Abstract - Edge histogram descriptor (EHD) is an efficient texture representation method originally proposed in MPEG-7 to express the local edge distribution in an image. To efficiently utilize the edge and orientation features of rich veins located inside a finger, in this paper, we propose a finger vein recognition method using edge histogram descriptor. Different from the original usage that divides the image space into $4 \times 4$ sub-images, we investigate the relationship between finger vein recognition performance and partition style of input image. The optimal parameter is searched for final recognition. Additionally, the nearest neighbor classifier with Euclidean distance metric is employed for matching. Experimental results on an available finger vein database, MMCBNU_6000, show that the proposed method performs better than those using state-of-the-art algorithms.

Keywords: finger vein recognition, edge histogram descriptor, orientation feature

1 Introduction

Automatic personal identification using biometric characteristics is increasingly developed over the last two decades. However, no biometric has been proved to be perfectly reliable, robust and secure. The defects of traditional biometrics and the growing demand for more friendly and secured biometrics systems have motivated researches to explore new biometric features and traits [1].

Finger vein recognition, being convenient, non-invasive and with high security, has attracted considerable attentions in the past decade. Compared with the traditional biometrics (e.g. fingerprint, facial image, iris, gait, etc), finger vein recognition has the benefits of high anti-counterfeiting, low cost, easy data acquisition with contactless operation, universality and liveness [2, 3]. Furthermore, since the veins are located internally within the living body, finger vein identification system is less affected by the outer skin surroundings (skin disease, humidity, dirtiness, etc). In contrast to the hand vein- or palm vein-based recognition system, finger vein has the advantage of smaller size of imaging device. Hence, finger vein recognition is considered to be one of most promising solutions for personal identification in the future [4].

Human vision is sensitive to edge features for image perception so that edges in an image are considered as an important feature to represent the content of an image [5]. Histogram, which is invariant to image translation and rotation, is the most commonly used structure to represent the local and global feature composition of an image. Using histogram to represent the edge distribution can describe the frequency and directionality of the brightness changes in an image [6]. An effective edge histogram descriptor (EHD) is proposed in MPEG-7 to express the local edge distribution in the image. Since EHD aims to describe the local edge distribution in efficient storage of metadata, only 80 histogram bins are contained in the edge histogram. The local histogram only using 80 bins may not be sufficient to represent the global features of the edge distribution. To improve the problem, Park et al. [5, 6] proposed an efficient use of local edge histogram descriptor. Semi-global and global edge histograms were generated from the local histogram bins to describe the global edge distribution in an image. Then, the local, semi-global, and global histogram bins were concatenated to represent the edge distribution of an image. The effectiveness using EHD for feature representation has been proved in the applications of image retrieval [5] and face recognition [7].

The orientation features and edges are abundant in finger vein images, since the veins are located and developed within the finger with random orientation [8]. Different finger vein image brings different blood vessel network, which produces difference of their edge histograms. Hence, to efficiently utilize the edge and orientation features, in this paper, we present a finger vein recognition method using edge histogram descriptor. The original idea in edge histogram operator [5, 6] is to divide an image into nonoverlapping sub-images. We believe the best performance may be achieved with other partition style. Here, the performance obtained by dividing the finger vein image into several numbers of sub-images is evaluated to search the optimal way of image partition. Compared with the existing methods using such orientation features as local binary pattern code (LBPC) [9], local direction code (LDC) [10], Gabor filter [11], and Steerable filter [12], the proposed method shows its superiority with lowest equal error rate (EER) value.

The rest of this paper is structured as follows. Section 2 briefly introduces the preprocessing for ROI localization. Finger vein feature representation using local edge histogram descriptor is reported in Section 3. Section 4 provides
experimental results that verify the proposed algorithm. Finally, conclusion is given in Section 5.

2 ROI localization

Image preprocessing is a crucial process in a finger vein identification system. This process always includes ROI localization, image denoising, and image enhancement. Since the acquired images in our established database have good image quality, image denoising and image enhancement are not necessary in our finger vein identification system. Hence, image preprocessing in this paper only contains ROI localization. To correctly localize the ROI from the acquired image, a robust finger vein ROI localization method based on flexible segmentation is employed in this paper [13].

Fig. 1 Block diagram illustration of ROI localization.

