A Dorsal Vein Recognition System Based on Score Fusion Technique Combining Local and Statistical Features

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Abstract

The numerous problems of the traditional security technologies have led to a rise in developing biometric systems. Many traditional biometric systems, such as fingerprint, face, and iris systems have been studied extensively in the previous decades .Nowadays the concept of using the dorsal vein pattern in authentication that uses the vast network blood vessels underneath a person's skin showed to be a proven biometric technique. Different trails have been done to extract veins patterns and build systems that can give good performance. In this paper, we proposed an automatic system for human identification based on their dorsal vein patterns. Within this approach preprocessing steps are implemented to get the enhanced grayscale images with visible and clear veins. Two features extraction techniques are used, Principle Component Analysis (PCA) and Scale Invariant Feature Transform (SIFT), to get eigenveins and keypoints respectively. Statistical distance classifiers are implemented for classification. Finally the results from both classifiers are fused using simple min rule. The system has been successfully tested on a database of 100 users using MATLAB version 2009. The obtained results show that the proposed system outperforms the results of each individual system (PCA, SIFT).

Keywords: *Biometrics, Dorsal hand vein pattern, PCA, SIFT.*

1. Introduction

There is a demand in producing suitable security barriers which are reliable and low-cost instead of the traditional-based security technologies especially when our society gets more and more computer dependent. Biometrics are seen as the way forward as it provide the good level of security by recognizing people based on their personal characteristics.

Vein pattern recognition is the biometric technique that attracting the attention of researchers recently. This biometric technique uses the characteristics of the shape and pattern of the veins under the skin to identify people .The advantages of this biometric trait are: difficulty of forgery due to its position underneath the skin, uniqueness, long term stability which means that the shape of the vein pattern will never change over the life time only by their size as well as the little effect of the environmental conditions such as temperature, humidity on the vein image. Due to these advantages, the vein pattern can be considered as a more reliable biometric technique for both verification and identification purposes and thus in turn encourages the researchers for focusing their efforts in developing the dorsal hand vein security system by trying different techniques and methods to get a system that is suitable for different applications.

Any biometric system usually consists of these main components: image acquisition unit, image preprocessing unit, features extraction unit, classification unit and decision making unit [1].

This paper contains the following sections: section 1 is the introduction, section 2 is a review of related previous works, section 3 explains in details our proposed biometric recognition system using dorsal hand vein patterns and section 4 introduces the experimental results of the proposed system, while section 5 presents conclusions and the last section 6 contains acknowledgment .

2. Review of Related Works

A number of studies based on the veins patterns on the back of the hand as a biometric trait have appeared in the literatures.Tanaka and Kubo [2] developed hand vein acquisition device using near Infra Red(NIR) imaging and employed phase only correlation and template matching for user verification. Lin and Fan [3] have presented an approach for the personal verification using dorsal veins images. They have detailed the formation of thermal vein pattern images from the thermal IR camera operating in (3.4 – 5) µm range.

They used the integration of multiresolution representations for the post processed thermal vein patterns.M. Khairy [4] proposed a hand vein verification prototype,he applied a long sequence of operations for vascular structure extraction from NIR images such as hand region segmentation, smoothing, hand vein pattern segmentation and noise reduction. After these steps he obtained binary images. A correlation-based matching technique called the rigid registration was implemented on these images to make the decision of verifying the person with the claimed identity or not. K. Wang et al [5] built another hand vein recognition system .Their system based on multi supplemental features. The binary images are obtained after preprocessing steps. Multi features extraction techniques are used simultaneously to compute different features from the binary images such as features based on the vein geometry, K-L conversion transform and invariable moment. The distances classifiers were used such as the weighted Euclidean distance classifier and minimum distance classifier to get the primary results after each features extraction technique. The system gets the final decision from fusing the results of different classifier. [5] noted that the fusion reduce the errors that occur because of depending on single features recognition. Ajay Kumar et al [6] designed a new approach to authenticate individuals using integration of topopologies of vein triangulation with hierarchical matching and geometry features with distance based classification to achieve the performance improvement. The proposed method is fully automated and employs palm dorsal hand vein images acquired from low-cost, near infrared, contactless imaging. Yunxin Wang et el [7] built a system for human verification based on dorsal hand veins. They preprocessed their images to remove the background and reduce image noises. Then they extracted SIFT features to describe the information of the hand veins. Finally they calculated the Euclidean distances for their features and found the ratio between closest and the second-closest distances and selected the nearest distance as the optimal match.

