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The Use of Spatial Distribution of the Local Histogram Based Features for Finger's Veins Biometrics

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors contributed in designing the proposed system. Author REF wrote the programming code, made the tests, analyzed the results and stimulated the conclusions. Author LEG was the supervisor for whole parts of the work. Both authors read and approved the final manuscript.

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Abstract

Finger vein authentication is a new biometric technique utilizing the vein patterns inside of fingers for personal identity verification. Vein patterns are different for each finger belong to each person; and as they are hidden underneath the skin's surface, this makes finger vein detection a secure biometric for individual identification. The vein grid images are acquired using infrared (IR) cameras. The acquired images are of low contrast and blurred in nature; so, an effective contrast enhancement step is required to expand the values of brightness range in the input vein image. The deal with low quality finger vein image represents the major concern of this work, beside to the selection of proper features to efficiently distinguish between individuals.

In this paper a feature vector of the local histogram moments of gray finger image is proposed to represent the veins attributes; the main reason for used local moments is their ability to reflect the statistical behavior of veins variation at each part of finger image. The extracted features are assembled as a feature vector; which, in turn, is used to distinguish different individuals. Nearest Neighbor classifier are used to make recognition decisions in the matching stage. The system is tested using a database consisting of 3,816 images. This dataset was constructed by capturing 6 samples for each of the 3fingers (i.e., index, middle and ring) that belong to one of the 2 hands of the 106 subjects. The achieved identification results of the proposed system indicate high recognition performance which is 99.52%, while the verification test results indicate error rate 0.003%.

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Keywords: Fingers recognition; histogram moments; contrast enhancement; ROI; veins segmentation.

1 Introduction

The most crucial responsibility of any technological development, regarding the access control issue, is to make assurance of providing a unique and secure identity for an individual. This demand issue is still a major challenge for organizations. Currently the biometric identification and authentication processes are the most growing technologies that utilized to elicit the true identity for an individual. Biometrics, which uses human physical and behavioral characteristics, have concerned more and more attention and becomes one of the most accepted and capable alternatives to the traditional password or PIN based authentication techniques [1].

Although many biometrics authentication systems have been developed, each type has its own demerits based on its characteristics, capturing device, database and the behavior of its characteristics. Taking into consideration the challenges facing the current recognition systems, now the development concerned led to designing new generations of biometric recognition systems which rely on more integrity features which are less affected by the surrounding environment to enhance the functionality of personal authentication and recognition that depends on the vein pattern [2].

Finger vein biometric system can verify user's identity by recognizing the pattern of vascular grid in his/her finger. Finger vein recognition utilizes the vascular patterns of a person's finger as user identification data. It had been proved that finger vein pattern is accurate enough for human biometric identification, like fingerprints [3]. The pattern of vascular in finger is: (i) unique to every person, (ii) even twins have different patterns and (iii) furthermore, this pattern will not vary by aging [4]. Finger veins biometric are robust and steady human authentication more than other biometric technologies, so it is considered to be one of the most reliable biometrics for personal identification.

Accurate and reliable finger vein recognition is a challenging task; it depends heavily on the quality of the finger vein images. Finger vein image represents the thermal signature of the vein pattern, so it is affected by environment conditions, such as: optical blurring, skin scattering problems, and the accuracy of sensation device. Therefore, finger vein images suffer from low contrast, with irregular shadings, and it is not always clear up to the extent some parts of the vein grid could not be recognized by the naked eye. Consequently, the raw vein image needs to be processed and enhanced to have the ability to allocate the vein grid by the recognition system.

During the last few years, many of researches have been directed toward developing the methodology of vascular based biometric systems due to their promising characteristics. Recent studies have introduced different methods for biometric recognition or verification systems. The following are some of the published studies concerned in this field:

- Nurhafizah Mahri et al. [5] have presented a finger vein recognition system based on phase correlation. In the proposed algorithm, they utilized phase-only correlation (POC) function at the matching stage. The involved preprocessing method was simple (i.e., without need for finger vein pattern extraction at all). They used a database consist of 2040 images collected from 51 individual, four fingers for left hand and same for the right hand. The conducted test results showed that the best attained EER value was 0.98%.
- YU Lu et al. [6] introduced a finger vein recognition system based on matching score level fusion of Gabor features for single trait. Histogram equalization was used for quality enhancement of finger vein image. The database used to evaluate their system was SDUMLA-HMT database; it consists of 3816 images collected from the left and right hand four fingers belong to 106 individuals; with six samples taken for each finger. The test results showed that the recognition rate was 98.79% and EER was 2.84%.

