A multimodal authentication for biometric verification system using palmprints and fingers

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Abstract: Trusted identification approaches play a critical role in everyday life and daily activities of humans. Hand as a physiological characteristic that has high acceptability and stability that contains several biometrics components has attracted the attention of many scholars so that almost all parts of it are considered as a member of the biometric system. The proposed method in this research is verification by a color image of the palm of the hand and the index, middle, ring and little fingers which is implemented by a new method for extracting texture features on images of 177 individuals from the Hong Kong Polytechnic University Contact- Free 3D / 2D Hand Images Database. The proposed feature extraction method is the use of Turn Counts in each of Gabor's filters applied in different directions and scales on each of the RGB components of the images individually. Before classification, a binary genetic algorithm is applied to use the best combination of features for each color component. The system performance has been studied in unimodal and multimodal modes using the SVM classification and the best result is obtained based on combining the features of the palm and four fingers with an EER of 0.67 ± 0.13. Also, the effectiveness of this method has been investigated by generalizing the feature extraction method on other databases in this domain.

Keywords: Biometric, Verification, Palm, Fingers, Gabor Transform, Turn Counts

1. Introduction

The issue of security is very important in every area including access to sensitive and important information, use of facilities specific to certain individuals, access to computer networks and entry into the strategic sites such as military places. With the advent of biometrics conventional verification methods have been altered in biometric systems and are being replaced by methods based on symptoms. Biometric methods are based on the individual features of each individual and are the best methods for verifying the identity of individuals because all of these features are associated with the person and belong to him [30].

According to the studies the user verification systems that use a biometric method often have noisy data and unlimited error rates. Therefore, in order to improve the efficiency, multimodal biometric systems are used [32]. In recent years, numerous studies have been carried out in the field of multimodal biometric systems. Unlike the Unimodal Biometric Systems that use only one biometric characteristic, the Multimodal Biometric Systems combine two or more biometric properties to authenticate each other that usually solve the problems of associated with the lack of comprehensiveness of unimodal systems and on the other hand, they are more resistant to noise and inter and intra-class variations [1,2]. Also, these systems are more resistant to fraud because it would be difficult for a fraudulent to simulate several biometric features of a real user at the same time. During the recent years, the hand biometric system has attracted the attention of many researchers. The approaches presented in the field of hand biometrics show that these approaches have a relatively high efficiency in authentication. Of course, it should also be noted that hand in an effective organ in biometric systems so that its different parts such as palms, fingers, fingerprints, blood vessel patterns on both sides and hand geometry are used as biometric features [3-5,52].

The importance of selecting palms and fingers as biometrics is due to several reasons, including the main lines in palms and fingers that are still recognizable in low-resolution images [31]. It is also clear that the identical twins also have different patterns in the palm of their hands and fingers [6]. Another advantage of biometrics is its high acceptability, as well as the sustainability of its information. Only one camera is used in combining the biometric features of the palms and fingers and an image is analyzed for both features which is more cost effective than other multimodal methods.

Also, in this method, a great part of the initial processing is on the palm of the hand and the fingers which also improves the system speed. These features have caused the multimodal systems to be considered as a good option for authentication applications. In other words in multimodal domain of the hand, it is possible to provide effective and high-accuracy approaches based on the combination of palm-finger distinguishing features.

The proposed authentication system is a multimodal system based on palm and finger attributes which will be examined in different situations. The main stages of a biometric system include data collection, preprocessing, feature extraction and classification. In this research, the Hong Kong Polytechnic University's Contact-Free 3D / 2D Hand Images Database will be used as the main database in which more data will be presented in preprocessing. Extracting the Region of Interest (ROI) of the palms and fingers and improving the quality of the images will be performed in preprocessing stage. Also, feature extraction based on the number of Turn Counts (TCs) of the Gabor filters in each of the RGB components will be introduced as a new method in feature extraction stage. Using the genetic algorithm, a combination of top features in each step is identified and the classification will be performed by the support vector machine. Finally, the results will be generalized on other databases.

In Section 2 a review of the literature and research on the palm image is presented and the multimodal methods are examined. The main idea and the proposed solution which involves obtaining the ROI for feature extraction, choosing a combination of superior features with the genetic algorithm and classification is discussed in Section 3, in Section 4, the evaluation and generalization of the results will be discussed and finally, conclusions and suggestions are provided in Section 5.

2. Review of literature

Kong and Zhang successfully used two-dimensional Gabor filter for palm identification [8]. In the proposed method, the Gabor features are calculated by applying the Gabor function on hand images and coded at the pixel level as Hamming. This method was improved by Zuo et al., so that features were extracted based on the SMCC method which obtained based on the second derivative of Gabor filters on different scales and directions [9].

