A New system for offline Signature Identification and verification

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Abstract—Biometric features have great importance in authentication systems nowadays. One of the most important and conventional biometrics is signature. In this paper, we proposed a system which has two independent phases for offline signature identification and verification. The identification phase is based on TSR (triangle spatial relationship) that is a rotation invariant feature extraction method. Also, a symbolic representation of signature has been employed to make using TSR possible. In the verification phase, a hybrid method is proposed that combines discrete wavelet transform, Gabor filter, and image fusion methods. Experimental results on some benchmarks have confirmed the robustness and precision of proposed method together with its robustness against translation, scaling, and rotation.

Keywords: offline signature identification and verification; triangular spatial relationship; discrete wavelet transform; Gabor; image fusion.


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1- INTRODUCTION

In the verification phase of an authentication system, the person identity is confirmed with regard to his/her claim while, in identification mode, the person identity is established among those enrolled in a database without using any predefined data (Jain, Flynn and Ross, 2007; Vielhauer and Dittmann, 2005). A handwritten signature is a biometric feature that is the result of a complex process that depends on the psychophysical state of the signer and conditions under which the writing signature occurs (Impedovo and Pirlo, 2008). There are a lot of researches in signature verification and identification field, but finding a more accurate and robust method is a challenge yet.

There are a lot of researches in this scope, for example, Emli-mari Nel, Johan A.du Preez and B.M.Herbst (Nel ,Preez and Herbst , 2005) proposed a method that extracts dynamic information from static signatures by creating Hidden Markove Model (HMM). They used Viterbi algorithm ( Rabiner and Juang, 1986) to match an available dynamic exemplar with created HMM and determine pen trajectory of the static image.

Also, in (Hanmandlua et el., 2005), a method for signature verification and forgery detection based on fuzzy modeling has been proposed. In this method, the features that consist of angles are extracted using the box approach and are assigned to a fuzzy set. The authors introduced a new fuzzification function with structural parameters to develop a complete forgery detection and verification system.

In another work, C.Senol and T. Yildirim (Senol and Yildirim, 2005) presented an approach for offline signature verification based on a Conic Section Function Neural Network (CSFNN). In this method, Local and global features are extracted from samples and fed to CSFNN for classification. They also used MLP and RBF Networks and compared classification results of CSFNN with results of MLP and RBF Networks.

As another approach, a method for off-line signature verification has been proposed that uses a combination of the Modified Direction Feature (MDF) and additional features such as the centroid, surface area, length, and skew by using two different neural network classifiers: Resilient Back propagation (RBP) and Radial Basis Function (RBF) network (Nguyen et al., 2006).

Using Gradient, Structural, and Concavity (GSC) features to extract global, statistical, and geometrical features of the signature for signature verification and identification has been considered in (Kalera, Zhang and Srimili, 2004). The authors used statistical measures like Bayes and K-nearest neighbor classifier for verification and identification respectively.

Chen and Srihari (Chen and Srihari, 2005) proposed an approach that obtains an exterior contour of signature to define a pseudo-writing path. In this approach, some curves are extracted using a dynamic time warping (DTW) method. In addition to these curves, some features based on Zernike moments are extracted. Finally, a harmonic distance is used to measure signature similarity. When this method combined with an approach based on word shape, the overall performance increased.

J.F. Vargas et al. described an off-line signature verification methodology based on gray level information. They measured the stroke gray-level variations by means of wavelet analysis and statistical texture features (Vargas et al., 2010). Also, the Wavelet Analysis is used in this method to estimate the global influence of ink-type, and properties of the Co-occurrence Matrix are employed as features that represent individual characteristics at local level.

A probabilistic graphical model is proposed by Hairong Lv et al. (Lv et al., 2010) for off-line signature verification. The authors used discrete landmark points as the features and represented these features by a unique graphical model. In this model, just simple relationships among landmark points are considered and the concept of feature roles according to their location in forgery and genuine signatures is considered.

Sabounir et al. (Sabourin, Genest and Prêteux, 1997) proposed an approach based on visual perception. In their approach, granulometric size distributions (Doughey et al., 1992) have been used for definition of local shape descriptors and evaluating the natural local variations of the writing trace of the signature. Also, they employed two types of classifiers: nearest neighbor and threshold classifier. To integrate these classifiers, voting approach has been used. Improving the reliability of offline signature verification systems has been considered in (Bertolini et al., 2010) by using an ensemble of classifiers based on graphometric features that was built by using a standard genetic algorithm and assessing different fitness functions to drive the search. In this work, the shape of the signature is simulated by using Bezier curves and then graphometric features are extracted from these curves.

