# **Dynamic Programming Optimisation for On-line Signature Verification.**

Ronny Martens, Luc Claesen IMEC vzw Kapeldreef 75, 3001 Heverlee, Belgium Tel.: 32(0)16-28 12 11 Fax.: 32(0)16-28 15 01 E-mail: martens@imec.be

### Abstract.

In this paper, we focus on the use of the Dynamic Time Warping (DTW) technique in the signature verification area. The DTW-algorithm originates from the field of speech recognition, where it is a highly appreciated component of speaker specific isolated word recognisers. A few years ago the DTW-algorithm has been successfully introduced in the area of on-line signature verification. The characteristics of speech recognition and signature verification are however rather different. Starting from these dissimilarities, our objective is to extract an alternative DTW-approach that is better suited to the signature verification problem.

# 1. Introduction.

Due to technological advances, the last decades are characterised by a growing importance of man-machine relationships. In a majority of these interactions the most critical problem that is encountered is the automatic verification of the human's identity. So far, almost all verification systems have been non-biometric. This means that passwords, physical keys or PIN-codes are used for verification. The drawbacks of this approach are obvious. First of all a non-trivial effort (remembering a password, carrying a key) is required from the person who is identifying himself. Secondly, the system can be fooled rather easily. These problems explain the growing interest in biometric identity verification. Biometric systems use a behavioural or physiological characteristic to check a persons identity. This type of features allows to circumvent the drawbacks mentioned higher. An overview of the different biometric identity verification approaches can be found in [1].

In this work, we focus on on-line signature verification. This means that we try to extract stable and

idiosyncratic features out of the way a person signs. The signals used for this purpose are pen-tip positions, forces on the paper etc. On-line signature verification is a concept that has already proven its value. An overview of the available literature can be found in [2] and [3].

Section 2 - the most important one - is devoted to the timing aspect of signature analysis. In section 3, we start with situating these timing aspects in the complete verification process. Afterwards, we evaluate the feasibility of our approach by integrating it into a simple but complete system. Conclusions are drawn in section 4.

# 2. The timing-aspect.

In this section, we focus on how to handle time when doing signature verification. In section 2.1 we illustrate the benefits of using timing information in signature verification. In 2.2 the difficulties that are encountered when dealing with time are briefly described. Finally, 2.3 concentrates on the technique that is used to tackle the problems described in 2.2, namely dynamic time warping.

### 2.1 On-line versus off-line.

On-line systems show - see [2] - some very attractive features when compared to their off-line antipodes. First of all the amount of off-line input data is 2 orders of magnitude higher. This has a very negative effect on both the necessary storage capacity and the time needed to do the verification. A second, more important, disadvantage of off-line systems has to be found in their performance. While the use of on-line techniques results in FAR<sup>1</sup>s and FRRs of less than 2 percent, off-line experiments show 5 to 10 percent of misclassifications. Detailed results about on-line and off-line system tests can be found in [2].

<sup>&</sup>lt;sup>1</sup> FAR = False Acceptance Rate, FRR = False Rejection Rate

#### 2.2 Nature of timing differences.

From 2.1 one might conclude that the use of timinginformation is a blessing for the developer of verification systems. This is not exactly right, as dealing with time correctly is far from trivial. Several ways to use timing information have been reported ([2] and [3]). The most important decision to take is whether timing differences between several verification attempts are considered linear or not. This problem has already been addressed indirectly in [4], where correlation and DTW are compared. The authors denote no significant difference. In the next paragraph we formulate some criticism.

As illustrated in [5], using DTW for signature verification results in both "form information"- and "motion information"-parameters. "Motion information" has no counterpart when verifying using correlation-based techniques. Unfortunately, in [4], this extra amount of information is not taken into account when verifying a signature. As illustrated in [7], using both types of information the error rate is reduced by almost an order of magnitude. In [7] an EER of 8.9% is acquired for verification based on form information. Using form and motion parameters, the EER is 1.6%.