The rotation and displacement of images in hand images are factors that reduce the efficiency of the Gabor-based systems [10]. On the other hand, while Gabor's function is almost resistant to brightness and contrast, changes made to the image brightness can have a detrimental effect on the system accuracy. To solve this problem Kong et al proposed the directional image displacement approach [7]. In this method, they calculated the Hamming distance for each case separately and selected the shortest distance as the final answer. Kong's method's problem in addition to increase the volume of calculations was to consider the displacement only in a limited range. Using the Gabor function Arivazhagan et al. apply the turn invariant features to classify the palm texture [56]. They computed the texture features by calculating the mean and variance of the filtered image. In this method the circular displacement of the feature components were used to become turn invariant to ensure that all images have the same principal orientation. However, this method is applicable for regular images and is not suitable for hand images with irregular texture.

Wu et al used WEF to distinguish the palm texture [11]. In this approach, they split the palm into several scales by wavelet transform and calculated the WEF values by calculating the local energy of the wavelet coefficients in different directions and scales to describe the palms. In this method, the system performance was evaluated for different wavelet functions in different scales. A remarkable point in this study was the effect on the type of wavelet function and the stages of the wavelet composition in the accuracy of the authentication system. Yih et al. used the modified haar energy (MHE) to identify the palms [12]. They initially applied the modified haar transform to the image and calculated normalized MHE values at different levels. Then they integrated the computed MHE values at different levels with a coefficient proportional to the accuracy level presented in the system to obtain the characteristic vector.

As the Gabor-based methods in the wavelet transform based method the displacement, turn and brightness variations have an adverse effect on the system performance. To solve this problem, Yang et al. suggested a statistical method for identifying the palm texture that was insensitive to turn [13]. Accordingly they transferred the palm images to the wavelet amplitude and calculated the dominant coefficients of the principle lines using the directional context modeling. Then the context values of each coefficient were defined as a function of its neighbors. After calculating the directional context values a set of statistical characteristics including the center of mass, density, distance propagation, and energy were defined for describing the palm of the hand.

The internal and external wrinkles on the fingers are one of the biometric features that can be used to for authentication. Formation of the patterns of the lines of this area goes back to the prenatal period which is determined by the genes [14]. Li et al (2014) used the internal surface of the fingers as a biometric authentication system for the first time [15]. They collected 1423 images of 73 people using the CCD digital camera. The resolution of the image base used in the study was 1792 * 1200 which was reduced to less than 70 dpi after pre-processing. They also used only the middle finger for authentication. The two methods of spatial and line features are used for feature extraction that in the first method the finger length and in the second method the middle phalanx of the middle finger were analyzed. In the second method using a defined mask the morphological operators and phalanx line threshold were extracted and used as a feature.

Liu et al. used the optimized local binary pattern (LBP) to overcome the displacement problem [16]. According to this method, the neighbors of the LBP operator were optimized according to the fingers' features. Given that the outstanding lines on the surface of the fingers are vertical, 8 neighbors are selected in the horizontal direction around the center pixel. Since the initial LBP operator has 8 circular pixels around the central pixel, the proposed method can better detect the displacement horizontally.

Saini and Sinha used a multi-faceted biometric system of palms and faces to identify individuals [17]. They used Gabor-wigner transform (GWT) to extract features from palm and face images. This transform provides an analysis of the space-frequency simultaneously on the components of a biometric image. The Particle swarm optimization (PSO) method was then used to select the dominant features. The results show that the accuracy of the multimodal system is increased compared to the unimodal state.

Perumal and Ramachandran used the back lines of the fingers and palm image in the biometric system [18]. They first extracted the local back lines of the fingers. Then they obtained distinctive features using Scale invariant feature transform (SIFT) and Speeded up robust features (SURF) algorithms and frequency characteristics. SIFT is formed by local patterns around the key points of the decomposed image. The SURF feature vectors are also derived from local patterns around the key points detected by upgraded filters. Using EMD, the frequency range of pixel levels is also obtained in each image.

Anitha and Rao provided a multimodal biometric system using the internal surface features of the middle, ring and index fingers as well as geometric features of the hand [19]. The geometric features of the hand are obtained by calculating the distance between the key points and the finger attributes are reached by the LBP algorithm.Arulalan et al. proposed a multimodal based on the middle finger and iris image [20]. The features of iris images were extracted using the wavelet coefficients and line based features for the middle finger image.

Raghavendra and Nath applied the combination of palm and hand veins for verification purposes [21]. In this study, they examined the pattern of the back of the hand veins and its combination with palm images. In order to extract the features of the images of the back of the hand veins four masks with different size were suggested and compared with standard edge detectors such as sobel and reported improvement in the results.

Chuadhary et al. used the features of palm, fingerprint and face images for authentication [22]. In this study, using the palm image in unimodal state a better result was obtained compared to the other two methods. The best result is obtained by combining all biometrics with a true acceptance rate of over 92% which is increased by 10% relative to the unimodal case.

