ON-LINE SIGNATURE VERIFICATION USING GLOBAL FEATURES

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ABSTRACT

On-line signature verification based on global features in an integration with Fisher Linear Discriminant Analysis (FLD) have been proposed in this paper. In the verification phase, distances of features of test signature are calculated against their corresponding template. Finally, these distances become inputs to FLD. User-dependent threshold has been used to evaluate the performance of our proposed method in comparison to other existing methods. We have used single-session and mix-session protocols for the evaluation of our proposed method using SUSIG database. Experimental results demonstrate the superiority of our approach in On-line signature verification in comparison with other techniques.

***Index Terms*—** On-line signature, global features, Fisher Linear Discriminant Analysis (FLD), user-dependent.

1. INTRODUCTION

Signature verification is a behavioral biometric that is categorized into two main classes: *Off-line Signature Verification* and *On-line Signature Verification* based on the data acquisition equipment. Off-line Signature verification deals only with the shape of the signature whereas On-line signature verification is based on the dynamic features of signature in addition to its shape. However, this paper deals with feature-based On-line signature verification where each signature is represented by a feature vector [1], [2], [3], [4]. However, the use of different features have been reported by different researchers in past and their comparative analysis have also been done in-order to prove their effectiveness in the verification process.

In our proposed approach, we have used a set of 35 global features for the representation of a signature as reported in [5]. Training process is done by using 3 and 5 signatures and finally FLD is used in the verification phase. We have used user-dependent threshold [6], where a threshold was selected for each user individually in such a way that the Equal Error Rate (EER) of the system is minimum. We have used SUSIG database for the evaluation of our proposed system. Experimental results shows that our proposed approach has out performed the method propsoed in [7].

The paper is organized as follows. The second section deals with the acquisition of signature data and preprocessing steps. The third section is dedicated to the design and structure of our proposed system and finally in the last section, experimental results and concluding remarks are presented.

2. DATA ACQUISITION AND PREPROCESSING

For the experimental evaluation of our proposed system, we have used a public database SUSIG [7] whose details are given in Section 4.1 of this paper. Every time, a signer signs in different way and in different areas of the tablet. So, there is a need to make all the signatures of the ith signer to be *translation, rotation and scale invariant*. Details of each preprocessing step is given below.

Translation invariance is achieved by subtracting the mean of each independent trajectory (horizontal,vertical) of each jth signature of ith signer from its respective trajectory as suggested in [8]. Principal Component Analysis (PCA) has been used to make all the signatures of the ith signer to be rotation invariant. The Principal Component (PC) of each signature is rotated to the angle of the PC of base signature for each ith signer [9]. Result of translation and rotation invariance is shown in Figure 1 b). Now, the next preprocessing step is to make signatures *scale invariant* in a way that the aspect ratio between the horizontal and vertical trajectory of a signature remains same as in the original un-scaled version of signature. It is achieved by using the following pair of equations:

$$\begin{aligned} Ratio_j^i &= \frac{max(x_j^i)}{max(y_j^i)} \\ y_j^i &= \frac{y_j^i - min(y_j^i)}{max(y_j^i) - min(y_j^i)} \\ x_j^i &= \left(\frac{x_j^i - min(x_j^i)}{max(x_j^i) - min(x_j^i)}\right) \times Ratio_j^i \end{aligned} \tag{1}$$

After making all the signature *scale invariant*, the vertical trajectories of each signature will be scaled from zero to one and

