Development of a System with Online Signature Biometric for Access Control Application

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Abstract. Online signature verification system is a technique based on behavioural biometrics which is gaining popularity for its widespread acceptability due to ease of use and forge proof features. Online (dynamic) signatures are captured from pressure sensitive tablets, signature pads, tablet PCs for further processing. This paper depicts the working mechanism of such a system capable of verifying the true signers as well as detecting the forgery attempt. After the signature data collection, the signatures were preprocessed for future use. A set of total 58 different features (local, global and normalized) were extracted from the online signature data. The system presents a binary classification technique since the test signature is categorized into one of the two classes (genuine or false). Template matching based Dynamic Time Warping (DTW) classifier is used for training and testing purposes with an average recognition rate of 90% for true signers. A separate version of the system was also developed which blocks random and skilled forgeries with a high level of accuracy though the TN rate is higher than the system described here.

Introduction

An Online Handwritten signature is essentially an electronic signature that can be 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 the message or document that has been sent is unchanged. There are numerous applications possible for online signature verification system e.g. cheque processing in banks, POS, Forgery Detection, Access Control System, Office Automation, ATM Transactions and also as a component of Multimodal Biometric Systems. Mimicking a dynamic signature means the forger has to mimic all the dynamic parameters of a signer like velocity, acceleration, pressure exerted on the tablet surface, pen inclination angle etc. which is nearly impossible. This makes the online signature verification a robust Behavioural Biometric application.

Signature is a special variant of handwriting [1] which has some intra and inter-class similarities among several writers. Tappert et al. [2] shows a detailed discussion of online signature recognition. Some recent works [3], [4] show promising results with template matching based classifiers like DTW though different techniques and classification algorithms (GMM, HMM, time series analysis etc.) are also useful in online signature verification technique. Kholmatov et al. has also used DTW based classifier, which was applied on SVC 2004 signature dataset with a 2.8% error rate [5].

Our present work computes three kinds of features (local, global, normalized), trains the system with dynamic time warping (DTW) based classifier. The performance of the above system has been evaluated using in house data-set collected from CDAC staff members in Kolkata and the system has a higher recognition rate in case of true signers. The process flow diagram for online signature verification system (Fig. 1) is given below. This software system is a standalone utility developed using Dot Net Framework, choosing Visual C# as the programming language.
Data Collection Experiments

This system uses commercially available Wacom STU signing pad with sampling rate of 200 samples per second and a pressure sensitivity level in the range of \{0-1024\} units. The raw signature data is captured in the form of time series data which contains x, y coordinates along with adjacent absolute pressure values, azimuth, tilt angle and packet-time information. The online signature data collection procedure was performed in two modalities: guided mode and unguided mode. In each mode, the signers were asked to contribute 20 signatures (10 in guided & 10 in unguided mode) on the writing panel of the software interface (Fig. 2), hence a total of 20 signatures for each signer were stored in signature database. In guided mode, all the signers were instructed to sign with their maximum possible variations (slow, medium and fast signatures) in the signatures so that we get the maximum variability and robustness in our training data. In unguided modality, the signers were free to sign; there were no restrictions during collecting the data. To observe the impact of these two data collection modalities were one of the main aims of this developmental phase. Nearly 80 signers have given their data from our organization so far in both modalities. Further, collection of data will be going on whenever it is possible.
Processing Signature Data

The software provides the processing of raw online signature data for further use. The steps involves are i) Valid pressure point detection, ii) Removal of unnecessary coordinate values during transition in strokes and iii) Elimination of duplicate points caused by hand trembling of the signers. In [5], [6], pre-processing tasks weren’t done. In this work, stroke normalization task was discarded to avoid loss of valuable information from the signature curve there by lowering recognition accuracy of signature verification or forgery detection.

