A STROKE BASED ALGORITHM FOR DYNAMIC SIGNATURE VERIFICATION

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Abstract

Dynamic signature verification (DSV) uses the behavioral biometrics of a hand-written signature to confirm the identity of a computer user. This paper presents a novel stroke-based algorithm for DSV. An algorithm is developed to convert sample signatures to a template by considering their spatial and time domain characteristics, and by extracting features in terms of individual strokes. Individual strokes are identified by finding the points where there is a 1) decrease in pen tip pressure, 2) decrease in pen velocity, and 3) rapid change in pen angle. A significant stroke is discriminated by the maximum correlation with respect to the reference signatures. Between each pair of signatures, the local correlation comparisons are computed between portions of pressure and velocity signals using segment alignment by elastic matching. Experimental results were obtained for signatures from 10 volunteers over a four-month period. The result shows that stroke based features contain robust dynamic information, and offer greater accuracy for dynamic signature verification, in comparison to results without using stroke features.

Keywords: *Dynamic signature recognition; biometrics; stroke based algorithm; signal processing.*

1. INTRODUCTION

Biometrics authentication has been defined as "automatic identification or identity verification of an individual based on physiological and behavioral characteristics" [1]. It is often preferred over traditional methods (e.g. passwords and keys) because of their unreliability and inconvenience. Dynamic signature verification (DSV) is a biometric technology which is seeing increasing interest for these applications. DSV not only looks at the signature's appearance, but also at the process an individual uses to form the signature. This is done by analyzing the shape, speed, stroke, pen tip pressure and timing information during the act of signing. Dynamic signature verification systems undertake the following processing steps: 1) Enrollment -acquisition of several biometric sample signatures, 2) conversion of the sample signatures to a biometric template, 3) acquisition of live data from the person to be verified, and 4) comparison of templates to calculate a similarity score, in order to determine whether a newly acquired test signature represents the same individual as stored signatures.

Plamondon and Srihari [2] wrote a comprehensive survey of handwritten signature recognition. Many different approaches and techniques have been applied to DSV such as: feature values comparison [3,4,5,6], time warping or dynamic matching [7], signal correlation [8], neural network [9,10], hidden Markov models [11], regional correlation method [12,13], Euclidian or other distance measure [14], wavelets [15], etc. This paper presents a novel stroke-based algorithm to represent DSV features. Stroke boundaries are determined, and the corresponding features are calculated and applied to discriminate genuine signatures from forgeries.

2. SYSTEM SETUP

The proposed DSV system is illustrated in Fig. 1. It consists of four subsystems: data acquisition, signature preprocessing, feature extraction, and signature verification. In the data acquisition subsystem, signatures are acquired and digitalized by a digital pad using the standard Windows Tablet input API [16], and the system can be straightforwardly extended to other similar devices. We modified the application to measure the raw data every millisecond. A total of four channels of raw data are measured: the sampling time t, x position, y position, and pressure p. A representative signature is shown in Fig. 2. The pressure values and position are represented by the filled dot size, and the open circles indicate moments when the pen lifted up from the pad surface. Based on the four channels of raw data, the velocity, acceleration and angle signals are computed in the signature preprocessing subsystem. In addition, the dynamic signature signals are re-sampled and normalized to a standard length and missing data points interpolated before being sent to the feature extraction subsystem.

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DYNAMIC SIGNATURE VERIFICATION SYSTEM

