ENHANCED DTW BASED ON-LINE SIGNATURE VERIFICATION

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ABSTRACT
This work describes an enhanced technique for on-line signature verification. The distance between two signatures is computed by dynamic time warping (DTW) method. The reference signatures are used to assign special parameters for each signer, which makes the system cover the intra signer variation. Several features are extracted. Systems with single and multi-features are tested. Curvature change and speed enhance success verification rate. The experiments have been carried out using the SUSIG online signature database. The best result for ROC area under curve is 99.5 with equal error rate 3.48%, and the best result for equal error rate is 3.06% with ROC area under curve 99.43.

1. INTRODUCTION
Automatic person identification and verification have become topics of interest in the last decade. Biometrics is divided into two categories: physiological and behavioral biometrics. Physiological biometrics is based on the physical properties of the human body, i.e., fingerprint, face and iris. Behavioral biometrics deals with personal behavior, e.g., signature verification.

Signature verification is an accepted personal identity method in the commercial community. Two main types of signature verification are available. The first is the off-line signature verification where the signature is signed on a paper and scanned as an image. The second type is the on-line signature verification which employs a digitizing tablet or a pressure sensitive pen to store pen movement and other dynamic information.

Different features are studied and compared here. The goal of this work is to select the best feature combination to minimize the verification error. In addition, the reference signatures are used to determine user dependant thresholds. These thresholds characterize the intra-signer variance within the reference set.

The paper is organized as follows. Section 2 provides a brief description of the signature verification problem. Section 3 describes Dynamic Time Warping (DTW) algorithm that will be a major component of the proposed method. Section 4 outlines the proposed technique that involves the feature selection method and the verification process. Experiments using the available signature database with the resulting outcomes are explained in section 5 and the paper is concluded in section 6.

2. SIGNATURE VERIFICATION TECHNIQUES
Online signature verification methods are different in feature selection, classification methodology and preprocessing. Features that have been used in signature verification are discussed in [1]. These features include the differences between two consecutive points in x and y coordinates, the absolute y-coordinate with reference to the center of the signature, the sine or cosine of the angle with the x-axis and the grey values in the pixel neighborhood.

Focusing on the classification methodology, different approaches can be found to measure the similarity between test signature and signer model. Dynamic time warping [2] and hidden Markov model (HMM) [3] are widely used. Vector quantization (VQ) pattern recognition algorithm is also tested [4]. In the Signature Verification Competition 2004 (SVC04), DTW and HMM based systems were shown to be the most competitive and the system based on DTW comes first. Also in [4] HMM, DTW and VQ are tested and DTW was shown to outperform the HMM-based method.

Preprocessing tasks were used in order to resample signatures, then all the signatures are represented using the same number of points; therefore, a simpler distance measurement between vectors can be applied [5].

3. DYNAMIC TIME WARPING (DTW)
In order to match two signatures of different lengths, it is necessary to use Dynamic Time Warping (DTW) algorithm [6]. DTW is a widely used algorithm for matching data vectors with different lengths. DTW algorithm finds the optimal non-linear path between the two vectors such that the overall distance between them is minimized, i.e., if we have two signals:

\[ Q = q_1, q_2, ..., q_n \]
\[ C = c_1, c_2, ..., c_m \]

Then to align these two signals using DTW, we construct an n-by-m matrix called the warping matrix where the \((i, j)\) element of the matrix corresponds to the absolute difference.

\[ d(i, j) = |q_i - c_j| \]

Optimal path can be found using dynamic programming to evaluate the following recurrence.
\[ \gamma(i,j) = d(i,j) + \min\{ \gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1) \} \]

where \( d(i,j) \) is the distance found in the current cell, and \( \gamma(i,j) \) is the cumulative distance of \( d(i,j) \) along with the minimum cumulative distances from the three adjacent cells.

4. THE PROPOSED DTW TECHNIQUE

The proposed technique is similar to previously published works on on-line signature verification. However, a new feature selection method and the classifying criteria will be enhanced.

4.1. Feature Extraction

On-line signature features can be classified in two types: global and local. Global features are features related to the signature as a whole, such as the average speed, the signature width and height, and total number of samples. Local features are related to a specific sample point along the signature trajectory such as pressure (force) exerted and curvature change between successive points on the signature.

