

## LETTER

# Finger Vein Recognition with Gabor Wavelets and Local Binary Patterns

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**SUMMARY** In this paper, a new finger vein recognition method based on Gabor wavelet and Local Binary Pattern (GLBP) is proposed. In the new scheme, Gabor wavelet magnitude and Local Binary Pattern operator are combined, so the new feature vector has excellent stability. We introduce Block-based Linear Discriminant Analysis (BLDA) to reduce the dimensionality of the GLBP feature vector and enhance its discriminability at the same time. The results of an experiment show that the proposed approach has excellent performance compared to other competitive approaches in current literatures.

**key words:** finger vein recognition, Gabor wavelet, local binary pattern, BLDA

## 1. Introduction

As a new biometric technology, finger vein recognition has recently attracted more and more attention in the field of personal identification [1]–[3]. Like other traditional biometric characteristics (such as face, iris, fingerprints, etc.), the finger vein has the following advantages: uniqueness, universality, permanence and measurability. Furthermore, personal identification based on finger vein is immune to fake fingers and forgery. The imaging of finger vein requires near-infra-red (NIR) illumination to extract the complex vascular structures residing inside the finger. However, the finger vein images are not always clear and sometimes contain irregular shadings and highly saturated regions. The key issue is how to extract and represent finger vein features from NIR images. During the last decade, several methods such as repeated line tracking [2], curvature method [4], minutiae descriptors [5], Gabor filters and morphological processing [6], etc., have been proposed for finger vein recognition. All of these methods always utilize features extracted from the segmented blood vessel network. However, the low quality of finger vein images may cause segmentation errors during the feature extraction process and degrade the performance of finger vein recognition. To solve this problem, local texture descriptors have gained attention for finger vein recognition, such as the

methods based on Local Binary Pattern (LBP) [7] and their variants [8], [9] which have been applied to the finger vein recognition. In fact, LBP represents the first-order circular derivative pattern of images, which fails to directly extract more discriminative information in the input finger vein image.

Although the current finger vein recognition methods can achieve good performance, these works failed to consider the fact that the finger vein is essentially a kind of network containing rich directional information. Inspired by the work of Zhang [10], we find that the Gabor filter has good characteristics in space frequency, space position and direction selectivity of finger vein global patterns. Moreover, LBP can effectively reflect and quantize the local features for representing vein patterns. Motivated by this, we combine the local patterns with the multi-scale and multi-orientation Gabor wavelets for finger vein recognition. In fact, the combination of Gabor wavelets and LBP, namely GLBP, can enhance the representation of the finger vein and describe the global direction information and local features effectively. We also introduce Block-based Linear Discriminant Analysis (BLDA) to reduce the dimensionality of the proposed GLBP feature vector and enhance its discriminability. The experimental results demonstrate that our proposed approach has excellent performance compared to the other competitive approaches in current literatures.

The remaining of the paper is organized as follows. Section 2 introduces the proposed finger vein representation approach. The proposed finger vein recognition approach is given in Sect. 3. In Sect. 4, the experimental results including comparisons with other approaches and analysis are presented in detail. Finally, the conclusion is drawn in Sect. 5.

## 2. Finger Vein Representation Based on GLBP

The overall framework of the proposed finger vein representation based on Gabor wavelets and Local Binary Patterns (GLBP) is illustrated in Fig. 1. In this approach, a finger vein image is modeled as a feature vector by the following procedure: (1) An input finger vein image is normalized and filtered by multi-scale and multi-orientation Gabor wavelet kernels to obtain the multiple Gabor Magnitude Pattern Maps (GMP); (2) Each GMP Map is further divided into non-overlapping rectangle blocks with specific size, and converted to Local Binary Pattern Map (GLBP); (3) The gray-level histogram of GLBP Map is computed for each

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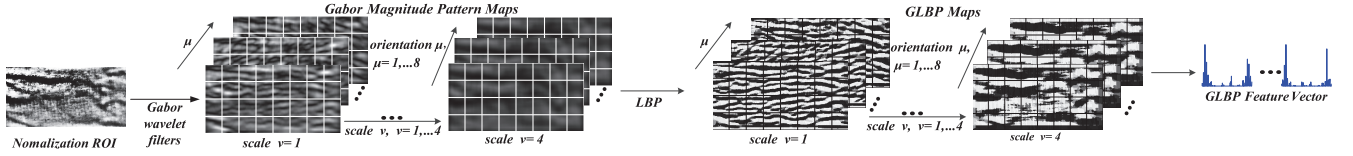
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**Fig. 1** The framework of the Finger vein GLBP representation.

block region; (4) The region histograms of all the GLBP Maps are concatenated to form the final feature vector of the finger vein. The following sub-sections will describe the procedure in details.