One of the main issues that should be considered in signature analysis is variations in the signature patterns. To consider this issue, a verification approach has been proposed by B.Fang (Fang et al., 2003) that contains two methods to track the variations of the features or strokes of the signatures. First method is based on the optimal matching of one-dimensional projection profiles of the signature patterns to measure positional variation between them. The second method is based on the elastic matching of the strokes in two-dimension signature patterns to measure variation of the relative strokes positions. M.A.Isnaill and Samia Gad (Isnaill and Gad, 2000) developed a recognition technique based on multi stage classifier and combination of global and local features. They also introduced a Fuzzy verification method.
Chalechale and Mertins (Chalechale and Mertins, 2003) introduced a fast method for signature recognition. This method uses line segment extraction based on chain code representation of edge maps. This method is suitable for using on parallel machines.

Porwik (Porwik, 2007) 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.

In our previous work (Ghandali and Ebrahimi Moghaddam, 2009), we introduced a method for offline signature identification and verification that its feature extraction phase was based on the discrete wavelet transform and image reduction approach. In this method, we solved problems of the scale and translation of different signature samples of one person. Although the results of this work were satisfactory; we could improve the results in the present paper by using a rotation invariant feature extraction method and solving problem of rotation of different signature samples of one person.

Here, a system with two separate phases for offline signature identification and verification is proposed that are scale, translation and rotation invariate. In identification phase, the signatures are represented in a symbolic view by using a local center of gravity and TSR (Triangle Spatial Relationship) approach as a rotation, scale, and translation invariant method is employed to extract features. The verification phase is a hybrid approach that uses discrete wavelet transform (DWT), Gabor filter, and image fusion. DWT and Gabor filter are used in feature selection phase while image fusion is employed in generating a unique pattern by considering different sample of each person. In verification phase, a preprocessing step is used to make this phase rotation invariant like identification phase.

![Fig. 1. The overall framework of proposed method](image)

Fig. 1 shows the overall framework of the proposed method; first step of the method is preprocessing that is used by both identification and verification phases. Identification phase consists of blocking by central lines operation, extraction local COGs, labeling and symbolic representation, applying TSR, making symbolic image database and finally comparing operation. Verification phase consists of another preprocessing stage, applying DWT, applying Gabor Transform, image fusion operation, making pattern of person’s signature, and finally comparing operation. The details of this figure are described in section 4 and 5. To
evaluate the proposed system, it has been tested on two databases. First one is a Persian database which consists of 540 true samples and 180 forged ones were acquired from 90 persons. Another database is English and Chinese standard GPDS database which consists of 540 true samples and 180 forged ones have been acquired from 60 persons. Experimental results confirmed the method precision, robustness, and independency from different languages.

The rest of the paper has been organized as follows: in section 2, signature databases are introduced. In section 3, Preprocessing steps are discussed. In section 4, feature extraction for identification process, the way of signature symbolic representation and identification approach with corresponding experimental results are presented. In section 5, DWT and Gabor based feature extraction for verification process, method of image fusion and corresponding experimental results are discussed. Finally, section 6 concludes the paper.

2- SIGNATURE DATASET

As it was said in the last section, two signature datasets were employed to evaluate the proposed method. For the first one that is a Persian dataset, the signature samples were acquired from 90 persons. Every signer was asked to sign six times using black pen on a white sheet of paper. These signatures were stored as genuine signature samples in database. Volunteers asked to imitate true signature samples of all persons. Two samples for each person are collected as forgery signature samples and they stored in database. Therefore, a set of signature data consisting of 540 true samples and 180 forged samples was used for testing the proposed system. These signatures were scanned into the computer at an 8 bit, 300 dot-per-inch (dpi) resolution.

In addition, GPDS standard database (GPDS Signature Verification database, 2009) which consists of English and Chinese signatures has been employed for verification purpose. These signatures were acquired from 60 persons. There are nine true samples and three forged samples for each person. Experimental results on these two databases have confirmed the robustness and precision of proposed method together with its robustness versus translation, scaling, rotation, and independency from different languages.

