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A Personal Identification Method Based on the Geometrical Patterns of Veins Grid in a Finger

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Abstract

As a new biometric technique, finger recognition has attracted lots of attentions and used in wide range of applications. Finger vein recognition is a physiological characteristics-based biometric technique; it uses vein patterns of human finger to perform identity authentication. Vein patters are network of blood vessels under a person's skin. Even in the case of identical twins the finger-vein patterns are believed to be quite unique. This makes finger vein detection a secure biometric for individual identification. In this paper a feature set based on the local binary projections of veins grid body is proposed to be used for personal identification. The proposed system consists of three main stages, which are: preprocessing, feature extraction, and matching. Since near infrared NIR vein images suffer from low contrast, and low noise; which make the extraction task of accurate veins grid become hard. For this reason a sophisticated preprocessing process needs to be accomplished to ensure high identification rates. The applied steps in preprocessing stage are: histogram equalization (to improve the contrast of the image). Also the brightness compensation step is applied to suppress the background and to make grid body more visible, and to make the segmentation task easier. Finally two levels of thinning are applied to make the grid appearance more localized.

Due to fast implementation, and both rotation and scale invariant features requirements; a feature set based on the local binary projection (in four directions: vertical, horizontal, main diagonal, and second diagonal) is adopted. The geometrical moments are calculated for the four direction projections which represent the discriminating local finger vein features.

The developed system was tested over SDUMLA-HMT finger-vein database collected from 106 volunteers using their index, middle and ring fingers of both hands. The collection for each of the 6 fingers is repeated for 6 times to obtain 6 finger vein images. The test results indicated that the equal error rate of our proposed is 99.2%. Increasing the number of learning sample leads to improvement the identification rate up to (100%).

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Keywords: Finger vein; blood vassal; near infrared; binary projection; geometrical moments.

1 Introduction

The increasing demand for providing a unique and secure identity for citizens, customers or stake holders, made automatic personal identification one of the most significant demanding tasks. Thus, some researchers are provoked to discover new biometric features and characters. Biometrics, which uses human physical and behavioral characteristics, has 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]. As compared to traditional identification techniques such as personal Identification Numbers (PINs), passwords, the biometric techniques based on human physiological qualities can ensure higher security and more convenience for the consumer, hence the biometrics-based automated human recognition are now attractive more and become more popular in a huge range of inhabitant applications. Many biometric systems were adopted, but each type has its merits and demerits, Finger print is a popular trait for recognition but it can be easily spoof using dummy fingerprint, sensitive to dirt, wet and age. Facial recognition is sensitive to the face expression and age. Voice recognition is also depends upon the environmental condition and not secure from the recorded voice. Considering the challenges in the current recognition systems, now the development concerns have directed toward designing new generations of biometric recognition systems which depends on more robust features to enhance the tasks of human authentication and recognition [2].

Finger vein biometric system can verify person's identity by recognizing the pattern of blood veins in his/her Finger. Finger vein recognition uses the vascular patterns of an individual's Finger as personal identification data. It has been shown that finger vein pattern is distinctive enough for human biometric identification, like fingerprints [3]. The pattern of blood veins in the Finger is unique to every individual, even twins have different patterns and apart from size, this pattern will not vary over the course of a person's lifetime.

For capturing a vascular network, hemoglobin plays an important role by absorbing infrared light, and after absorbing infrared light the vein patterns are captured. Distance is very important in absorbing infrared light between skin and vessels: bigger distance leads to more noise in the captured image [4].

Vein patterns are located inside the body. Therefore, it provides a high level of accuracy due to the uniqueness and complexity of vein patterns of the finger. It is difficult to forge. Finger vein systems provide user friendly environment. Therefore, finger vein is a good candidate for biometric recognition system. 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.

