# Spectrum Analysis Based on Windows with Variable Widths for Online Signature Verification

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## Abstract

*In this paper, an online signature verification scheme based on spectrum analysis and Mahalanobis decision is proposed. We firstly divided signatures to a number of frames with variable widths according to the characteristics of the time sequences, and then employed the Fast Fourier transformation(FFT) to extract the spectrum of signatures. The distance between the Fourier coefficient within the corresponding frames is computed, and the Mahalanobis decision making is employed. Experimentation demonstrates that spectrum analysis based on windows with variable widths is effective for online signature signals.*

## 1 Introduction

Stirred by the need for positive identification of personal in law enforcement, information security operations, and commercial transactions, there is an increasing interest in electronic means of identification and authentication. Up to now, several biometric features have been studied and proved useful, including signature, fingerprint, face, speech, iris, and retina pattern. Among these features, the signature is one of the oldest means of identity validation both for the author of a document or the initiator of a transaction.

In early off-line cases, signatures are verified through examination of the digitized images. Since the signature image conveys none of the dynamics of writing, it gives poor results with very high acceptance rates of forgery.[1, 3] Recently, many methods have been developed for online signature verification, in which signatures are collected using a special instrument such as a digital tablet. Online signatures include some dynamic information (such as velocity, acceleration and spectrum), which are more difficult to imitate than the static shape of signatures. So online signature verification can often give better performance than the off-line[1]. Signature dynamics can be described by the time sequences of coordinate of the pen-point or by transforming the time sequence to frequency domain[2]. Lam and Kamins[3] used the largest 15 harmonics derived from the Fast Fourier Transform(FFT) as dynamic features. Because of signer's hesitance or discontinuity, signatures are unstable even for the same individual. In order to preserve "short time stationary", WU et. al[2, 4] divided signatures into several equal-width frames at first and then employed the FFT transform and the spectrum analysis. But considering the physical and psychomotor process to produce a signature, it is probably not appropriate to assume the changing speed of coordinate in such a fixed frames is consistent. So this paper propose a new strategy that divides the signatures into a number of frames with variable widths and then employs the FFT transform and spectrum analysis.

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## 2 PreProcessing

### 2.1 The Data

The signature data used in this paper is from the MCYT database, which is licensed for research and includes 100 subjects. For each subject, there are 25 genuine signatures and 25 forgeries. A signature includes 5 time sequences (such as position in $x$-axis, $x(t)$; and position in $y$-axis, $y(t)$; etc.)[5]. In this paper only the position sequences $x(t)$ and $y(t)$ are considered.

### 2.2 Normalization

Signatures may be initiated anywhere on the signing tablet, resulting in different $X$ and $Y$ coordinates even though the signatures are identical to each other. Thus, all signatures are normalized for location by subtracting from each point the centroid of the signature:[3]

$$x_1(t) = x(t) - \overline{x}, \quad y_1(t) = y(t) - \overline{y} \tag{1}$$

Then all signatures are scaled according to:

$$\begin{aligned} x_2(t) &= K * x_1(t) / \left[ \sum \left( x_1(t)^2 + y_1(t)^2 \right) \right]^{0.5} \\ y_2(t) &= K * y_1(t) / \left[ \sum \left( x_1(t)^2 + y_1(t)^2 \right) \right]^{0.5} \end{aligned} \tag{2}$$

where $K$ is a constant equal to 16 in this work.

### 2.3 Segmentation

#### 2.3.1 Segmenting signatures according to variation of position

To ensure that the changing speed of coordinates are time stationary within the frames, in this paper signatures are segmented according to the variation of $x$ sequence.

The variation of $x$ sequence can be easily detected by computing the derivative of $x$ sequence. Here the derivative is computed as:

$$d_x(t) = [x_2(t+1) - x_2(t)]/2 + [x_2(t+2) - x_2(t)]/2 \tag{3}$$

In order to separate arcs with large variation or libration on $x$-axis, let

$$d_x^{th}(t) = \begin{cases} 0 & |d_x(t)| < T_0 \\ d_x(t) & else \end{cases} \tag{4}$$

$T_0$ is a threshold and in this paper $T_0 = \max |d_x(t)|/4$.

After setting the threshold, it is easy to detect some segments satisfying $d_x^{th}(t) \neq 0$, denoted as $s_i$, then the process of segmenting a signature is as follows:

1. Combine all the adjacent segments (e.g. $s_i$ and $s_{i+1}$) satisfying the time interval between which is less than the smaller time duration of them.

2. For the combined segment, if the time duration is more than a threshold $T_1$, then the start and end point are selected as location to segment signature. Otherwise, only the end point is selected.

3. For the others segments, if the difference of $X$ coordinate between the start and end point is more than a threshold $T_2$, then the end point is selected as location to segment signature.

