Online Signature Verification Using Dynamic Time Wrapping and Extended Regression

Toai Q.Ton[1], Tung Thanh Pham[2]

***Abstract*—Online signature verification is one of the biometric features which can be used for identity in the financial transaction, contract document, as well as being used to authenticate the materials.In this paper, we present a system using Dynamic Time Wrapping (DTW) and extended regression to verify the online signatures. Our system will extract 20 features in each points of the signature, andthe system will standardize these features before they enter into the system for training or testing.When conducting authentication, a user's signature is considered to be correct when the similarity measure calculated by using DTW and extendedregressionisusedtocalculatethesimilarityindexofthetwos ignaturesis greater than a threshold.The validity of the proposed method was tested on the public SVC2004 signature database.**

***Index Terms*— Biometrics, Online signature verification, Dynamic Time Wrapping.**

I. INTRODUCTION

Abraham, Dolan, Double and Stevens [1] explained that authenticity is what can be done based on knowledge, the character of the object. There's a whole set of personal characteristics, often defined as biometrics and can be used for identification or authentication, such as fingerprints, retina, DNA and handwriting and especially signature [2]. Therefore,it is not a coincidence that these properties are used in legal science to solve crime cases.

When using computer to collect signature by a digital pen tablet, we obtain information about the shape of the signature and we also obtained dynamic information of the signature. This dynamic information generates "online"signature.This concept shows a string of sample points shipping information during the process of signing up.In other words, each the dynamic information is a function according to time of signing process. Thus, the signing process generates a set of the data function over time. Theonlinesignature helps facilitate forthe authentic signature because the dynamic information is more difficult to forge than the image of the signature. So, if anyone wantsto forge signatures, they need more work. However, this problem is still challenging problem in biometrics becauseof the large intra-class variation and when considering forgeries, small inter-class variation[3].

There are many different approaches in data classification of signature. The current methodscan be divided into two classes:

1) Feature based approaches [4]. In this approach, a signature is represented by a vector consisting of a set of global features thatare extracted from the trajectory of the signature.

2) Function based approaches [5]. In this approach, a signature is represented by the functions of the time, including the local properties of the signature (ex:position trajectories (x, y), velocities, accelerations, pressures, and more).

In this paper, we study and apply of Dynamic Time Wrapping to calculate the distance between signatures (the function-basedapproach) and extended regression is used to calculate the similarity of signatures. The experimental results show that the system gives a quite good result compared with other systems (will be described in section VII).

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II. PREPROCESSING

In preprocessing stage, signature location is normalized and the jagged of signature is removed.

A. *Normalizationofsignaturelocation*

On the surface of tablet, users can sign in any location.With each the positions, whether we sign up signaturesmost exactly, we also acquired coordinates (x (t), y (t)) differ.To system independent with positions we need to normalize the coordinates (x (t), y (t)).

The formula for calculating the center ofthe signature:

$$x_g = \frac{\sum_{t=1}^{T} x(t)}{T} \quad (1)$$

$$y_g = \frac{\sum_{t=1}^{T} y(t)}{T} \quad (2)$$

Where, T is the length of signature.

The coordinates are normalized by the formula:

$$x_{new}(t) = x(t) - x_g \quad (3)$$

$$y_{new}(t) = y(t) - y_g \quad (4)$$

B. *Smoothsignature*

Some tablet devices have a low resolution can make the signature jagged. The extracting local features from jagged signature used for authentication can lead to very poor enforcement system. Smoothing signature is required to perform before further processing.

Gauss filter is used to smooth small oscillating anomaly in signatures while retaining its entire structure. One feature of Gauss is the weighting filter decreases from the center of the filter, the pixels near the center weighted far higher than the center pixel.

One-dimensional Gaussian function is defined:

$$f_i = \frac{e^{-\frac{i^2}{2\sigma^2}}}{\sum_{j=-2\sigma}^{2\sigma} e^{-\frac{j^2}{2\sigma^2}}} \quad (5)$$

Coordinates (x (t), y (t))of signature distinct smoothed Gaussian filterf_i:

$$x_{new}(t) = \sum_{i=-2\sigma}^{2\sigma} f_i * x(t+i) \quad (6)$$

$$y_{new}(t) = \sum_{i=-2\sigma}^{2\sigma} f_i * y(t+i) \quad (7)$$

Fig.1 illustrates the signature is filtered using a Gaussian filter

(a) (b)

Fig. 1.(a) original signature. (b) Signature after filtering by Gaussian filter

III. FEATURE EXTRACTION

A. Data collection

Signaturesdata are given to the program with the digital pen. Each time a user signs a signature, the program will collect a data stream. They are a set of five components (x, y, p, altitude and azimuth).These parameters can be considered as the function of time t (t is the time index of sampling):

- $x(t)$: x coordinate at time t
- $y(t)$: y coordinate at time t
- $p(t)$: p pressure at time t
- altitude(t): the angle between the pen and the projection of the pen when it draws onto the plane of the drawing equipment (0-90)
- azimuth(t): clockwise angle to the pen projection onto the plane of the drawing equipment (0-359)

A raw online signature S is represented by

$$S = \{(x(t), y(t), p(t), \text{altitude}(t), \text{azimuth}(t))\}_{t=1..T} \quad (8)$$

B. Feature extraction

Because the features of the signature is depend on the signer very much, so we extracted some dynamic featuresf(t) at t time.

