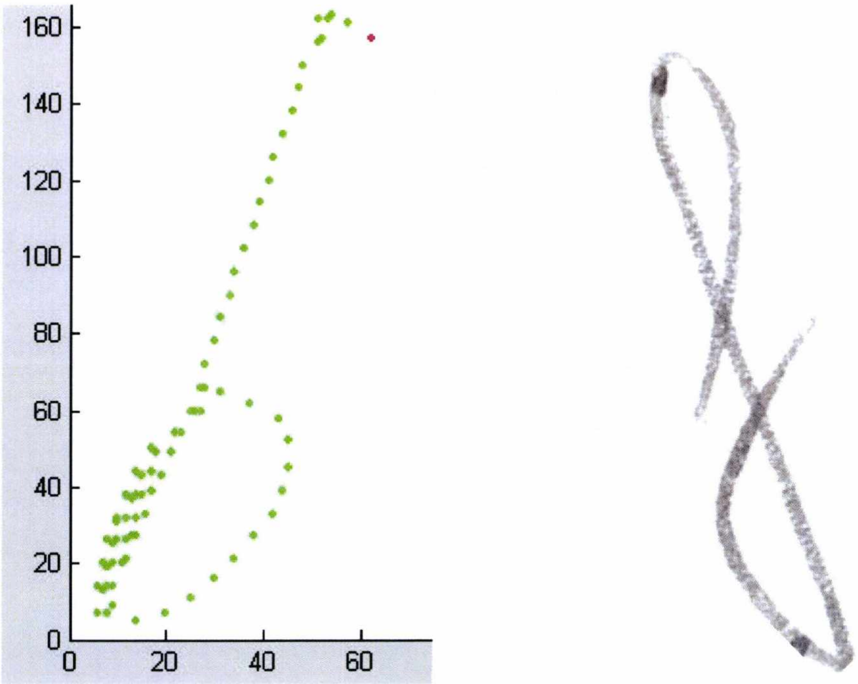


Figure 3.3: (a) graph of an initial signature (b) Completed image rotated 180°

3.3 Experimental Set-up and Acquisition

The experiments to capture handwritten signatures (genuine and forgeries) were all carried out with the mentioned subjects in section 3.3.1. These subjects voluntarily took part in an exercise to write their own signature on a graphics tablet. The physical environment consisted of a room, with a table and two chairs and was well ventilated. The room was also temperature regulated to the standard room temperature of 21°C. The sole occupants at any given time were the individual participants and the data collector. This therefore gave the subjects room for no distraction and a feeling of security as no one was there to watch or copy sensitive information that was being provided. The subjects were also asked to try to imitate some signature samples acquired from other writers. Later on they were asked to perform a simple verification exercise of identifying which out of a mix of signatures were genuine or forged. Finally, they were presented with a set of signatures and asked to rate their perception of the complexity of the signatures on a scale of 1 – 10. A detailed description of the experimental protocol follows.

3.3.1 Procedure and Participants

An advertisement was placed in the local press and on the University of Kent website inviting interested volunteers to take part in an experiment relating to signature analysis. Equally, as the emphasis of this thesis is on issues relating to the elderly, arrangements were also made to collect some data in an Elderly Care home in Harrow, London. These two sources provided a rich source of data. The data collection exercise was spread over a period of three months, and each volunteer was offered a modest payment as an incentive to take part. Permission was sought and obtained from the University Ethics Committee to undertake this exercise, in accordance with University procedures for studies involving human participation.

The data collection sessions took place at the Department of Electronics at the University of Kent and each session typically lasted not more than 2 hours. 150 subjects in all took part in the signature collection, and an analysis of their demographics is documented in Chapter 4. The collection environment itself was organised such that it provided as much as possible a natural and comfortable signing experience for the participants Subjects were given the opportunity to ask any questions and voice any concerns. Instructions were issued to each subject in an identical way (i.e. a "script" was produced), explaining the process and procedure that would follow. Prior to the data collection, the subjects were required to sign a consent form, which included a statement of how the data would be used including confidentiality and provided contact details for future reference. Otherwise, any individual who was unhappy or whose questions had not been answered satisfactorily was allowed to withdraw.

The signature acquisition was achieved by means of a graphics tablet, as described above, but with a sheet of paper overlaid on the tablet surface. With the subject using an inked pen for the writing process, this provided a natural feel to the user, who simply wrote a signature on a piece of paper in a familiar way. The pen used, although quite complex in its operation, looked and felt quite normal with natural blue or black ink used, whilst also providing visual feedback to the writer, although the pen could still be used and signature capture take place without ink or by tracing. The use of ink was an added feature that made the user experience feel natural.

In order to provide some specific reference samples, particularly for standardisation purposes in some of the tests, ten volunteers from the Image Processing and Computer Vision Research Group in the department (a mix of both staff and students) each donated 15 genuine signature samples for experimental purposes. They were advised that attempts would be made to forge or imitate their signatures, to which they gave their consent. The ten subjects were defined as the pool of "target subjects". These target signatures were unsurprisingly seen to be of varying styles and lengths. The signatures were obtained using the same apparatus described earlier and the static and dynamic features (these features are briefly mentioned in Chapter 1 and elaborated on in greater detail in Chapter 4) stored for use and later analysis. The static signature image that was collected on the paper was then scanned at a resolution of 600dpi and the scanned image (an example of a static feature) saved on a computer for later static feature analysis. The paper that had the signature image was then laminated to preserve the paper and image and to enable handling by the subjects should they wish to. Some of the signatures donated by 3 of the 10 volunteers are shown in Figure 3.4(a-c). These 3 volunteers are represented as Subjects 101, 102 and 103.

In addition to these "target" subjects, a total of 140 further participants took part in this study. Each participant donated 15 signatures, resulting in a total of 2250 genuine signatures for use within the study. The first task was the donation of 15 original signature samples on a sheet of paper. The sheets were a mixture of boxed areas (as can be seen on some official forms that require signatures or at the back of a credit card- thereby applying a space constraint) and a short line (denoting the typical line seen on cheque leaf) Also the first task included the writing of 2 pieces of text, one in cursive and the other in capital letters. 10 out of the total of 150 participants were the volunteers described above. They therefore provided a source of forgery/imitation target samples. The remaining 140 participants agreed to perform the forgery or imitation task, where they were asked to forge 3 signature samples (assigned at random from the target test set) 3 times. The same 3 randomly selected original signatures were provided to all the participants. This equates to 9 imitations per signer and therefore gave a total of 1260 forged or imitated samples. Figure 3.5 (a-c) shows samples of the forged signatures. As shown the images in Figure 3.5a are the 'imitated' signature images of the original images shown in Figure 3.4a, Figure 3.5b shows the forgery or imitation attempts of the signature images of Figure 3.4b, while the last images in Figure 3.5c are some attempts to imitate the original signatures shown in Figure 3.4c. Each participant was allowed practice time; this enabled the subject to 'familiarize' him/herself with the target image and to become more 'skilled' (The definition of skilled and unskilled forgers has been given in Chapter 1). The participants that agreed to take part in this 'forgery' task all had the chance to examine the laminated copy of the signature that was being imitated. They equally were allowed practice time of up to 5mins. Although in practice most of them took about 3mins. The majority of the participants (80%) practised 6 -7 times per signature sample before supplying a final sample which was regarded as the attempt. A note was made of any comments made during the forgery process, issues like how difficult or how easy the subjects might be finding the task. This test was carried out over two sessions; the second non-obligatory session was the forgery task. This task was undertaken by all the participants. During the task the subject had the laminated target signature in view at all times. It was easier to separate both tasks so that the users were not tired and secondly each subject had that choice of whether to take part in both or not. Figure 3.5 also shows that the forged signature samples vary in their shape, form and similarity to the original samples provided.

A further aspect of this experimental investigation was to explore some practical aspects of the processes used in human verification of signatures, an experience quite common in everyday life, especially for those working in certain industries (sales, banking, etc), though also more generally. The results and analysis of this part of the experiment will be presented in Chapter 6.

Another segment to the data collection exercise was aimed at an investigation of the concept of "complexity" in handwritten signatures, and involved asking subjects to undertake a rating of samples on the basis of their perceived complexity. This is dealt with in greater detail in Chapter 6 where both the recognition experiments and the complexity experiments are compared with a view to understanding the effect that one might have on the other.

Figure 3.4a: Samples of Original Signatures from Subject 101

Figure 3.4b: Samples of Original Signatures from Subject 102

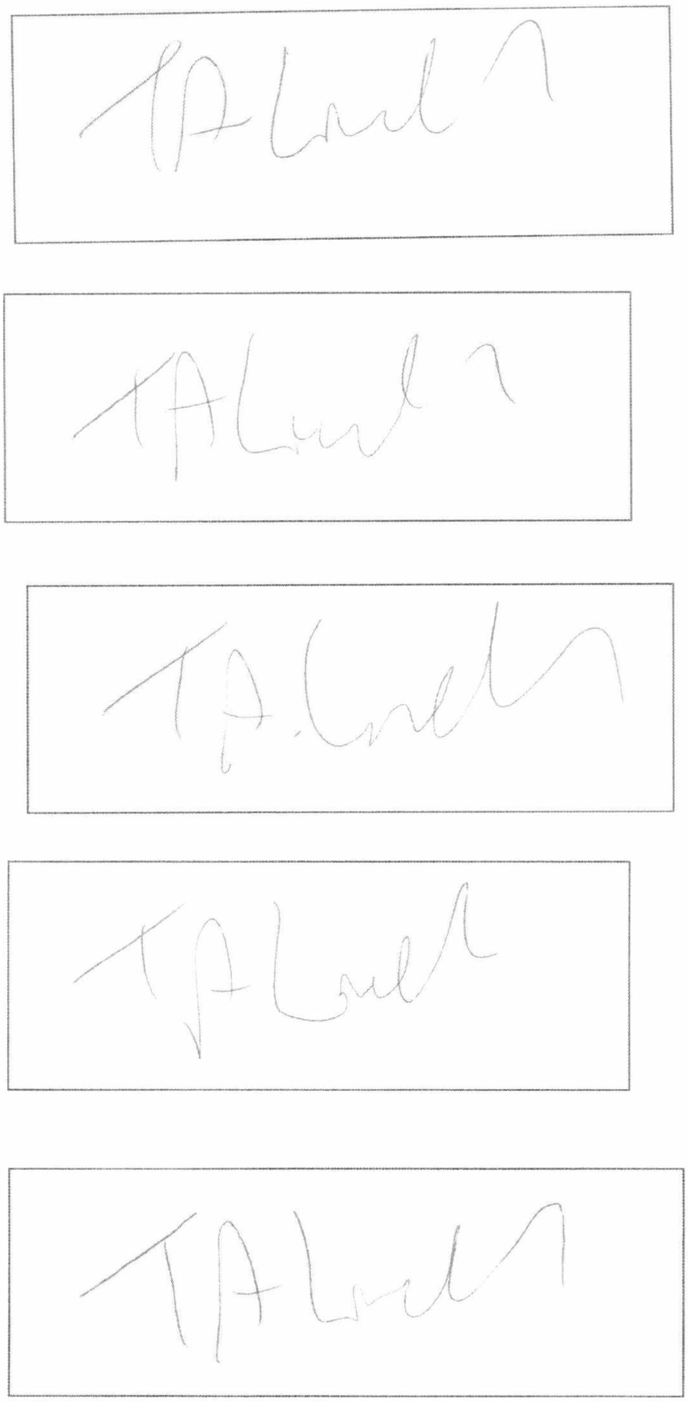


Figure 3.4c: Samples of Original signatures from subject 103

Figure 3.5a: Samples of Signature Forgeries of Subject 101

Figure 3.5b: Samples of Signature Forgeries of Subject 102

Figure 3.5c: Samples of Signature Forgeries of Subject 103

Pre-processing

This data is unique in that the signature data exists both as static images or static data and dynamic data since it was acquired dynamically. The data collection also afforded the opportunity for the creation of a forgery database of signatures. These samples (original and imitated) largely donated by the same individuals allowed the use of the data to investigate the writing process in handwritten signatures. For completeness, the static images were scanned and stored on computer drives. This provided a dual source of data in addition to the reconstructed digitized signature files if required. These digitised files were stored as numbers representing x- and y- coordinates. The reconstruction can take place with the aid of the saved time stamps. The usefulness of this is that one can observe the starting point and direction that each author traversed when executing a signature. Of particular relevance here, is the fact that the ability to view the reconstruction of the signature can help in the detection of forgeries - as the only data that is usually available to an impostor is usually the static signature image. These images and files are analysed and used for the experimental chapters.

For feature extraction, pre-processing was performed; it included pen-up and pen-down extraction and detection for signature image reconstruction. This was because the detection of the beginning and end of a signature was based on a combination of start time vs. end time and the pen-up vs. pen-down periods which corresponded to when the pen was on the tablet and also a non-zero pressure reading. 45 features were extracted in total from each signature image produced (forged or original). Chapter 4 deals in greater detail with the analysis of these features. The typical features extracted were the velocity, acceleration, time duration, width to height ratio and the pen up to pen down ratios. These were derived using various mathematical equations and the computer time stamps of the files captured. The features extracted also made it possible to further investigate if any unique properties could be associated with the elderly.

3.4 Conclusion

A description of the data collection methods have been presented here. This has enabled an appreciation of the extent and amount of useful data obtained. The apparatus and setup of the experiment has been detailed including the room condition which was at normal temperature and environment set to give the participants a relaxed experience. The format of the output from the capture software was detailed, the typical features that will be extracted were also mentioned and the kind of device errors one would normally expect was explained. The advantage of scanning and being able to reconstruct the static image if necessary was also highlighted. All this has resulted in a huge database of 2250 genuine signatures and 1260 forged signatures. Samples of these genuine and forged signatures were shown as an illustration only. This has made available a bulk of data for use and analysis in the subsequent experimental chapters. Finally, data pre-processing was explained in the context of the data collected.

By applying several experimental studies Chapter 4 now seeks to extract features based on the data collected in Chapter 3. It details the features which serve as differentiators between the young and the elderly.

Chapters 1 and 2 looked at the theory or embodied a theoretical approach to our argument. While chapter 3 has now served as a source of data that will now equip us practically, by way of experimentation, assess the inclusivity of the elderly. The next chapter, Chapter 4 performs a necessary step by extracting feature differentiators between the elderly and the younger. This way, an analysis of the various age groups is easily performed and comparisons achieved by the ready data available.

Chapter 4

Handwriting Characteristics in Relation to Ageing

Comprehension of the characterisation of a given signature sample in relation to the age of the writer (and, especially, analysing writing features in order to distinguish between elderly or younger writers) is the focus of this work and has a lot of relevance in the world today. In the discussion of Chapter 2, the elderly have already been identified as a vulnerable group within society, and therefore being able to distinguish their signature and handwriting samples would greatly assist the protection of this population group.

In this chapter, the dominant distinguishing and discriminatory features that separate the elderly from younger writers will be assessed by means of a statistical methodological approach. Once again, for the purposes of this study, we define "the elderly" as those individuals with an age above 60, and the "younger" writers as being individuals with an age below 21.

For the purpose of this task, various feature extraction techniques are employed in obtaining information from writing samples. Algebraic and/or mathematical feature extraction methods are generally used for the identification and calculation of features in the pattern recognition field. Within this field, it is known that handwritten signature features can be classified into one of the following two categories- Static or Dynamic. For example [14, 138], among others, applied these approaches. The work here complements this and also highlights other features which may be characterised as hybrid static/dynamic features.

The task of feature extraction is a complex one and the processes employed will be explained here. Chapter 3 explained the data collection process and therefore highlighted the rich source of the data available which is relevant to the work reported in this chapter.

Features are extracted both from genuine and from forged signatures samples and an analysis of features extracted from these signatures according to age is performed. By analysing these different features it will be possible to explore any likely relationships between factors such as the age of an individual, the form of the signature and the features which have been extracted for example, pen velocity, acceleration, slant, etc. Additionally forged signatures are also analysed in this context.

Because of the physical similarities in the writing process in tasks relating both to writing a signature and writing pure text, consideration is given here to features commonly adopted in handwritten text analysis. This is applied to both imitated and genuine text, including the features generally derived in the signature analysis process. The samples collected as described in Chapter 3 were used for this task.

The analysis performed and the results obtained are relevant to a number of areas, including forensic document inspection, automatic signature verification and automatic handwriting analysis research.

4.1 Introduction

Various feature extraction methods have been thoroughly reviewed in Chapter 1 but the most significant and relevant of these are highlighted. The material of this chapter focuses on appropriate methods of extracting features in general, pre-processing techniques, selection, optimization and classification. This is all done with a view to highlighting the 'best' set of features from the set extracted that uniquely distinguish the elderly from the younger subjects.

In this chapter, an investigation into the stability and discriminatory capability of a number of writing features commonly extracted from writing samples and signatures is carried out. In particular the difference in the analytical power of features across a range of different writing tasks is investigated. This was carried out across different population demographics and across subjects on an age-related basis both as they execute their own signatures and whilst imitating (forging) other signature samples.

Recently, there has been renewed interest in the way in which elderly subjects may be subject to automated identification procedures most especially when it comes to signature authentication and verification. Principally this is due to the perceived lack of an appropriate method for easily identifying individuals who fall into the upper age bracket. In relation to both acceptability and performance, Fairhurst et al [43] and Guest [139] support these claims. In particular, there is a desire to support the elderly and to manage considerately and sensitively their exposure to biometric systems in general.

The feature extraction procedure for static images differs significantly from the extraction procedure applied to on-line dynamic information and both methods and results will be demonstrated. The importance of accurate feature extraction cannot be overstated; this is because the classification, recognition and verification rates achieved by a system are hugely dependent on this phase in the verification process. Reduction in the dimensionality of data and combination or resolution of highly correlated features is an additional enhancement and procedure that has been employed within this work due to its ability in ensuring the accurate determination of a feature set, both unique to an individual or group of individuals and best suited to a particular processing task.

Global geometric features and local grid features were two feature representations studied in [140]. These features include the signature height and width, slant angle, vertical centre of gravity of black pixels, maximum horizontal projection, area of black pixels and the baseline shift of the signature image. Their roles in identifying forgeries were studied individually and collectively by means of experimentation on a database of 450 signatures. They were able to achieve a verification rate of over 90% when utilizing the combination of both global geometric and local grid features. The result obtained when using this combination strategy was better than that seen in the individual feature representations which showed the performance of the subsystem using seven global geometric features and the calculation of the Euclidean distance resulting in an FRR of 8.8% and an FAR of 15.7%. This was achieved using skilled forgeries.

Here, in this chapter, the feature error rate calculations (i.e. FRR and FAR) will not be considered, however the results of this study were obtained using 15 genuine samples per signer, provided by elderly participants. The results show that the dynamic (constructional) features represent valuable writer-specific characteristics that can help greatly in discriminating between elderly writers and their younger counterparts as opposed to static features that are harder to discriminate. The benefits of applying the dynamic (constructional) features can also be found in the works reported in [141].

Numerous reported studies have investigated computer-based assessment of text for writer identification by analysing 'static' features that are conventionally assessed by human document examiners, extracting and examining novel 'dynamic' constructional features from time-sequenced data and inferring dynamic properties from the static image.

In [142], Franke and Grube proposed a method to establish pseudo dynamic data by assessing the ink intensity variations of the writing trace. This method was derived from forensic experience and improved by utilising digital image processing algorithms. A further study by Sita and Rogers, [143] examined the use of pressure for writer identification. Using a group of 24 subjects the authors failed to identify any distinction in pressure between normal and simulated (forgery) handwriting. Eastbrooks [144] presented another study on the effects of handwriting pressure on writer identification. In this study the author describes a procedure to measure relative pen-pressure from the static image with the use of the confocal laser scanning microscope. The author claims that *"relative depth values of simulated and traced signatures are similarly measured and are generally found to be clearly distinguishable from genuine signatures*". Additionally, an article by Spagnolo et al., [145] presented a holographic method of identifying a writer from the pen-pressure exerted on the paper in the process of writing. This technique constructs a three-dimensional image from the interference patterns of two laser beams used to scan an object - in this case a sample of handwriting. The resulting image can be interpreted as a series of troughs of varying depths, denoting the pressure of the pen strokes used to make them. The effects of writing speed on signature simulation were investigated by Halder-Sinn and Funsch [146] and by Phillips et al [147]. In both studies, 12 subjects were asked to trace and copy a historical signature. Capturing responses on a graphics tablet, kinematics' analysis was performed on the speed and pressure of writing. The variability of samples was also measured. It was found that pen pressure varies more with speed during free non-traced simulations. Writing speed was established to be an important factor influencing line quality and spatial correspondence during signature simulation (imitation).This has significant relevance to our study on the elderly as it includes close examination of the varying writing speeds across the age groups.

Other studies assessing aspects of automatic writer identification include the following; Wirotius et al., [148] considered the distribution of the pixel levels within an ink line and identified a link to pressure and writing speed. Schomaker et al., [149] proposed the use of an edge-based directional probability distribution as a feature in writer identification to compliment a number of non-angular features, whilst Ueda proposed an interesting pattern matching method for writer identification in [150]. This method was independent of stroke width, resulting in improved identification results. Another interesting approach for writer identification employs fractal construction of a reference base as a feature [151]. This feature is closely related to writing style. Bensefia et al. [152] propose to exploit graphemes using an information retrieval paradigm to describe and compare a questioned handwritten sample to each sample of handwriting held in a reference database. In [153] directional element features and linear transforms are used for effective writer identification, and [149], describes an automatic signature identification method using fragmented connected-component contours. An evaluation of the performance of edge-based directional probability distributions as a feature in writer identification, comparing to other non-angular features is carried out in [154]. Said et al. [155] performed texture analysis by means of a multi-channel Gabor filtering technique. Bovino et al. describe a multi-expert signature verification method in their system [138] using a stroke-oriented description of signatures. Matsuura and Thumwarin, [156] transform the time sequences of displacement and its directional change using the wavelet transform. He et al. [157], propose a wavelet-based generalized Gaussian density method for offline writer identification, while, Schmidt and Hunermann, [158] use the features extracted from an ellipse that is obtained from processing the velocity-space diagram and extract a series of features. These include the position of an ellipse, angle of the ellipse's main axes to the x-axes, and the radii of the ellipse.