M.Soni et al [8] experimented with a new verification system based on the hand vein patterns. This system contained many of the preprocessing steps such as segmentation, filtering, binarization, dilation, skeletonization, and finally the CCL algorithm (Connected Component Labeling) to label all desired connected components and discard others. After that the froking points, points that have at least three bifurcations, are extracted. They recorded the positions and orientations of the froking points. Finally they concatenated a feature vector that contains all these froking points. The matching percentage was calculated and the distance based classification method is used to give the final decision after comparison with a predefined threshold. Y-Ding et al [9] proposed a new approach to extract LBP (Local Binary Pattern) features from hand vein images. Firstly they decomposed the original image with two-level haar wavelet and got 8 coefficient matrices. They kept the components that have high weight. They obtained LBP features from each component individually. Finally all LBP features of different components are fused. Then the decision was made based on the nearest neighbor classifier to recognize people. They found that their method performed better than original LBP and traditional multi-scale LBP; also this method solved the problem of the limited local information in the original LBP.

3. Proposed System

Depending on just one biometric trait as in unimodal biometric systems causes many problems and limitations. Some of these systems may be enhanced to overcome problems. In this paper, we introduce a novel biometric system based on the vein patterns at the back of the human hands. We have used the idea of multimodal but on single biometric trait. The following framework (see Figure 1) shows the workflow of the system. We will describe all these components in details.

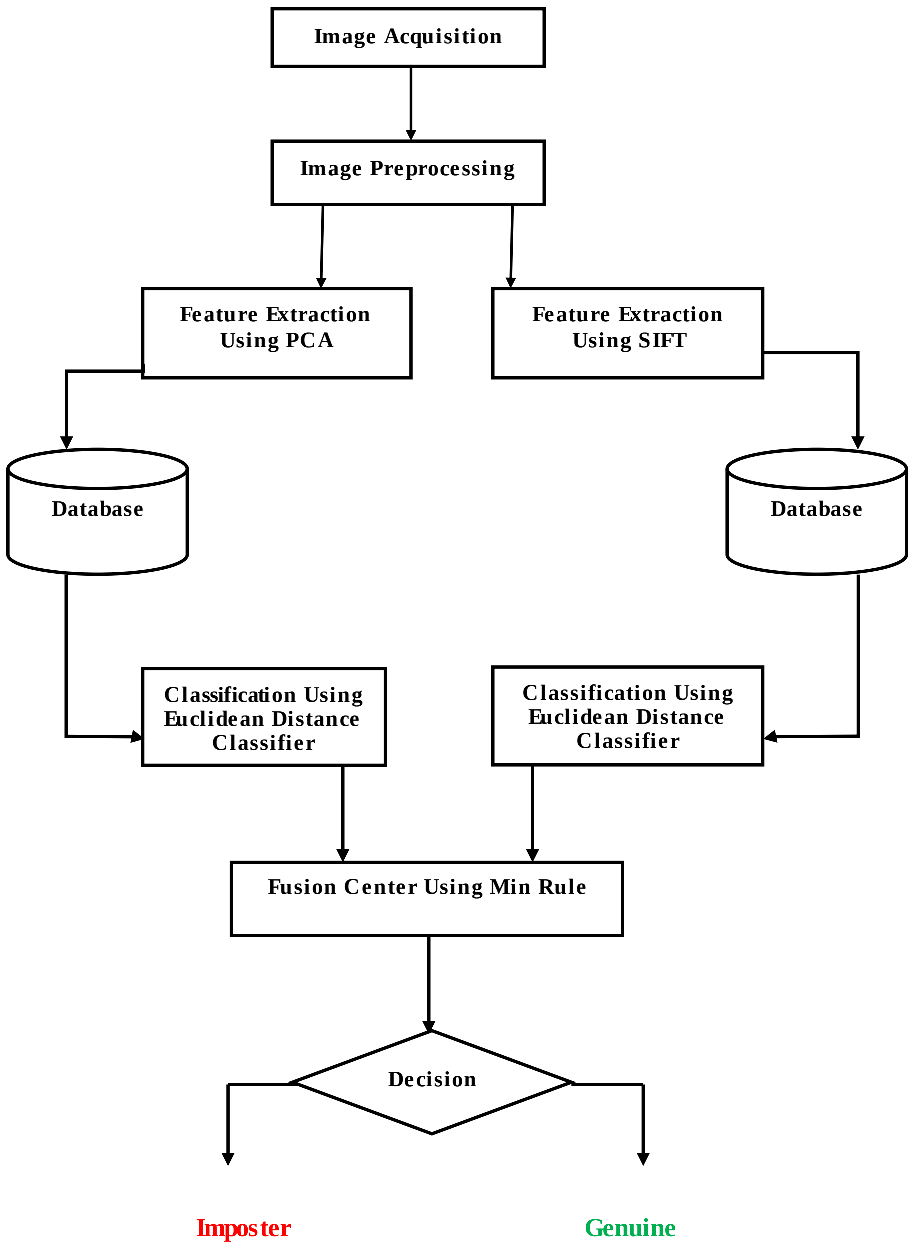

Fig.1 Workflow of the proposed system

A. Image Acquisition Unit

It is the most important stage because the accuracy of the entire system ultimately depends on the quality of images that are acquired by this unit. As veins are internal, their structure cannot be discerned in visible light. A vein image can be obtained by X-ray scanning, ultrasonic scanning or infrared scanning. X-ray and ultrasonic are used to capture vein images in medical treatment, but they are not suitable for identification due to the health case.