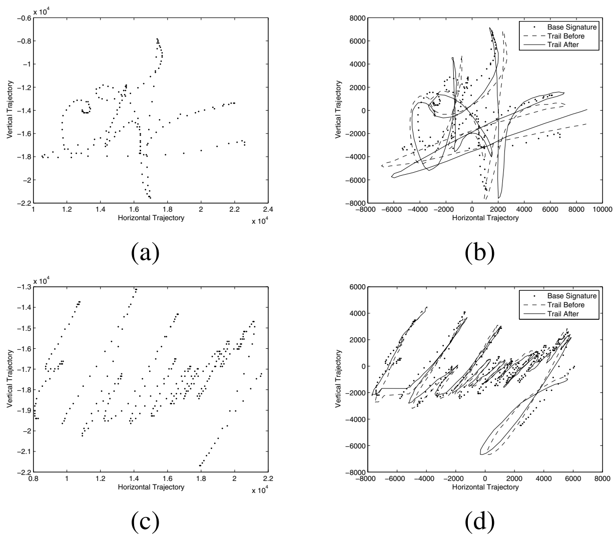

Fig. 1. a), c) are Base Signatures, b) and d) are another genuine signatures of the same signers. It is obvious from the (b) and (d) that after rotation invariance eigen vectors of base-signatures and tests are at same angle and they are translation invariant.

the horizontal trajectories will be scaled from zero to the ratio between the un-scaled vertical and horizontal trajectories as shown in Figure 2 b).

3. PROPOSED SYSTEM

Like every biometric system, our proposed system consists of two phases: Training and Verification. In *training phase*, a set of 35 global features that were reported to be among the most the consistent features [1], [5], has been extracted for each trainging signature of ith signer. In this way, each signature is represented by 35 dimensional feature vector. A set of 35 global features used in this paper is shown in Table 1. For the training purpose, we have used 3 and 5 genuine signatures for each ith signer.

In *verification phase*, a test signature of ith signer is declared as “genuine” or “forgery”. After preprocessing an incoming test signature, features are extracted and a distance is calculated between the template and the test signature of ith signer. These distances are given as an input to Fisher Linear Discriminant (FLD) which treats the test signature distance as a feature representing an external class to that of the known authentic sample signatures used to generate the template. These are used to train FLD which works to maximize the between-class distance while minimizing within-class distance.

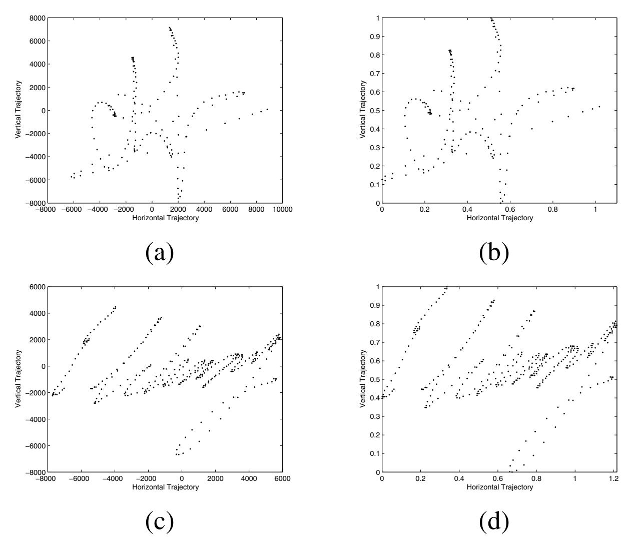

Fig. 2. a), c) before scale invariance, b) and d) after scale invariance

4. EXPERIMENTAL RESULTS

To check the authenticity of our proposed system, we have used a public database namely: SUSIG Database [7]. We have trained our system using only 3 and 5 genuine signatures which has become a standard for training On-line Signature Verification System.

4.1. SUSIG Database

The SUSIG database has been constructed from signature data acquired via two types of pressure-sensitive tablets. The first type of tablet enables real-time visual feedback through an LCD display while the user makes a signature, from which a *visual sub-corpus* was collected. In the second tablet, no visual feedback was available, effectively forcing the user to construct their signature blindly, collected as a *blind sub-corpus*. Each sub-corpus incorporates signature data from 100 people, with each signer contributing multiple samples of their signature. In total, this has resulted in a database of more than $3,000$ genuine signatures. In addition to the genuine signatures, a set of $2,000$ skilled forgeries make up the remaining part of the database.