In this paper, $T_1$ and $T_2$ equal 20 and $(\max(x) - \min(x))/4$, respectively.

An example for segmentation of signatures is displayed in Fig. 1.

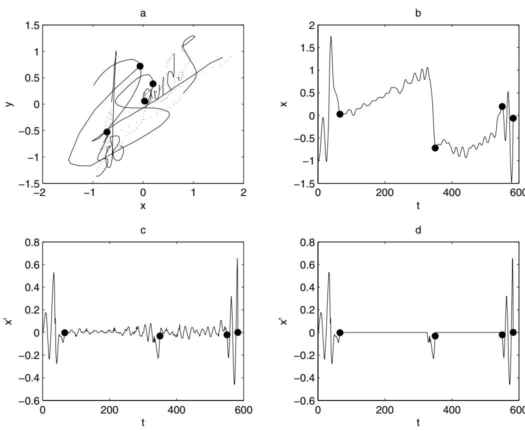


**Figure 1. Segmentation of signatures**

Segments gained from the above steps are denoted as $s_i^e$ and their end points are denoted as $e_i$.

Because of unstableness of signatures, the number of segments of genuine signatures from the single signer may be different. Then, for each subject the segments between instances need to be aligned.

#### 2.3.2 Processes of determining the number of segments and positions to divide signatures to frames

At first, the reference signatures are segmented according to the approach above. The time index of end point for segments is denoted as $t_j^e = t_{j,1}^e, t_{j,2}^e, \ldots, t_{j,n_j}^e$, here $j$ denotes the $j$th reference, $n_j$ equals the number of segments for the $j$th reference and $t_j^e$ is normalized to $[0, 1]$.

Secondly, select a reference whose segments number is the maximum as the templet, say, the $j_0$th reference, then

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compute the probability of each end point $e^i$ to be selected to segment all the signatures from a single subject as follows:

$$p_i = \frac{\sum\limits_{\substack{k=1,2,\ldots,n_j \\ j=1,2,\ldots,m}} v_{j,k,i}}{m} \tag{5}$$

Where $i \leq n_{j_0}$ and $i$ denotes the subscript of end points for a template and

$$v_{j,k,i} = \begin{cases} 1 & t^e_{j,k} - t^e_{j_0,i} = \min\limits_{i=1,2,\ldots,n_{j_0}} t^e_{j,k} - t^e_{j_0,i}; \\ 0 & else. \end{cases} \tag{6}$$

Where $m$ is equal to the sum of references, and $k$ defines the subscript of ends point for signatures other than the templet.

Thirdly, determine the number of segments and time index to segment signatures for the subject. The end points which satisfy $p_i \geq 0.5$ are selected as locations to segment the templet, and the number of segments equals the sum of selected end points. The time index for the end points selected is equal to :

$$t^e_{j_0,i} = \frac{\sum\limits_{\substack{k=1,2,\ldots,n_j \\ j=1,2,\ldots,m}} t^e_{j,k} * v_{j,k,i}}{p_i * m} \tag{7}$$

Where $i \leq n_{j_0}$. By removing the end points which does not satisfy $p_i \geq 0.5$, the expected end points are produced and can be denoted as $e^s_i$, and the time indexes of these points are denoted as $t^e_{s,i},\ i = 1, 2, \ldots, n_s$, where $n_s$ is the number of segments for the subject. Then signatures can be segmented simply according to the time index.

#### 2.3.3 Overlapping size

Before Fourier transformation is utilized, segments of signatures are usually multiplied with a window so as to decrease the influence of discontinuity. Therefor, adjacent segments should include some overlapped sample points to avoid the loss of information. And the length of overlapping is:

$$\delta_t = 0.5 \min_{i=1,2,\ldots,n_s} t^e_{s,i} - t^e_{s,i-1} \tag{8}$$

where $t^e_{s,0} = 0$.

### 2.4 Re-sample of Segments

Each segment of signatures should be re-sampled to ensure that the aligned segments include the same number of sample points. The sum of sample points for the $i$th segment of the templet is denoted as $N^i_{j_0}$. Then, for each signature claimed to the single subject, the expected sum of $s^e_i$ equals:

$$N^i_s = 2^{inter(\log_2 N^i_{j_0})} \tag{9}$$

And re-sample each segment according to:

$$x^i_3(t) = x^i_3(t \times \frac{N^i_s}{N^i_j}), \quad y^i_3(t) = y^i_3(t \times \frac{N^i_s}{N^i_j}) \tag{10}$$

### 2.5 Combine the $x$ and $y$ Sequences into Complex Series

For all of the following sections, a signature is represented by a complex function of time $f(t)$, with the $x$ coordinates as the real part and the $y$ coordinate as the imaginary part.

$$f^i(t) = x^i_3(t) + j * y^i_3(t) \tag{11}$$

Like the $x$ and $y$ sequences, $f(t)$ consists of a number of $f^i(t), 1 \leq i \leq n_s$.