While IR spectrum exhibit marked improvements in the quality of captured images and can reduce the effect of many problems such as humidity and surface features such as moles, warts, and hair on the image. There are two choices that focuses on imaging of vein patterns by infrared light, the far-infrared (FIR) imaging and the near-infrared (NIR) imaging, which are suitable for capturing human bodies images in a non-harmful way. NIR imagining is more preferable than thermal (FIR) imagining because thermal cameras are highly expensive and highly sensitive to ambient conditions.

In our work, a low cost CCD camera (charge-couple device) is used for capturing NIR images. An infrared filter installed on the camera objective lens to prevent the visible light from reaching its sensor array to construct a pure infrared image for the back of the hand. A hand attachment frame is added for constraining the person's hand because the vein pattern is best defined when the skin on the back of the hand is taut i.e. when the fist is clenched. When the target is placed on a scanner, an infrared light passes through the tissue and the rays are absorbed by the red blood cells (Hemoglobin). So, the veins will appear as black lines while the rest of the region structure appears as white. An example of our NIR images can be seen in Figure 2.All our images are grayscale images and of size 240*320 [4].

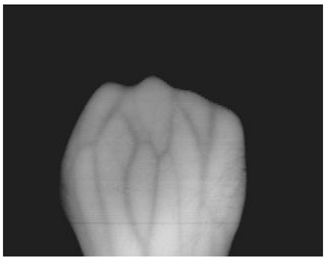

Fig.2 Sample of the NIR acquired images

B. Image Preprocessing Unit

In this unit we applied several steps to enhance the images and get rid of the background and unuseful information to facilitate the next steps. Preprocessing steps are described below:

In this work, the global threshold technique is firstly implemented on our images to separate the foreground pixels from background pixels .The global threshold value is empirically selected to be 0.126. Then the morphological operation that is called "erosion" was implemented on the obtained image to erode away the boundaries of regions of foreground pixels using a disk-shaped structuring element with radius equals 5.Figure 3 shows an example of the binarized eroded image.

Fig.3 A binarized eroded image

The obtained mask in Figure 3 is applied to the original image (in Figure 2) to get the image with required object (hand) on a black background as in Figure.4.

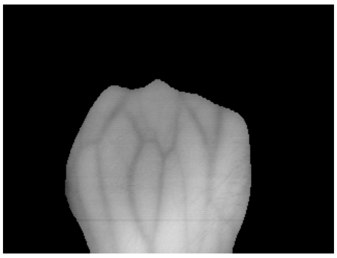

Fig.4 object (hand) on a black background

Then the hand object in the image is rotated and scaled by using affine transformation as in Figure 5.

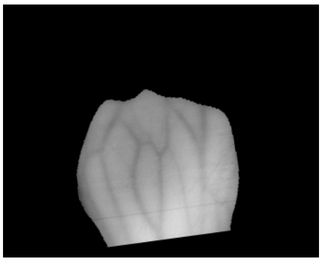

Fig.5 Image after transformation

After that Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is implemented on the previous image to enhance its contrast as in the figure below.

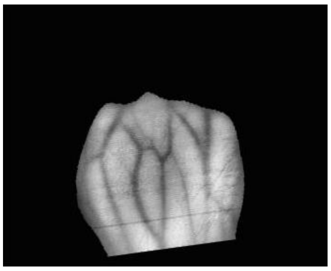

Fig.6 Image after implementing CLAHE algorithm

The resultant image from the previous steps still needs some enhancements; therefore filtering is required. A 3X3 unsharp contrast enhancement filter is implemented on the image followed by an 11X11 averaging filter. The obtained image after implementing these two filters can be shown in the figure below:

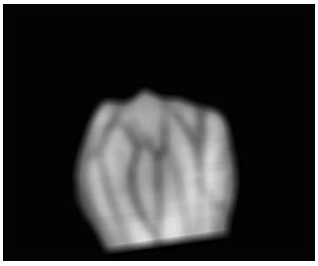

Fig.7 Image after filtering

Then final hand image is cropped to keep the hand region only and center it in the image.Figure.8 shows the image with clear vein pattern centered in the image and all other data removed.

