An Ensemble Classifier Approach for Static Signature Verification Based on Multi-Resolution Extracted Features

Mohamad Hoseyn Sigari[1,2], Muhammad Reza Pourshahabi[1] and Hamid Reza Pourreza[1]

[1]*Machine Vision Research Lab., Computer Engineering Department, College of Eng.*
Ferdowsi University of Mashhad, Mashhad, Iran
[2]*Control and Intelligent Processing Center of Excellence (CIPCE)*
Electrical and Computer Engineering Department, College of Engineering
University of Tehran, Tehran, Iran
hoseyn_sigari@ieee.org, reza.pourshahabi@gmail.com, hpourreza@um.ac.ir

Abstract

Ensemble classifier is a combining approach to improve the accuracy of the simple classifiers. In this article, we introduced a new method for static handwritten signature verification based on an ensemble classifier. In our introduced method, after pre-processing stage, signature image is convolved with Gabor wavelets to compute the Gabor coefficients in different scales and directions. Three different feature sets are extracted from resulting Gabor coefficients using statistical approaches. A nearest neighbor classifier classifies each feature set by an adaptive method. The proposed ensemble classifier combines the output of the three simple classifiers, which are essentially the same. Although these simple classifiers looks the same, but the different input feature set and the adaptive thresholds related to each classifier makes them to be different with each other. Therefore, from the viewpoint of the classifiers combination, the proposed method can be considered as a feature level combination type. The proposed method was evaluated by applying on two datasets: Persian and South African signature datasets. Experimental results shown our proposed method has the lowest error rate in comparison with other methods.

Keywords: *signature verification; ensemble classifier; classifier combination; multi-resolution analysis; Gabor wavelet*

1. Introduction

Nowadays, identification and verification is vital in security and resource access control. An interesting method for identification and verification is biometric approaches. 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. Handwritten signature is one of the oldest biometrics.

Handwritten signature verification is simple, fairly secure, inexpensive, non-intrusive and acceptable in society. Nevertheless, it has some drawbacks: higher error rate in comparison with 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 that is written in a special style but Persian signature contains some curves and symbols [1, 2].

The goal of signature verification is examination of an input signature to determine whether it is genuine or forgery. Therefore, 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.

(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 moment.

(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 verification: (1) static or offline and (2) dynamic or online. In the offline type, the input of the system is a 2D image of the signature. In contrast, in the online type, the input is the signature trace in time domain. In 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 2D coordinates and t as the time of sampling. Therefore, in the online type, the time attribute of each sample helps us to extract useful information such as the start and stop points, speed 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 error rate in the online type is lower than the offline type, but the online type has a major disadvantage; it is online. So, it cannot be used for some important applications such as check cashing, which the signer cannot sign on a digital tablet.

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 the acceptance rate 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. 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.

In this paper, we propose an ensemble classifier for static signature verification, which uses a feature-level classifier combination method. The structure of the paper is organized as follow: In this part, an introduction was presented; afterward related works will be reviewed in section 2. The structure of the proposed system, the details of the pre-processing, the feature extraction method and the classification approach are explained in section 3. Section 4 reports the experimental results, and the last section is about the conclusions, and future works.

2. Related Works

In this section, a review on static handwritten signature verification methods is presented.

Ozgunduz et al [3] 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 [4] presented a quasi multi resolution approach for offline signature identification and verification. First, all signatures 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 and therefore, feature extraction acts like a multi-resolution processing.

Deng et al [5] proposed a wavelet-based offline signature verification system. This system extracts robust features within different signatures of the same class and verifies whether a signature is forgery or not. After pre-processing stage, the system starts with a closed contour tracing algorithm to extract the closed contour of the signature. The curvature data of the closed contours are decomposed to low and high frequency bands using wavelet transform. Then the zero crossing information corresponding to the curvature data are extracted as features. Classification stage in this system is very simple and performed only by applying a threshold. The threshold value which is used for verifying an input signature is calculated automatically based on the distribution of the features in each class. Experimental results were done on two different signature databases: English and Chinese; these results show that nationality had no effect on the system accuracy.

Herbst et al [6] 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 was applied to extract features. A grid relation between the features of the input signature and the features of the reference signatures was created using Dynamic Programming. Afterward, matching analysis was done to accept or reject the input signature.

Coetzer et al [7] 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 was used in this paper.