Curvature changes are the most successful features reported in previous works. It is easy to find features to describe these changes, as for example, the \( x \) and \( y \) coordinates relative to the first sample point, \( \delta x \), \( \delta y \), \( \sin \alpha \) and \( \cos \alpha \), where \( \alpha \) is the angle between two successive points.

Another method related to the changing curvature was proposed in [3] where the angle between two successive points was found. The angle space is quantized into 16 quantized directions (\( QDir \)).

Quantized Directions (\( QDir \)) was calculated according:

\[ \theta = \tan^{-1}\frac{\delta y_j}{\delta x_j} \quad \forall \; j = 2,3,\ldots, N \]

\[ QDir(s_j) = n \quad \text{if} \quad \theta < \frac{n\pi}{L}, \text{and} \theta \geq \frac{3\pi - n\pi}{L} \]

\[ n = 2,3,\ldots, L \quad L = 16 \]

Speed was calculated between two successive points, using the following:

\[ Speed(s_j) = \sqrt{\frac{\delta y_j^2 + \delta x_j^2}{dt_j}} \quad \forall \; j = 2,3,\ldots, N \]

\[ dt_j = t(j) - t(j-1) \]

For each feature, DTW is applied to each reference set pair as shown in numerical example in Table (1). Intra-signer variations are defined as the average of nearest pairs DTW costs and the average of farthest pair DTW costs [2].

<table>
<thead>
<tr>
<th></th>
<th>Sig 1</th>
<th>Sig 2</th>
<th>Sig 3</th>
<th>Sig 4</th>
<th>Sig 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sig 1</td>
<td>0</td>
<td>120</td>
<td>125</td>
<td>97</td>
<td>112</td>
</tr>
<tr>
<td>Sig 2</td>
<td>120</td>
<td>0</td>
<td>45</td>
<td>95</td>
<td>88</td>
</tr>
<tr>
<td>Sig 3</td>
<td>125</td>
<td>45</td>
<td>0</td>
<td>98</td>
<td>110</td>
</tr>
<tr>
<td>Sig 4</td>
<td>97</td>
<td>95</td>
<td>98</td>
<td>0</td>
<td>102</td>
</tr>
<tr>
<td>Sig 5</td>
<td>112</td>
<td>88</td>
<td>110</td>
<td>102</td>
<td>0</td>
</tr>
</tbody>
</table>

Table (1) DTW for speed matching pair wise

The nearest signature for each one is Sig 4, Sig 3, Sig 2, Sig 2 and Sig 2 respectively, with DTW costs are 97, 45, 45, 95 and 88 respectively. Their average is 74. The farthest signature for each one is Sig 3, Sig 1, Sig 1, Sig 5 and Sig 1.
respectively, with DTW costs being 125, 120, 125, 102 and 112 respectively, averaging 117. The signer model contains:
- The reference set (Sig 1-5) features vectors,
- The average of nearest pairs DTW costs ($avrMin_f$),
- The average of farthest pair DTW costs ($avrMax_f$),
where $f$ denotes a feature.

4.3. Verification

In order to verify a signature with specific signer, the signature feature vectors are calculated (see section 4.2.). These feature vectors are matched with all reference set of this signer. The minimum cost is selected as nearest signature ($SMin_f$) and the maximum cost is selected as farthest signature ($SMax_f$) from the reference set. The differences between ($SMin_f$), ($avrMin_f$), and between ($SMax_f$), ($avrMax_f$) are calculated as:

$$
diffMin_f = \frac{SMin_f - avrMin_f}{avrMin_f},
$$

$$
diffMax_f = \frac{SMax_f - avrMax_f}{avrMax_f}.
$$

These two differences for each feature are used for the classifying decision. A large negative difference refers to a genuine signature, while a large positive indicates a forgery signature. Test signature is considered to be genuine if the following condition is satisfied:

$$
diff_{total} = \sum_f (diffMin_f + diffMax_f) \leq T_{th}
$$

The threshold, ($T_{th}$), is the confidence level that separates genuine and forgery signatures and is used to draw Receiver Operator Characteristic (ROC). The value assigned to ($T_{th}$) is dependent on the number of features used in the system.

5. EXPERIMENTS AND RESULTS

5.1. Database

The SUSIG (Sabanci University Signature database) is an online signature database, skilled forgeries were collected such that forgers saw the actual signing process played-back on the monitor and had a chance of practicing [7]. Signatures collected by Interlink Electronics’s ePad-ink tablet which has an LCD screen dimensions of 3x2.20 inches with a 300 dpi spatial resolution. The tablet has a sampling rate of 100Hz, recording at each sample point the $x$, $y$ coordinates of the signature’s trajectory, pressure in $z$-axis (128 levels), the time stamp and end points of segments.