3. Proposed method

3.1 Database

Based on the database in the field of hand images, the applied database containing color images of palms and fingers was Contact Free PolyU 2D/3D. This database has been compiled to enhance the user's level of use of the hand imaging machine with a completely non-contact system [23]. It is also the first base to provide 3D images of the hand to the researchers. The images were obtained in 2011, during the first four months of the year from 177 volunteers aged 18-54 in two seasons. The distance between two seasons was non-constant and varied from one week to three months. The images were taken in the indoor environment and in three parts with a significant difference in light. In this research, the image databases of CASIA [36], CASIA Multi-Spectral Palmprint Image Database V1.0 [37], IIT Delhi Touchless Palmprint Database (Version 1.0) [38] and Hong Kong Polytechnic University (PolyU) Palmprint Database [39] are also applied to generalize the extracted features and evaluate the system provided. Six typical images of each database are shown in Figure 1(a).

3.2 Preprocessing

Preprocessing is one of the important steps in biometric authentication systems through hand images. In fact, when images are received through digital cameras, they may include noise, transitions, and turning. Accordingly preprocessing is used to correct these problems and calculate the ROI for feature extraction [33]. Hence the set of actions taken to prepare the image for feature extraction are called preprocessing.

The use of palm image as a physiological feature in biometric systems has been well considered among scholars and researchers and therefore certain approaches have been defined in preprocessing and feature extraction. However, the use of finger images as another physiological feature in biometric systems has not been widespread in this area due to its recent emergence and no certain approach is defined in different parts of this system. However, due to the similarities between features, textures and common key points between the palms and fingers, one can use the processing approaches in the palm of the hand in different parts of finger processing with slight modifications.

3.2.1 Preprocessing of palm images

The optimal palm area should consist of a major part of the principal lines because these lines create the main features in the palm of the hand. Based on the conducted studies, these lines form in prenatal period and vary among identical twins [24]. Also, wrinkles that are

thinner than the principal lines and are irregularly distributed throughout the palm of hand, play a significant role in case of similarity of the principal lines between the people and can display more differences [34]. Therefore, in addition to the principal lines, the wrinkles are used in methods for extracting texture-based features.
According to the method presented in the first step, after transforming the color images to the grayscale, a low-pass Gaussian filter is applied to the image to eliminate the image noise. By applying this filter, the image is smoothed slightly so that it does not cause any interference in the images during the binary process of noise. In the second stage of its preprocessing, the image is binarized using an appropriate threshold. Image binarization is of great importance so that the binarized image should be uniform, without a cavity, and homogenous. Accordingly it is necessary to use optimal threshold and morphological operations.
The most important part of the hand preprocessing is to obtain the points based on which the ROI is extracted. These points are considered key points according to their importance, and the third preprocessing step is to find these points. Among the various methods available to obtain key points these points are calculated according to Lin et al. in this study [25]. This method can be used for both palms and fingers. In this method, after the image binarization, the coordinate of the boundary pixels of the image are calculated using the tracking algorithms. Then, the Euclidean distance of these points is estimated and stored by W_m (the middle point of the wrist). The distribution diagram of this vector is plotted and the first three local minima in Figure 1(b) step 1 which are specified as KP1.2, KP1.3 and KP1.4 are computed. These points are the key points for extracting the ROI shown in Fig. 1 (b) step 2.
In the fourth stage of preprocessing, the images are normalized to extract the effective features. Accordingly all images are rotated in the same size of the angle created between the vertical line and the passing line from the points KP1.2 and KP1.4 to be collinear.
The coordinate axes are defined in the fifth stage of the preprocessing. The vertical axis is the line passing through the key points KP1.2 and KP1.4 and the horizontal axis is the line perpendicular to the middle of the horizontal line. With the coordinate axes and the size of the ROI of the palm which has the constant value of 128 * 128 here, the ROI is calculated. Finally it is cut and in order to improve the image quality, for each RGB component the contrast-limited adaptive histogram equalization operator (CLAHE) is used.

