Perceptual analysis of handwritten signatures for biometric authentication

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Abstract: The Internet has stimulated increased activity to address key problems relating to the implementation of reliable and robust biometric identity checking. Although not always the biometric modality most readily adopted in such an environment, the handwritten signature continues to offer many advantages over some other more commonly considered biometrics. The authors address some key issues relating to the nature of the handwritten signature and, especially, the strategies used by humans in analysing signature data. Through experimental studies and an analytical investigation, the paper identifies characteristics of the signature which influence its resilience to fraudulent penetration, pointing to some important principles on which to build procedures for both automated and non-automated identity authentication.

1 Introduction

Biometric identity checking is now a research area of diverse and rapidly increasing activity. The development of Internet applications has itself stimulated some of this activity, but the scope for the productive application of biometric technologies is, of course, far wider than this.

Of the many biometric modalities now available, care must be taken in any specific application, and especially in high interactive scenarios such as Internet transactions, to choose a modality which is appropriate to the application of interest and, more importantly in many situations, to adopt a modality which will be found acceptable to the community of users at whom the application is directed. One way to address this issue is to consider a multimodal processing structure, and this is an approach which has been investigated by many researchers, either focusing on a fixed set of modalities or, more recently, seeking greater flexibility through the implementation of systems which are more generically adaptable and reconfigurable [1–7].

However, there are many situations, especially many of those typically encountered in Internet applications, where the implied complexity of a completely flexible multimodal structure may not be appropriate. In these circumstances, it is important to seek a biometric modality which provides both a high degree of accuracy in performance yet is considered acceptable by the greatest number of possible users. In this respect, the handwritten signature provides an option which largely meets these criteria, yet this is a modality often not considered the primary choice by systems designers. The handwritten signature in fact offers a range of advantages over some other modalities, including familiarity to a wide user group, a known and established legal status, acceptability by the public, the elimination of common concerns about unwelcome connotations or health factors associated with some other modalities, and the convenience in execution afforded to users [8, 9].

In this paper we consider some aspects of signature checking which are both of intrinsic and direct relevance to many current situations where this biometric is adopted, especially for biometric identity checking by humans, but which will also raise some important questions about how to improve techniques which are used to automate these processes. We thus describe some investigations into human signature checking, and from a detailed experimental study we identify and characterise some important aspects of signatures and signature analysis which underpin the effective use of the handwritten signature as a means of authenticating claimed identity. Though this in itself suggests some practical procedures which could have an immediate impact on transactions conducted across the medium of the Internet, we also demonstrate how our investigation can have a direct influence on the way in which more effective automated processing techniques can be evolved. The paper thus addresses two fundamental, but closely linked practical issues: an understanding of human performance in biometric identity checking using a common and almost universally accepted biometric modality, and techniques which might allow the incorporation of human capabilities into machine-based processing.

2 Background

In the field of document analysis and recognition, several studies have been concerned with the exceptional ability of humans in reading and recognising handwritten script. Some of these studies have attempted to measure the handwriting recognition performance of human readers, in order to identify an optimum recognition rate for automatic systems, whereas some others have carried out a more detailed study identifying perceptually important features involved in human handwriting reading and recognition.

Barrière and Plamondon [10] performed an experiment where human subjects were asked to identify letters in mixed-script handwritten words. The mean letter recognition rates reported were 86.6% for a group of six readers that had access to limited linguistic knowledge (as the words

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were written in a non-native language) and 92.8% for five readers with access to an extended linguistic context (the text was written in their native language). In [11] the achieved average character recognition rate of 10 human readers was 96% and was comparable with the reported system performance. Linguistic knowledge was not applicable, since the handwritten samples were random letter sequences. Two separate tests with groups of 3 and 17 human readers, reported in [12], gave an average of 81.17% and 76.88% respectively, for case-insensitive recognition of characters extracted from handwritten words without linguistic context. In addition, it was reported that the machine recognition accuracy was comparable with the average human recognition performance. Schomaker and Segers [13] reported a human 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 less important than consonants for the word recognition process. Lorette [14] highlighted the importance of knowledge gained from human perception in order to design more adequate handwriting reading systems, and extensively analysed human perceptual properties of handwriting and reading. The proposed perceptually important elements 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 for recognition only the use of a small number of significant primitives, without considering the unstable parts of the handwriting.