Many algorithms were proposed and implemented to recognize finger vein; some of them are demonstrated below:

- Gongping Yang et al. [5], have proposed a 2D PCA method to extract features of finger veins, then for classification they used KNN classifier for each individual. Besides, the SMOTE technology was adopted to solve the class-imbalance problem. They had used a custom database, collected from 80 individuals' index fingers of right hand, where each index finger contributes 18 finger vein images. The experiments showed that the recognition rate was 99.17%.
- Park [6] discussed an approach of finger vein recognition by combining the local features of Local Binary Pattern (LBP) and the global feature information of the finger veins based on Wavelet transform. The two score values by the LBP and Wavelet transform were combined using support vector machine (SVM). They had used a custom database, which consist of 4,000 finger vein images, 10 images for each of 8 fingers (without using the thumbs of both hands) from 50 persons. The test results have been expressed in terms equal error rate (EER); and it was 0.011%.
- Wang and et al. [7] proposed a finger vein recognition system, for feature extraction they proposed a method based on dividing vein image into blocks and for each image sub-block, the wavelet-moment based features and PCA features are extracted. They had tested the algorithm using images

from a custom finger vein image database. The database includes five images each of 300 individuals' finger veins. The experimental results showed that the error rate FAR was 0.7%, and the rejection rate FRR was 1.05%.

- Naoto Miura and et al. [8], proposed a personal identification technique based on patterns of veins in a finger. To get the vein pattern from blurred original image, the line tracking operation based on randomly varied starting points was carried out repeatedly. Authors indicated that the attained test results are equal error rate (0.145%).

2 Proposed Scheme

The proposed system layout is demonstrated in Fig. 1. It is consist 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.

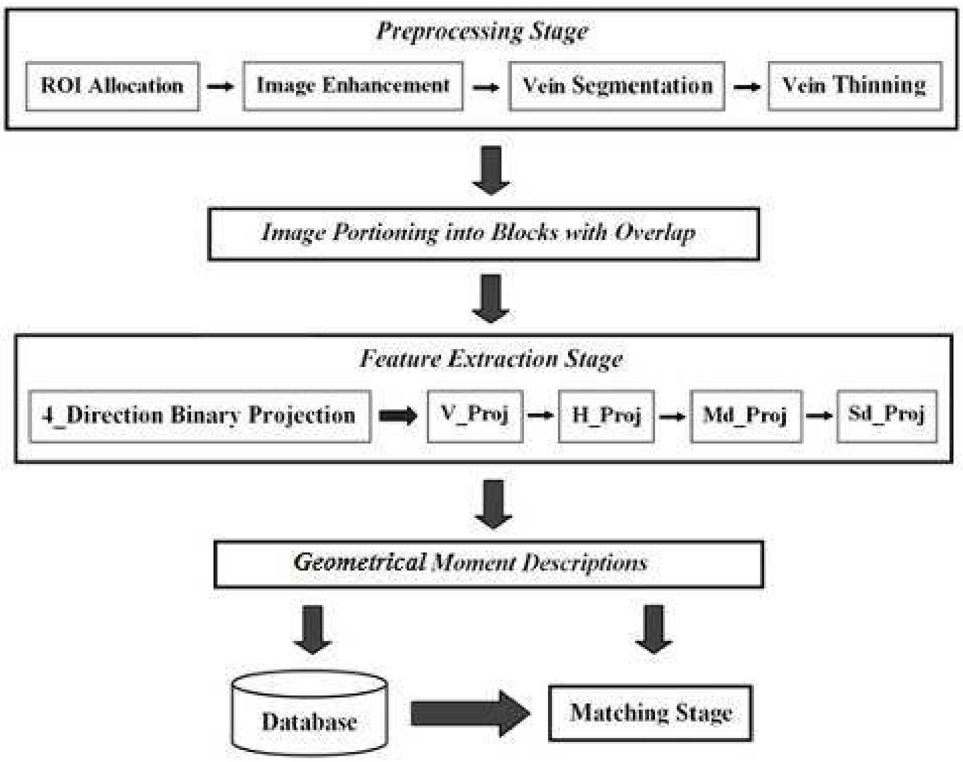

Fig. 1. The proposed system layout

2.1 Preprocessing

The involved steps of this stage are the followings:

2.1.1 Allocation of ROI

The original image is captured with undesired backgrounds, which increase the required computation complexity and scale down the accuracy of matching. Sobel edge detection operator was applied to segment the finger region from the background by highlighting the edges of the finger. It uses a pair of 3×3 convolution masks, one estimating the gradient in the x-direction and the other estimating gradient in y–direction [9]. Two major horizontal lines are allocated to represent the upper and lower edges of finger area. The resulting rectangle represents the finger area. The image cropped according to the highlighted rectangle, then cut it away from the rest of the image, as shown in Fig. 2. The cropping points are selected according to the following two conditions:

i. The pair of the horizontal edge points has an acceptable width according to a value of the minimum length of the allowable length. The suitable value of allowable length was assigned by testing.
ii. The distance that separates the pair of the edge points is between (55%) and (65%) of the original image height.

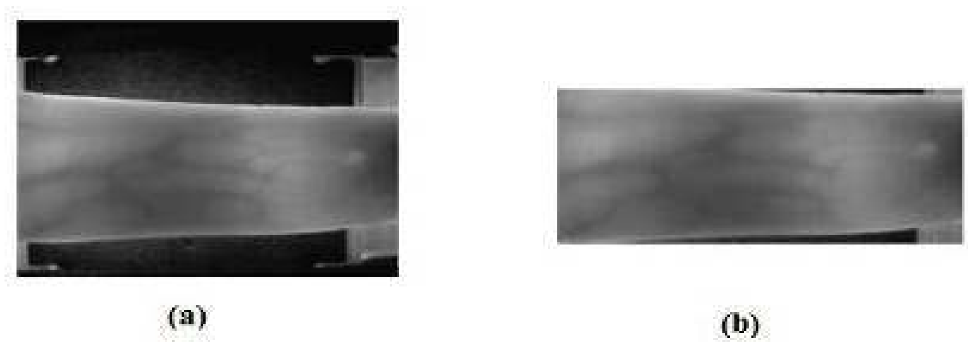

Fig. 2. ROI extraction, (a) Original image, (b) Extracted finger

2.1.2 Image enhancement using histogram equalization

The vein patterns images are acquired using infrared (IR) cameras. The acquired images have low contrast and they are blurred in nature; therefore, contrast enhancement step is required to expand the range of brightness values in the input vein image; such that the image can be efficiently displayed in suitable manner that desired by the analyst, see Fig. 3.

The veins image patterns are enhanced using histogram equalization method. The involved steps of this method lead to redistribute the histogram of the original image in, order to produce a uniform population density [10]. The widening of brightness density is obtained by grouping the adjacent grey values which are close to certain value. Thus, the number of grey levels in the enhanced image is less than the number of grey levels in the original image. This effect is suitable to discriminate the vein regions from the background.

In histogram equalization, each pixel is assigned a new intensity value according to its previous intensity level. Let $p(n)$ denotes the normalized histogram of the nth level in image, so:

$$p(n) = \frac{number\ of\ pixels\ with\ intensity\ n}{total\ number\ of\ pixels} \tag{1}$$

Where, n=0, 1, 2, …, 255.

The histogram equalized value for each grey level (n) value is determined using:

$$g(n) = round\left((L-1)\sum_{i=0}^{n} p(i)\right) \tag{2}$$

Where L is the number of possible intensity values (in this work, L is set 256).
The enhanced image, $G'(x,y)$, by histogram equalization method is determined using:

$$G'(x,y) = g(G(x,y)) \quad (3)$$

Where, *G*() is the original vein image.