Fig. 1 shows the block diagram illustration of the ROI localization method used in this paper, which contains a set of steps, namely segmentation, orientation correction, and ROI detection. In order to reduce the processing time, the acquired image is resized to 120×160 with ‘bicubic’ interpolation primarily. To get the pure foreground, finger region is segmented from the resized image using an extended edge operator. For the images in the abnormal case, elaborate binarization is utilized to remove the false background caused by the influences from uneven illumination, scattering, and improperly collection. With the middle points obtained from the finger region, the orientation angle can be calculated using least-squares estimation. Afterwards, the resized image is orientation corrected according to the estimated angle. For ROI detection, we extend the method used in [4], since the ROI of the images in our database is defined as a fixed region, based on searching the reference line in the second knuckle. Owing to the width of ROI varies with different finger, geometry normalization is necessary to eliminate the geometry variations. In this paper, all localized ROIs are normalized to 60×128 pixels with ‘bicubic’ interpolation.

3 Feature extraction and matching

In this paper, EHD is employed as feature representation method for finger vein identification.

3.1 Local edge histogram descriptor

The EHD basically represents the edge distribution using 5 types of edges in each local area, called a sub-image. Usually, an image is divided into 4×4 nonoverlapping blocks, which is shown in Fig. 2. Thus, the image partition always creates 16 equal-sized sub-images regardless of the size of the original image [6]. Edges are grouped into five categories (Fig. 3): horizontal, vertical, 45 diagonal, 135 diagonal and non-directional edges. Thus, for each sub-image, five bins of edge histogram can be obtained, corresponding to the above five categories.

Fig. 2 Definition of sub-image and image-block.

Fig. 3 Five edge types: (a) horizontal edge, (b) vertical edge, (c) 45 diagonal edge, (d) 135 diagonal edge, and (e) non-directional edge.

Fig. 4 Five edge filters: (a) horizontal filter, (b) vertical filter, (c) 45 diagonal filter, (d) 135 diagonal filter, and (e) non-directional filter.

To characterize the edge distribution, the sub-image is further divided into small square blocks called image-block (Fig. 2). The number of image-blocks is constant and independent of the original image dimensions. The size of image-block is proportional to the size of original image to deal with the images with different resolutions. Mean values of the four sub-blocks are obtained first. Then they are convolved with five filters shown in Fig. 4. Hence, five directional edge magnitudes are calculated, corresponding to five edge types. If the maximum magnitude value is larger than a threshold, the image-block is considered having the corresponding edge type. After the edge extraction from all the image-blocks, we can obtain the edge distribution of this
sub-image. Thus, we compute five histogram bins for each sub-image. Afterward, each histogram is normalized by dividing each bin with the total number of image-blocks in the sub-image. Since an image is usually divided into $4 \times 4$ sub-images, we have total 80 ($4 \times 4 \times 5$) bins for the edge orientation histogram.

### 3.2 Global and semi-global edge histogram descriptor

Only 80 bins in edge histogram are not sufficient to represent the global edge features. To represent the image with global edge distribution, global and semi-global edge histograms are directly extracted from the local edge histograms in [5, 6]. Since there are 5 edge types, the global edge histogram can be obtained by adding the 16 local edge histograms. Hence, the global edge histogram has five bins. For the semi-global histograms, four connected sub-images (as shown in Fig. 5) are connected to compose a semi-global histogram. For $4 \times 4$ sub-images, we can get 13 different clusters. Consequently, we have total 150 (80 (local) + 5 (global) + 65 (semi-global)) histogram bins for each image. Clusters from 1 to 4 and 5 to 8 emphasize the vertical and horizontal edge connectivity, respectively.

Fig. 5 Clusters of sub-images for semi-global histograms [5].

### 3.3 Feature representation using EHD

The usage of EHD in [5, 6] just divided an image into $4 \times 4$ nonoverlapping blocks. However, we believe a better performance can be obtained if the features contain more edge information. Hence, in this paper, we test the performance using different kinds of partition styles. Furthermore, to get more abundant edge information in each sub-image, each image pixel is considered as a basic unit (image-block) here.

Suppose the finger vein image is divided into $m \times n$ nonoverlapping sub-images. For the local histogram, it has $m \times n \times 5$ bins. For the global histogram, it has 5 bins, no matter how many sub-images there are. For the semi-global histograms, we have $m+n+5$ clusters. Thus, $m+n$ histograms are generated similar with the clusters from 1 to 8 in Fig. 5. It also has 25 bins for 5 histograms as shown from 9 to 13 in Fig. 5. These 5 histograms are generated from 4 sub-images located in each corner (4 corners) and another 4 sub-images located in the middle of the image. Therefore, there are total $m \times n \times 5+5+[(m+n)\times 5+5\times 5]$ bins for each finger vein image when the input image is divided into more than $4 \times 4$ sub-images.

