A Method of On-Line Signature Verification with Consistent Spectral Features

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Abstract—Consistency analysis of signature features has significant effect on the performance and robustness of on-line signature verification. Inorder to improve the performance of on-line signature verification, we propose a method of on-line signature verification based on spectral consistent features, in which the consistent and effective information is extracted of signature features to be used in verification. In our works, spectral consistency of features is analyzed by statistics along with the consistent penalty factor. The consistent spectral features are obtained dynamically by the wavelet packet reconstruction with consistent sub-bands. Similarity between test signature and reference is calculated by proposed CPF-DTW to improve the robustness. Several experiments are carried out both on CDB and DB1 which consists of 8150 signatures from 190 individuals in total, the best results of our proposed method are given by EERCDB=2.25% and EERDB1=2.38% respectively which indicate the effectiveness and robustness of our proposed methods.

Keywords-on-line signature verification; consistent spectral features; consistency analysis; wavelet packet; CPF-DTW

I. INTRODUCTION

As requirements of information security and identity verification increases, biometrics is gaining popularity as a more trustable alternative to password based security systems. Signature verification is a widely acceptable biometrics due to signatures having been established as a particular behavior. Experiment results indicate that accuracy of signature verification is not lower than other biometrics.[1-2]

During on-line signature verification process, the authenticity of test signature is evaluated by matching its features against those stored in knowledge base for given individual. Dynamic time warping (DTW) is a nonlinear optimization method, which is widely used in on-line signature verification. DTW provides normalization and alignment of both sequences as a computational technique to make a matching between two time series, which might have different number of samples.[3-6]

Wavelet transform is an effective signal processing method for its ability of analyzing details of local signal features both in temporal and spectral domains. Nakanishi[7] use discrete wavelet transform to extract the high frequency components of signature, and test signatures are verified by adaptive signal processing. Zhang[8] propose a method of zero-crossing points of signature feature extraction based on wavelet transform, and DTW is used for signature verification. Wang[9] propose a method of on-line signature verification based on wavelet packet. Nanni[10] combined discrete wavelet transform along with discrete cosine transform to extract local information of signature.

In our works, the wavelet packet is used to obtain the spectral information of signature. Consistency of different sub-bands at given level are analyzed by statistics and consistent sub-bands are extracted dynamically. Consistent spectral features, which are obtained by WP reconstruction with selected consistent sub-bands, are used in signature verificaion.

The rest of the paper is organized as, in section II, spectral consistency analysis along with the spectral consistent features extracted dynamically. In section III, we propose CPF-DTW to calculate the feature similarity of reference and test signature. Several experiments are carried out both on CDB and DB1 to prove the effectiveness and robustness of our proposed method in section IV. Finally, some conclusions are given.

II. SPECTRAL CONSISTENCY ANALYSIS OF ON-LINE SIGNATURE

A. Wavelet Packet Analysis of On-Line Signature

Signal is decomposed into two parts by passing through low-pass filter and high pass filter during Wavelet Packet (WP) decomposition, and is represented by low-frequency wavelet coefficients and high-frequency wavelet coefficients. WP decomposition is given,

$$\begin{cases} d^{j+1,2i}(k) = \sum_l d^{j,i}(l) \cdot h_0^*(l-2k) \\ d^{j+1,2i+1}(k) = \sum_l d^{j,i}(l) \cdot h_1^*(l-2k) \end{cases} \quad (1)$$

Where, h0 and h1 are quadrature mirror filters, $d^{j,i}$ denotes the coefficients of WP, or sub-bands, j is the level of WP decomposition, i denotes the number of coefficient sets at level j, and i=0, 1, …, 2^j-1. In the WP, both approximation and detail coefficients are decomposed to create the full binary tree.