### 2.1 Gabor Magnitude Patterns

The Gabor wavelet kernels [11] are defined as Eq. (1).

$$\psi_{\mu,\nu} = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{(-\|k_{\mu,\nu}\|^2 \|z\|^2 / 2\sigma^2)} \left[ e^{ik_{\mu,\nu}z} - e^{-\sigma^2/2} \right] \quad (1)$$

where  $\mu$  and  $\nu$  define the orientation and scale of the Gabor filters,  $z = (x, y)$  denotes the pixel in image,  $\|\cdot\|$  denotes the norm operator, and the wave vector  $k_{\mu,\nu}$  is expressed as Eq. (2):

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu} \quad (2)$$

where  $k_\nu = k_{\max}/f^\nu$  is the sampling frequency of the filter. The parameter  $k_{\max}$  is the maximum sampling frequency, and  $f^\nu$  is the spacing factor between kernels in the frequency domain.  $\phi_\mu = \pi\mu/8$  shows the direction selection of filters, and  $\sigma$  determines the ratio of Gaussian window width with wavelength.

Let  $I(z)$  denotes an image, the convolution of image  $I(z)$  and a Gabor kernel  $\psi_{\mu,\nu}$  are defined as follows:

$$O_{\mu,\nu}(Z) = I(z) * \psi(z_0) = \int I(z) \psi_{\mu,\nu}(z - z_0) d^2z \quad (3)$$

where  $z = (x, y)$ ,  $*$  denotes the convolution operator, and  $O_{\mu,\nu}(Z)$  is the convolution result composed of the real part  $\text{Re}_{\mu,\nu}(Z)$  and imaginary part  $\text{Im}_{\mu,\nu}(Z)$ . Based on these two parts, magnitude  $\text{Mag}_{\mu,\nu}(Z)$  can be computed by Eq. (4).

$$\text{Mag}_{\mu,\nu}(Z) = \sqrt{\text{Re}_{\mu,\nu}^2(Z) + \text{Im}_{\mu,\nu}^2(Z)} \quad (4)$$

Four scales  $\nu \in \{1, \dots, 4\}$  and eight orientations  $\mu \in \{1, \dots, 8\}$  Gabor kernels are used in this paper. The choice of four scales and eight directions can be guaranteed to obtain the veins of various widths and extending directions in the image. Each image convolves the 32 Gabor filters, and 32 Gabor Magnitude Patterns (GMPs) are generated.

### 2.2 Local Binary Pattern (LBP)

The LBP compares the intensity of the center pixel in a  $3 \times 3$  window with that of its 8-connection neighbors [12]. A neighbor is assigned a binary value 0 or 1 according to

whether its intensity is lower or higher than that of the center pixel, as Eqs. (5) and (6).

$$\text{LBP} = \sum_{p=0}^7 \text{sign}(g_p - g_c) 2^p \quad (5)$$

$$\text{sign}(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases} \quad (6)$$

where  $g_c$  is the intensity value of the center pixel and  $g_p$  is the intensity value of its neighbors in LBP window. We denote the result of LBP operator at position  $(x, y)$  of  $(\mu, \nu)$ -GMP as  $\text{GLBP}(x, y, \mu, \nu)$ .

### 2.3 GLBP Feature Representation

The generic vascular network is highly unique in human fingers and varies from thick to thin. Moreover, the quality of finger-vein images can vary across the user population and be highly influenced by the imaging conditions. Therefore, we utilize local gray histogram to summarize the region property of the GLBP Maps and reduce intra-class variations by the following procedure.

Firstly, each GLBP Map is spatially divided into multiple non-overlapping blocks with specific size. Secondly, each block is binned in a histogram and all the block histograms concatenated over a GLBP Map to produce a GLBP histogram descriptor. Finally, all GLBP histogram descriptors from all the GLBP Maps are concatenated into a single feature vector to represent the given finger vein image. Assuming each GLBP Map is divided into  $M$  blocks  $R_1, R_2, \dots, R_M$  with the same size. A GLBP histogram descriptor of GLBP Map  $(\mu, \nu)$ -GMP is computed, and all the histogram descriptors computed from the regions of all the GLBP Maps are concatenated to a feature vector  $\mathfrak{R}$  as the final finger vein image representation.

$$\mathfrak{R} = (H_{1,1,1}, H_{1,1,2}, \dots, H_{1,1,M}; H_{1,2,1}, H_{1,2,2}, \dots, H_{1,2,M}; \dots; H_{8,1,1}, H_{8,1,2}, \dots, H_{8,1,M}; \dots; H_{8,4,1}, H_{8,4,2}, \dots, H_{8,4,M}) \quad (7)$$

where  $H_{\mu,\nu,r}(\mu = 1, \dots, 4, \nu = 1, \dots, 8, r = 1, 2, \dots, M)$  denotes the histogram descriptor of the  $r$ -th block in the GLBP Map with  $\mu$  scale and  $\nu$  orientation.

