Dynamic Signature Verification System Using Statistics Analysis

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***Abstract*— In this paper, a new technique for dynamic signature modeling and classification framework is proposed. Raw dynamic data obtained from a digitizer are analyzed using statistic tools. The variation within the same person signatures is obtained for effective signature training and accurate classification of genuine signature against all kind of forgeries. The proposed system is robust enough to prevent forgery of dynamic signatures. It has False Rejection Rate (FRR) of 0.2% for genuine signatures and False Acceptance Rate (FAR) of 0.25%, 0% and 0% for skilled, simple and random forgeries respectively. These results are better in comparison with the results obtained from previous systems**.

Keywords – Signature verification, Dynamic features, Forgeries.

1. INTRODUCTION

Signature verification is one of the most important research areas in the field of pattern recognition because signature is widely accepted for person identification in comparison with other biometric traits like voice, face, fingerprint and iris. Signature verification involves authentication of a person claimed signature in order to determine whether the claimed signature belong to the claimer or not. Signature verification can be done manually or automatically. Automatic signature verification can be classified into two categories: on-line (dynamic) and off-line (static). In off-line technique, signature is obtained on a piece of paper and scanned to a computer system while in on-line technique signature is obtained on a digitizer connected to a computer system. Dynamic signature verification involves comparison of two parameter vectors, that is, a template signatures stored in the system database and a test signature. The verification process is based on dynamic features captured during the process of writing the signature with a special pen on a digitizing tablet. [1] [2].

The aim of any signature verification system is to detect signature forgeries. Signature forgeries can be classified as random, simple and skilled forgery. Random or zero-effect forgery is any scribbled written signature of a genuine signature of another person. A simple or casual forgery is forged by a forger who is familiar with the name of that person but has no access to his/her genuine signature samples. Skilled forgery is a forged signature of a person forged by a forger who has unrestricted access to one or more genuine signature samples of that person. [3].

A digital signature is quite different from dynamic (on-line) signature, it is a code embedded into a message. It is used to authenticate the identity of the sender of a message or the signer of a document, and possibly to ensure that the original content of a message or document after being sent is unchanged. All digital signature technologies employ Public Key Infrastructure (PKI) [4].

Alisher Kholmatov et al [5] proposed an on-line signature verification system that uses local features of the points on the signature trajectory which includes x-y coordinates relative to the first point of signature trajectory, the x and y coordinate differences between two consecutive points and the curvature differences between two consecutive points while Jain et al[6] developed an on-line signature system that uses nine local features which includes the x and y coordinate differences between two consecutive points (Δx, Δy), curvature β, gray values in 9x9 neighborhoods, the sine and cosine of the angle with the x-axis, absolute and relative speeds. Also Ohishi et al [7] presented a PPI (pen-Position, pen-Pressure, and pen-Inclination) algorithm for on-line pen input verification. And Tong Qu et al [8] proposed a novel stroke-based feature for Dynamic System Verification (DSV).

Some previous systems mentioned above conducted preprocessing such as resampling, normalization and alignment of signatures before training and classification of signatures in order to obtain robust signature features of equal length. In many cases vital information needed to generate robust feature are lost in the process. In this paper, preprocessing of raw data from digitizer is avoided. Alignment of unequal length of signature of the same person was not done during training or classification process and still we were able to develop a robust algorithm for effective signature verification using statistical analysis.

The rest of the paper is organized as follows Section 2 provides the description of the proposed system; these include feature extraction, signature training, threshold selection and classification. Section 3 shows the experimental results and finally, conclusion is presented in section 4.

II. PROPOSED SYSTEM

The proposed dynamic signature verification algorithm flows is shown in Fig.1. It consists of input data acquisition, feature extraction, generation of template, and classification method. In this paper, signatures preprocessing is not carried out on raw dynamic data in order to preserve the timing characteristics of the user signatures. Actually preprocessing stage is an important stage in automatic signature verification systems particularly when acquired signatures have been corrupted but in many cases unique properties of the user signatures are lost during preprocessing. In [6], preprocessing was done; they uniformly re-sampled the signatures at equal interval points along the signature curve. Also in [7], preprocessing was carried out, they re-sampled signature curve in such a way as to retain the critical points while in [5], [9][10] they didn't perform any preprocessing. In this work, we didn't preprocess the raw data because the same equipment are used throughout the period of data collection.

