Off-Line Persian Signature Identification and Verification Based on Image Registration and Fusion

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***Abstract*— Signature verification and Identification has great importance for authentication purpose. Persian signatures are different from other signature types because people usually do not use text in it and they draw a shape as their signature, therefore, a different approach should be considered to process such signatures. In this paper, a method for off-line Persian signature identification and verification is proposed that is based on Image Registration, DWT (Discrete Wavelet Transform) and Image Fusion. Training signatures of each person are registered to overcome shift and scale problem. To extract features, at first, DWT is used to access details of signature; then several registered instances of each person signatures are fused together to generate reference pattern of person's signatures. In the classification phase, Euclidean distance between the test image and each pattern is used in different sub-bands. Experimental results confirmed the effectiveness of the proposed method. However, the proposed method has been tested on Persian signature database but we believe it can be extended for other languages.**

Index Terms—**Signature verification and Identification, Image registration, Center Of gravity, Image fusion**

I. Introduction

Signature verification is a biometric approach in person authentication. The researches about handwritten signature identification and verification systems have been doing for decades. In 2008, Larkins and Mayo have introduced a person dependent offline signature verification method that is based on Adaptive Feature Thresholding(AFT) [2]. AFT enhances the method of converting a simple feature of signature to a binary feature vector to improve its representative similarity with training signatures. The authors have used combination of spatial pyramid and equimass sampling grids to improve representation of a signature, based on gradient direction. In classification phase, they used DWT and graph matching methods. In another work, Ramachandra et al. have proposed Cross-Validation for Graph Matching based Offline Signature Verification (CGMOSV) algorithm in which Graph matching compares signatures and the Euclidean distance measures the dissimilarity between signatures [3]. In addition, Asma Shakil et al. analyzed the performance of different features for HMM based online and offline signature verification [4]. They used speed, angle along the trajectory, pen pressure and acceleration as online features and pixel density, center of gravity, distance and angle as offline features. They showed that all online features are good in distinguishing between genuine and skilled forgeries. In offline features, angle and distance are good while pixel density and center of gravity are not. In 2007, Kovari et al. presented an approach for offline signature verification, which was able to preserve and take usage of semantic information [5]. They used position and direction of endpoints in feature extraction phase. Yu Qiao, Jianzhuang /liu and Xiaoou Tang [6] proposed a method for offline signature verification that used online handwriting attributes for registration. They introduced conditional random fields for matching an offline signature image with online signatures that leads to extract the writing trajectory from the signature image. Ptor Prowik [7] introduced a three stages method for offline signature recognition. In this approach the Hough transform, center of gravity, and horizontal-vertical signature histograms have been employed. Using both static and pseudo dynamic features that were processed by DWT has been addressed in [8]. The verification phase of this method is based on fuzzy net. Using the enhanced version of the MDF (Modified Direction Feature) extractor has been presented by Armand, Blumenstein, and Muthukkumarasamy[9]. Two different neural classifiers such as Resilient Back Propagation (RBP) neural network and Radial Basis Function (RBF) network have been used in verification phase of this method. In 2005, Chen and Srihari [10] described an approach that obtains an exterior contour of the image to define a pseudo-