### 3.4 Matching

There are various similarity metrics to evaluate the similarity from two histograms, such as histogram intersection, log-likelihood ration and chi-square. As the edge orientation histogram is normalized by dividing the total number of image-blocks in each sub-image, in this paper, we employed Euclidean distance for measuring the similarity of two histograms from two images.

### 4 Experimental results

All the experiments in this part are implemented on our established database which is named MMCBNU_6000 [14, 15]. For equitable comparison, all experiments are performed on the localized ROI, without any post-processing like image denosing and enhancement.

#### 4.1 Finger vein dataset

MMCBNU_6000 consists of finger vein images captured from 100 volunteers, who are students and professors in CBNU from Asia, Europe, Africa, and America, coming from 20 different countries. The ages of volunteers are from 16 to 72 years old. Statistical information of the nationality, age, gender, and blood type of each volunteer is available for deep analysis on the finger vein image. Since the length of the thumb and the little finger is too short, compared with other three fingers, each subject was asked in the capturing process to provide images from his or her index finger, middle finger, and ring finger of both hands in a standard office environment (rather than a darkroom). The collection for each of the 6 fingers is repeated 10 times to obtain 10 finger vein images. For each image collection, the subject was asked to input his or her finger optionally. Our finger vein database is composed of 6,000 images. Each image is stored in “bmp” format at 480×640 pixels size.

Fig. 6 Some finger vein image samples in MMCBNU_6000. Each row represents six images from six captured fingers of a person.
### 4.2 Searching optimal parameters

There are two parameters that will affect the performance of finger vein system using the proposed method. One is the number of sub-images. The other one is the threshold that is used for comparing with the maximum magnitude value. To investigate the optimal parameters, we design two experiments with performance evaluation using EER, which is the value where the False Accept Rate (FAR) is equal to the False Reject Rate (FRR). In addition, the receiver operating characteristic (ROC) curve generated by adjusting the matching threshold is also created for comparison. In both of these two experiments, five finger vein images from one individual are selected as the training set, while the rest five images are used as the test set. Hence, the training database and testing database are both composed of 3,000 images. Each finger is considered as an individual.

The first experiment is designed for searching the optimal threshold, while the partition style is $4 \times 4$ in this experiment. Fig. 7 shows the EER values with varying threshold. As mentioned above, the threshold is applied for deleting some useless points with weak edge. Thus, the matching performance enhances a little when the threshold increases from 0 to 2. However, with further increasing the threshold, some useful edge information is lost, which results in the enhancing EER values. Hence, the threshold is fixed to be 2 in the later experiments.

![Fig. 7 EERs with increasing threshold.](image)

The second experiment aims to investigate the optimal partition type. Table I shows the EERs with the varying partition styles. With the increasing number of sub-images, the EER values are decreasing with different extents. It shows the lowest EER of 1.34% when an image is divided into $8 \times 8$ sub-images. However, with the further increasing of the number of partitioned sub-images, the EER value enhances a little. The EER value is 1.46% when the input image is divided into $9 \times 9$ sub-images, which is larger than that of dividing image in to $8 \times 8$ sub-images. Additionally, the larger number of sub-images would cause longer processing time for feature extraction and matching. Hence, the optimal partition style is dividing a ROI image into $8 \times 8$ nonoverlapping sub-images.

![Fig. 8 ROC curves obtained using different methods.](image)

### 4.3 Matching performance comparison with existing methods

In order to ascertain the performance improvement using the proposed method, state-of-the-art algorithms such as...
as LBPC [9], LDC [10], Gabor filter [11], and Steerable filter [12] are implemented for comparison.

Fig. 8 shows the ROC curves using different feature representation methods. All these methods extract the directional features for image representation. It is clearly illustrated that the proposed method outperforms the existing methods such as LLBP [9], LDC [10], Gabor filter [11], and Steerable filter [12]. This attributes the efficient extraction orientation features by using EHD. Furthermore, edge histograms extracted from $8 \times 8$ sub-images can further effectively represent the orientation and edge features in a finger vein image, other than that extracted from $4 \times 4$ sub-images.

5 Conclusions

In this paper, we proposed a finger vein recognition method using edge histogram operator. Instead of dividing the input image into $4 \times 4$ sub-images, we investigated the performance with different non-overlapping partition styles. Experimental results, performed on our established finger vein database MMCBNU_6000, demonstrate that the optimal partition style is dividing the ROI image into $8 \times 8$ non-overlapping sub-images. In addition, the proposed method performs better than state-of-the-art algorithms that use directional features. In the future, we will devote ourselves to the investigation of new edge operators with 8 orientations and apply that in EHD.

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7 References