Some of these findings may be extended for the perceptual processes used in signature recognition and verification by humans. In this case contextual information is not directly present, even though knowledge about possible letter combinations forming syllables, as well as familiarity with plausible surname instances, may assist the reading of certain types of handwritten signatures and, thus, the recognition-verification process, but this would not be the case for incomprehensible shape-oriented signature samples. Nevertheless, there is much to be gained from knowledge related to human perceptual processes regarding the reading and recognition of cursive script, while highlighting the limited available investigations concerning the human perception of handwritten signatures, their verification and identification of forgeries.

Studies in the signature verification literature concerning human performance in verifying signatures or identifying forgeries are extremely limited. Fairhurst, *et al.* [15] have reported the performance of humans in verifying the authenticity of handwritten signatures in relation to their judged complexity. Randolph and Krishnan [16] report some of the elements that experts look for when spotting forgeries. The properties that frequently appear in forgeries are:

- improper spelling
- shaky handwriting
- retracing and retouching
- vertical weaving

Ramesh and Murty [17] provided their signature samples to two teams of document examiners for verification. The results obtained from the human experts displayed a 100% success in correctly identifying simple forgeries, and a 75% success in identifying skilled forgeries, while with respect to the genuine signatures the experts identified correctly 82% of the samples. Within a different framework, Brault and Plamondon [18] assessed comparatively the opinion of the imitators employed in their study and that of an expert document examiner, in ranking eight signatures on their apparent imitation difficulty, and found the opinions almost inverted.

It is clear, however, that a greater understanding of human perception of signature data would be potentially enormously beneficial in increasing the reliability of signature checking, especially if such an understanding can be related more directly to situations prevailing in practical scenarios.

3 Experimental investigation of signature characteristics

3.1 Number of reference samples

An important question in developing an effective understanding of human signature characteristics relates to the potential for human analysis when, as is often the case in practice, only small amounts of information are available. This generally relates to the number of reference samples available from which a signature 'model' can be constructed.

Hence, we can formulate a basic research question:

> *Question 1:* How is human perception of signatures influenced by the number of reference samples available?

In a first experiment (experiment 1), subjects were asked to view a range of signature samples, based on a set of five target signatures of varying perceived 'complexity', some of which were genuine samples and some of which were forgeries (generated in a separate experiment with a disjoint set of subjects, each of whom produced the imitations from a visual inspection of a genuine sample). In total each subject viewed ten genuine and ten forged samples from each of the five target groups. Each subject was asked simply to classify each sample as 'genuine' or 'forgery', in comparison with a genuine sample which was in view simultaneously, as would be the case, for example, in checking a signature against a 'model' written on some reference document. Further details of this scenario can also be found in [15].

In experiment 2, a different group of subjects took part in a similar experiment where the same number of genuine and forgery samples were shown for each target signature, but this time the participants were provided with five original samples of the target signature constantly in view as reference samples.

Some results relating to errors in subjects' categorisations obtained from the two experiments are displayed in Table 1. In these results the total error was measured as the overall number of erroneous classification decisions made divided by the total number of samples presented to the subjects, the false rejection rate (FRR) as the number of genuine samples

Table 1: Average human verification performance in the two experiments

	Experiment 1	Experiment 2
Correct classification, %	73.83	84.07
Total error, %	26.17	15.93
FRR, %	44.67	26.50
FAR, %	7.67	5.36

falsely rejected divided by the total number of genuine samples presented and, similarly, the false acceptance rate (FAR) was measured as the number of forgeries falsely accepted divided by the total number of forgeries presented.

Although not described in detail here, statistical tests on the two sets of data used in experiment 1 and experiment 2, have provided evidence of a significant difference between their corresponding mean values with respect to the total error and the FRR, concluding that the corresponding population means differ [19]. However, this was not the case with respect to the FAR, leading to some interesting conclusions concerning the observed change in the error rates when a larger number of reference samples are provided for the signature checker. Although a reduction in the FAR consequently cannot be assumed at the population level, both the total error and the FRR are expected to decrease when more reference samples are provided for comparison. Hence, there is evidence here that, contrary to the common practice in human signature checking which has evolved with the increasing penetration of card-based transactions, both increased security and greater convenience to genuine signers, can be achieved if a set of reference signature samples, rather than a single sample, is available for identity confirmation.

3.2 Complexity and variability versus verification performance

An observation of human performance in the verification of the individual target signatures in experiment 1 showed variations in their error rates, which can be explained in a variety of ways. The results may be related to such characteristics as the degree of complexity of the signatures, and the degree of intrinsic variability that the targets embody reflected through the genuine samples included in the test set, especially since no information was available to the experimental subjects about the degree of skill of the 'forgers' involved in the forgery attempts.