From the above we conclude that DTW-based techniques are superior to those based on correlation. Furthermore, since the basic difference between DTW-and correlation-based techniques is the ability to deal with non-linear timing differences, we derive that these are indeed an essential aspect of signing. This observation is illustrated in Figure 1. The figure shows the non-linear nature of the timing-differences between the pressure patterns of 2 signatures produced by the same signer.



Figure 1: Presence of non-linearities. Image (a) is linked to the pressure pattern in full line in (c), (b) to the pattern in dashed line.

# 2.3 DTW-algorithm.

First (2.3.1), we describe the DTW-approach that has been used in signature verification so far. Afterwards (2.3.2), we oppose this approach to our alternative warping technique.

**2.3.1. Classical approach.** The objective of the DTW-algorithm is to find an optimal time-alignment (Figure 2) between 2 patterns R and T.



Figure 2: Time-alignment between R and T.

A complete description of the algorithm that performs this kind of operation can be found in [7]. There have been no adaptations when migrating the technique from speech recognition to signature verification. As mentioned in [7], the problem for which the algorithm is intended should have the following properties:

(1) The patterns to be compared are time-sampled with a common and constant sampling period.

(2) We have no a priori knowledge about the relative importance of different parts of the patterns.

**2.3.2.** Alternative warping. Since we have a large set of genuine signatures at our disposal, condition (2) is not satisfied. In [6] we describe a method that allows to deal with information about the relative stability of different local phenomena present in a signature. The solution that is proposed consists of disconnecting the DTW-stage and the feature extraction process. Condition (1) can in general be satisfied easily. We claim however that using a single sampling rate for reference and test pattern should be avoided. This is explained further.

A signature does not contain relevant information above 20 to 30Hz. (see [2]). In Nyquist-terms this means it is useless to sample our reference patterns faster than 60Hz. Sampling at higher rates means introducing redundancy, which generally complicates the construction of a good classifier. We conclude that from the reference signal point of view we should not oversample our data.

From the test signal point of view the situation is obviously completely different. In the classical DTWapproach, when matching a certain time-segment to another one, 3 conclusions can be drawn (Figure 3).

- The length of the reference segment is considered too long. As a result it is reduced to 0, while the length of the test segment is not changed (case a).
- The length of both the reference and the test segment should be left intact (case b).
- The length of the test segment is too long. It is reduced to 0, while the reference segment remains unchanged (case c).

Figure 3 reveals the drastical nature of the time-corrections.



Figure 3: Local shape of the warping-path.

This means that in order to avoid extravagant distortion of the signals to be compared, we should oversample drastically.

Combining both factors, it is clear that condition (1) will affect the performance of the algorithm in a negative sense. We should critically sample our reference pattern, while oversampling the test pattern.

A second important feature of a good DTW-approach for signature verification is that the technique should be asymmetric. This means in our case that the reference pattern should not be deformed.

We can conclude that instead of using a warping-path with a local shape as depicted in Figure 3, we should use one that looks like in Figure 4.



Time for reference signal

# Figure 4: Preferred shape for local warping path.

Algorithm 1 describes how to compute the time alignment between a pattern R (Reference) and T (Test) taking into account the characteristics mentioned before.

$$D(i,j) = +\infty \Leftrightarrow (i,j) \neq (1,1)$$

$$\begin{split} D(i,j) &= 0 \Leftrightarrow (i,j) = (1,1) \\ \text{For } i=1..N \\ &\text{For } j=1..M \\ &d_{shorter} = \left\| R_i - T_j \right\| + D(i-1,j-(F-1)) \\ &d_{equal} = \left\| R_i - T_j \right\| + D(i-1,j-(F-1)) \\ &d_{longer} = \left\| R_i - T_j \right\| + D(i-1,j-(F+1)) \\ &D(i,j) = \min(d_{shorter}, d_{equal}, d_{longer}, D(i,j)) \\ &\text{end for} \end{split}$$

# Algorithm 1: Alternative warping.

The nodes of the optimal path are included when computing the alignment with minimal D(N,M). The symbols that are used have the following meaning. N/M is the number of samples in the reference/test pattern. F is the number of times that T has been sampled faster than R. As mentioned before, R should be critically sampled.