## 3. Finger Vein Recognition Based on GLBP

The procedure of the proposed finger vein recognition is shown in Fig. 2. This approach includes two phases: enrollment and verification. In enrollment phase, finger vein

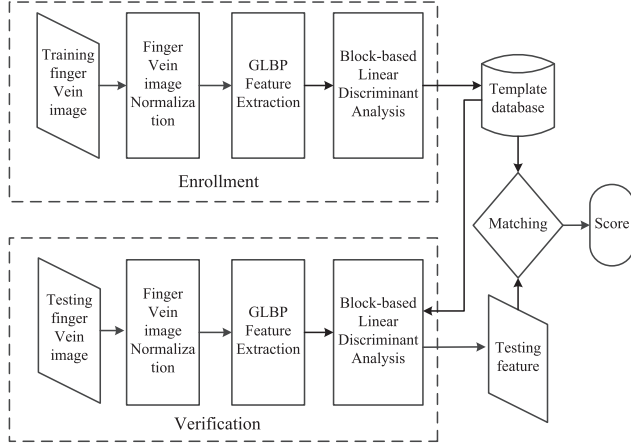


Fig. 2 Finger vein recognition workflow.

images are normalized firstly, and Gabor wavelets with LBP operator are used to extract the finger vein GLBP feature vectors. For every GLBP feature vector, we train the enrollment samples to get the projective matrices using LDA method based on blocks, and then store these projective matrices and the dimension reduced vectors as template into the database. During the verification phase, the projective matrices are taken out for the testing samples to extract lower dimension feature vectors. Finally, the dimension reduced testing vectors are compared with the reference templates for matching based on the nearest neighbor classifier.

### 3.1 LDA Based on Blocks

The basic idea of LDA based on blocks [13] is to divide the high-dimensional GLBP descriptor into multiple feature segments (corresponding to different spatial blocks in GLBP Maps), then apply LDA to each segment, and finally combine the results of all the block-wise LDA. Since the dimensionality of the input block segment for each LDA is much lower, the LDA's "small sample size" problem can be well overcome. We describe the procedure of BLDA projection and feature extraction in Algorithm 1 and Algorithm 2, respectively.

## 4. Experimental Evaluations

### 4.1 Database

The finger vein image database employed in this paper is The Hong Kong Polytechnic University Finger Image Database Version 1.0 [14]. There are 156 subjects with six images per-subject employed for our performance evaluation. In addition, we use the method [6] to preprocess the finger vein image and normalize the region of interest (ROI) with the fixed size (128 \* 256) pixels.

### Algorithm 1 Procedure of BLDA projection.

#### Input:

$T$ , the training set with  $N$  normalized finger vein image;  $M$ , number of blocks for LDA learning.

#### Output:

BLDA projection matrices  $W = \{W_1, W_2, \dots, W_M\}$ .

- 1: For each image  $I \in T$ , according to 2.3 sub-section, compute its GLBP feature vector,  $\mathbf{X} = (H_{1,1,1}, H_{1,1,2}, \dots, H_{1,1,M}; H_{1,2,1}, H_{1,2,2}, \dots, H_{1,2,M}; \dots; H_{8,1,1}, H_{8,1,2}, \dots, H_{8,1,M}; \dots; H_{8,4,1}, H_{8,4,2}, \dots, H_{8,4,M})$ ;
- 2: For each block  $B_i, (i = 1, 2, \dots, M)$ , concatenate its histograms of all the scales and orientations to get one sequence:  $B_i = (H_{1,1,i}, H_{1,2,i}, \dots, H_{8,4,i})$ . Thus, each image is represented as  $M$  sequences  $B_i$ ;
- 3: Obtain  $M$  feature sets  $S_i (i = 1, 2, \dots, M)$  by collecting the features of the same spatial block from each of the  $N$  training images,  $S_i = \{B_{1,i}, B_{2,i}, \dots, B_{N,i}\}$ , where  $B_{j,i} (i = 1, 2, \dots, M)$  denotes the histogram sequence from the  $i^{\text{th}}$  block of the  $j^{\text{th}}$  training image;
- 4: For each representation  $S_i$  is first projected to a PCA subspace and get Fisher Linear Discriminant matrices  $W_i$  and store the projection matrices  $W = \{W_1, W_2, \dots, W_M\}$  into the template database;

### Algorithm 2 Feature extraction using projection matrices.

#### Input:

Normalized finger vein image  $J$ ,  $M$  and  $W = \{W_1, W_2, \dots, W_M\}$  with the same meanings as those in Algorithm 1.