Ferrer et al [8] introduced some new geometric features for offline signature verification based on signature curvature and distribution of strokes in Cartesian and Polar coordinates. 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 [9] extracted appropriate features by using Local Radon Transform applied to the signature curvature. The extracted features were classified using SVM classifier. Their proposed method is robust against to the noise, translation and scaling. Experimental results were implemented on two signature databases: Persian (Iranian) and South African.

Pourshahabi et al [10] presented an offline signature identification and verification using Contourlet Transform. Contourlet is a two dimensional multi-resolution transform that extracts curves with different thicknesses and curvatures from an image. 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 South African.

McCabe et al [11] assessed the effect of different conditions on the performance of MLP in signature verification systems. The experiments comprised the following conditions: various MLP structures, different learning algorithms and selecting negative samples for training phase. In an experiment, they used an ensemble classifier using a MLP per class (signer) and concluded that ensemble classifier has lower error rate than other cases.

Panton et al [12] introduced a signature verification system based on DRT and ensemble classifier of HMMs. This system trains a HMM classifier per different local DRT features and also trains a HMM for global DRT features. Afterward these HMM classifiers are selected to form an optimal ensemble classifier using a simple selection method. They showed that ensemble classifier and local DRT features could decrease the system error rate about 31%.

3. The Proposed System

The proposed system consists of two main parts. After signature acquisition and image pre-processing, signature images are analyzed by Gabor wavelet. Gabor wavelet coefficients of each image are processed based on three different statistical methods and then three feature sets are extracted from each image. Next, a Nearest Neighbor (NN) classifier classifies each feature set and finally, the results of all classifiers are fused and the final decision is made. Figure 1 shows the diagram of the proposed system; the details of each part will be explained in the following sections.

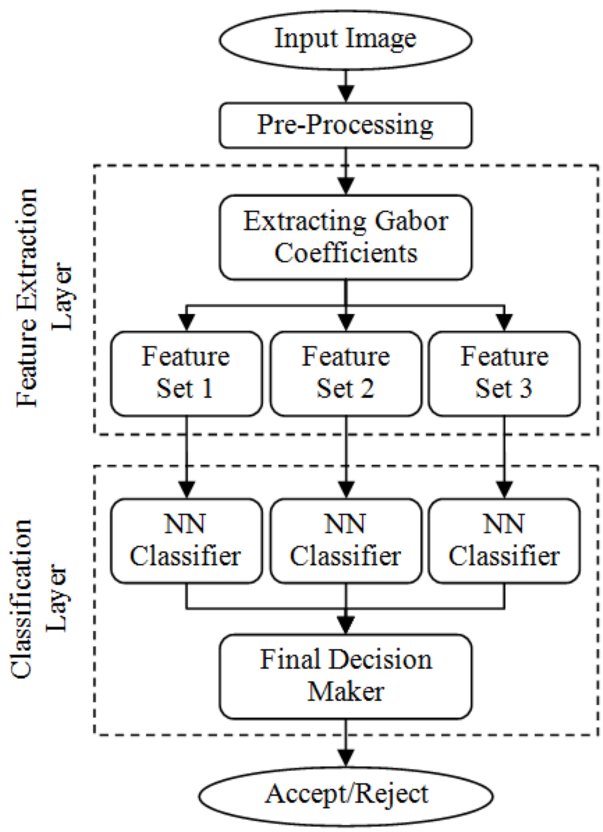

Figure 1. Flowchart of the Proposed System.

3.1. Pre-Processing

The pre-processing stage is the first part of the proposed system, which consists of rotation normalization, determination of the outer rectangle of the signature, size normalization and finally image enhancement.

3.1.1. Rotation Normalization

In order to accomplish rotation normalization, the signature image is rotated as far as the minimum inertia is located in the horizontal wise. This method was presented by Kalera et al [4]. In this method the signature contour is indicated with C that comprises of N pixels.

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

$X(i)$ = the vector which includes x and y coordinates of the ith pixel of the signature contour

$u(i)$ = x coordinate of the ith pixel of the signature contour

$v(i)$ = y coordinate of the ith pixel of the signature contour

The $(\bar{u}, \bar{v})$, the 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 moments, $\overline{u^2}$ and $\overline{v^2}$ of the signature contour are 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.

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

3.1.2. 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).

3.1.3. 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 height and the width of the signature are computed and then the larger one is selected. A constant number is also chosen as normal size (in this paper it is 200 pixels). Now the height and the width of the image will be changed by a constant aspect ratio until the larger dimension is equaled to the normal size. Therefore, in the signatures with width greater than height, the normalization will be based on the width, and vice versa.