Results from two further experiments on the perceived complexity and the intrinsic variability of the target signatures were used in order to assess the relation of these two factors with the corresponding verification error rates. In experiment 3, judgments on the perceived complexity of the target signatures were obtained from subjects who were asked to assign a score to each of the five target signatures (on a scale from 1 to 10) indicating their perceived degree of complexity. In experiment 4 a different group of subjects were presented with five genuine samples from each of the five target signatures and were asked to rank the target signatures according to their perceived relative consistency. The degree of intrinsic variability of the target signatures plays an indirect role in forming the differences in the individual rates. Since the intrinsic variability of the targets is not known it is assumed to have been regarded by the subjects equally among the targets. However, the targets' intrinsic variability differs substantially, as observed from the experimental results, and being reflected in the test samples is expected to have influenced the error patterns accordingly.

The possible connections between the complexity and intrinsic variability of signatures, and the effect this might have on human verification processing, is a very important issue in developing strategies for practical biometric testing, and hence this will be examined in more detail.

Hence, a further question of interest may be formulated as follows:

> *Question 2:* In a situation where only a single reference sample is available for model construction, what is the relationship between verification performance and (*a*) signature complexity, and (*b*) sample variability?

In order to examine statistically the relationship between the complexity and intrinsic variability of the target signatures, and their corresponding error rates, the Spearman rank correlation coefficient (rs) [20] was computed as the perceived similarity data were ordinal. The results (Table 2) reveal that the perceived intrinsic variability of the targets has a perfect positive correlation with the total error ($rs = 1.000$) and the FRR ($rs = 1.000$), but a negative correlation ($rs = -0.872$) with the FAR. Furthermore, the rank correlation results obtained between the perceived complexity and the total error ($rs = -0.400$), the FRR ($rs = -0.400$) and the FAR ($rs = 0.205$) provide insufficient evidence to determine whether these variables are related. Thus, it is shown that the primary factor responsible for the different error rates obtained is the intra-class variability of the target signatures. Increasing perceived intra-class variability is associated with an increase in the total error, an increase in the FRR and a decrease in the FAR.

In order further to explore these issues, note also that, apart from the significant correlation results, further evidence about the effect of intrinsic variability with respect to the error rates may be presented if a group of targets with similar complexity values is examined, and this leads to the next question of interest:

> *Question 3:* What is the effect of sample variability in targets with similar complexity values?

Relevant data is presented in Table 3. The arrows displayed show the direction of change of the variables in question. Indeed, the pattern of change in the error rates with respect to increasing variability, for samples with similar complexity values, is the same as that previously reported. Therefore, increasing variability leads to an increase in the total error, an increase in the FRR and a decrease in the FAR, and thus more genuine signatures are rejected, on the grounds that they differ considerably from the original. However, as

Table 2: Spearman's rank correlation coefficient with error rates from experiment 1

Spearman's rs	Perceived complexity	Perceived variability	Total error, %	FRR, %	FAR, %
Perceived complexity	1.000				
Perceived variability	−0.400	1.000			
Total error, %	−0.400	1.000 **	1.000		
FRR, %	−0.400	1.000 **	1.000 **	1.000	
FAR, %	0.205	−0.872	−0.872	−0.872	1.000

** correlation is significant at the 0.01 level (two-tailed)

Table 3: Effect of variability in targets with similar complexity values

		Variability rank pos.	Total error, %	FRR, %	FAR, %
Group of similar complexities	target 2	4 ↑	27.50 ↑	50.83 ↑	4.17
	target 1	3	26.67	46.11	7.22
	target 3	1	21.67	26.39	16.94 ↓

a result of the stricter judgements fewer forgeries are falsely accepted.

In a similar way, in order to evaluate the role of complexity in the classification decisions and hence in the error rates obtained, it is essential that the intrinsic variability of the targets is kept the same. For this reason target signatures with a very similar degree of perceived intra-class variability were grouped together, thus forming a 'stable' set A scoring low in the perceived variability rank, and an 'unstable' set B of higher variability rank judgements. We can then formulate the next question of interest, as follows:

> *Question 4:* What is the effect of sample complexity in signatures with similar perceived intra-class variability?