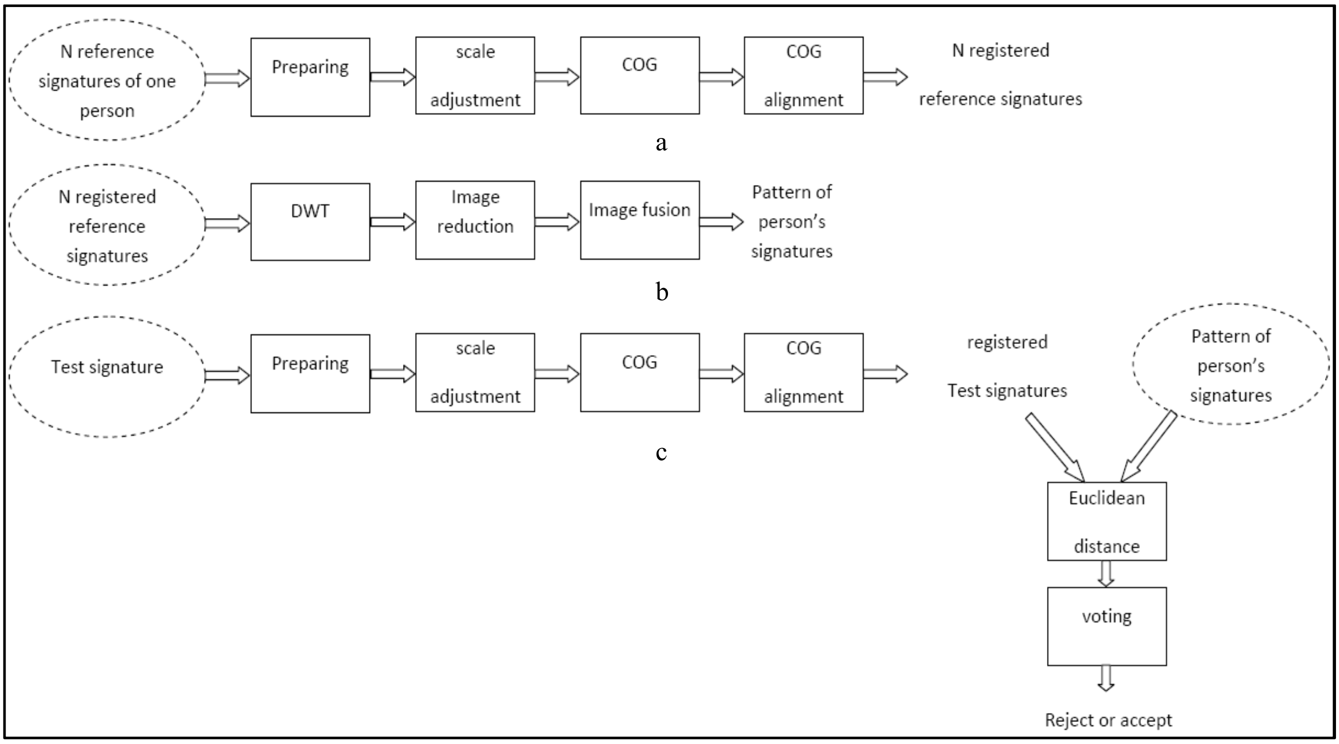


Figure 1. The overall frame work of the proposed method.

writing path. To match two signatures a dynamic time warping (DTW) method has been employed to segment signatures into curves. In addition, some features based on Zernike moments have been extracted. Finally, a harmonic distance has been employed to measure similarity of signatures. When this method combined with an approach based on word shape, the overall performance is increased. In 2002, Shen , Qiang and Pan [11] developed a method for Chinese offline signature verification method based on the combination of different type of geometric global and local features. Envelop of the signature, cross-count feature, center of gravity of sub-regions, distance between vectors mode of center of gravities, and area of embedded white space are the features that have been considered by these authors. In 2000, Judstino, et al. [12] used simple features and a HMM based learning process in signature verification. The aim of this method was to obtain the best representative signature model by using cross-validation process for each author. They presented an automatic threshold detection method to accept true signatures and reject false ones. Peter Shaohua et al. [13] proposed a method that includes a closed-contour tracing algorithm to extract static and dynamic curvature information and wavelet transform to extract stable features. They used an optimization-based dynamic thresholding algorithm to detect skillful forgeries.

Most of the mentioned methods have been tested on some specified databases; therefore, they considered the attributes on these databases in development. To have a precise method for signature verification the behavioral features of person should be considered. Therefore, the method should consider the attributes of people in culture and language and it should be customized on. In our previous work, we introduced a method for Persian signature verification and identification based on image fusion [1], so that, there were some problems in image fusion state that caused undesired results of fusion.

