Finger Vein Recognition Using Log Gabor Filter and Local Derivative Pattern

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Abstract

Finger vein recognition is a promising personal identification technology due to its advantages over other existing biometric recognition. In this paper, a novel finger vein recognition method is proposed based on Log Gabor filter and Local Derivative Pattern. Through combining Log Gabor convolution magnitude and Local Derivative Pattern operator, the extracted finger vein feature vector is more discriminative. Blocked Principal Component Analysis algorithm is further applied to reduce the dimension of extracted feature vectors and improve recognition performance. The experimental results show that the proposed approach significantly outperforms other similar approaches.

Keywords: Finger vein recognition, Log Gabor filter, Local Derivative Pattern

1. Introduction

As a new biometric technology, finger vein recognition begins to be adapted to the increasing demand of personal identification in current society. Compared to other traditional biometric characteristics (such as face, iris, fingerprints, *etc.*), finger vein has the following advantages [1]. (1) Contact-less: the imaging procedure of finger vein requires near-infra-red (NIR) illumination to extract the vascular structures residing inside fingers by a non-contact way. (2) Live-ness: finger vein pattern can only be imaged and recognized on living fingers with blood flow, thereby offering strong anti-spoofing capabilities. (3) Security: finger vein is the hidden structure that is extremely difficult to be stolen with a high degree of privacy, and the personal identification based on finger vein is immune to fake fingers and forgery. Therefore, finger vein recognition has recently attracted more and more attention in the research field of personal biometric identification [2-6].

However, finger vein NIR images are not always clear and there are a proportion of low-quality finger vein images in the captured images. The key issue in finger vein recognition is how to extract and represent features from NIR images effectively. Feature extraction becomes a critical step in the finger vein recognition procedure. Different methods, such as repeated line tracking [2], curvature method [3], minutiae descriptors [4], Gabor filters [5] and binary pattern based methods [6], *etc.,* have been proposed for finger vein feature extraction. These existing methods can be roughly divided into two categories: global feature extraction and local feature extraction. The global feature extraction methods [2-3] are applied the geometric shape, topological structure, or curvature information from the segmented blood vessel network as finger vein features. However, the low quality of finger vein images may cause segmentation errors during the feature extraction procedure and degrade the performance of finger vein recognition [7]. The local feature extraction methods, including Local Binary Pattern (LBP) [4] and their variants [6-8], are applied to extract finger vein feature without blood vessel

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segmentation. Although the local feature extraction methods can achieve better recognition performance than the global feature extraction methods, these works fail to consider the fact that finger vein is essentially a kind of network containing rich directional information.

To solve the above problems, a new approach is proposed in this paper for finger-vein recognition. Inspired by the work of [6], we find that Log Gabor filters have more powerful characteristics than Gabor filters in space frequency, space position and direction selectivity of finger vein global pattern. Moreover, LBP only represents the first order circular derivative pattern and fails to extract the high order discriminative information from finger vein local pattern. Conversely, Local Derivative Pattern (LDP) [9] can effectively reflect and quantize the local directional information hidden in finger vein local pattern. In this paper, the combination of Log Gabor filter and LDP, namely GLDP, is proposed to extract both the global structure and the local direction information from finger vein images. In addition, Blocked Principal Component Analysis (BPCA) method is introduced to reduce the dimensionality of the extracted GLDP feature vector and enhance its discriminability. The experimental results show that the proposed approach can significantly improve the recognition performance compared to other existing approaches.

The rest of the paper is organized as follows: Section 2 presents the proposed GLDP feature extraction approach. Section 3 describes the proposed finger vein recognition algorithms in detail. Section 4 presents the experimental results to verify the validity of the proposed approach. Finally, Section 5 concludes this paper.