Although the targets in each set have similar perceived intra-class variability, the change in the error rates with increasing complexity is exactly the opposite for the two sets (Table 4). For the stable group A increasing complexity causes an increase in the total error, an increase in the FRR and a decrease in the FAR, whereas the opposite takes place for the unstable group B. Thus, with increasing complexity, a decrease is observed in the total error and the FRR, whereas the FAR is increased. It seems that increasing complexity, for the stable set, leads to stricter judgements with respect to the authenticity of signatures, resulting in more genuine signatures being rejected and fewer forgeries being falsely accepted. On the other hand, for the unstable set, the increasing complexity seems to have caused confusion to the subjects leading to more signatures being accepted, both genuine samples and forgeries.

In a different approach, if the error rates obtained from experiment 2 are used, the available knowledge about the targets' perceived intra-class variability should cancel out the actual errors caused by the inherent variability of the target signatures reflected through the test samples. Therefore, the effect of complexity on the error rates would now be obvious. The individual error rates corresponding to each of the five target signatures, with intra-class variability knowledge available displayed a different pattern from that of experiment 1. This prompts the next question to be considered:

> *Question 5:* In a situation where multiple (5) reference samples are available for model construction, what is the relationship between verification performance and (*a*) signature complexity, and (*b*) sample variability?

The Spearman rank correlation results of experiment 2 error rates with the perceived complexity and intra-class variability of the targets (Table 5), demonstrate that a significant positive relationship exists between the perceived target complexity and the FRR $(rs = 0.900)$, while with respect to the total error and the FAR a positive $(rs = 0.800)$ and a negative $(rs = -0.821)$ correlation coefficient were respectively obtained. On the other hand, no evidence of correlation between the perceived variability and the total error $(rs = 0.100)$, the FRR $(rs = 0.000)$ or the FAR $(rs = -0.051)$ were shown. Therefore, as discussed

Table 4: Targets with similar perceived intra-class variability in experiment 1

Sets		Perceived complexity	Total error, %	FRR, %	FAR, %
A stable	target 4	8.2 ↑	21.94 ↑	38.06 ↑	5.83
	target 3	4.1	21.67	26.39	16.94 ↓
B unstable	target 1	5.8 ↑	26.67	46.11	7.22 ↑
	target 2	4.8	27.50	50.83	4.17
	target 5	1.8	33.06 ↓	61.94 ↓	4.17

Table 5: Spearman's rank correlation coefficient with error rates from experiment 2

Spearsman's *rs*	Perceived complexity	Perceived variability	Total error, %	FRR, %	FAR, %
Perceived complexity	1.000				
Perceived variability	−0.400	1.000			
Total error, %	0.800	0.100	1.000		
FRR, %	0.900 *	0.000	0.900 *	1.000	
FAR, %	−0.821	−0.051	−0.821	−0.975 **	1.000

* correlation is significant at the 0.05 level (two-tailed)
** correlation is significant at the 0.01 level (two-tailed)

Table 6: Targets with similar perceived intra-class variability in experiment 2

Sets		Perceived complexity	Total error, %	FRR, %	FAR, %
A stable	target 4	8.2 ↑	18.39 ↑	33.57 ↑	3.2
	target 3	4.1	10.89	13.57	8.2 ↓
B unstable	target 1	5.8 ↑	17.32	30.71 ↑	3.9
	target 2	4.8	17.50 ↑	29.29	5.7 ↓
	target 5	1.8	15.54	25.36	5.7

earlier, knowledge of the intra-class variability of the targets, available in experiment 2, is shown to cancel out the effect of the actual inherent variability of the targets on the error rates.

Thus, it is shown that in experiment 2 the major influence on the formation of the error rates was caused by the targets' degree of complexity. The emerging pattern reveals that increasing complexity leads to an increase in the total error and the FRR, but to a reduction in the FAR. This is the actual pattern regarded for the stable set A (Table 4) in experiment 1. The new error rates for the two sets of similar variability ranking judgements (Table 6) validate the general complexity pattern reported for experiment 2.

Seeking an integrated view of these important issues overall leads to the final important question to be addressed:

> *Question 6:* What are the interrelations between complexity/variability which influence changes in verification performance observed when different amounts of reference data are available?

The results presented so far show that knowledge about the instability of the targets in set B has balanced back the change in the error rates reflecting the effect of complexity. As a consequence, different reductions or increments in the error rates are evident among the five targets, which is justified in order to accommodate the large shift in the direction of the error rates (from Table 4 to Table 6). According to the results analysed earlier, a general reduction in the error rates from experiment 1 to experiment 2 would have been expected. However, the different reductions with respect to the individual targets (Table 7) prove the effect of both the complexity and the intrinsic variability of the targets. (It is emphasised that the figures presented in Table 7 show *changes* in error rates, not absolute values.)