Overall the feature extraction methods described above provide a useful source of routines to be considered in our experimental study.

4.2 Feature Extraction and Module Design

Chapter 3 details the usual procedure for data acquisition; however, here we modify the traditional schematic of a biometric system such as that shown in Figure 4.1 and obtain the scheme shown in Figure 4.2.

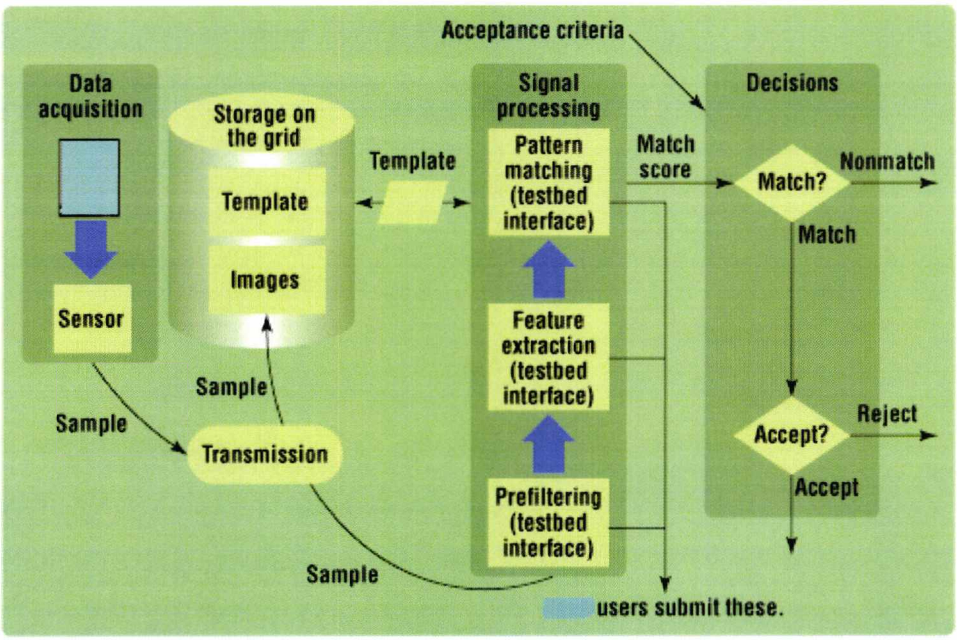


Figure 4.1: Traditional Biometric Process

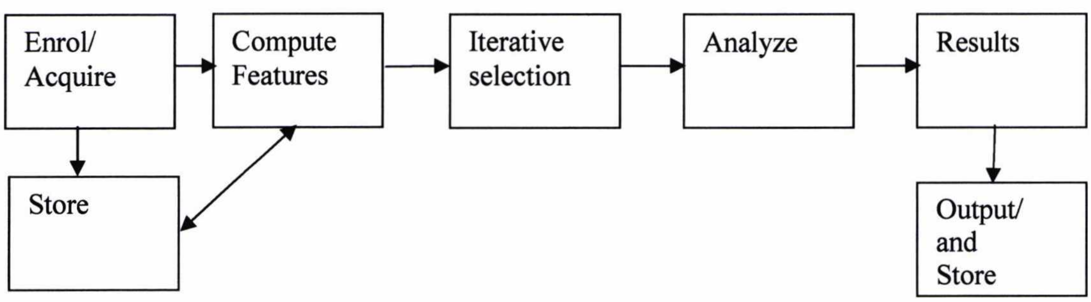


Figure 4.2: Modified Process

To grasp an understanding of the fundamental differences in the processes shown in Figures 4.1 and 4.2, a detailed explanation of the flows is outlined next.

In Figure 4.1, an outline of the 'normal' flow any commercial biometric package would go through is shown. It starts with data acquisition which can for sake of an example be a user enrolling in a fingerprint authentication package. Various techniques can then be employed to initially observe the data collected and visually display the various demographics if required. The next stage then involves the feature extraction which in most cases may be combined with a classification stage. This is the crucial difference between the Figures 4.1 and 4.2, Within Figure 4.2; the various classification schemes typically employed are conspicuously absent. This is because the emphasis here was on specific feature extraction. The final subtle but not too critical a difference is that in our case we are not employing the end product to commercial use.

This diagram Figure 4.2 details the flow and process employed in the experiments here. Particular attention is paid to the feature selection and extraction components of Figure 4.2. Various parameters such as the total time taken to execute, the horizontal velocity, the slant, etc, are used to represent a given signature sample supplied by an elderly subject. The same parameters are obtained for all the participants in our study and tabled in the results section.

The problem of identifying the *k* best features that may be used to distinguish the two age groups of particular interest here is described in the next section, and the process used to discriminate between the groups is explained. Note, however, that the routines used can be applied to any feature extraction problem.

4.3 Experimental Procedure

In order to provide a source of data for use in aiding the investigation of the unique and distinguishable features of the elderly writing, the following procedure is adopted:

4.3.1 Signature Capture, Text Capture and Imitation of both Text and Signatures

A group of twenty-four elderly subjects and twenty-four younger subjects took part in this experiment. They were selected from a general population of writers, all comprising members of the general public. These individuals were asked to sign their normal signature on a tablet capture device as mentioned and explained in Chapter 3. Each person provided 15 original samples on different sheets of paper, one sample to each sheet. Figure 4.3 illustrates by way of example a signature sample from an elderly individual.

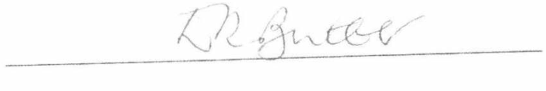


Figure 4.3: Example of an Elderly signature sample

During the same session, each participant was then presented with two pieces of text, one written in capital (upper case) letters and the other in small (lower case) letters to write out in their normal handwriting. The same capture device as above was used. Timing measurements showed that, on average, sample donation took each participant between 5 and 6 minutes to complete each task. Figures 4.6, 4.7, 4.8 and 4.9 show elderly and younger individuals writing samples of both cursive and capital (upper case) text. Figure 4.10 shows an elderly participant's attempt at copying the upper case writing, with a segmented illustration of the original upper case word in printed form. Additionally, it is worthy of note that one can readily notice that the text contains all the letters of the English alphabet.

Finally, the subjects were given, as an optional procedure, the task of attempting to imitate the text writing style and signature provided by another individual. As highlighted in Chapter 1, these samples are designated unskilled imitations or unskilled forgeries. The samples to be imitated were selected from the first 10 participants who enrolled. They were all members of the Image Processing and Computer Vision Group at the University of Kent. The signatures obtained therefore, were random in nature but equally presented a mixture of visually diverse signature styles. All the participants but one agreed to perform this optional imitation task. Detailed results of which are presented in Chapter 6. Each participant involved was allowed time to practice and become comfortable with imitating each of the 3 signature samples they were provided. Figures 4.4 and 4.5 respectively show samples of an elderly person and a younger individual as they practise the signature image to be imitated.

Practice Sheet 1

Reference Number: 22125
CS Reference Number: 10006

1

Figure 4.4: Imitation practices by an elderly volunteer

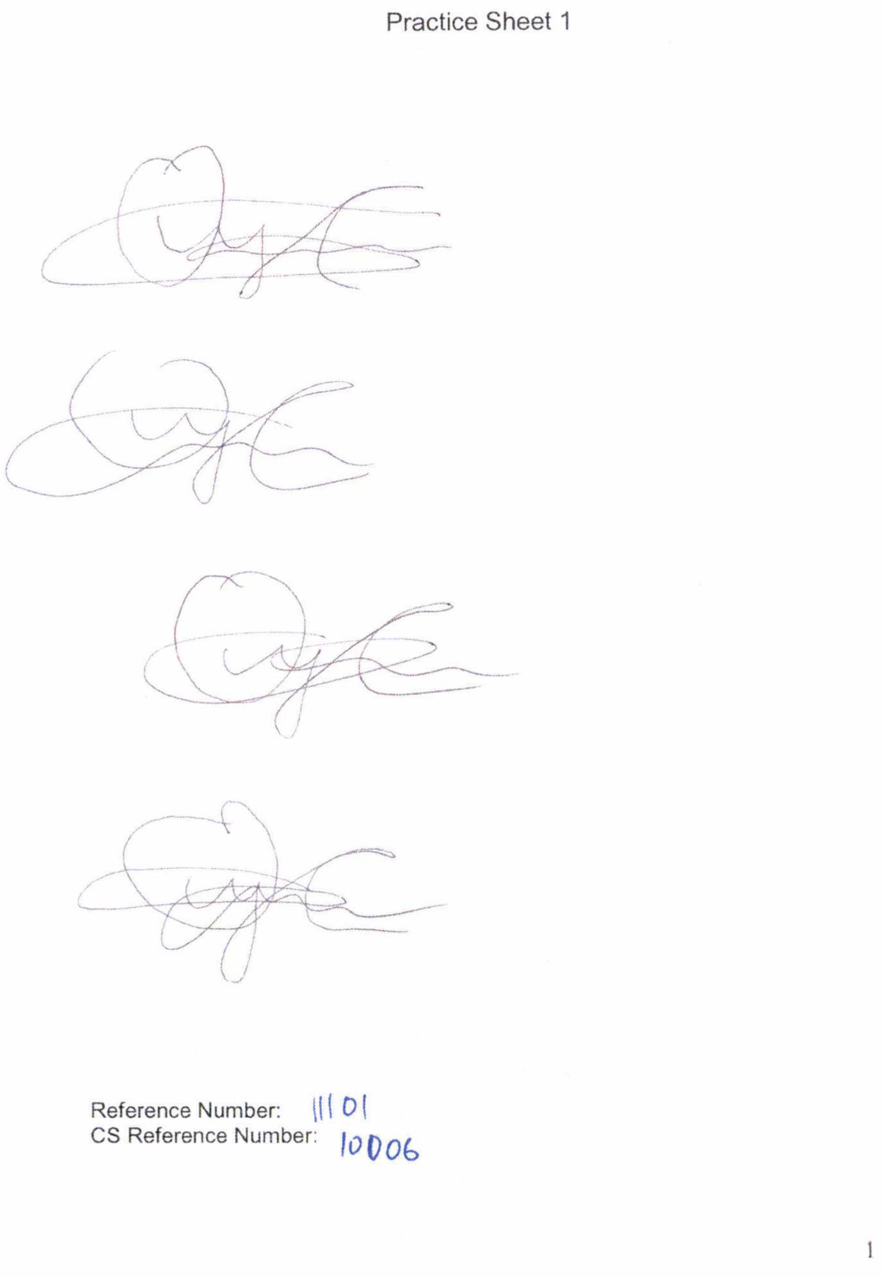
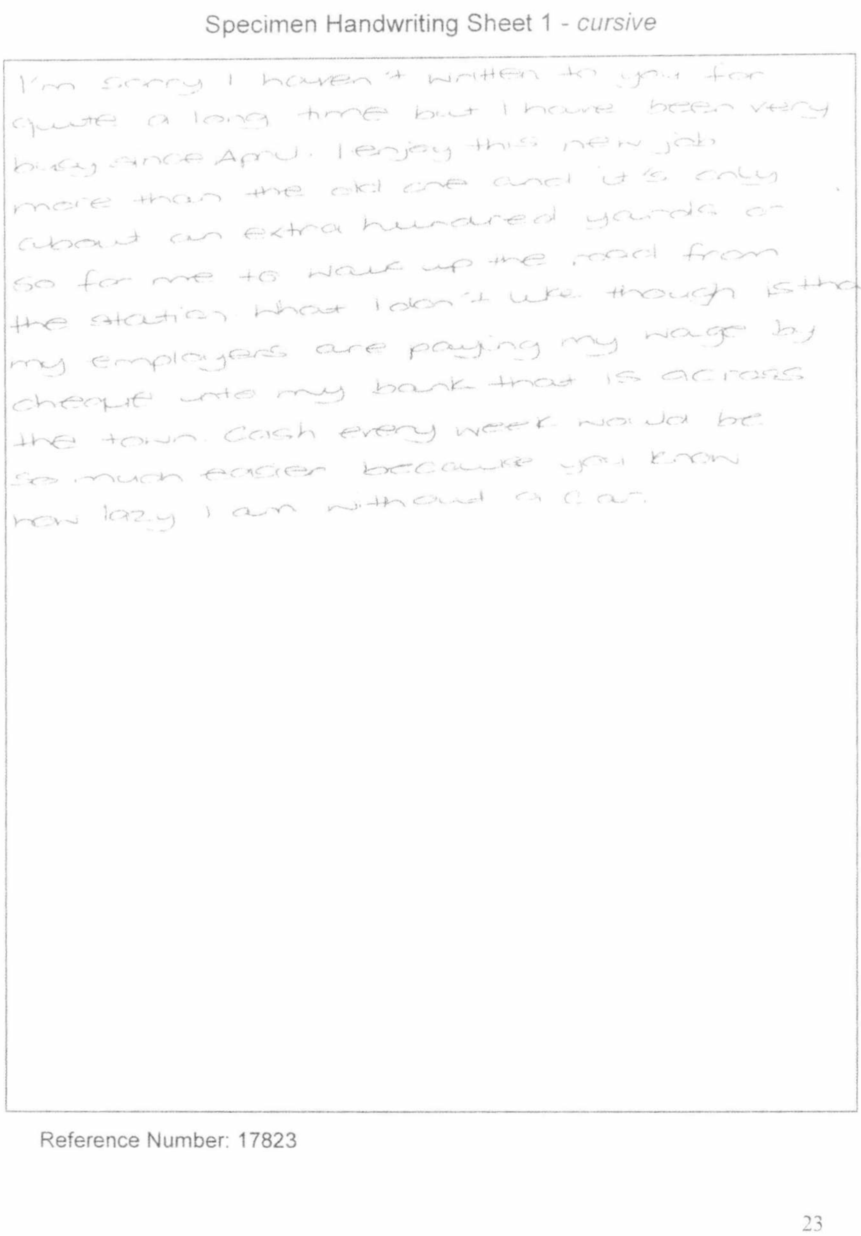


Figure 4.5: Imitation practices by a younger volunteer



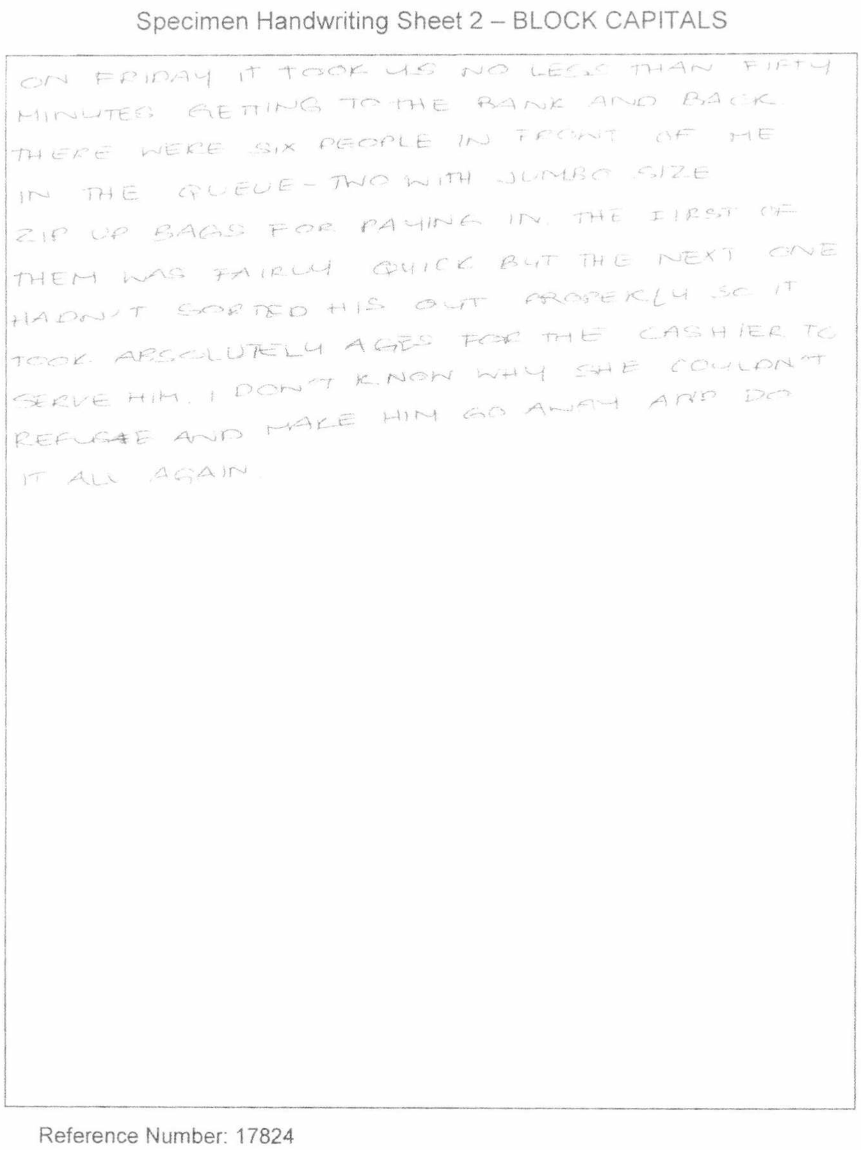
Specimen Handwriting Sheet 1 - *cursive*

I'm sorry I haven't written to you for quite a long time but I have been very busy since April. I enjoy this new job more than the old one and it's only about an extra hundred yards or so for me to walk up the road from the station. What I don't like though is that my employers are paying my wage by cheque into my bank that is across the town. Cash every week would be so much easier because you know how lazy I am without a car.

Reference Number: 17823

23

Figure 4.6: Cursive text of a younger participant

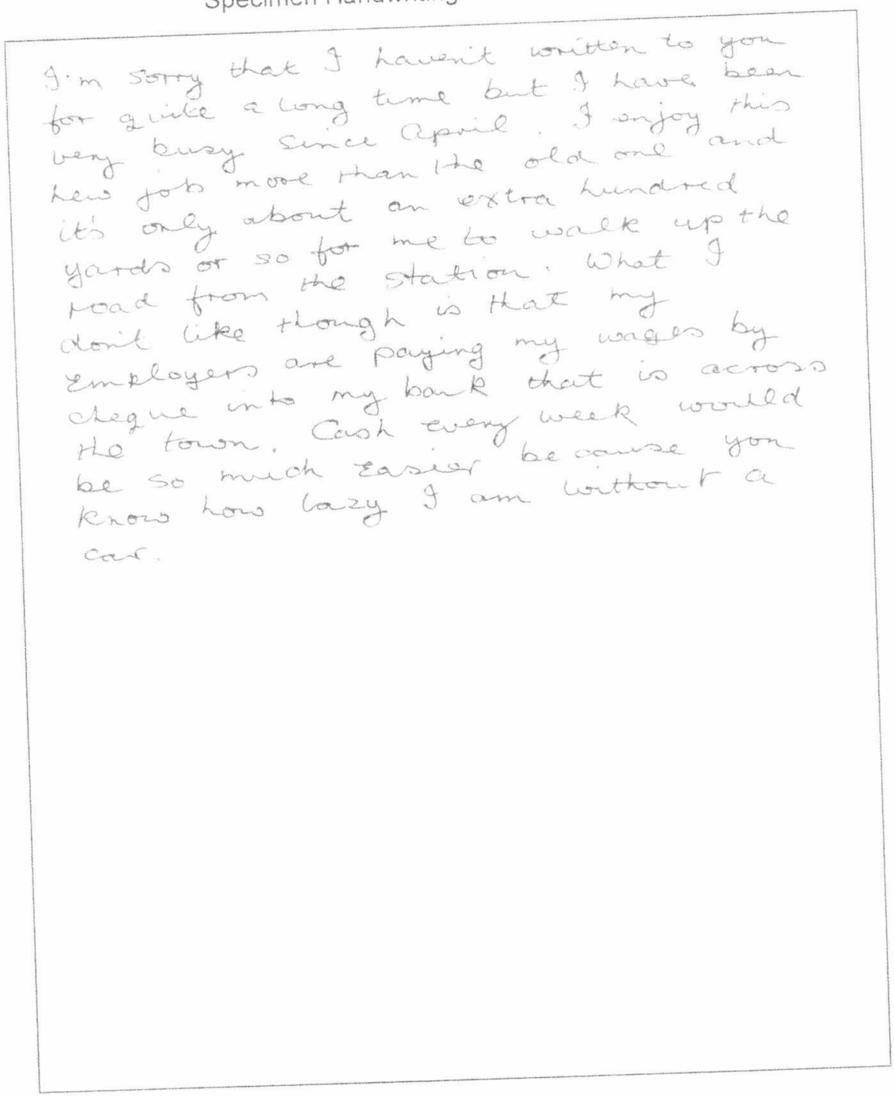

Specimen Handwriting Sheet 2 – BLOCK CAPITALS

ON FRIDAY IT TOOK US NO LESS THAN FIFTY
MINUTES GETTING TO THE BANK AND BACK.
THERE WERE SIX PEOPLE IN FRONT OF ME
IN THE QUEUE - TWO WITH JUMBO SIZE
ZIP UP BAGS FOR PAYING IN. THE FIRST OF
THEM WAS FAIRLY QUICK BUT THE NEXT ONE
HADN'T SORTED HIS OUT PROPERLY SO IT
TOOK ABSOLUTELY AGES FOR THE CASHIER TO
SERVE HIM. I DON'T KNOW WHY SHE COULDN'T
REFUSE AND MAKE HIM GO AWAY AND DO
IT ALL AGAIN.