2. GLDP Feature Extraction for Finger Vein Image

The framework of the proposed finger vein feature extraction approach based on GLDP is illustrated in Figure 1. In this approach, a finger vein image can be modeled as a feature vector by the following procedure:

(1) A normalized finger vein image is filtered by the multi-scale and multi-orientation Log Gabor filters to obtain the Log Gabor Magnitude Pattern (LGMP); (2) Each LGMP is divided into non-overlapping rectangle blocks with specific size, and further converted to Log Gabor Local Derivative Pattern (GLDP) by LDP operator; (3) The gray-level histogram of GLDP is computed in each block region; (4) The region histograms within all scales and all orientations are concatenated to form the final feature vector of finger vein image. The following subsections describe this procedure in detail.
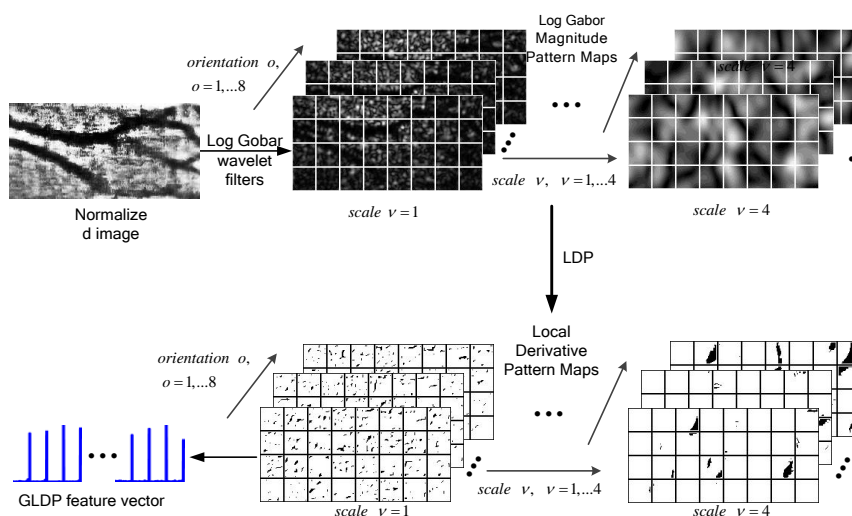

Figure 1. The Framework of the Finger Vein GLDP Feature Extraction

2.1. Log Gabor Magnitude Pattern

Log Gabor filters [10] are proposed to overcome the bandwidth limitation in traditional Gabor filters. Compared to Gabor filters, Log Gabor filters have two special characteristics [10]. Firstly, there is no DC component in the Log Gabor transfer function. Secondly, the Log Gabor transfer function can be extended by a large range in frequency. In a polar coordinate system, 2D Log Gabor transfer function [11] can be defined as Equation (1):

$$G(\rho,\theta) = e^{-\frac{\log^2\left(\rho/u_0\right)}{2\sigma^2}} e^{-\frac{(\theta-\vartheta_0)}{2\sigma_\theta^2}} \tag{1}$$

where (ρ,θ) represents the polar coordinates, u_0 is the filter's central frequency, θ_0 is the orientation angle, σ and σ_θ are the radial and angular bandwidth, respectively. Filter bandwidth is controlled by σ and filter orientation is controlled by θ. The real and imaginary parts of 2D Log Gabor filter shapes transformed into spatial domain are shown in Figure 2.

