Optimised Feature Extraction for On-Line Signature Verification.

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Abstract.

In this paper, we discuss the construction of an on-line signature verification system. Because the major difficulties that are encountered in on-line signature verification and in user-specific isolated word recognition are very similar, systems based on dynamic time warping are very popular in both research areas. However, the availability of a rather large number of reference patterns in the signature verification problem makes the utilisation of a more sophisticated feature-extraction process desirable. The optimisation of this feature extraction step is the main aim of this paper. It is shown that the discrete wavelet packet tree can play a central role of importance in this process. The feasibility of our approach is demonstrated by building and evaluating a complete on-line signature verification system, using our own special-purpose input instrument, the SmartPen™.

1. Introduction.

The most fundamental difference between our civilisation and previous ones is without any doubt the tremendous degree of automation that has been reached. This evolution is still going faster and faster at present. As a consequence the number and importance of man-machine interactions is steadily growing. This poses us to a relatively new problem: how to automatically verify the identity of a human being?

Until very recently a majority of the techniques used for this purpose has been non-biometric.

Typical examples of this approach are the use of pass-words, physical keys or PIN-codes. There are 2 major disadvantages linked to the use of these methods. First of all, a system based on non-biometric characteristics can be fooled rather easily by a deliberate criminal. Secondly, non-biometric identity verification requires a non-trivial user-effort, like remembering a pass-word or carrying a key. These 2 reasons explain why a lot of research is done in biometric identity verification.

Biometric identity verification means that some kind of physiological (e.g. fingerprint) or behavioural (e.g. typing rhythm) characteristic is used to do the actual verification stage. A description of the alternative approaches can for instance be found in [1]. In this paper, we limit ourselves to one specific form of biometric identity verification, based on the use of the human signature. An excellent overview of the area is given in [2] and [3]. Signature verification can be performed on-line or off-line. While the latter technique is more generally applicable, the former leads to a better system performance. In this paper we discuss the on-line variant.

The chapters in this paper describe step by step how a signature is verified. Chapter 2 focuses on the collection and pre-processing of the signals used for verification. Chapter 3 deals with the feature extraction process. The last step in the verification is the construction of the discriminant function. This step is very briefly described in chapter 4. In chapter 5 we evaluate the performance of the complete system that we

have built. We finish by making some conclusions in chapter 6.

2. Data collection and Pre-processing.

There exist 2 approaches to do the data collection for on-line signature verification. Most authors ([4], [5], [6]) use a simple tablet to gather handwriting signals. The disadvantage of the tablet is however that it does not provide us with complete information about the dynamics of the handwriting process, but only about the 2 dimensional movement of the pen-tip over time. Our verification-instrument (the SmartPen™; see Figure 1 and [7]) contains angle sensors, measuring the angle of the pen-shaft relative to the writing surface, and a force sensor, capturing the complete force patterns that are produced when a person is signing.
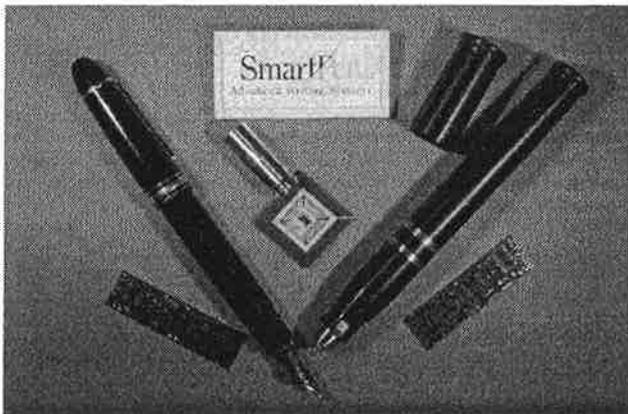

Figure 1: The SmartPen.

The 5 signals produced by the SmartPen are low-pass filtered with cut-off frequency 40 Hz. The effect of rotations of the pen relative to the signers hand is eliminated by redefining the co-ordinate system that is used. The new reference axis's are chosen as the ones with extreme energy contents.

3. Feature Extraction.

The existence of non-linear timing differences between 2 signatures that have to be compared is one of the most annoying aspects that has to be dealt with in signature verification. Fortunately, this problem has already been solved for speech recognition, by means of the Dynamic Time Warping (DTW) algorithm. We discuss the technique very briefly in 3.1.

Afterwards, the actual parameter extraction process is described in detail in 3.2-3.4.

