# Offline Handwritten Signature Identification and Verification Using Multi-Resolution Gabor Wavelet

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**Abstract**

In this paper, we are proposing a new method for *offline* (*static*) handwritten signature identification and verification based on *Gabor wavelet* transform. The whole idea is offering a simple and robust method for extracting features based on Gabor Wavelet which the dependency of the method to the nationality of signer has been reduced to its minimal. After pre-processing stage, that contains noise reduction and signature image normalisation by size and rotation, a *virtual grid* is placed on the signature image. Gabor wavelet coefficients with different frequencies and directions are computed on each points of this grid and then fed into a classifier. The *shortest weighted distance* has been used as the classifier. The weight that is used as the coefficient for computing the shortest distance is based on the distribution of instances in each of signature classes.

As it was pointed out earlier, one of the advantages of this system is its capability of signature identification and verification of *different nationalities*; thus it has been tested on four signature dataset with different nationalities including *Iranian*, *Turkish*, *South African* and *Spanish* signatures. Experimental results and the comparison of the proposed system with other systems are consistent with desirable outcomes. Despite the use of the simplest method of classification i.e. the nearest neighbour, the proposed algorithm in comparison with other algorithms has very good capabilities. Comparing the results of our system with the accuracy of human's identification and verification, it shows that human identification is more accurate but our proposed system has a lower error rate in verification.

**Keywords:** Signature Identification; Signature Verification; Multi-Resolution Analysis; Gabor Wavelet; Nearest Neighbour.

## 1 INTRODUCTION

Nowadays, person identification (recognition) and verification is very important in security and resource access control. For this purpose, the first and simple way is to use Personal Identification Number (PIN). But, PIN code may be forgotten or may be misused. Now, an interesting method for identification and verification is biometric approach. Biometric is a measure of identification or verification that is unique for each person. Always biometric is carried along with person and cannot be forgotten. In addition, biometrics usually cannot be misused. Handwritten signature is one of the oldest biometrics.

Handwritten signature identification or verification is simple, fairly secure, inexpensive, non-intrusive and acceptable in society. Nevertheless, it has some drawbacks: lower identification rate with respect to other biometrics, non-linear changes with size changing and dependency to time and emotion. Another problem of processing the handwritten signature is the differences between signatures from different nationalities. For example, European signature is the same as his/her name written in a special style but Persian signature contains some curves and symbols [1, 2, 3].
Signature processing can be used for two different purposes: (1) *identification* (*recognition*) and (2) *verification* (*authentication*); signature verification is more useful than signature identification in both practical systems and researches. In signature identification, the input is an unknown signature and system must identify the owner of that. But the goal of signature verification is examination of an input signature to determine whether it is genuine or forgery. So, in the verification system the major problem is the presence of signature forgery. There are three types of forgery:

(1) *Random forgery*: this type of forgery is not intentional. If the forger uses the name of a person in his/her own style to create a forgery, it is known as the random forgery. In fraudulent cases, the majority of them are random forgeries, and they could be easily detected.

(2) *Simple or casual forgery*: the forger does not have any prior experience and imitates the signature in amateur style. This imitation is done by observing the signature just in a matter of time.

(3) *Expert or skilled or simulated forgery*: the most difficult forgeries are created by expert forger who has experience in copying the signatures. The forgery signatures that are created in this way will be almost a genuine replica.

There are two types of signature identification and verification: (1) *static* or *offline* and (2) *dynamic* or *online*. In the offline type, input of the system is a 2-dimentional image of the signature. In contrast, in the online type, the input is the signature trace in time domain. In the online type, a person signs on an electronic tablet by an electronic pen and his/her signature is sampled. Each sample has 3 attributes: x and y in 2-dimentions coordinates and t as the time of sampling. Therefore, in the online type, the time attribute of each sample help us to extract useful information such as start and stop points, velocity and acceleration of signature stroke. Some electronic tablets in addition of time sampling, can digitize the pressure. This additional information existing in the online type will increase the identification rate in comparison with the offline type. Although the accuracy rate in the online type is higher than the offline type, but the online type has a major disadvantage; it is online. So, it cannot be used for some important applications that the signer cannot be presented in the singing place.

In this paper, we propose an offline signature identification and verification system, which emphasizes on feature extraction using Gabor wavelet. Extracting suitable and robust features are more important than selecting a classifier. So, in our proposed system, we used a simple classifier known as nearest neighbor.

Remain of this paper is organized as follow: in section 2, some previous works are reviewed. Section 3 is a brief description of our proposed system. Section 4, 5 and 6 are about pre-processing, feature extraction and classification of the proposed system respectively. Section 7 shows experimental results on four different signature databases. The last section of this paper is about the conclusions and future works.

## 2 RELATED WORKS

In this section a short review on offline handwritten signature identification and verification systems is presented. Major of these researches are about signature verification, however some of them are about signature identification.