Here, we propose a method for registration of one person signature samples in order to solve shift and scale problems that caused some problems in fusion phase of our last method. As a result, we can obtain better pattern of person's signatures. In this method, each person's signatures are registered to obtain unique scale for them and match their Center Of Gravity (COG). A person's signatures have a unique form in different situations, and the differences may exist in details, therefore DWT (Discrete Wavelet Transform) is used to access high pass information of them. These information are fused to obtain pattern of each person's signatures that contains all detail information of his/her signatures. The proposed fusion method in present paper is different from out last work because of adding registration process. In addition, to enhance difference between a genuine signature and the forgery one, high-frequency information is used in classification phase. The Euclidian distance between the test and trained pattern in each sub-band is used as the classifier in identification and verification phase. Fig. 1 shows the overall approach of proposed method. Fig. 1.a shows the first step of method that prepares the sample signatures and Fig. 1.b shows preparing of each person pattern. In Fig. 1.c the testing procedure in verification and identification is

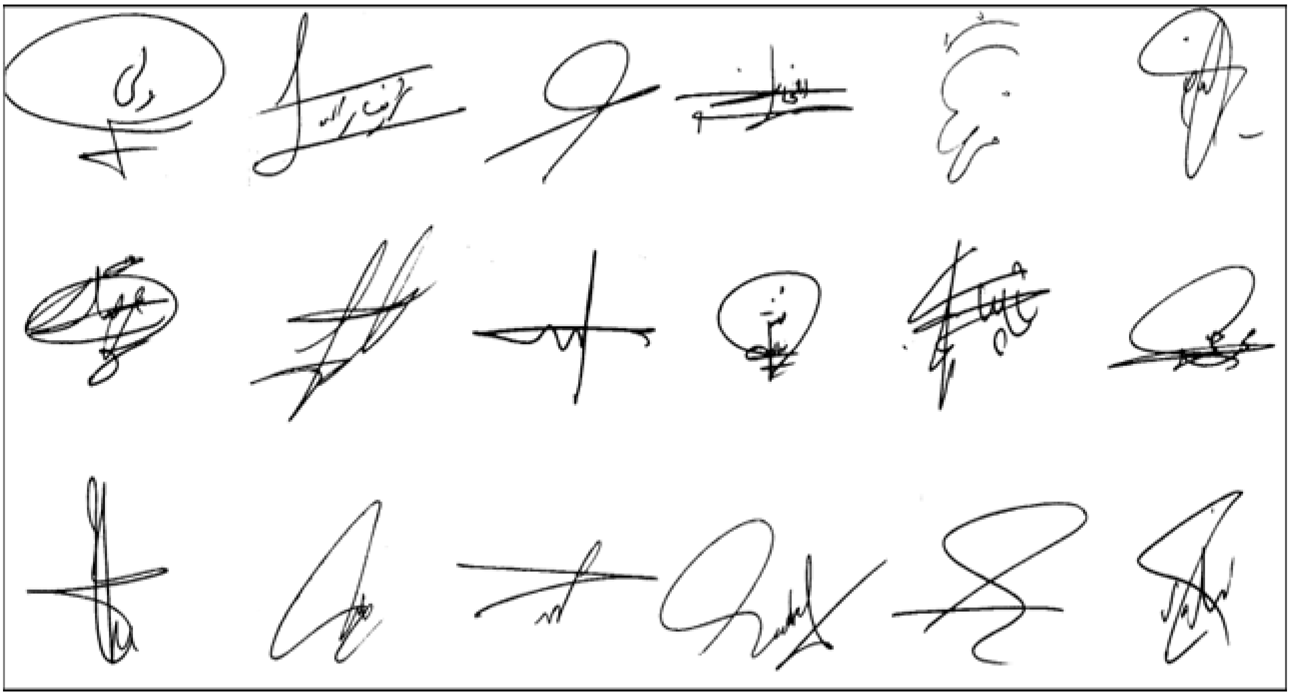


Figure 2. Genuine signatures samples

shown in overall. The experimental results of proposed method were satisfactory and showed that it had better results in compare with related works in terms of FAR (False Accept Rate) and FRR (False Reject Rate).

The rest of paper is organized as follows: In Section 2, the signature database and preprocessing steps are described. Section 3 discusses feature extraction phase. The identification and verification approaches are presented in section 4. In section 5, the experimental results and the selection of training samples are mentioned, and finally section 6 concludes the work.