A. Data Acquisition Device

The proposed system used quality graphics tablet from Wacom as capturing device. The tablet is as shown in Fig. 2. It is intuos3 A6 model with USB interface. This tablet provides 100 samples per second contain values for pressure, x and y co-ordinate points for every sample. The system is able to capture signature samples both at pressure and non-pressure sample points [11].

The raw signature data available from the tablet consists of three dimensional series data as represented by (1) where (x(t), y(t)) is the pen position at time t , and p(t) ϵ {0,1,… ,1024} represents the pen pressure.

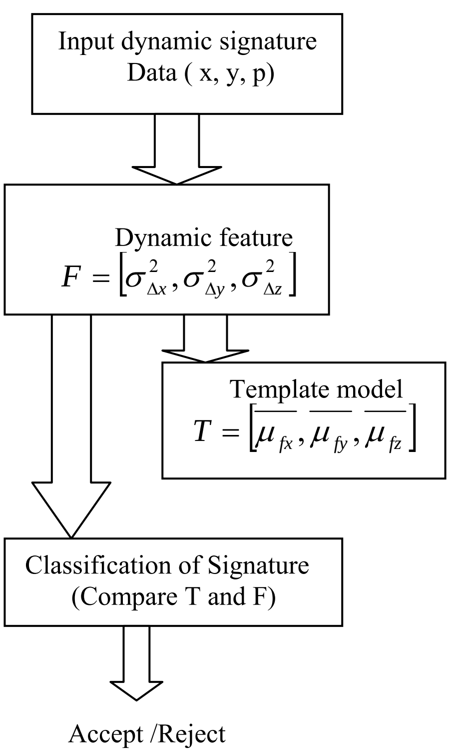

Fig.1. Proposed dynamic signature verification system algorithm flow.

Fig. 2. On-line signature graphics tablet.

$$S(t) = [x(t), y(t), p(t)]^T \quad t = 0,1,2, \dots, n \qquad (1)$$

An example of signature sample captured by this device is shown in Fig.3 and the raw data charts are shown in Fig.4 and Fig.5, the corresponding segmented raw data values are as shown in Table 1.

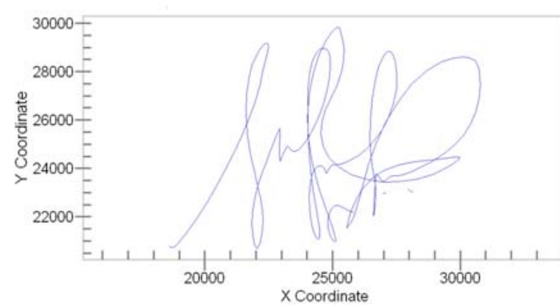

Fig.3. Example of a dynamic signature sample

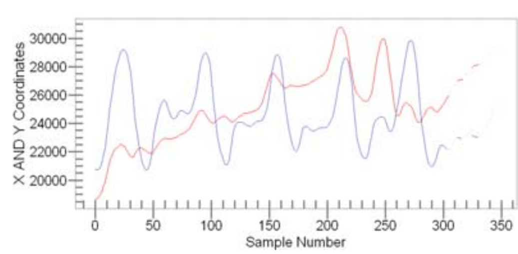

Fig. 4. Data chart of X and Y versus Sample Number. The red curve represents X and blue curve represents Y

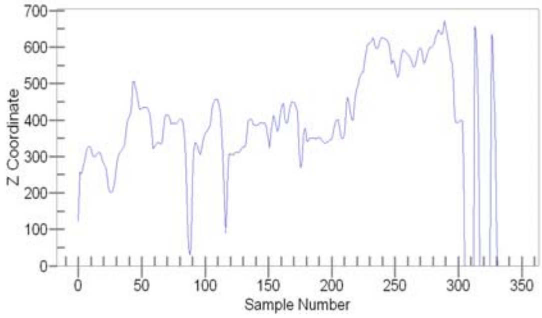

Fig.5. Data chart of pressure value (Z coordinate) versus Sample Number

TABLE 1. SIGNATURE RAW DATA (X, Y, P)

Sample No.	X	Y	P
1	18620	20778	122
2	18691	20728	258
3	18762	20728	253
4	18844	20780	257
5	18940	20888	275
6	19084	21068	292
7	19275	21329	311
8	19517	21677	324
9	19803	22120	327
10	20117	22654	326
:	:	:	:
:	:	:	:
50	21867	22188	429
51	21951	22779	432
52	22087	23356	434
53	22250	23866	434
54	22408	24281	434
:	:	:	:
:	:	:	:
101	24225	23223	419
102	24295	22759	442
103	24359	22378	449
104	24412	22054	457
:	:	:	:
:	:	:	:
200	28694	24173	397
201	29032	24377	400
202	29399	24635	401
203	29772	24965	385
:	:	:	:
:	:	:	:
340	29175	24780	0
341	29244	25015	0
342	29301	25295	0