Reconstruction algorithm of WP is given,

$$d^{j,2i}(k) = \sum_l \left(d^{j+1,2i}(l) \cdot h_0(k-2l) + d^{j+1,2i+1}(l) \cdot h_1(k-2l) \right) \quad (2)$$

As for on-line signature verification, let F_k is the feature for a given signature, the spectral information of the coarse approximation coefficients and the detail coefficients of signature will be obtained by WP decomposition, we call these coefficients as sub-bands for convenience. Namely, for the feature F_k, the sub-bands of $d_{F_k}^{L,i}$ at level L will be obtained.

B. *Spectral Consistency Analysis of On-Line Signature*

From the perspective of the kinematic, signature is a rapid and skilled human action, like the ballistic movement, and is a habit formed during long time writing. The signature is mainly determined by the dynamics of muscle system, such as signature position, the structure of signature, duration of writing, pressure, velocity and acceleration, etc., which are dependent on the writer himself. There are different consistent components of signatures dependent on writing habits; furthermore, the differences also exist in different spectral domain of the same feature. In this paper, we propose a method of spectral consistency analysis and consistent spectral information extraction dynamically. Furthermore, consistent spectral features are obtained by WP reconstruction with the consistent sub-bands.

For a given individual, feature F_k is decomposed by WP decomposition, sub-bands at level L are given as $d_{F_k}^{L,i}$. In order to ensure the validity of spectral consistency analysis, all sub-bands at level L are normalized by max-min normalization. The similarities of sub-bands is calculated by DTW, i.e. $Dist_{(p,q),F_k}\left(\hat{d}_{p,F_k}^{L,i}, \hat{d}_{q,F_k}^{L,i}\right)$, where, p and q are reference signatures of the given individual, and p≠q, $\hat{d}_{F_k}^{L,i}$ denotes the normalized sub-bands

$$\hat{d}_{F_k}^{L,i} = \frac{d_{F_k}^{L,i} - d_{min_{F_k}}^{L,i}}{d_{max_{F_k}}^{L,i} - d_{min_{F_k}}^{L,i}} \quad (3)$$

Where, $d_{min_{F_k}}^{L,i}$ and $d_{max_{F_k}}^{L,i}$ denotes the minimum and maximum values of $d_{F_k}^{L,i}$ respectively.

During the DTW matching, there might be one-to-one matching points and one-to-many matching points, out of these, the one-to-one matching points are called direct matching points (DMP) in this paper. Generally, DMP indicates higher similarity and more consistent between two matching sequences, vice versa. The DMP in DTW matching is shown in Fig. 1.

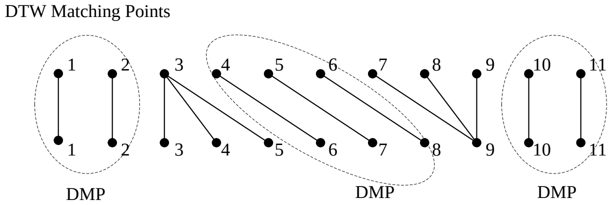


Figure 1. DMP in DTW Matching of Two Sequences

The Consistent Penalty Factor (CPF) of DTW matching is defined,

$$K_{CPF} = \frac{N_{DMP}/\min(N,M)}{\min(N,M)/\max(N,M)} \quad (4)$$

Where, N_{DMP} is the number of DMP in DTW matching, $N_{DMP} \le \min(N,M)$, N and M are numbers of sampled points included in two signatures respectively. The numerator denotes similarity of the two sequences according to DTW matching, and the denominator denotes similarity of the two sequences according to the number of sampled points. Consistent penalty factor of DTW matching indicates that the greater K_{CPF}, the higher similarity and consistency between two sequences.

According to the statistics, the consistency of sub-bands $d_{F_k}^{L,i}$ is analyzed by the mean value and standard deviation of similarities. The mean value indicates the similarity of the sub-bands of $d_{F_k}^{L,i}$ at level L, and the standard deviation indicates the discrete degree,

$$\mu_{i,F_k} = \frac{1}{L_s}\sum_{p=1}^{L_s} Dist\left(\hat{d}_{p,F_k}^{L,i}, \hat{d}_{q,F_k}^{L,i}\right) \quad (5)$$

$$\sigma_{i,F_k} = \sqrt{\frac{1}{L_s-1}\sum_{p=1}^{L_s}\left(Dist\left(\hat{d}_{p,F_k}^{L,i}, \hat{d}_{q,F_k}^{L,i}\right) - \mu_{i,F_k}\right)^2} \quad (6)$$

Where, Ls is the number of references for a given individual.