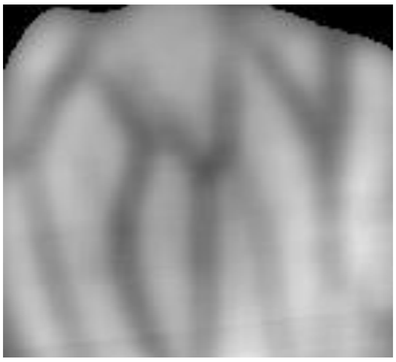

Fig. 8 Preprocessed centered image

C. Feature Extraction Unit

Each biometric trait has unique features that can be measured to identify or verify a person. In this stage the collected data are analyzed and these unique characteristics are extracted. There are many algorithms employed for features extraction. According to the selected biometric and its application the suitable features extraction technique can be chosen [1, 10]. Here we apply two algorithms, Principle Component Analysis (PCA) and Scale Invariant Feature Transform (SIFT).We used these algorithms to extract the valuable features from each image as a trail to solve the problems related to depending on just single features extraction method .The obtained feature vectors after applying these algorithms are called eigenvector or (eigenveins) and keypoints respectively.

1. Feature Extraction Using Principle Component Analysis (or PCA)

PCA is one of the valuable techniques which widely used in all forms of analysis because of its simplicity. The jobs of PCA may be differ from redundancy removal to feature extraction and data compression, etc [11]. In recognition field, PCA was used originally on human faces and on hand geometry. In this paper we applied it on the veins gray scale images. PCA uses a transformation to convert a set of possibly correlated variables into a set of values of uncorrelated variables called principle components. The number of principle components is always less than the number of original variables. In another meaning, PCA describes the data economically. It generates a set of orthogonal axes of projections known as the eigenvectors, of the input data distribution in the order of decreasing variances [12].

In general, recognition of images using PCA takes three basic steps. The transformation matrix is first created using the training images. Next, the training images are projected onto the transformation matrix. Finally, the test images are identified by projecting them into the subspace and comparing them with the trained images in the subspace domain.

The PCA Steps:

Mathematically, we wish to find the principal components of the set of images, or the eigenvectors of the covariance matrix of the set of images. The obtained eigenvectors are ordered and they can be thought of as a set of features that together characterize the variation between veins images. The principle component analysis is called “eigen values” or “eigenveins” in the case of vein images. The detailed equations and steps of this explanation are described below [11, 12]:

1. First we must organize our dataset. Let a hand vein image $A(x,y)$ be a two dimensional mXn array of intensity values. Let the training set of images $\{A_{1,}A_{2,}A_{3,}\ldots\ldots.A_N\}$. The average of this set is calculated as in eq(1).

$$\overline{A} = \frac{1}{N}\sum_{i=1}^{N} A_i \qquad (1)$$

Where N is the number of training images.

2. Calculating the Covariance matrix C using the eq(2):

$$C = \frac{1}{N} \sum_{i=1}^{N} (A_i - \overline{A})(A_i - \overline{A})^T \qquad (2)$$

3. The Eigenvectors and corresponding eigenvalues are computed by using the eq(3):

$$CV = \lambda V \qquad (3)$$

Where V reperents the set of eigenvectors associated with its eigenvalue λ.

4. The eigenvectors and their corresponding eigenvalues are paired and ordered from high to low.

5. Each of the mean image will be projected into the new space (eigenspace) using eq(4):

$$W_i = V_i^T (A_i - \bar{A}) \qquad (4)$$

6. In the testing phase each image should be projected into the same eigenspace that created during the training phase.

2. Feature Extraction Using Scale Invariant Feature Transform (or SIFT)

SIFT is an algorithm in computer vision; It was published by David Lowe. SIFT detects and extracts the local features that are invariant to image scaling and rotation, and partially invariant to changes in illumination and 3D camera viewpoint. Large number of the SIFT features (SIFT keypoints) can be extracted from typical images. Also it is important to notice that SIFT keypoints are highly distinctive, which allows a single image to be correctly matched with high probability against a large database of features [13].Figure 9 shows in a diagram the SIFT steps.