# 3. Evaluation.

In this section we evaluate the performance of the alternative DTW approach that has been described. First (3.1), we briefly describe the complete system we use for verification. Afterwards (3.2), an evaluation of the use of our warping approach is made.

#### 3.1 System description.

A complete signature verification system deals with a number of sub-problems. The essential ones [3], are the data-acquisition, the feature extraction and the classification. They are addressed in sections 3.1.1-3.1.3.

**3.1.1. Data-acquisition and pre-processing.** We can discriminate between 2 data-acquisition trends. A first class of researchers uses a simple tablet to gather pen-tip positions as a function of time while a person is signing. The other group tries to collect more useful signals by building a special-purpose input device. We opt for the second approach. The instrument used is called the SmartPen<sup>TM</sup> [8]. It looks like a normal pen, but the sensors that are mounted inside allow to measure 3D forces on the pen-tip and 2D angles of the pen-shaft. The actual pre-processing of these signals is described in [6].

**3.1.2. Feature extraction.** The purpose of the feature extraction process is to condense the person dependant information in a signature into a small set of parameters, retaining as less person-independent information as possible. The DTW-step is an essential subpart of this process. Since we don't try to optimise the intrinsic quality of the parameters, but only the performance of the

DTW step, we use 2 very simple parameters:  $x_{Form}$  and  $x_{Motion}$  as defined in [5]. These features are computed for each of the 5 signals. Parameters guaranteeing a better performance are described in for instance [6].

**3.1.3. Classification.** The final step is to extract a binary decision (genuine-forgery) out of the extracted features. We opt for Mahalanobis decision making.

#### 3.2 Results.

The database used here contains 360 signatures from 18 persons, collected over 3 months. For each person 15 signatures are used for classifier-construction. The other signatures are test originals. As forgeries for a certain person, we use the genuine signatures produced by the other signers. Figure 5 displays the EER<sup>2</sup> as a function of the computational effort for the 2 DTW-alternatives.



Figure 5: Comparison of DTW-alternatives.

The figure should be interpreted as follows. On the horizontal axis we see the effort used to do the warping. Since in our alternative DTW-approach only the testpattern is oversampled, there is a linear relationship between the oversampling factor and this effort. In the classical DTW-approach this relationship is quadratic. The vertical axis of Figure 5 is the EER. It is clear that the effect of oversampling the test-pattern is much more advantageous with our DTW-approach than with the classical one. This is easy to understand since in this last case the 2 crossing factors mentioned in section 2.3.2 are no longer present. The drastic growth of the EER at high oversampling factors in the adapted DTW-approach is due to an increase in FRR. This effect exists because the maximum time-discrepancy that can be corrected by the DTW-algorithm gets smaller than the actual one between different original signatures.

# 4. Conclusion.

We have examined the characteristics of the classical DTW-approach from the viewpoint of on-line signature verification. The most important disadvantage is the need for equal sampling rates in reference and test pattern. By presenting an alternative approach that does not have this requirement, we are able to almost halve the EER. This improvement can be realised by critically sampling the reference pattern, and at the same time seriously oversampling the test pattern. Since the useful signing information is concentrated in a very small 30 Hz. range, the oversampling raises no efficiency problems. Another important factor for the increased performance of our technique is the fact that the reference pattern is not deformed during the DTW-stage.

#### 5. Acknowledgement.

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<sup>&</sup>lt;sup>2</sup> The EER (Equal Error Rate) is the percentage of errors for a certain database that occurs when FAR and FRR are equal.