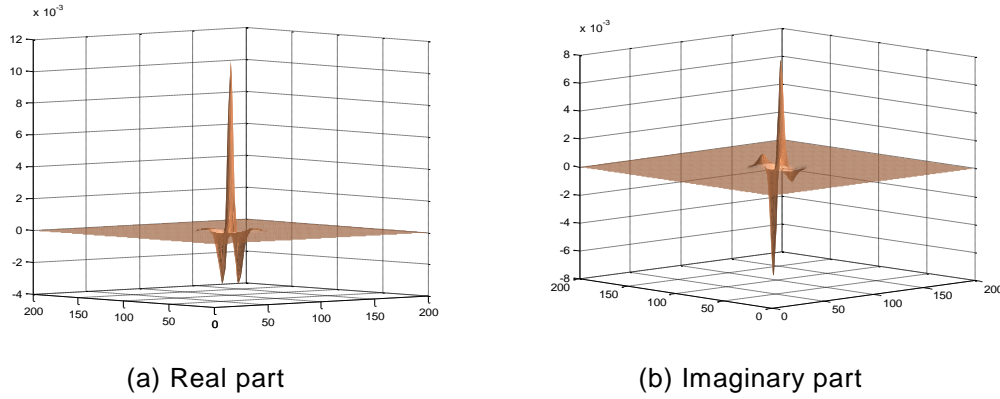(a) Real part   (b) Imaginary part

Figure 2. The Illustration of 2D Log Gabor Filter Shapes in Spatial Domain

In this paper, Log Gabor filters are applied with the following parameters: filter orientation $o \in \{0, \pi/8, 2\pi/8, \cdots, 7\pi/8\}$ and filter scale $s \in \{0,...,3\}$ (their corresponding centre frequencies are 1/3, 1/6, 1/12, and 1/24, respectively). The choice of four scales and eight directions can be guaranteed to obtain finger veins of different width and various directions in images. Let $I(Z)$ denote a normalized finger vein image, the convolution between image $I(Z)$ and Log Gabor filter $G_{s,o}(z)$ is defined as Equation (2):

$$I_{s,o}(Z) = I(z) * G_{s,o}(z) \tag{2}$$

where $G_{s,o}(z)$ is a Log Gabor filter with scale s and orientation o, $I_{s,o}(Z)$ is the convolution result and symbol $*$ denotes the convolution operator. $I_{s,o}(Z)$ is composed of the real part $\text{Re}_{s,o}(Z)$ and imaginary part $\text{Img}_{s,o}(Z)$. Based on the two parts, the magnitude value $Mag_{s,o}(Z)$ at each pixel position can be computed by Equation (3).

$$Mag_{s,o}(Z) = \sqrt{\text{Re}_{s,o}^2(Z) + \text{Img}_{s,o}^2(Z)} \tag{3}$$

Each image is convolved with 32 Log Gabor filters in this paper, and 32 Log Gabor Magnitude Patterns (LGMP) are totally generated.

2.2. Local Derivative Pattern

Local Derivative Pattern (LDP) operator [9] is a high order image texture descriptor. Compared to the first order directional local pattern extracted by LBP, LDP can extract the higher order derivative direction information in the local region. LDP encodes the variations of the neighborhood derivative direction, which can offer more discriminative information than LBP. Therefore, the second order LDP is introduced to calculate the derivative variation in LGMP.

The first order LDP operator of each pixel in an image is applied by subtracting its neighbor pixels according to the derivative directions along 0, 45, 90 and 135 degrees. Let I_0 be a pixel in an image I, and I_j, $j = 1, \cdots 8$ be the neighbor pixels around I_0 (see Figure 3).

I_1	I_2	I_3
I_8	I_0	I_4
I_7	I_6	I_5

Figure 3. Eight Neighbor Pixels Considered in LDP

The four first order derivatives at I_0 can be calculated by Equation (4).

$$
\begin{aligned}
I'_{0^o}(I_0) &= I(I_0) - I(I_4) \\
I'_{45^o}(I_0) &= I(I_0) - I(I_3) \\
I'_{90^o}(I_0) &= I(I_0) - I(I_2) \\
I'_{135^o}(I_0) &= I(I_0) - I(I_1)
\end{aligned}
\tag{4}
$$

The second order LDP operator in direction $\alpha = 0^o, 45^o, 90^o, 135^o$ at I_0 can be defined as Equation (5).

$$
LDP_\alpha(I_0) = \left\{ f\left(I'_\alpha(I_0), I'_\alpha(I_1)\right), f\left(I'_\alpha(I_0), I'_\alpha(I_2)\right), \cdots, f\left(I'_\alpha(I_0), I'_\alpha(I_8)\right) \right\}
\tag{5}
$$

where $f(\ )$ is a binary function defined as Equation (6).