Reference Number: 17824

24

Figure 4.7: Block text from a younger participant


Specimen Handwriting Sheet 1 - *cursive*

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for quite a long time but I have been
very busy since April. I enjoy this
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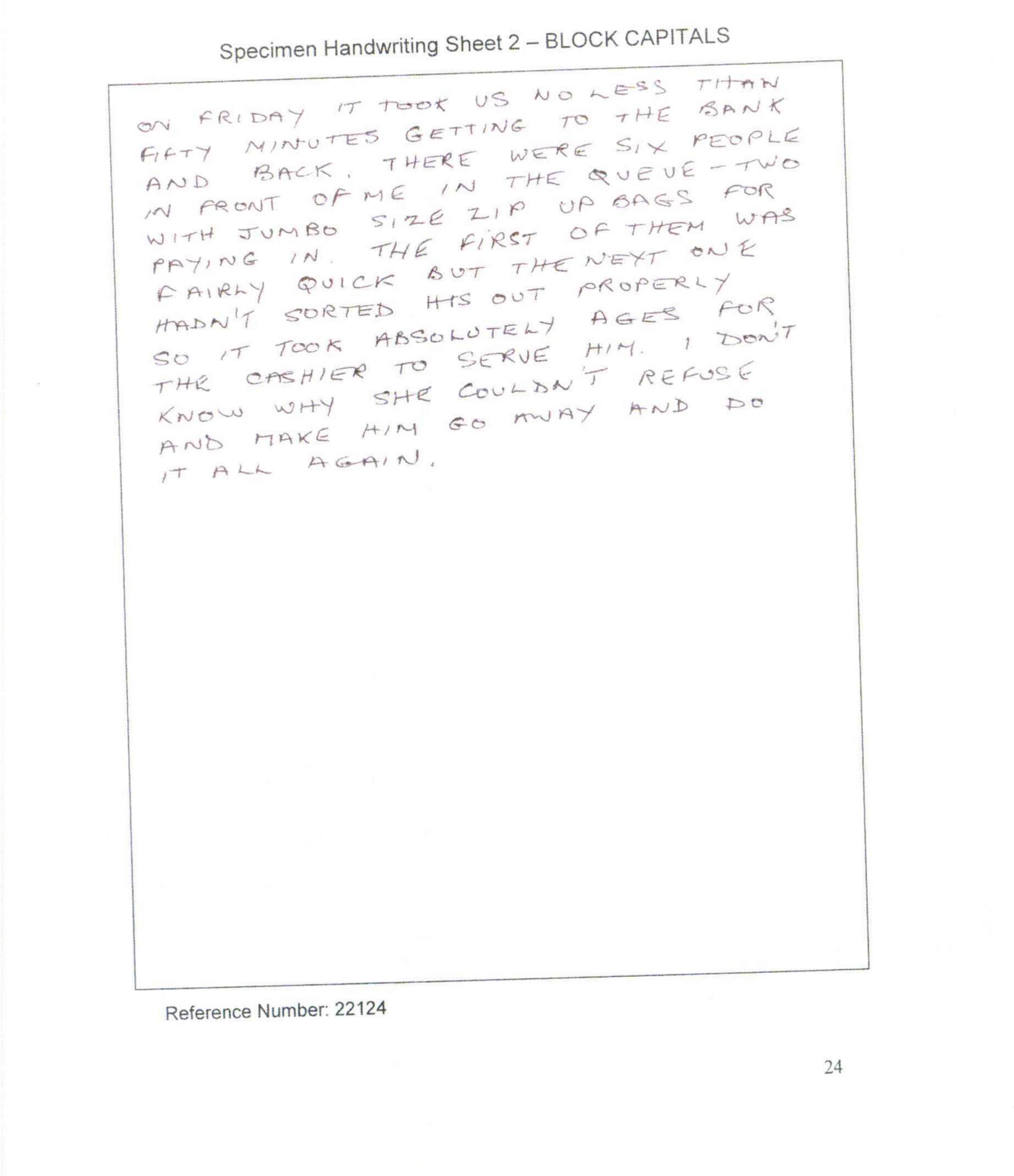
yards or so for me to walk up the
road from the station. What I
don't like though is that my
employers are paying my wages by
cheque into my bank that is across
the town. Cash every week would
be so much easier because you
know how lazy I am without a
car.

Reference Number: 22123

23

Figure 4.8: Cursive text from an elderly participant



Specimen Handwriting Sheet 2 – BLOCK CAPITALS

ON FRIDAY IT TOOK US NO LESS THAN
FIFTY MINUTES GETTING TO THE BANK
AND BACK. THERE WERE SIX PEOPLE
IN FRONT OF ME IN THE QUEUE - TWO
WITH JUMBO SIZE ZIP UP BAGS FOR
PAYING IN. THE FIRST OF THEM WAS
FAIRLY QUICK BUT THE NEXT ONE
HADN'T SORTED HIS OUT PROPERLY
SO IT TOOK ABSOLUTELY AGES FOR
THE CASHIER TO SERVE HIM. I DON'T
KNOW WHY SHE COULDN'T REFUSE
AND MAKE HIM GO AWAY AND DO
IT ALL AGAIN.

Reference Number: 22124

24

Figure 4.9: Block text from an elderly participant

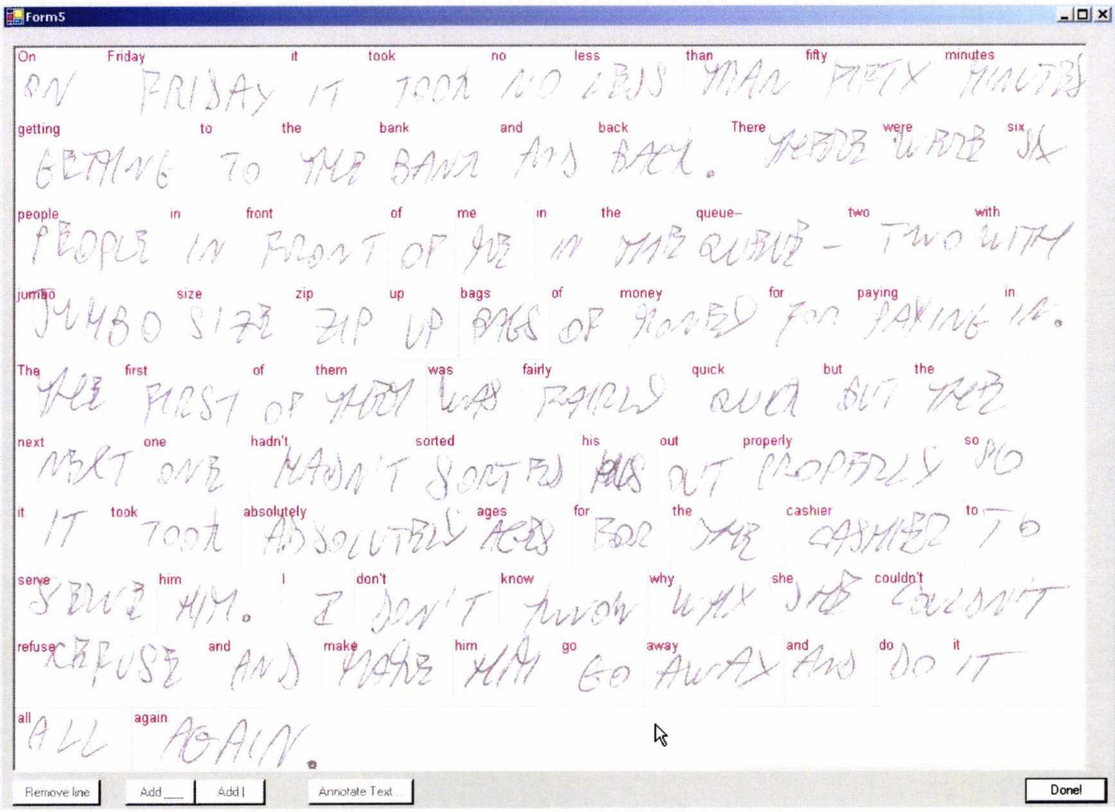


Figure 4.10: Segmented text showing the typeset text being copied

4.4 Analysis of Results

4.4.1 Statistical Analysis and Feature Extraction

A comprehensive feature pool was created based on some of the most widely used features in the area of automatic handwriting analysis as highlighted in Plamondon [14]. This feature pool contains an extensive collection of dynamic and static characteristics of signing a signature and writing a piece of text. Features such as velocities, pen-pressures, altitudes, azimuths, handwriting dimensions, and moments are calculated directly from the signals available from the digital tablet. This extraction was explained in Chapter 3.

The data acquired by the digitizer is represented by a time sequence of x and y pen coordinates, pen-pressure, altitude and azimuth. Table 4.1 provides details of the feature vector, based on a pool of features consisting of 35 features and corresponding IDs. These represent both the process of writing (dynamics – features 1-19, 23-31) and the shape of the handwriting sample (static – features 20-22, 32-35).

Feature ID	**Feature Description**
1	Average horizontal velocity
2	Maximum horizontal velocity
3	Average vertical velocity
4	Maximum vertical velocity
5	Average Cartesian velocity
6	Maximum Cartesian velocity
7	Maximum horizontal velocity - minimum horizontal velocity
8	Maximum vertical velocity - minimum vertical velocity
9	Maximum horizontal velocity - average horizontal velocity
10	Maximum vertical velocity - average vertical velocity
11	Maximum horizontal velocity - maximum vertical velocity
12	Average pen-pressure
13	Maximum pen-pressure
14	Average altitude
15	Maximum altitude
16	Average azimuth
17	Maximum azimuth
18	Number of pen-ups
19	Pen-down to pen-up ratio

20	Slant
21	Width
22	Height
23	Writing Duration
24	Average pen-pressure acceleration
25	Maximum pen-pressure acceleration
26	Average azimuth acceleration
27	Maximum azimuth acceleration
28	Positive duration of horizontal velocity
29	Negative duration of horizontal velocity
30	Positive duration of vertical velocity
31	Negative duration of vertical velocity
32	Orientation
33	Inertial ratio
34	Aspect ratio
35	Spread

Table 4.1: Feature Vector.

Most of the features are calculated directly from the digitizer's signals and are self-explanatory (for example, 21 (Width) and 22 (Height) refer to the entire signature width and height). However, features such as 20 (Slant) and 32 to 35 (Spread) require some more explanation.

Slant (Feature 20) is calculated by correcting the baseline to the horizontal then an extraction of the down-strokes from the signature image. This is followed by an elimination of the initial and final strokes (as being inconsistent with the main slant), and then finally a calculation of the average angle. Down strokes are used for slant measurement because they are more invariant than the upstrokes [159]. This may be due to the fact that up-strokes are often used to connect individual portions of a signature. In addition, this is confirmed by the visual judgment of people [160], which is also examined in the context of a study of the concept of writing "complexity", as described in a subsequent chapter (Chapter 6).

Features 32 to 35 (Calculated according to Equations 4.2 to 4.5 respectively) are derived from central moments (Equation 4.1). Moments have been used extensively in image processing and pattern analysis and are widely used in handwriting recognition [161] and in writer identification [162].

The central moments μ of the (p,q)th order of handwriting samples of N sample points comprising x and y pen coordinate positions are calculated according to the Equation 4.1.

$$\mu_{pq} = \sum_{i=1}^{N} (x_i - \bar{x})^p (y_i - \bar{y})^q \qquad \text{Equation 4.1}$$

Where p,q = 0,1,2,.......,∝

$$\theta = \frac{2}{\pi} \arctan\left(\frac{\mu_{02} - \mu_{20} + \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{2\mu_{11}} \right) \qquad \text{Equation 4.2}$$

Where θ = Orientation

$$I = \frac{\left(\frac{(\mu_{20} + \mu_{02}) + \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{2} \right) - \left(\frac{(\mu_{20} + \mu_{02}) - \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{2} \right)}{\left(\frac{(\mu_{20} + \mu_{02}) + \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{2} \right) + \left(\frac{(\mu_{20} + \mu_{02}) - \sqrt{(\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2}}{2} \right)} \qquad \text{Equation 4.3}$$

Where I = Inertial Ratio

$$A = \frac{1}{2}\left(\frac{\mu_{20} - \mu_{02}}{\mu_{20} + \mu_{02}} + 1\right)$$ Equation 4.4

Where A= Aspect Ratio

$$S = \frac{2\sqrt{(\mu_{20} + \mu_{02}) / \sum_{i=1}^{N} x_i^0 y_i^0}}{\sqrt{(x_{\max} - x_{\min})(y_{\max} - y_{\min})}}$$ Equation 4.5

Where S = Spread

Some examples of the feature vectors calculated from different writing exercises (signature and free form handwriting (cursive)) are presented in Figure 4.11. In the graph representing *average* horizontal velocity (Feature ID 1(F1)), there is an observable difference in feature distribution for signatures, when compared to text writing. The average horizontal velocity of signatures shows higher maximum values, as well as greater amplitude than that observed during free form handwriting. Average altitude (F14), on the other hand, shows another interesting relation between signature and free form handwriting. We can see that the average altitude remains stable within a writer's sample no matter what writing exercise the sample was taken from. A curve representing maximum pen-pressure acceleration (F25) shows high variation in signature signal and a high maximum signal for free form handwriting. Finally, a curve representing the spread (F35) of handwriting shows significant differences in all writing exercises undertaken, although the nature of those differences varies. We can also see in Figure 4.11 that the values for the free form handwriting are the lowest, followed by the signature. The signature curve, however, has mean values somewhere in the same region as the free form handwriting, but shows much higher amplitude. These are just some examples of features extracted. Table 4.2 shows the dimensions for all measured features.

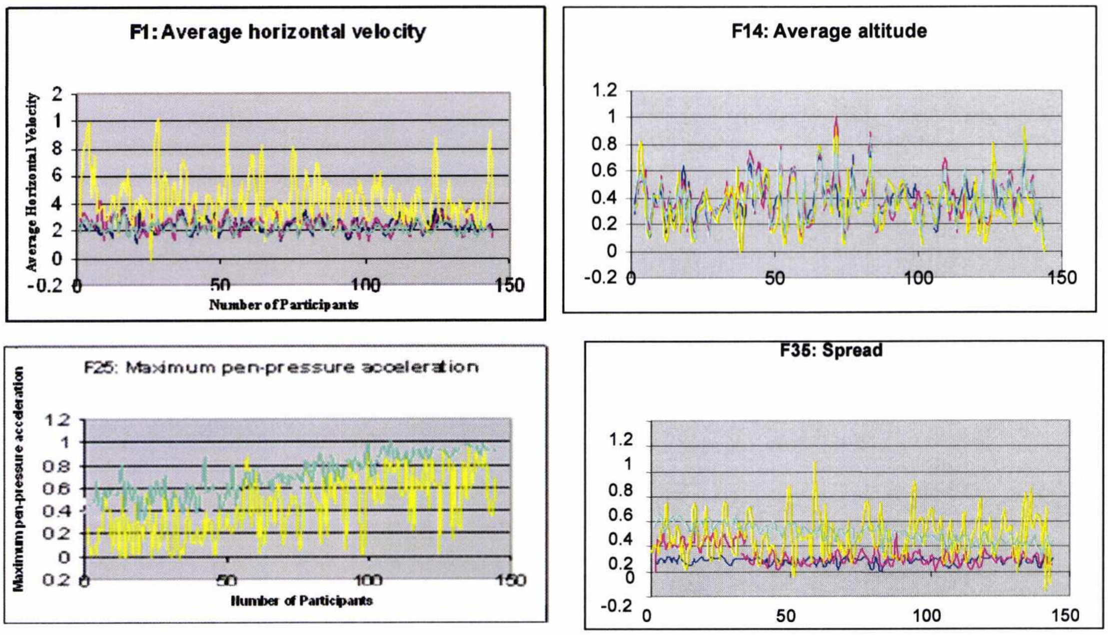


Figure 4.11: Examples of feature distribution.

Features	ID	Units
Velocity	1, 11	10^{-2} *mm/ms*
Pen-pressure	12, 13	*Levels* 0 - 1023
Altitude, azimuth, slant	14-17, 20	10^{-1} *degrees*
Pen-ups	18,19	dimensionless
Height, width	21,22	10^{-2} *mm*
Duration	23, 28-31	*Ms*
Angular acceleration	24-27	10^{-2} mm/ms^2
Moments	32-25	Dimensionless

Table 4.2: Units of measurements for the given feature vector.

After constructing the feature vector, it is possible and essential to check the features for correlation. The correlation coefficient *c* measures the strength of the linear relationship between any two features *F1* and *F2* by means of the expression defined in Equation 4.6.

$$c = E\left[\left(\frac{F1-\mu_{F1}}{\sigma_{F1}}\right)\left(\frac{F2-\mu_{F2}}{\sigma_{F2}}\right)\right] \qquad \text{Equation 4.6}$$

Where *F1* and *F2* are any two features with means and standard deviations $\mu_{F1}, \mu_{F2}, \sigma_{F1,} \sigma_{F2}$ respectively, *c* is a linear correlation coefficient and E is the expected value operator.

The correlation coefficients are analysed so that in the practical application of an identity verification system one of two highly correlated features can be removed. Otherwise, not only will the system become inefficient, but it can also be prone to error or bias, as will be illustrated. Let us suppose that, for example, Feature 1 results in a value suggesting the sample A was in fact written by writer B. Then if Feature 2 is highly correlated to Feature 1, we will expect the same recommendation. As a result, we see similar factors affect the decision of a verification system to a greater extent than with other features (for example, in a decision-making process based on feature-voting). If such a recommendation is not correct, the system might take the incorrect decision in a critical biometric system. Table 4.3 presents the highly correlated features on a pair-wise basis, where *F1* and *F2* are two features IDs, and *c* is a correlation coefficient.

F1	2	2	4	4	6	8	9	16	23	23	23	23	29
F2	9	11	8	10	7	10	11	17	28	29	30	31	31
C	0.99	0.94	0.88	0.99	0.95	0.88	0.94	0.90	0.90	0.89	0.89	0.89	0.92

Table 4.3: Highly correlated features.

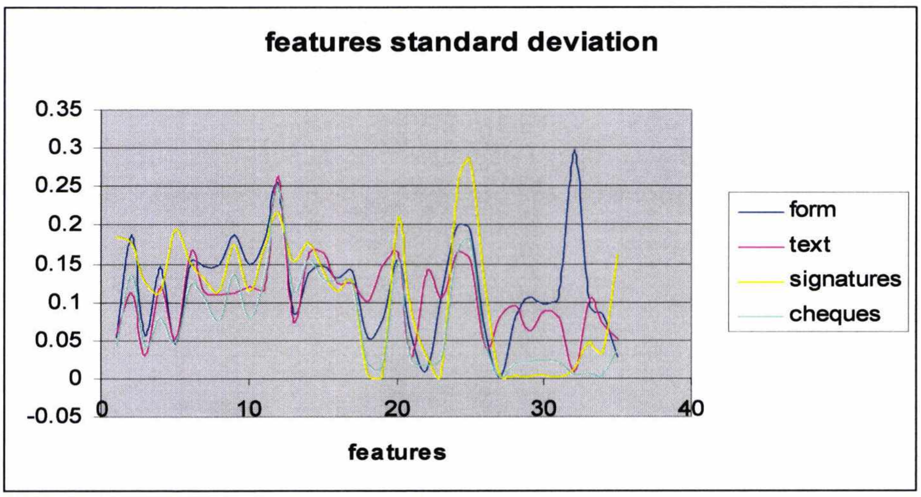
Table 4.3 demonstrates the following relationships. *Maximum horizontal velocity* (Feature ID 2) is highly correlated to (*maximum horizontal velocity – average horizontal velocity)* (Feature ID 9) and (*maximum horizontal velocity – maximum vertical velocity)*

(Feature ID 11), which is not surprising as Feature 2 is a component of Features 9 and 11. A similar picture is observed for *maximum vertical velocity* (Feature ID 4), as it is highly correlated to two features which it is a component of, and *maximum Cartesian velocity* (Feature ID 6) being correlated with *maximum horizontal velocity – minimum horizontal velocity (*Feature ID 7). Feature pairs 8, 10 and 9, 11 are highly correlated as they consist of the same components. A very interesting relationship is seen between *average azimuth* (Feature ID 16) and *maximum azimuth* (Feature ID 17), a high correlation coefficient of 0.89 is calculated. This tells us that the amplitude of azimuth stays the same with little or no change. Finally, *writing duration* (Feature ID 23) is shown to be highly correlated to the features describing different components of the time duration of velocities (Feature IDs 28 to 31), which is not surprising, considering they are representing the components of the first writing duration. Typically, when building a verification system, it would be beneficial to remove one of two highly correlated features in each case.

4.4.2 Feature Comparison and Normalization

Here, we analyse the differences between features extracted from samples of an individual's handwritten signature and those extracted from samples of more general handwritten text. In particular, each feature is analysed separately to investigate which features might be used to discriminate between writers on an age-related basis, and to identify which one of the two tasks (text writing and signature construction) offers the better possibility of providing distinguishable features. This sort of analysis may be very important for a number of practical applications (for example, in the field of forensic handwriting analysis), but is of general interest to the handwriting analysis research community. As different features describe different properties of the handwriting process, they are not always directly comparable to each other. As an example a mean value of, say, 10 in the writing duration of text does not necessarily equate or relate to the same mean value of 10 (if seen) in signature duration. It is therefore wise to normalize them in order to combine them into the useful feature vectors. Normalization is achieved by scaling and translating the raw feature values so that they fall within a range of values between 0 and 1.

After all the features are normalized, it is possible to combine them based on the sample patterns i.e. it is possible to compare values from both text and signature. Figure 4.12 shows the mean and standard deviation curves for the features, based on the signature and normal text writing.



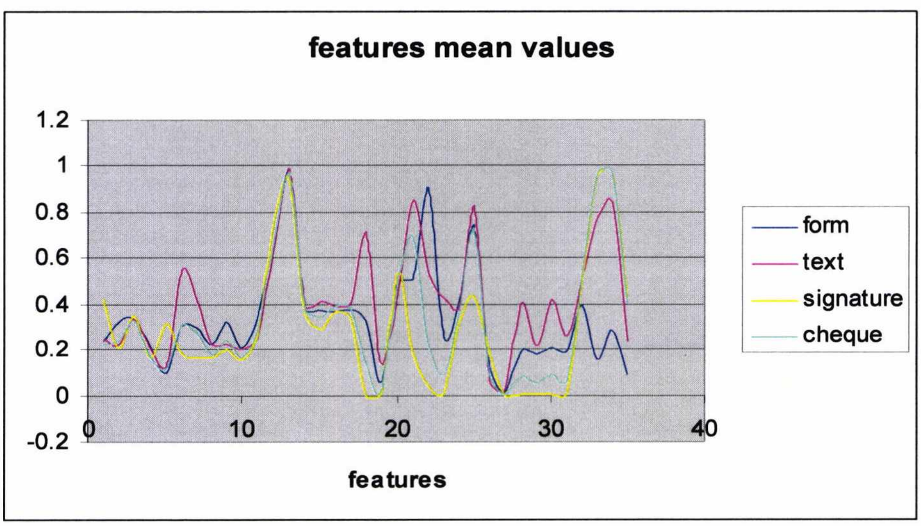


Figure 4.12: Feature curves for different sample patterns.

