Online Signature Verification Discriminators

Nazaruddin Omar [1]
Prof Dr Norbik Bashah Idris [2]

[1] Faculty of Computer Science & Information Technology
Universiti Teknologi Malaysia, Skudai, Johor, Malaysia
nazar@rndtm.com.my

[2] Center for Advanced SoftwareEngineering (CASE)
Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

Abstract

Contemporarily, the internet has been heavily used for the electronic commerce especially in the areas of finance and banking. The transactions of the finance and banking on the internet involve use of handwritten signature as a symbol for consent and authorization. Online signature verification is one of the biometric techniques that are widely accepted as personal attribute for identity verification. Hence, it is vital to have an automatic handwritten signature verification system that is fast, reliable and accurate to avoid attempts to forge handwritten signatures, which has resulted in heavy losses for various financial institutions. This paper presents the implementation of an online signature verification system (OSV) using dynamic features as the discriminatos. It will describe the functions and modules of the system, explain on the approach used, and discuss the performance results of the system, which are measured based on the false rejection rate (FRR), and false acceptance rate (FAR). The former means the rate of genuine signatures that are being incorrectly rejected while the latter means that forgeries that are incorrectly accepted. The experimental results showed that the features based on number of stroke, and vertical speed are sufficient to be used to discriminate genuine samples from forgery sample based on the given threshold.

Keywords: *Online Signature Verification, image processing, neural networks, false rejection rate (FRR), false acceptance rate (FAR).*

1.0 Introduction

The need for a reliable means of personal identification as depicted in Figure 1, presents a challenge to almost any large modern organization. Biometrics authentication has been defined as "automatic identification or identity verification of an individual based on physiological and behavioral characteristics" [1].

This system provides multimedia application developers with an engine for online signature verification. Unlike offline verification, online verification uses not only the shape of an individual's signature, but actually logs the pen timing and pressure throughout the duration of the signing process.

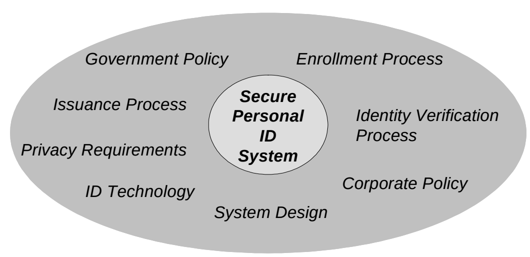


Figure 1: Factor influencing Secure Personal Identification System

Signatures have long been the primary form of legal attestation throughout most of the world and people are accustomed to it. Online signature verification relies on measurement of the pen trajectory, which has been shown to provide significantly improved performance compared to a static signature measurement.

Plamondon and Srihari [2] wrote a comprehensive survey of handwritten signature recognition. Many different approaches and techniques have been applied to OSV such as: feature values comparison, time warping or dynamic matching, signal correlation, neural network, hidden Markov models, regional correlation method, Wavelet, Euclidian or other distance measure.

This paper will evaluate on the dynamic signature features in order to expose their differences as discriminators of genuine signatures from forgeries and to propose the way to take it into account while performing a signature verification procedure. The paper is organized as follows. The next section will describe the methodology used for the OSV. Section 3 will elaborate on the experiments and results, and finally Section 4 will conclude the paper.

2.0 Methodology

The proposed OSV is illustrated in Figure 2. The OSV system consists of four (4) main processes, which are the Data acquisition, Feature Extraction, Verification Process and Evaluate Process.

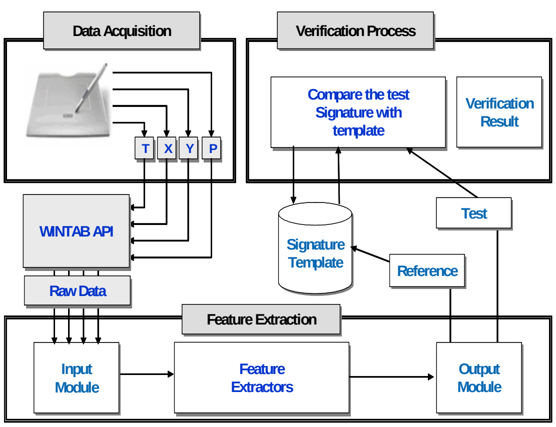


Figure 2: Block diagram of the functional steps in the Online Signature Verification system

2.1 Data acquisition

Signatures are captured with a digitizer graphic tablet with cordless pressure-sensitive pen. Signature capturing software is written in C++ in accordance with WinTab specification [4]. The maximum pressure level is 256. There are 56 genuine signers and each of them contributes 10 genuine signatures. The signature samples are shown in Table 1. Each of the genuine signer is forged and 10 samples of the forged signature are collected.

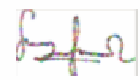
Sample Signature	Genuine	Forge
A		
B		
C		

Table 1: Sample Signature

2.2 Feature Extraction

The set of dynamic signature features are calculated from primary data include total number of points, x, y coordinates and level of pressure and time of each point. The selected features are frequently reported in literature, which are Total Time, Total Time Pen is Up, No of Stroke and Mean of Vertical Speed (y).

2.3 Verification Process

The verification process is a three-step procedure. The first step is to compute reference features. The second step is to calculate the error rates. The third step is to compare the error rates with threshold. If the error rate is less or equal to the threshold, the signature is accepted, otherwise it is rejected.