Frias-Martinez et al [4] proposed an offline handwritten signature identification system using Support Vector Machines (SVM) and compared this system with another system which used Multi-Layer Perceptrons (MLP) as classifier. Both of these systems have been tested with two different feature extraction approaches: (1) extracting some global and moment-based features, (2) using raw bitmap data of signature image as feature vector. Their proposed system used just one signature per class as training data similar to the practical systems. Experimental results show that SVM is better than MLP for classification in both approaches of feature extraction.

Ozgunduz et al [5] described an offline handwritten signature identification and verification system using the global, directional and grid features of signatures. Before extracting features, all signature images were pre-processed by background elimination, noise reduction, width normalization and thinning the stroke. SVM is used to identify or verify the signatures. Experimental results show that the performance of SVM is higher than MLP.

Kalera et al [6] presented a quasi multi resolution approach for offline signature identification and verification. First, all signature were normalized by rotation. Then GSC (Gradient, Structural and Concavity) features are extracted and fed into a Bayesian classifier. Gradient features are local; and structural and concavity features are global. So feature extraction acts like a multi-resolution processing.

Deng et al [7] proposed a wavelet-based offline signature verification system. This system extracts robust features that exist within different signatures of the same class and verify whether a signature is a forgery or not. After pre-processing stage, the system starts with a closed contour tracing algorithm to extract closed contour of signature. The curvature data of the closed contours are decomposed to low and high frequency bands using wavelet transform. Then the zero crossings information corresponding to the curvature data are extracted as features. Classification stage in this system is very simple and performed by applying a threshold. The threshold value used for verifying an input signature is calculated automatically based on the distribution of features in each class. Experimental results were done on two different signature databases: English and Chinese; these results show that nationality had no impact on the nature of the system.

Herbst et al [8] designed a signature verification system using Discrete Radon Transform and Dynamic Programming. First, all signatures are normalized by Translation, Rotation and Scaling. Then Radon Transform has been applied to extract features. A grid relation between features of input signature and features of reference signatures has been created using Dynamic Programming. Afterward, matching analysis was done to accept or reject the input signature.

Coetzer et al [9] have used Radon Transform and Hidden Markov Model (HMM) for offline signature verification. Features are extracted by Radon Transform and fed to a HMM classifier. The ring topology of HMM classifier has been used in this paper.

Ferrer et al [10] introduced some new geometric features for offline signature verification based on signature curvature and distribution of strokes in Cartesian and Polar coordination. These features were used by HMM, SVM and Nearest Neighbor (NN) classifiers to verify an input signature image. Experimental results shown that HMM is more accurate than SVM and NN classifiers.

Kiani et al [11] extracted appropriate features by using Local Radon Transform applied to signature curvature and then classified them using SVM classifier. Their proposed method is robust with respect to noise, translation and scaling. Experimental results were implemented on two signature databases: Persian (Iranian) and English (South African).

Pourshahabi et al [12] presented an offline signature identification and verification using Contourlet Transform. Contourlet is a two dimensional multi-resolution transform that extracts curves from an image with different thicknesses and curvatures. In this paper, after signature normalization, features were extracted using Contourlet Transform and then classified by Euclidean Distance. This method was applied on two signature databases: Persian (Iranian) and English (South African).

# 3 PROPOSED SYSTEM

The proposed system is consisting of three stages: (1) *pre-processing* stage, (2) *feature extraction* stage and (3) *classification* stage. In pre-processing stage, noise elimination of the signature image is performed. Rotation and size normalization of the signature image are also achieved in this stage. Feature extraction stage is based on the computation of Gabor wavelet coefficients on specific points of the pre-processed signature image. Extracted features (wavelet coefficients) are then fed to a classifier. In the signature identification system, the identity of the signer is recognized in the classification stage whereas; in the signature verification system the forgery or genuine type of the signature is determined. The diagram of the proposed system is shown in Figure 1.

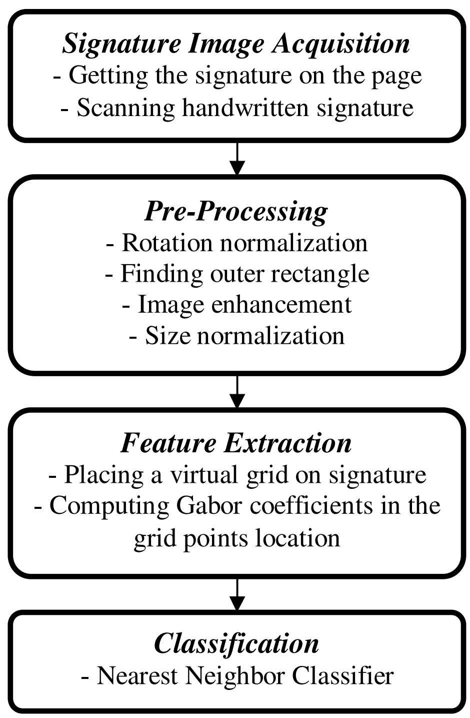


**FIGURE 1:** Flowchart of the proposed system.

# 4 PRE-PROCESSING

This is the first part of the proposed system, consisting of rotation normalization, determination of the outer rectangle of the signature, size normalization and finally image enhancement.