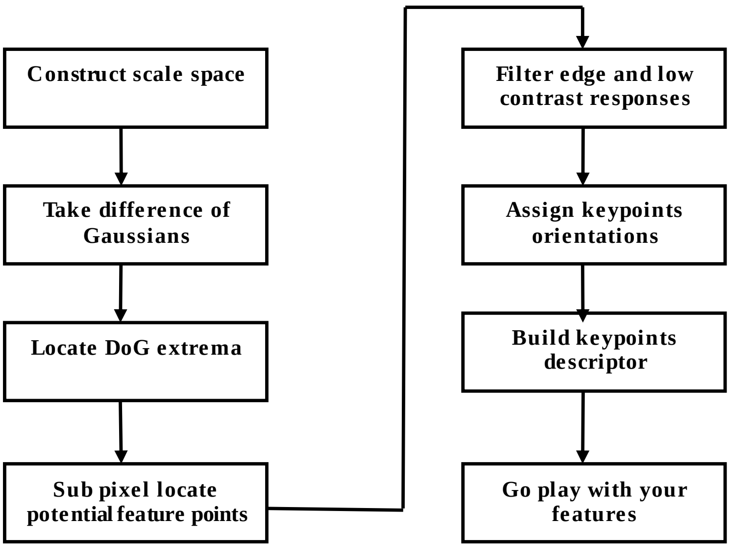

Fig.9 SIFT algorithm overview diagram [14]

The SIFT Steps:

The details of calculating SIFT keypoints from an image can be explained in the following steps [13]:

1. Scale-space extrema detection: This step is implemented efficiently by using difference-of-Gaussian (DOG) function from different image scales to identify extrema; potential interest points that are invariant to scale and orientation. These points can be found after searching all scales and orientation but in our implementation we used 6 scales and 4 orientations. Now we have much less points than pixels. But in the same time, there are still lots of points and many bad points must be removed.

2. Key point localization: The purpose of this step is to filter points and eliminate ones that have low contrast or located on the edge from the above calculated keypoints. In simpler words, the keypoints are selected based on their stability. This means that here we improve keypoints and throw out bad ones.

3. Orientation assignment: In this step we remove effects of scale and rotation .From the above steps we got a set of good points. We will choose a region around each point and the scale of point to choose correct image L, with the closest scale, so that all computation are performed in a scale invariant manner.

For each image, L, at this scale, the gardiant magnitude, $m(x, y)$, and orientation , $\theta(x, y)$,is precomputed using pixels differences as in eq (5) and (6) respectively.

$$m(x,y) = \sqrt{\left(L(x+1,y) - L(x-1,y)\right)^2 + \left(L(x,y+1) - L(x,y-1)\right)^2} \quad (5)$$

$$\theta(x,y) = tan^{-1}\left(\left(L(x,y+1) - L(x,y-1)\right) \Big/ \left(L(x+1,y) - L(x-1,y)\right) \right) \quad (6)$$

4. Key point descriptor: The feature descriptor is computed by the gradient magnitude and orientation in a local region around the keypoint weighted by a Gaussian window. In this paper, we apply a slight modification on the traditional SIFT. While in traditional SIFT key point descriptor typically uses a set of 16 histograms, aligned in a 4×4 grid, each with 8 orientations we never used a histogram instead of it we used a 3x3 grid around the local extremum at x, y and then we align our gradient to this grid. And as we mentioned in step no.1 we used just 4 orientations instead of 8 orientations because we considered that left and right are the same orientation but with different signs.

In testing phase we will apply all the previous steps exactly similar to what happened in the training set to get the keypoints from the image.

Our hand veins images are analyzed by the SIFT algorithm, the SIFT keypoints are indicated in Figure 10, where the starting point, length and direction of each arrow denote the location, scale and assigned orientation of feature point respectively. It can be seen that SIFT algorithm can extract many stable feature points along blood vessels, which contain more information than the bifurcation and ending points.

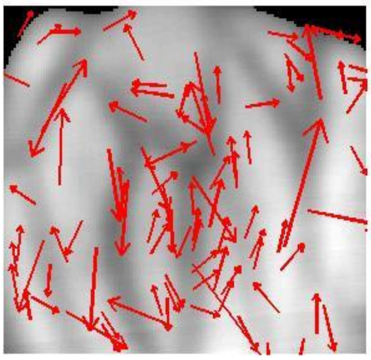

Fig.10 SIFT features (keypoints) for hand vein image

D. Classification Unit

This unit is responsible of data classification based on the training set i.e. it uses features and learned models to assign a new pattern to a category (class) [15].

1. Classification in PCA

After applying PCA steps on the input tested image we got the eigenvector of tested image .The classification for the tested image occurs after the comparisons of its eigenvector with the eigenvectors of the trained images in the eigenspace.In this paper we used the Euclidean distance classifier for classification purpose. It is the most common use of distances because of its simplicity. The distances between the eigenvectors of the projected trained images and the tested one were calculated .Because our authentication mode is identification, this means that it is a one to many matching (comparisons). The system will return the minimum of all distances between the eigenvector of the tested image and the eigenvectors of the trained images with the number of the person that gave this distance, let us say that we got (DS_PCA) from this part. We calculated the Euclidean distance as follows:

$$D(x, y) = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2} \qquad (7)$$

Where x, y in the data set X and x_i, y_i are the ith coordinates of x and y, respectively.