Information about the intra-class variability of the targets, which was supplied by the availability of five reference samples in experiment 2, is more beneficial for a simple and unstable target rather than for a complex and stable one. In fact the more complex and stable the target the smaller the percentage of the reductions and hence, the smaller effect

Table 7: Percentage of reductions affected both by the complexity and the intrinsic variability of the targets

Description	Sample	Reductions, % TE	FRR	FAR
complex + stable	target 4	16.2	11.8	45.1
complex + unstable	target 1	35.1	33.4	46.0
simple + stable	target 3	49.7	48.6	51.6
simple + unstable	target 5	53.0	59.1	− 36.7 *

* a negative value indicates an increase
TE: total error

the knowledge about their intrinsic variability had on the error rates. Furthermore, it is apparent from the results that it is the simple signatures that benefit most from available knowledge about their variability, regardless of whether they are stable or unstable. With the evident merits being reductions in the error rates for targets with combinations of different degrees of complexity and variability, the very unstable signatures with low-to-medium degrees of complexity (targets 2 and 5), exhibit a significant increase in the FAR instead of a reduction. Nevertheless, it is seen that they generally benefit from the available knowledge about their variability, as a result of their large reduction in FRR, compared to an increase of their relatively small FAR.

4 Discussion

A number of further interesting conclusions may be drawn from this analysis regarding the inherent complexity and variability of signatures as perceived by humans and their relation to the error rates that are likely to occur during a visual verification of their authenticity. According to the experimental results of this study, complex signatures are more likely to lead to more rejections of their genuine samples during a human visual verification and to fewer forgeries being falsely accepted, as opposed to simple signatures. With respect to the intra-class variability of signatures, stable signatures are generally more likely to have fewer of their genuine samples being falsely rejected, and more forgeries being mistaken for genuine, in comparison to unstable signatures. This is an interesting result since it may have been expected that a stable signature would not suffer from falsely accepted forgeries. However, it seems that a stable signature is more likely to be susceptible to a fraudulent sample being mistaken as genuine, rather than an unstable signature. This can be justified since in situations where no knowledge about a signature's variability is available, as for instance in experiment 1, the tolerance shown with respect to the variability of a signature by a human checker may be actually larger than the degree to which the stable signature in practice varies, and this would lead to generally more samples being authenticated, including prospective forgeries.

Considering both the complexity and intra-class variability of signatures, as determined from the results of this study, a signature that is both complex and unstable would be more susceptible to a fraudulent sample being falsely accepted than a complex and stable, or a simple and unstable signature would be. This may suggest that the combination of a complex signature with high intra-class variability could lead to more confusion for the subjects, thus resulting in more signatures being accepted, both genuine samples and forgeries, and hence this could be reflected in a low FRR and a high FAR. On the other hand, a signature that is both simple and stable resulted in a greater FAR than any other combination. However, this was not a result of confusion, but rather, as already explained, of higher instability intuitively expected.

Finally, the simple and stable signature is that which incurs the highest likelihood of susceptibility to forgery penetration, when no information about its stability is available. A way to tackle this would be to demand additional reference samples to be implemented, and this would reduce the false acceptances by as much as 50%, according to the results of this study. However, more reference samples would not favour a significantly unstable signature, if reduction of the FAR is the priority. Therefore, knowledge about the perceived complexity and intra-class variability of signatures could assist in the right implementations being made in order to manage the expected error rates, since the prediction about the likelihood of a false rejection or false acceptance error would now be possible.

5 Conclusions

In this paper we have reported and discussed an experimental study of human perception of handwritten signatures, covering both genuine and forged samples. The results obtained have provided new insights into some of the factors which will influence the way in which the signing process can be made more robust when human checking is involved. These in turn have suggested ways in which human strategies for signature checking might also influence the implementation of automated processing in emerging systems, where important factors such as the number of available reference samples, signature sample variability, and the complexity of signature forms, can now be taken into account.

This sort of study is therefore relevant both to scenarios where internet transactions carry a degree of direct human intervention and those where the entire identification process is to be executed automatically. A further important aspect of this work, however, is that it demonstrates how the handwritten signature can be used more reliably as a biometric modality embedded within an application domain, which might often more naturally seek to adopt alternative biometric technologies. This study therefore supports the exploitation of a modality that still offers many potential benefits to system users and, more importantly, provides a greater degree of choice and flexibility both to system designers and to user populations.

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