## 4.1 Rotation Normalization

In order to accomplish rotation normalization, the signature image contour is rotated in so far as the minimum inertia is located in the horizontal wise. This method has been presented by Kalera et al [6]. In this method the signature contour is indicated with C that comprises of N pixels.

$$C = \left\{ X(i) = \begin{bmatrix} u(i) \\ v(i) \end{bmatrix}, i = 1, \dots, N \right\} \tag{1}$$

$X(i)$ = the vector comprising of x and y coordinates of the $i^{th}$ pixel of the signature contour

$u(i)$ = x coordinate of the $i^{th}$ pixel of the signature contour

$v(i)$ = y coordinate of the $i^{th}$ pixel of the signature contour

The $(\bar{u}, \bar{v})$ coordinates of the center of gravity of the signature contour are obtained according to (2) and (3).

$$\bar{u} = \frac{1}{N}\sum_{i=1}^{N} u(i) \tag{2}$$

$$\bar{v} = \frac{1}{N}\sum_{i=1}^{N} v(i) \tag{3}$$

The second order moment, $\overline{u^2}$ and $\overline{v^2}$ of the signature contour is then obtained according to (4) and (5).

$$\overline{u^2} = \frac{1}{N}\sum_{i=1}^{N} (u(i) - \bar{u})^2 \tag{4}$$

$$\overline{v^2} = \frac{1}{N}\sum_{i=1}^{N} (v(i) - \bar{v})^2 \tag{5}$$

The orientation of the minimum inertia axis is determined according to the orientation of the minimum eigenvector of the following matrix.

$$I = \begin{pmatrix} \overline{u^2} & \overline{uv} \\ \overline{uv} & \overline{v^2} \end{pmatrix} \tag{6}$$

### 4.2 Finding the Outer Rectangle

The outer rectangle is the smallest rectangle surrounding the signature contour. It is determined by applying a threshold on the horizontal projection and vertical projection of the binary image. Image binarization is done using Otsu [13] method. By finding the outer rectangle, signature image will be robust to displacement (shift).

### 4.3 Size Normalization

In so many signature images, the signature elongation is in horizontal or vertical direction. Considering this point, a method is presented for size normalization. In this method at first, the length and the width of the signature are computed and then the larger one is selected. A constant number is also chosen as normal size. Now the length and the width of the image will be changed in the case that the larger dimension will be equaled to this constant normal size. Therefore, in signature images with larger width than length, the normalization will be based on the width, and vice versa. The constant normal size in this paper is considered as 200 pixels.

### 4.4 Image Enhancement

The resulted binary image in previous section is employed for the image enhancement operation. The white signature contour is located in the black background in this binary image. At first, closing operation is applied on the complement of this binary image. Closing operation is one of the morphological operations including dilation and erosion. Unwanted gaps in the signature contour are removed by closing operation. Afterward all of the spot areas containing lower pixels than a specific number are omitted, whereby all of the probable noisy areas are deleted. This operation is achieved by detecting all of the white connected components in the binary image and counting their pixels.

In the enhanced gray-level image, the gray-levels corresponding to the white pixels in the binary image preserve their values and other pixels value are set to white gray-level.

## 5 FEATURE EXTRACTION

In the proposed system, Gabor wavelet is used as feature extractor. Initially, Gabor wavelet and its specifications is introduced and then the application of Gabor wavelet in the proposed system as feature extractor is explained.

### 5.1 Gabor Wavelet

Gabor wavelet is obtained by multiplying a sinusoid function with a Gaussian function in time domain. By convolving a signal with the Gabor wavelets, the frequency information of the signal nearer to the center of the wavelets is obtained. A one-dimensional Gabor wavelet is shown in (7):

$$W(x, x_0, \omega) = e^{-\sigma(x-x_0)^2} e^{-i\omega(x-x_0)} \tag{7}$$

In (7), $x_0$ is the center of wavelet, $\omega$ is the angular frequency ($\omega = 2\pi f$) and $\sigma$ is the radius of Gaussian function.

Convolution of Gabor wavelet and a given function $g(x)$ is defined as follow:

$$C_{x_0,\omega}(g(x)) = \int_{-\infty}^{+\infty} g(x) W(x, x_0, \omega) dx \tag{8}$$

In general, the result of the convolution is a complex number that comprises of real and imaginary parts:

$$C_{x_0,\omega}(g(x)) = a_{real} + ia_{imag} \tag{9}$$

Gabor wavelet coefficients can be stated based on angle and magnitude or based on real and imaginary parts as follow:

$$a_{real} = |a| \cos \angle a \tag{10}$$

$$a_{imag} = |a| \sin \angle a \tag{11}$$

$$|a| = \sqrt{a_{real}^2 + a_{imag}^2} \tag{12}$$

$$\angle a = \arctan(a_{imag} / a_{real}) \tag{13}$$

In the above equations, $a$ is the complex coefficient of Gabor wavelet, $a_{real}$ and $a_{imag}$ are real and imaginary parts of $a$; $|a|$ and $\angle a$ are amplitude and angle of $a$.