II. Database And Preprocessing

Because there was no standard database for Persian signatures, we gathered a database. This database consists of 90 signers. Each signer has six genuine signatures. In addition, two forgeries for each signer have been created such that each one has different forgery quality types: simple forgeries and semi skilled forgeries [14]. Fig. 2 shows some samples of gathered database signatures. These signatures have been preprocessed before verification and identification. Preprocessing of source signatures includes preparing and registration. The registration procedure only considers the relative translation and scale between images. In the following sub-sections these two phases are described.

A. Preparing the Source Images

The first preprocessing phase consists of two steps:

Step1: A noise removal- counting filter is applied to remove the noise.

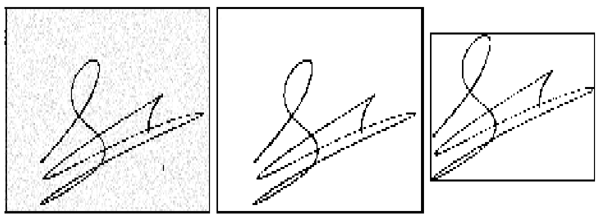
Step2: The image is cropped to the bounding rectangle frame of the signature. This frame touches the signature at four different directions: left, right, top and bottom.

Fig. 3 shows a sample signature that above steps have been applied on.

B. The Registration Procedure

Image registration is an important prerequisite for image fusion. The signatures may have relative translation, scale and rotation with regard to each other. The task of image registration is aligning the source image with regard to another one [15]. The registration process in proposed method consists of two steps. The result of registration overcomes scale and shift problems. These are the steps of registration:

Step1: To overcome scaling problem, the maximum length and width of all person's signatures are found. Then



(a) (b) (c)

Figure 3. (a) A sample Persian signature (b).Image after applying counting filter on (a) (c). image after fitting frame

each person's signature is resized to the maximum length and width (see Fig. 4(b)).

Step2: To overcome shift problem, the signatures are centered at a fixed new frame. The Center Of Gravity (COG) of each person's signatures are obtained and aligned to the ($X_{avg,i}$, $Y_{avg,i}$) where

$$X_{avg,i}=\frac{1}{m}\sum_{j=1}^{m} X_{j,i}$$
$$Y_{avg,i}=\frac{1}{m}\sum_{j=1}^{m} Y_{j,i} \tag{1}$$

$X_{j,i}$ is the first coordinate of COG of j^{th} signature instance of person i and $Y_{j,i}$ is the second coordinate of COG of j^{th} signature instance of person i . Fig. 4 shows the results of applying these steps on a sample signature.

The following algorithm is used to calculate COG of a signature:

i. In each horizontal line L_y with vertical coordinate y, count the number of black pixels (N_y). Vertical COG of image is calculated as follow:

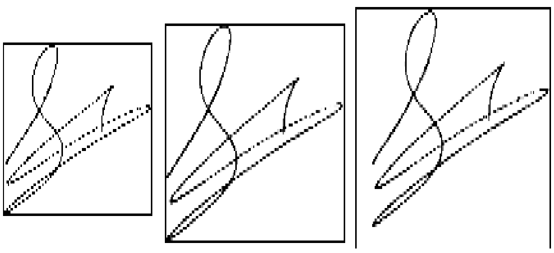
$$COG_V=\frac{\sum yN_y}{\sum N_y} \tag{2}$$

ii. In each vertical line L_x with horizontal coordinate x, count the number of black pixels,(N_x). Horizontal COG of image calculate as follow:

$$COG_h=\frac{\sum xN_x}{\sum N_x} \tag{3}$$

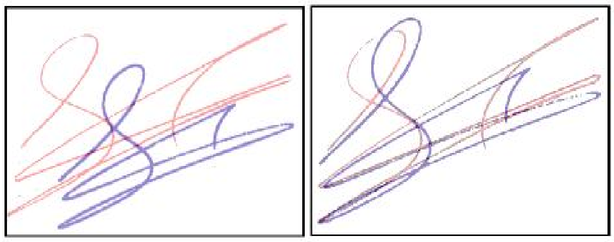
iii. COG of image is calculated as follows:

$$COG = (COG_h , COG_v) \qquad 4)$$



(a) (b) (c)

Figure 4. (a) A sample Persian signature (b)the result after applying step1 of registration process (c) the result after applying step 2



a b

Figure 5.Two signatures before registration (b) Two signatures after registration

Fig. 5 shows the effects of registration on two signatures.