$$
f\left(I'_\alpha(I_0), I'_\alpha(I_i)\right) = \begin{cases} 0, & if \ \ I'_\alpha(I_0) \cdot I'_\alpha(I_i) > 0 \\ 1, & if \ \ I'_\alpha(I_0) \cdot I'_\alpha(I_i) \leq 0 \end{cases}, \ i = 1, \cdots, 8
\tag{6}
$$

Thus, the second order LDP code of the given pixel I_0 in direction $\alpha = 0^o, 45^o, 90^o, 135^o$ can be further obtained by Equation (7).

$$
LDPcode_\alpha(I_0) = \sum_{i=1}^{8} f\left(I'_\alpha(I_0), I'_\alpha(I_i)\right) 2^{8-i}
\tag{7}
$$

The second order LDP encoding result at a pixel I_0 in Log Gabor Magnitude Pattern of the image I with scale s and orientation o is denoted as $LDPcode_\alpha^{s,o}(I_0)$, $\alpha = 0^o, 45^o, 90^o, 135^o$. Finally, the proposed Log Gabor Local Derivative Pattern (GLDP) of the image I is defined as a set of the four directional $LDPcode_\alpha^{s,o}(I_0)$ shown in Equation (8).

$$GLDP_{s,o}(I) = \left\{ LDPcode_{\alpha}^{s,o}(I_0) \mid \forall I_0 \in I, \ \alpha = 0^o, 45^o, 90^o, 135^o \right\} \tag{8}$$

where s and o represent the corresponding scale and orientation of Log Gabor filter.

It can be seen from the above equations that the LDP operator encodes each pixel in LGMP of the image I and generates $GLDP_{s,o}(I)$ codes consequently.

2.3. GLDP Feature Representation

Since the quality of finger-vein images is highly influenced by the imaging conditions [7], the feature representation of the proposed $GLDP_{s,o}(I)$ is summarized by the proposed Algorithm 1.

Algorithm.1 GLDP Feature Representation

Input: I, a input normalized finger vein image; m, the number of blocks for LGMP; Log Gabor filters of orientation $o = 0, \pi/8, 2\pi/8, \cdots, 7\pi/8$ and scale $s = 0, ..., 3$;

Output: the feature vector F.

Step 1: For the image I, I is convolved with Log Gabor filters of orientation o and scale s by Equation (1)-(3) to obtain 32 LGMPs;

Step 2: For each LGMP, the corresponding $LDPcode_{\alpha}^{s,o}(I)$ is computed by Equation (4)-Equation (7), and each LGMP is spatially divided into m non-overlapping blocks with specific size;

Step 3: For each LGMP, $LDPcode_{\alpha}^{s,o}(I)$ in each block of the LGMP is binned to a gray histogram $h_{s,o,b}$, $b = 1, 2, ..., m$;

Step 4: For each LGMP, all $h_{s,o,b}$ are concatenated into a single histogram sequence $H_{s,o} = (h_{s,o,1}, ..., h_{s,o,m})$ to represent the given LGMP;

Step 5: Concatenating all $H_{s,o}$, $o = 0, \pi/8, 2\pi/8, \cdots, 7\pi/8$, $s = 0, ..., 3$, as the final feature vector F to represent the image I;

Step 6: Output F.