In image processing, the two-dimensional Gabor wavelet transform is used. These wavelets are the result of the multiplication of a sinusoid function by the two dimensional Gaussian function. The sinusoid signal extracts frequency information corresponding to its frequency and the Gaussian function determines the region of effects of the sinusoid signal. Therefore, Gabor wavelet operates as like as a local edge detector. Larger wavelength of sinusoid will cause the wavelet to be more sensitive to the edges with larger width and vice versa. By increasing the length of the radius of the Gaussian function, frequency information related to the larger area of the image will be extracted. The two dimensional form of Gabor wavelet is as follow:

$$w(x, y, \theta, \lambda, \varphi, \sigma, \gamma) = e^{-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \varphi) \tag{14}$$

In which we have:

$$x' = x \cos\theta + y \sin\theta \tag{15}$$

$$y' = -x \sin\theta + y \cos\theta \tag{16}$$

By convolving the two dimensional Gabor wavelets with the image, wavelet coefficients can be computed. These coefficients will be in the form of a matrix, which each of its elements is a wavelet coefficient related to its corresponding pixel of the input image. The absolute value of the coefficients of pixels related to edges will be much greater. In the Gabor wavelet there are five control parameters: $\theta$, $\lambda$, $\varphi$, $\sigma$ and $\gamma$.

$\theta$ determines the orientation of the wavelet. This parameter rotates the wavelet around its center. The orientation of the wavelet specifies the angles of edges that the wavelet responds to them. In many cases, $\theta$ includes values between zero and $\pi$. As the symmetric property of the wavelet, $\theta$ values between $\pi$ and $2\pi$ are redundant.

$\lambda$ specifies the wavelength of cosine signal or in other words it specifies the frequency of the wavelet. Wavelets with larger wavelength are more sensitive to the gradual changes in the image and wavelets with smaller wavelength are more sensitive to the edges.

$\varphi$ is the phase of the sinusoid. Generally, Gabor wavelets are based on the cosine or the sine waves. Here, cosine waves are real parts of the wavelet and sine waves are imaginary parts of it. In most of the researches, the phase is assumed to be zero or $\pi/2$. Thus, if the phase value is assumed to be zero and $\pi/2$, real and imaginary parts of the convolution are obtained, which are the parts of complex numbers.

$\sigma$ denotes the Gaussian radius. The length of the Gaussian radius, determines the size of the region that should be affected by the convolution. This parameter is usually proportional to the wavelength, so we would have $\sigma = c\lambda$.

$\gamma$ specifies the aspect ratio of the Gaussian. Generally, this parameter is set to 1.

As can be seen, the independent parameters of Gabor wavelet are the rotation angle ($\theta$) and the wavelength ($\lambda$). Other parameters are usually set to their default values or determined based on independent parameters.

### 5.2 Gabor Wavelet Coefficients as Feature Vector

In the proposed system, features are extracted based on Gabor wavelet. As said before, each 2D Gabor wavelet can detect specific edges with respect to the direction of rotation angle and the wavelength of wavelet; therefore, Gabor wavelet is restricted by two factors:

- Direction of edge which is related to the rotation angle
- Width of edge which is related to the wavelength

In order to detect all of the edges in an image, many Gabor wavelets must be used with lots of rotation angles and wavelengths; but it is not practical. To overcome this issue, Gabor wavelet coefficients are only computed for limited number of rotation angles and wavelengths.

Selected rotation angles have to cover all of the degrees between 0 and $2\pi$, uniformly. As the symmetric property of Gabor wavelet, Gabor wavelets with rotation angles between $\pi$ and $2\pi$ are the same as their corresponding ones with rotation angles between 0 and $\pi$. For example, for given parameters, Gabor wavelet with rotation angle equal to $\pi/6$ is as the same as wavelet with rotation angle equal to $7\pi/6$. Accordingly the quantized rotation angles between 0 and $\pi$ are sufficient to cover all of the angles. For example $0,\frac{\pi}{8},\frac{\pi}{4},\frac{3\pi}{8},\frac{\pi}{2},\frac{5\pi}{8},\frac{3\pi}{4},\frac{7\pi}{8}$ can be considered as quantized rotation angles. The more number of rotation angles, the more accuracy for edge detection and more computational complexity as a result.

The wavelengths are selected based on the application. The narrower edges can be detected by smaller wavelengths and vice versa. The number of wavelengths depends to the variety of edges in the image. The selection of different wavelengths results in multi-scale or multi-resolution processing.