3.2.2 Preprocessing of fingers images

Fingers' image is a relatively new authentication method based on physiological characteristics that has been considered as a biometer in a small scale due to similar features found in the palm of the hand.
In this study in addition to the palm images, the images of the index, middle, ring and little are also used for verification as unimodal and in combination.
Regarding the common points between the stages of extraction of the ROI of the palms and fingers, the only important point to extract the fingers is to obtain the coordinates of the fingertips in addition to the coordinates between the fingers root which is calculated in the ROI of the palms. Thus having two sets of key points of root and tip of fingers, the fingers are extracted. After transforming the color images to grayscale, applying a low pass filter, binarization of the image and obtaining three key points KP1.2, KP1.3 and KP1.4, which are common with the extraction of the ROI of the palms, the other two points should be obtained to extract the index and little fingers to complete the first series of the key points. These two points are the outer points of the little and index fingers that cannot be extracted using the previous method so these points should be calculated separately. Since the key points in the outer parts of the little and index fingers are always lower than the KP1.4 and KP1.2 points, in order to obtain these points 15 pixels should be added to the horizontal coordinates of the points KP1.4 and KP1 and then they should tend to the nearest boundary. The first obtained boundary pixels can be considered as the point of interest. These points are called KP1.1 and KP1.5, and the key points of the first series are completed.
In order to obtain the key points of the second series, which include the coordinates of the fingertips, the local maxima are calculated in the distribution diagram obtained by calculating the Euclidean distance of the coordinates of the boundary pixels with the point W_m instead of the minimum points that are used in extracting the ROI of the palms. Local maxima are the coordinates of the fingertips. In this way, the key points of the second series are also calculated. The key points of the first and second series as well as their position on the main images are shown in Figure 1 (b) step 2. Here the extraction of the ROI for the index finger is described using the two series of key points which is the same for the rest of fingers.
Using the KP1.4 and KP1.5 points, the approximation width of the index finger can be approximated. By estimating the distance between the points of KP2.4 and the midpoint of the passing line from points KP1.4 and KP1.5, the approximate length of the index finger can also be estimated. The images are normalized using the angle created between the passing line from points KP1.4 and KP1.5 and the horizontal line, and the rectangle surrounding the index finger is estimated by the length and width of the finger. In order to improve the image quality, the CLAHE operator is used for each of the RGB components. Also, the length of all images of the ROI of the index finger is considered to be the mean of the largest and the smallest index fingers. Figure 1(b) step 3 shows the ROI of palm and fingers.

3.3 Feature extraction

The purpose of feature extraction is to map a multi-dimensional space into a less-dimensional space so that in this mapping there is the possibility to detect the initial space [35]. In order to authenticate an image by its patterns, one must derive a series of general or specific information from the image that is called feature extraction. In this research the feature extraction method is texture-based which will be explored below.

The main lines and wrinkles in the palms and fingers are the most important factors in authentication. These lines and wrinkles, which are part of the edges of the image, have variations in their graylevel. After applying Gabor filters in each of the RGB components, it is possible to show stronger lines and wrinkles in different directions and scales. On the other hand, the TCs can be an appropriate measure for detecting significant changes in the value of graylevels, which, if used for each of the Gabor filters, can create more targeted features than normal conditions. Thus the proposed feature extraction method is called the Turn Counts Based Gabor Filter (TC_BGF). The general steps for extracting the feature are shown in Figure 2(c).

3.3.1 Gabor Filters

Gabor filters, Gabor filter banks, Gabor transform, and Gabor wavelet transform are widely used in image processing, machine vision, and pattern recognition [26]. In general, the Gabor function can be used as a powerful tool for extracting local optimal features in the frequency and space domains. This function can create the exact time-frequency location in 2D images. In addition, this function is resistant to brightness and contrast changes of images. Based on these features, it can be expected that Gabor function is an effective method for texture feature extraction.

The Gabor wavelet is the result of combining a sine wave with Gaussian push. Wavelets are combined with an unknown wave to obtain information from that unknown wave. To simulate the behavior of Gabor wavelet behavior, two steps are necessary: 1) Making Gabor filter with mathematical relations and 2) applying Gabor filter convolution with the original image.

Several mathematical relations have been used for Gabor filter one of which is presented here based on [40].

$$g(x, y, \lambda, \sigma, \theta, \varphi) = g_R(x, y, \lambda, \sigma, \gamma, \theta, \varphi) + j g_I(x, y, \lambda, \sigma, \gamma, \theta, \varphi) \quad (1)$$

$$g_R(x, y, \lambda, \sigma, \gamma, \theta, \varphi) = \frac{\gamma}{2\pi\sigma^2} \exp\left(-\frac{x_r^2+\gamma^2 y_r^2}{2\sigma^2}\right) \cos\left(2\pi\frac{x_r}{\lambda}+\varphi\right) \quad (2)$$

$$g_I(x, y, \lambda, \sigma, \gamma, \theta, \varphi) = \frac{\gamma}{2\pi\sigma^2} \exp\left(-\frac{x_r^2+\gamma^2 y_r^2}{2\sigma^2}\right) \cos\left(2\pi\frac{x_r}{\lambda}+\varphi\right) \quad (3)$$