Firstly, the image I is convolved with Log Gabor filters of orientation $o \in \{0, \pi/8, 2\pi/8, \cdots, 7\pi/8\}$ and scale $s \in \{0, ..., 3\}$ to obtain 32 LGMPs. Secondly, the corresponding $LDPcode_{\alpha}^{s,o}(I)$ in each LGMP is computed by Equation (4)-(7), and each LGMP is spatially divided into multiple non-overlapping blocks with specific size. Thirdly, $LDPcode_{\alpha}^{s,o}(I)$ in each block of the LGMP is binned to a gray histogram $h_{s,o,b}$, $b \in \{1, ..., m\}$. Fourth, all $h_{s,o,b}$ are concatenated into a single histogram sequence $H_{s,o}$ to represent the given LGMP in the scale s and orientation o. Finally, all $H_{s,o}$ are further concatenated as the final feature vector F to represent the image I, where $F = (h_{0,0,1}, ..., h_{0,0,m}, h_{0,1,1}, ..., h_{0,1,m}, ..., h_{7,3,1}, ..., h_{7,3,m})$.

3. Finger Vein Recognition Based on GLDP Feature

In this paper, the two approaches are applied to measuring the similarity between two GLDP feature sequences: the direct matching measurement and the Blocked PCA method.

3.1. Direct Matching

There are different measures used to provide the similarity metrics for histogram matching. The histogram intersection (see Equation (9)), performs slightly better than other direct matching metrics in the finger vein recognition.

$$D(p,q) = \frac{\sum_i \min(p_i, q_i)}{\sum_i q_i} \qquad (9)$$

In Equation (9), p and q respectively represent the two histograms, which are compared of each i bins in histogram intersection. Using this measurement, the similarity of two GLDP feature sequences F^1, F^2 can be obtained by Equation (10).

$$S(F^1, F^2) = \sum_{s=0}^{3} \sum_{o=0}^{7} \sum_{b=1}^{m} D(h^1_{s,o,b}, h^2_{s,o,b}) \qquad (10)$$

where $\quad F^1 = (h^1_{0,0,1}, ..., h^1_{0,7,m}, h^1_{1,0,1}, ..., h^1_{1,7,m}, ..., h^1_{3,0,1}, ..., h^1_{3,7,m})$ and $F^2 = (h^2_{0,0,1}, ..., h^2_{0,7,m}, h^2_{1,0,1}, ..., h^2_{1,7,m}, ..., h^2_{3,0,1}, ..., h^2_{3,7,m})$.

Although the computation of Equation (10) is very efficient, the direct matching procedure is not good enough for the high feature dimension of GLDP representation. For example, when the number of $h_{s,o,b}$ histogram bins is $2^8 = 256$ and $m = 32$, the dimension of $H_{s,o}$ is computed as $4*8*2^8 = 8192$ and the final dimension of feature vector F is $32*8192 = 262114$. Due to the "small sample size" problem, Principal Component Analysis (PCA) algorithm [12] cannot be directly applied to reduce such high dimension of feature vector. Thus, the PCA approach based on blocks is alternatively presented.

3.2. PCA Based on Blocks

The basic idea of PCA based on blocks is to divide the high-dimensional GLDP feature vector into multiple segments (corresponding to different spatial blocks in LGMP), and then PCA algorithm is applied to each segment. The projected results of all the block-wise PCA (BPCA) are finally concatenated as the reduced feature vector. Since the dimension of the segmental sequences for PCA algorithm is much lower, the "small sample size" problem can be greatly weakened.

In PCA algorithm, all eigenvalues and eigenvectors are calculated and sorted during the training procedure of projection matrices. The eigenvectors corresponding to the top largest eigenvalues are chosen to construct the projective matrix, which projects the testing higher dimensional vectors into the lower dimensional space. Given the training vector set $\{x_1, x_2, \cdots, x_m\}$ and $\sum_1^m x_i = 0$, the objective function of PCA is defined in Equation (11).

$$J_{PCA}(W) = \arg\max_{W} W^T S_t W \qquad (11)$$

where S_t is the covariance matrix of x_i, $i = 1, 2, ..., m$ and $S_t = \frac{1}{m} \sum_{i=1}^{m} x_i x_i^T$. Through solving the eigenvalues and eigenvectors of the covariance matrix S_t, PCA method seeks for the optimal projective matrix $W = [v_1, v_2, \cdots, v_k]$ according to the objective function defined in Equation (11), where $v_1, v_2, \cdots, v_k$ are the eigenvectors corresponding to the first k largest eigenvalues of S_t. In the experiments, the value of k is set to 0.9.