Fig. 2 shows some selected signatures of two datasets. Chosen signatures of Persian database and GPDS database are shown in Fig. 2 part (a) and part (b) respectively.

3- PREPROCESSING

In the proposed method, some simple preprocessing steps are used to improve the system verification and identification performance.

In the first step, a counting based noise removal approach is applied on the input image to remove small dots and isolated pixels. The denoising is done by using a 5*5 mask; if number of black pixels is less than a specified threshold then the corresponding point is considered as noise and is removed. It is worth mentioning that this simple noise removal method does not work well in high intensive noises. In other words, high intensive noise may affect the method performance also.

In the second step, image is converted to a binary one such that signature is white and background is black. To convert input image to a binary one, a simple threshold based approach is used.

After it, the shape of signature is fitted within a rectangular frame. This frame touches the signature at four sides: left, right, top, and bottom. The time and space complexity is reduced effectively by eliminating useless information in this step.
To make same size different signature samples of each person, the maximum length and maximum width of different samples of each person are found. Then each sample is resized by using maximum length and width and they are centered at a fixed new frame.

4- IDENTIFICATION

The recognition process determines the owner of a given test signature that is one of the known writers in the database. This section consists of feature extraction, symbolic representation of signature, TSR and experimental results.

4-1- Feature extraction

The extracted features should be stable and involve the characteristics of the original image and cause the system correctly distinguishes one class from the others.

To extract features, a mesh that consists of 15 lines and intersects in the image center is superimposed on the signature image (as shown in Fig 3.a). Each slice of this mesh is considered as a sub-image; therefore, 16 sub-images are created. The centroid of the signature is taken as the origin. Then, Center of Gravity (COG) is locally calculated at each sub image in polar form (see Fig.3 (b)) by following algorithm:

![Fig. 3. (a) central lines (b) local center of gravities](image)

In each radius \( r \), count \( N_r \) as the number of white pixels, then the radial center of image gravity is calculated as follows:

\[
COG_r = \frac{\sum r N_r}{\sum N_r}
\]  

(1)

In each angle \( \theta \), count the number of white pixels, \( N_\theta \), then the angular center of image gravity is calculated as follows:

\[
COG_\theta = \frac{\sum \theta N_\theta}{\sum N_\theta}
\]  

(2)

Image gravity Center is shown by following pair:

\[
COG = (COG_r, COG_\theta)
\]

(3)

4-2- Symbolic representation of signature

Image registration is an important prerequisite for image processing applications which there are more than one image of an object in them such as image fusion, signature identification, and verification. In signature identification and verification systems, there are databases that consist of some signature samples of each person and systems are trained based on these samples. The authentications of persons are determined by comparing their input signature with signatures that are stored in these databases. The train and test signatures of a person may have translation; scale, and rotation with regard to each other while such items have side
effects on identification and verification precision. The task of image registration is to align different samples of an image with regard to each other.

After extracting center of gravity, the area size of each sub-image is calculated, then, sub-image with maximum area is chosen and its center of gravity is labeled as '1'. Afterward, in the clockwise direction, other COGs are labeled sequentially. This labeling technique makes features invariant to rotation. Each certain COG in signatures of a person with various degrees of rotation has an identical label. Fig.4 shows the results of applying such method on two different samples of a specified person signature. These labels create a symbolic image that should be represented in a database. To represent mentioned symbolic image, Triangular Spatial Relationship (TSR) approach is employed. TSR is invariant to translation, rotation, scaling, and flipping (Guru and Nagabhushan, 2001) and is described in next sub-section.

4-3- **Triangular spatial relationship**

A triangular spatial relationship (TSR) is based on creating triangles between each three non-collinear components in a symbolic image.
In Fig. 5, three non-collinear components of a signature are shown. These components are COGs that were described in subsection 4-1. Connecting these components makes a triangle. M₁, M₂, and M₃ are the midpoints of the sides of this triangle and ϴ₁, ϴ₂, and ϴ₃ are the smaller angles at midpoints as shown in Fig. 5. TSR of these three components is defined by the following set:

\[
\{(A,B,C,\theta_3),(A,C,B,\theta_2),(B,A,C,\theta_3),(B,C,A,\theta_1),(C,A,B,\theta_2),(C,B,A,\theta_1)\}
\]

In order to choose one quadruple out of six ones in the above set, the following conditions are used.