The analysis of variance approach (commonly referred to as ANOVA) was employed in the next part of our study. This is a statistical method for detecting factors that produce variability in observations. It statistically assesses whether there is a significant difference between the population mean of the experiments or whether the differences occurred purely by chance. The hypothesis of no effect (null hypothesis) can be tested by testing for equality of several population means. The approach is to compare the means of sum of squares that are in fact estimators of a common population variance. The comparison between the actual variations of the group averages is expressed in terms of the V ratio (Equation 4.7).

$$V = \frac{v_f}{v_E}, \qquad \text{Equation 4.7}$$

where v_f is a found (measured) variation of the group averages and v_E is an expected variation of the group averages. Thus if the null hypothesis is correct V is expected to be about 1, whereas "large" V indicates a location effect. This location effect relates to the variance that is distorted due to interference. In order to determine how big V should be before the null hypothesis is rejected it is necessary to compute the value of p, reporting the significance level.

By analysing the variances of mean curves (Figure 4.12) no significant differences were revealed between the writing types, when the entire set of features were used ($F(3,136)=1.31$, $p< 0.27$). On the other hand, the curve representing standard deviation of the above features exhibit significant differences between the signature and text sample types, as concluded by the analysis of variances($F(3,136)=2.67$, $p<0.04$). However, by eliminating unrepresentative features from the feature set, it is possible to confirm the hypothesis that a handwriting pattern can be assigned to one of 2 pattern types (signature or text) with high degree of confidence. For this purpose, let us initially consider the distance measure between the pattern type curves shown in Figure 4.12. The Euclidean distance for each feature is calculated using Equation 4.8. This is done per writing pattern in order to obtain the distance between the two patterns and observe the differences.

$$(DISTANCE)_i = \Delta(t_i, s_i) \qquad \text{Equation 4.8}$$

where i is a feature ID, t, s are text and signature pattern types respectively.

After all distances are calculated, and are sorted in descending order, so that the features exhibiting largest differences are presented at the beginning of the Table (see Table 4.4).

Feature ID	**F33**	**F22**	**F34**	**F18**	**F21**	**F23**	**F30**
Distance	1.33	1.32	1.15	1.06	0.99	0.67	0.64
Feature ID	**F28**	**F25**	**F35**	**F32**	**F6**	**F31**	**F5**
Distance	0.62	0.61	0.59	0.54	0.53	0.45	0.43
Feature ID	**F1**	**F29**	**F7**	**F19**	**F26**	**F9**	**F2**
Distance	0.39	0.38	0.37	0.31	0.23	0.21	0.21
Feature ID	**F24**	**F15**	**F12**	**F11**	**F3**	**F8**	**F27**
Distance	0.19	0.19	0.18	0.18	0.15	0.15	0.14
Feature ID	**F10**	**F4**	**F13**	**F20**	**F17**	**F14**	**F16**
Distance	0.14	0.14	0.13	0.13	0.09	0.07	0.05

Table 4.4: Between-pattern distances sorted in descending order.

Figure 4.13 shows the distances presented graphically. From this graph, it is possible to see that after about 18 features, the curve starts to flatten out, therefore dividing into roughly 2 slope regions (1-18, 18-35).

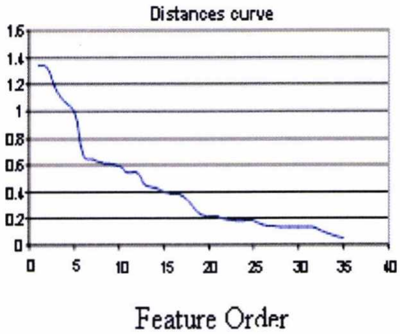


Figure 4.13: Distances

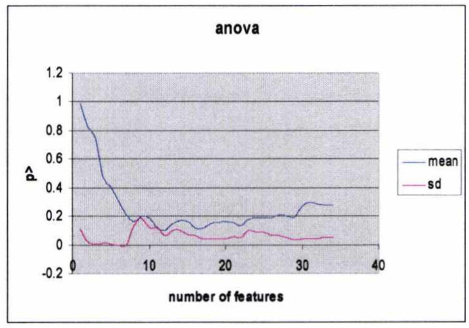


Figure 4.14: ANOVA p values

The ANOVA values of the mean and standard deviation are represented by the curves in Figure 4.14, based on the features defined in Table 4.4. These represent the ANOVA significance levels, p, using 2 to 35 features in the order shown in Table 4.4. The optimal number of features to be used to discriminate between different pattern types has been established to be 18 ranked first features from Table 4.4 ($F(3,68)=2.02$, $p<0.11$ for mean and $F(3,68)=2.93$, $p<0.03$ for standard deviation).

4.4.3 Between-Feature Analysis

The above analysis was based on a combination of all 35 presented features. Here, an analysis is carried out on each feature separately with respect to age characteristics. The aim here is to determine which features contribute to the discrimination between the two age groups of interest, as described earlier. The variances of the required features are analysed and ANOVA tables constructed. As per the formal definition, the significant differences in features occur when $p<0.01$. Tables 4.5 to 4.7 represent a list of features that can be used to discriminate between personal characteristics already mentioned such as handedness and the gender of the participants.

4.5 *Original Data Samples*

Initially, the analysis of variance is performed on the feature vectors representing the original data samples (see Table 4.5). The table values represent the feature IDs, where the significance level calculated from the ANOVA analysis was shown to be $p < 0.01$.

		Feature ID											
Age	*Both text and signature*	2	4	8	9	10	11	12	13	15	17	24	32
Age	*Text*	5	12	23	24	25	28	29	30	31			
	signature	5	12	18	23	24	25	28	29	30	31		

Table 4.5: Age Discriminatory Features.

The first row shows analysis of variance between the feature vectors representing the original samples of different target patterns (i.e. text and signature). The number of features is shown to discriminate between the handwriting samples of the two different age groups. The first of these features is the *maximum horizontal* velocity (2) followed by the *maximum vertical velocities (4)*, and these two features are components of (8, 9, 10, 11). This shows that a writer performs different handwriting tasks with a different velocity. Next, it can be seen that the features related to pressure, *average pen-pressure, maximum pen-pressure* and *average pen-pressure acceleration* (12, 13, and 24 respectively) follow closely. Finally, the last two features that can contribute to target pattern discrimination according to age are *maximum azimuth* and *orientation* (id 17, 32).

Table 4.5 also presents the analysis of feature vectors derived from six different age groups (18-30, 31-40, 41-50, 51-60, 61-70, and over 70). Here it can be observed that there are different features which show that a writer's age can be estimated from his/her handwriting. Here *velocity* is a very strong discriminator (features 2, 6, 7, 8, 9, 11). Other features that are useful for the determination of a writer's age are similar for both text and signature. These features are *pen-pressure* (12), *number of pen-ups* (18, for signature only), slant (20, form only), *writing duration* (23), *average* and *maximum pen-pressure acceleration* (24, 25), and finally, *positive* and *negative duration of horizontal* and *vertical velocities* (28 to 31).

4.6 *Forged (Imitated) Data Samples*

Table 4.6 presents the results of analysis of variance for the forged data. The features extracted represent information from the forgery tasks that the participants were asked to carry out, as was explained in Chapter 3. As mentioned earlier, the database contains 9 samples of forged signatures for each of 140 participants (all apart from first 10 subjects, whose handwriting data were used as forgery targets).

		Feature ID							
Targets	*All*	5	6	7	8	15	26		
Age	*signature*	12	13	23	25	28	29	30	31
	Text	12	23	25	29				

Table 4.6: Forged Data Samples for Subjects 11 to 150.

From the analysis of the forged handwriting samples using analysis of variance (ANOVA), the following observations can be made. When comparing signature and text patterns, features representing *velocities* (5, 6, 7, and 8), *maximum altitude* (15) and *average azimuth acceleration* (26) can contribute to the content discrimination. Interestingly, the age of a forger, on the other hand, can be estimated by *pen-pressure* features (12, 13, 25), and by *writing duration* features (23, 28 – 31).

4.7 *Original versus Forged Data Samples*

Finally, Table 4.7 presents the results of a comparison between a subject's original and forged data samples. The goal here is to determine the features that exhibit significant variation when a subject is writing in his/her own writing style, in contrast to when he/she is attempting to copy somebody else's signature or handwriting.

			Feature ID																	
Pattern	**All**	*signature*	1	7	12	13	18	21	22	24	25	26	35							
Age	**group 1**	*signature*	1	5	7	12	13	18	19	21	22	23	24	26	29	30	31			
	group 2	*signature*	1	2	5	6	7	23	26	28	29	30	31							
	group 3	*signature*	26	28	30															
	group 4	*signature*	1	5	20	22	23	24	25	26	28	29	30	31	33	34	35			
	group 5	*signature*	1	23	24	26	28	29	30	31										
	group 6	*signature*	1	5	22	23	24	25	26	28	29	30	31	35						
	group 1	*Text*	1	6	7	12	13	19	21	22	23	24	25	26	28	29	30	31	32	35
	group 2	*Text*	1	5	23	24	26	28	29	30	31									
	group 3	*Text*	1	5																
	group 4	*Text*	1	5	23	24	26	28	29	30	31									
	group 5	*Text*	1	5	19	23	24	26	28	29	30	31								
	group 6	*Text*	1	5	19	22	23	24	26	28	30	32	35							

Table 4.7: Original versus Forged Data Samples for Subjects 11 to 150

A very interesting result is apparent from Table 4.7. It is observed that the features that can be used to distinguish an original writing sample from a copied writing sample are represented by velocities (mostly horizontal, 1, 5, 6, 7), pen-pressures (12, 13, 24, 25), pen-ups (18, 19), handwriting shape and dimensions (21, 22, 32-35), writing durations (23, 28-31) across different groups in the database population. Nevertheless, features representing altitude and azimuth (14, 15, 16, 17, 27), which are connected closely to physical characteristics, such as hand and arm position relative to its natural orientation, do not appear in this table. From this, one conclusion, which may be drawn, is that these features stay stable for each writer, no mater if he/she is writing in his/her usual manner, or trying to copy someone else's writing. These features, therefore, can be effectively used for writer verification applications.

4.8 Summary and Conclusion

This chapter has produced significant insight into features that distinguish various age populations. Here, in this chapter a lot of effort has gone into identifying the features that significantly separate the age groups. Age related characteristics have been observed and a conclusion that is readily drawn is that velocity related features stand out when considering age. A look at the attempts to imitate the signature images reveals that one's natural features creep in and therefore the features are similar. In other words no observed effect is seen whether one is imitating or producing a genuine signature sample. Several methods were used to analyze the features extracted within the age groups studied. Investigations into the creation of forgeries in relation to the forger's own handwriting reveal a relationship of sorts as explained above however new techniques may seek to follow and explore this information derived and establish better relationships.

The work here is further investigated in the next chapter, Chapter 5, and expands on the resource here by examining the intra-class variations that exist within participants from an elderly population.

An in-depth look at the elderly population is carried out in the next chapter. This is indeed interesting as all along separation from and comparison between the young and the elderly has always been the focus. Here, we seek to examine the stability or otherwise of the features that the elderly poses. These same features are the ones that readily distinguish them from the younger. This links with central theme of this thesis by also stressing that these intra-class variations must be factored in when understanding the effects and characteristics of the elderly.

Chapter 5

Stability of Signatures within an Elderly Population

Biometric devices are increasingly being deployed in the context of individual identification, yet the levels of performance likely to be achieved are varied and very dependent on specific task conditions.

The accuracy of these systems depends to a considerable extent on the nature and consistency of the individuals and data collected from them. This chapter seeks to use data from experiments carried out to demonstrate the intra-class and inter-class differences and similarities within a person's signature as an example of the inconsistencies that exist within the signature samples obtained.

The rich source of data described in Chapter 3 will form the basis for the experiments described and the discussion which arises from their analysis. The motivation here is fundamentally to explore more about variability within individual characteristics, but with a particular emphasis on the elderly. The results seen previously in Chapter 4 are built upon here, and we continue to work with the 10 target signatures previously described as a basis for discussion.

5.1 Motivation

In the previous chapter, the features that uniquely identify or aid the separation of two age groups, specifically the elderly and the younger groups previously referred to, were examined in great detail. Using traditional statistical methods, it was discovered that by and large, velocity and time-dependent features provide an effective data source for separation between the groups.

Here, however, our focus is to examine the extent to which any intra-class variation i.e. differences within an individual's signature, is pronounced. We know for certain that natural variations do exist and humans exhibit this tendency to produce variations when repeating signing tasks. In pattern recognition, people who exhibit large variations in samples are typically referred to as 'goats' [163] This phenomenon is important when designing systems for identification, because we cannot justify the exclusion of these individuals neither should we expose them to unnecessary hardship when using biometric systems - due to frequent false rejections. Handwritten signatures exhibit natural variations or instability. A wide range of factors could cause this effect, such as psychological state, environmental conditions, writing materials used, the physical state of the signer and natural physiological factors e.g. the natural mechanisms of writing to mention a few. The extent of the differences perceived naturally varies from individual to individual.

Elastic Matching procedures are the most common and widely used methods to calculate the variability of a person's signature. To use this method effectively, one must have knowledge of the dynamic and static features of the signature in question. The procedure is carried out on a set of a person's genuine signatures

Dynamic Time Warping (DTW) was used in [164] in conjunction with x-y features to attain an accuracy of 90.6% when trying to recognize online handwritten data as an initial step, before computing the variation. It is a technique that finds optimal alignment between two time series if one time series may be warped non-linearly by stretching or shrinking it along its time axis. This warping between 2 time series can then be used to find the similarity between them. Fang et al [165] agree that there are variations in signatures written by the same person and state that these variations could occur in the shape or in the relative positions of the characteristic features. They therefore proposed two methods for tracking these variations. One measured the positional variation while the other measured the stroke variation. Their results were obtained using statistical analysis and produced comparable results. Dimauro et al [166] and Congedo et al [167] propose a measure of the local stability in on-line signatures. The local stability index is obtained from the frequency of direct matching points identified through an Elastic Matching procedure between a signature and each of the other reference signatures. In [23] Sabourin et al utilize an off-line approach using direction information and segmenting a signature into arbitrary shaped primitives to propose a static similarity measure using dynamic programming for the matching of a reference primitive set and a test primitive set.

The parameter –based one method [15] – a commonly used approach - was found to be quite applicable to this research as the variability or instability of an elderly person's signature is the main focus of the study. . The dissimilarity between reference samples, in a parametric approach, may be calculated as the distance between their parameter values from the mean values of the reference set. The variability or instability of an elderly person's signature as is the focus of this thesis can be deduced or is readily apparent from the mean and standard deviation values of the feature vectors in a reference set. In order to measure this, one may consider a set of features and look at the correlation or the spread of values to observe the intra-class variations

5.2 Signature Instability within a Population of Elderly Subjects

From the works cited above in section 5.1, it is clear that there exists a natural variation within genuine signature samples from any particular writer, but the extent to which this occurs across different populations is not known. Here we particularly aim to highlight the variability ranges observed within an elderly population but, before we consider some experimental data, we first highlight a few previously reported studies worthy of mention.

Guest [168] has carried out a series of experiments to assess the stability of signature systems across an elderly population. Using three experiments and a data set of 274 signatures it was found that there are a number of features that do show instability as a function of age. His study pointed out that features relating to execution time and pen dynamics such as velocity and acceleration exhibited significant differences and are to be taken into consideration when designing biometric subsystems. In [169], the author developed software to use four static features of a signature to measure the variations in a person's signing. Elsewhere, the experimental results reported in [170] claim that the simple features such as *X-*, *Y-coordinates*, the *speed* of writing and the *angle* with the *X-*axis are amongst the most consistent.

Other studies include [124] in which the authors examined the differences that arise within a person's genuine signature when using different capture methods. They found that the elderly when compared to the younger individuals do have significant variations when exposed to signing on different digitizers. They raised issues such as device type being taken into consideration when document examiners look at questioned signatures and the effect thereof. In [29], the authors examine the use of simple distances to measure the intra-class dissimilarity in handwritten signatures. Their observations show that the intra-class dissimilarity could be determined by relatively simple techniques. By creating a confusion matrix and using the *leave-one*-out protocol on a set of 690 signatures, they show conclusively that a direct comparison does yield excellent results. Here the author compares distances observed between classes and same writer distances. The class distance refers to the natural template variation observed automatically. The goal really was to determine whether simple relatively obvious distances could yield good results. Their results show 48 out of 50 signatures were correctly classified as being intra-class as opposed to inter-class with the only trade-off in this case being speed. Finally, Plamondon in his study, [171] looked at the invariance of velocity profiles. He first considers the handwritten signature as a vector addition of successive simple rapid movements. These velocity profiles are in turn represented by *delta-lognormal* equations which can then be broken down for comparison into small elements. Based on the above characterization he was able to critically evaluate the authenticity of signatures provided and determine intra-class membership.

Figure 5.1 below illustrates the intra-class variations appearing in the signatures of the individuals participating in this study.

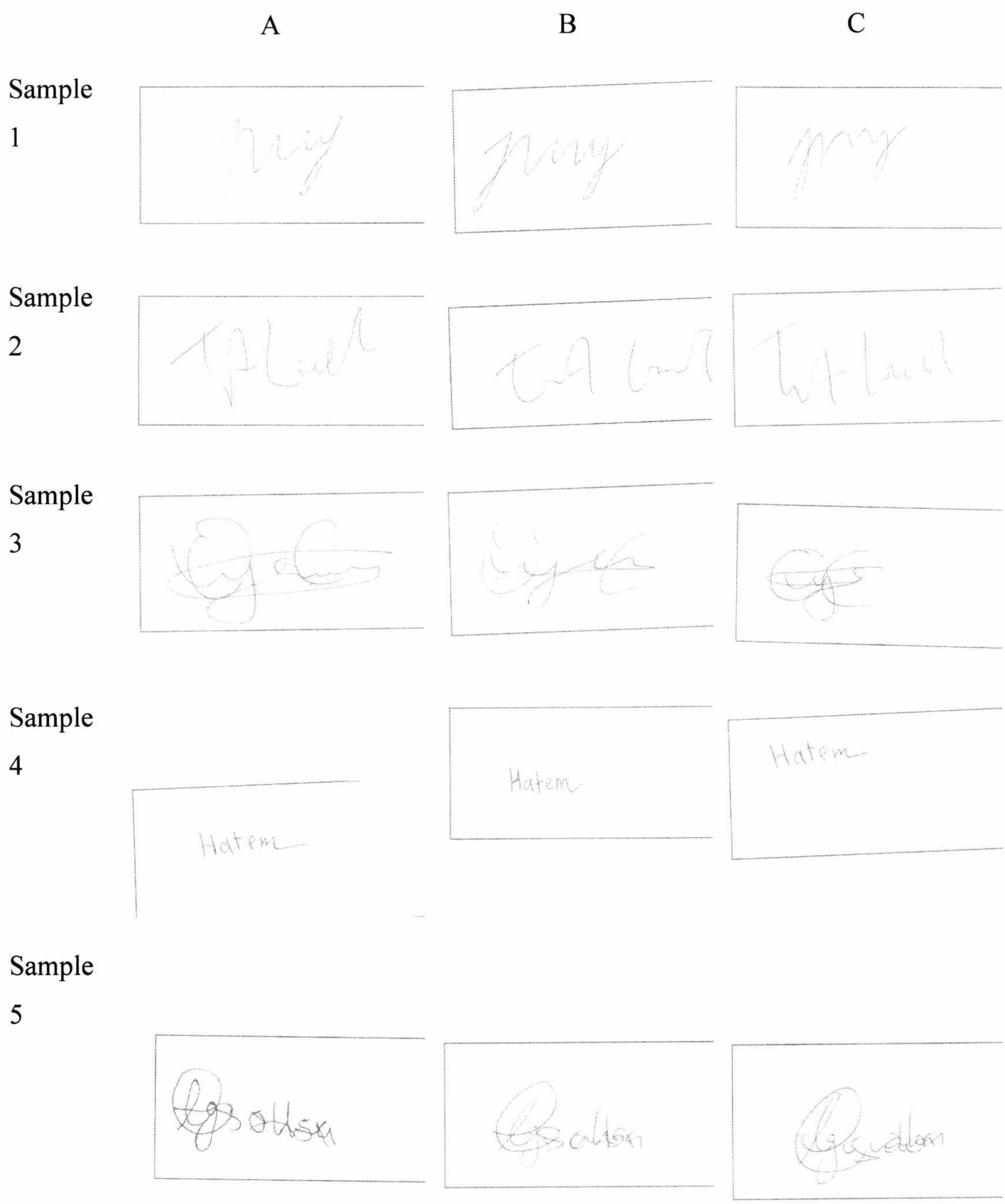


Figure 5.1 showing variations within people's signature

5.3 Experimental Procedure

In a bid to capture the intra-class dissimilarity, the experiment below was carried out.

Twenty subjects, half comprising of university students and the other half members of the public, drawn from a wide range of different nationalities were selected to undergo this experiment.

Ten subjects, all from the Computer Vision Research Group in the Electronics Department at the University of Kent, participated in this experiment. These ten subjects were treated as the younger set of participants and were aged between 20 and 25 years. Ten other subjects were selected from the group of over 65 year old participants to form the set of elderly participants. Each participant signed his or her original signature 15 times. They were instructed to try to be as consistent as possible in their signing. The duration of the experiment was about 4 minutes in total.

Before the start of the signing process, the individuals were given the opportunity to question what they were doing and were provided with an explanation of consistency. For the purposes of this study, consistency here refers to the 'goat' theory, where you have seemingly different looking signatures produced by the same author. This explanation was in the form of visual examples of so-called inconsistent signers. Note however that this was restricted to images only and not the underlying dynamic features that they possessed. It was also explained to the participants that there are dynamic features that exist and that analysis of the dynamics can also reveal 'hidden' variations. It was felt however as an exemplar that some signatures that were signed by individuals that showed visual inconsistencies were shown to any participant that asked. The results obtained here are therefore not restricted to static variations alone.