Figure 4, illustrates the main procedure of GLDP feature dimensional reduction based on BPCA. For clarity, the procedure of BPCA projection and feature reduction are described in Algorithms 2 and 3, respectively. Thus, the workflow of the finger vein recognition based on BPCA algorithm is illustrated in Figure 5. This recognition approach includes two phases: enrollment and verification. In enrollment phase,

finger vein images are normalized firstly, and then Log Gabor filters with LDP operator are applied to generate the GLDP feature vectors. All GLDP feature vectors of the enrollment samples are trained to obtain the projective matrices by Algorithm 2. The reduced feature vectors from the enrollment images are served as the reference templates by Algorithm 3. Both the projective matrices and the reference templates are stored in the database. During the verification phase, the projective matrices are taken out from the template database to reduce the dimension of the testing feature vectors by Algorithm 3. Finally, the matching score between the reduced dimension vectors and the reference templates is matched by Euclidean Distance.
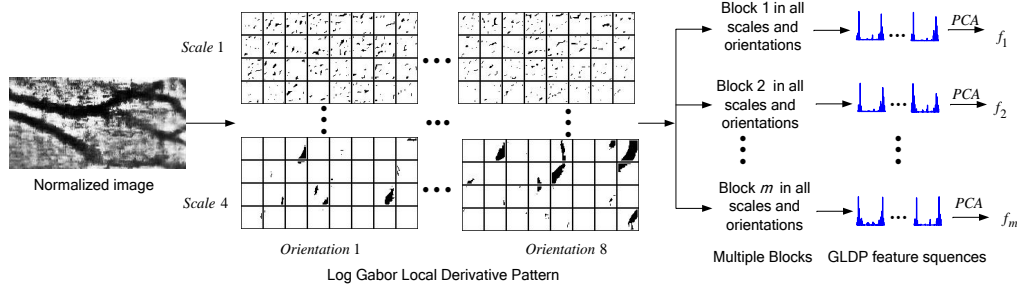

Figure 4. GLDP Feature Dimensional Reduction Based on BPCA

Algorithm. 2 Procedure of BPCA Projection

Input: T, the training set with n normalized finger vein images; m, the number of blocks for PCA projection;

Output: the projective matrices W_i, $(i=1,2,...,m)$.

Step 1: For each image $I \in T$, according to Algorithm 1, computing its GLDP feature vector, $F = (h_{0,0,1},...,h_{0,7,m},h_{1,0,1},...,h_{1,7,m},...,h_{3,0,1},...,h_{3,7,m})$;

Step 2: For each block i, $i \in \{1,\cdots,m\}$ in F, concatenating its histograms of all scales and all orientations as one histogram sequence $H_i = (h_{0,0,i},...,h_{0,7,i},h_{1,0,i},...,h_{1,7,i},...,h_{3,0,i},...,h_{3,7,i})$. Thus, each image is represented as m histogram sequences H_i, $(i=1,2,...,m)$;

Step 3: Obtain m feature sets $S_i = \{H_{j,i} | j=1,2,...,n, i=1,2,...,m\}$ by collecting the features of the same spatial block from each of the n training images, where $H_{j,i}$ denotes the histogram sequence from the ith block of the jth training image;

Step 4: For each block i, $i \in \{1,\cdots,m\}$, all $H_{j,i}$, $(j=1,2,...,n)$ is served as the training set to obtain the projection matrices W_i, $(i=1,2,...,m)$ according to Equation (11);

Step 5: Output the projective matrices W_i, $(i=1,2,...,m)$ into the template database.

Algorithm. 3 Feature Vector Reduction using Projection Matrices

Input: The normalized testing finger vein image I, m and W_i, $(i=1,2,...,m)$ with the same meanings defined as Algorithm 2;

Output: The reduced feature vector f.