3.1 Dynamic Time Warping.

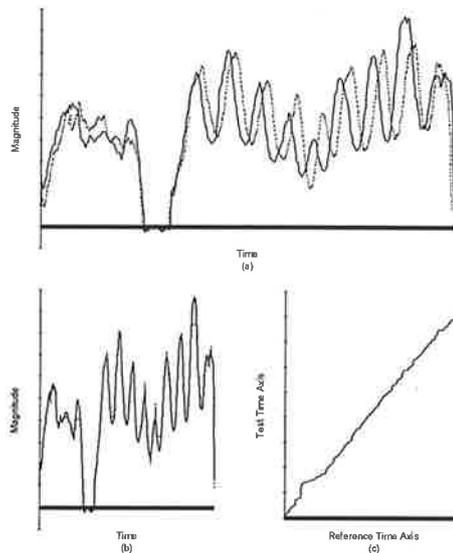The presence of non-linear timing differences in handwriting is illustrated in Figure 2a.

Figure 2: Non-Linear Timing Differences.
(a) Their presence in a pressure signal.
(b) Form information.
(c) Motion information.

The output of the DTW-algorithm [8] consists of 2 types of information. Form information (Figure 2b) reveals how well the patterns to be compared resemble to each other after removal of the timing-differences. Motion information (Figure 2c) describes how the time-axis's of both patterns are related to each other.

This form and motion information is used to extract suitable verification parameters. The classical way of doing so [8] is directly copied from speech recognition and consists of computing the Euclidean distance between the time aligned signals of reference and test pattern for form information or between the warping path and the diagonal for motion information. In [9] it has been shown that decoupling the DTW-stage and the actual feature extraction allows us to improve the verification performance. However, [9] also reveals that taking the decision parameters as the sample values at different timing instances is not a wise choice, as the parameters suffer from 2 disadvantages. There are too many of them and furthermore, they are highly correlated.

In the next few sections we reveal how techniques originating from signal compression can be utilised in order to increase the quality of the feature extraction process drastically.

3.2 Form Parameters.

A very promising approach to signal compression is the use of wavelet packet trees ([10], [11]). The single tree algorithm [11] allows to select out of a large class of potential basis's the for a specific signal most appropriate one. A further evolution, the double tree algorithm [10], makes it possible to adapt the basis that is used dynamically over time. The criterion we use to select the optimal set of basis functions is minimal Shannon-entropy [12]. The parameters that are extracted using this approach are not only local in time and frequency, but also highly decorrelated.

As illustrated in Figure 3, decorrelating the parameters before constructing a discriminant function results in an EER[1] of 3.9%. Using simple time-samples the EER equals 5.5%[2].
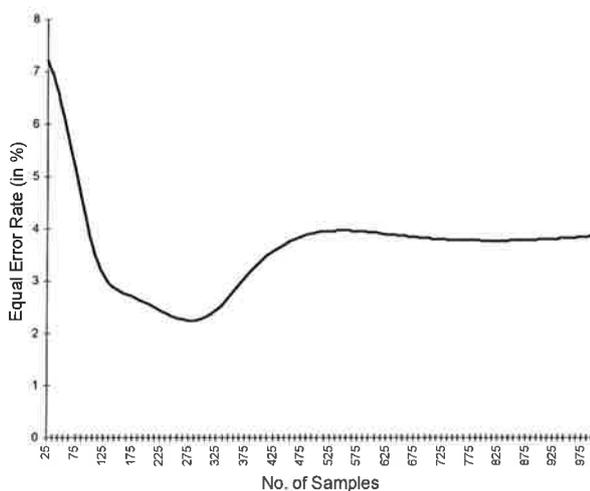

Figure 3: Effect of limiting parameter set.

[1] EER = Equal Error Rate. This is the percentage of misclassifications that occurs when False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal.

[2] Our database consists of 360 genuine signatures produced by 18 persons over a period of 3 months. 55 different persons produced a random forgery for each of the originals.

The effect of limiting the number of parameters is even more impressive. The EER using about 300 parameters for one signature is 2.3%. The EER using all available parameters is 3.9%.

3.3 Motion Parameters.

For the motion information parameters, we can do exactly the same observations as in 3.2. The decorrelation property of the transformation results in a decrease of the EER from 19.4% to 15.0%, while limiting the number of parameters that are used for classification further reduces the EER to 7.9%.

3.4 Consistency information.

The 5 different signals we have at our disposal for verification are individually time-aligned. It is clear that for a genuine signer a time-correction for one type of signal should also be present for another type of signal. We call the degree of resemblance between the warping-paths of the 5 different signals consistency information. Our experience shows that this type of information is not local, nor person dependant. This is why we use the Euclidean norm of the vector containing the standard deviations of the warping-path for the different time samples between the 5 signals involved as a consistency information parameter. Using only this type of parameter we obtain an EER of 10.2%.