5.3.1 Analysis

For analysis, 20 signatures were used. 10 donated by the elderly and 10 produced by the younger. The assessments were carried out on the dynamic features of the signatures and later on the static images. Initially, the intra-class properties of each group (elderly and younger) are shown individually and then a comparative analysis is carried out.

The graphs in Figures 5.2 and 5.3 reveal significant underlying properties that exist in the respective groups. The Figures (5.2 and 5.3) show respectively the younger and the elderly variations in signature velocities when considering 15 original samples from each person. It is observed that the elderly participants considered, present higher intra-class variability when compared to the younger participants. In other words, the range of variability was more pronounced within the elderly population.

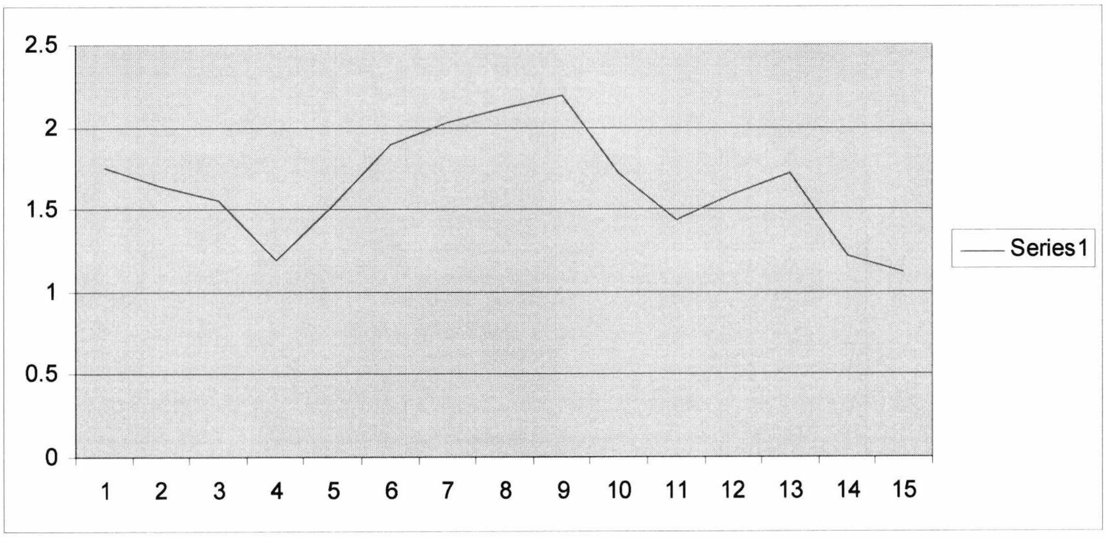


Figure 5.2: Intra-class Variations within the Elderly

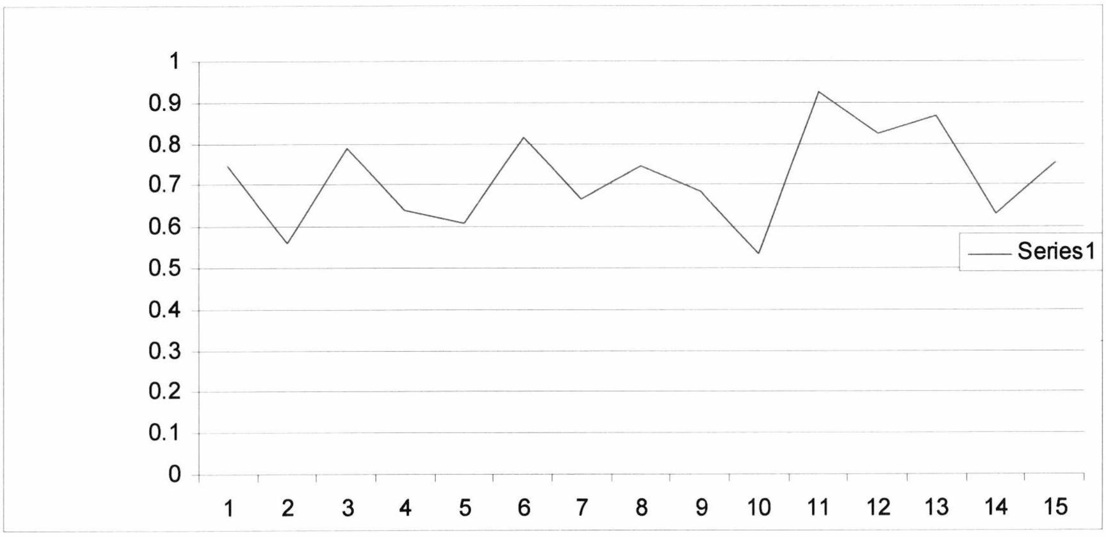


Figure 5.3: Intra-class Variations within the Young

Standard deviation results (recorded in Table 5.1) also confirm the visual results seen. The above conditions are observed when considering vertical velocity as one of the dynamic features, but further tests to support the observation that the elderly produced more intra-class variability were then carried out on the signatures using the time-dependent moment feature.

	Young	Elderly
Mean	0.72	1.65
Standard Error	0.03	0.08
Median	0.75	1.65
Standard Deviation	0.11	0.33
Sample Variance	0.01	0.11
Kurtosis	-0.81	-0.66
Skewness	0.06	0.02
Range	0.39	1.08
Minimum	0.54	1.12
Maximum	0.92	2.20
Sum	10.80	24.73
Count	15	15
Largest(1)	0.92	2.20
Smallest(1)	0.54	1.12
Confidence Level(95.0%)	0.06	0.18

Table 5.1: Descriptive Statistics Showing Intra-Class Differences Amongst the Elderly and the Young

Figure 5.4 serves as a contrasting find when compared to the results above. Here, the elderly participant displays a more consistent result across the 15 original samples provided. This sole elderly individual presents variations that are more consistent with that of the younger individuals. As shown, after normalization, the variation seen is that of +/- .025 as opposed to the 1.1 dispersion ranges. This single sample can be treated as an outlier, which can present some confusion and suggests a difficulty in classifying or identifying the groups according to their intra-class variability.

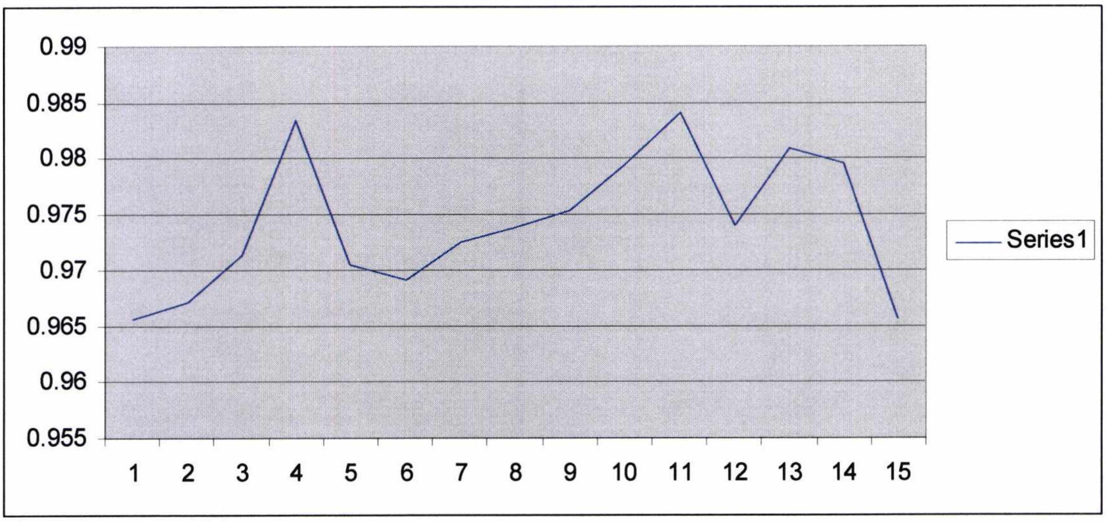


Figure 5.4: Elderly Outlier in Intra-Class Variations in the Elderly

It is important to stress that for the purpose of the work reported here, the emphasis is to determine the intra-class variability within the data collected. Because data collection procedures and feature measurements differ from case to case, it is necessary to consider these variations as unique to this data set only. However, what is clear from the results is the marked distinction of characteristics in the elderly population, as they show a wider dispersion in their intra-class feature measurements.

The use of standard measures of central tendency – the mean- and the standard deviation as a measure of variability is mathematically relevant to our work since it helps us in the analysis of the data obtained. This is because the intervals are similar and the data points used in the calculation of both statistics are the same. Other non-parametric measures such as the median and IQR (inter-quartile range, which is a measure of statistical dispersion) are displayed in Table 5.1 Indeed, some of the subjects' analysed result in equal mean and modal values, hence further strengthening the case to use descriptive statistics as a means of analysis.

Nonetheless, considering the apparent inconsistency displayed in subject-Elderly-(Figure 5.2 and Table 5.1) a low IQR range is seen, which tends to raise doubt over the stance taken. This stance refers to the notion as observed by the results of the analysis that the elderly display a more varied range in intra-class variation. Therefore, an attempt is made to further analyze the results. The use of box-plots, as shown in Figure 5.5 below provides another visual aid in determining the inherent variability within the subjects' genuine signature samples. It provides a visual comparison between the elderly and the younger variability results. This shows a more stable intra-class range amongst the younger participants. This stable range refers to a low variability amongst the samples provided. The form of the box-plots emphasizes the asymmetry of the data. Note that the representation given here is that of parametric statistics and is significant because it fits a normal distribution which is advantageous when performing hypothesis testing.

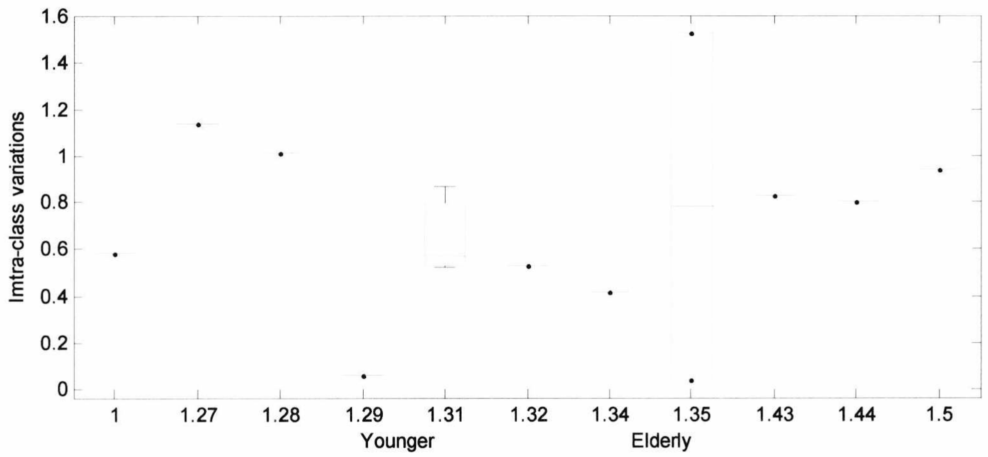


Figure 5.5: Intra-Class Variability for both the Young and the Elderly

The existence of outliers is observed but has little effect on the median and IQR values and therefore will not be discarded as is the practice within statistical analysis. One must consider the effect or not of outliers, as has been considered in this piece of work. The nature of the data above supports the decision not to discard the outliers because the confidence level is maintained at 95%. This confidence level indicates a high likelihood that the population mean lies within that range and that the data comes from a normal distribution.

5.4 Alternative Approaches

A heuristic approach using shape descriptors to determine a measurement of the inherent intra-class variations that exist between genuine signatures is found to be quite apposite.

A review of the various shape analysis techniques used for shape representation, description and matching, is given in [172]. These are divided into contour-based and region-based methods, using either structural or global approaches. Contour-based approaches are seen to be the more popular and exploit only the shape boundary information. Continuous and discrete formulations are two different approaches used for contour shape modelling. It is important to note that global contour shape representation techniques usually compute a multi-dimensional numeric feature vector from the shape boundary information. The matching between shapes is a straightforward process, which is usually conducted by using a distance metric, such as Euclidean distance or city block distance. Point (or point feature) based matching is also used in particular applications.

Three different groups of methods were considered in this study for the assessment of the dissimilarity between genuine signatures. Here there is a particular emphasis on the elderly as this group is the main focus of the study. To measure the intra-class variations in a genuine signature authored by an elderly individual, the Harmonic Mean dissimilarity measure was considered as proposed in [173]. In this method the dissimilarity between pairs of genuine samples was measured using the Elastic Matching procedure described in [174] and the Shape Matrix similarity measure as highlighted in [175] was investigated and surveyed. Here, Sabourin et al proposed an improved similarity measure between two Shape Matrices. Their approach outperforms all global shape factors designed and evaluated on the same database and experimental results are comparable to those obtained with local approaches.

5.5 Conclusions

This chapter has extensively examined the intra-class differences or variability in terms of the original signatures produced by elderly subjects. These differences show that there are wide variations that occur in the elderly as opposed to the younger subjects when considering their original features. The experimental results obtained from statistical measures show a marked difference. The issue of the inclusion of outliers was considered and other approaches to intra-class variability of signatures were studied and examined. It was observed that the inclusion or exclusion of outliers had no effect on the overall outcome of the results. The Chauvenet's Criterion was used to test this data which was assumed to be normal. The data passed the tests therefore making the outliers candidates for inclusion in the overall data calculations. We therefore conclude that the signing process is characterised by an element of variability. This intra-class variability is more pronounced in an elderly population that was considered in the work carried out. This in itself can lend more information to academics, industry analysts and biometric businesses. It therefore does provide an insight into how to best design biometric solutions with elderly subjects comprising a part of the end-user group. This is especially in scenarios where the solution is based on the use of the handwritten signature modality.

Having exhaustively examined the variability of signatures in this chapter, in the next we look at the concept of the "complexity" of the handwritten signature from a viewpoint of human perceptual judgement. Perceptual judgments are carried out and the possibility of a link between high variability and complexity is investigated. The influence of one over the other is investigated to see if there may be any effect on the participant's judgment when the additional factor of age is considered.

An additional dimension is sort in the next chapter where we seek to understand the behaviour of the elderly when performing natural day to day tasks. An example of such a task is seen in the inspection of signatures by check-out staff in the retail sector. There is evidence to show that the elderly now work longer as elaborated in Chapter 2 and as such the next piece of work is relevant. We seek to draw a link between the forgability of signatures and the age of the beholder. Results seen will aid the design of systems or the education of the elderly when carrying out this not so trivial task.

Chapter 6

Complexity and Forgeability of Signatures in Relation to Ageing

Understanding ideas of the "complexity" of an object is a subject matter which has been widely researched in the field of psychology, but the potential significance of such a concept in other fields is apparent and cannot be ignored [176-178]. For the purpose of this thesis, we are specifically concerned to consider the idea of complexity in relation to the perceived complexity of a handwritten signature by a human observer. The reference here to complexity is also meant to imply that a sense of perceived difficulty of some sort exists when observing any signature image as one would expect intuitively.

This chapter focuses on the perceived complexity of handwritten signatures and, in particular, aims to investigate whether, and to what extent, there might be a link between perceived complexity and the "forgeability" of signatures. In this context we use the term "forgeability" to refer to the ability of a non-skilled forger to imitate another writer's signature to a degree such that the imitated signature will deceive a casual (non-expert) observer into believing that the signature sample was genuine. We will report a number of detailed experiments which help us to capture an understanding of this phenomenon.

More specifically, we aim to investigate these concepts such that, observed differences in the perception of complexity by different age groups are considered, with a particular emphasis on the characteristics of the elderly. These differences are accentuated by comparing test populations at the two ends of the age spectrum covered by our available experimental data , in this case subjects in the age range {18 – 21} and those in the age range {>65} respectively.

Consideration is also given to the factors that most influence the decision of a subject to assign a particular complexity value to a particular signature pattern, to investigate the possibility of a link between these factors and the complexity estimates derived both from an elderly population and a younger set of participants.

In the previous chapters, various attributes of handwritten signatures within an elderly population were studied. Here we seek to determine whether there is any inherent relationship between these attributes and the way in which the signatures are perceived in practice.

Our experiments are carried out using static signature images and the results analysed. Also, since the primary focus of the work is to study the signature characteristics of the elderly, we have a particular interest in exploring issues such as complexity and observational patterns within this population group.,

It must be stressed that, although the academic research field of handwritten signature analysis is quite mature [179, 180], relatively little work has been reported in the field of perceived complexity of signatures.

6.1 Introduction

The handwritten signature is an attribute that is personal and in most cases is expected to be unique to an individual; hence the handwritten signature is generally to be regarded as a viable biometric modality. Because of its personal nature and the inherent need for an individual to protect him/herself from fraud, theft, impersonation, etc, it is reasonable intuitively to expect there to be a natural, and perhaps sometimes rather subtle, subtle attempt at incorporating a degree of complexity into the composition of one's signature. This might be expected to provide some basic safeguard to make fraudulent imitation of one's signature more difficult.

Considering first the general situation, Betke et al [181] derived two relevant descriptors for objects, one of them being the scalar measure of an object's *complexity* that is invariant under affine transformation. This measure was defined to be the ratio of the product of the object area and $2\Pi^2$ to the coherence volume V of the object. Their measure of complexity had a strong inverse relationship to the level of recognition ambiguity. A method for recognizing objects subject to affine transformation imaged in thousands of complex real-world scenes was developed. The method utilized in this case showed that the level of recognition ambiguity decreases exponentially with increasing object and scene complexity, which in itself is an interesting find. The second descriptor is a generalized coherence scale that has great practical value because it corresponds to the width of the object's autocorrelation peak under affine transformation and so provides a physical measure of the extent to which an object can be resolved under affine parameterization.

Found and Rogers [182] claim that there exists no test available in the field of forensic science to serve as a guide as to the perceived complexity of handwriting traces. However, they note the importance of having such a test and as such provided a model for testing complexity using discriminant function analysis. Their methodology was based on expert perception of how easy or difficult it would be to imitate a set of signatures, and therefore it has great relevance here. Their model used two variables (number of turning points and number of intersections and retraces) to classify signatures into three complexity groupings. In their proposed model, 300 signatures were studied and when compared to the complexity perception of a group of fourteen forensic experts, it was found that up to 72.9% of their perceptions of complexity were predicted by the model. These two variables are also reported in [183] as being an indication of the degree of complexity of a written signature.

Another approach to the measurement of complexity is proposed by Schlick et al [184]. Entropy-reliant complexity measures are estimated based on variable length Markov chains and the well known Shannon guessing game. Although the methods used in this approach are developed with the needs of the Human-Computer Interaction (HCI) community mainly in mind, it can be seen that an understanding of the notion of perceived complexity has a more general role to play in analysing individual responses in user interaction with displayed images.

An equally interesting approach to analysing complexity is to be found in the field of *fractal dimensions,* which is a bit beyond the scope of this piece of work. As mentioned earlier, the concept of complexity of general object shape has been researched quite widely in the field of psychology [185-187]. Some of the physical measures used in the characterisation of shapes in these studies include features such as the number of turns on the contour, line length, arc length, size of angles, area, compactness, jaggedness, and the use of statistical moments.

In the next section, an in-depth look into the notion of perception of the complexity of handwritten signatures by human subjects is described. In addition, various experiments used to support our research are demonstrated.

6.2 Perceived Complexity of Handwritten Signatures

Plamondon and Brault [174, 188] state in their study that the visual perception of complexity has a bearing on the ease with which an impostor might successfully forge a signature. They proposed an algorithm to quantitatively measure the difficulty that a potential forger will experience in an attempt to reproduce a signature dynamically. In a series of experiments, they show that the process of imitation is made up of a series of tasks which include perception and preparation. They report a relation between reaction time and the signature complexity. Their work is centred explicitly on forgery scenarios and the assertion that a potential forger finds it harder to imitate a signature with several targets than one with fewer targets is reported. This leads to a link between complexity of a signature, form and number of crossings as reported in the literature.

Fairhurst et al [7] report various experiments carried out on the issue of perceptual analysis of the handwritten signature. Their work on human signature analysis shows a modest spread in the perceived complexity of handwritten signatures within a test group while showing a general agreement at both ends of the complexity scale but with a problem assessing quantitatively the intermediate signatures. This leads to the investigation of the merits of two opposing hypotheses regarding the errors associated with complex signatures: On the one hand, it might be argued that highly complex signatures are associated with high false acceptance and the second that the highly complex signatures are associated with low false acceptance. It is possible to find either opposing hypothesis plausible because one would reasonably expect a 'complex' signature to be so confusing to the untrained observer, such that any alteration is not easily perceived. While conversely, it can be argued that a 'complex' signature that is being imitated would more often be rejected because the casual observer would be more sceptical and always be thrown off by the sheer complexity of the image. . In short, we stress that signatures generally vary in degree of complexity. The ability to forge these complex signatures is still a subject for debate and we will provide our findings that support either argument in a later section. Some of these issues are investigated further in the work to be reported here. Additionally, Fairhurst et al [189, 190] further strengthen the argument for more research to be carried out into the complexity of signatures by showing the need for an understanding of human performance in biometric identity checking and developing techniques which allow incorporation of human capabilities into machine-based processing.

Related work on the optimal condition for human recognition of words in relation to constituent features can also shed some light on to our concerns. For example Schomaker and Segers [191] report a human, printed word recognition rate of 87.9%, after exposure to the words of the lexicon. Specifically, the first and last letters of the words were found to be very important for the recognition process, as well as vertical strokes, crossings, high curvature points, and curled endings of final strokes. Moreover, vowel characters were found to be less important than consonants for the word recognition process. Lorette [192] highlighted the importance of the knowledge gained from human perception in order to design more adequate handwriting reading systems, and extensively analyzed human perceptual properties of handwriting and reading. The elements deemed to be perceptually important include the trajectory of the ink trace, the visual shape of the handwritten image, the singularities and regularities, the fundamental down-strokes, the local relative positions, the relative sizes of primitives and letters, the discriminative signs, and the apparent fuzziness. On the other hand, it was suggested that for recognition only the use of a small number of significant primitives is necessary, without considering the unstable parts of the handwriting such as the width of the character.