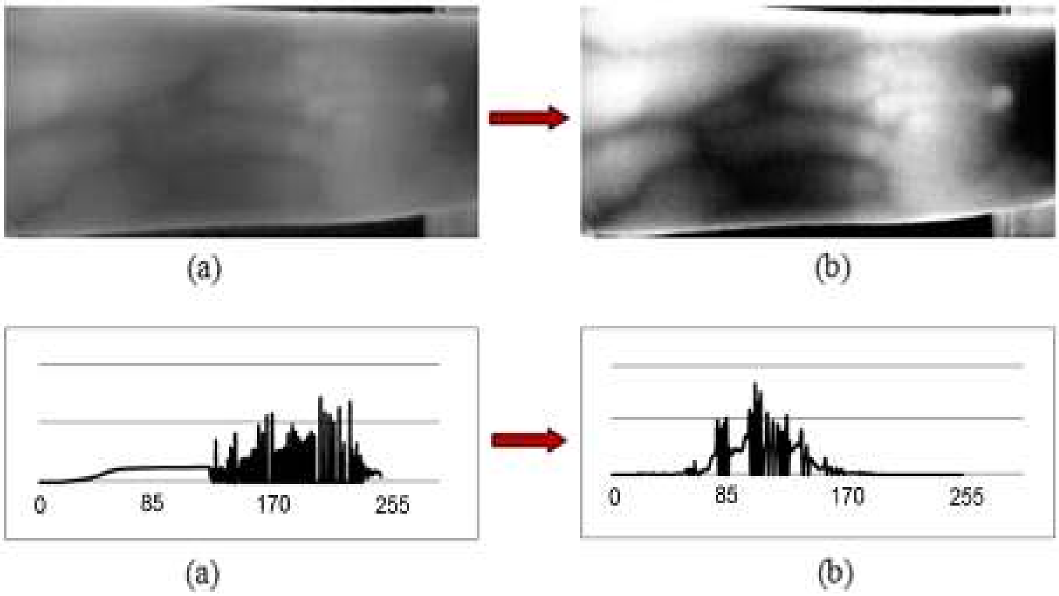

Fig. 3. Image enhancement (a) Before applying histogram equalization, (b) After applying histogram equalization

2.1.3 Image segmentation

This stage implies the following:

2.1.3.1 Brightness compensation

As the finger vein image is affected by the light source and the depth of veins parts below the finger skin, so the resulted images may show different brightness/ contrasts distribution for the regions of veins and other finger tissues. 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. First, we have to calculate the mean (m_{xy}) and standard deviation (σ_{xy}) of the finger vein image region that surrounding each pixel (x,y) are determined, then the contrast stretching and brightness elimination is achieved by applying the following mapping equation:

$$G''(x,y) = \frac{A}{\sigma_{xy}}\left(G(x,y) - m_{xy}\right) + 128 \quad (4)$$

Where, $G'(x,y)$ is the pixel value of the enhanced image using histogram equalization method, and $G''(x,y)$ is the new pixel value due to application of the above equation. The suitable value of *A* is assigned by testing. Since the vein image brightness was enhanced and the produced image from the brightness compensation consists of only two values (0 and 255), as shown in Fig. 4. The binarization process is quite simple, it is only assigning the gray image pixel that has a value greater than ‘0’, which mean ‘255’ a value of ‘1’.

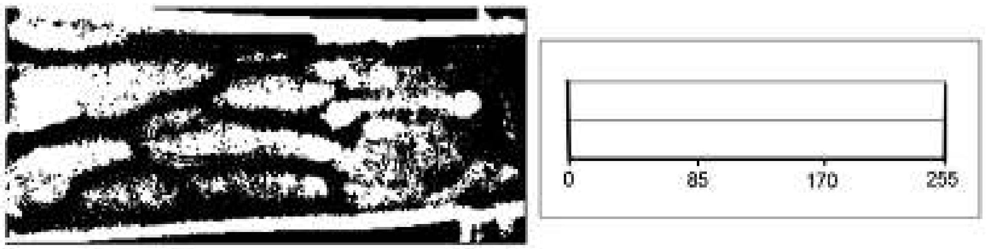

Fig. 4. Image after applying brightness compensation

2.1.3.2 Noise elimination

This step is necessary to eliminate the noise that would appear due to segmentation by threshold. To allocate, accurately, the shape of veins the produced binary image should be enhanced by reducing the noise points (i.e., the gaps/ pores); the existence of these unwanted points affects the form, structure or shape of veins traces. The concept of noise removal by applying morphological operations is adopted and it is quite simple. [11]. The morphological "Erosion" & "Dilation" operations are an effective choice to remove and fill the small objects of the binary image without altering the overall shape and size of the large objects (veins object). Beside to these operators, the seed filling operation is used to collect the unwanted small noise patches and to remove them [12].