3.1.4. Image Enhancement

The resulted binary image in the 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 255.

3.2. Feature Extraction

In the proposed system, the features are extracted using statistical analysis of Gabor coefficients. In this section, first, Gabor wavelet is described briefly and then the feature extraction method will be explained.

3.2.1. Gabor Wavelet and Gabor Coefficients

Gabor wavelet is produced by multiplying a sinusoid function with a Gaussian function in spatial domain. By convolving a signal with the Gabor wavelet, the frequency information of the signal nearer to the center of the wavelet is obtained. A 1D 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 the wavelet, ω is the angular frequency ($\omega = 2\pi f$) and σ is the radius of the 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, which is named Gabor coefficient. Gabor wavelet coefficients can be stated based on angle and magnitude or based on real and imaginary parts.

In image processing, the 2D Gabor wavelet transform is used. These wavelets are the result of the multiplication of a 2D sinusoid function by the 2D Gaussian function. The sinusoid function extracts frequency information corresponding to its frequency and the Gaussian function determines the region of effects of the sinusoid function. 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 considered. The 2D form of Gabor wavelet is as follow:

$$w(x,y,\theta,\lambda,\varphi,\sigma,\gamma) = e^{-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}} \cos(2\pi\frac{x'}{\lambda}+\varphi) \tag{9}$$

In which:

$$x' = x\cos\theta + y\sin\theta \tag{10}$$

$$y' = -x\sin\theta + y\cos\theta \tag{11}$$

By convolving the 2D Gabor wavelets with the image, wavelet coefficients can be computed. In Gabor wavelet there are five control parameters: θ, λ, φ, σ and γ.

θ 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, θ includes values between zero and π. As the symmetric property of the wavelet, θ values between π and 2π are redundant.

λ 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 sharp edges.

φ is the phase of the cosine signal. Generally, Gabor wavelets are using the cosine or the sine waves. Here, cosine waves are the real parts of the wavelet and sine waves are the 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 $\pi/2$, the real and imaginary parts of the Gabor coefficients are calculated respectively.

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

γ 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 (θ) and the wavelength (λ). Other parameters are usually set to their default values or determined based on the independent parameters.

In the proposed system, features are extracted based on Gabor wavelet, which can detect the edges of an image. The two main attributes of an edge are direction and width of edge, which are related to the rotation angle and wavelength of Gabor wavelet respectively.

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 numbers of rotation angles and wavelengths.

Selected rotation angles have to cover all of the degrees between 0 and 2π, uniformly. As the symmetric property of Gabor wavelet, Gabor wavelets with rotation angles between π and 2π are the same as their corresponding ones with rotation angles between 0 and π. Accordingly, the quantized rotation angles between 0 and π are sufficient to cover all of the angles. 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 on the variety of the edges in the image.

In the proposed system, we use $\left\{0,\frac{\pi}{8},\frac{\pi}{4},\frac{3\pi}{8},\frac{\pi}{2},\frac{5\pi}{8},\frac{3\pi}{4},\frac{7\pi}{8}\right\}$ and $\{2,2\sqrt{2},4\}$ for rotation angles and wavelengths respectively, therefore, there are 24 different Gabor filters. After convolving a signature image by all Gabor filters, 24 2D coefficient matrixes are obtained, which are denoted by C_i while $i \in \{1,2,..,24\}$ and the size of these coefficient matrixes are equal to the image size. Next, three feature sets are extracted based on these coefficient matrixes; the feature extraction methods will explained in the next sections.

3.2.2. The First Feature Set

We assumed that the size of the signature image is N×N, therefore the size of each Gabor coefficient matrix is equal to N×N. The AM matrix is the pixel-wise arg-max of coefficient matrixes and defined as below:

$$AM = \arg\max_{\forall i}\{C_i\} \tag{12}$$

According to the above definition, AM is a N×N matrix that is composed from natural numbers between 1 and 24.

The first feature set is the histogram of AM and counts the dominant edges in different width and orientation. The length of the first feature set is 24.