Some of these findings may be extended to illuminate the perceptual processes used in signature recognition and verification by humans.

Next we illustrate by way of various experiments, how humans, and especially the elderly who are the principal focus of this work, perceive complexity in handwritten signatures and show how some useful and valuable conclusions can be drawn from such a study.

6.3 Experimental Methodology

Here we investigate the judgement of individuals about the perceived degree of complexity in signature presented for inspection. The process of imitating (forging) target signatures is also captured and this allows further insight into the ability of individuals to correctly classify signatures as being genuine or not, and error rates are calculated to support a quantitative analysis of such behavioural characteristics.

Our experimental approach consisted of 3 parts:

6.3.1 Estimating Signature Complexity

The aim here was to gauge experimentally how individuals perceived signatures from the viewpoint of how "complex" the form of the signature appears to be. A group of 150 participants took part in an experiment to determine the perceived complexity of various handwritten signatures. The participants were drawn both from the University community and the general public and varied in age and gender. The age of the youngest participant was 19 whilst that of the eldest was 79. The specific population characteristics including a histogram of age distribution are shown in Table 6.1 and Figure 6.1.

Age Groups	18-29	30-40	40-50	50-60	60-70	Over 70
Number of Participants	82	16	9	16	17	10
Percentage distribution	55.00%	10.50%	6.00%	10.50%	11.30%	6.70%
Original Writing Language	English	Western	Non Western			
	81.00%	8.00%	11.00%			
Gender	Male	Female				
	39.90%	60.10%				
Participants	Students	General Public				
	55.00%	45.00%				
Handedness	Right	Left				
	91.00%	9.00%				
Average Age	37					
Minimum Age	19					
Maximum Age	79					

Table 6.1: Characteristics of Participants

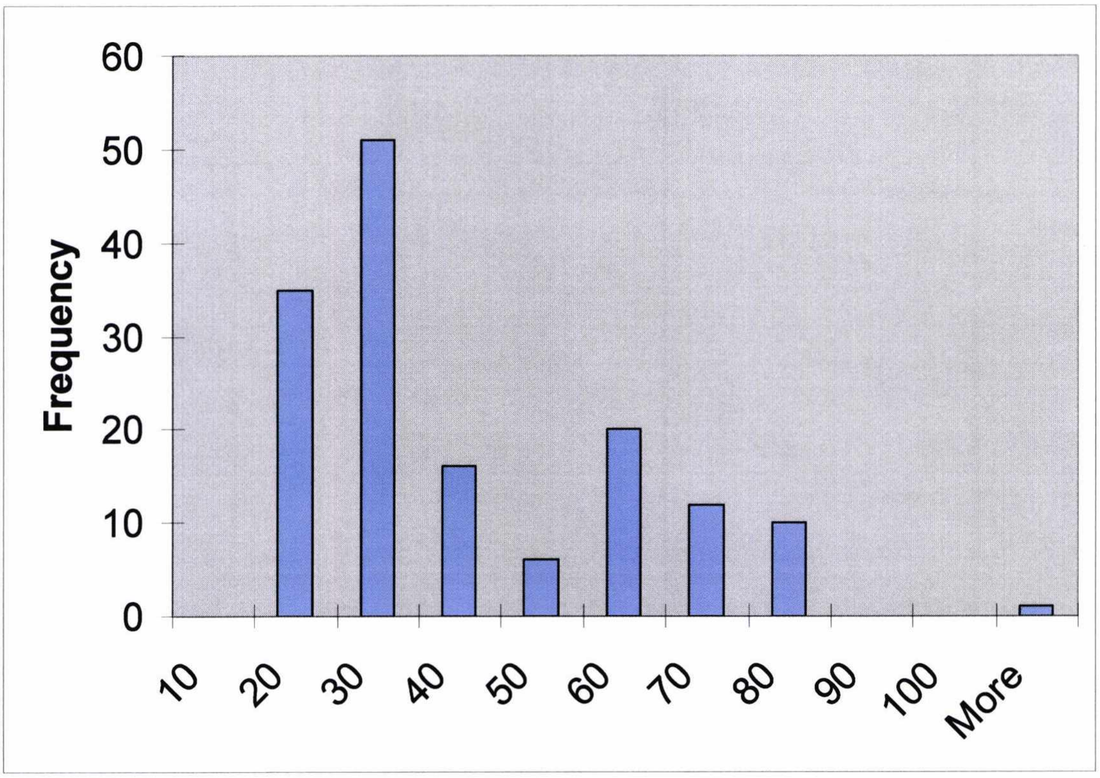


Figure 6.1: Histogram Showing Age Distributions of Participants

Ten people were selected at random from a set of twenty students (members of the research group) who volunteered to supply their signatures. These signatures were used as the target signatures for this experiment. Details of the collection of these signatures were outlined in Chapter 3. Analysis of the dynamic and static features of these ten signatures was carried out in greater detail in Chapter 4

The 10 target signature images are shown in Figure 6.2. These signatures were captured as previously described in detail in Chapter 3. The signature images captured were scanned at a resolution of 100dpi onto A5 size laminated sheets. The scanning process and settings of the resolution was set to the best quality in order to preserve the image quality and appearance of the signatures.

Figure 6.2: Signatures Samples Obtained

Each participant was shown the set of 10 target signatures in the same order (the same order was shown to all, thereby establishing consistency) and asked to rate the complexity of each signature on a scale of 1 to 10; 10 being highest complexity and 1 being lowest complexity. The subjects were not given any indication of a measure or definition of complexity but instead were asked to make that judgement themselves in assigning their chosen rating. Flash cards containing the name and signature of the individual that produced the sample were shown to them. The inclusion of the name of the author of the signature aided the participant's reading of the signature image. Comments made by the participants also showed that the inclusion of the name of the signature donor helped in the complexity rating of a target signature. With each flash card in view in turn, the participants were allowed 10 seconds to assign their rating to each target signature. This process of assigning complexity ratings was performed on an individual basis and answers given were not changed later neither was any help provided by the researcher. Also, the participants had only one signature at a time to rate so no comparison to another signature was made.

Figure 6.2 shows the 10 signatures in the order presented to the subjects, while Figures 6.3 and 6.4 show the perceived complexity rating for each of the ten signatures.

As the participants made their choices, all comments made about the basis for the recorded complexity judgement were noted and were therefore available for further analysis later. The outcome of such an analysis is detailed later in Section 6.3.2 and reveals some interesting observations regarding the perceptual ability of the subjects and the factors that most influenced them in assessing the complexity of the target signatures.

6.3.2 Analysis of Results

The study found that for every signature there is a measure of inherent complexity that is portrayed. This is consistent in all the findings from the experiments. Overall none of the signature received a zero rating for complexity. On this basis emphasis was therefore placed on examining the characteristics of the 'complex' signatures and whether there is a general agreement as to which signatures exist at either end of the complexity rating scale.

Some observations and statistical data on the results are shown in Table 6.2; specifically, the popular measures of central tendency are utilised and are shown in the Table.

		Initial Complexity Rating		
Signature	Mean	Median	Mode	Standard Deviation
1	7.5	8	8	1.8
2	3.9	4	2	2.0
3	4.2	4	3	1.7
4	6.2	6	5	1.9
5	3.8	4	2	2.1
6	7.4	8	7	1.8
7	5.0	5	5	2.4
8	8.2	8	10	1.7
9	1.8	1	1	1.2
10	5.7	6	6	1.9

Table 6.2: Signature Complexity Statistics

It is observed in Table 6.2 that Signature 9 had the lowest perceived complexity response while Signature 8 had the highest perceived complexity response. The results show an upper and lower bound on perceived complexity of signatures as represented by the target set by humans. The mean lower bound in complexity values of all the 150 participants was 1.8 and the upper bound was 8.2. A visual representation in the form of a histogram is provided below in Fig.6.3, showing the complexity rating for each signature.

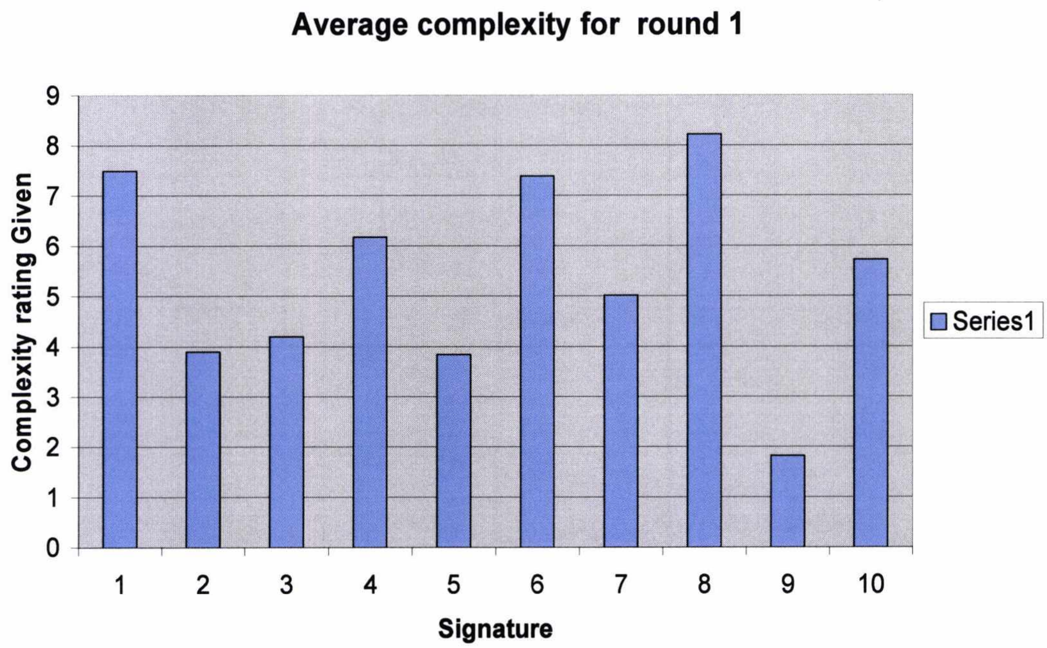


Figure 6.3: Initial Average Complexity Responses

The concept of "skewness" is also applied in the analysis of the findings here. *Skewness* is defined as the degree of asymmetry of a distribution. Positively skewed data (rightward skewness), have the following attributes: mean>median>mode, while negatively skewed data (leftward skewness) have mean<median<mode. A symmetrical data distribution shows mean=median=mode.

Signatures 2,3,4,5 and 9 appear positively skewed, signature 8 appears negatively skewed and signatures 1, 6, 7 and 10 show no difference in their respective measures of central tendency, thereby showing a symmetric distribution. The significance of these skewness observations is that there is a presence of outliners in the captured data. This also raises the question of inclusion or not of these outliners in data analysis. However, for the research we are carrying out it is best to represent a true output of what was captured.

The histogram above in Fig 6.3, shows that there is a general agreement amongst the participants in the choice of complexity rating at both extremes of the complexity scale while the complexity rating of the middle-rated signatures appear to differ from individual to individual. This is not surprising, as we have to bear in mind that this shows evidence of uncertain human responses and a more confused decision-judgement.

Subsequently, the participants were asked to rate for a second time the complexity of the same ten signatures, which were again shown in the same order as the previous experiment. This second experiment took place at time interval after the first rating experiment ranging from one hour to two weeks. This was to enable the testing of consistency of the complexity rating process, and to see if any intermediate tasks such as forgery attempts will change the perception of signature complexity.

The observed complexity ratings of the signatures after the time interval had elapsed are shown below. The results are interesting and revealing, showing a distinct and definite shift in the skewness but with identical values of standard deviation. Signatures 1, 2, 3, 4 and 5 now exhibit symmetrical distributions while Signatures 9 and 10 are positively skewed and Signatures 6, 7 and 8 negatively skewed. Table 6.3 and Figure 6.4 show the values and the pictorial views respectively.

		Complexity After Intermediate Task		
Signature	Mean	Median	Mode	Standard Deviation
1	7.5	8	8	2.0
2	4.5	4	4	2.1
3	5.1	5	5	1.8
4	6.6	7	7	1.8
5	4.9	5	5	2.0
6	8.2	8	9	1.5
7	6.3	7	8	1.9
8	8.5	9	10	1.4
9	2.5	2	1	1.7
10	5.7	5	5	2.0

Table 6.3 2nd set of Signature Complexity Statistics

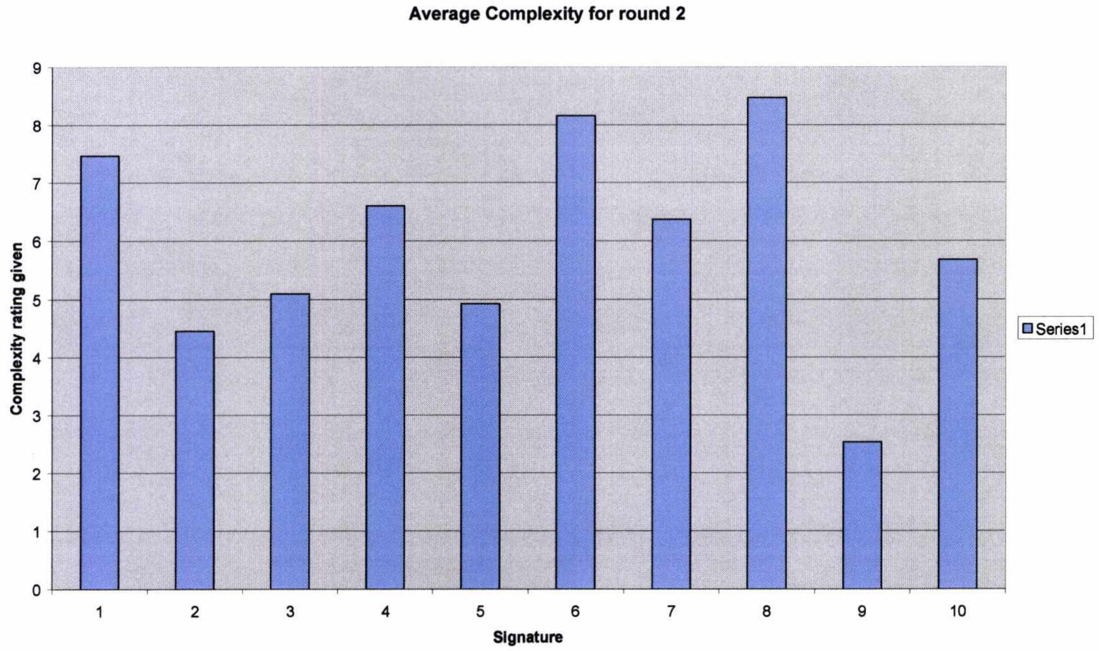


Figure 6.4: Average Complexity Responses

This gives an insight into the perceptual characteristics of human subjects in relation to the concept of complexity. As we know human behaviour is especially difficult to model or in fact predict.

It is worth noting the general agreement in the extremes of the scale of complexity as is shown in the histogram of Figure 6.5b. As seen from the histograms, a near perfect correlation or linear relationship exists between the two samples, these two samples relate to the complexity estimates obtained at two time intervals. Complete or perfect linear correlation is confirmed by reference to Figure 6.5a. Here, the correlation seen is 0.9. This then points to the fact that the subjects are indeed consistent in their perception of complexity and that time has no effect on such a decision. Furthermore, as will be demonstrated later, even the attempted forgery of these signatures did not undermine this consistency. In other words, the fact that one of the intermediate tasks was to forge or imitate signature samples did not make the subject vary their complexity estimates.

A test of the correlation between the first and second experiments was carried out using the Spearman Rank Correlation Coefficient. The Spearman rank correlation coefficient is one example of a correlation coefficient others include the Pearson's product moment. It is usually calculated on occasions when it is not convenient, economic, or even possible to give actual values to variables, but only to assign a rank order to instances of each variable. It may also be a better indicator that a relationship exists between two variables when the relationship is non-linear. However, here the relationship is seen to be linear.

Commonly used procedures, based on the Pearson's Product Moment Correlation Coefficient, for making inferences about the population correlation coefficient make the implicit assumption that the two variables are jointly normally distributed. When this assumption is not justified, a non-parametric measure such as the Spearman Rank Correlation Coefficient might be more appropriate.

However, in this instance, there are a mix of distributions so the former method is used. Table 6.4 shows a correlation coefficient of 0.98 between the two rounds and the scatter plot provided in Figure 6.5a is also shown.

Av. Complexity round 1	Av. Complexity round 2	Correlation
7.50	7.46	
3.90	4.46	
4.20	5.10	
6.18	6.61	0.98
3.84	4.93	
7.40	8.16	
5.02	6.38	
8.22	8.47	
1.82	2.54	
5.73	5.68	

Table 6.4: Correlation Statistics

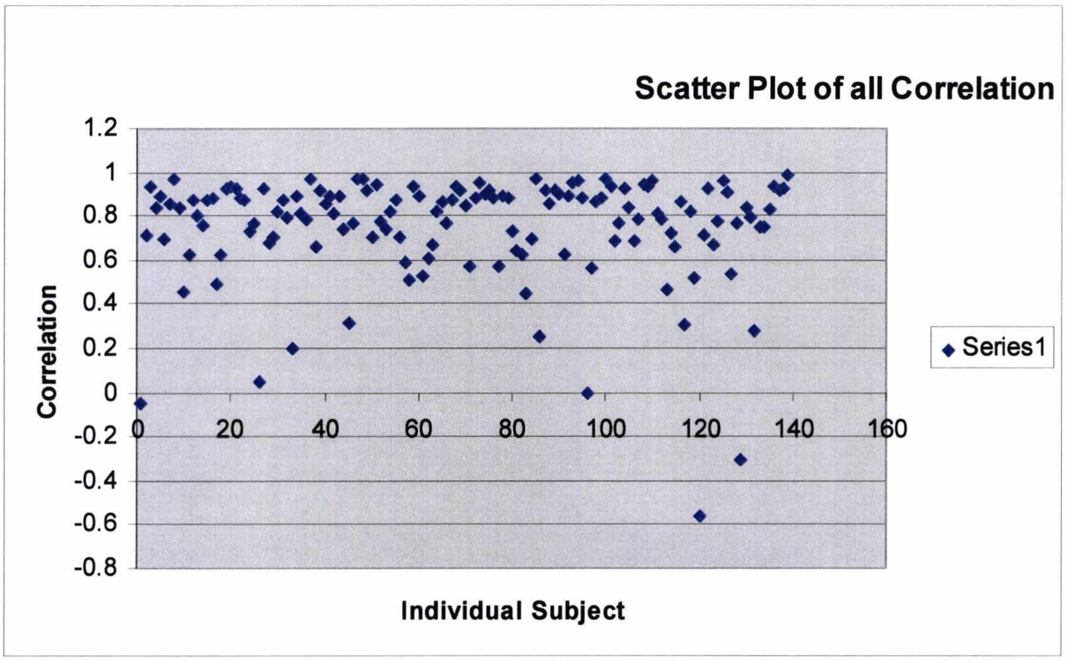


Figure 6.5a: Complexity Correlation

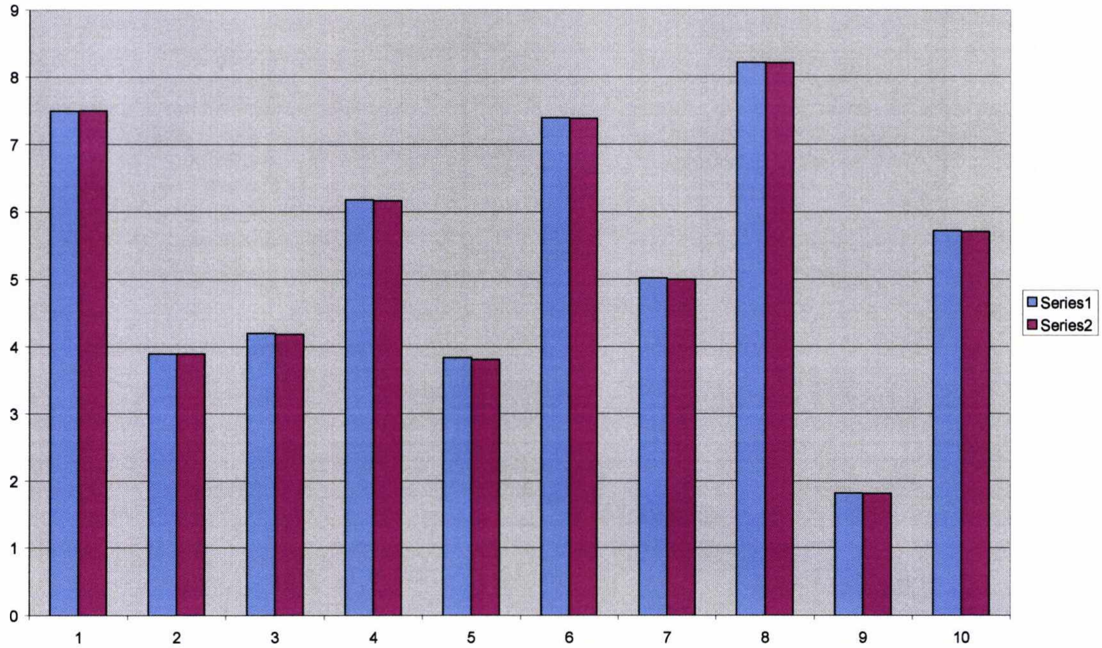


Figure 6.5b: Complexity Histogram Showing Values Before and After Intermediate Task

A closer examination of the effects of age on responses, a principal focus of this work, is possible by considering Figure 6.6 below. For the purposes of this work the "elderly" population was taken to be defined as including those over the age of 60, while we similarly define a "younger" population as including all those participants between the ages of 18 and 20. In our experiments, we will generally compare results within these two populations to illustrate changing performance with age.

