A different approach to off-line signature verification using the modified DTW algorithm

Wei Tian & Jingyuan Lv

Abstract— An different approach to off-line signature verification is described in the paper. This proposed system is based on projection profiles of signatures in different directions and modified dynamic time warping (DTW) algorithm. By using the projection profiles of signatures, the scheme employed the modified DTW algorithm for optimal matching and carried out training and verification. The modified algorithm incorporates stability of signature and reduces the accidental identification of factors. The experimental results with English and Chinese signature databases confirm the effectiveness of the proposed technique and show its ability to yield high verification rates.

1. Introduction

In general, handwritten signature verification can be classified into two kinds—online verification and off-line verification. Since the online approach can acquire more dynamic information than the off-line one, the latter is certainly more difficult to deal with. In the paper, we shall concentrate on the off-line signature verification problem.

In the last few decades, researchers have made great efforts on off-line signature verification. For matching various pattern recognition strategies like Neural Networks models [1], Time Warping [2], Hidden Markov Model (HMM) [3,4] and Support Vector Machine (SVM) [3], fuzzy modeling[5], stroke extraction[6] have been employed.

In this paper, we propose a new off-line signature verification method that uses projection profiles of signatures in different directions and modified DTW algorithm. Modifications were made to the basic DTW algorithm to account for stability of various components of a signature. The modified DTW can be used to determine the optimal alignment between two sequences with different lengths. The effectiveness of the proposed method is evaluated on a database of 936 authentic signatures from 39 authors and 1170 forgeries from 39 forgers.

The remainder of the paper is organized as follows: Section 2 introduces dynamic time warping for off-line signature verification. Section 3 is devoted to the modified dynamic time warping algorithm and training and verification process. Experimental results are presented in section 4. The paper ends with conclusions and future work in section 5.

2. DTW for off-line signature verification

There are inevitable variations in the signature patterns drawn by the same person. The present proposal is to track the positional variations of the features of the signature patterns and build a statistics of these variations from the training set. The one-dimensional projection profiles of the signature patterns are optimally matched using dynamic time warping. The positional variations are then derived from the resulting warping function. Figure 1 shows the vertical projections for different signatures, and Figure 2 shows the resulting warping function.

Let the two projections to be matched be called the reference projection and the verification projection, and let them be denoted by \( S^r = s^r_1, s^r_2, \ldots, s^r_k \) and \( S^v = s^v_1, s^v_2, \ldots, s^v_k \). The warping function \( w^* ( S^r, S^v ) = (i^*_1, j^*_1, \ldots, i^*_L, j^*_L) \) to be found is defined as the function which minimizes the overall distortion \( D \):

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projection at position $j^v_k$:

$$D_{w'}(S^r, S^v) = \min_{w(S^r, S^v)} \sum_{k=1}^{L} \left\| s^v_k - j^v_k \right\|$$  \hspace{1cm} (Eqn.1)

The warping function $(i^v_k, j^v_k)^*$, gives the positional distortion of the input projection relative to the reference projection. With $s^v_k$ optimally matched to $s_k^r$, it indicates that point $i^v_k$, 1 ≤ $i^v_k$ ≤ L1 of the reference projection is shifted to point $j^v_k$, 1 ≤ $j^v_k$ ≤ L2 in the input projection. Figure 3 shows the comparison of vertical profiles before and after optimal matching.

$$I'_{ij}^r = \frac{1}{N-1} \sum_{i=1}^{N} \Delta'_{ij}^r$$  \hspace{1cm} (Eqn.2)

Thus the score computed takes into account the stability of different sections of a person’s signature. Once the Projection stability factor of the various components of the signature have been determined, this information needs to be incorporated into the computation of the ‘Dissimilarity measure’. We modify Eq. (1) to incorporate stability:

$$D_{w'}(S^r, S^v) = \min_{w(S^r, S^v)} \sum_{k=1}^{L} \left\| s^v_k - j^v_k \right\|$$  \hspace{1cm} (Eqn.3)

B. algorithm Solution

The optimal matching problem given by Eq. (3) can be efficiently solved by using dynamic programming [7, 8]. Optimal matching by dynamic programming is a well-known method and has been applied to various problems. The algorithm is:

1) Initialization:

$$g(i^r_k, j^v_k) = g(1,1) = d(i^r_k, j^v_k) = d(1,1)$$  \hspace{1cm} (Eqn.4)

2) Dynamic equation:

$$g(i^r_k, j^v_k) = \min \left\{ g(i^r_k, j^v_k-1) + d(i^r_k, j^v_k), g(i^r_k-1, j^v_k-1) + 2d(i^r_k, j^v_k), g(i^r_k-1, j^v_k) + d(i^r_k, j^v_k) \right\}$$  \hspace{1cm} (Eqn.5)

Where, $j^v_k - r \leq i^r_k \leq j^v_k + r$, $r$ is the range of the adjustment. In this paper, r=2.