TABLE 1: 20 FEATURES RELATED TO THE MOVEMENT OF THE SIGNER.

No.	Feature name
1-2	The normalized coordinates $(x(t) - x_g, y(t) - y_g)$ compared to the center of the signature(x_g, y_g)
3	The pressure p(t)
4-5	Two angle: altitude(t) and azimuth(t)
6-7	Speed in x and y directions: $v_x(t) = x'(t), v_y(t) = y'(t)$
8	The magnitude of the velocity line: $v(t) = \sqrt{x'(t)^2 + y'(t)^2}$
9-10	Acceleration in directions of the x and y:$a_x(t) = v_x'(t)$,$a_y(t) = v_y'(t)$
11	Absolute acceleration:$a(t) = \sqrt{a_x^2(t) + a_y^2(t)}$
12	Tangential acceleration:$a_{tt}(t) = v'(t)$
13	The press derivation:$\Delta p(t) = p'(t)$
14	The α angle between the absolute velocity vector and the x axis: $\alpha(t) = \arcsin\frac{v_y(t)}{v(t)}$
15-16	Sine, cosine of the α angle: $\sin\alpha(t) = \frac{v_y(t)}{v(t)}$,$\cos\alpha(t) = \frac{v_x(t)}{v(t)}$
17	Derivation of α angle:$\Delta\alpha(t) = \alpha'(t)$
18-19	$\sin\Delta\alpha(t)$and$\cos\Delta\alpha(t)$
20	$\beta(t)$ is the angle between two adjacent line segments at each coordinate

With signature in Fig.2, we have a list of some features are calculated in Table 1.

Fig.2. Sample signature

x	y	v_x	v_y	v	a_x	a_y	a	a_{tt}
586	727	-7.1	-0.2	7.1028	0.28	-0.3	0.3753	-0.2687
578	727	-6.8	-0.5	6.8183	0.39	-0.3	0.4687	-0.3681
572	726	-6.4	-0.8	6.4498	0.46	-0.3	0.5235	-0.4270
566	725	-5.8	-1	5.8855	0.57	-0.3	0.6350	-0.5033
560	724	-5.3	-1.2	5.4341	0.67	-0.3	0.7468 6	-0.5465
555	723	-4.5	-1.7	4.8104	0.72	-0.4	0.8188	-0.5140
551	721	-3.7	-2.1	4.2544	0.71	-0.4	0.8249	-0.4115
548	718	-3	-2.5	3.9051	0.66	-0.4	0.7932	-0.2174

Table 1. Some features

So, looking for another aspect, the signature is considered as a feature matrix:

$$O = \{o_{k,t}\}_{t=1..T}^{k=1..20} \quad (9)$$

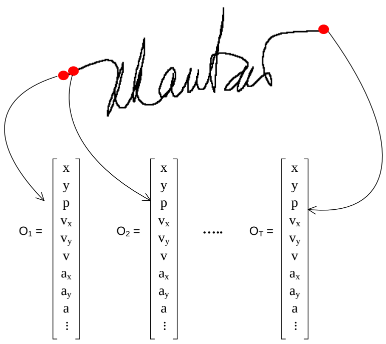

Fig. 3. The signature observation

C. Feature normalization

The features will have different range of values. Without normalization, the feature with large range of value will have more weight than the feature with small range of value. Therefore, we need normalize so that the feature values achieve zero average and unit standard deviation.

$$o_t = \frac{v_t - \mu}{\sqrt{\Sigma}} \quad (10)$$

Where,μ and Σ are the average sample and cross-covariance matrix of the feature vectors v_t(t = 1, 2 ... T).

IV. CALCULATION OF SIMILARITY BETWEEN TWO SIGNATURES

A. Calculate the distance between two points

Two points on two different signatures is two 20-dimensional feature vectors, have the same corresponding components. Therefore, we can use Euclidean distance to calculate the distwo-feature vectors.

Call$o_{.i}^{test}$ and$o_{.j}^{ref}$ is the i^{th} point of thetesting signature and the j^{th} point of the reference signature corresponding, the Euclidean distance between two the point is

$$D_E\left(o_{.i}^{test}, o_{.j}^{ref}\right) = \sqrt{\sum_{k=1}^{20}(o_{k,i}^{test} - o_{k,j}^{ref})^2} \quad (11)$$

B. Aligns two signatures by Dynamic Time Warping

To compare the two signatures with differing lengths, we will take advantage of a well-known method was used in speech recognition, which is Dynamic Time Warping(DTW).DTW algorithm has two purposes, firstly it used for calculating the distance between two signatures, secondly it find points on two signatures for comparison each other to calculate the distance between two signatures.These points form the optimal alignment to compare two signatures

To calculate the distance between a test signatureO^{test} and a reference signature O^{ref}, we build a matrixwith $(N+1)x(M+1)$size (DTW matrix).Where Nis the length of the signature O^{test} and M is the length of the signatureO^{ref}.