III. FEATURE EXTRACTION

In the feature extraction phase, at first, DWT is applied to a preprocessed signature to obtain sub-images that contain high frequency bands. Then feature matrix of each sub-image is created by using an image reduction method. Finally, matrixes of different signature samples of each person are fused to obtain pattern of his/her signatures. The result of fusion is used as the feature vector. In the following subsections, the steps of feature extraction are described in more details.

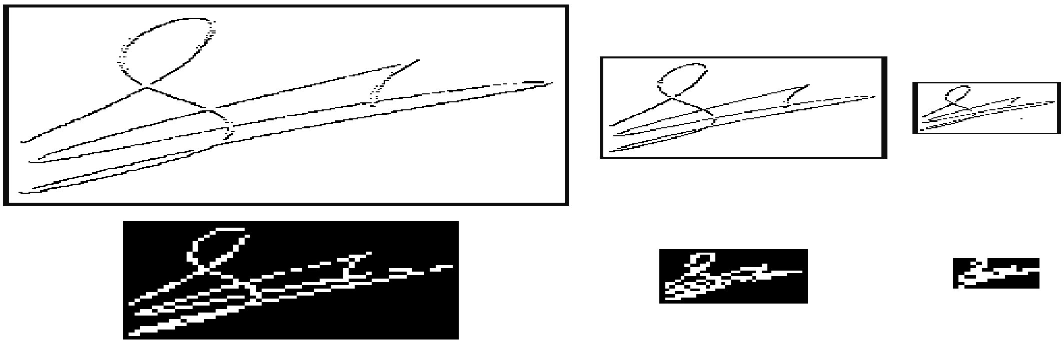
A. Discrete Wavelet Transform

The multi resolution wavelet transform decomposes a signal into low pass and high pass information. The low pass information represents a smoothed version and the main body of the original data. The high pass information represents data of sharper variations and details. DWT (Discrete Wavelet Transform) decomposes the image into four sub-images when one level of decomposition is used. One of these sub-images is a smoothed version of the original image corresponding to the low pass information and the other three ones are high pass information that represent the horizontal, vertical and diagonal edges of the image respectively. When two images are similar, their difference would be existed in high-frequency information. A DWT with N decomposition levels has $3N + 1$ frequency bands with $3N$ high-frequency bands [16]. By considering these attributes, DWT is used in reduction step that is described in following sub-section in more details.

B. Image Reduction

At first step of reduction the high pass sub-images of DWT are partitioned to 5*5 blocks. Because of down sampling operation in DWT, sizes of sub-images of each level are different from next level (about 2 times). With regard to this fact, in the before reduction, these sub-images are resized to the nearest dimension of 5 multiples. It is obvious that the number of blocks of sub-images in each level is different from other levels. Resizing is used just because of using 5*5 blocks in partitioning and does not have any effects in results.

In the second phase of reduction, a matrix is assigned to each sub-image that its dimension corresponds to the number of blocks of this sub-image. Each cell of this matrix consists of '1'or "0". It consists of "1" if 5% of its corresponded block



(a) (b) (c)

Figure 6. First row: 3 high frequency sub-images in 3 levels of decomposition. Second row: matrixes of applying image reduction on sub-image of first row.

pixels in sub-image are black unless '0' is stored in. This matrix is called sub-image feature matrix and presented by M_{pj_k} that means feature matrix of j[th] signature of p[th] person with k[th] sub-image. M_{pj_k} has the same features of its original signature. For an image with 3N high-frequency bands, there are 3N M_{pj_k} matrixes. Fig. 6 shows 3 sub-images of DWT in 3 levels of decomposition and results of applying image reduction on them.