Where, $g_R(x, y, \lambda, \sigma, \gamma, \theta, \varphi)$is the real part of the Gabor filter and $g_I(x, y, \lambda, \sigma, \gamma, \theta, \varphi)$ is the imaginative part of the Gabor filter; where:

$$x_r = x cos\theta + y sin\theta \quad (4)$$

$$y_r = -x sin\theta + y cos\theta \quad (5)$$

x and y are the coordinates of a point of the image, θ is the turn angle of the Gabor filter and φ is the offset phase. This parameter shows the symmetry of the Gabor function. For φ equal to zero or 180 Gabor filter is symmetric or even. Also for φ equal to 90 or -90 the filter is asymmetric or odd. σ Gaussian function length’s push, λ represents the wavelength of the sine wave’s frequency wavelength and γ is the space diagram rate. If the gamma is equal to one, the shape of the supported range will be circular and if it is smaller than one, it will turn elliptically towards the theta angle.

Some of these parameters play a more important role in the production of the Gabor filter which is called effective parameters in the generation of the Gabor filter. By giving different values to the effective parameters on the production of the Gabor filter, a collection of filters is obtained called the Gabor filter bank.

In this study, Gabor filters in six directions and four scales and a total of 24 filters for palm images with four directions and four scales and a total of 16 filters for applying to finger images are used.

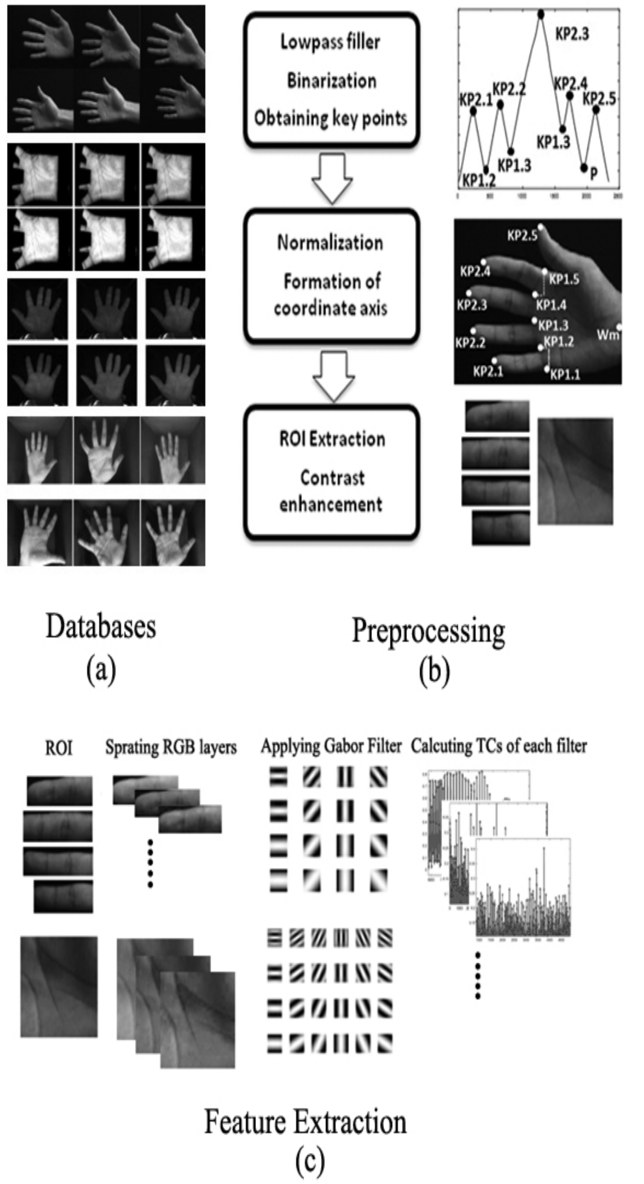

Fig.1 six typical images of each databases (a), general steps of preprocessing (b) general steps of feature extraction (c)

3.3.2 Turn Counts

Transforming images to a one-dimensional vector is a new method for feature extraction. In these methods, images are transformed into one dimension in different ways and then various methods are used for feature extraction.

One of the methods for transforming images to a one-dimensional vector is to use the Zigzag scan method. The advantages of this method are that the matrix coefficients are increased by frequency respectively. In the proposed method, after applying genuine parts of the Gabor filters to the ROI of the palm and finger images, each filter is transformed to one dimension by Zigzag scanning and the TCs are calculated for the first half, the second half, and the total vector.