Extraction of Features

A set of total fifty eight features were obtained from the online handwritten signature data which were divided into three categories

a. **Local Feature** - A set of 8 features which were directly obtained from the raw time series data. They are \( \Delta x, \Delta y, \Delta p, \Delta T, \Delta v, \Delta a, \Delta \text{azimuth}, \Delta \text{tilt} \), \( \Delta p/\Delta x, \Delta p/\Delta y, \Delta y/\Delta x \) whereas the features are computed using the following equations (1) to (8).

\[
\Delta X = x(t) - x(t-1) \tag{1}
\]
\[
\Delta y = y(t) - y(t-1) \tag{2}
\]
\[
\Delta p = p(t) - p(t-1) \tag{3}
\]
\[
\Delta T = T(t) - T(t-1) \tag{4}
\]
\[
\Delta v = v(t) - v(t-1) \tag{5}
\]
\[
\Delta a = a(t) - a(t-1) \tag{6}
\]
\[
\Delta \text{azimuth} = \text{azimuth}(t) - \text{azimuth}(t-1) \tag{7}
\]
\[
\Delta \text{tilt} = \text{tilt}(t) - \text{tilt}(t-1) \tag{8}
\]

\( \Delta x, \Delta y \) represent the change in \( x, y \) coordinates for two successive sampling points, \( \Delta p \) corresponds to change of absolute pressure between two successive sampling points, \( \Delta v, \Delta a \) correspond to changes instantaneous velocity, instantaneous acceleration between two adjacent sampling points computed as \( \Delta v = \Delta x/\Delta T \) and \( \Delta a = \Delta v/\Delta T \). \( \Delta \text{azimuth} \) and \( \Delta \text{tilt} \) are the changes in azimuth and tilt angle between two adjacent sampling points respectively.

b. **Global Feature** - A set of features which are single valued in nature for a single signature curve. Total 49 features were calculated in [7] where Lee et al. showed a detailed global and normalized feature set in connection with majority based classifier. Some of the features from [8] were used in this work. All the features present in appendix A of [8] are used, where some work related to handwriting analysis for deception detection [8] has been presented by Asok et al. Some examples of similar type of features are signature length(l), signature width(w), aspect ratio(l/w) of the signature, total signing duration(Tw), total pen down time on tablet surface(Ts) etc.

c. **Normalized Feature** - Some features were constructed from the global features rectifying the demerits of higher sensitivity through linear normalization. These features are supposed to behave less erratic on genuine signature features as well as in case of forged signatures. Mean Velocity-Maximum \( V_x \), Minimum \( V_x \) - Average \( V \) are some examples of normalized features. A detailed description was provided by Lee et al. in his work [7], where all such normalized features were listed in Appendix B that has been used in this developmental work.
System Description

Each registered user submitted 10 genuine signatures to the system, out of which six signatures are used to generate 15 distance values by cross-aligning the signature features to the same length using Dynamic Time Warping (DTW) (Fig. 5). These distance values are used to measure the variation within each user’s signatures, so as to set user-specific thresholds for accepting or rejecting a test signature. Given six reference signature samples $S_1$, $S_2$, $S_3$, $S_4$, $S_5$ and $S_6$, these signatures are cross aligned to obtain 15 distance values ($C_6^2$). The mean ($m_i$) and standard deviation ($\sigma_i$) of the distance $d_{12}$, $d_{13}$, $d_{14}$, $d_{15}$, $d_{16}$, $d_{23}$, $d_{24}$, $d_{25}$, $d_{26}$, $d_{34}$, $d_{35}$, $d_{36}$, $d_{45}$, $d_{46}$ and $d_{56}$ are calculated and used to set the threshold ($T_k$) for each user based on each feature as given in equation (9).

\[
0 \leq T_k \geq m_i + 2\sigma_i \quad (9)
\]

The notation $d_{mn}$ indicates the Euclidean distance between $m^{th}$ and $n^{th}$ signature, computed in equation (10). Euclidean distance measure has been used to measure the distances between two similar feature vectors of signatures (equation 10), whereas $x$ and $y$ are two distinct feature vectors with coordinate sample points like $x = \{x_1, x_2, \ldots, x_i\}$ and $y = \{y_1, y_2, \ldots, y_j\}$ etc.