Median filter is used to eliminate burrs in the finger vein image after applying morphological operations and make the borderline smooth. It is widely used as it is very effective at removing noise while preserving edges. The vein grid in some regions is so thin (as the physical nature of the vein grid), so if we apply thinning methods directly without applying median filter it will produce a disjoint grid as shown in Fig. 5.

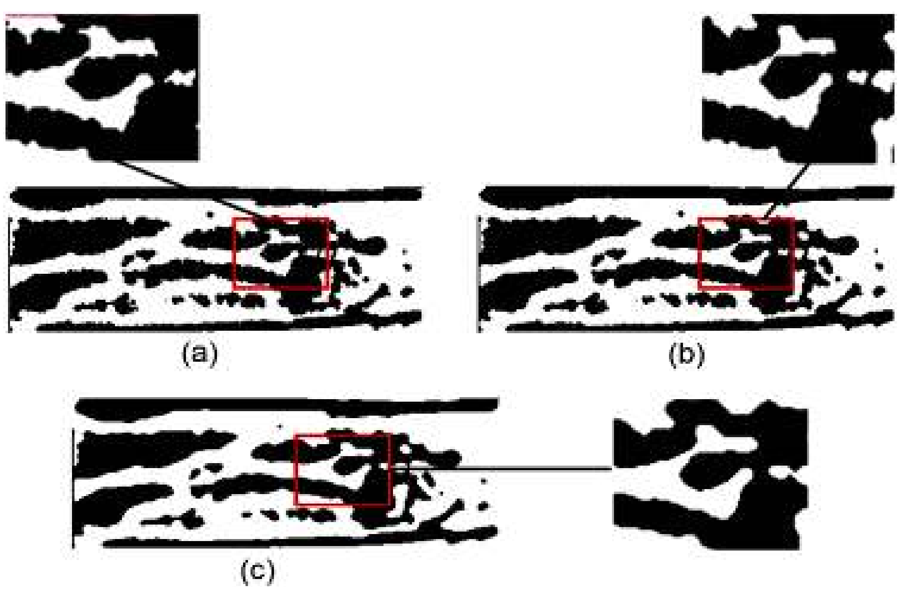

Fig. 5. Noise elimination, (a) Seed image after applying 5_times Dilation, (b) Dilate image after applying Erosion, (c) Erosion image after applying Median filter

2.1.3.3 Thinning

It is used to remove the selected foreground pixels from a binary image. This operation is used to join up the output of edge detector by shrinking the veins traces to a single pixel thickness for better performance. The direct thinning the vein body up to single pixel leads to losing some important information and may, effectively, alter the overall vein grid shape. For that we have made thinning to vein grid by applying fine thinning algorithm; which consists of three main operations: integration operation then the normalization operation and finally binarize the resulted image [13]. Then we applied the ZS algorithm to reduce the vein width into a single pixel. These three steps are applied as follows:

1. Integration: the aim of this step is to relatively increase the brightness of the vein's center, and relatively reduce the brightness of the vein's sides in order to make the vein grid as thin as possible. It works by moving a window of size (*n*x*n*) over the image pixels and calculate the new value by applying the following equation:

$$I^{'}(x,y) = \sum_{j=-r}^{r} \sum_{i-r}^{r} I(x+i, y+j) \tag{5}$$

$$r = \frac{1}{2}(n-1) \tag{6}$$

Where, $I'()$ is the resulted integrated image, $I()$ is the input image and n is the window size.