The TCs of a signal indicates the degree of signal variability. The TCs of the signal was first used by Wilson to analyze the Electromyographic (EMG) signal [27]. Rangayyan also used the number of TCs of Vibroarthrographic (VAG) signal as a feature to distinguish between healthy people and those with knee disability [28]. The turn is detected in a sample data in a given time signal when the following two conditions are met simultaneously [29]:

1) When the change occurs in signal direction i.e. the derivative sign changes
2) The absolute magnitude of the difference between the current sample and the next sample is greater than a threshold

The detection of the given signal's turn {x(n)}, n=1,2,...,I consists of two steps:
1) Signal turn detection: the sequence (k) is the turns of the given signal x(n) if:

$$[x(n)-x(n-1)][x(n+1)-x(n)] < 0 \quad \text{for} \quad 2 \leq n \leq I-1 \quad (6)$$

2) Principal turn detection: The s(k) turn is chosen when the difference between itself and the previous turn is greater than a threshold. That is:

$$|S(k)-S(k-1)| \geq th \quad (7)$$

The threshold value is 0.5 σ_v that σ_v is chosen as the deviation from the part of the signal that is being analyzed. Accordingly for each RGB component of the palm images 72 features and for each RGB component of the index, middle, ring and little fingers' image 48 features are extracted.

3.4 Selection of superior features

The high volume of feature vectors, especially when combining the features of different images to study the multimodal systems, will have a negative effect on the performance of the authentication system because some of the features may be redundant and non-informative. Therefore, a set of the best features must be obtained to achieve the correct precision.

There are many techniques including principal component analysis (PCA), Particle swarm optimization (PSO) and Genetic algorithm (GA) to calculate superior features and reduce volume [42-44]. GA is a highly adaptable and effective method for selecting features because of the possibility to adjust and modify its configuration. This algorithm which is inspired by natural selection and genetic replication, maintains a set of solutions that are called individuals or chromosomes in a population.

To select a subset of features in GA a fitness function must be defined to evaluate the capability of recognizing each subset of the features. The definition of fitness function is one of the most important parts of the GA which is discussed based on the method presented in [41] here. Based on this method, the fitness function is defined using a kNN-based classification error to achieve a set of combinatorial features that increase optimal accuracy. Based on the shortest distance between test data and training sets in the feature space the kNN algorithm uses the Nearest Neighbors to solve the classification problem. Other parameters of the genetic algorithm are: Number of generations = 300, Mutation Probability = 0.1 and Crossover Probability = 0.8.The crossover function is also considered as arithmetic.

3.5 Classification

The evaluation of an authentication system is of great importance in both fields of verification and identification. These systems must be properly evaluated to ensure their correct operation. The system evaluation should be done with appropriate methods and relevant criteria. Using inappropriate criteria can exaggerate the system performance. Therefore, in this research several methods are used for evaluating the performance and system e.g. considering of the average performance characteristics after 10 times of implementation for the stability of the results, studying the various compounds of the biometric members, using EER criteria as an important parameter in biometric systems and evaluating the performance of the extracted features on other databases in this area. But before the presentation of the results, there will be a brief overview of the type and classification process.

Support vector machine is a machine learning method in vector space, which aims to find decision boundaries between two classes, so that the distance between two samples of educational data from two classes is maximal. SVM is widely used because of its ability bring linearly inseparable data into a higher dimensional space and separate them with linear hyper planes and transfer them to the lower dimension.

If there is a category of labeled training data $\{x_i, y_i\}_{i=1}^{l}$ for a two-class classifier where $x_i \in R_n$ is the input data and $y_i \in \{-1,1\}$ is the class labels, the SVM for the classification of the two-class classification in the form of a quadratic programming (QP) based on the constraints of the inequality will be as follows:

$$\text{Min } J(w, b, \xi) = \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \qquad (8)$$

With constraints:

$$y_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i, \ \xi_i \geq 0, i = 1, \ldots, l \qquad (9)$$

Where, w is the normal vector of the hyperplane, b is equal to the bias, φ(x) is a nonlinear function mapping x_i to a higher-dimensional feature space, and C is a setup constant that compromises between maximizing the margin of classification and minimizing incorrect classification.

The classification that takes place in authentication systems should divide the genuine and impostor people into two groups. Therefore, the classification process in this case is a two-class classification. But the problem is that the genuine and impostor people are not distinguishable which means that each person is considered to be genuine compared to him and an impostor compared to other members of the database. Therefore, for solving this problem the method that introduced in [45] is used. The classification steps are shown in Figure 2.

In this way, three randomly selected images of 10 genuine images per person are selected as the source and 20 randomly selected images from databases are considered as impostor images. Then the features of the genuine images are calculated by the difference between the features of the source images with the rest (seven genuine images) and the mean criterion of the matrix is used to produce the artificial features of the genuine people. The same thing is done with the features of impostor images and the artificial features of the impostor people are also produced. By defining reference samples and producing artificial features the training stage is facilitated by designing a classifier for all individuals rather than using a class for each person. 60 percent of the data from each genuine and impostor groups is used randomly as training data and rest are used as test data. Finally, after ten times of repeating the mean EER is calculated as the final error of the system.