4. Classification.

The classifier used in this work is the simplified Mahalanobis distance metric. For a detailed description see [9]. The classification vector is the union of the form, motion and consistency information parameter vectors. The covariance matrix that we use is person specific for all parameters but the consistency information parameter. This last parameter is considered population-specific.

5. Global System Performance.

We have build a complete signature verification system using the techniques we mentioned so far. Its performance, using the same database as

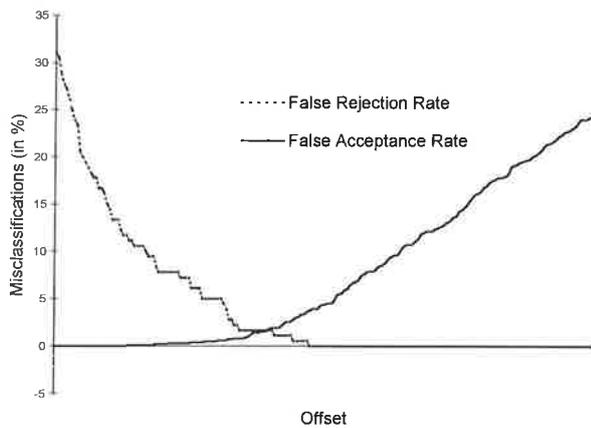mentioned earlier in this paper, is shown in Figure 4.

Figure 4: System-Performance.

As can be seen, genuine signatures and forgeries are separated almost perfectly (EER=1.2%).

6. Conclusion.

By decoupling the DTW and the actual feature extraction stage, we can build on-line signature verification systems with a higher performance than traditional ones. The reason has to be found in the quality of the parameters that can be extracted. Good parameters should be local in both time and frequency domain, and highly decorrelated. The wavelet packet tree concept offers the possibility to extract parameters with these characteristics, in the data compression area. The approach is evaluated for use in the signature verification area, by incorporating it into our own verification system.

7. Acknowledgement.

8. References.

[1] B. Miller, "Vital signs of identity", IEEE spectrum, pp. 22-30, Feb. 1994.

[2] R. Plamondon, G. Lorette, "Automatic Signature Verification and Writer Identification - State Of The Art", Pattern Rec., vol. 22, no. 2, pp. 107-131, 1989.

[3] F. Leclerc, R. Plamondon, "Automatic Signature Verification: The State Of The Art -- 1989-1993"; Int. J. Pattern Rec. Art. Intell., vol. 8, pp. 643-660, 1994.

[4] J. Bromley, J. W. Bentz, L. Bottou, I. Guyon, Y. Lecun, C. Moore, E. Säckinger, R. Shah, "Signature Verification Using a "Siamese" Time Delay Neural Network", Int. J. of Pattern Rec. Art. Intell., vol. 7, no. 4, pp. 669-688, 1993.

[5] B. Wirtz, "Stroke-Based Time-Warping for Signature Verification", Proc. of ICDAR'95, pp. 179-182, 1995.

[6] K. Huang, H. Yan, "On-Line Signature Verification Based on Dynamic Segmentation and Global and Local Matching", Optical Engineering, vol. 34, no. 12, pp. 3480-3487, 1995.

[7] L. Claesen, D. Beullens, R. Martens, R. Mertens, S. De Schrijver, W. de Jong, "SmartPen: An Application of Integrated Microsystem and Embedded Hardware / Software CoDesign", ED&TC'96 User Forum, pp. 201-205, 1996.

[8] Y. Sato, K. Kogure, "On-Line Signature Verification Based on shape, Motion, and Writing Pressure", Proc. of ICPR'82, pp. 823-826, 1982.

[9] R. Martens, L. Claesen, "On-Line Signature Verification by Dynamic Time-Warping", Proc. of ICPR'96, vol.3, pp. 38-42, 1996.

[10] K. Ramchandran, M. Vetterli, C. Herley, "Wavelets, Subband Coding, and Best Bases", Proc. of the IEEE, vol. 84, no. 4, pp. 541-560, 1996.

[11] K. Ramchandran, M. Vetterli, "Best Wavelet Packet Bases in a Rate-Distortion Sense", IEEE Trans. Image Process., vol. 2, pp. 160-175, 1993.

[12] R. Coifman, M. Wickerhauser, "Entropy-Based Algorithms for Best Basis Selection", IEEE Trans. Information Theory, vol. 38, no. 2, pp. 713-718, 1992.