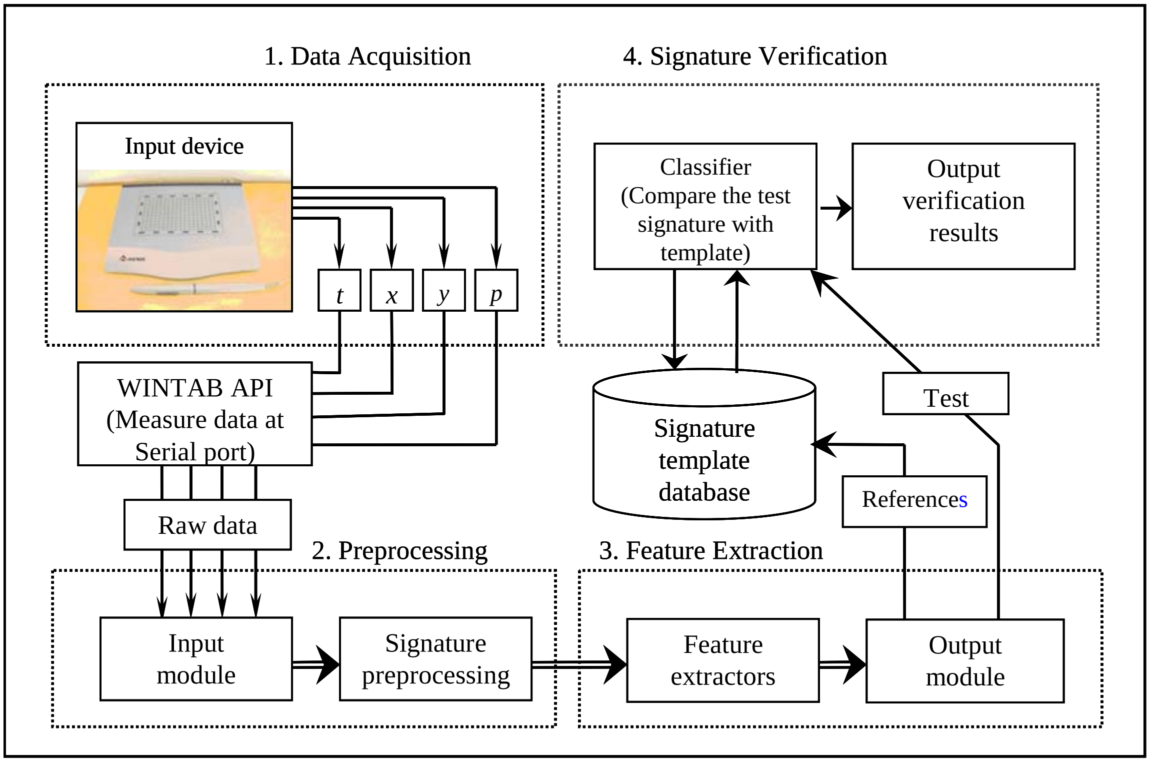

Fig. 1. Block diagram of the functional steps in the dynamic signature verification system.

Subsequently, feature information from the input dynamic signature is calculated by pre-configured feature extractors. For the training signatures, the extracted sample feature vectors are stored in the signature template database; for a test signature, the calculated feature vector is sent to the signature verification subsystem and compared against an enrolled template by a signature classifier and a match score calculated. A verification decision is made by comparing the match score with a threshold.

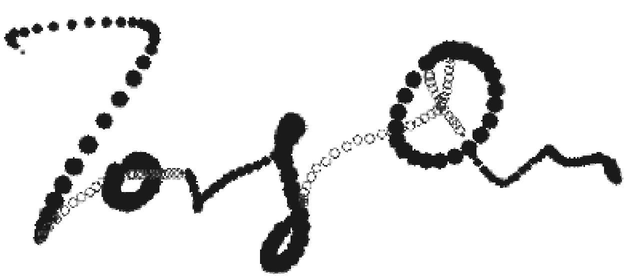

Fig. 2. Representative dynamic signature data.

3. FEATURE EXTRACTION

According to Lee, an individual's signatures are remarkably consistent [6]. Our algorithm attempts to find these consistent behavioral dynamic characteristics (or features) which are inherent to the particular person. Such features can be used to identify genuine signatures from forgeries. Global features are characteristics of the entire signature, such as: pen-up time, mean or variance of the x and y displacement signal in a number of sliding windows, number of pen ups and downs, variance of pressure signal in a number of sliding windows, number of sign changes in the x and y velocities and x and y accelerations, number of zero values in the x and y accelerations, etc.

