

On-line and Off-line Signature Verification Using Relative Slope Algorithm

Sudarshan Madabusi, Vivek Srinivas,
Sudharsan Bhaskaran, Muthukumaran Balasubramanian
Department of Information Technology
Sri Venkateswara College Of Engineering, Anna University
Pennalur, Sriperumbudur, Tamilnadu-602105, India

Abstract - This paper presents a novel *RELATIVE SLOPE BASED* algorithm for online and offline signature verification system capable of effectively establishing an individual's identity based solely on their handwriting characteristics. Current technologies in signature verification systems use various algorithms for Feature point extraction, Regression approach, Markov method, Split and merge and genetic algorithms. We have proposed a slope based model, in which the input signature is divided into many segments using optimized HMM method, then the slope of every segment is calculated with respect to its previous segment, obtained after normalization of the signature. This feature of each segment is stored along with the two tier time metric information, which ensures lesser overhead with better performance while processing.

Keywords - Slope based algorithm, segmentation, normalization, optimized HMM, Pattern recognition.

1. INTRODUCTION

Signature verification is a biometric and behavioral attribute. Many biometric verification systems are based on iris, retina, face, finger print, which are all based on physical attributes but signature is a behavioral biometric attribute. Even though they are difficult to forge compared to the signature verification system the cost involved in the hardware for these systems is large and they are complex to design. Moreover these systems require large processing time compared to the signature verification system. An important advantage of the signature verification compared with other biometric attributes is its traditional use in many common commercial fields such as e-business, which includes on-line banking transactions, electronic payments, access control and so on. So signature verification is a very popular research area right now. Generally, it is accepted that an individual's signature is unique, though it is not proved experimentally. In fact signature verification is a difficult pattern problem because the intra-class variations could be large.

Signature verification systems could be of two types, namely *online signature verification* system and *offline signature verification* system based on the available data in the input.

Offline (static) signature verification takes as input the image of a signature and is useful in automatic verification of signatures found on bank checks and documents. Online (dynamic) signature verification uses signatures that are captured by pressure-sensitive tablets that extract dynamic properties of a signature in addition to its shape. Dynamic features include the number and order of the strokes, the overall speed of the signature, the pen pressure at each point etc. and make the signature more unique and more difficult to forge. As a result, online signature verification is more reliable than offline signature verification.

However in this paper we present a novel feature based on the slope of the segments extracted through the *optimized HMM* method, which can be used for both online and offline verification. Here the traditional *HMM* model is changed to *optimized HMM* model which is explained in further sections. Additionally, two features based on the time metric information are also extracted, which can be used for the online verification systems alone. The first feature is a global variable based on the total time required to complete the signature. The second feature is local time based information based on the length of the signature completed in unit time which is explained in detail in the further sections.

In evaluating the performance of a signature verification system, there are two important factors: the false rejection rate (FRR) of genuine signatures and the false acceptance rate (FAR) of the forged signatures. Since obtaining actual forgeries is difficult, two forgery types have been defined. They are, *skilled forgery* which is signed by a person who has had access to the genuine signature for practice. A *random* or *zero-effort forgery* is signed without having any information about the signature, or even the name of the person whose signature is forged.

II. EXISTING TECHNOLOGY

Most commonly used on-line signature acquisition devices are pressure sensitive tablets with or without LCD screens, together with smart pens capable of measuring forces at the pen-tip exerted in three directions. More

than 40 different feature types have been used for signature verification [8], [6], [5]. Features can be classified in two types: global and local. Global features are features related to the signature as a whole, for instance the signing speed, signature bounding box, and Fourier descriptors of the signature's trajectory.

Local features correspond to a specific sample point along the trajectory of the signature. Examples of local features include distance and curvature change between successive points on the signature trajectory. In Jain et al. [8], some of these features are compared in order to find the more robust ones for signature verification purposes. Other systems have used Genetic Algorithms to find the most useful features [4]. Due to the variability in signing speed, two signatures belonging to the same person may have different trajectory lengths (hence feature vectors of differing lengths). Therefore, the dynamic time warping algorithm with some variant of the Euclidian distance [8], [5], [3] and Hidden Markov models [2] are commonly used in aligning two signatures. Number of signatures taken during the user enrollment also varies: between 3 and 20 samples are used in previous signature verification systems.

In the verification process, the test signature is compared to all the signatures in the reference set, resulting in several similarity values, which can be treated as a distances between signatures. Then we have to choose a method to combine these distance values into a single value, representing the dissimilarity of the test signature to the reference set, and compare it to a threshold to make a decision. A single dissimilarity value can be obtained from the minimum, maximum or the average of all the distance values.