2. Classification in SIFT

In SIFT case; we also computed the Euclidean distances between the keypoints of the trained images and the keypoint of tested one as in eq(7).Many one to many matching process were done. Since our system contains keypoint descriptor for each image, therefore we have 4 distances as a result for comparison the new keypoint descriptor with the keypoints descriptors of one person. So we calculated the mean of distances for each four keypoints (for the same person) and the system will return the minimum distance of all the distances with the number of the person that gave this distance. So let us say that we got DS_SIFT from this step.

3. Fusion Scores (Distances) Using Min Rule

In this step, we combined the scores (smallest distances) that were already recorded from PCA and SIFT as we mentioned above. Because of our fusion occurred after getting scores (distances) so it is a score level fusion. It is commonly preferred in biometric systems because matching scores contain sufficient information to make genuine and impostor case distinguishable [16, 17].

Using the minimum rule means choosing the minimum of the distances [18]. Thus the final score (DS_Final) is given by,

$$\text{DS\_Final} = \text{Min } [(\text{DS\_PCA}, \text{DS\_SIFT}) \qquad (8)$$

E. Decision Making Unit

Within this unit, the final distance (DS_Final) was compared against a certain threshold value to make the final decision about identifying the person either as a genuine or as an imposter [1]. We used a trial and error concept to get the best threshold .Our results show that the optimal threshold is 0.18.

If the distance is below this threshold, so the person is identified with the number of the person that we got with this distance, else this person is considered as imposter.

The results after fusion are more improved if we compare them with the results obtained based on each part individually as we will show in the next section.

4. Experimental Results

A. Database Description

All recognition techniques are dataset dependent .Therefore, it is necessary to describe the database that was used for testing the system performance. The used dataset have variations in the alignment between the images which is the main problem in our data. It consists from 100 classes (for right and left hands) with 5 images per class. Therefore, we have 500 images in our hand veins database. We used 4 images in training phase and 1 image in testing phase. We dedicated 90 classes as genuines (legitimate users) and the other 10 class as imposters and reported the experimental results.

B. Performance Measures

ROC curve (Receiver Operating Characteristics), AUC(The area under the ROC curve) ,EER (Equal Error Rate) and accuracy are the most important measures in any biometric system .These measures give an enough perception about the overall performance.

ROC curve is often plotted by using True Positive Rate (or TPR) against False Positive Rate (or FPR) for different thresholds. FPR (1 – specificity) is represented by x-axis and TPR (sensitivity) is represented by y-axis. Thus, ROC curve is a plot of a test's sensitivity vs. (1-specificity) as well. This plot must start from coordinate (0, 0) and end at coordinate (1, 1).

The second measure, AUC, is another measure of how well this system is. A higher AUC indicates a more accurate system because this means that the system has a high TPR and a low FPR.

While the third measure, EER, which is also called Crossover Error Rate (CER) can be easily obtained from the ROC curve. It considers as the intersection point between the Type I error plot (FPR plot) and the Type II error plot (FNR plot) above different thresholds, where FPR measures the percentage of invalid inputs which are incorrectly accepted while FNR measures the percentage of valid inputs which are incorrectly rejected. A lower EER indicates a more accurate system because it means that the system has less error in both FP and FN cases.

The last measure is accuracy that represents the efficiency of the proposed system [18].We calculated and recorded the above measures for PCA, SIFT, and their combination (see table (1)).

1. PCA Results

Figure 11 and 12 shows the ROC curve and EER that obtained from PCA algorithm alone respectivelly.From these figures we can notice that the performance of PCA is efficient in the term of ROC, AUC and accuracy .The results show that AUC of PCA equals to 99.672 % and accuracy equals to 96.544 % but until now the another important performance measure (EER) is still high because it equals to 3.3951 %.