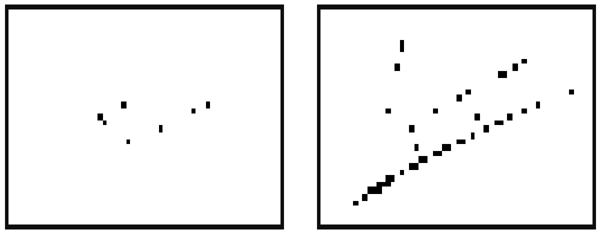
C. Image Fusion

As it has been mentioned in image reduction step, for each person's signature there are 3N feature matrixes M_{pj_k} $(1 \le k \le 3N)$, which obtained from reducing each high pass sub-image of signature. If there are S signatures samples for each person in desired database, S*3N feature matrixes exist for each person. Corresponding matrixes of different samples are fused together to obtain 3N pattern matrixes that contain information of all S samples. The results of fusion phase for person p with k decomposition levels are called Mf_{P_k} $(1 \le k \le 3N)$. Equation (5) explains the recursive formation procedure of Mf_{P_k} [17][18] that is a fusion method:

$$Mf_{P_k}^{new} = \frac{1}{num+2}\left(num * Mf_{P_k}^{old} + M_{pjk}\right) \qquad (5)$$
$$1 \le k \le 3N, 1 \le num \le S-1,$$
$$2 \le j < S$$

In this equation, the value of *num* is increased by 1 in each recursive call. Mf_{P_k} for all persons is stored in $table_k$, therefore, there are 3N $table_k$ such that $1 \le k \le 3N$ and N is specified decomposition level. These tables are used as the feature vector.

Fig. 7 compares the effects of registration process on fusion results of two feature matrixes M_{pj_k} of two signatures of one person. In Fig. 7, just common pixels in two images have been shown. We can see that after registration, number of common pixels between two signatures is more than before.



(a) (b)

Figure 7. (a) Common pixels of two reduced sample signatures before registration (b) Common pixels of two reduced sample signatures after registration.

IV. Identification And Verification Methods

In the verification and identification phase, the processing of test (input) signature is same as trained ones but without fusion phase. Therefore, after processing the input signature *3N* matrixes will be created. These matrixes are called M_{test_k} $(1 \le k \le 3N)$.

For identification purpose, M_{test_k} is compared with all entries of $table_k$ by using the Euclidean distance(Ed). The Euclidean distance (Ed) is defined as follows:

$$D_k = \| M_{test_k} - M_{rp_k} \|, 1 \le k \le 3N \qquad (6)$$

For each sub-image *k,* the entry of $table_k$ with lowest distance with input image is selected. The distance value of selected entry should be lower than a specified threshold *T.* The most frequent selected entry in different sub-images is considered as signature owner.

The step by step procedure of identification is as follows:

Step 1: Preprocess test signature.

Step 2: Apply DWT whit N decomposition levels on test signature.

Step 3: Reduce test signature and obtain 3N, M_{test_k}

Step 4: Calculate Euclidean distance between M_{test_k} and Mf_{P_k}

Step 5: p=p+1 and repeat step 4 until p = Number of individuals in database.

Step 6: If the lowest distance < T then select the owner of this lowest distance in sub-image k.

Step 7: k = k+1 and repeat step 4 until k = 3N.

Step 8: The person that has the majority of sub-images is selected as signature owner.

In verification phase, M_{test_k} is compared only with Mf_{P_k} of complainant p using the Euclidean distance. If distance Mf_{P_k} with input signature in the majority of sub-images $1 \leq k \leq 3N$ is less than a threshold value (T), signature is accepted unless it is rejected. The step by step procedure of verification is as follows:

Step 1: Preprocess test signature.

Step2: Apply DWT whit N decomposition levels on test signature.

Step3: Reduce test signature and obtain 3N, M_{test_k}

Step4: Calculate Euclidean distance between M_{test_k} and Mf_{P_k} where p is complainant person.

Step5: If Euclidean distance < T then test signature is accepted in sub-image k else rejected.

Step 6: k=k+1 and repeat step 4 until k=3N

Step7: If in majority of sub-images test signature is accepted then test signature is finally accepted else it is finally rejected.