SUSIG consists of signatures 100 signers; each signer supplied 20 samples of his/her signature in two different sessions, supplying 10 signatures at each session, approximately one week between the two signing sessions. SUSIG has big variety signatures in length, short one is 64 samples per signature and long one is 860 samples per signature. Figure (2) shows samples from the database.

Previous results were published using this database [7]. The authors have obtained 4.70% of False Rejection Rate and 3.45% False Acceptance Rate. This result will be used as a reference result. The authors removed 6 signers from public release for security issues, so the available signers were just 94.

Figure (2): Sample genuine signatures from the SUSIG

5.2. Results

The system accuracy was calculated according to verification protocols of the database [7]. First five signatures were taken from session 1 as reference set for user. The other five from session 1 and all ten from session 2 were used to calculate False Rejection Rate (FRR). Ten forgery signatures were used to calculate False Acceptance Rate (FAR).

Two methods are used to evaluate ROC graphs. Area Under Curve (AUC) is the area under the curve relative to the total scale (100*100). Equal Error Rate (EER) is the point on the curve when FRR equal to FAR. AUC is more accurate measure than Equal Error Rate (EER).

For the first experiment, each feature was tested alone. Results are shown in Table (2) and Figure (3). These single feature systems did not show satisfying results.

<table>
<thead>
<tr>
<th>Feature</th>
<th>AUC of truth</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>$QDir$</td>
<td>98.07</td>
<td>6.67</td>
</tr>
<tr>
<td>$sin,a$</td>
<td>99.10</td>
<td>5.02</td>
</tr>
<tr>
<td>$cos,a$</td>
<td>99.01</td>
<td>4.62</td>
</tr>
<tr>
<td>$Speed$</td>
<td>98.66</td>
<td>4.32</td>
</tr>
<tr>
<td>Pressure</td>
<td>96.66</td>
<td>8.20</td>
</tr>
</tbody>
</table>

Table (2) Different single feature systems
The second experiment aims to select the best features combination. These combinations consist of one of the curvature change features group (QDir, sin $\alpha$ and cos $\alpha$) speed and pressure. The used combinations are shown in Table (3). Figure (4) shows the ROC curve results. Table (3) shows the AUC and EER results.

<table>
<thead>
<tr>
<th>Features</th>
<th>AUC of truth</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>QDir + speed</td>
<td>99.15</td>
<td>4.31</td>
</tr>
<tr>
<td>QDir + speed + Pressure</td>
<td>99.34</td>
<td>3.81</td>
</tr>
<tr>
<td>cos $\alpha$ + speed</td>
<td>99.43</td>
<td>3.06</td>
</tr>
<tr>
<td>cos $\alpha$ + speed + Pressure</td>
<td>99.45</td>
<td>3.76</td>
</tr>
<tr>
<td>sin $\alpha$ + speed</td>
<td>99.50</td>
<td>3.48</td>
</tr>
<tr>
<td>sin $\alpha$ + speed + Pressure</td>
<td>99.46</td>
<td>3.75</td>
</tr>
</tbody>
</table>

Table (3) Different multi-feature systems

Experimentally, it was found that the system used the features $\sin \alpha$ and speed gave the best result according to AUC. But the best EER gained by the system used the features cos $\alpha$ and speed. We expect if the database is big and the curves will be smoother the system used $\sin \alpha$ and speed will be a better candidate system even in EER. Results showed that using more than one feature improves the success rate in signature verification. The speed found to be an effective feature.

6. CONCLUSION

In this work, we have demonstrated the effects of using separate and combined features for on-line signature verification. Multi-systems were shown to outperform the single feature ones. Correlation between the used features must be very small. Curvature change ($\sin \alpha$ and cos $\alpha$) and speed are the most efficient features, and each of them can cover the other’s shortcomings. Pressure gave slight enhancement.

Systems could cover intra signer variation. Special parameters were extracted from the signer reference set. Verification process was based on these parameters. The summation condition in verification process guides the system for accurate decision.

For future work, dynamic time warping will be studied in depth for optimal path finding method. Weighted features in verification condition will be studied as well. We consider adding weights in the verification condition. Different classifiers will be experimented and compared with DTW.

7. REFERENCES