B. Dynamic feature Extraction.

Different techniques have been used in the previous works in order to extract predominant features from dynamic signature data. They can be broadly divided into: feature-based approach, in which feature vector consisting of global values are derived from the whole signature trajectory, examples include total time, total path length and number of crossings while in the function-based approach time sequences are used to describe local properties of signatures, examples include pen position, pressure, velocity and acceleration [1][2][5].

In this study, we employed the function based approach. The raw data at each of the sampling points are used to generate robust feature that captured the variability within signatures of the same class. Fig. 6 shows the feature extraction diagram of x and y values. Δx corresponds to change of x between two successive sampling points, Δy corresponds to change of y between two successive sampling points, Δp corresponds to change of p between two successive sampling points, and these values are calculated using (2), (3) and (4) respectively.

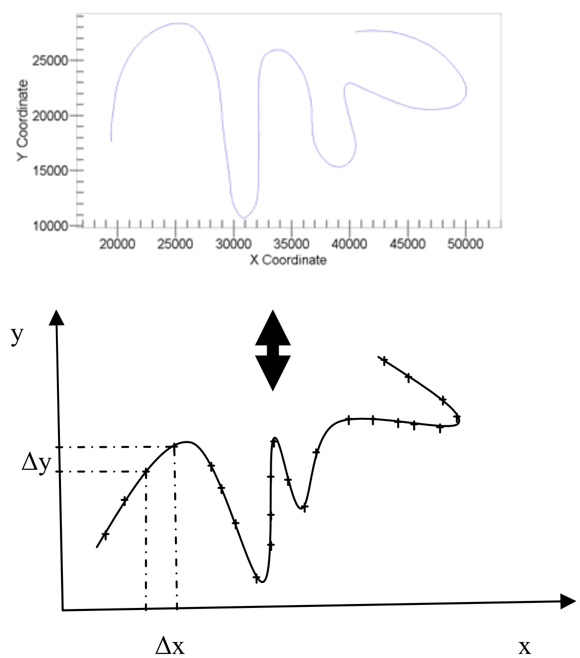

Figure 6. Feature extraction computation for Δy and Δx

$$\Delta x = x(t) - x(t-1) \quad (2)$$

$$\Delta y = y(t) - y(t-1) \quad (3)$$

$$\Delta p = p(t) - p(t-1) \tag{4}$$

The mean vectors of Δx, Δy and Δp are obtained using (5), (6) and (7) respectively while the variances are obtained using (8), (9), and (10) respectively.

$$\overline{\mu_{\Delta x}} = \frac{1}{N}\sum_{i=1}^{N} \Delta x_i \tag{5}$$

$$\overline{\mu_{\Delta y}} = \frac{1}{N}\sum_{i=1}^{N} \Delta y_i \tag{6}$$

$$\overline{\mu_{\Delta p}} = \frac{1}{N}\sum_{i=1}^{N} \Delta p_i \tag{7}$$

$$\sigma_{\Delta x}^2 = \frac{1}{N}\sum_{i=1}^{N} (\Delta x_i - \overline{\mu_{\Delta x}}) \tag{8}$$

$$\sigma_{\Delta y}^2 = \frac{1}{N}\sum_{i=1}^{N} (\Delta y_i - \overline{\mu_{\Delta y}}) \tag{9}$$

$$\sigma_{\Delta p}^2 = \frac{1}{N}\sum_{i=1}^{N} (\Delta p_i - \overline{\mu_{\Delta p}}) \tag{10}$$

Each of user signatures is represented by a three dimensional feature vector $F = \left(f_x, f_y, f_p\right)$. The feature is formed using (8), (9) and (10). The feature vector is $F = \left[\sigma_{\Delta x}^2, \sigma_{\Delta y}^2, \sigma_{\Delta p}^2\right]$ and the magnitude of feature vector is obtained using (11)

$$|F| = \sqrt{f_x^2} + f_y^2 + f_z^2 \tag{11}$$

C. Training and Classification.

Each of the registered users submitted 7 genuine signatures to the system, out of which 5 signatures are used to generate the signature template so as to set user-specific threshold for accepting or rejecting a test signature. Given 5 reference signature samples S1, S2, S3, S4 and S5, they are represented by their feature as in (12).