a) If AB>AC>BC then \((A,B,C,\theta_3)\) is chosen
b) If AB>BC>AC then \((B,A,C,\theta_3)\) is chosen
c) If AC>AB>BC then \((A,C,B,\theta_2)\) is chosen
d) If AC>BC>AB then \((C,A,B,\theta_2)\) is chosen
e) If BC>AB>AC then \((B,C,A,\theta_1)\) is chosen
f) If BC>AC>AB then \((C,B,A,\theta_1)\) is chosen

Therefore, TSR of any three non-collinear components is represented by a quadruple. For a signature, TSR can be calculated among every combination of three non-collinear components. Therefore, each signature is represented by some TSRs. The number of TSRs for each signature is as follows:

\[
\text{number of TSR (NTSR)} = \binom{\text{NSB}}{3} - \text{number of three collinear components}
\]

Where NSB is number of sub-regions that is equal to 16.

Finally different samples of each person are fused and result is stored in the database. To fuse different samples, the following simple algorithm has been used:

a) In all training signatures, find quadruples that their three first elements are same.
b) Make a new quadruple with these first three elements, as pattern quadruple.
c) Use median of angles of these training quadruple as angle of pattern quadruple.

The Computation of symbolic database using TSR took 75 hours for Persian database and 60 hours for standard GPDS database on a system with AMD Phenom II X4 3.4 GHz processor and 4GB RAM.

4-4- Experimental results

To test the proposed method, the two described databases in section 2 have been used. In this way, test signatures were compared with all persons in database as follows: for each quadruple of test signature, quadruples which their three first elements are same as test ones are determined. Then angles of determined quadruples are compared with angle of test one to select the person that has smallest distance. These operations are performed for each quadruple of test signature and a person is assigned to it. Finally, the owner of test signature is the person with majority in quadruples of test signature.

The experimental results showed the recognition ratio of 91% for Persian database and 90% for standard GPDS database with proposed method when 60 different signatures was selected for test. In addition, to test the ability of method versus rotation, the test signature has been rotated in different angles. Table 1 shows the average recognition ratio of signature databases versus various orientations. As shown in this table, if the rotation angles are multiple of \(360/n\) where \(n\) is number of sub images, the recognition ratio are same as zero rotation angle. Otherwise, the recognition ratios are a little different from zero rotation angle and are similar to each other. Therefore, with higher values of \(n\), higher number of angles have a recognition ratio same as the zero rotation angle. This confirmed the rotation invariant property of proposed identification system.

<table>
<thead>
<tr>
<th>Orientation</th>
<th>Identification (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>91</td>
</tr>
<tr>
<td>7.5</td>
<td>86.6</td>
</tr>
<tr>
<td>15</td>
<td>90</td>
</tr>
<tr>
<td>22.5</td>
<td>91</td>
</tr>
<tr>
<td>45</td>
<td>91</td>
</tr>
<tr>
<td>112.5</td>
<td>91</td>
</tr>
</tbody>
</table>
5- Verification

In signature verification phase, the presumed identity of the signer is confirmed by comparing extracted features of test signature and stored features. The features used during the verification phase are not same as those used in identification phase. This section consists of four required steps for verification: preprocessing, feature extraction, similarity measure, and experimental results. The proposed method improved the results of our previous work (Ghandali and Ebrahimi Moghaddam, 2009), by solving rotation problem of different signature samples and using Gabor filter in feature extraction phase.

5-1- Preprocessing

In addition to the preprocessing operations as explained in section 3, another operation is used in verification phase in order to solve rotation problem.

For each signature sample of a person, maximum horizontal projections are calculated. Average of these maximum horizontal projections is obtained. If distance between the horizontal projection of each signature sample and average value is lower than a threshold (T) then interval[-10°, +10°] of angles is considered for solving rotation problems unless interval [-40°, +40°] of angles is considered. First, each signature sample image is rotated by +40 (or +10) in the clock wise orientation and its horizontal projection is calculated. Then the image is rotated in the anti clock wise direction with step -2 and in each angle the horizontal projection of the image is calculated. The rotation is continued until -40° (or -10°). The angle that creates bigger horizontal projection is considered as rotation angle and the image is rotated by this angle.

5-2- Feature extraction

In the feature extraction phase, two kinds of features are extracted: global and local. Center Of Gravity (COG) is used as a global feature and Gabor and Discrete Wavelet Transform are used for extracting local features.