3) Final Solution:

$$D_{w'}(S^r, S^v) = g(l_1, j_1)/L1 + L2$$  \hspace{1cm} (Eqn.6)

C. Training and Verification Phase

Fig. 2 Illustration of optimal matching between the vertical projection (on the vertical axis) and the reference projection (on the horizontal axis). The warping function maps the reference projection at position $i^r_k$ to the input projection at position $j^v_k$.

Fig. 3 Comparison of vertical profiles before and after optimal matching.

### 3. modified DTW algorithm

A. modified algorithm

We propose a modification to the basic dynamic time warping algorithm described in Section II that incorporates a Projection stability factor for better off-line signature verification.

**Definition 1**: Projection stability Point $i^r_k$ of a signature $S^r$ with respect to $S^v$ is a point If and only if:

1) for $i^r_k$, $\forall$ $m = 1, \cdots, L$, $m \neq k$, $i^v_m \neq i^v_k$

2) for $j^v_k$ with respect to $i^r_k$, $\forall m = 1, \cdots, L$, $m \neq k$, $j^v_m \neq j^v_k$
During the training phase, the statistics on the vertical projection positional variations is built up from the set of training samples. The scores $\lambda^r$ on the dissimilarity measures for each of the signatures are computed and stored for comparison with the verification signatures. The training process algorithm is:

\[
I^r_{ik} = \frac{1}{N-1} \sum_{t=1}^{N} \Delta^r_{it}
\]

for \( r=1 \ldots N \) \( (v! = r) \)

\[
D^w_{w'}(S',S^v) = \text{Min}_{w(S',S^v)} \sum_{k=1}^{L} I^r_{ik} \left\| S^v_{ik} - S^m_{ik} \right\|
\]

\[
\lambda^r = \max(D^w(S',S^v))
\]

End

In verification process, Let $S^n$ represent a verification signature, the verification process algorithm is:

For \( r=1 \ldots N \)

\[
D^w(S',S^n) = \text{Min}_{w(S',S^n)} \sum_{k=1}^{L} I^r_{ik} \left\| S^n_{ik} - S^m_{ik} \right\|
\]

\[
w^r = \frac{1}{\lambda^r} D^w(S',S^n)
\]

\[
\tau = \text{sum}(w^r)
\]

End

If \( \tau < T \), the signature is true, otherwise is forgery. \( T \) is threshold.

4. Experiments

In the experiments, we test our system on the database which is a publicly available database from http://www.gpds.ulpgc.es/download/index.html [9]. The database is with a total of 39 writers: 24 genuine signatures for each person plus 30 forgeries of his/her signature. For these signatures, 12 genuine signatures chosen randomly of each person are used for training and the remainders are used for testing the proposed system. In addition, FRR, FAR and Eavg are adopted to evaluate the characteristic of the signature verification problem. The average error rate Eavg is calculated according to the following formula: $\text{Eavg} = (\text{FRR} + \text{FAR})/2$. Where false rejection rate (FRR) is when an authentic signature is rejected and false acceptance rate (FAR) is when a forgery is accepted.

Then the final results of the proposed method, and the scheme not modified with one experiment and different threshold T, are compiled in Table 1. The relative FRR, FAR and the average error rate for different values of the threshold value are also listed. As shown in the table, the choice of the threshold value is critical for the performance of the system. We find that with a threshold value of 1.5, the system is able to distinguish forgeries and genuine signatures with an average error rate of about 9.165%. It can also be observed that around a threshold value of 1.6, the system has close to 0% FRR, 23.33% FAR, and about 11.67% rejection rate for average error rate.

The training and test procedure is repeated 10 times in order to obtain reliable results. Fig. 4 shows the comparison of FAR, FRR for whole 39 person with $T = 1.6$. In our scheme, the minimum of Eavg is 13.63% for person 26 and the maximum value is 25.42% for person 37. The average error rate for the total 39 person is 15.46%. Fig 5 shows the final comparison of Eavg for whole 39 person with the not modified and modified schema. It can be seen that our final result is better than not modified scheme.

![Fig. 4 Comparison of different schemes](image)

![Fig. 5 Average error rate comparison with the not modified and modified schema](image)
signatures were shown for them. Therefore 30 forgeries of each genuine signature were obtained by 6 forgers. Then the signatures were scanned into the computer at resolution of 300dpi.

Table 2 shows the final results of the not modified and modified schema using our own database. From the table, it can be seen that Eavg is 18.96% by the modified method, and 24.09% by the not modified method. The modi is able to reduce the average error rate about 5.13%.

5. Conclusion

In this paper, we have proposed a novel approach to off-line signature verification. The proposed system uses the projection profiles and modified dynamic time warping. The modified algorithm was made to account for stability of various components of a signature and reduce the writer’s environmental factors or different characteristics of accidental impact. The entire system was tested by using a public database and our database and yielded an average error rate of 15.46% approximately, and its effectiveness was confirmed when compared with the other existing schemes.

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References


Table 1

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