The convolution of Gabor wavelet with all of the pixels of an image is computationally complex, especially when the number of rotation angles and wavelengths are increased. Furthermore due to too many computed coefficients, feature selection or dimensionality reduction methods might be needed. To overcome this problem, Gabor wavelets are applied on only a few points (pixels), instead of all pixels of the image. These points are selected uniformly over the image which they

are placed on a virtual grid. The distance between non-diagonal adjacent grid points are named as grid distance, which are equal to a constant value.
The main reason of uniform distribution of grid points is that we do not have any prior knowledge about the shape and structure of signatures. This will become significant when one of the purposes is developing such a system that deals with signatures from different nationalities.
As the Gabor wavelet is translation, rotation and scale variant, in pre-processing stage the signature image have to be normalized by translation, rotation and scale (size).
In the proposed method for extracting features, a virtual grid is placed on the signature image that is shown in Figure 2. Then Gabor coefficients are computed on cross points of virtual grid in given rotation angles and wavelengths. These Gabor coefficients form the feature vector. The cross point of virtual grid is named as feature point.

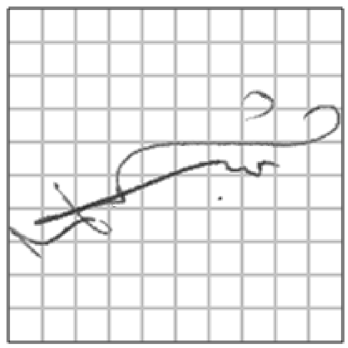

**FIGURE 2:** A virtual grid was placed on signature image.

Total number of features per signature image is pertaining to grid distance, number of rotation angles and wavelengths. For example, considering a signature image with 200x200 pixels and its grid distance equal to 20, the virtual grid consists of 9x9=81 feature points. By assuming 5 wavelengths and 8 rotation angles for Gabor wavelet, there are 5x8=40 coefficients per feature point, therefore the feature vector of each signature image comprises of 81x40=3240 coefficients totally.

The proposed method for feature extraction is independent of the nationality of signers. Unlike many other systems, the proposed system has high performance in identification and verification of signatures with different nationalities due to its independency of shape and structure of signature.

## 6 CLASSIFICATION

There are two different purposes in our system: (1) signature identification and (2) signature verification. Classifier type and classification procedure for each of these purposes are different from another, but both of them are based on distance.

In identification, classifier must determine the class of an input sample. In this case, the input of the system is a signature and the output is a class number that determines the class of input signature. In other word, the ultimate goal of identification is recognizing true class of an unknown input signature. To do this task, we used nearest neighbor classifier in our system. So, the class of input sample signature is same as class of the nearest training sample.

In verification, classifier must examine an input signature to determine whether it is genuine or not. Therefore, the input of a signature verification system has two parts: (1) a signature and (2) a claimed signer (class). Classifier must verify or reject claimed signer, whether is it genuine or forgery? In our proposed system for signature verification, classifier calculates distance of the input signature from all sample signatures of claimed class in the feature space. If minimum distance is less than a threshold, the input signature will be accepted; otherwise it will be known as a forgery signature and will be rejected.

There are many methods to calculate the distance between two points, for example: City Block (Manhattan) Distance, Euclidean Distance and Mahalanobis Distance. Euclidean Distance is a famous method that calculates the distance between two points $P_1=(x_1,x_2,x_3,\ldots,x_n)^T$ and $P_2=(y_1,y_2,y_3,\ldots,y_n)^T$ in n-dimension space by the formula:

$$D = (P_1 - P_2)^T (P_1 - P_2) \tag{17}$$

Mahalonobis Distance is a generalized form of Euclidean Distance that weighted each dimension of space by a matrix named *A*. *A* is a square and usual symmetric matrix.

$$D_A = (P_1 - P_2)^T A (P_1 - P_2) \tag{18}$$

Matrix *A* has two main effects on calculating this distance:
(1) Diagonal elements of matrix *A* change the weights of different dimensions, as weighty dimensions will have major effects. In other word, the points that have equal Euclidean Distance from an origin are on a hyper-sphere, whereas in Mahalanobis Distance, the points place on a hyper-ellipse. If matrix *A* is an identity matrix, hyper-ellipse will be converted to hyper-sphere and Mahalanobis Distance will be equal to Euclidean Distance. But if matrix *A* is a diagonal matrix, diameters of hyper-ellipse will be in parallel with the main axes of the space.

(2) In more general form, matrix *A* is a square matrix with non-zero values on non-diagonal elements. In this case, matrix *A* is same as the affine transform matrix. So, the points those have equal Mahalanobis Distances from an origin will be on a hyper-ellipse which can be rotated around some or all main axes.

In our proposed system, Mahalonobis distance is used for classification which *A* is a diagonal matrix. Matrix *A* must be computed for each class using training genuine samples, so for computing distance of an input sample from each class, we must use corresponding *A* matrix of that class. Because of applying diagonal condition on *A*'s, only the diagonal elements of matrix *A* must be computed and other elements are considered to be zero.