A forgery is considered to be *skilled*, if the forger is to some degree, aware of the the signing process prior to committing the signature. This has been simulated by first animating the trajectory of a particular genuine reference signature on the LCD of the tablet and giving the intended forger the opportunity to practice formulating the signature. Of the forged signatures collected in this manner, a subset were considered *highly skilled* when the trace of the signature trajectory was left on the LCD screen of the tablet (after animation) for the forger to explicitly trace over. The forgers

Table 1. List of Features Used

Feature #	Feature Description
F1	Average writing speed
F2	Maximum writing speed
F3	Time of maximum speed
F4	Total signing duration
F5	Total pen down duration
F6	Minimum horizontal writing speed
F7	Time of min. horizontal writing speed
F8	Total dots recorded
F9	Average dot execution time
F10	Number of pen ups
F11	Time of 2nd pen down
F12	Duration of $V_x > 0$
F13	Duration of $V_x < 0$
F14	Duration of $V_y > 0$
F15	Duration of $V_y < 0$
F16	Average positive V_x
F17	Average negative V_x
F18	Average positive V_y
F19	Average negative V_y
F20	Total $V_x = 0$ events recorded
F21	Total $V_y = 0$ events recorded
F22	Maximum V_x - Average V_x
F23	Maximum V_y - Average V_y
F24	Maximum V_x - Minimum V_x
F25	Maximum V_x - Minimum V_y
F26	Maximum V_y - Minimum V_y
F27	(Max. X time)/(Total time of pen down)
F28	(Min. X time)/(Total time of pen down)
F29	(Max. X time-Min. X time)$\times$(Max. Y time-Min. Y time)
F30	Initial X - Minimum X
F31	Final X - Maximum X
F32	Final X - Minimum X
F33	(Max. X time -Min. X time)/(Max. Y time -Min. Y time)
F34	Standard deviation of X
F35	Standard deviation of Y

in this final group were also given feedback outlining how close they were to the reference signature, such that further improvement could be made in each successive forgery. The quality of highly-skilled forgeries was thereby expected to be much higher than the standard skilled forgery.

We have used user-dependent threshold while using the single-session and mixed-session protocols [7]. Table 2 presents the EER of our system using 3 and 5 training signatures and also the EER of the system proposed by Alisher Kholmatov [7]. Our proposed method have outperformed the Kholmatov results on SUSIG database, whose method won the first prize in first SVC 2004. Fig. 3 c), d) and Fig. 4 c), d) shows the results of our proposed method. Fig. 3 e) and Fig. 4 e) shows the result of the system proposed in [7] while using 5 genuine signatures for the training purpose. It is clear

Table 2. Results for the SUSIG database and protocols

Protocol	Subcorpus	EER% of system used in [7]	EER% of our proposed system user-dependent	
		Train 5 Genuine	Train 3 Genuine	Train 5 Genuine
Mixed-Session	Visual	2.10	1.96	1.57
Single-Session	Blind	2.85	2.43	1.81

from the Table 2 that our proposed method has outperformed the system proposed in [7], even when we have used only 3 genuine signatures for training purpose in case of both blind and visual sub-corpus.