3.2.3. The Second Feature Set

The second feature set is based on a special co-occurrence matrix, which is defined over AM to compute the distribution of co-occurring values at a given neighborhood. As the AM is formed by natural numbers between 1 and 24, the co-occurrence matrix $CO_{\Delta p,\Delta q}$ for a given neighborhood $(\Delta p, \Delta q)$ is a 24×24 matrix and defined as below:

$$CO_{\Delta p,\Delta q}(i,j) = \sum_{p=1}^{N}\sum_{q=1}^{N}\begin{cases}1 & \text{if } AM(p,q)=i \text{ and } AM(p+\Delta p, q+\Delta q)=j \\ 0 & \text{else}\end{cases} \tag{13}$$

In this paper, we use three different neighborhood and their corresponding co-occurrence matrix as second feature set: $CO_{0,1}$, $CO_{1,0}$ and $CO_{1,1}$. Therefore, the second feature set is composed of three 24×24 matrixes and describes the texture of the image by computing the distribution of co-occurring dominant edges with different widths and orientations at a given neighborhood.

3.2.4. The Third Feature Set

The third feature set is another form of co-occurrence matrix, which is named BCO. First, we apply a constant threshold on each of the coefficient matrix C_i and convert them into some binary images which are denoted by BC_i.

$$\forall p,q \quad BC_i(p,q)=\begin{cases}1 & if\ C_i(p,q)\geq th\\ 0 & else\end{cases} \tag{14}$$

Next, BCO is computed based on the below equation:

$$\forall i,j\in\{1,2,...,24\} \quad BCO(i,j)=\sum_{p=1}^{N}\sum_{q=1}^{N}BC_i(p,q)\cdot BC_j(p,q) \tag{15}$$

In the above equation, the multiplication between $BC_i(p,q)$ and $BC_j(p,q)$ is equal to the logical conjunction between these operands, as they are logical variable.

The third feature set is 24×24 BCO matrix that describes the texture of the signature image like two other feature sets, but from different viewpoint. BCO matrix computes the distribution of co-occurring edges with different widths and orientations at a given pixel.

3.3. Classification

The classification phase in the proposed system uses an ensemble classifier. The proposed ensemble classifier consists of three simple classifiers, which are based on Nearest Neighbor (NN). The final decision maker combines the decisions of the simple classifiers to determine the final decision.

3.3.1. The Simple Classifiers

The proposed ensemble classifier consists of three simple NN-based classifiers that use Euclidean distance. Each simple classifier uses one of the feature sets, from the three feature sets described before. In the other word, the simple classifiers in ensemble classifier are equal, but their input features are different.

Each classifier must examine an input signature to determine whether it is genuine or forgery. Therefore, the input of a signature verification system has two parts: (1) a signature image and (2) a claimed signer (class). The classifier must verify or reject the claimed signer, whether it is genuine or forgery. In our proposed system for signature verification, each simple classifier calculates the distance of the input signature from all training samples of the claimed class in the corresponding feature space. If the 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. Verification process can be modeled mathematically as below:

$$\begin{cases} I\ is\ acceptable\ as\ genuine\ \ signature\ \ of\ class\ c & if\ \min_{l}\{\|I-S_{c,l}\|\}\leq th_c\\ reject & else\end{cases} \tag{16}$$

In the above equation, I is the input signature, c is the claimed class, $S_{c,l}$ is the lth training sample of class c and th_c is its corresponding threshold. All training samples for each class are only genuine and we do not use forgery signatures as training sample.

The considered threshold for classifying genuine and forgery signatures is determined adaptively and separately for each class. The threshold for class c is equal to the average distance of the training samples $S_{c,l}$ from the prototype of the class. In our proposed system, we use the average of the training samples as prototype of each class. Therefore, th_c is computed using the below equation:

$$th_c = \underset{l}{average}\left\{ \left\| S_{c,l} - \underset{l}{average}\{S_{c,l}\} \right\| \right\} \tag{17}$$

3.3.2. Final Decision Maker

Each simple classifier of ensemble determines whether the input signature is genuine or not, independently. Finally, a combination method combines all the decisions and produces the final output.

There are many combination methods to build ensemble classifiers [14]. In this paper, three common combination methods are tested: (1) Majority Vote (MV), (2) Weighted Majority Vote (WMV) and (3) Cascade Combination (CC).

Majority vote is perhaps the simplest and most popular combination method that is used extensively in ensemble classifiers. In MV method, all classifiers operate in parallel structure independently. The output of the final decision maker is determined based on the votes that are much more than other votes. For the 2-class classification problems, such as signature verification, the number of voters must be odd.

In MV method, all classifiers in the ensemble classifier have equal importance, but in WMV, the importance of each simple classifier is different. In WMV method, vote of each classifier is weighted by a coefficient in the range (0,1), while more important classifier has more weight. MV method is a special case of WMV when the weight of all classifiers is equal to a positive constant number (for example 1). In this paper, the weight of ith classifier is denoted by w_i and is determined based on the EER of each classifier as below:

$$w_i = 1 - EER_i \tag{18}$$

According to the above equation, the weight of the classifiers has a negative linear relation with EER of the classifier, while the more accurate classifier has more weight.