- Xuzhou Li et al. [7] have proposed finger vein recognition method based on personalized discriminative bitmap which selects the stable bits from PBBM. The database used in this system was consist of 4080 images acquired from 34 individual, with four fingers for each and 30 samples for each finger. They utilized gray normalization to obtain uniform distribution for the gray levels which caused good enhancement for finger vein images. The test results showed the met recognition rate for this system was 96.75%.
- Ko et al. [8] have developed a human identification system based on simple finger vein pattern matching method, for embedded environments, using image histogram as a feature vector. They used spatially invariant Gaussian distribution blurring model to deblur and enhancing finger vein images. The used database consists of 500 images taken from 100 individual five samples for each. The test results indicated 97.60% success rate.

2 Materials and Methods

The layout of the proposed system is demonstrated in Fig. 1. It consists of four main stages, which are analogues to those used in most biometric systems: (I) Capture of the finger vein image pattern, (II) Preprocessing of the image, (III) Feature pattern extraction from the image, (IV) Pattern matching and make the outcome decision.

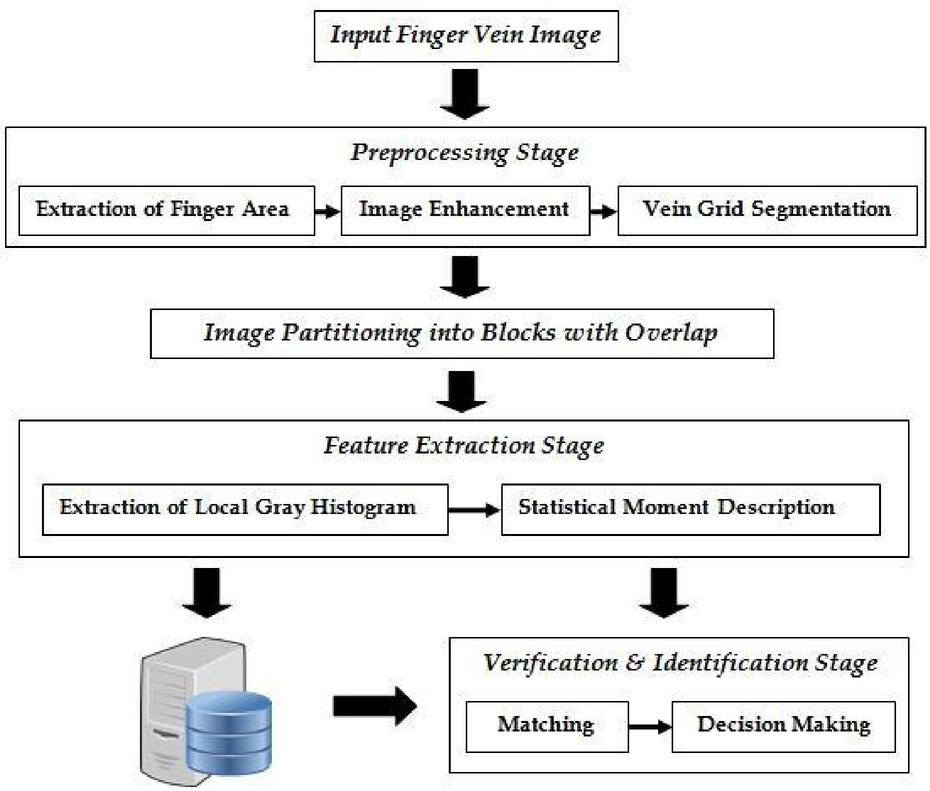


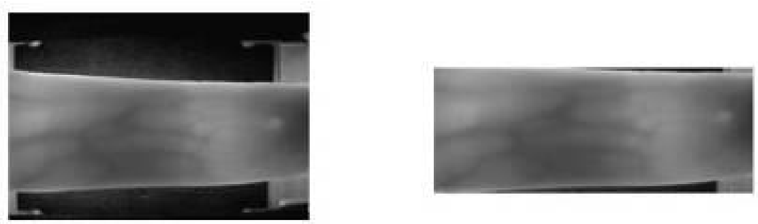
Fig. 1. The proposed system layout

2.1 Preprocessing

The involved steps of this stage are illustrated in the followings sub-sections:

2.1.1 Allocation of finger area

The original finger image is captured with undesired backgrounds, which increase the required computation complexity and scale down the accuracy of matching. In our developed system, Sobel edge detection operator was applied to segment the region of a finger from the background by highlighting the edges of the finger [9], as shown in Fig. 2.



(a) (b)

Fig. 2. ROI extraction, (a) Original image, (b) Extracted finger

2.1.2 Image enhancement using histogram equalization

The veins image patterns are enhanced using histogram equalization method. This method leads to redistribute the original image histogram in order to obtain a uniform population density [10]. The widening of brightness density is procured by grouping the adjacent grey values to certain value. Thus, the grey levels number of the enhanced image is less than the number of grey levels belong to the original image. This effect is suitable to discriminate the vein regions from the back ground as shown in the Fig. 4.