For a given class, if the samples in a given dimension are more distributed, these samples will have more variances in that dimension. Therefore, this dimension will not be a significant dimension and then, the corresponding diagonal element of matrix *A* will have small values. On the contrary, if the samples in a given dimension are more concentrated, this dimension will be an effective dimension and as a result, the corresponding diagonal element of matrix *A* will have bigger number.

## 7 EXPERIMENTAL RESULTS

In the signature identification, the system evaluation is determined by the correct classification rate (CCR). The accuracy of such a system is equal to the ratio of the number of correct identified signatures to the total number of signatures. More efficient systems results in closer value of CCR to one. Achieving the CCR=1 is difficult especially in a system with a large numbers of signers.
Unlike many biometric systems which is used for identification, that are evaluated by CCR, in the signature verification system, False Rejection Rate (FRR) and False Acceptance Rate (FAR) are two types of error rates and are used for evaluating the system. FRR and FAR are also named as Type 1 error and Type 2 error. FRR is related to the rejection of genuine signatures and FAR is pertaining to the acceptance of forgery signatures. In an ideal signature verification system, both of FRR and FAR must be approached to zero, but existing systems cannot achieve this purpose. Considering the application of verification system, a trade off should be determined between the FRR and FAR. Decreasing the FAR results in increasing FRR and vice versa.

In literatures another term is defined as the Equal Error Rate (EER). When system parameters are tuned in a way that the FRR is equal to FAR, this equal value is considered as EER. Usually EER is considered as the optimum state of the verification system.

### 7.1 Experiment Results on Iranian (Persian) Signature Database

To test our proposed system, we use a common Persian signature database, which contains 20 classes. There are 20 genuine and 10 expert forgery signatures per class. This database is available online at [14]. All of the signatures were signed by black pen on 10x10 cm white paper and scanned by MICROTEK ScanMarker 3630 at 300 DPI resolutions. The pre-processing stage was applied on all images. All of the algorithms were implemented in MATLAB 7.1 environment.

Except the $\lambda$ parameter, other parameters were set to their default values as stated before. The $\lambda$ as the main parameter is tested with different values. Five parameters of the Gabor wavelet were determined as follows.

- $\theta$ has to cover the angles between 0 and $\pi$ degree. In the proposed system $\theta$ includes $0, \frac{\pi}{8}, \frac{\pi}{4}, \frac{3\pi}{8}, \frac{\pi}{2}, \frac{5\pi}{8}, \frac{3\pi}{4}, \frac{7\pi}{8}$.
- $\varphi$ was set to 0 and $\pi/2$. 0 and $\pi/2$ refer to real and imaginary parts of the wavelet respectively.
- $\sigma$ is usually proportional to the wavelength i.e. $\sigma = c\lambda$. In the proposed system $c$ was set to 3.
- $\gamma$ determines the aspect ratio of the mask, that was equal to 1 in order to form a square mask.

Two different value sets were investigated for $\lambda$ parameter: $2\sqrt{2},4,4\sqrt{2},8$ and $4,4\sqrt{2},8,8\sqrt{2}$. By selecting these two sets, the effect of wavelength on the system performance can be examined. In addition, the grid distance is set to 10 and 20 in two different experiments.

Table 1 shows the CCR of the proposed system on the Persian signature database. In this test, there are 10 samples for training and 10 samples for testing.

**TABLE 1:** Signature identification results on Iranian (Persian) signature database

| $\lambda$ | Grid Distance | CCR (%) |
|---|---|---|
| $2\sqrt{2},4,4\sqrt{2},8$ | 10 | 97.5 |
| | 20 | 98.0 |
| $4,4\sqrt{2},8,8\sqrt{2}$ | 10 | 99.5 |
| | 20 | 100 |

The EER values related to signature verification on the Persian signature database is illustrated in Table 2. In this experiment, 10 genuine signatures were used for training phase and 10 genuine and 10 expert forgery signatures were used for test phase. Experimental setup is similar to the real world conditions that there is no forgery samples for training phase and the system must be trained only by genuine samples.

**TABLE 2:** Signature verification results on Iranian (Persian) signature database

| $\lambda$ | Grid Distance | EER (%) |
|---|---|---|
| $2\sqrt{2},4,4\sqrt{2},8$ | 10 | 17.0 |
| | 20 | 19.5 |
| $4,4\sqrt{2},8,8\sqrt{2}$ | 10 | 15.0 |
| | 20 | 17.0 |

According to the experimental results on the Persian signature database shown in Table 1 and 2, $4,4\sqrt{2},8,8\sqrt{2}$ were selected as $\lambda$ values and the grid distance was set to 10.

### 7.2 Comparison With Other Methods

In this section, the proposed system is compared with some methods with different signature databases. These databases are from countries with different signature styles. The proposed system is also compared with the subjective method (human discrimination capability).