Considering the similarity, discrete degree of sample signature and consistent penalty factor of DTW matching, the statistical model of spectral consistency analysis of feature is given,

$$J_{st_{i,F_k}} = K_{CPF} \cdot \frac{1}{\mu_{i,F_k} \cdot \sigma_{i,F_k}} \quad (7)$$

According to the spectral consistency analysis, the greater value of $J_{st_{i,F_k}}$, the more consistent sub-bands of $d_{F_k}^{L,i}$, vice versa. Consistent sub-bands of feature are extracted dynamically according to the analysis of different feature dependent on individuals. And the consistent spectral features are obtained dynamically through by the WP reconstruction with consistent sub-bands dependent on individuals according to (2).

III. ON-LINE SIGNATURE VERIFICATION

There are some of most relevant approaches used in on-line signature verification, such as template matching approaches, statistical based approaches and structural based approaches. When template matching approaches are considered, it is difficult to conduct point-to-point matching between test signature and reference for a given individual because there could be different sample points included in the test signature and reference. The most common approaches are using DTW for signature matching. During DTW matching, it allows the compression or expansion of the time axis of two signatures to obtain the minimum distance. In this sense, DTW could solve the problem of signature matching very well in most cases.

During DTW calculation, distances of all sample points included in test signature to all sample points included in reference are calculated first. Then the optimal path is planned by dynamic programming to obtain the minimum distance of the two sequences.

To improved the robustness of on-line signature verification, we introduce the CPF in similarity calculation of signature features, denoted as CPF-DTW,

$$\mathrm{DIST}\left(\mathrm{s^{ref}},\mathrm{s^{tes}}\right)_{\mathrm{F_k}} = \frac{1}{\mathrm{K_{CPF}}}\cdot \mathrm{Dist}\left(\mathrm{s^{ref}},\mathrm{s^{tes}}\right)_{\mathrm{F_k}} \qquad (8)$$

Where, $\mathrm{DIST}\left(\mathrm{s^{ref}},\mathrm{s^{tes}}\right)_{\mathrm{F_k}}$ is the similarity CPF-DTW of feature $\mathrm{F_k}$ between reference and test signature, $\mathrm{K_{CPF}}$ is the consistency penalty factor of DTW, $\mathrm{Dist}\left(\mathrm{s^{ref}},\mathrm{s^{tes}}\right)_{\mathrm{F_k}}$ is the DTW distance of feature $\mathrm{F_k}$ between reference and test signature.

As for the verification, according to the threshold stored in knowledge base, we could output the verification result of genuine or forgery according to voting rule. The decision-making tag matrix of test signature is given as

$$\mathrm{Vote}\left(\mathrm{s^{ref}},\mathrm{k}\right) = \begin{cases} 1 & \text{if } \mathrm{DIST}\left(\mathrm{s^{ref}},\mathrm{s^{tes}}\right)_{\mathrm{F_k}} \le \mathrm{TH}_{\mathrm{s^{ref}},\mathrm{F_k}} \\ 0 & \text{others} \end{cases} \qquad (9)$$

The voting rule in defined as if $\sum_{1\le \mathrm{s^{ref}} \le \mathrm{L_s}, 1\le \mathrm{k} \le \mathrm{L_c}} \mathrm{Vote}\left(\mathrm{s^{ref}},\mathrm{k}\right) \ge \mathrm{COUNT_{vote}}$, the test signature is genuine, otherwise, the test signature is forgery. Where, $\mathrm{COUNT_{vote}}$ is the numbers of confirmed tag, Ls is the numbers of references, and Lc is the numbers of features used in verification. $\mathrm{TH}_{\mathrm{s^{ref}},\mathrm{F_k}}$ is the decision threshold of feature $\mathrm{F_k}$ for given individual reference $\mathrm{s^{ref}}$.