A signature may also be considered a sequence of strokes. Dimauro et. al. [17] defined strokes as "a sequence of fundamental components, delimited by abrupt interruptions". This motivated our development of a stroke-based algorithm. The first processing step is to detect the stroke boundaries. Our algorithm defines stroke boundaries as points where there is a 1) decrease in pen tip pressure, 2) decrease in pen velocity, and 3) rapid change in pen angle. An example, and the corresponding pressure, velocity and angle signals are plotted in Fig. 3. Visually, there often exists high similarity between the corresponding strokes of genuine signatures, but much lower similarity between the strokes of genuine signatures and that of forgeries. Template comparison is conducted between each pair of signatures, by calculating the correlation between corresponding strokes. We define a "significant stroke" as the maximum correlation between the reference signatures. The correlation value and stroke length for the significant strokes are extracted as DSV features. In Figure 4, the stroke-based pressure signals are illustrated between five genuine signatures and two forgeries. The same user signed the 5 genuine signatures, and others imitated the 2 forgeries. Even for the 5 references, different strokes exhibit different variations among the repetitions. The correlation coefficients between the strokes for all 5 genuine references were calculated for the data of Fig. 4. Before calculating the correspondence between signatures, the stroke alignments are conducted and all strokes are elastically stretched to the same length, in order for stroke boundaries to occur at the same movement in all signatures. In this example, the 4^{th}–4^{th} stroke pairs have the highest correlation. We thus define this stroke as a significant stroke for the signature template. This stroke has correlation values for the genuine-genuine pairs that are much higher than for the forgery-genuine pairs. For example, the lowest significant stroke's correlation value between the genuine-genuine pairs is 0.9199 (G1-G2 pair), while the highest value between genuine-forgery pairs is 0.7267 (G4-F1 pair). We select the mean significant stroke of all the references as a feature in the template. The average correlation between the 4^{th} stroke between F1 and all the genuines (G1-G5) is only 0.6302 (The value is 0.1706 for F2; both are far from the average correlation between 4^{th} stroke among references 0.9670). We also use other features of the significant strokes such as stroke length, and stroke duration time etc.

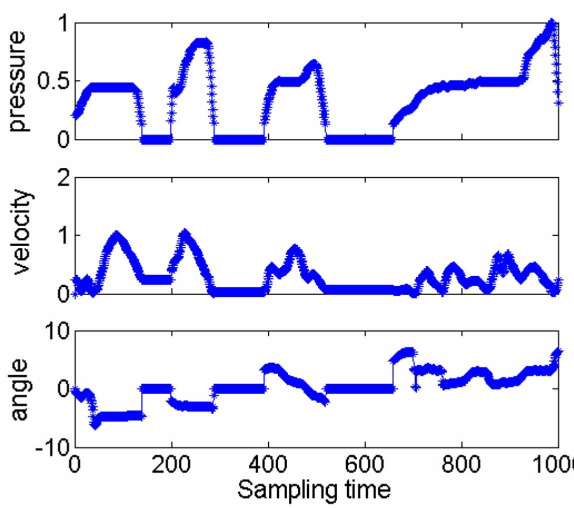

Fig. 3. Pressure, velocity and angle signals for a sample.

4. SIGNATURE VERIFICATION

The reference signature template is based on a set of sample signatures and for each feature the mean and standard deviation have been computed. We thus represent the reference signature by a vector of the feature value means (μ) and a vector of the standard deviations (σ). Lee [6] noted that, in order to obtain good estimates of μ_i and σ_i of feature *i's* value for the genuine reference signatures, it is necessary to have a minimum of three to five (N) sample signatures. Fig. 5 illustrates the comparison process for each feature. This threshold is selected independently for each given user and feature. For higher variations among enrollment signatures for a user, a higher threshold is required. To verify the identity of an unknown user, the system checks to see if each feature value of the test signature lies within the allowed range of that reference feature. If the test feature value falls within the assigned threshold, the test is assigned a weight. The signature classifier discriminates by evaluating the entire accumulated value in the assignment of a percent match of the test signature compared to the signature template.

