Abstract: This study has proposed the algorithm for signature verification system using dynamic parameters of the signature: pen pressure, velocity and position. The system is proposed to read, analyze and verify the signatures from the SUSig online database. Firstly, the testing and reference samples will have to be normalized, re-sampled and smoothed through pre-processing stage. In verification stage, the difference between reference and testing signatures will be calculated based on the proposed thresholded standard deviation method. A probabilistic acceptance model has been designed to enhance the performance of the verification system. The proposed algorithm has reported False Rejection Rate (FRR) of 14.8% and False Acceptance Rate (FAR) of 2.64%. Meanwhile, the classification rate of the system is around 97%.

Key words: Dynamic, signature verification, standard deviation, threshold and probabilistic model, velocity

INTRODUCTION

Signatures are composed of special character and flourishes and therefore most of the time they can be unreadable. Also, intrapersonal variations and interpersonal differences make it necessary to analyze them as complete images but not as letters and words put together. Signatures have been the primary mechanism both for authentication and authorization in legal documentation in recent years.

Based on different applications, signature verification system can be operated in two different modes (Plamondon and Srihari, 2000, Seiler et al., 1996); online and offline mode. In the online mode, the signature verification is dealing with the instant inputs from the system such as credit card verifier. For offline mode, the verification is done on the recorded signatures such as bank’s document verification (Dimauro et al., 1997, 1999).

Generally, signature verification system can be categorised into two types: dynamic and static. The dynamic signature verification system is dealing with signal processing while the static signature verification system is more on image processing. Some techniques applied in static signature verification systems are neural networks (Bajaj and Chaudhury, 1997; Huang and Yan, 1997; Karouni et al., 2011), model based approaches (Huang and Yan, 2002; Wen et al., 2009) and wavelets transform (Deng et al., 1997). Meanwhile, Dynamic Time Warping (DTW) (Fenton et al., 2006) and Gaussian Mixture Modelling (GMM) methods (Miguel-Hurtado et al., 2007, 2008) have been introduced for dynamic automated signature verification system. Basically, DTW is used in pre-processing to remove the intrinsic variability from user signature by aligning the acquired signal. GMM is used to model the probabilistic distribution of the set of pseudo-distances and to calculate the likelihood ratio between the sample and reference signature.

There are other approaches which based on the concept of filters (Tanaka and Bargiela, 2005). Firstly, global features of the signature, such as average velocity are considered through Euclidian distance. In the second filter, local features are considered. Strokes are segmented using the minima of the velocity and encoded before comparing them using DTW (Miguel-Hurtado et al., 2007, 2008) and signer-specific thresholds. On the other hand, Linear Prediction Coding (LPC) cestrum and Neural Networks (Wu et al., 1997) are proposed in the dynamic signature verification system. LPC is used in the pre-processing stage and its coefficients are used as the input to the neural networks. The neural networks (Mailah and Han, 2008) mostly used in the verification process. Besides that, performance could be improved by fusing static and dynamic signature verification techniques (Alonso-Fernandez et al., 2009).

In this research, the signatures will be pre-processed through normalization and re-sampling. A simple and efficient method, standard deviation has been proposed for the verification stage with estimated threshold as the condition. Finally, a probabilistic based signature acceptance criterion has been designed to refine the verification results.
MATERIALS AND METHODS

The overview of the system is shown in Fig. 1. The SUISig Online Database (Sabanci University, 2004) consists of two parts, namely visual and blind sub-corpus. Visual sub-corpus was collected using Interlink Elec. ePad Ink signature tablet with built-in LCD screen while blind sub-corpus was collected using Wacom Graphire2 pressure sensitive tablet. For each subject there are 20 genuine and 10 forgery signatures. Genuine signatures were collected in two different sessions. The proposed system database contains 25 genuine signers and 25 forgery signers from the SUISig database. Each signer will produce 10 samples of signature. Thus, there are 500 signatures in total for this experiment.

For each signature, the information from three dynamic features such as x-coordinate, y-coordinate, and pressure, have been used in this study. Meanwhile, the velocity, v is derived by using differentiation. The training samples are shown in Fig. 2.

Samples for reference signature
Sample 1 (S1): x1, y1, p1, v1
Sample 2 (S2): x2, y2, p2, v2
Sample 3 (S3): x3, y3, p3, v3
Sample 4 (S4): x4, y4, p4, v4
Sample 5 (S5): x5, y5, p5, v5

Sample for testing signature
Sample T (S6): xT, yT, pT, vT

Pre-processing: During the pre-processing stage, the input signature will undergo normalisation and re-sampling. The main purpose of normalization is to scale all the values into the range of zero to one as shown in Fig. 3. Linear scaling is used for the normalization of the vector (S) which represents signature parameters such as x-coordinate (x), y-coordinate (y), pressure (p) and velocity (v).

\[ S = \frac{S - \min(S)}{\max(S) - \min(S)} \]  

The Maximum (max) and minimum (min) values in the vector S are the global maximum and minimum points for the normalized signal.