Each of the users signature template is obtained by finding the mean and variance of the feature vector components using (13), (14), (15) and (16), (17), (18) respectively.

The mean values of each of the corresponding feature vector components are used to form the template feature vector (T) as represented by (19). The magnitude of the template feature vector is obtained using (20)

$$\begin{aligned}
F_1 &= \left[\sigma_{\Delta x1}^2, \sigma_{\Delta y1}^2, \sigma_{\Delta z1}^2\right] \\
F_2 &= \left[\sigma_{\Delta x2}^2, \sigma_{\Delta y2}^2, \sigma_{\Delta z2}^2\right] \\
F_3 &= \left[\sigma_{\Delta x3}^2, \sigma_{\Delta y3}^2, \sigma_{\Delta z3}^2\right] \\
F_4 &= \left[\sigma_{\Delta x4}^2, \sigma_{\Delta y4}^2, \sigma_{\Delta z4}^2\right] \\
F_5 &= \left[\sigma_{\Delta x5}^2, \sigma_{\Delta y5}^2, \sigma_{\Delta z5}^2\right]
\end{aligned} \tag{12}$$

$$\overline{\mu_{fx}} = \frac{1}{K}\sum_{i=1}^{K} \sigma_{\Delta xi}^2 \tag{13}$$

$$\overline{\mu_{fy}} = \frac{1}{K}\sum_{i=1}^{K} \sigma_{\Delta yi}^2 \tag{14}$$

$$\overline{\mu_{fz}} = \frac{1}{K}\sum_{i=1}^{K} \sigma_{\Delta zi}^2 \tag{15}$$

$$\sigma_{fx}^2 = \frac{1}{K}\sum_{i=1}^{K} (\sigma_{\Delta xi}^2 - \overline{\mu_{fx}}) \tag{16}$$

$$\sigma_{fy}^2 = \frac{1}{K}\sum_{i=1}^{K} (\sigma_{\Delta yi}^2 - \overline{\mu_{fy}}) \tag{17}$$

$$\sigma_{fz}^2 = \frac{1}{K}\sum_{i=1}^{K} (\sigma_{\Delta zi}^2 - \overline{\mu_{fz}}) \tag{18}$$

$$T = \left[\overline{\mu_{fx}}, \overline{\mu_{fy}}, \overline{\mu_{fz}}\right] \tag{19}$$

$$|T| = \sqrt{\overline{\mu_{fx}^2} + \overline{\mu_{fy}^2} + \overline{\mu_{fz}^2}} \quad (20)$$

The magnitude of the variance within the feature vector components of the five training signatures is calculated using (21). The value of T and V are used to obtain individual threshold (Th) value for each of the registered users as given in (22).

$$|V| = \sqrt{\left(\sigma_{fx}^2\right)^2 + \left(\sigma_{fy}^2\right)^2 + \left(\sigma_{fz}^2\right)^2} \quad (21)$$

$$|T| - |V| \geq Th \leq |T| - |V| \quad (22)$$

Whenever a test signature comes into the system, the signature pass through the feature extraction algorithm and the magnitude of feature vector of the test signature is calculated, and then compare with the magnitude of the template vector. If the value obtained is within the assigned threshold then the test signature is accepted as genuine signature otherwise it is rejected as forged signature.

III. EXPERIMENT RESULTS.

To show the efficiency of the proposed dynamic signature verification system, the system is tested using 1000 genuine signatures from 500 users, 400 skilled forgeries, 400 simple forgeries from 100 forgers and 400 random signatures. Table 2 shows the dynamic signature verification results for the proposed system. The FAR and FRR results obtained from the proposed system are better in comparison with the results obtained from previous systems.

TABLE 2. VERIFICATION RESULTS

Type of signature	**Number**	**Number accepted**	**Number rejected**	**FRR**	**FAR**
Genuine signature	1000	998	2	0.20	-
Skilled forgery	400	1	399	-	0.25
Simple forgery	400	0	400	-	0.00
Random forgery	400	0	400	-	0.00

IV. CONCLUSION

In the proposed system, a statistical technique is used to generate signature template and classification algorithm. The system is different from previous systems in terms of signatures training and classification method. The system used variation within sampling points of high quality raw data from digitizer to obtain a robust three dimensional feature vector without re-sampling or alignment of signatures. The experimental results have shown that the proposed system is better in comparison with previous systems in its ability to give low error-rates against all kinds of signature forgeries.

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