For each sample of signature, its COG is calculated. The average of these COGs is considered as a global feature. For extracting local features, Gabor, and discrete wavelet transform (DWT) are used as follows: at first, Daubechies discrete wavelet transform (DB4-DWT) with N decomposition levels is applied to a preprocessed signature image to obtain sub-images with high pass information. Each high pass sub image (HH, HL and LH) is fitted into a 55*55 pixel image by using BILINEAR interpolation (Db4-DWT) with N decomposition levels is applied to a preprocessed signature image to obtain sub-images with high pass information. Each high pass sub image (HH, HL and LH) is fitted into a 55*55 pixel image by using BILINEAR interpolation method. A grid with size 11*11 is applied on each sub-image. Coefficients of convolving Gabor filter with sub-images in junction points of grid are used as local features. As a result, a 11*11 matrix M_{ik} is created which represents coefficients of jth instance of person i in sub-image k, where 1 ≤ k ≤ 3N.

Each person’s signatures have a unique main body in different situations; however, difference may exist in details. In the other words, low pass information of different signature samples of one person are the same as each other, and their differences exist in their high pass information; consequently, we used DWT to extract high pass information that exist in HH, HL and LH sub images. In order to obtain a unique pattern of person signatures, different samples of a person are fused based on high pass information. This pattern includes all details of his/her signatures. Equation (4) shows the image fusion approach:

\[ M_{ik}^{new} = \frac{1}{num+2}(num * M_{ik}^{old} + M_{ik}^{fus}); 1 \leq k \leq 3N; 2 \leq num \leq C - 1; 1 \leq j \leq C; \]

where \( M_{ik} \) is the pattern matrix of kth sub-image of ith person, C is number of training samples. Therefore, for each person 3N pattern matrices are stored in the database.

5-3- Similarity measure

In the verification phase, the processing of test signatures are same as trained ones but without fusion step. A test signature is preprocessed and its local and global features are extracted. Therefore 3N matrixes, that are named M_{testk} (1 ≤ k ≤ 3N) are created. Features of the test signature are compared with features of complainant person in database by using Euclidean distance and dynamic threshold. The threshold value is calculated by using average and standard deviation of feature values of all training signatures of a person as Eq. 5.

\[ T_i = \mu_i \pm \sigma_i \]

In Eq. 5, \( T_i \) is threshold of person i. In addition \( \mu_i \) and \( \sigma_i \) are average and standard deviation of features of person i. This threshold is based on the structure of normal function. Since data usually have normal random structure, so this dynamic threshold is suitable for our application. By using this dynamic threshold, there is not any requirement to adjust the threshold of similarity measurement when database is changed. In the other words, this dynamic threshold is independent of database and automatically is calculated with regards to signature samples of each person.

In the verification phase, at first, the COG of test signature is compared with COG of complainant p. If there is any difference between them, the test signature is rejected otherwise it is accepted. Second, \( M_{testk} \) is compared with \( M_{pk} \) of complainant p using
Euclidean distance. If distance $M_{pk}$ with test signature in the majority of sub-images $1 \leq k \leq 3N$ is less than a dynamic threshold value ($T$), signature is accepted otherwise it is rejected. The step by step procedure of verification is as follows:

Step 1: Preprocess test signature.

Step 2: Compare COG of test signature and complainant $p$.

Step 3: If there is any difference between them, test signature is rejected otherwise it is accepted.

Step 4: Apply DWT with $N$ decomposition levels on test signature.

Step 5: Extract features by using Gabor and obtain $3N$ matrixes $M_{testk}$.

Step 6: Calculate Euclidean distance between $M_{testk}$ and $M_{pk}$ where $p$ is complainant person.

Step 7: If Euclidean distance $< T$ then test signature is accepted in the sub-image $k$ otherwise rejected.

Step 8: $k=k+1$ and repeat step 4 until $k=3N$.

Step 9: If in majority of sub-images, test signature is accepted, it is accepted for whole signature otherwise it is rejected.

6- EXPERIMENTAL RESULTS

The proposed methods were tested on the gathered Persian database and English and Chinese standard GPDS database which have been described in section 2. 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.

Since the number of decomposition levels and training samples have effect on system performance to find the best parameters, different parameter setting were examined. Results of using six, seven, and eight decomposition levels versus three, four, and five training samples are shown in Table II. As it is shown, the best verification rate (average error rate) is about 6.95% when five training samples and eight decomposition levels are applied. Because of this fact, these parameters are used in the rest of experimental results.