Step 1: For image I, its block-based representation H_i, $(i=1,2,...,m)$ is calculated by Steps 1-2 in Algorithm 2;

Step 2: For image I, its ith block low-dimensional vector f_i is calculated by the linear

transform $f_i = (W_i)^T H_i$, and concatenate all f_i, $(i=1,2,...,m)$ as the final reduced feature vector $f^T = \left[f_1^T, f_2^T, ..., f_m^T \right]$;

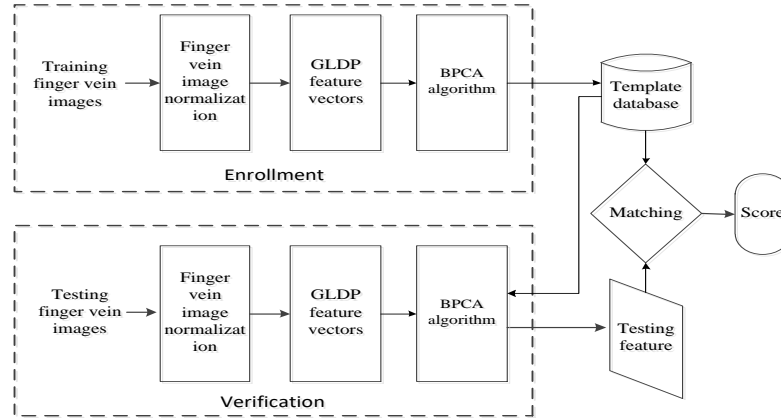Step 3: Output the feature vector f.

Figure 5. Finger Vein Recognition Workflow based on BPCA

4. Experimental Results and Analysis

4.1. Experiment Setup

The proposed finger vein recognition approach is evaluated on The Hong Kong Polytechnic University Finger Image Database [13]. The database consists of 3134 touch-less NIR finger vein images with the resolution of $513 * 256$ pixels. There are randomly selected 100 fingers with six vein images per-subject for the recognition performance evaluation. In addition, the method [14] is applied to preprocess the finger vein images and normalize the region of interest (ROI) with the fixed size $(128 * 256)$ pixels.

In the recognition experiments, 3 samples per-subject are used for the training procedure and 3 samples for the testing procedure. In order to decide how the parameters of the proposed algorithm affect the recognition performance, all the experiments are evaluated on the same test scale. The evaluation protocols of False Match Rate (FMR), False Non-Match Rate (FNMR), and Receiver Operator Characteristic (ROC) curve [15] are applied in this paper. The Equal Error Rate (EER), the point where FNMR is equal to FMR, is always used to evaluate the recognition performance in biometrics. Note that the lower value of EER shows the better recognition accuracy for biometric applications.

4.2. Parameter Selection

The transfer function of Log Gabor filters is designed with respect to the quadrature pair filters in the frequency domain [16]. In the implementation of Equation (1), the parameters are empirically tuned based on the criterion that the parameter values can lead to the lower EER. As a result, the parameters of Equation (1) are set as the following: there are eight filter orientation $\theta_0 \in \{0, \pi/8, 2\pi/8, \cdots, 7\pi/8\}$ where the bandwidth of the filters are controlled by the parameter $\sigma_\theta = \{0.85, 0.75, 0.65, 0.55\}$, and the central frequencies at four scales are set to $u_0 \in \{1/3, 1/6, 1/12, 1/24\}$. Due to the characteristics of the LDP operator, the size of block is set to be the power of 2. In the experiments, the number of blocks is chosen by 16, 32, 64, and 128. In Algorithm 1, the number of histogram bins is set to 256.