The main reason for re-sampling is to sample the wavelength of the signature into the desired wavelength further processing. The wavelength of the signature is directly affected by the number of recorded data during the signing process. The more data is recorded, the longer the wavelength is. Thus, each signature might have different wavelengths. In order to compare them equally, both data needs to be re-sampled and smoother as shown in Fig. 4.
A total of five signatures have been re-sampled to the same wavelength. Let $I_{\text{ref}}$ be the average wavelength of the reference signature,

$$I_{\text{ref}} = \frac{I_1 + I_2 + I_3 + I_4 + I_5}{5}$$

(2)

$I_{\text{final}}$ be the wavelength of the testing signature and $I_{\text{init}}$ is the wavelength of the re-sampled testing signature,

$$I_{\text{final}} = \frac{I_{\text{init}}}{I_{\text{ref}}}$$

(3)

After the re-sampling process, the reference signal, $S_{\text{ref}}$ can now be constructed as,

$$S_{\text{ref}} = \frac{S_1 + S_2 + S_3 + S_4 + S_5}{5}$$

(4)

$$d = \left| S_T - S_{\text{ref}} \right|$$

(5)

**Fig. 4:** Resampled samples

**Fig. 5:** Difference in magnitude between reference and sampled signals

**Fig. 6:** FRR & FAR for (a) X-coordinate, (b) Y-coordinate, (c) Velocity, and (d) Pressure
Veriﬁcation: In veriﬁcation process, the difference between reference signature, S_{ref} and testing signature, S_{r} can be calculated by using standard deviation and compared it to the estimated threshold. If the difference between standard deviation, SD and estimated threshold is low, the signature will be accepted as the genuine signature.

\[
d^2 = (S_T - S_{ref})^2 \quad (6)
\]

\[
SD = \sqrt{\frac{d^2}{I_{ref}}} \quad (7)
\]

where, \( d \) is the difference between reference and testing signatures as shown in Fig. 5.

Threshold estimation: The purpose of doing this is to achieve lower FAR and FRR. A good signature veriﬁcation system should have a good balance on its sensitivity to the variation of the signature. First of all the standard deviation between the genuine reference signal and the genuine testing signals need to be collected for each parameter (x, y, p and v). Minimum and maximum standard deviation values are selected for threshold estimation, TH_{a} where TH is the controlling threshold and a can be either x, y, p or v.

\[
TH_{a} = \text{max} - (\text{max} - \text{min}) \text{ TH} \quad (8)
\]

Next, the difference between reference and testing samples (FRR) is being compared to the estimated threshold. If the value does not exceed the threshold, the signature will be accepted and via versa. Same steps are repeated for forgery samples to calculate FAR. As a result, the rate of false rejection and false acceptance can be obtained as in Table 1 and 2:

\[
\text{FRR} = \left( \frac{\text{No. of false rejection sample}}{\text{No. of genuine signature}} \right) \times 100\% \quad (9)
\]

\[
\text{FAR} = \left( \frac{\text{No. of false acceptance sample}}{\text{No. of forgery signature}} \right) \times 100\% \quad (9)
\]

By using the information found in Table 1 and 2, FRR and FAR graphs are plotted in Fig. 6. From Fig. 6, Equal Error Rate (EER) for each parameter can be obtained as shown in Table 3.

Probabilistic acceptance criterion: Based on the EER obtained from the previous section, we found that the information of x-coordinate and y-coordinate are the most dependable followed by the pressure and velocity. A probabilistic acceptance criterion has been proposed in this section to accept a signature with condition:

\[
X \land Y \lor (P \lor V) = \text{ACCEPT} \quad (10)
\]

To accept a signature, X and Y and either P or V must give a TRUE output. This means the system will accept a signature when X is accepted, Y is accepted, and either P or V or both is accepted.

RESULTS AND DISCUSSION

In order to verify the efficiency of the proposed probabilistic criterion in Dynamic Signature Verification System, an experiment using different combinations of the dynamic parameters had been conducted. The result obtained is shown in Table 4.

From Table 4, the combination of x-coordinate, y-coordinate, pressure and velocity is the best combination as expected. Although the error rate is not the lowest, this
Combination provided a balance of performance between FRR and FAR.

**CONCLUSION**

In conclusion, this study has presented a simple and efficient approach for dynamic signature verification system. A reliable signature verification system has been designed with the success classification rate of 97%. The algorithm has proven that, x-coordinate and y-coordinate and pressure and velocity are sufficient and effective for dynamic signature verification. In future, the aim will be to reduce the FRR with more testing samples being added with the equality of genuine and forgery signatures.

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