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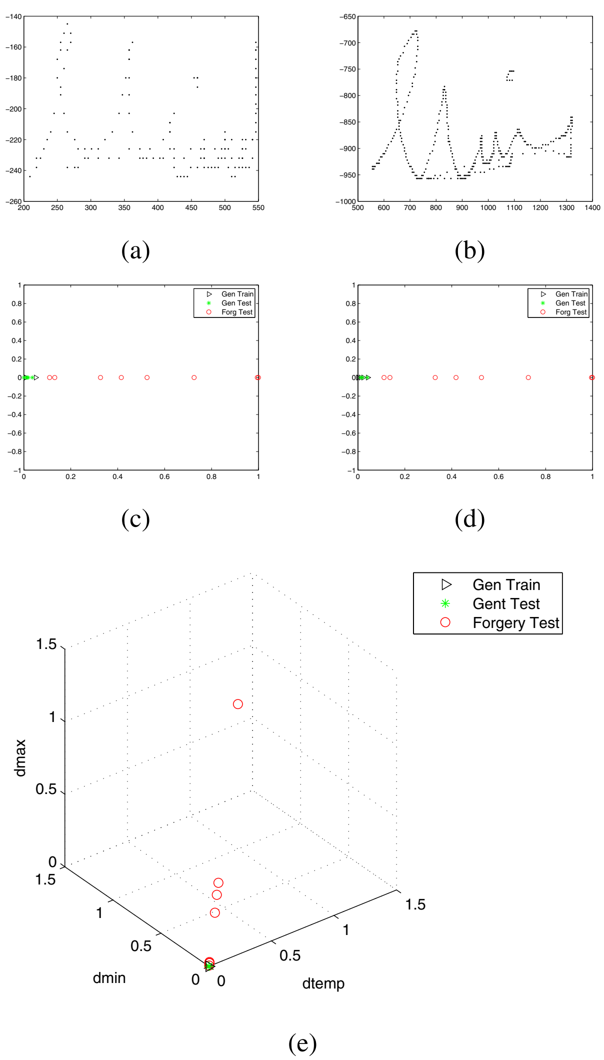

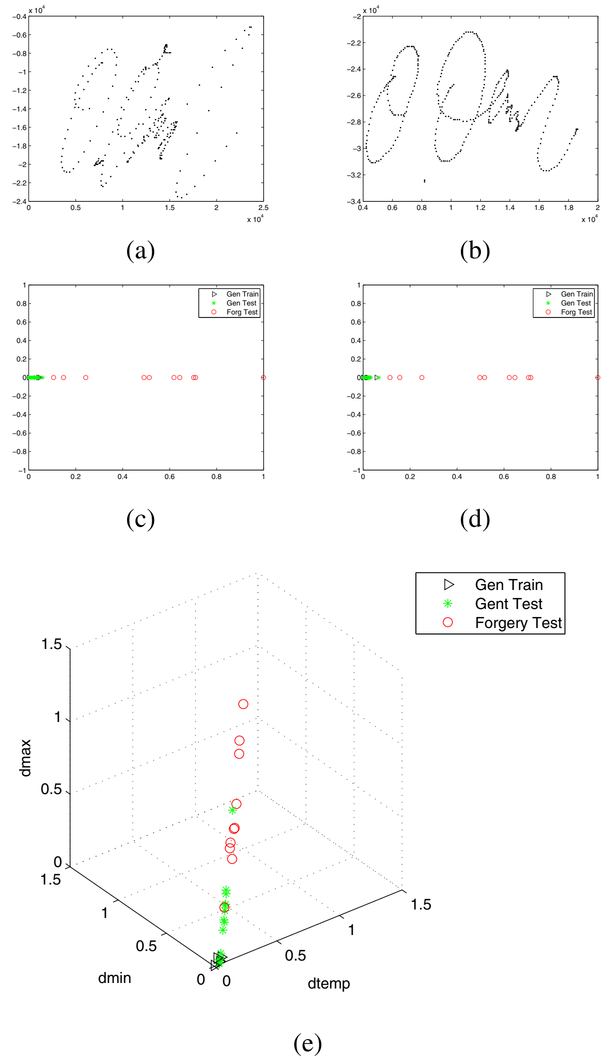

Fig. 3. Blind Sub-corpus. a) Genuine signature, b) Forgery Signature, c) and d) represents the separation between genuine and forgery by using the our proposed method when training was done by using only 3 and 5 genuine signatures, e) represents the separation between genuine and forgery by using the method proposed in [7] when training was done by using 5 genuine signatures. All of the distances are scaled between zero to one for better pictorial representation of the scatter plots.

Fig. 4. Visual Sub-corpus. a) Genuine signature, b) Forgery Signature, c) and d) represents the separation between genuine and forgery by using the our proposed method when training was done by using only 3 and 5 genuine signatures, e) represents the separation between genuine and forgery by using the method proposed in [7] when training was done by using 5 genuine signatures. All of the distances are scaled between zero to one for better pictorial representation of the scatter plots.