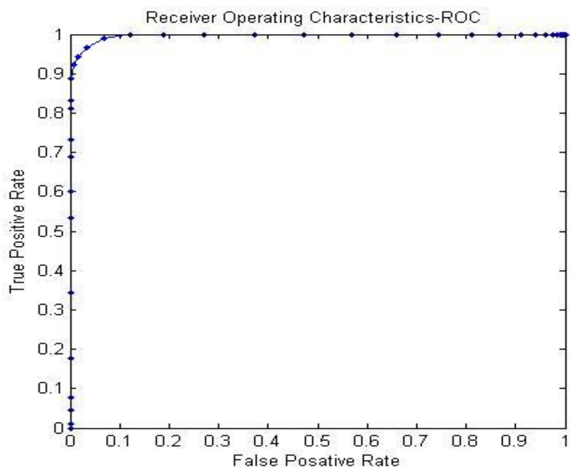

Fig.11 The ROC for PCA part alone

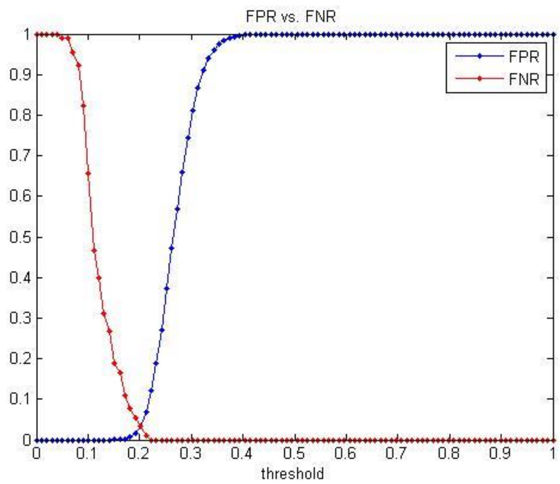

Fig.12 The EER plot for PCA part alone.

2. SIFT Results

Figure 13 and 14 shows ROC and EER that obtained from SIFT algorithm alone respectively. From these figures we can see that the performance of SIFT is less than the performance of the PCA in ROC, AUC, EER measures. From the shape of the ROC we calculated the AUC, it equals 94.281 % .While EER is too high in SIFT, it equals 12.823 %.These results caused decreasing in the accuracy in the SIFT part to be 83.322 %. This means that when we compare the results of PCA with the results of SIFT, we find that PCA is more accurate than SIFT but it didn't reach to the optimal performance required from the biometric system.

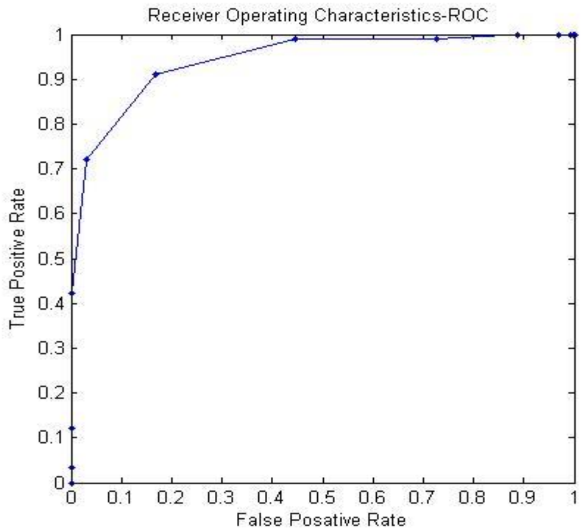

Fig.13 The ROC for SIFT part alone

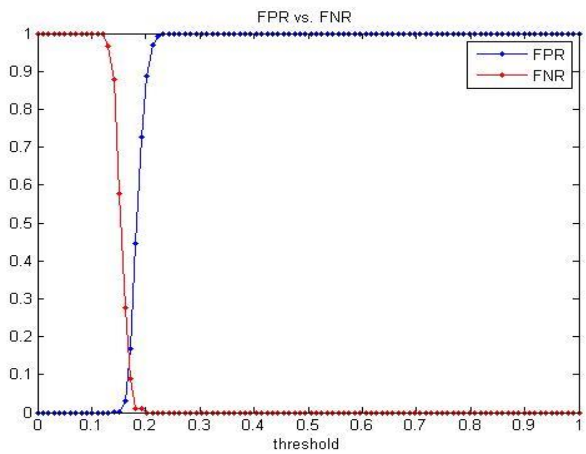

Fig.14 The EER plot for SIFT part alone.

3. Combined Algorithms (PCA and SIFT) Results

Due to the problems in the performance results that we got from both PCA and SIFT, we decided to combine both of these algorithms as a trial to solve the problems that appeared if we deals with each algorithm individually. Figure 15 and 16 shows ROC and EER of the combined system respectively. From these figures we notice that the AUC is high, it is equal to 99.702 % while the EER decreased to be 1.33 %.This leads to increasing the accuracy to be 98.456 %. The obtained results shows that the combined system outperformed both PCA and SIFT since we didn't depend on single features extraction and classifier to make the final decision. We made our decision based on two features extraction algorithms and two classifiers, which means that the combination of these algorithms and classifiers manipulates the errors occurred from dealing with these algorithms individually.