\[
d_{mn} = |x - y| = \sqrt{|x_i - y_i|^2} \quad (10)
\]
When a test signature ($S_{test}$) is signed, the feature vectors of the test signature is pair wise aligned with each of the six reference signatures using DTW. Six distance values are obtained (Fig.4). The distance of test signature ($S_{test}$) from the six reference signatures $S_1$, $S_2$, $S_3$, $S_4$, $S_5$ and $S_6$ is calculated (equation 11).

$$D_{test} = \frac{(d_{test1}+d_{test2}+d_{test3}+d_{test4}+d_{test5}+d_{test6})}{6} \quad (11)$$

If the observed value of $D_{test}$ lies within the threshold for that particular feature, we accept the value.

In a similar fashion, each of the features is evaluated with its predefined threshold limit which was set earlier during training session. If all the features of the $D_{test}$ conforms the threshold, the signature is verified or else as not verified.

The upper limit of the threshold for each of the features is set as twice the standard deviation of the feature vector assuming normal distribution with 95.45% values of that sample lie within that threshold.

**Dynamic Time Warping**

Dynamic Time Warping (DTW) is a template matching based classifier; mainly used for computing distance matching between two equal or unequal strings[9,10]. Basically it’s a pairwise comparison of the feature vectors of time series data. The classification is based on the nearest match of that particular sample with the test sample through the distance measure technique. DTW is effective in this case as there may have missing information or varying lengths of the vectors, on condition that the sequences are long enough for matching[11]. The above figure (Fig. 6) depicts that the ith point of the curve 1 matches with the closest point of curve 2 that DTW allows it to match with[12].

![Figure 5. Cross alignment in reference signatures from S1 to S6.](image)
Experimental Results

The team has developed two separate versions of the system and separately tested them having different classification accuracies. In the first prototype, the decisive features are absolute pressure, velocity, acceleration, pen down time, average writing speed, maximum Y coordinate, minimum Y coordinate, total signing duration, aspect ratio and number of strokes in a signature. After a rigorous offline testing on the dataset of eighty signers (1600 signatures), these features were chosen over other features. An average recognition accuracy of approximately 90% was seen in true signer cases. Certain parameters were kept in mind while developing the forgery prevention system, e.g. the overall look, all dynamic parameters, pen up & lifts (number of stroke will be different in that case), ink blots. A new curvature based feature was introduced into this system which represents the shape of the forged signature. Both random and skilled forgery testing were adopted. It was ensured that the skilled forger is trained before forging the signatures and the performance of the prototype is tested from each point. This system performs really well in case of random and skilled forgeries, where an average accuracy rate of approximately 85% was noticed. The following table (Table 1.) shows the performance measure of the DTW classifier in terms of confusion matrix. The sensitivity (TPR) and specificity (TNR) and F1 Score of the DTW classifier are 0.857, 0.894 and 0.878 respectively.

Table 1. Confusion matrix for the signature classification.

|                     | True Signer | Forgery |
|---------------------|-------------|---------|
| Test says “True Signer” | TP = 0.90   | FP = 0.10 |
| Test says “Forgery”   | FN = 0.15   | TN = 0.85 |

Conclusion and Future Work

A robust prototype of Online Signature Verification System (Behavioural Biometric Application) for both verification and forgery prevention has been developed with certain accuracy. A prototype version has been installed and tested in real life situation at the examination department in a government university in West Bengal, India. It has been placed to utilize the prototype system to collect and train the system for another 2000 genuine signers, to identify parameters which may improve forgery detection. Such effort will help in developing a compact system with high accuracy rate for both signature verification of genuine signer and forgery detection. The final system will be a component of behavioural biometric based robust access control infrastructure for several sensitive work spaces including VIP zones at several Government of Jharkhand offices in India.

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