2. Normalization: is a process of improving the intensity contrast between the center of veins and its sides. It implies the following steps:

   a. For each non zero pixel, open a window with size of (*n*x*n*) and calculate the mean value of all pixels within the window. Then, the following thresholding criterion is applied:

$$I_{th}(x,y) = \begin{cases} I(x,y), & if\ I(x,y) \geq \alpha m \\ 0, & otherwise \end{cases} \tag{7}$$

   b. Do value scaling doing mapping using the following equation:

$$I_R(x,y) = \frac{1}{m} I_{th}(x,y) \tag{8}$$

And then, find the global maximum pixel value [I_{max}=max(I_R())].

   c. Calculate the normalization value for each pixel by applying the following equations:

$$I_{norm}(x,y) = Slp \times\ I_R(x,y) \tag{9}$$

$$Slp = \frac{I^{'}{}_{max}}{I_{max} \times \alpha} \tag{10}$$

Where, $I_R()$ is the final process image array, $I_{norm}()$ is the edge normalized image array, I'_{max} is the maximum found pixel value.

   d. Finally, the following thresholding criterion is used:

$$I_{norm}(x,y) = \begin{cases} 255, & if\ I_{norm}(x,y) > 255 \\ I_{norm}(x,y), & otherwize \end{cases} \tag{11}$$

3. Binarization: This stage aims to allocate the center of a vein. In this stage, the gray image is converted to binary image to keep only the region of interest.

Then we apply the Zhang-Suen algorithm (ZS algorithm) is applied (i.e., a fast Parallel Algorithm for Thinning Digital Patterns) to reduce the vein width down to single pixel [14]. These procedures are applied iteratively until no further points are deleted. Fig. 6 shows a sample of thing result.

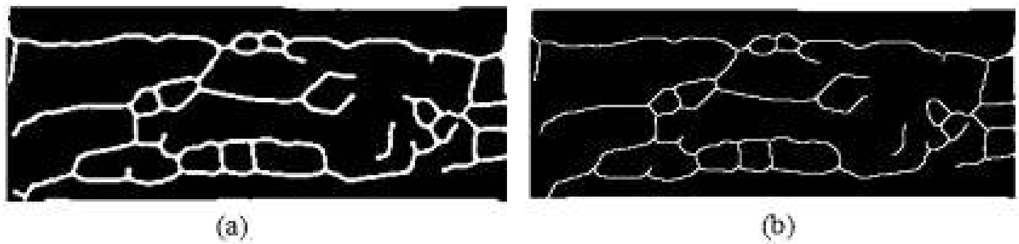

Fig. 6. Image thinning, (a) Fine thinning image, (b) Parallel thinning image

2.2 Extraction of Local Projection of Vein Grid

Projections of a binary image indicate the number of pixels in each column, row, or diagonal in that image. We refer to them as horizontal, vertical, or diagonal projections, respectively. Although projections occupy much less memory that the image they were derived from, they still contain essential information about it, so it can be used as a features for recognition of objects. Horizontal and vertical projections of an image provide knowledge about the position of the object in the image, while horizontal, vertical, and diagonal projections of an image provide knowledge about the orientation of the object in that image. When the projection vectors of a region are calculated in reference to the center of the region along the major direction, the result is a rotation-invariant vector description (often referred to as a “signature”) of the region. Projections in the direction of the coordinate axis are often consider as quickly analyze the structure of an image [15].

The involved steps for determining the Local Projection of Vein Grid are the following:

Step 1: Divide the vein image into overlapped blocks. Overlapping is adopted to compensate the small finger geometrical shifts (i.e., positioning or rotations) occurred during the image capturing stage. The value of overlapping length is taken as a ratio of block length. The block length is obtained by dividing the image into number of blocks, as shown in Fig. 7. The effects of both the number of blocks and overlapping ratio values are tested to find their suitable values; which should lead to best recognition rate, as shown in table (1). Since the width and height of the image are not equal, so the block dimensions (i.e., width and height) are not equal.