## 3 Feature Extraction

As stated previously, segments of signatures are firstly multiplied with a hamming window:

$$f^i_1(t) = f^i(t) * w(t) \tag{12}$$

and

$$w(t) = 0.54 - 0.46\cos(2n\pi/N^i_s) \tag{13}$$

Then calculate the spectrum for each segment as follows:

$$C^i = |FFT(f^i_1(t))| \tag{14}$$

$C^i$ includes $N^i_s$ harmonics. In order to decrease the number of features, some authors have placed the cut-off limit to eliminate the high frequency components at 15Hz, 20Hz, and 30Hz.[3] In this paper, we select 20Hz as the upper limit.

## 4 Discriminant Analysis

Euclidean distance between spectrum of corresponding segments and the mean vectors of references is defined as:

$$d_i = \left\| C^i - M^i \right\| \tag{15}$$

where $M^i$ is the mean of $C^i$, and it's estimated by $M^i = \sum_{j\in[1,m]} C^i_j/m$, $j$ represents subscript of reference signature and $m$ equals the number of references. In this paper, the $d_i$s are regarded as similarity measurement of signatures.

Furthermore, it should be noticed that according to Eq.10, the timing aspect of signatures have been changed before FFT is utilized. As it is know, the time warping is an important information for online signature verification[6], so the duration of signatures should be included for consideration of similarity between signatures and can be denoted as $d_0$. Then, the distance between submitted signature and references is measured by $D = (d_0, d_1, \ldots, d_{n_s})$.

Instead of classification, the focus of this paper is the feature extraction algorithm, which is the variable width window based spectrum analysis, so the simplified Mahalanobis decision making is used. The simplified Mahalanobis distance can be computed as:

$$D_M(X) = (X - \overline{D})' \Delta^{-1} (X - \overline{D}) \qquad (16)$$

where $X = D$ is the distance vector from a signature to the references, $\overline{D} = \sum_{j \in [1,m]} D_j$ is a good estimate for the mean vector of the reference signatures, and

$$\Delta = \frac{1}{m} * \sum_{j \in [1,m]} diag((D_j - \overline{D_j})(D_j - \overline{D_j})') \qquad (17)$$

If $D_M$ is less than a threshold selected previously, the testing signature is accepted as a genuine one, otherwise the testing signature is rejected as a forgery.

# 5 Experimental Results

In this paper, 15 genuine signatures for each signer are used as reference, and the left 10 genuine signatures and 25 forgeries are used as testing signatures.

Experimental results are displayed in Fig.2, where FRR and FAR means false reject rate and false accept rate respectively. Both them can be represented as a function of the classification threshold and can be described by a tradoff curve using the classification threshold as a parameter.

For comparison, this paper implemented the equal width window based spectrum analysis too. And the trade-off curves for these experiments are displayed in the single Fig.2.

In Fig.2, the "fft" means FFT are employed to extract features, the "2 frames" means signatures are divided to 2 frames equally before FFT, and the "v frames" means signatures are divided to a variable number of frames through the approach proposed in this paper.

From Fig.2, it can be found that for the approach based on the window of variable widths, the equal error rate(EER) equals 0.07, and for the others displayed in the figure, the EER are greater than 0.09.

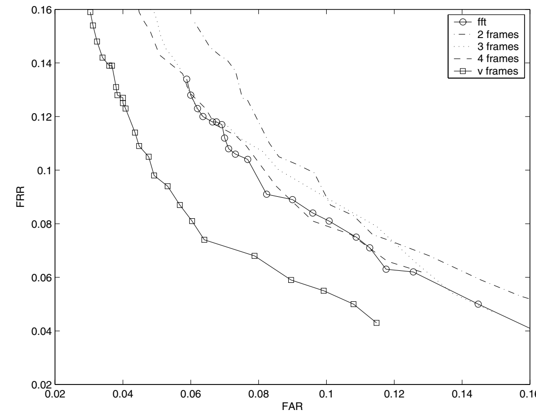


**Figure 2. Error trade-off curves**

# 6 Conclusion

This paper proposed a spectrum analysis method based on the window with variable width for online signature verification. This method firstly divided signatures to some frames with variable widths according to the characteristics of the time sequences and then used the FFT to extract features. Experimental results showed that the proposed method can improve the spectrum analysis. So it can be expected to achieve better performance of signature verification which based on spectrum analysis. The room left from improvement is how to make use of these spectrums in order to construct a better similarity measurement between signatures. In this paper, time sequences are divided according to the variation of the time sequences' derivative. In the future it is hoped that this method can be generalized. Say, time sequences can be divided according to the correlative coefficient, so that this method can be also put into good use for more time sequences.

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