2.1.3 Image segmentation using local stretching

Finger vein images are affected by the light source and the depth of veins parts below the finger skin; the resulted images may show different brightness/ contrasts distribution for the regions of veins and other finger tissues. So, without compensating this local brightness variation and enhancing the contrast will cause significant degradation in the efficiency of features extraction and, consequently, on the cognition tasks.

In the proposed system the local variation of brightness is compensated using local contrast stretching [11]; that is a set of different thresholds was used for different target pixels depending on their neighborhood/local information. Generally, this technique is sensitive to background noise due to the non-uniform local variation in image illumination (i.e., the case of poor illuminated image or vessels bleeding) which causes segmentation and cognition accuracy degradation; because many of image pixels cannot categorized as foreground or background. To handle this quality poorness local thresholding will be the better solution in comparison with global-based techniques.

At first, a local stretching method is applied by partitioning the enhanced image into non-overlapped blocks, each of size ($n\times n$). Then, for each block in the partitioned image ($n\times n$), a window of size ($L\times L$), where $L>n$, is opened for scanning the surrounding neighbors of the block, since the brightness of pixels belong to a region are strongly correlated. Then the mean, $m_{(x,y)}$, and standard deviation, $\sigma_{(x,y)}$, for the opened window are calculated. Finally, for each pixel lay in the block ($n\times n$) contrast stretching is applied using the following equation:

$$G'_{str}(x,y) = \begin{cases} 0 & if\ G(x,y) \le Min \\ 255\,\frac{G(x,y)-Min}{Max-Min} & if\ Min < G(x,y) < Max \\ 255 & if\ G(x,y) \ge Max \end{cases} \quad (1)$$

where,

$$Min = Mean - \alpha_1 \times Std \quad (2a)$$

$$Max = Mean + \alpha_2 \times Std \quad (2b)$$

In this work, the test results indicated that the parameters setup (block size $n \times n = 2 \times 2$, scanning windows depth=20, as shown in Fig. 3, the used process is algebraic and it is not a complex operation so it is not highly affected by the block size. Multiplication factors $\alpha 1=0.5$, $\alpha 2=0.1$) led to best results. Fig. 4 shows samples of the vein images and their corresponding histograms before and after the enhancement stage.