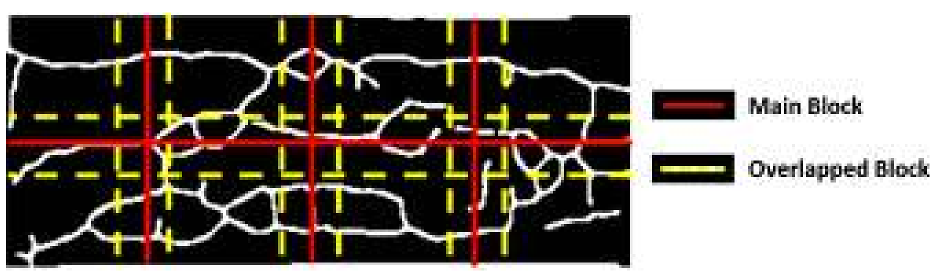

Fig. 7. Image partitioning

Step 2: For each block generate vertical and horizontal projection of an image $I(u,v)$, with $0 \le u \le M$, $0 \le v \le N$, which defined as:

$$P_{hor}[y] = \sum_{x=0}^{M-1} I[x,y] \quad for\ 0 \le y \le N \tag{12}$$

$$P_{ver}[x] = \sum_{y=0}^{N-1} I[x,y] \quad for\ 0 \le x \le M \tag{13}$$

The horizontal projection $P_{hor}(y)$ is the sum of the pixel values in the image row y and has length N corresponding to the height of the image. On the other hand, a vertical projection $P_{ver}(x)$ of length M is the sum of all the values in the image column x.

Step 3: Perform rotation on each block, which maps the position picture element in an input image block onto a position in an output image block by rotating it through 45° angle as in equation:

$$x' = (x - x_c)\ cos\theta - (y - y_c)\ \sin\theta + x_c \tag{14}$$

$$y' = (x - x_c)\ \sin\theta + (y - y_c)\ \cos\theta + x_c \tag{15}$$

Where (x_c,y_c) are the coordinates of the center of rotation (in the input image block) and θ is the angle of rotation with clockwise rotations having positive angles.

If the output locations are outside the boundary of the image then it will be neglected, which mean pixel locations out of which an image has been rotated are usually filled with black pixels.

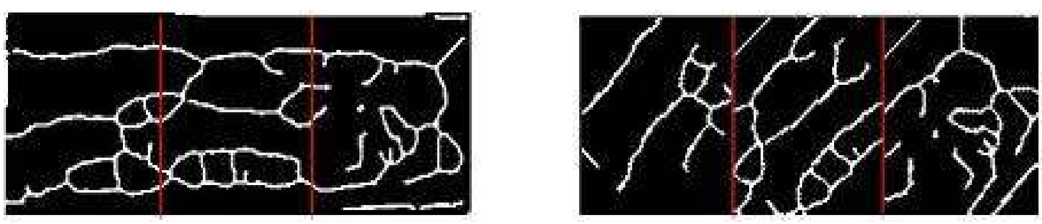

Fig. 8. Image rotation after dividing it into 3-blocks

Step 4: Recall **Step 3** for each rotated block to obtain the main and second diagonal projection.

Step 5: After the stage of projections calculation along the four directions (i.e., vertical, horizontal, main diagonal and second diagonal). Then, from each direction image the geometrical moments and the norms are calculated, separately; then they assembled in one features vector to be treated as a signature vector for the finger vein image. The Geometric moments of objects provide efficient local description; then have been used extensively in image analysis applications. They need low computation cost. Although they are sensitive to noise; they show good invariance under linear transformations [16]. In this work we had use central moments. Central moments are used in preference to ordinary moments. They computed in terms of deviations from the mean instead of from the zero, and provide description to spatial distribution of the vein grid. For a density function *f*(*x*) the geometrical moments of order p (i.e., *m*(*p*)) are defined as:

$$m_p = \sum_{x=0}^{N-1} \left(x - mean_{f(x)}\right)^p \times f(x) \tag{16}$$

The norm of order p for a density function *f*(*x*) is defined as:

$$\|Norm\|_p = \sum_{x=0}^{N-1} |x - mean_{f)}|^p \times f(x) \times sign(x - mean_f) \quad (17)$$