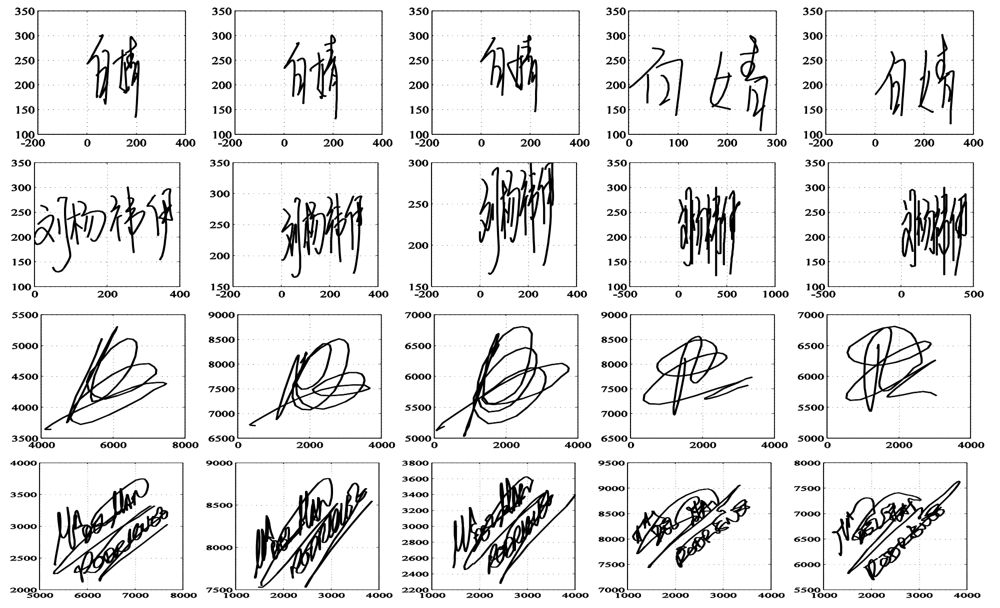
IV. EXPERIMENTATION

A. *On-Line Signature Verification Dataset Description*

Several experiments based on large scale datasets are carried out to prove the effectiveness and robustness of the proposed method. The datasets contain Chinese signature dataset and Western signature dataset which include 8150 signatures of 190 individuals. The construction of on-line signature verification database is shown in TABLE I. Some signatures are shown in Fig.2

TABLE I DESCRIPTION OF ON-LINE SIGNATURE VERIFICATION DATASET

Signature Details	**Chinese Dataset(CDB)**	**MCYT_Subcorpus_100 Dataset(DB1)[11]**
No. of References	90*5=450 (Genuine)	100*5=500 (Genuine)
No. of Test Signatures	90*10=900 (Genuine) 90*20=1800(Skilled forgeries)	10*20=2000 (Genuine) 10*25=2500(Skilled forgeries)



(a) (b) (c) (d) (e)

Figure 2. Signatures of data sets

Where (a) reference signatures; (b) and (c) genuine signatures; (d) and (e) skilled forgery signatures

B. *Feature Extraction*

6 features are extracted to be used in our works, i.e. $\mathrm{F\_Base} = \{\mathrm{X, Y, Vx, Vy, a_c, P}\}$. Out of these, feature $\mathrm{X(n)}$, $\mathrm{Y(n)}$ and $\mathrm{P(n)}$ are obtained directly from signature acquisition devices.