V. Experiments

A. Optimal Selection Of Training Samples

Person's signatures in different situations are not similar to each other; therefore, it is important how to select training signatures. For selecting *m* training samples from a set includes S signatures instances, the following steps have been used for each person [8]:

Step1: apply mentioned preprocessing on a person's signatures, then without doing DWT apply image reduction on preprocessed original signatures so one feature matrix is obtained that is called $x_i, 1 \leq i \leq S$ where S is number of instances for each person. This matrix is used as a feature vector.

Step2: find the similarity between each two samples, x_i and x_j by using the following equation:

$$S_{ij} = \frac{(x_i, x_j)}{\sqrt{(x_i, x_i)(x_j, x_j)}}; 1 \leq i \leq S, 1 \leq j \leq S \quad (7)$$

$$i \neq j$$

Where $(*,*)$ is scalar product of two matrixes.

Step3: compute mean value and standard deviation of similarities signature and other signatures in that are calculated in *Step2* by using following equations. In the following equations, u_i shows the mean value and σ_i shows the standard deviation of similarity .

$$u_i = \frac{1}{M-1} \sum_{j=1, j \neq i}^{M} S_{ij} \quad (8)$$

$$\sigma_i = \frac{1}{M-1} \sum_{j=1, j \neq i}^{M} (S_{ij} - u_i)(S_{ij} - u_i)^T \quad (9)$$

Step4: select *m* signatures that have maximal $\left\| \frac{u_i}{\sigma_i} \right\|$.

In the specified database the *S* value was equal to 6 and *m* was equal to 5.

B. Results

The proposed methods were tested on the gathered database. In the proposed method, number of decomposition levels is so important in order to access more detail of an image. In addition, the number of training samples that are fused to generate the pattern of a person's signature is important.

Results of using six, seven, and eight decomposition levels with three, four, and five training samples are shown in Table1. The best recognition rate was about 92.2% when five training samples and eight decomposition levels were used.

Verification results are reported in terms of False Acceptance Rate (FAR),which means a forgery signature is considered as a genuine signature, False Rejection Rate (FRR),which means a genuine signature is considered as a forgery signature, and average error rate (Average) which is the average of the FAR and FRR. As shown in the Table1, Average error is 9.8% when five training samples and eight decomposition levels are used and it is 9.175% by using five training samples and seven decomposition levels. Table 2 compares the verification results of proposed method with some related works. The best values of methods are considered in Table 2. As it is shown in this table, the proposed method outperformed the related works in average by using less samples for each person. It means that by increasing number of training samples, it may have results that are more precise.

Table1. Experimental results of proposed method on desired database. As it is shown in this tables the results are satisfactory.

Number of training samples	Decomposition level	% of identification	FAR	FRR	Average
5	8	92.2	8.5	11.1	9.8
5	7	91.1	7.25	11.1	9.175
5	6	91.1	5	17.6	11.3
4	8	87.22	7.25	13.3	10.275
4	7	88.8	6.25	15.5	10.875
4	6	88.8	3.75	21.5	12.625
3	8	73.6	7.5	17.7	12.6
3	7	77.8	5	18.8	11.9
3	6	77.8	3.75	29.5	16.625

Table2. Comparison of proposed method with some related works

Methods		FRR(%)	FAR(%)	Average	Language	Number of individuals	Number of training
Geometric Center [19]		0.98	20.83	10.905		-	8
Naiv Bayes [20]		9.95	13	11.47		55	15
HMM [21]		14.1	12.6	13.35	English	160	12
Fuzzy net [8]		13.26	11.89	12.57	English	39	12
SVM [21]	Linear	21.06	18.54	19.8	English	160	12
	Poly	15.41	15.64	15.53	English	160	12
	RBF	15.41	13.12	14.27	English	160	12
Previous our work [1]		8.9	10	9.63	Persian	90	5
proposed		11.1	7.25	9.175	Persian	90	5

VI. CONCLUSIONS

In this paper, we introduced an approach for identification and verification of off-line signatures. The proposed approach used DWT for extracting details and Euclidean distance for comparing features. To create a feature vector several instance signatures of a person are reduced and fused while in fusion phase, high frequency sub-bands are used. A registration method is employed to improve the fusion process. The experimental results were satisfactory and they improved some related work. In the future, we are going to extend and test the proposed method on signatures from other languages to develop a language independent method.

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