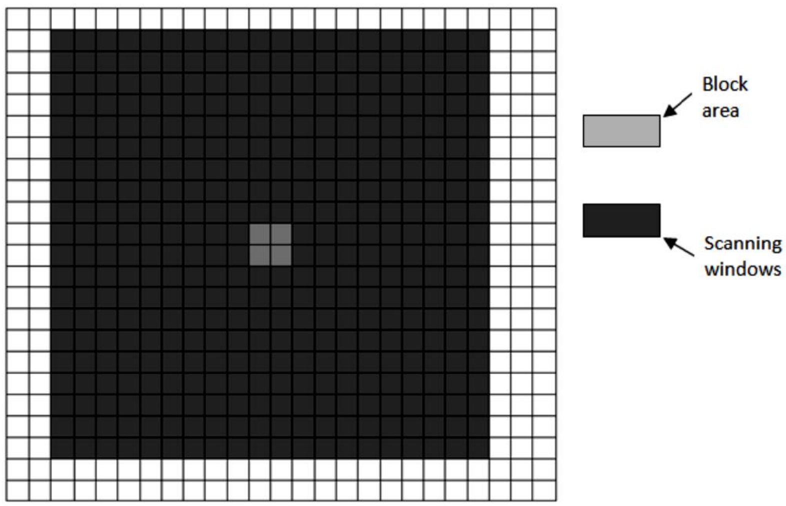


Fig. 3. The scanning window and image blocks areas

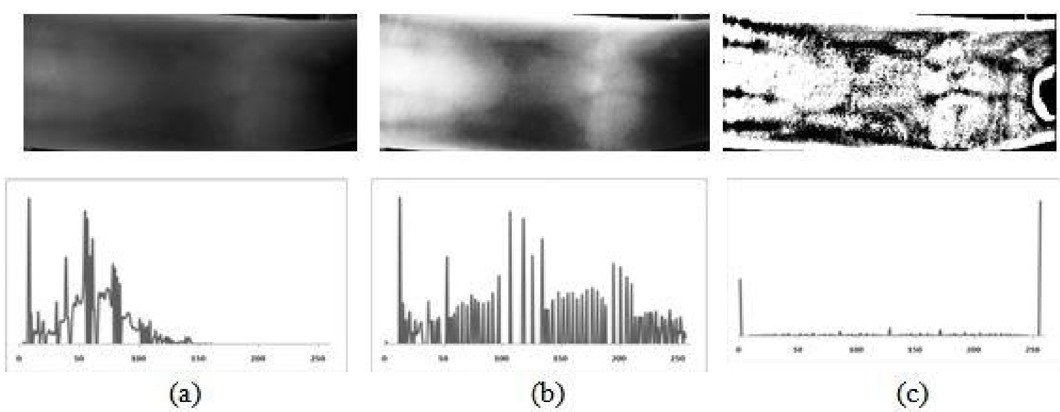


Fig. 4. Histogram enhancement steps, (a) Original image, (b) Image after histogram equalization, (c) Image after local stretching

2.2 Feature extraction

Based on the ability of gray histogram to represent the statistical information of global gray and local gray; so, a histogram based feature set that can overcome the variation in samples within a class was adopted.

Also, the these feature did not requiring performing complex preprocessing operations to enhance the gray finger image. The involved steps of this stage are:

Step 1: Partition the enhanced finger image into a number of overlapped blocks.

Step 2: The histogram of each block was calculated to obtain the grayness behavior blocks as shown in Fig. 5, then the mean of raised intensities is calculated:

$$mean = \frac{1}{s}\sum_{k=0}^{255} hist(k) \times k \tag{3}$$

Step 3: Determine the statistical norms to build the feature vector of the image. Image moments are usually used for describing objects after segmentation [12]. The adopted moments are the central moments instead of the ordinary moments. They are computed in terms of deviations from the mean instead from the origin. They provide full description of the spatial distribution of the vein grid. The function of such moments is, mostly, selected to have some attractive property or feature.

$$\|Norm\|_p = \frac{1}{N \times N}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} (I(x,y) - mean)^p \;\; sign(I(x,y) - mean) \tag{4}$$

Where the value of P as taken to be bounded with the range [0,1].