2.4 Evaluate Process

The performance of each feature as a discriminator of a genuine signature from forged one is based on the false rejection rate (FRR).The false acceptance rate (FAR) are computed as functions of a decision threshold.

3.0 Experiment and Results

The purpose of the experiment is to measure the performance of OSV based on error rate and threshold using four (4) type of feature, which are:

- feature 1: which is based on time,
- feature 2 : which is based on pen-up time
- feature 3 : which is based on no. of stroke
- feature 4 : which is based on mean of vertical speed.

Wacom tablet is used to collect the data for experiments. A signer can write his signature naturally and confirm it through his eyesight because the signature is displayed on the computer monitor. A number of 56 voluntary signers constructed the database. Every signer wrote his genuine signatures 10 times. To collect high-quality forgeries, forger is shown how the genuine signature being constructed and then try to sign as close as possible the displayed signature.

In the experiment, 3 genuine signatures were used for reference signatures, and all the 10 genuine signatures were used for test. As a forgery, 10 signatures were used for test. Thus, there are 560 genuine signatures and 560 forge signature used for the experiment.

To show the effect of the discriminative feature selection, 4 kinds of experiments based on the selected features were compared as shown in Table 1, Table 2, Table 3 and Table 4.

The comparison was based on the reduction rate of false rejection rate and false acceptance rate. Table 1, Table 2, Table 3 and Table 4 shows the error rate percentage verses threshold percentage. We have examined how the error rate varies when the threshold is changed. From all four features we have tested, feature 1 and feature 2 showed a crossing point (common ERR). Meanwhile feature 3 and feature 4 did not show any crossing from the given threshold calculated.

4.0 Conclusion

This paper has presented an OSV system and described the methodology used, and experiment and results based on 560 genuine and 560 forge samples signature. The experimental results showed that feature 3 and feature 4 are sufficient to be used to discriminate genuine samples from forgery sample based on the given threshold.

The experimental results are encouraging, although we have to notice that further evaluation on more dynamic features are necessary. More features based on dynamic features will be introduced to give more discriminate input for evaluation process.

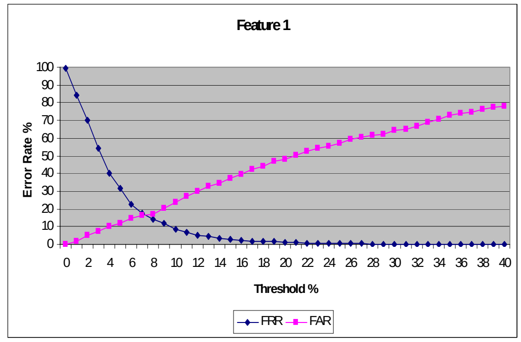


Table 1. Threshold vs Error Rate Based on Time (Feature 1)

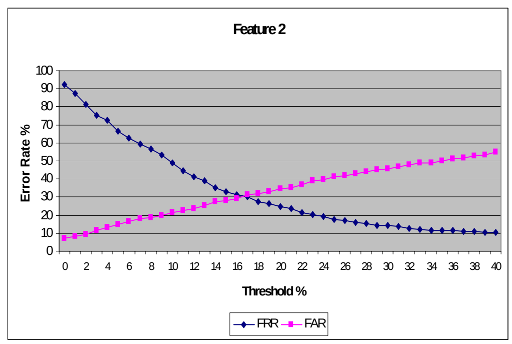


Table 2: Threshold vs Error Rate Based on Pen Time Up (Feature 2)

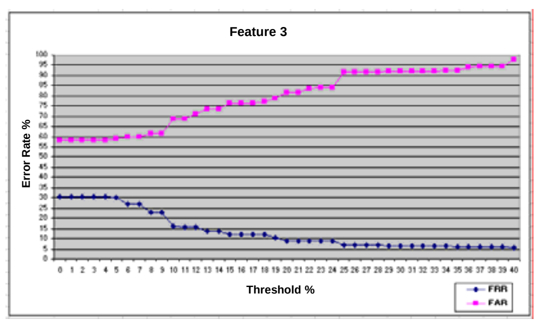


Table 3: Threshold vs Error Rate Based on No of Stroke

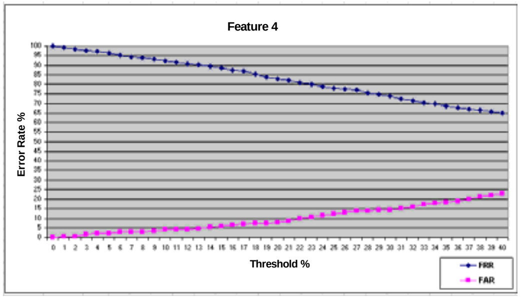


Table 4: Threshold vs Error Rate Based on Mean of Vertical Speed

References

[1] Wayman, “National Biometrics Test Center Collected Works”, ver. 1.3, San Jose State University, Aug. 2000

[2] R. Plamondon and S. Srihari, “On-line and Off-line Handwriting Recognition: A Comprehensive Survey”, IEEE Trans. Pat. Analysis Mach. Intell., vol. 22, no. 1,pp. 63-84,2000.

[3] L. L. Lee, T. Berger, and E. Aviczer, “Reliable On-line Signature Verification Systems”, IEEE Trans. Pat. Analysis Mach. Intell., vol. 28, no. 6, pp. 643-647, 1996.

[4] Windows tablet AFT, http://www.lcs-telegraphics.com.