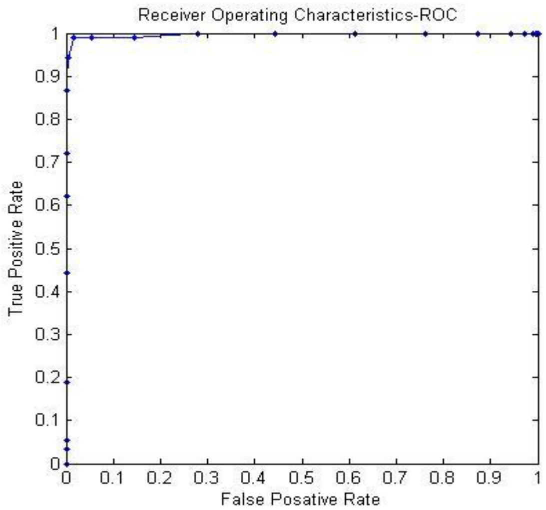

Fig.15 The ROC for Combined system

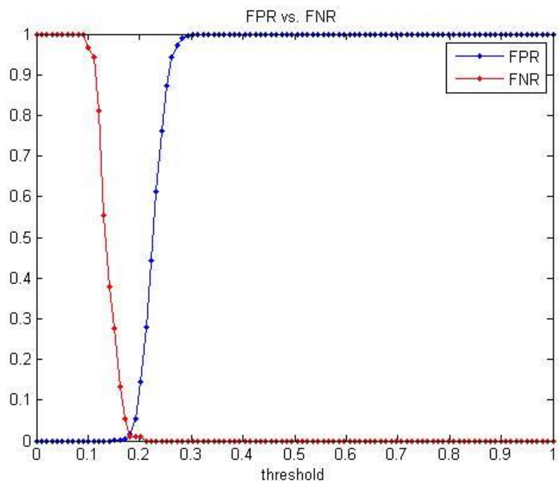

Fig.16 The EER plot for combined system.

According to the above plots and discussions we got the following table:

Table 1: Performance measures for PCA, SIFT, and combined system

Performance measures (%)	PCA	SIFT	Combined (PCA+SIFT)
AUC	99.672	94.281	99.702
EER	3.3951	12.823	1.33
Accuracy	96.544	83.322	98.456

From this table we can see that AUC increased in combination phase by 0.03% and by 5.421% in comparing with PCA and SIFT respectively .While EER decreased in combination phase by 2.0651 % and by 11.493 % in comparing with PCA and SIFT respectively .The accuracy also increased in combination phase by 1.912 % and by 15.134% in comparing with PCA and SIFT respectively. These results show how the combination is more efficient. We can notice also that depending on single path (either PCA or SIFT) to identify a person is less time consuming and may be less complex than combining both of these paths to identify a person but this system may be more suitable and useful in the applications when high level of security is required, while depending on just one path either PCA or SIFT path may be more suitable in applications when low or intermediate level of security is required.

C. Comparison with Other Systems

We have compared the results obtained by the proposed system with the results of previous works got from the same database and from another databases. The results are given in table (2) for the proposed system and for several previous systems.

Table 2: Comparative summary of related works on hand vein (back surface) based authentication

Ref.	Imagining	Methodology	Authentication mode	Database	Performance
[2]	NIR	Phase only correlation and template matching techniques	verification	25 users	FPR – 0.73 % FNR- 4 %
[3]	Thermal Imaging	Multi resolution analysis and integration	verification	32 users	FPR – 1.5 % FNR - 3. 5%
[4]*	NIR	Correlation based matching algorithm (rigid registration)	verification	100 users	FPR - 0.03% FNR- 7.84%
[5]	NIR	Features extraction based on (vein geometry ,K-L transform, invariable moment)and fusion distances based classification results	recognition	100 users	FPR -0 % FNR - 0.5 %
[6]	NIR	Integration of topopologies of vein triangulation with hierarchical matching and geometry features with distance based classification	recognition	100 users	FPR- 1.14% FNR - 1.14%
[7]	NIR	SIFT features with distance based classification	verification	108 users	FPR -0 .002% FNR - 0.93 %
[8]	NIR	Features extraction based on vein geometry with distance based classification method	verification	314 users	FPR –not given specifically FNR- 0.03%
[9]	NIR	LBP features with nearest neighbor classifier	recognition	102 users	FPR-0.02% FNR-0.02%
Combined system in this paper	NIR	Features extraction based on (PCA,SIFT) and fusion distances based classification results	recognition	100 users	FPR-1.11 % FNR – 1.5%

-The sign (*) in Table 2 refers to the same database.

5. Conclusion

In this paper we introduced a system that recognizes people automatically based on their veins patterns at the back of their hands with 98.45% efficiency (efficiency is calculated as in [4]). The system used multi features extraction algorithm and score fusion of multi classifier result. It overcomed the disadvantages of depending on a single method for features extraction and single classifier decision in recognition. It used the idea of multimodal biometric system but on a single biometric trait. The performance measures in the fused system (PCA and SIFT) outperforms the performance of each individual algorithm. According to the level of the required security we can select the more suitable choice for each application, either the individual or the combined paths.

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