A breakdown of the experimental population according to age reveals some interesting facts, as is apparent by considering the data in Figure 6.6. Here, we see the average complexity values chosen by each age group

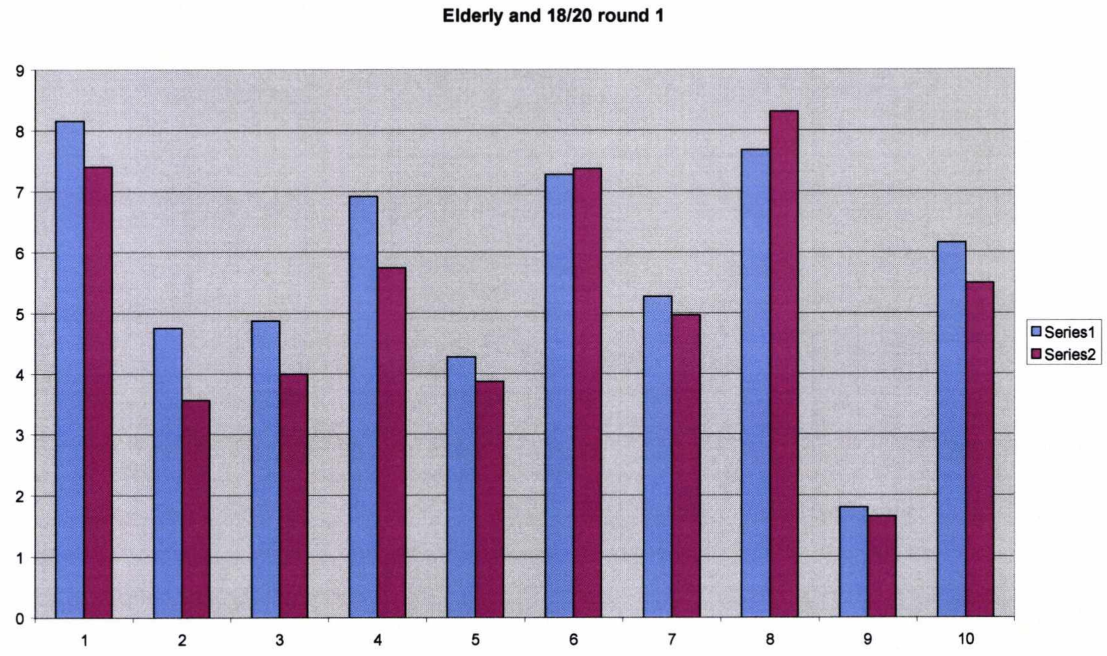


Figure 6.6: Elderly and Younger (18/20) Complexity Results

It is noted on closer inspection that the elderly group, when compared to the younger group, generally assign a higher rating of complexity for 80% of the target signatures shown to them. This remains constant over the two experiments. Therefore age can be seen to have an effect on the perceived complexity of signatures. Table 6.5 provides the results of the complexity estimates given by the elderly.

The other interesting thing to observe here is the fact that the signature selected as the most complex (Signature8) was rated much higher in the case of the younger observers in comparison with the ratings assigned by the elderly observers. Thereby we find that the elderly have brought their experience to bear in the decision making process

The features of the least complex and most complex (as rated by the participants in these experiments) will be analysed for comparison later.

		Complexity Ratings Assigned by the Elderly Population		
Signature	Mean	Median	Mode	Standard Deviation
1	8.2	8	7	1.5
2	4.8	4	2	3.0
3	4.9	5	5	2.0
4	6.9	7	7	2.1
5	4.3	4	4	2.4
6	7.3	8	9	2.0
7	5.3	5	5	2.8
8	7.7	8	10	2.2
9	1.8	1	1	1.4
10	6.2	6	6	2.1

Table 6.5: Statistics of Complexity Estimates by the Elderly

As is seen, there is an overwhelming symmetry in almost all the cases and the elderly agree on the complexity of signatures. This is evidenced by the variation in the values of standard deviation.

As mentioned earlier, during the execution of these tests, participants were also asked to undertake some other interspersed handwriting tasks. One such task was to attempt to forge or imitate three signatures chosen from the ten original target signatures.

6.3.3 Analysis of Signature Forgery Attempts

In a bid to investigate the possibility of a link between perceived complexity of signatures and the ease of accurately forging signatures, a further experiment was conducted as follows.

Two popular hypotheses are tested here. One assumes that a more complex signature should be harder to forge than a less complex one, and therefore under verification should produce a low false acceptance rate. An alternative and opposing hypothesis suggests that a less complex signature should be easier to forge and as such result in a high FAR. Conversely there are similar arguments. One would think that an 'easy' or less complex signature would have noticeable variations if attempts were made to forge it therefore any casual observer might accept a forgery as a genuine sample. This however also can be argued that a less complex signature would always have high FAR's because humans may be more forgiving of 'imperfections and we can only safely say that *when two signature samples are completely identical then one is most definitely a forgery.*

Thus, a task given to subjects (although this was an optional task) was to ask them to imitate (i.e. "forge") a subset of the target signatures. The subjects that agreed to partake in this experiment were each presented with 3 signatures to imitate 3 times. Prior to this they were given at least 5 minutes to 'practice' forging these signatures. This exercise allowed us to build up a base of information about the performance of "non-skilled" forgers with respect to the target signature data. Subjects were allowed practice time and both static and dynamic features were extracted from the data captured. This was documented in more detail in Chapter 3. The benefit of this was the fact that a valuable forgery database was created.

In almost all the cases the process and experience of performing signature forgeries was an unfamiliar one to the participants but provided useful insight into non-skilled attempts at forgery and the inherent difficulties of performing such a task.

6.3.4 Verification of Signatures

The task undertaken here provided a realistic scenario of a situation in which signature checking takes place manually i.e. by human physical inspection. The purpose here was to investigate performance rates in practice while visually inspecting the signatures. Additionally, an assessment was undertaken to establish if there were any links existing between such rates and the perceived complexity values obtained. The same participants that took part in the earlier tasks were then asked to consider a set of signatures that unknown to them were an equal mix of genuine and forged signature samples of an individual. After this and as a test of their consistency and to see if the intermediate task affected their perceptual judgement of complexity, they were then asked to rate the same signatures on the same scale of 1 to 10 and in the same order. The effect on complexity was addressed in the previous section where we showed a high degree of correlation between the 2 complexity tasks. That is before forging and afterwards.

As noted above, this is an area in which relatively little work has previously been reported, even though a lot of work has been carried out in the area of handwritten signature verification in general.

Fairhurst and Kaplani [7] performed various extensive experiments and on analysis, came to the conclusion that signatures rated with a higher complexity makes imitation more difficult. This leads to more errors in perceived authenticity due to the increased inherent flexibility in assessment.

Each participant was shown a mix of three original and three forged signatures in the same order and was the same person's signature, with a genuine version of the signature available for inspection throughout the process. They were then asked to classify each presented sample as "forged" or "genuine".

The original image was provided in hard copy form and thus subjects could handle its carrier document and view it as desired. No time limits were imposed but the decision process took, on average, 10 minutes per person for the whole test.

The samples used in this experiment were those obtained from the data collection procedure outlined in Chapter 3 and the 3rd signature from each target sample was selected. This third sample was selected because it was felt that each participant's third attempt at forging or imitating would be the nearest or best attempt; one that closely matched the target signature. In other words this sample would be the one most likely to be accepted as genuine.

Results

The use of humans in performing classification functions (as opposed to automated methods) is questionable but necessary as it does provide knowledge of human processing of signatures as occurs in real life.

The result of the human performance in identifying whether the signatures were genuine or imitated is presented in the following Table 6.6.

Sig 1	**31.37%**	**5.88%**	**19.60%**	**13.72%**	**29.41%**	**62.74%**
Av						
FRR	**35.94%**					
AV						
FAR	**18.29%**					
Sig 2	**37.25%**	**7.84%**	**23.52%**	**17.64%**	**78.43%**	**41.17%**
Av	**52.28%**					

FRR						
AV						
FAR	**16.33%**					
Sig 3	**49.01%**	**3.92%**	**19.60%**	**45.09%**	**80.39%**	**88.23%**
Av						
FRR	**72.54%**					
AV						
FAR	**22.87%**					
Sig 4	**14.81%**	**44.44%**	**40.74%**	**85.18%**	**11.11%**	**37.03%**
Av						
FRR	**56.78%**					
AV						
FAR	**20.98%**					
Sig 5	**5.55%**	**0%**	**24.07%**	**75.92%**	**24.07%**	**25.92%**
Av						
FRR	**33.33%**					
AV						
FAR	**18.51%**					
Sig 6	**70.37%**	**7.40%**	**14.81%**	**0%**	**38.88%**	**51.85%**
Av						
FRR	**53.70%**					
AV						
FAR	**7.40%**					
Sig 7	**16.00%**	**2.00%**	**6.00%**	**12.00%**	**44.00%**	**12.00%**
Av						
FRR	**22.00%**					
AV						
FAR	**8.66%**					
Sig 8	**30.00%**	**10.00%**	**10.00%**	**10.00%**	**56.00%**	**22.00%**
Av						
FRR	**32.00%**					

AV FAR	**14.00%**						
Sig 9	**36.00%**	**20.00%**	**8%**		**24.00%**	**50.00%**	**24.00%**
Av FRR	**31.33%**						
AV FAR	**22.66%**						

Table 6.6: Verification Results

The table also shows that the
Highest FAR: Signature Verification 3, Sig 4 = 45.09% FAR (23).
Lowest FAR: Signature Verification 6, Sig 4 = 0% FAR (0).

	Sig. 1	**Sig. 2**	**Sig. 3**	**Sig. 4**	**Sig. 5**	**Sig. 6**	**Sig. 7**	**Sig. 8**	**Sig. 9**	**Total**
FRR %	35.94 %	52.28 %	72.54 %	56.78 %	33.33 %	53.70 %	22.00 %	32.00 %	31.33 %	**43.32 %**
FAR	18.29 %	16.33 %	22.87 %	20.98 %	18.51 %	7.40 %	8.66 %	14.00 %	22.66 %	**16.63 %**

Table 6.7: Summary of Error Rates and an Average

It shows in Figure 6.7 that the average FRR obtained was 43.32% while an average FAR of 16.63% was observed. The FRR was calculated as the percentage of genuine signatures being falsely rejected and the FAR was calculated as the percentage of forgeries being falsely accepted. We see that generally the participants were better at identifying forgeries. These results are comparable with results previously reported in the literature [18, 188, 190].

However, further analysis of these figures, with emphasis on the elderly and how they perform, shows some interesting error rating results, as detailed in Table 6.8.

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	FRR (%)	FAR (%)
Elderly	47.71	24
Younger	47.32	15.02

Table 6.8: Error Rates According to Age Groups

It is observed that the elderly group perform very similarly to the younger group when it comes to identifying authentic signatures as evidenced, by the FRR percentage values shown. However, with respect to the FAR values, the elderly group appear to show more susceptibility to accepting forgeries as genuine samples. We can see that age does play a role here.

As shown in Figures 6.7 and 6.8, we see a distinct separation in the error ratings presented by the two age groups.

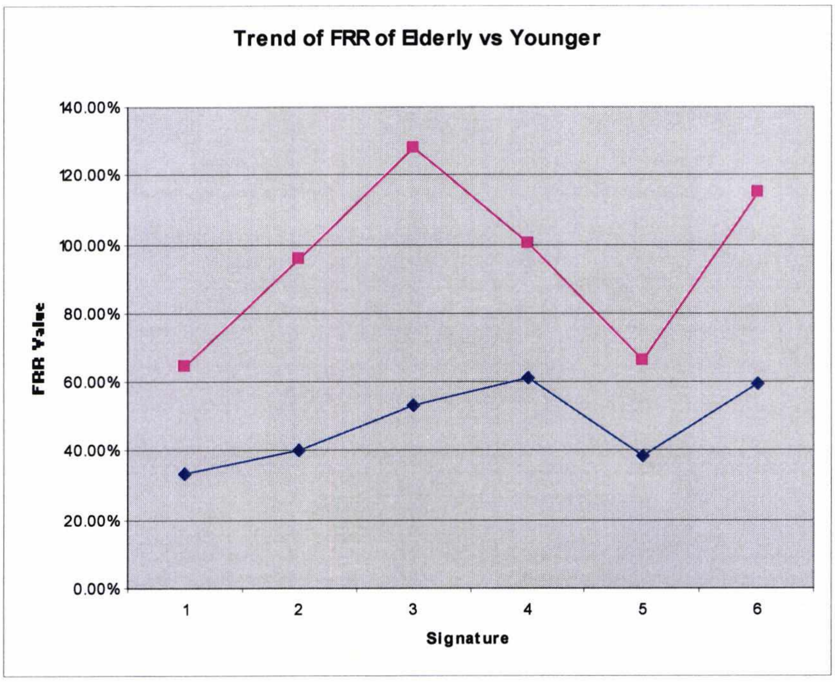

Figure 6.7: FRR for the Elderly and the Younger

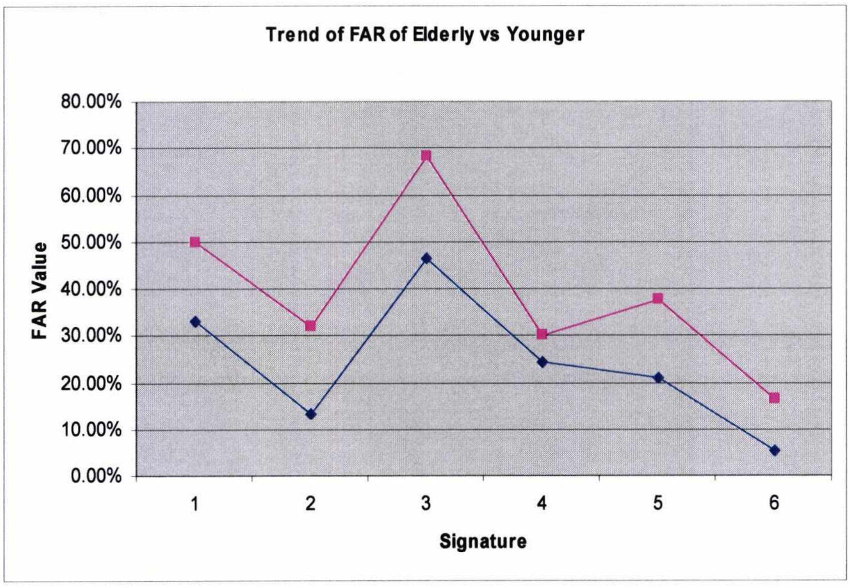

Figure 6.8: FAR for the Elderly and the Younger

With these error rates now established it is now possible to investigate if there is a relationship with the complexity scores associated with the respective target signatures. Indeed, from the data shown in Figure 6.9 we may conclude that as complexity increases the false acceptance rate decreases, while as complexity increases the false rejection rate increases.

We may express this in an alternative way as follows:

If C= Perceived Complexity

And

FRR= False Reject Rate

FAR= False Accept Rate

Then $C \propto 1/FAR$ and

$C \propto FRR$

The above equation(s) mean that Complexity C is inversely proportional to FAR and directly proportional to FRR, and therefore following can be stated:

$C = K * FRR$

and

$C = K/FAR$

Where K = constant of perceived complexity

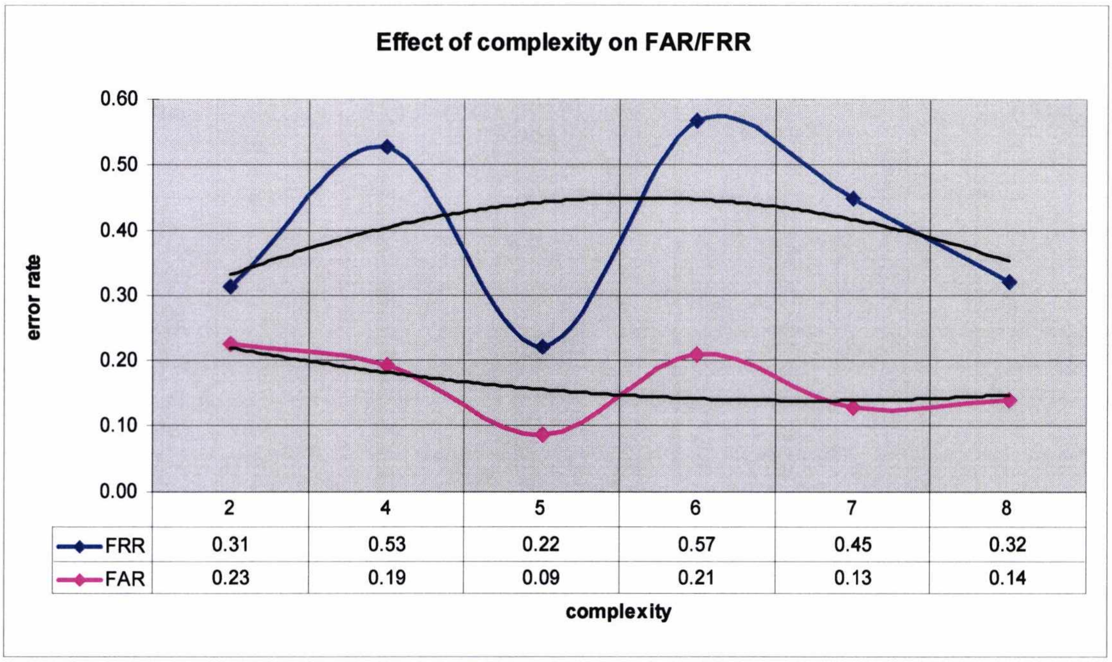

Figure 6.9: Effect of complexity on error rates

The strong correlation between the responses presented in Table 6.4 strengthens the argument that is being made here as seen in the Figure 6.9. We notice interestingly that at Complexity 5 there is a huge dip in error rates but the trend still continues. This dip could be attributed to the fact that the signatures chosen to have a complexity of 5 are 'mid-range' and so no distinct classification could be attributed to them. That is they are border line complex and borderline not complex. The error rates then show that these set of signatures are more susceptible to confusion and therefore individuals err on the side of being positive and therefore are more forgiving and tolerant.

These signatures that fall in this range are difficult to analyse and as such an attempt will not be made here to characterize for certain the observation seen.

6.4 Elderly Responses to Complexity

The aim of these experiments that follow, was to measure the responses of the elderly in a task to determine their perception of complexity and to understand better, particularly by asking questions about how they judged the complexity of the samples presented and what most influences their perception of complexity of signatures. The experiments were designed to gauge their performance when presented with representative signatures of varying degrees of form and style, such as might be found in realistic practical scenarios.

6.4.1 Procedure

The participants in this experiment were 20 elderly individuals resident at a local care home. The eldest resident and participant was a lady aged 92, while the youngest was aged 74. Table 6.9 shows the distribution of these participants.

Age Groups	70-75	75-80	80-85	85-90	90-95	Over 95
Number of Participants	3	6	3	6	2	0
Percentage distribution	15.00%	30.00%	15.00%	30.00%	10.00%	0%
Original Writing Language	English	Western	Non Western			
	90.00%	10.00%	0.00%			
Gender	Male	Female				
	25.00%	75.00%				

Handedness	Right	Left
	95.00%	5.00%
Average Age	76	
Minimum Age	74	
Maximum Age	92	

Table 6.9: Elderly demographics

Due to the sensitivity and care required in undertaking experimentation with a subject group such as this, a lot of time was spent with each subject, answering all their questions, allaying any concerns they had and understanding their responses. Each participant was asked to rate the complexity of the same set of 10 signatures as those used in the previous experiments (to maintain consistency). The complexity scale was again from 1 to 10 and the signature flash cards contained genuine signatures with the actual names of the signers displayed below the signature.

Subsequently, they were given a set of 5 responses to views that could affect choice or selection of complexity of signatures. These responses were selected from the literature [193] and during the data collection process (explained in chapter 3), a note was made of the comments each participant passed during the execution of the complexity task. These comments were in the form of factors that most influenced their decision as to what comprised a complex signature or not.

A ranking of each comment was required of the participants and then by simple voting decisions, the highest to lowest choice of comment was produced .The time taken by each individual subject for the whole task varied between 10 and 20 minutes. The time taken was exacerbated by the need to provide this particular group of participants with a more in-depth explanation of the tasks during the entire process.

6.4.2 Results

The results obtained in this experiment are shown in Table 6.10

	1	**2**	**3**	**4**	**5**
Signature 1	2	3	5	4	1
Signature 2	4	1	3	5	2
Signature 3	4	1	2	3	5
Signature 4	5	3	2	1	4
Signature 5	5	4	2	3	1
Signature 6	3	5	2	1	4
Signature 7	1	2	4	3	5
Signature 8	2	5	3	1	4
Signature 9	4	5	1	3	2
Signature 10	2	3	4	1	5

Signature length (1)
No of Loops (2)
No of Crossing lines (3)
Readability (4)
Forgeability (5)

Table 6.10: Responses of the Elderly to Factors That Affect Choice of Complexity

The measures displayed in Table 6.10 show the modal quantities for each response, indicating the most frequently occurring number. The subjects were advised that there were no right or wrong answers but to just make an individual judgment and respond as they felt.