The distance of the test signature to the closest reference signature has been found as most useful (giving the lowest error rates) in [8], however other criteria, such as the average distance to the reference signatures or the distance to a template signature can also be used. Template generation is generally accomplished by simply selecting one or more of the sample signatures as templates [5], [11]. Various thresholds can be used in deciding whether the distance between the test signature and the reference and/or template signatures are acceptable. Two types of threshold selections are reported: *writer dependent* and *writer independent* thresholds [8]. In writer dependent scenario, thresholds are calculated for each user individually, whereas in writer independent one, a global threshold for all the writers is set empirically during the validation phase of the system.

III. PROPOSED DESIGN FOR SLOPE BASED APPROACH

Broadly the signature verification system consists of *Training or Learning subsystem* which involves getting various sample signatures from the user. Second, *Feature extraction subsystem* which involves selecting various features from the signature and storing them. Third, *Verification subsystem* which involves comparing the signature to be verified with the profile signature. Functionally these subsystems can be classified as follows.

A. Data Acquisition

For data capturing any ordinary or pressure sensitive tablet and a pen is used. Existing tablets are capable of sampling data at 100 samples per second. At each sample point the data obtained are

$X(t), Y(t), P(t)$ where $t = 1, 2, 3, \dots, T$

$X(t)$ and $Y(t)$ represent the x co-ordinate and y co-ordinate of a point at time t . $P(t)$ represents the pressure at time t . Even though this data is returned by usual tablets it is not required for this algorithm thus reducing hardware cost.

B. Preprocessing

Preprocessing deals with two factors: redundancy of points due to slow pen movement and the extending strokes at trajectory change.

Due to the high sampling rate of the tablet, some sample points mark the same trajectory point, especially when the pen movement is slow. Most verification systems resample the input so as to obtain a trajectory consisting of equidistant points [8], [4], [3]. This is often done in order to remove redundant points to speed up the comparisons and to obtain a shape-based representation, removing the time dependencies. Jain et. al [8] separately keeps track of the local velocity values and uses them in aligning two signatures.

However eliminating redundant point also results in significant loss of information since the seemingly redundant data incorporates speed characteristics of the genuine signer. Another problem with resampling is that the critical points of the signature may be lost; critical points are sometimes added separately to the set of equidistant points obtained after resampling to solve this problem. We found that the benefits of not resampling significantly outweigh the disadvantage of not normalizing for speed.

For preprocessing another factor which is usually ignored is extending strokes at critical points. For this problem a solution is presented in [7].

Even though in this solution the critical points are normalized we lose important data corresponding to a genuine signature. Instead we can store the co-ordinates of the critical points where this normalization is applied. Later these values can be used in verification. This improves the performance of the verification system.

C. Feature Extraction

The features extracted in this system are a local slope based feature and global time metric information. Another important local feature is length of signature completed per time unit. These features are explained in detail in further sections.

D. RELATIVE SLOPE EXTRACTION

After data acquisition we obtain two sequence of co-ordinates which are

$$X = \{x_1, x_2, x_3, \dots\}$$

$$Y = \{y_1, y_2, y_3, \dots\}$$

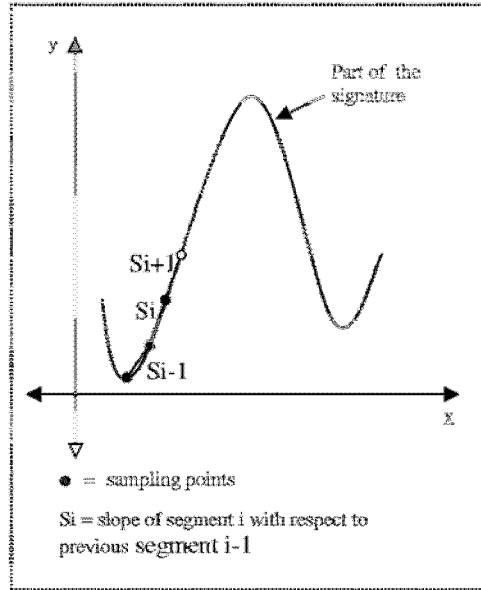


Fig.1. Curve showing the part of a signature and its segments

Using optimized HMM we calculate the segments of the signature (Fig.1). Then these segments can be combined to form a line segment. The number of segments combined can be decided based on the level of accuracy required. When the number of segments combined are more the accuracy is decreased

but when number of segments are less the processing time is more and amount of data stored is also more. So a balance can be reached based on the requirements.