In both MV and WMV methods, simple classifiers are used in a parallel structure to build the ensemble classifier. In CC method, serial (cascade) architecture is used to form the ensemble classifier. In CC method as depicted in Figure 2, the simple classifiers operate serially, which means that where a simple classifier accepts a signature, the ensemble classifier will accept it. In this method, a signature is a forgery sample if and only if, all the simple classifiers reject it as a forgery signature.

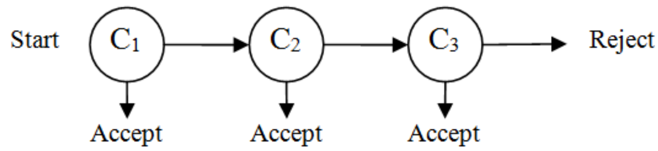

Figure 2. Architecture of Cascade Combination Method

According to the architecture that is shown in Figure 2, the FAR of the simple classifiers must be less than the FRR to get better accuracy. If the FRR of the simple classifiers was less than the FAR, we still can use CC method but with different architecture. In this case, a signature will be a genuine sample if all the simple classifiers accept it as genuine signature.

In the proposed CC method, the order of the simple classifiers plays a major role, while they must be sorted based on ascending order of FAR to achieve the maximum accuracy. In the other word, the FAR of the classifier C1 must be lower than C2 and the FAR of the classifier C2 must be lower than C3.

4. Experimental Results

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 in [15]. 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 R2008a.

4.1. Experiments on the Simple Classifiers

Testing each simple classifier is the first phase of the experiments. As mentioned before, the simple classifiers are the same, but their input features are different. The result of each simple classifier for signature verification is shown in Table 1. According to the results in Table 1, the best EER is related to the first feature set.

Table 1. The Result of Experiments on each Simple Classifier

Classifier Name	Feature Set	FRR (%)	FAR (%)	EER (%)
NN_1	1st Feature Set	35.0	5.0	20.0
NN_2	2nd Feature Set	44.5	1.0	22.75
NN_3	3rd Feature Set	39.0	3.0	21.0

4.2. Experiments on the Ensemble Classifier

In this paper, three common combination methods were proposed to combine the output of the simple classifiers and make the final decision: (1) MV, (2) WMV and (3), CC.

In both of the MV and WMV, the order of the simple classifiers is not important and they operate in parallel. In MV method, the importance of all simple classifiers is equal, but in WMV method, the classifier which has lower EER, has more weight. According to Table 1, the weights of classifiers NN1, NN2 and NN3 are 0.8, 0.7725 and 0.79 respectively. In CC method, the simple classifiers must be sorted based on ascending order of FAR values for building the best ensemble classifier. According to Table 1, the order of the classifiers in CC architecture, which is shown in Figure 2, is NN2, NN3 and NN1. In this architecture, however the NN1 has the lowest EER with respect to the other simple classifiers, but it is used as the third step classifier in the CC method.

The performance of these three different combination methods is investigated and the results of these experiments are shown in Table 2.

Table 2. The Result of the Experiments on Different Combination Methods

Combination Method	FRR (%)	FAR (%)	EER (%)
MV	38.0	0.5	19.25
WMV	37.5	0.5	19.0
CC	16.0	8.5	12.25

According to the results in Table 2, the best combination method is CC that achieved 12.25% as EER. However, each combination method improves the accuracy of the signature verification system in comparison with the simple classifiers, but MV and WMV have less capability to improve the performance of the ensemble classifier. In addition, the EER of MV and WMV methods show that there is no significant difference between VM and WMV in combining the output of the simple classifiers. Perhaps it is related to the few numbers of the simple classifiers. In the other word, WMV is more efficient rather than MV if the number of the simple classifiers is increased.

4.3. Comparison with Other Methods

In this section, the proposed system is compared with some methods on two signature databases. The proposed system is also compared with the subjective method (human discrimination capability).

4.3.1. Persian Signature Database

The database which is used in this experiment is the same as the one that used in the before experiments, that is available online in [15]. The EER of the proposed system is 12.25% on this database.