#### 7.2.1 Persian Signature Database

The database that is used in this experiment is the same as the one that used in the previous section and contains 20 classes [14]. The CCR and EER of proposed system are 100% and 15% respectively.
The proposed system is compared with Mohamadi's [15] method, Kiani et al's [11] method, Pourshahabi et al's [12] method. Mohamadi [15], proposed a signature identification system based on PCA and MLP and achieved CCR equal to 91.5%. Kiani et al [11] presented a signature verification system which employed local Radon transform and SVM. In the average case FAR and FRR are 20% and 10.5% respectively. Pourshahabi et al [12] extracted features using Contourlet transform and classified them by Euclidian distance. CCR is equal to 100% in signature identification, FAR and FRR are 14.5% and 12.5% respectively in signature verification.
In Table 3**Error! Reference source not found.**, the comparison of the proposed system with the methods stated in [11], [12] and [15] are shown. The CCR of the proposed method is better than the CCR in [15] and is equal with the CCR in [12]. However the methods which presented in [11] and [12] have lower FRR compared to our proposed method, but the difference of EER between our proposed method and these methods is negligible.

**TABLE 3:** Comparison of proposed system with other systems on Iranian (Persian) signature database

| Method | Signature Identification | Signature Verification | | |
|---|---|---|---|---|
| | CCR (%) | FAR (%) | FRR (%) | EER (%) |
| Kiani et al [11] | - | 20.0 | 10.5 | 15.25 |
| Pourshabi et al [12] | 100 | 14.5 | 12.5 | 13.5 |
| Mohamadi [15] | 91.5 | - | - | - |
| The proposed system | 100 | 15.0 | 15.0 | 15.0 |

#### 7.2.2 South African Signature Database

This database contains 924 English signatures collected from South Africa which used in [9] in order to evaluate signature verification system. There are 22 classes in this database. There are 10 genuine signatures for training purpose, 20 genuine signatures, 6 simple forgery signatures and 6 expert forgery signatures in each class for test.

The proposed system achieved the EER rate equal to 6.3% and 16.8% for simple and expert forgery respectively. However the results show that the proposed system has higher error rate in simple forgery compared to the method presented in [9], but it is more reliable for expert forgery signatures.

Kiani et al [11] achieved the average FAR and average FRR equal to 0.5% and 42.7% respectively for simple forgery. In addition, the average FAR and average FRR of their system are equal to 12.1% and 42.7% respectively for expert forgery. Pourshahabi et al [12] reported 2.3% and 23.2% as the FAR and FRR respectively for simple forgery. In this system, FAR and FRR for expert forgery are 22.7% and 23.2% respectively. All of these results are summarized in Table 4. From Table 4, it is obvious that the proposed system is the most reliable system against expert forgery signature.

**TABLE 4:** Comparison of the proposed system with other systems on South African signature database

| Method | Simple Forgery | | | Expert Forgery | | |
|---|---|---|---|---|---|---|
| | FAR (%) | FRR (%) | EER (%) | FAR (%) | FRR (%) | EER (%) |
| Coetzer et al [9] | 4.5 | 4.5 | 4.5 | 18.0 | 18.0 | 18.0 |
| Kiani et al [11] | 0.5 | 42.7 | 21.6 | 12.1 | 42.7 | 27.4 |
| Pourshahabi et al [12] | 2.3 | 23.2 | 12.75 | 22.7 | 23.2 | 22.95 |
| The proposed system | 6.3 | 6.3 | 6.3 | 16.8 | 16.8 | 16.8 |

### 7.2.3 Turkish Signature Database

This signature database is used by [5] and comprises 40 classes. There are 8 genuine signatures and 4 forgery signatures in each class. 30 different individuals other than genuine signers signed all of the forgery signatures.

Ozgunduz et al [5] presented a signature verification method by considering three types of features: (1) global features, (2) directional features, and (3) grid features. The FAR and FRR of this system are 11% and 2% respectively, while the proposed system achieved the FAR and FRR equal to 10% and 8% respectively. The results of the comparison are presented in Table 5.

**TABLE 5:** Comparison of the proposed system with the other system on Turkish signature database

| Method | FAR (%) | FRR (%) | EER (%) |
|---|---|---|---|
| Ozgunduz et al [5] | 11.0 | 2.0 | 6.5 |
| The proposed method | 10.0 | 8.0 | 9.0 |

### 7.2.4 Spanish Signature Database

Spanish signature database is collected by Frias-Martinez et al [4]. This database includes 228 signatures from 38 persons (6 signatures per class). They proposed a signature identification system based on SVM and compared that with similar system that used MLP. In the best case, their system can identify an input signature with CCR equal to 71.2%. In their experiment, only 1 training signature is used per class, therefore, it is very similar to the real world conditions. They concluded that the global features are better than raw bitmap features and SVM classifier has higher CCR compared to MLP. In the same experimental conditions, our proposed system could achieve higher CCR (77.3%) in comparison with the method presented in [4].