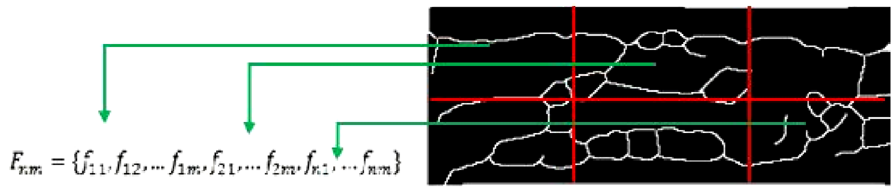

Fig. 9. The vector of the characteristic features

2.3 Matching

In this stage, the degree of matching between two vein patterns is calculated. The extracted vein features list of the input image can directly be compared with the stored templates by using *K*-nearest Neighbor rule (KNN), it has been one of the most well-known supervised learning algorithms in pattern classification, and it has several main advantages: simplicity, effectiveness, intuitiveness and competitive classification performance in many domains [17]. KNN is used as a metric to evaluate the similarity degree between the feature vector of input pattern and the tested template(s).

3 Results and Discussion

The dataset used for testing in this research is taken from SDUMLA-HMT finger-vein database that is publicly available [18]. 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. Every image is a grayscale that is stored as "bmp" file format with 320×240 pixels in size.

Test Set 1: In this experiment, a set of 2,544 samples had been used for training to build the KNN 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). The *K* value is assigned to be 1 in KNN. The test results showed that each moment gave different recognition rate as shown in Table 1; a. Also, the overlapped partitioning had improved the recognition accuracy and helps to overcome on the partial loss in low-quality finger vein image and shifting in the localized vein grid; as shown in Tables 2 and 3.

Table 1. The recognition rate versus the used geometrical moment with block size (18×9) & overlap ratio (0.5)

Moment	Recognition rate
Standard deviation (m_2)	98.11%
Skewness (m_3)	98.11%
Kurtosis (m_4)	96.77%
$\text{Norm}_{1/2}$	98.82%
$\text{Norm}_{3/4}$	**99.21%**
$\text{Norm}_{1/2}$ & $\text{Norm}_{3/4}$	97.24%

Table 2. The recognition rate for different block size using $norm_{3/4}$ feature, and the overlap ratio is set (0.5)

Block size	Recognition rate
16 × 7	97.56%
17 × 8	98.11%
18 × 9	**99.21%**
20 × 10	98.42%

Table 3. The recognition rate for different overlap ratio using $norm_{3/4}$ $moment_{1/2}$ and block size (18×9)

Overlap ratio	Recognition rate
0.2	96.30%
0.5	**99.21%**
0.9	96.85%

Test Set 2: In this test, the feature $Norm_{3/4}$ is used, the used block size is set (18×9), and overlap ratio is taken (0.5); which led to best results as shown in test set (1). In this set of tests, the number of training samples fed to KNN classifier was varied. As shown in Table 4, the increasing in training samples leads to improve the recognition accuracy.

Table 4. The recognition rate versus the number of training and testing samples

Number of Samples	Recognition rate
1908 training, 1908 testing	93.86%
2544 training, 1272 testing	99.21%
3180 training, 636 testing	**100%**

4 Conclusions

In this research, we described a personal identification method based on the geometrical patterns of veins grid in a finger. The extracted features for representing the veins pattern from an unclear original image are the geomtrical moments of the local binary projections. Before feature extraction stage the finger vein image was well enhanced. The developed preprocessing stage produced an accurate localization of vein grid, and the best attained recognition rate was 99.21%.

The experimental results showed that the adopted moment gave different recognition rate, and the partitioning into overlapped blocks (instead of non-overlapped blocks) had improved the recognition accuracy because it is useful for compensating the small shifts in the localized finger veins network, and increasing the training samples improve the recognition accuracy to reach 100%.

For future work, our module can be extended in different direction such as: using another enhancement method that may provide us with higher enhancement, applying another type of features, using another matching method which may increase the power of our system, and finally using a dedicated hardware to speed up the processing time.

Competing Interests

Authors have declared that no competing interests exist.

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