DTW algorithm:

Initialization:

$$DTW[0,0] = 0, DTW[i,0] = DTW[0,j] = \infty \quad \text{Where } i \in [1, N+1], j \in [1, M+1] \quad (12)$$

$$DTW[1,1] = D_E\left(o_{.1}^{test}, o_{.1}^{ref}\right) \quad (13)$$

Recursion: with other each point (i, j), consideration from left to right, from bottom to top, $DTW[i,j]$ is calculated as following:

$$pre[i,j] = argmin\begin{Bmatrix} \mathrm{DTW[i-1,j]}, \\ \mathrm{DTW[i,j-1]}, \\ \mathrm{DTW[i-1,j-1]} \end{Bmatrix} \quad (14)$$

$$\mathrm{DTW[i,j]} = D_E\left(o_{.i}^{test}, o_{.j}^{ref}\right) + DTW[pre[i,j]] \quad (15)$$

Backtracking: Optimal alignment was rebuilt by backtracking. The last point (N, M) connected topoint pre(N, M), point pre(N, M) is connected to point pre(pre(N, M)), ... This process is repeated until the first point (1, 1).

The distance between reference and test signatures will be stored at the upper right corner of the DTW matrix: $D(O^{test}, O^{ref}) = DTW[N,M]$

C. Similarity calculation

To calculate the similarity of test signature O^{test} and reference signature O^{ref}, we follow these steps:

Step 1. We used DTW to determine optimal alignment between two signatures.

Step 2. Stretch twosignatures to two signatures of equal length. This is done as following: if the point$o_{.i}^{ref}$ in the signature O^{ref} is aligned into k (k>1) point in the signature O^{test}, we will relax by repeating (k-1)times $o_{.i}^{ref}$. SignatureO^{ref} is done in the same way.

Step 3: After a relaxing two signatures, we have two signatures with same length. Next, we apply the following equation to calculate the similarity of two signatures.

$$similarity = \frac{[\sum_{j=1}^{20}(\sum_{i=1}^{T}(o_{ji}^{test} - \bar{o}_j^{test})(o_{ji}^{ref} - \bar{o}_j^{ref}))]^2}{\sum_{j=1}^{20}\sum_{i=1}^{T}(o_{ji}^{test} - \bar{o}_j^{test})^2\sum_{j=1}^{20}\sum_{i=1}^{T}(o_{ji}^{ref} - \bar{o}_j^{ref})^2} \quad (16)$$

Where, $\bar{o}_j^{test}$ and $\bar{o}_j^{ref}$ represent the mean of the j^{th} dimension for the signature of o^{test} (o^{ref}).

V. TRAINING

To deal with intra-class variability, inherent to the signing process, a number of genuine signature samples should be stored for each user. Previous results show that five signatures is a reasonably low number and could still provide good results in practical scenarios [10].

Five genuinesignatures of a person are used and the similarities betweenthese signatures are calculated two by two and the average often obtained similarities is used for determination of thedecision boundaries.Decision boundary related to the signatures of thei^{th}person is determined by following

$$T_i = \frac{\sum_{j=1}^{10} similarity_j}{10} \quad (17)$$

VI. VERFICATION

In order to verify a test signature Y, the similarity of Y with each of training signatures belonging to the i^{th}person is calculated and the mean value of these similarities are considered as the similarity of Y with the training stage signatures.We call it s_i.

To accept or reject test signature Y which is claimed to bebelonged to the i^{th} person, if the condition of $s_i > T_i$ isfulfilled, then the input signature will be verified, otherwise, it will be rejected.

VII. EXPERIMENTS

To test the research result, we carried out the experiments on a SVC2004 database [8] including:

- 40 users
- 1 user: 20 real signatures + 20 professional forged signatures

Testing:

- Select randomly 5 real signatures for training
- Test 1: 10 real signatures + 20 professional forged signatures
- Test 2: 10 real signatures + 20 pseudo-random signatures(obtained from other users)

The above process is repeated 10 times to ensure reliability with each time we can calculate EER deviation. After 10 trials, we can calculate the EER average.

The results on the skill forged:

TABLE 2: COMPARISON WITH SOME OTHER METHODS

Signature verification system	%EER
The proposed algorithm	6.95
Reference [6]	7.20
Best SVC2004 [7]	6.90
Reference [9]	7.00
Reference [14]	7.02

TABLE 3: RESULT OF GROUPS ARE TESTED IN SVC2004 COMPETITIONS [7]

Group Code	%EER
219b	6.90%
219c	6.91%
206	6.96%
229	7.64%
219a	8.90%
214	11.29%
218	15.36%
217	19.00%
203	20.01%
204	21.89%

VIII. CONCLUSION

Compared with the systems of SVC2004 competition, our system resultsin the top 3 on skill forged signature and have better results than other systems on random forged signature.

Compared with the DTW + ER^2 method of Lei [6] offer:Results of system is studied better of 0.25% on the professional forged signature.

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