Formation of the feature matrix

We considered:

- 10 Genuine images for each person
- 20 impostor images that are selected accidentally for each person
- Features of them in a feature matrix

Use reference samples

- Consideration 3 Genuine images as reference samples from each person are selected accidentally (Flexible)

Formation of the difference of feature matrix

- Computing subtraction of Features of other images with features of reference samples for each person
- Convert them into a vector by one of the Mean, Min or Max operators

Classification by SVM

- 60% of data used for training
- 40% of data used for test
- Repeat 10 times
- Calculate mean of EER

Fig.2 general steps of classification by one classifier for all person of database

4. Evaluation of results

The study of the performance of the unimodal and multimodal biometric systems in different states based on EER criteria is considered. Biometric authentication system creates three types of errors including:

1) FAR or false acceptance rate: This determines the possibility of accepting the fraudulent user rather than the genuine one. This parameter should be as small as possible. This error is important for security systems, so that a person should not falsely enter a high security system.
2) FRR or false rejection rate: This scale indicates the extent to which the genuine person is not accepted erroneously (excessive sensitivity). This parameter should be as low as required. This error is important for criminological systems so that no one should be mistakenly rejected in a criminal system.
3) EER or equal error rate: Decreasing FAR increases FRR unintentionally. The point where the FAR is equal to FRR is the EER. The lower amount of this parameter indicates the better sensitivity and proper balance of the system.

In Figures 3 to 6, the FRR is shown in terms of the FAR for unimodal and multimodal modes with an average of 10 repetitions. According to the results the lowest EER of 1.88% is obtained in the classification of unimodal systems in palm image system and the middle finger with the EER of 2.01 has the best performance among the finger images. In the bimodal systems the lowest EER is achieved by the combination of features of the index and middle fingers with a value of 1.56%. Also, the best combination in the tri-modal classification is the combination of index, middle and ring fingers. The results have been improved by combining the features of the fingers so that by combining the features of the four fingers the EER is reduced to 0.98%. Finally, the least EER of 0.67 is calculated by the addition of the palm image features to fingers.
The generalize ability of features extraction methods is one of the important points in biometric systems so that the extracted features based on the given databases have high discrimination power in other databases. To do this test the hand image databases are used the results of which are given in Table 1. It should be noted that in CASIA Multi-Spectral Palmprint Image Database V1.0 database the images associated with the white light are separated and classification is made based on the palm and middle and ring fingers after extracting the ROI and feature. Also, Table 2 compares the proposed method with some of the work done in this field.