Interpreting the observations shows that the elderly subjects consider the number of loops as a prime motivating factor in considering the complexity of a signature. In 90% of the cases, there was a total agreement in choosing this option first when questioned about the factor that weighed most. The factor judged to be least influential was signature length. A relationship is sought between these responses and the complexity (perceived) of the signatures. A graphical illustration of the responses the subject group when asked to rate complexity of the signatures on a scale of 1 – 10 is shown in Figure 6.10

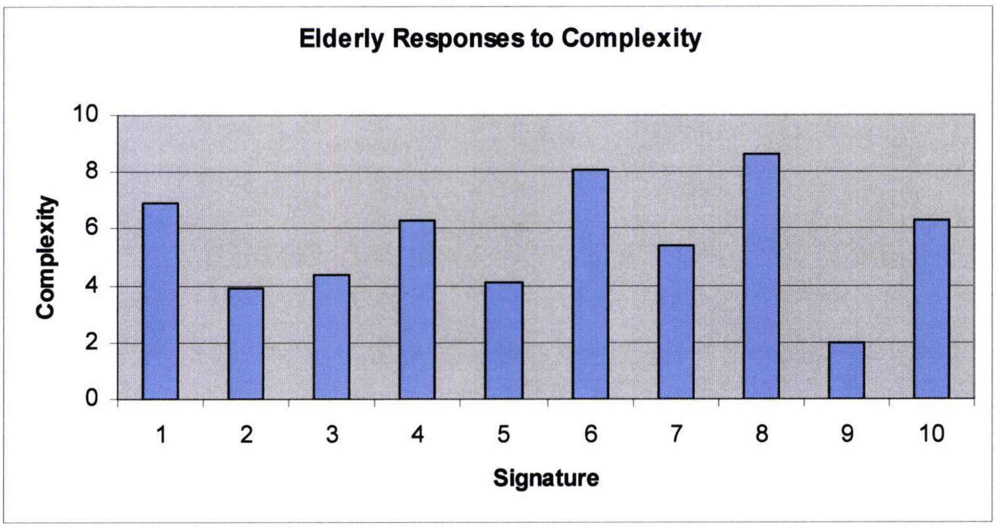

Figure 6.10: Complexity Responses by the Elderly

Interestingly, the same complexity pattern as seen in the earlier complexity experiment is observed despite being obtained from a totally different set of individuals. That is, the same signatures were selected as most complex and least complex with similar numerical values assigned to them. This is despite being from a totally different set of subjects. The distribution in figure 6.10 is assessed statistically to strengthen the claims, using the central measures of tendency and the equations 6.1 and 6.2

Kurt equation. Equation 6.1

$$\left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \qquad \text{Equation 6.1}$$

Skew equation. Equation 6.2

$$\frac{n}{(n-1)(n-2)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^3 \qquad \text{Equation 6.2}$$

S=standard deviation

Mean	Median	Mode	Skew	Kurt
6.9	7	8	-0.39	-1.24
3.9	4	4	-0.61	-0.16
4.4	4.5	3	0.04	-1.46
6.3	6	6	0.51	0.66
4.1	4	3	1.43	2.97
8.1	8	9	-0.68	0.62
5.4	5	8	0.66	-1.06
8.6	8.5	8	-0.04	-1.46
2	2	1	0	-2.13
6.3	6.5	8	0.04	-1.38

Table 6.11: Statistics of the complexity response

In Table 6.11 it is essential to note that the values are calculated with a 95% confidence rating and are seen to be normal. These measures exhibit signs of being from the same normal distribution as is evidenced by the skewness and kurtosis values obtained. We observe also that signatures 8 and 9, which are of particular interest here because they are perceived as the most and least complex, have a near zero skewness, therefore showing total agreement across the population.

This provides conclusive proof that signatures vary in form and complexity and that there is an inherent perception of the complexity in all the signature samples examined. Note that Signature 9, which is deemed to be the least complex, has the generally agreed attribute that the readability of the signature has a real influence on its complexity. This suggests that the more legible a signature is the less complex it is perceived to be. Another observation is that the intrinsic ability to forge the signature seems to have an effect on the perceived complexity of a signature. The signature pattern in question (Signature 9) had no loops hence we draw the conclusion that this absence of loops was the core reason or link to its selection as least complex.

For Signature 8, which was rated by the elderly subjects as the most complex perceptually, the Number of loops attribute was the most influential, while the Forgeability was, by a small margin, the next most influential. The lowest ranked attributes were Readability and Correlation with signer's name.

6.5 Younger Responses

The experiment described in Section 6.4 was repeated, but this time with the test population of subjects from the youngest age group (18 to 21) in order to determine the differences with the elderly group and to make a direct comparison. Again, we were concerned not only with rating perceived complexity, but with understanding what signature attributes led to individual judgements.

6.5.1 Procedure

The participants here were 20 subjects, all University of Kent students from different nationalities and ages between 18 and 20. Each subject was shown the same set of signature flash cards used in the experiment with the elderly group, as described in Section 6.4.

Perhaps unsurprisingly, the time taken to explain the procedure to this group of subjects was significantly less than the time spent with the elderly subjects. Each participant was asked to rate the complexity of the same set of 10 signatures as those previously used (to maintain consistency). The complexity scale was again from 1 to 10 and the signature flash cards contained genuine signatures with the actual names of the signers displayed below the signature.

Subsequently, the subjects were given a set of 5 responses to characterization of complexity of signatures (as before). These responses were selected from the literature and during the data collection process (Explained in chapter 3) a note was made of the comments each participant passed during the execution of the complexity task.

A ranking order of each comment was required of the participants and then by simple voting decisions the highest to lowest was produced. The entire process time per person varied and averaged between 5 and 10 minutes.

6.5.2 Results

The figures in Table 6.12 show the modal quantities for each response. A remarkable difference is observed in these results when compared with those of the equivalent experiment conducted with the elderly group. Here, the younger subjects are seen to consider the ability to forge a signature as most important in the judgment of perceived complexity of the handwritten signature.

Younger	**1**	**2**	**3**	**4**	**5**
Signature 1	5	3	2	4	1
Signature 2	4	2	3	5	1
Signature 3	4	5	2	3	1
Signature 4	5	3	2	4	1
Signature 5	5	4	2	3	1
Signature 6	3	5	2	4	1
Signature 7	4	2	5	3	1
Signature 8	5	2	3	4	1
Signature 9	5	2	4	3	1
Signature 10	5	3	4	2	1

Signature length (1)
No of Loops (2)
No of Crossing lines (3)
Readability (4)
Forgeability (5)

Table 6.12: Responses of the younger to factors that affect choice of complexity

Interpreting these observations shows that the younger subjects consider the signature length as least important. This response was observed in 90% of the cases. This also interestingly corresponded to the reaction and observations the elderly subjects provided. So the two age groups agree on factors that least affect complexity but differ on what most affected complexity. A graphical illustration of the responses the younger participants provided when asked to rate or state the perceived complexity of the signatures on a scale of 1 – 10 is shown in Figure 6.11

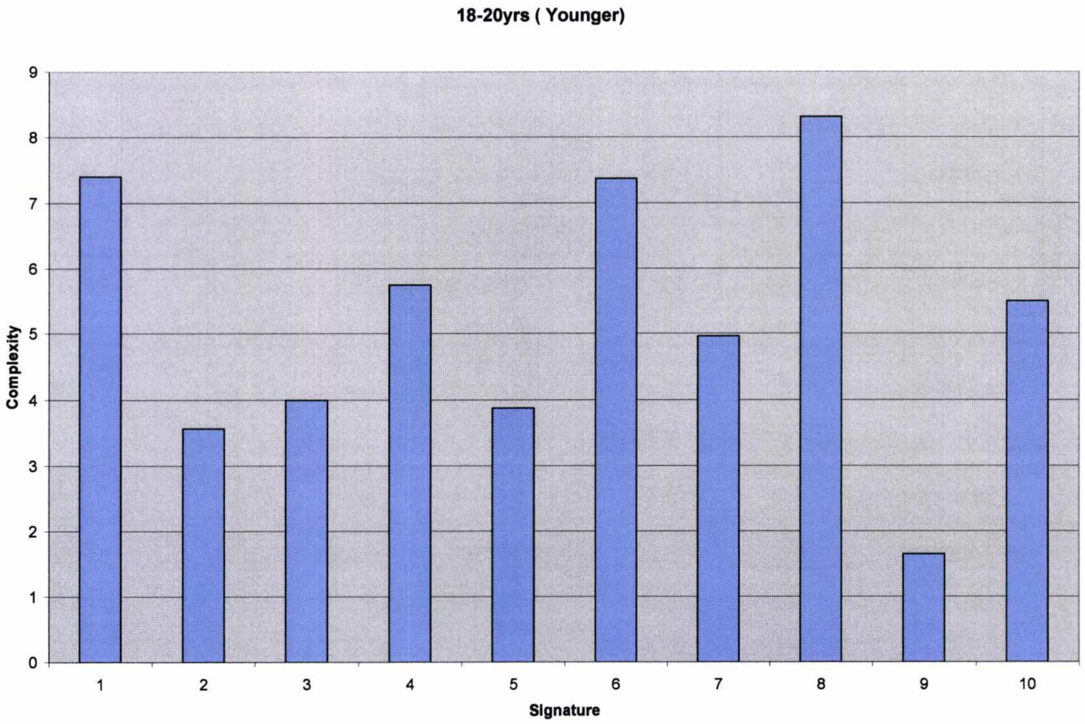

Figure 6.11: Complexity responses by the younger group

The pattern seen here indicates an overwhelming correlation in complexity estimates and signifies the same upper and lower values in perceived complexity values as seen in the earlier experiment that was carried out on the younger subjects. The distribution shown in Figure 6.11 is also assessed statistically as before, using the central measures of tendency and the equations previously adopted. Table 6.13 shows these values.

Mean	Median	Mode	Skew	Kurtosis
7.4	8	8	-0.58	-0.76
3.4	3	2	0.61	-1.18
4.2	4	3	0.04	-1.91
5.9	6	7	-0.10	-0.24
4.3	4.5	3	-0.14	-1.62
7.7	8	8	-0.71	1.77
5.3	5	5	0.34	-0.37
8.4	8.5	9	-0.11	-0.62
1.7	1	1	1.26	-0.07
5.1	5	5	-0.21	-0.99

Table 6.13: Statistics of the complexity response by the younger

From table 6.13, we note that the values are calculated with a 95% confidence and are seen to be normal. These measures exhibit signs of being from the same normal distribution and is evidenced by the skewness and kurtosis values obtained. Observe also that signatures 8 and 9 which are of particular interest and are the most and least complex in terms of perception have a near zero skewness therefore showing total agreement across the population. The significant elements are illustrated below and compared/contrasted with the outcomes with the elderly group.

Signature 9 was selected as the least complex by both population sets. However; the younger group was more aggressive in their choice resulting, in the assignment of the value 1 as the perceived complexity in 95% of the population. This compares with the value 2 most commonly chosen by the elderly subjects. What is equally of interest is the fact that in the course of these experiments the younger participants were resolute in their choice of forgeability as being the factor that most influenced their assignment of complexity values. This was irrespective of whether it was most complex (signature 9) or least complex (signature 8). By contrast, in the case of the elderly, the number of loops attribute and the signatures' readability attribute were most important for the most and least complex signatures respectively.

These observations demonstrate some perceptual differences that vary according to the age of the subject, with respect to signature complexity. It also points to the fact that various age groups invoke different attributes in decision making when presented with the task of signature inspection. It becomes apparent that it is important to take such factors into consideration when designing systems that entail use by these groups. A particular bias towards the elderly has shown that from their responses one could easily adapt systems to suit them. As we factor in their responses in designing biometric systems we can safely characterize the elderly users easily from the results we have obtained. Also, these results could aid the safe-guarding of the more vulnerable members of our society and, especially in the present context, the elderly. This knowledge and insight gained here in how the elderly judge complexity of signatures can help protect the elderly from identity abuse and aid their analysis in verification of genuine signatures. Once such application could be in the electronic point of sales, where due to the ever ageing population still at work till later on in life, we still find over 70's in active work.

6.6 Conclusions

The notion of perceived complexity of handwritten signatures has been reviewed and its potential prominence and importance in the field of handwritten signature verification has been highlighted.

A number of experiments were carried out to investigate the perception of a wide-ranging population to various samples of handwritten signatures. In order to focus specifically on our target group of principal interest, and to investigate the effect of age on perception, experiments were carried out using two age extremes – a group of younger and a group of elderly subjects. Our focus was largely on the elderly, but the younger age group served as a specific comparison. Results of the experiments were extensively analysed.

Statistical and visual aids were employed to evaluate the responses observed. Proof that the samples and responses had statistical significance and were obtained from a normal distribution was produced. Further work was carried out to observe and analyse the link between complexity and the ability to forge signatures and the error rates generated from attempts to properly classify the genuine and forged signature samples. Performance according to age showed some interesting results. Finally, mathematical relationships and equations were derived from the results obtained. Perception remarks and factors that most influenced the choice of particular complexity ratings were analysed and this led to evidence that the factors adopted when asked to rate the complexity of a given signature sample do vary according to the age of the subjects.

In conclusion, interesting insights into the perceptual ability of the elderly to rate complexity of static signature images have been useful and do provide genuine insight into the cognitive reactions that the elderly inherently possess. Being able to measure the complexity of signatures and the perceived judgement carried out by the elderly can give us the ability to predict susceptible users and therefore lead to designing of systems that safeguard them.

In the next chapter, we draw final conclusions from the results obtained from the preceding chapter. We propose useful techniques and methods to safeguard the vulnerable age group - the elderly.

In this chapter, we have concluded all the experiments and hence applied the theoretical arguments espoused in the earlier chapters 1, 2 and 3. Conclusive results have been shown and the next chapter concludes the thesis with the highlights and achievements and also makes some concrete recommendations as to improving the inclusivity of the elderly building on the huge information provided.

Chapter 7

Conclusion

7.1 Summary of Thesis and Contributions

This thesis has focused on the need for, and awareness of, the use of proper biometric systems that cater for the elderly. Biometric technology as a means for authenticating the identity of individuals is now part of our everyday lives. The elderly population is an ever increasing one and as such it is important to highlight and make sure we understand the biometric implication. Discussions around useful features that distinguish the elderly from other individuals have been held. Results of the knowledge gained from implementations and experiments carried out in Chapters 4, 5 and 6 offers and present the context and a summary of the contributions made in the field. These contributions make it possible for researchers to increase their knowledge and proffer improved biometric systems.

Chapter 1 focused on the increasing need to adopt technology that protects the elderly. The advantage and bias towards the handwritten signature as a useful biometric is highlighted, especially as it finds widespread use in our everyday lives. Issues around the process of signing signatures were fully examined with an additional look at imitating and the perceived complexity of the handwritten signature. Several issues concerning the inherent variability of signatures, the different styles and variations encountered and the existence of forgeries, were approached with respect to the elderly. The difference in the acquisition processes and types of handwritten signature verification systems were analysed throughout with a deep bias towards the elderly. The difficulties that one can encounter with this group were also mentioned. Furthermore, reviews of useful research studies that have been carried out are cited. Techniques, methods and major advances in the field of handwritten signature verification are extensively researched. Several methods were briefly analysed in the context of building an automatic signature verification system, separately evaluated through a static and a dynamic approach.

Although limited studies exist, a brief look at the extent of human performance in visually inspecting the authenticity of handwritten signatures was also examined with emphasis on the elderly population. Performance issues were examined in relation to the various results observed and obtained when using static or dynamic features. Particular attention is drawn to the fact that despite the fact that human checking of signatures is on the increase and remains in constant use, there seems to be a lack of proper investigation into the issues that surround such methods. The literature reviews revealed an important find i.e. the fact that literature is sparse that deals with static or off-line methods. On-line systems were shown to possess higher performance indicators when compared to their off-line counterparts. More so, the fact that there seems to be a lack of focus by academics, manufacturers and governments in relation to the biometric use by the elderly seems to be the prevalent reality. Finally, suggestions as to further investigation into the use of biometric systems are made and a break down of the structure of the thesis is set out.

The subsequent chapters were engaged with the development of a unique approach to understanding the elderly and their use of biometric systems. Chapter 2 considered an in-depth investigation into the issues that elderly individuals face when using biometric systems. This highly over looked group are prone to be disadvantaged when use and design of these biometric systems takes place. In addition to the emphasis on the widespread integration and full inclusivity of the elderly, an assessment of the technical and non-technical impact of biometric systems adoption in an ageing society was carried out. Current and future trends with regards to biometric deployment and usage scenarios within an elderly population were investigated. A review of major biometric modalities with respect to physiological changes and the issues of template ageing then followed. Finally, the chapter concluded by stating policy direction by way of a roadmap to be engaged by technology researchers and governments alike.

The acquisition process of signature data was essential and necessary as a first step. This was needed as a handwritten signature database containing both forgeries and originals was used for the various experiments including the human perception ones and analysis that took place in latter chapters. The acquisition of these signatures was carried out dynamically, by means of a graphics tablet device, while the source of the large number of genuine and forged signatures collected was an experimental test with human subjects. The acquisition device used, the format of the data, the experimental protocols, and the digitised images are some of the issues discussed in Chapter 3. With this wealth of data obtained, Chapter 4 dealt with the handwriting characteristics in relation to ageing. Essentially, this took a bold step at characterising signature samples and handwritten texts in relation to the age of the writers. A statistical approach was taken to distinguish the young from the elderly subjects by examining the dominant features that separate these age groups. Using various feature extraction techniques, it was discovered that there are features that exist that readily discriminate between the elderly and the younger age groups. This theory was tested on both handwritten signatures and handwritten text because of the physical similarities that exist in the execution of both tasks. Problematic signers within the elderly population were identified and commonly referred to as 'goats'. Their existence within the samples used was considered and seen to have no overriding effect on the results obtained and therefore reflect a more realistic scenario. Data reduction, normalization and optimization were discussed with a view to removing redundant features when performing feature analysis and comparison.

A number of human perception experiments were carried out in Chapters 5 and 6 in order to obtain some insight into two characteristics of the handwritten signature- the intra-class variability and the perceived complexity. These stability issues are recognised as prevalent within an elderly population and hence deserve due attention. These chapters investigate the strengths and weaknesses of humans when undergoing inspection of signatures as is carried out in day to day activities.

The intra-class variations of signatures within an elderly population was analysed in Chapter 5, mainly in terms of both a comparative and statistical assessment. An objective measurement was carried out using several methods proposed in the literature. A discussion was held around the use of Shape Matrices as a similarity measure. It was recognized that the elderly possessed a higher degree of inherent variability within their intra-class populations that were examined. This in itself is useful as it will aid the development of biometric systems when these factors are taken into consideration.

The perceived complexity of signatures was examined from the point of view of static signature image analysis in Chapter 6. An experimental study with human subjects was carried out in order to assess the perceptual viewpoints and judgements of humans with respect to the degree of complexity inherent in signatures, while ten signatures of varying styles were employed. An elderly population were asked to consider complexity and remarks about factors that most influenced their complexity rating. The performance of humans in inspecting the authenticity of handwritten signatures was examined through experiments with human subjects. Each experiment was characterised by the availability of a number of genuine samples and forged (imitated) samples. Constantly in view was a genuine signature for comparison to reflect point of sales scenario. An analysis of the error rates obtained across the age population was carried out and conclusions drawn on the way the elderly perform.

7.2 Recommendations

This section forms the focus of this piece of work it is essential to highlight concrete recommendations that we make to improve the inclusivity of the elderly within biometric systems. It is worthy to note that the elderly do present or possess similar factors to that seen when examining unhealthy individuals. Therefore it is possible to see our recommendations having an application in that sector.

To fully embrace and include the elderly within biometric systems we must ensure that the following are in place:

- An early interaction during system design and roll-out to ensure feedback from this target group is incorporated. This will ensure that all comments made by elderly individuals that are contacted via focus groups are incorporated and are seen as representative.
- Increased awareness and training to be carried out at all spheres to encourage the elderly and increase their confidence in their ability to cope with computer-based technology. Various bodies should be encouraged to promote this training amongst the elderly. Funding for this should also be made available. Educational institutions should lead the way by admitting elderly individuals for this type of training.
- Increase the research funding and encourage participation in researching and understanding about how biometric data and biometric templates behave with ageing, specifically within an elderly population. We already know that the biometric modality: the iris, does not change from birth naturally. It will be useful to understand how others change and make sure that templates detect that prospective users may have aged.
- The creation and encouragement of much more collaborative effort amongst the various research communities looking at the elderly and biometrics. This can be achieved by establishing online groups and research journals and communities that are focused solely on this topic. This will further engage other interested parties.

- Standardization of enrolment procedures and interoperability of devices. Laws and procedures can be enacted to ensure that all those wishing to participate in the production of these devices adhere to the same standard.
- Commonality of features, databases, error/performance rates when designing and using biometric systems. This in turn will aid the standardization of reports. Dynamic features such as the velocity, time and acceleration have been shown to distinguish the elderly from the younger quite easily. Therefore incorporating these features when assessing or using the biometric systems will certainly aid their use.
- Adequate data protection and education. Elderly individuals have already been categorized as being very vulnerable as such steps like this can protect them better. Their data needs to be protected since this has been raised as a concern by the elderly individuals interviewed and also seen within the literature.
- Special user interfaces design for different age groups. Since the aged are associated with decline in sight and general mobility, one such special design could include larger screen sizes, larger fonts, and visual feedback effects and prompts to guide them through systems usage.
- Enact policies that aim generally to allow the elderly to retain their independence for as long as possible. Suggested policies include ones that promote independence and reliance on stay at home rather than care homes. We have seen that the elderly nowadays live longer and are working longer, therefore there should be no limit to age that one is allowed to work till. This will then make retirement voluntary.
- Policies exist that protect the elderly, especially against exploitation. These include making it an offence to exploit the elderly. Also making sure that prosecution and punishment is carried out by all guilty parties. We cannot overstate the fact that the elderly are the most vulnerable within the society and as such require this greater attention.
- Ensure effective design strategies which are targeted solely to cater for the elderly. These strategies include system adaptable devices that recognize

symptoms of the elderly are readily recognized. These symptoms include tremor and time delay when executing tasks.

- Ensure an awareness of the uniqueness of each biometric modality and its corresponding impact on the elderly. We fully researched the face, fingerprint, handwritten signature and voice. These modalities present qualities as one age such as presence of wrinkles, dry and broken fingerprints, increased time and slower velocities and broken voices respectively. Since each modality is unique and each has its own elderly 'effect' as illustrated one will be well advised to be aware of these features when using biometric systems.

On the basis of the 45 features we extracted, it is necessary to recommend that when considering dynamic features it is wise to remove highly correlated features. In our study we found that the features that contained or had a velocity component in it were usually highly correlated. Reduction in the number of these velocity based features used in experiments greatly improved the results achieved. Removal of these features did not affect performance and indeed reduced the number of features we had to 'handle'.

We noticed that the average altitude did not change no matter the task being undertaken. This was also irrespective of age.

With the elderly it was noticed that feature 'writing duration' presented most variation intra class and inter class.

Choice of one modality over the other is always down to choice and familiarity. Each modality has its own merits; however, as pointed out the Iris does not change during ones lifetime and hence is an excellent candidate for stability.

In conclusion the use of biometric systems by the elderly has been fully investigated; various proposals have been made to adequately accommodate this growing age bracket of the population. Since this is important, features that can be used to easily identify the elderly have been highlighted. A new database of original and imitated handwritten signatures has been constructed and invaluable knowledge gained on human perceptual judgements and methods elucidated which can provide necessary improvements within this exciting field of Biometrics.

In the words of Aristotle *"Those who wish to succeed must ask the right preliminary question"* I believe we have.

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