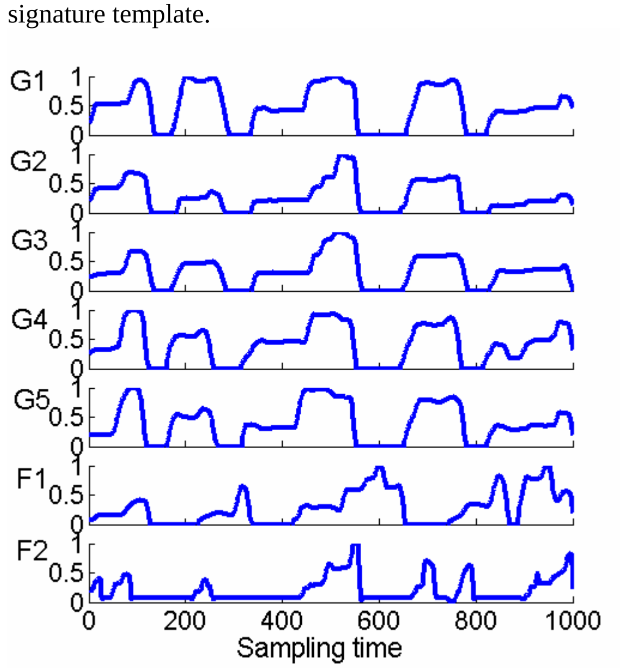

Fig. 4. Comparison of pressure stroke between genuine signatures and forgeries.

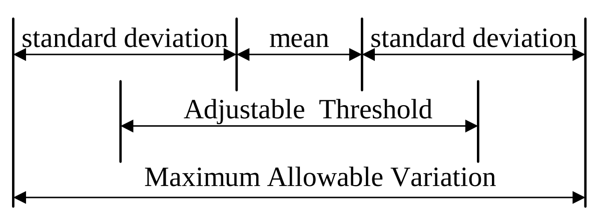

Fig. 5. Diagram of threshold adjustment for features.

Each user is required first to enroll into the system. In order to obtain a signature template, which can best reflects the user's signing process, a set of their signatures were recorded at different times and situations (when feeling happy, sad, excited, or tired, etc) [18]. All the collected genuine signatures were classified into training and verification classes. An experiment was performed to evaluate the performance of the verification system. A total of 110 signatures, split into 50 reference and 60 test signatures, from 10 volunteers were used in this experiment. Each volunteer performed 5 signatures to train their signature template, and performed another 3 genuine signatures as test signatures. In addition, for each template, three skilled forgery signatures were performed by other volunteers. First, we found the best four non-stroke features for the system (total time during the signing process, average writing speed, variance of pressure signal in 10 sliding windows, and mean of the *x* displacement signal in 10 sliding windows). When the threshold is set to be 75%, the system achieved a False Rejection Rate (FRR) of 30% and False Acceptance Rate (FAR) of 46.67%. Surprisingly, if the system included more non-stroke features, the FRR and FAR became worse. In order to evaluate the performance of the stroke based features, we added one or two stroke based features to the four non-stroke feature system. Based on the previous non stroke based feature system, if adding time duration for velocity significant stroke as the 1st stroke based feature and correlation coefficient for the pressure significant stroke as the 2nd feature, both of them can improve the system's FRR and FAR. If adding them together, better performance can be achieved. The FRR and FAR rate comparison is illustrated in Table 1.

Under the same experimental conditions, the stroke-based features can help system achieve better FRR and FAR rate than non-stroke based features. Thus, these results suggest that the stroke-based features contain robust dynamic information, and offer greater accuracy for dynamic signature verification, in comparison to without using stroke features.

Table 1. FRR and FAR data comparison.

	FRR	FAR
Non stroke feature system	30%	46.67%
Previous sys. + 1st stroke feature	13.33%	33.34%
Previous sys. + 2nd stroke feature	13.33%	20%
Previous sys. + 2 stroke features	6.67%	13.33%

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