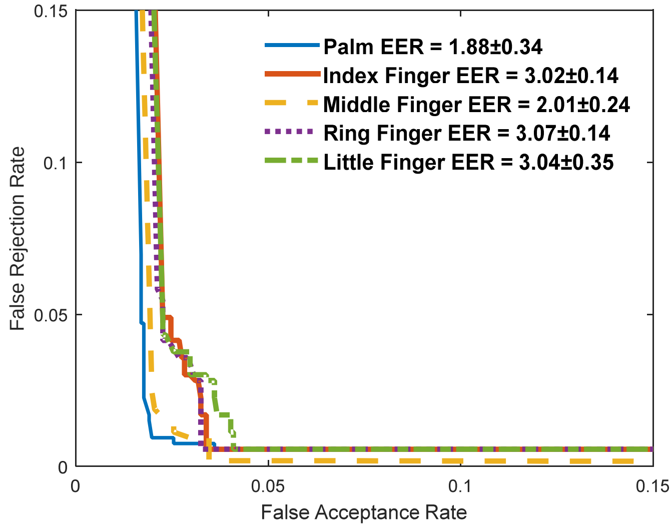

Fig.3 results of the classification for the unimodal modes after 10 times run

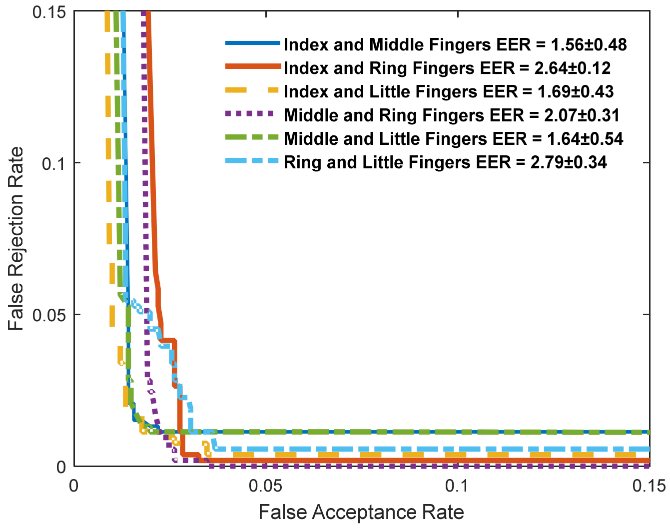

Fig. 4 results of the classification for the bimodal modes after 10 times run

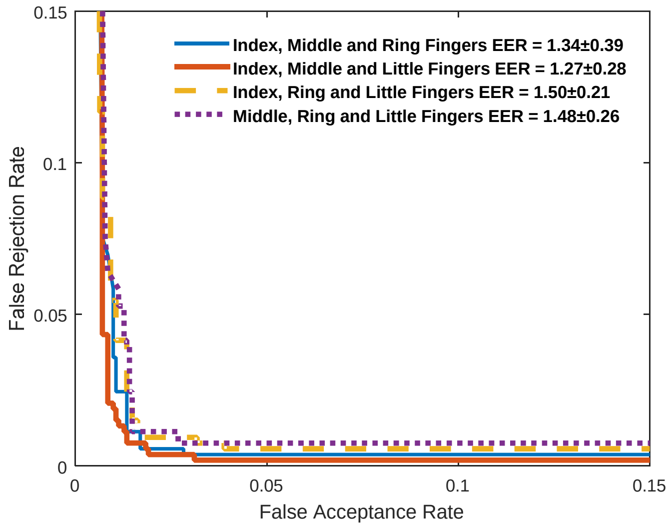

Fig. 5 results of the classification for the tri-modal modes after 10 times run

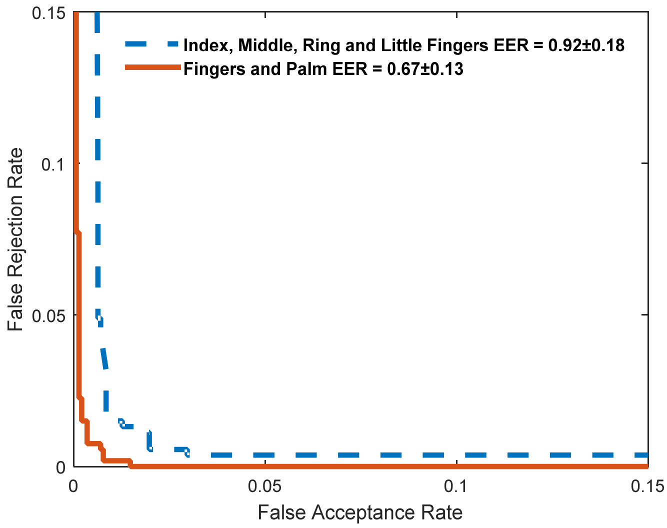

Fig. 6 results of the classification for all finger and all fingers with palm after 10 times run

Table 1. Results of generalization of proposed method on other databases after 10 runs

EER	Combination	Subjects	Database
0.67±0.13	Palm + Fingers	177	PolyU 2D/3D
4.12±0.23	Palm	312	CASIA
3.01±0.12	Palm	189	PolyU version 1
7.65±0.21	Palm	230	IIT
2.61±0.32	Palm + Middle + Ring	100	Multispectral

Table 2. Summary of related approaches for hand authentication

Author	Nub	kind	Feature	Classifier	EER
[49], 2014	638	Fingers	Fourier descriptors + Finger area function	Euclidean distance	3.69
[50], 2014	100	Palm + Fingers	Geometric feature + Harris corner detection	Euclidean distance	1.86
[48], 2015	230	Palm + Fingers	SIFT +Gabor	Euclidean distance	1.95
[51], 2015	177	Fingers	Finger Texture features	Probabilistic Neural Network	4.07
[47], 2016	177	Fingers	Variance coefficients LBP	Probabilistic neural network	1.81
[46], 2017	177	Palm	Curvelet transform+ hand geometric	SVM	1.56
Proposed	177	Palm + Fingers	TC_BGF	SVM	0.67

5. Conclusion

In this research the multimodal biometric system was tested based on palm and finger color images as a method for verification of individuals. Unlike many other multi modal systems, this system uses only one device to record data. Also, the results show that in addition to the palms, each of the fingers can be considered as a biometric system.

In the first phase of this study the goal was to use the color images of the palms as a principle member in the proposed system. In the second phase, fingers extraction and its authentication were also considered. After extracting the ROI of palms and fingers, the feature extraction in terms of texture-based properties was investigated. The proposed method was based on calculating the number of TCs of each Gabor filter. The optimal combination of features was calculated based on GA and classified by SVM classification. The use of sourcing in classification as well as the production of artificial features on the distance matrixes of genuine and impostor samples improved the performance of the verification system so that instead of using the classifier for each person, a classifier was used for all people. The results obtained by the feature combination of biometric characteristics and generalization of features were investigated on other databases and their efficiency was determined. Considering the features of the hand biometrics system, including high acceptability, sustainability and low cost it is intended to use this method as an appropriate method for verification in web-based systems.

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