<table>
<thead>
<tr>
<th>Number of training samples</th>
<th>Decomposition levels</th>
<th>False Rejection Rate (FRR)</th>
<th>False Acceptance Rate (FAR)</th>
<th>average error rate (Average)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>8</td>
<td>9.5</td>
<td>4.4</td>
<td>6.95</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>11.1</td>
<td>5.6</td>
<td>8.35</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>10</td>
<td>5.6</td>
<td>7.8</td>
</tr>
<tr>
<td>4</td>
<td>8</td>
<td>15.6</td>
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<td>10</td>
</tr>
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<td>4</td>
<td>7</td>
<td>16.7</td>
<td>4.4</td>
<td>10.55</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>16.7</td>
<td>4.4</td>
<td>10.55</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>23.3</td>
<td>7.8</td>
<td>15.55</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>24.4</td>
<td>7.8</td>
<td>16.1</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>27.8</td>
<td>10</td>
<td>18.9</td>
</tr>
</tbody>
</table>

Fig. 6 shows ROC (receiver operating characteristic) curve for Persian database when diverse static thresholds are used together with five training samples and eight decomposition levels for 90 persons in Persian database. Also, this figure shows the ROC curve for GPDS database for six training samples and eight decomposition levels of 60 persons. Note that train and test signatures were chosen randomly, and selected test signatures have been left out from training phase.
Fig. 6. ROC curve for Persian database and GPDS database

Table 3 compares the verification results of proposed method with some related works that all of them used standard GPDS database in their works. As it is shown in this table, the proposed method outperformed the related works in average.

Table 3 - Results of comparing proposed method with methods in (Larkins and Mayo, 2008; Tian, Qiao and Ma, 2007a; Nguyen et al., 2006; Ruiz-del-Solar et al., 2008; Tian, Qiao and Ma, 2007b; Nguyen et al., 2010; Rekik et al., 2011; Ferrer, Alonso and Travieso, 2005; Ghandali and Ebrahimi Moghaddam, 2009)

<table>
<thead>
<tr>
<th></th>
<th>(Larkins and Mayo, 2008)</th>
<th>(Tian, Qiao and Ma, 2007a)</th>
<th>(Nguyen et al., 2006)</th>
<th>(Ruiz-del-Solar et al., 2008)</th>
<th>(Tian, Qiao and Ma, 2007b)</th>
<th>(Nguyen et al., 2010)</th>
<th>(Rekik et al., 2011)</th>
<th>(Ferrer, Alonso and Travieso, 2005)</th>
<th>(Ghandali and Ebrahimi Moghaddam, 2009)</th>
<th>proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>FAR(%)</td>
<td>12.41</td>
<td>12.24</td>
<td>0.16</td>
<td>14.2</td>
<td>11.89</td>
<td>16.54</td>
<td>20</td>
<td>12.6</td>
<td>7.25</td>
<td>4.4</td>
</tr>
<tr>
<td>Eavg(%)</td>
<td>11.44</td>
<td>12.66</td>
<td>17.78</td>
<td>15.3</td>
<td>12.57</td>
<td>15.03</td>
<td>20</td>
<td>13.35</td>
<td>9.175</td>
<td>6.95</td>
</tr>
</tbody>
</table>

7- CONCLUSION

In this paper, a system with two separate phases for offline signature identification and verification was proposed. Identification phase was based on the local features and symbolic representation of signatures. TSR retrieval method was used to obtain rotation, scale, translation, and flipping invariant system. The experiments results show recognition rate of about 90% in two databases. Verification phase is based on the DWT, Gabor and image fusion. DWT is used to access high pass information of signatures that involve differences between signatures of one person. For feature extraction, convolution of Gabor with high pass information of signatures was used. To obtain a unique pattern for each person's signatures, his/her signature samples were fused together. The experiments results showed 4.4% and 9.5% as FAR and FRR respectively for Persian database. Likewise, 8.9% and 10.3% as FAR and FRR respectively for standard GPDS database. The experimental results confirmed the effectiveness of proposed methods and the results were better than many related work reports. In the future, we are going to use another types of classifiers like neural networks and Fuzzy classifiers, and use further features, like statistical, structural and geometrical features, in feature extraction phase.
REFERENCES