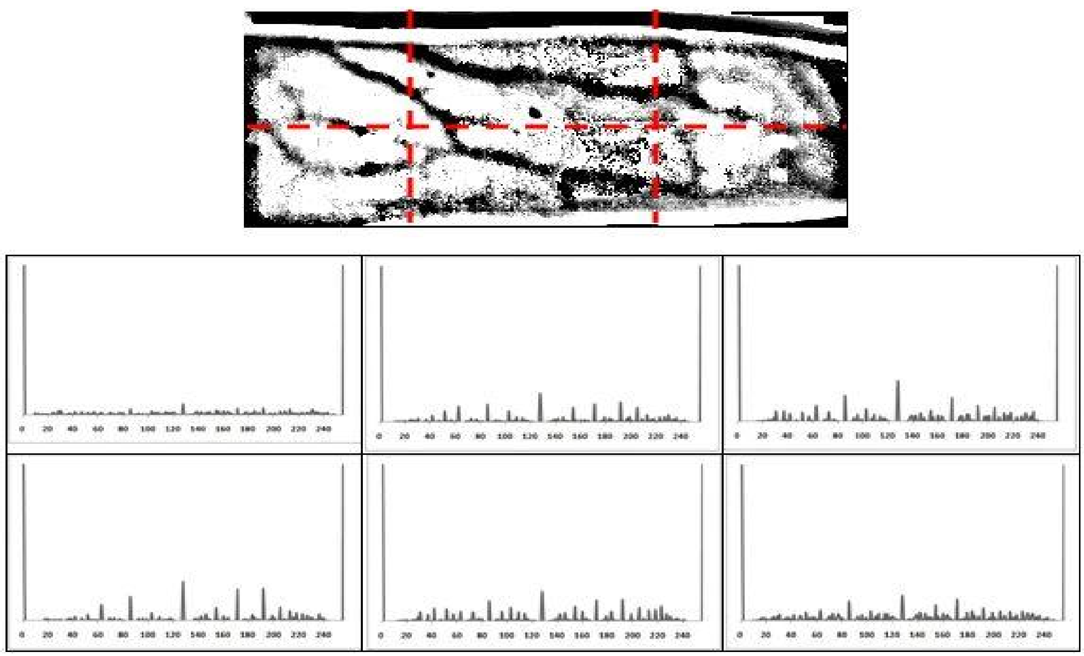


Fig. 5. Local histogram for gray image

2.3 Matching

The extracted features from finger vein images are stored in a database, then for each class a partitioning of samples into training and testing categories are done. In this stage, the nearest neighbor classifier was used to make the classification decision for each input image. This is done by comparing feature vector extracted from the input image with the stored templates of classes; it is classified according to the class whose template shows closest distance in the feature space. The nearest neighbor classifier is essentially based on the city block distance between a test sample and the specified training samples. In 1-nearest neighbor algorithm, the portend class of test sample x is set equal to the actual class ω of its nearest neighbor, where m_i is a nearest neighbor to x if the distance:

$$d(m_i, x) = max_j\{d(m_j, x)\} \quad (5)$$

3 Results and Discussion

The dataset used for testing in this research is taken from SDUMLA-HMT finger-vein database that is publicly available [13]. The device used to capture finger vein images is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. Every image is a gray scale that is stored in "bmp" format with 320×240 pixels in size. To construct the dataset, it was taken from 106 subjects. each one was asked to provide images of his/her index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated for 6 times to obtain 6 images for each finger. Therefore, the finger vein database is composed of 3,816 images. In the following experiments, a set of 2,544 samples had been used for training to build the NN classifier, and a set of 1,272 samples had been used for testing (4 images as training samples and the remaining two samples for testing).

3.1 Identification (recognition) results

The identification system performance is measured using the parameter correct recognition rate (CRR); which is the ratio between the number of correct recognition decisions (n_c) and the totals number of tried tests (n_T):

$$CRR = \frac{n_c}{n_T} \quad (6)$$

Table 1 illustrates the attained recognition results when applying statistical norm3/4 on the: (i) local histogram extracted from the original test samples (where only the clipping stage for allocating the finger area is applied; without making any image enhancement), and (ii) the local histogram extracted from the "enhanced image" (where the histogram enhancement methods are applied with the contrast stretching parameters $\alpha1$=0.5 & $\alpha2$=0.1). For both histogram cases the values of number of blocks and overlapping ratio parameters were varied. The test results indicated that the increase of overlapping ratio (up to some extent) had improved the recognition accuracy because it useful to compensate the effect of partial loss in low-quality finger vein image and the effect of shifting in the localized vein grid.