The proposed system is compared with Kiani et al's [9] method and Pourshahabi et al's [10] method. Kiani et al [9] presented a signature verification system which employed local Radon transform and SVM. In the average case, FAR and FRR of their proposed system are 20.0% and 10.5% respectively. Pourshahabi et al [10] extracted features using Contourlet transform and classified them by Euclidian distance. FAR and FRR are 14.5% and 12.5% respectively in their introduced signature verification method.

In Table 3, the comparison of the proposed system with the methods stated in [9] and, [10] are shown. According to the presented results, however [10] has lower FAR compared to our proposed method, but the EER of the proposed method is the lowest one.

Table 3. Comparison of Proposed System with Other Systems on Persian Signature Database

Method	FAR (%)	FRR (%)	EER (%)
Kiani et al [9]	20.0	10.5	15.25
Pourshabi et al [10]	14.5	12.5	13.5
The proposed system	16.0	8.5	12.25

4.3.2. South African Signature Database

This database contains 924 English signatures collected from South Africa which used in [7] in order to evaluate signature verification system. This database contains 22 classes. There are 10 genuine signatures for training purpose, 20 genuine signatures, 6 simple forgery signatures and 6 expert forgery signatures for test in each class.

The proposed system achieved the EER rate equal to 4.4% and 14.65% 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 [7], but it is more reliable for expert forgery detection.

Kiani et al [9] achieved the average FRR equal to 42.7%. In addition, the average FAR of their system is equal to 0.5% and 12.1% for the simple and expert forgery respectively. Pourshahabi et al [10] reported 2.3% and 23.2% as the FAR and FRR respectively for the simple forgery. In this system, FAR and FRR for the expert forgery are 22.7% and 23.2% respectively. All of these results are summarized in Table 4. By comparing the EER of the different methods in Table 4, it is obvious that the proposed system is the best method in both of the simple and the expert forgery detection.

Table 4. The 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 [7]	4.5	4.5	4.5	18.0	18.0	18.0
Kiani et al [9]	0.5	42.7	21.6	12.1	42.7	27.4
Pourshahabi et al [10]	2.3	23.2	12.75	22.7	23.2	22.95
The proposed system	1.5	7.3	4.4	22.0	7.3	14.65

5. Conclusion and Future Works

In this paper, a method based on classifier combination at feature level was introduced. The proposed method used three different feature types with three separate Nearest Neighbor classifiers, while each classifier can operate adaptively and separately. Three combination methods including majority vote, weighted majority vote and cascade combination, were investigated to combine the output of the simple classifiers and make the final decision. Although the experiments showed that all the investigated combination methods has lower EER compared to the simple classifiers, but the cascade combination acts as the best combination method.

The proposed method was evaluated on two databases: Persian signature database and South African signature database. In addition, it was compared with three other signature verification methods. Comparison results showed that the proposed system is better than other methods.

For future work, it is suggested to increase the number of feature types and test other classification methods instead of the Nearest Neighbor classifier. The proposed combination method is based on the feature level fusion. For the next experiments, other combination approaches such as fusion in the classification level are suggested, which employ different type of simple classifiers and combine them to take the final decision.

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Authors

Mohamad Hoseyn Sigari received his B.Sc. and M.Sc. degrees in computer engineering from Ferdowsi University of Mashhad and Iran University of Science and Technology, in 2006 and 2008 respectively with first class honor. At present, he is a Ph.D. candidate in the department of electrical and computer engineering, University of Tehran, Tehran, Iran. Also, he is a research assistant in machine vision research laboratory, computer engineering department, Ferdowsi University of Mashhad. His research interests are machine vision, biometric, semantic video analysis and intelligent transportation systems.

Muhammad Reza Pourshahabi received his B.Sc. in computer hardware engineering from Ferdowsi University of Mashhad, Iran, in 2006. He received the M.Sc. in computer software engineering from Ferdowsi University of Mashhad, in 2009. Now, he is a faculty member of computer engineering department, Salman institute of higher education, Mashhad, Iran. Also, he is a research assistant in machine vision research laboratory, computer engineering department, Ferdowsi University of Mashhad. His research interests are image processing, machine vision, medical image processing and biometric.

Hamid Reza Pourreza received his B.Sc. degree in electrical engineering from Ferdowsi University of Mashad, Iran, in 1989. He received his M.Sc. and Ph.D. degrees in electrical engineering and computer engineering from Amirkabir University of Technology, Iran, in 1992 and 2003, respectively. Now, he is an associate professor in the department of computer engineering, Ferdowsi University of Mashad, Iran. His research interests are image processing, machine vision, hardware design and intelligent transportation systems.