#### Output:

The dimension reduced feature vectors  $J_F = (F_1, F_2, \dots, F_M)$ .

- 1: For image  $J$ , calculate its block-based representation  $S_i, (i = 1, 2, \dots, M)$  according to Steps 1~2 in Algorithm 1
- 2: For image  $J$ , calculate its  $M$  low-dimensional vectors  $F_j$  using  $F_j = (W)^T S_j$ , and store the final reduced feature  $J_F = (F_1, F_2, \dots, F_M)$  into the template database;

### 4.2 Recognition Performance of GLBP with Parameter Selection

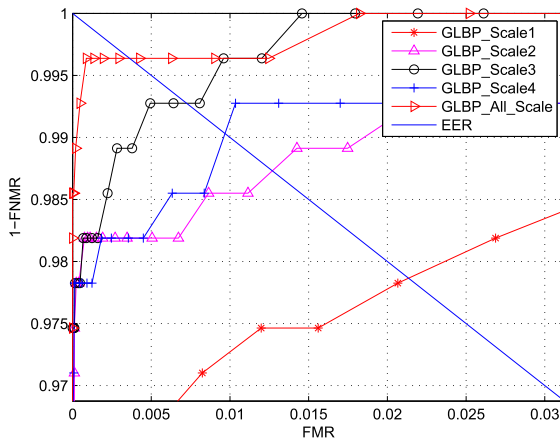
In finger vein recognition task, each subject use 3 samples for training and 3 samples for testing in different evaluations. In the recognition, False Non-Match Rate (FNMR) and False Match Rate (FMR) are represented as evaluation metrics in ROC curves. The equal error rate (EER), which is the point where FNMR is equal to FMR, is used to evaluate the verification accuracy in our experiments.

For the Gabor wavelets, the parameters are set as follows:  $\mu \in \{1, \dots, 8\}$ ,  $\nu \in \{1, \dots, 4\}$ ,  $\sigma = 2\pi$ ,  $k_{\max} = \pi/2$ ,  $f = \sqrt{2}$ . We provide the performance summary of the GLBP presentations proposed with the different number of blocks, i.e., the parameter  $M$  in Eq. (7). Due to the characteristics of the LBP operator, we set the size of block to be the power of 2. EER results changing with the number of blocks are shown in Table 1 and 32 blocks result the best EER performance. The reason is that small block size can not preserve enough directional information while the discriminability of the pattern in larger block is not enough.  $M$  is set to 32 that balances between discriminative information and robustness to the variations in GLBP operation.

We also provide the performance with the change of scale  $\nu$  while the direction  $\mu$  is fixed to  $\mu \in \{1, \dots, 8\}$  and  $M$  is 32. Figure 3 shows the EER for several cases at different

**Table 1** EER in the GLBP recognition with different number of blocks.

Blocks	128	64	32	16	2
EER	3.60%	0.70%	0.30%	1.10%	7.60%

**Fig. 3** ROC curves of GLBP with different scales.**Table 2** The EER for proposed approach & other approaches.

Approach	EER
Repeated line tracking [2]	5.57%
Maximum curvature [4]	2.59%
structural minutiae matching [5]	9.50%
Even Gabor with Morphological [6]	0.43%
local binary pattern [7], [8]	1.13%
proposed approach	0.30%

scales, the best EER can be realized only when we use the Gabor wavelet with all scales together to exploit the various widths of finger veins adequately in the ROI. In this case, GLBP can be represented effectively and BLDA has strong discriminative power.

Finally, the experimental results from other approaches using EER are summarized in Table 2. Note that, we have evaluated our proposed method based on the same finger vein image database [14] of the literature [6]. The result of our proposed method outperforms the conventional methods in [2], [4], [5] and [6]. In addition, we compare the proposed method with the LBP methods in [7], [8]. The results are in favor of the proposed finger vein recognition method.

## 5. Conclusion

In this paper, a novel finger vein recognition method based on GLBP is proposed. The new method is composed of two main steps: GLBP feature representation and BLDA. GLBP feature representation is used to improve the performance of finger vein recognition. BLDA is utilized to reduce the dimensionality of the GLBP feature vector and enhance its discrimination simultaneously. An experiment showed that the proposed method significantly enhanced the

finger vein recognition performance and outperformed existing approaches.

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