Table 1. The recognition results for SDLH method for both cases, original and enhanced image versus the overlapping ratio & block no

Overlap ratio	Recognition rate (%)					
	Original image			Enhanced image		
	7×3 BSZ	9×6 BSZ	11×9 BSZ	7×3 BSZ	9×6 BSZ	11×9 BSZ
0.0	97.48	98.58	99.29	97.56	99.29	98.34
0.1	97.56	98.97	98.58	98.05	99.29	98.89
0.2	97.79	99.29	99.45	98.34	99.52	99.21
0.3	96.54	98.66	98.96	97.56	99.37	99.37

Table 2 illustrates the recognition results for the histogram enhancement methods on variant local stretching parameters (e.g., $\alpha1$, $\alpha2$), and on different blocks number, the overlapping ratio is set 0.2 in all tests cases.

Table 2. The recognition results for SDLH method versus the block number (overlap ratio=0.2)

Number of blocks	Recognition rate (%)		
	A_1=0.2, A_2=0.07	A_1=0.5, A_2=0.1	A_1=0.8, A_2=0.4
8×5	99.37	99.21	98.19
9×6	99.21	99.52	98.19
10×7	99.45	99.13	97.48
11×8	99.21	98.66	98.66
12×9	98.89	98.82	97.41
13×10	98.82	98.11	97.41

3.2 Verification (authentication) results

The performance of verification system is evaluated using the Receiver Operating Characteristic (ROC) curve; it illustrates the False Rejection Rate (FRR) against the False Acceptance Rate (FAR) at different thresholds on the matching score:

$$FAR = \frac{A}{B}, \quad FRR = \frac{C}{D} \tag{7}$$

Where, *A* is the number of successful authentications by impostors, *B* is the number of attempts at authentication by unauthorized users, *C* is the number of failed attempts at authentication by authorized users, and *D* is the number of attempts at authentication by genuine users.

The system threshold value is obtained according to the Equal Error Rate (EER) criteria, (i.e., at the case FAR = FRR). Also the performance of biometric systems can be measured by accuracy (i.e., the proportion of correct predictions) without considering what is positive (*P*) and what is negative (*N*) [14].

$$ACC = \frac{TP + TN}{P + N} \tag{8}$$

Where *TP* is the number of genuine users that identified correctly, *TN* is the number of impostor users attempts that rejected by the system.

In order to measure FRR, for both proposed methods, the samples of each person have been matched against its template; which means it is matched actually against the templates four samples (depending on the number of training samples). After that the closest sample of the 4-samples template will considered as the best one, consequently the number of matching attempts is 8 for each subject for measuring FRR. While for measuring FAR, each sample belong to certain person is matched against all templates belong to other persons; which led to 5080 matching attempts. The values of attained FAR, and FRR for different matching threshold values have been determined in Tables 3 and 4.

Table 3 shows FAR, FRR and accuracy values for different threshold values for the method based on SDLH for the original finger image, the verification results is performed using the best parameters setup that produced highest recognition rate.

Table 4 shows FAR, FRR and accuracy values for different threshold values for the method based on LHG for the enhanced finger image, the verification results is performed using the best parameters setup that led to highest recognition rate.

The ROC curve between the FAR and FRR with various thresholds is plotted in Fig. 6. EER (equal error rate) measure which is defined "as the error rate of FAR and the FRR when they are equal". The EER is 0.008%, 0.003% for the threshold value equal to 0.009, 0.018, for the cases: original image, and enhanced image, respectively.

Many methods to recognize finger vein patterns have been developed and introduced in the literature. Table 5 illustrates the performance parameters for some of these methods in order to compare their performance with the proposed systems in this work; the conducted tests on the listed methods have used different datasets.