Features of $\mathrm{Vx(n), Vy(n), a_c(n)}$ are extracted by simple mathematical computation as,

- Linear Velocity in x-direction: $\mathrm{V_x(n)} = \left(\mathrm{X(n+1)} - \mathrm{X(n-1)}\right)/2$;
- Linear Velocity in y-direction: $\mathrm{V_y(n)} = \left(\mathrm{Y(n+1)} - \mathrm{Y(n-1)}\right)/2$;
- Centripetal Acceleration: $\mathrm{a_c(n)} = \left(\mathrm{V_x(n)}\cdot \mathrm{a_y(n)} - \mathrm{V_y(n)}\cdot \mathrm{a_x(n)}\right)/\mathrm{V(n)}$, where, $\mathrm{a_x(n)}$ and $\mathrm{a_y(n)}$ is the linear Acceleration in x-direction and y-direction, $\mathrm{a_x(n)} = \left(\mathrm{V_x(n+1)} - \mathrm{V_x(n-1)}\right)/2$, $\mathrm{a_y(n)} = \left(\mathrm{V_y(n+1)} - \mathrm{V_y(n-1)}\right)/2$, $\mathrm{V(n)}$ is the absolute velocity, $\mathrm{V(n)} = \sqrt{\mathrm{V_x(n)^2} + \mathrm{V_y(n)^2}}$.

C. Spectral Consistency Analysis

Experiments of spectral consistency analysis of on-line signature are carried out both on the CDB and DB1. For each given individual, the feature F_k is decomposed by WP, with dmey as mother wavelet, at level L=3, and the spectral consistency of each sub-bands is analyzed by the proposed method. The most three consistent sub-bands of the feature F_k are selected dynamically seen in TABLE II.

According to results, a useful conclusion is given that there are different consistent sub-bands of different features for given individual; simultaneously, there are different consistent sub-bands of given feature for different individuals. For example, as for given individual-1 in CDB, the most three consistent sub-bands are $\{d^{3,0}, d^{3,6}, d^{3,2}\}$ of feature X, and the consistent sub-bands are $\{d^{3,5}, d^{3,3}, d^{3,6}\}$ of feature Y. While as for given feature V, the most three consistent sub-bands are $\{d^{3,5}, d^{3,4}, d^{3,3}\}$ of individual-1, and the consistent sub-bands are $\{d^{3,1}, d^{3,6}, d^{3,0}\}$ of individual-3, etc. The same conclusion can also be concluded according to the results of experiments carried out on DB1.

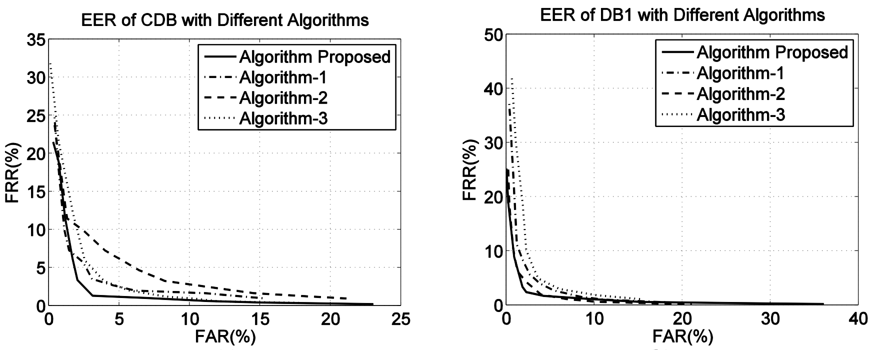
TABLE II STATISTICAL RESULTS OF SPECTRAL CONSISTENCY ANALYSIS OF FEATURES (PARTS OF SIGNATURES)