After the line segments are obtained (Fig.1) the relative slopes are calculated. The relative slope is slope of each line segment with respect to its previous line segment. Usually slope (S) of any line containing two points (x_1, y_1) and (x_2, y_2) are calculated using formula,

$$S = \frac{dy}{dx}$$

Where,

$$dx = x_2 - x_1 \text{ and}$$

$$dy = y_2 - y_1$$

In our system for the first segment we calculate the slope between the starting point of the first segment and the ending point of the last segment of the first line segment.

However, for the further line segments the slope is calculated based on the previous line segment (Fig.2) using the following steps.

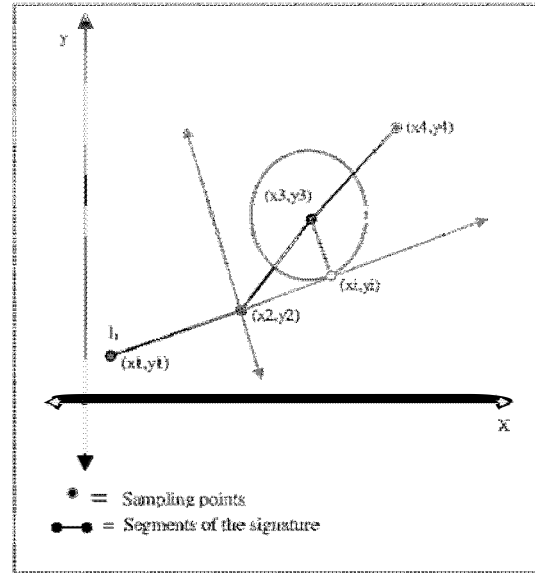


Fig.2. Calculation of relative slope of segments with respect to previous segments

1) To calculate the relative slope of the line containing the points (x_2, y_2) and (x_3, y_3) with respect to the previous segment, first we extend the line containing the points (x_1, y_1) and (x_2, y_2) and find the equation of this line (l_1).

The equation of line l_1 is,

$$\frac{(y - y_1)}{(x - x_1)} = \frac{(y_1 - y_2)}{(x_1 - x_2)} \quad (1)$$

$$yx_1 - yx_2 - y_1x_1 + y_1x_2 = xy_1 - xy_2 - x_1y_1 + x_1y_2$$

$$x(y_1 - y_2) + y(x_2 - x_1) + x_1(y_2 - y_1) + y_1(x_1 - x_2) = 0$$

Let,

$$A = y_1 - y_2$$

$$B = x_2 - x_1$$

$$C = x_1(y_2 - y_1) + y_1(x_1 - x_2)$$

Hence equation of line l_1 becomes,

$$Ax + By + C = 0 \quad (2)$$

2) Then we find the perpendicular distance (dy_i) between the point (x_3, y_3) and the line l_1 using the formula,

$$dy_i = \left| \frac{(Ax_3 + By_3 + C)}{(A + B)} \right| \quad (3)$$

3) Then we draw a circle with centre (x_3, y_3) and radius of length dy_i . Equation of this circle is

$$(x - x_3)^2 + (y - y_3)^2 = dy_i^2 \quad (4)$$

4) Next we calculate the point of intersection (x_i, y_i) of the circle and the tangent line l_1 using the formula,

$$x_i = \left| \frac{-am}{\sqrt{1 + m^2}} \right| \quad (5)$$

$$y_i = \left| \frac{a}{\sqrt{1 + m^2}} \right| \quad (6)$$

where,

m = slope of line l_1 and

a = radius of the circle.

5) Then we find the distance (dx_i) between the points (x_i, y_i) and (x_2, y_2) using the formula,

$$dx_i = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (7)$$

6) Finally, the value of relative slope S_i is,

$$S_i = \frac{dy_i}{dx_i} \quad (8)$$

So using this method we calculate the relative slope of each line segment with respect to the previous line segments and these values are stored.

ALGORITHM 1: Relative slope algorithm

Step1: Preprocess and normalize the signature
Step2: Divide the signature into segments using optimized HMM method
Step3: Based on requirements combine these segments into line segments
Step4: Calculate the relative slope value of each line segment with respect to the previous line segment

Step5: Carry Step4 till all the segments are processed Else Step6

Step6: Store the slope value of each segment which can be used for verification

Step7: End

E. TWO TIER TIME METRIC EXTRACTION

A two tier time metric information is also extracted. In first step global time required to put the entire signature is calculated and in second step we calculate the length of signature completed in unit time using following algorithm.