In another experiment, the proposed system is evaluated on this Spanish signature database by using more training samples. Table 6 shows the results of this experiment.

**TABLE 6:** Comparison of the proposed system with the other system on Spanish signature database

| Number of training samples | CCR (%) | |
|---|---|---|
| | Frias-Martinez et al [4] | The proposed method |
| 1 | 71.2 | 77.3 |
| 2 | - | 89.3 |
| 3 | - | 92.9 |

## 7.3 Comparison With Human Accuracy in Signature Identification and Verification

In this section, human accuracy in signature identification and verification is investigated. For this purpose, the Persian signature database, which was introduced in previous section, is used. As stated before, this database contains 20 classes and in each class, there are 20 genuine signatures and 10 expert forgery signatures. In the first experiment for signature identification, only genuine signatures are used: 10 signatures for training and 10 signatures for testing. In another experiment for signature verification, only 10 genuine signatures are used for training. 10 other genuine signatures and 10 forgery signatures are also used for testing phase. As you can see, in this experiment no forgery signatures were used for training similar to the real world conditions. For evaluating the human accuracy, 10 persons (25 to 36 years old) were invited to participate in these experiments.

In the first experiment for evaluating the human accuracy in signature identification, all of the training signatures were shown to each of the participant. Each participant could look at signatures without any time limitation. Moreover, during the testing phase, the participant could see the training signatures again. The participant had to identify the class of each test signature. There is not any specific order in displaying signatures to the participants and the signatures were selected randomly from different classes. All of the participants could identify signatures correctly, in other word the CCR of all 10 participants was 100%. Therefore, it can be concluded that the accuracy of the proposed system is the same as the accuracy of the humans.

In another experiment for investigating the human accuracy in signature verification, each participant can only look at 10 training genuine signatures pertaining to a specific class. Afterward genuine and forgery signatures corresponding to that class were randomly displayed to the participants in order to be accepted or rejected. This operation was repeated for all 20 classes. In Table 7 the FAR and FRR of each participant is shown.

As shown in Table 7, the average FAR and FRR of participants are 25.2 and 17.25 respectively. In the best case, the minimum FAR and FRR of participants are 22.5% and 15.5% that are related to person No. 3 and No. 8 respectively, while the EER of the proposed system is 15%. The average FAR and average FRR of the method presented in [11] are 20% and 10.5%. In addition, the FAR and FRR of Pourshahabi et al's [12] method are 14.5% and 12.5% respectively. These results show that the FAR of automatic systems and the humans are greater than FRR; therefore, it can be considered that the forgery signatures are expert type and are difficult to detect. In addition, with respect to the lower FAR of all automatic signature verification systems, it shows that these automatic verification systems are more accurate than the humans verification.

**TABLE 7:** Results of the human accuracy in signature identification and verification upon 10 subjects

| Subject | FAR (%) | FRR (%) |
|---|---|---|
| Person 1 | 26.5 | 17.5 |
| Person 2 | 28.5 | 18.0 |
| Person 3 | 22.5 | 16.5 |
| Person 4 | 23.0 | 19.5 |
| Person 5 | 24.5 | 16.5 |
| Person 6 | 27.0 | 16.0 |
| Person 7 | 25.5 | 17.5 |
| Person 8 | 24.0 | 15.5 |
| Person 9 | 26.0 | 18.0 |
| Person 10 | 24.5 | 17.5 |
| Mean | 25.2 | 17.25 |
| Standard Deviation | 1.86 | 1.16 |

## 8 CONCLUSION AND FUTURE WORKS

The algorithm, presented in this paper, is employing Gabor wavelet for feature extraction could achieve satisfying accuracy, although the simplest method i.e. nearest neighbor was used as the classification stage. As the pixel distribution of signature curvature is unknown overall image, unlike many current approaches, the proposed method is independent of the shape and the style of signature. The proposed system has higher performance in identification and verification of the signatures with different nationalities due to its independency of the shape and the structure of signatures. This is verified by testing the proposed system on 4 signature databases with different nationalities including Iranian (Persian), South African, Turkish and Spanish signatures. In addition, comparative experiments with 6 methods [4, 5, 9, 11, 12, 15] are presented. Even the system structure of the proposed method is simple; its accuracy is equal or even greater than the similar systems. According to another experiment, it was shown that the accuracy of our proposed system is equal to and greater than the human accuracy in signature identification and signature verification respectively.

Riesenhuber et al's [16] algorithm as a powerful method for object recognition is suggested for future works. This method is a hierarchical model inspired by the cortex structure of human's brain. The object recognition procedure in cortex employs a kind of hierarchical multi-resolution and -direction edge detection. This model is known as HMAX.

In the proposed system, the weighted distance was used in nearest neighbor classifier. It is suggested to use the other powerful statistical pattern recognition method such as SVM in classification stage.

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