Features	The Most Three Consistent Sub-Bands Of Features					
	CDB			DB1		
	Individual-1	Individual-2	Individual-3	Individual-1	Individual-2	Individual-3
X	$d^{3,0}$, $d^{3,6}$, $d^{3,2}$	$d^{3,0}$, $d^{3,4}$, $d^{3,3}$	$d^{3,0}$, $d^{3,2}$, $d^{3,4}$	$d^{3,0}$, $d^{3,4}$, $d^{3,5}$	$d^{3,0}$, $d^{3,1}$, $d^{3,6}$	$d^{3,0}$, $d^{3,1}$, $d^{3,2}$
Y	$d^{3,5}$, $d^{3,3}$, $d^{3,6}$	$d^{3,2}$, $d^{3,0}$, $d^{3,6}$	$d^{3,3}$, $d^{3,6}$, $d^{3,4}$	$d^{3,0}$, $d^{3,1}$, $d^{3,2}$	$d^{3,1}$, $d^{3,2}$, $d^{3,0}$	$d^{3,1}$, $d^{3,0}$, $d^{3,7}$
P	$d^{3,5}$, $d^{3,1}$, $d^{3,6}$	$d^{3,5}$, $d^{3,1}$, $d^{3,6}$	$d^{3,3}$, $d^{3,0}$, $d^{3,2}$	$d^{3,2}$, $d^{3,7}$, $d^{3,6}$	$d^{3,1}$, $d^{3,5}$, $d^{3,0}$	$d^{3,1}$, $d^{3,0}$, $d^{3,2}$
Vx	$d^{3,4}$, $d^{3,6}$, $d^{3,2}$	$d^{3,3}$, $d^{3,6}$, $d^{3,1}$	$d^{3,3}$, $d^{3,4}$, $d^{3,5}$	$d^{3,1}$, $d^{3,0}$, $d^{3,3}$	$d^{3,6}$, $d^{3,3}$, $d^{3,4}$	$d^{3,2}$, $d^{3,1}$, $d^{3,3}$
Vy	$d^{3,1}$, $d^{3,0}$, $d^{3,2}$	$d^{3,3}$, $d^{3,6}$, $d^{3,5}$	$d^{3,2}$, $d^{3,3}$, $d^{3,4}$	$d^{3,3}$, $d^{3,1}$, $d^{3,0}$	$d^{3,3}$, $d^{3,4}$, $d^{3,5}$	$d^{3,3}$, $d^{3,6}$, $d^{3,0}$
a_c	$d^{3,4}$, $d^{3,0}$, $d^{3,5}$	$d^{3,4}$, $d^{3,0}$, $d^{3,5}$	$d^{3,6}$, $d^{3,7}$, $d^{3,1}$	$d^{3,4}$, $d^{3,2}$, $d^{3,7}$	$d^{3,7}$, $d^{3,2}$, $d^{3,6}$	$d^{3,5}$, $d^{3,2}$, $d^{3,4}$

D. Experiment Results

Equal Error Rate (EER), at which both false reject rate (FRR) and false accept rate (FAR) are equal, is adopted to evaluate the performance of on-line signature verification. EER indicates the security level of a given biometrics system.

Comparison experiments are carried out on CDB and DB1. Algorithm-1 use traditional DTW to calculate the similarity, others are the same with proposed methods; algorithm-2 use fixed sub-bands to reconstruct the spectral feature, others are the same with proposed methods; algorithm-3 only use CPF-DTW to calculate the similarity without WP analysis and consistent spectral features extraction. The EER curves of on-line signature verification with different algorithms are given by Fig.3, and the results are shown in TABLE III. According to the results, it can obtain the lowest EER both on CDB and DB1 by our proposed method, which indicates the effectiveness and robustness of our proposed method of on-line signature verification with consistent spectral features.



(a) (b)

Figure 3. EER Curves of On-Line Signature Verification Based on Different Algorithms. (a) EER Curves of CDB; (b) EER Curves of DB1

TABLE III EER OF DIFFERENT ALGORITHMS OF ON-LINE SIGNATURE VERIFICATION (%)

Algorithms	Algorithm Proposed	Algorithm-1	Algorithm -2	Algorithm -3
CDB	**2.25**	3.52	5.77	3.87
DB1	**2.38**	3.86	3.46	4.56

V. CONCLUSIONS

We made attempts to extract effective and consistent information of feature used in on-line signature verification. Spectral consistency is analyzed during the WP decomposition, and more useful and effective information is extracted dynamically dependent on individual. Experiment results indicate the effectiveness and robustness of our proposed method.

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