Table 3. FAR, FRR and accuracy versus threshold values on the original images

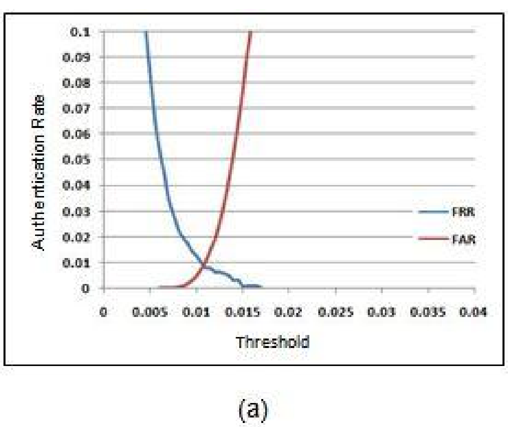
Threshold	FRR (%)	FAR (%)	Accuracy (%)
0.009	0.0173	0.0018	99.05
0.0095	0.0142	0.0031	99.14
0.01	0.0126	0.0049	99.13
0.0105	0.0102	0.0073	99.12
0.011	0.0079	0.0106	99.08

Table 4. FAR, FRR and accuracy versus threshold values on the enhanced images

Threshold	FRR (%)	FAR (%)	Accuracy (%)
0.016	0.0063	0.0004	0.9966
0.0165	0.0055	0.0008	0.9969
0.017	0.0055	0.0013	0.9966
0.0175	0.0039	0.0022	0.9969
0.018	0.0032	0.0034	0.9967

Table 5. Comparison of the proposed methods with previous studies

Reference	Method	Dataset (fingers × samples per each)	Performance
Yu et al. 2009 [15]	Minutiae points	50× 10 images	EER:00.76%
Mahri et al. 2010 [5]	Phase only correlation (POC)	204 × 10 images	EER:98.00%
Song et al. 2011 [16]	Mean curvature	125 × 9 images	EER:00.25%
Yang et al. 2012 [17]	$(2D)^2$ PCA	80× 18 images	CCR:99.17%
Lu et al. 2013 [6]	Score level fusion of gabor filter	636 × 6 images	CCR:98.79% EER:02.84%
Li et al. 2014 [7]	Personalized discriminative bit map (PDBM)	136 × 30 images	CCR:96.75%
Ko et al. 2015 [8]	Shift invariant pattern matching	100 × 5 images	CCR:97.60%
This study	SDLH	636 × 6 images	EER: 0.003% CCR: 99.52%



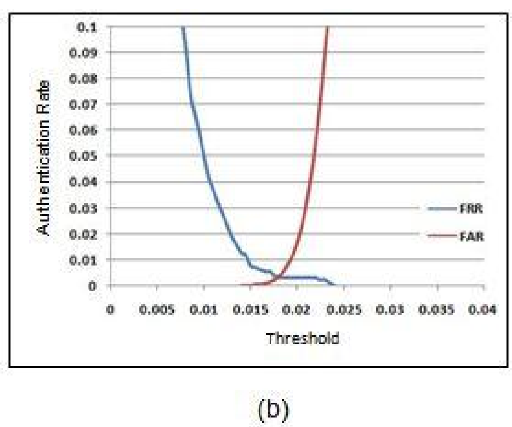


Fig. 6. The ROC curve for: (a) Original image (b) Enhanced image

4 Conclusion

In this paper, a personal verification and identification system is introduced for personnel cognition using their finger vein images. A new feature set is proposed in this work; it depends on the "Spatial Distribution of the Local Histogram", where the finger vein image is portioning into blocks, and spatial distribution of histogram of each block is obtained. Many tests have been conducted on the method using different parameters that effect the system which have different qualities. The experimental results showed that our system achieved high recognition rate when applying it on the raw image and the results are improved with the image enhancement to reach CCR 99.52%, and EER equal to 0.003%, which indicate high performance in recognition& verification. The tests results indicated that the proposed method produces high recognition rate with accuracy competitive with those achieved by other methods introduced in the literature.

Competing Interests

Authors have declared that no competing interests exist.

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