ALGORITHM 2: Time metric calculation algorithm

Step1: Calculate the total time required to put the signature

Step2: Preprocess and normalize the signature

Step3: Calculate the total length of the signature

Step4: Divide the total time into equal time units

Step5: Calculate the length of signature completed in each time unit by combining all the segments associated with that time duration
Step6: Carry Step5 till all the segments are processed Else Step7

Step7: Store the length value associated with each time unit.

Step8: End

F. SIGNATURE ALIGNMENT AND ENROLLMENT

During enrollment to the system, the user supplies a number of signatures, which are used for calculations of reference set distance statistics. Supplied signatures are pair wise aligned to find the distances between each pair. From these alignment scores, averages are calculated for the following, over the whole reference set:

- (1) Distance to nearest neighbour
- (2) Distance to farthest signature
- (3) Distance to the *template signature*, which is the signature with minimum average distance to all other supplied signatures.

The user signature is also dynamic in terms of height and width of the signature. Based on the size of the tablet the height and width varies. Hence the signature has to be adjusted to a standard size before enrollment. For this purpose we use *optimized HMM method*.

In the Hidden Markov Model the signature is divided into segments of equal size, but this segment characteristic varies when the height or width of the signature is changed. Hence to

optimize it, the segment size is also varied based on the size of the signature. That is the segment size is proportionately increased or decreased if the signature size varies.

G. VERIFICATION

Verification is the process of validating the user signature. It is done by comparing the user's signature with the profile signatures associated with the user's identity.

Each validation signature is compared to the reference set of signatures it claims to belong, giving a 3-dimensional feature vector (min, max, and template distance). The feature values are then normalized by the corresponding averages of the reference set and classifiers are trained to separate the genuine and forgery samples. We have used two classifiers: the Bayes classifier using the 3-dimensional feature vector and a simple thresholding scheme which is applied after normalizing the input data.

ALGORITHM 3 : Two level verification algorithm

Step1: Collect the validation signature to be tested from the user

Step2: Normalize the signature

Step3: Extract the global and local features consisting of relative slope value, global time, length per unit time of signature

Step4: In the first level of verification use relative slope value to compare with the profile signature values

Step5: Based on the comparison collect the three dimensional vector values and use one of the classifier schemes to separate genuine and forged signature

Step6: If the signature passes first level of verification then apply second level of verification based on time metric information

Step7: If the signature passes the second level of verification classify the signature as a genuine signature

Step8: End.

IV. ADVANTAGES OVER EXISTING ALGORITHMS

There are two significant advantages of this signature verification system which are relative slope based verification and two-level verification.

In this signature verification system we use relative slope based verification for each segment of the signature extracted. Existing systems employ individual segment feature verification. But in this system for each

segment we calculate its slope based on its previous segment. Hence the verification is more concrete and is able to adapt to instantaneous variations of the genuine signature.

The second advantage is, due to two separate levels of verification the forged signatures can be eliminated in the first level itself, thus reducing the overload of verifying other features in further levels. This helps in reducing the time required to verify a signature.

V. CONCLUSION

This paper proposed a relative slope based analysis for signature verification. It also proposes a optimized HMM model which adapts to variations in user's signature size. This system also uses two-tier time metric analysis for verification which reduces the system time required for verifying a signature.

REFERENCES

- [1] S. Connell and A.K. Jain. Template-based online character recognition. *Pattern Recognition*, 34(1):1-14, 2001.
- [2] J. J. van Gasterhout, H. Dolfing, and E. Aarts. On-line signature verification with hidden markov models. In *ICPR*, 1998.
- [3] R. Martens and L. Claesen. Dynamic programming optimization for on-line signature verification. In *ICDAR97*, page Poster, 1997.
- [4] X. Yang, T. Funahashi, K. Obaia, and Y. Uchikawa. Constructing a high performance signature verification system using a ga method. In *2nd New Zealand Two-Stream International Conference on Artificial Neural Networks and Expert Systems (ANNES '95)*, 1995.
- [5] T. Ohishi, Y. Komiya, and T. Matsumoto. On-line signature verification using pen-position, pen-pressure and pen-inclination trajectories. In *ICPR*, pages Vol IV: 547-550, 2000.
- [6] C. Vielhauer, R. Steinmetz, and A. Mayerhofer. Biometric hash based on statistical features of on-line signatures. *16th International Conference on Pattern Recognition*, 2002.
- [7] Mingfu Zou, Jianjun Tong, Changping Liu, Zhengliang Lou. On-line Signature Verification Using Local Shape Analysis. In *proceedings of ICDAR, 2003*
- [8] A.K. Jain, F.D. Griess, and S.D. Connell. On-line signature verification. *Pattern Recognition*, 35(12):2963-2972, December 2002.