The performance analysis of the proposed GLDP feature is presented in Figure 6. It illustrates the ROC curves' comparison between the direct matching method (GLDP Direct) and the BPCA method (GLDP+BPCA). As shown in Figure 6, EER results change with the number of blocks ($m = 16, 32, 64, 128$). It can be found that EER of the BPCA method is superior to that of the direct matching method in the different number of blocks. Moreover, the proposed BPCA method has the stronger discrimination than the direct matching method. In this case, the BPCA method using 32 blocks (GLDP+BPCA_m=32) results in the best EER performance. The reason is that the smaller block blocks cannot preserve the effective vein directional information while the distinction of vein pattern in the larger blocks is not remarkable. When the number of blocks m is set to 32, it is a balance between the directional information preservation and the discriminating pattern to achieve the optimal recognition performance.

The performance of BPCA method with the change of scale s is further analyzed when the orientation o is fixed to $\{0, \pi/8, 2\pi/8, \cdots, 7\pi/8\}$ and the number of blocks m is set to 32. From the Figure 7, it can be seen that the better EER performance can be obtain on scale 3 than on other single scales. However, the best EER can be obtained effectively when the Log Gabor filters with all scales are together exploited the various width of finger veins. The best EER performance of BPCA method can be calculated as 0.20% when the GLDP feature presentation is obtained by the four scales and eight directions of Log Gabor filters.
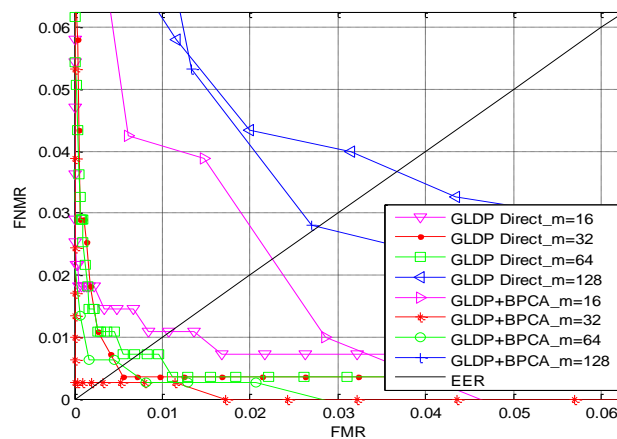

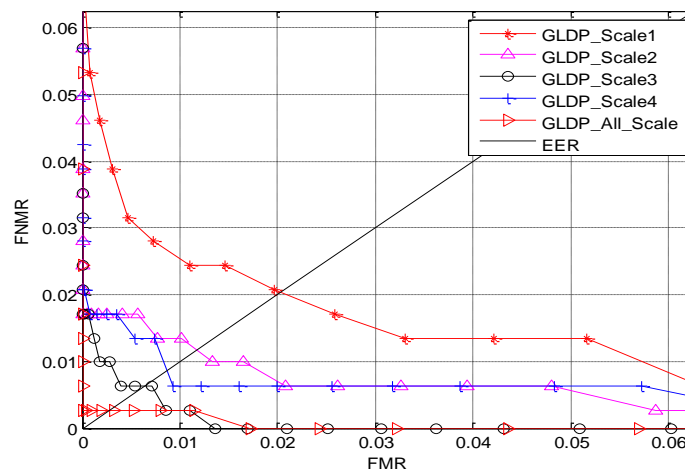**Figure 6. ROC Curves of Direct Matching Method and BPCA Method**

Figure 7. ROC Curves of GLDP Feature Using Different Scales

4.3. Comparable Results

In order to show the superiority of GLDP feature representation in finger vein recognition, the proposed approach is also compared with other existing approaches. The comparable experiments are conducted on the same finger vein images. The comparable results in terms of EER are summarized in Table 1. From Table 1, it is observed that the recognition performance of the proposed method performs significantly better than the other approaches [2-5]. Besides, the recognition accuracy for GLDP is obviously better than GLBP [6].

In addition, Figure 8, shows the ROC curves of the different approaches in Table 1. For clear comparison, some lower performance methods are shown in Figure 8a, and the rest higher ones are shown in Figure 8b. From Figure 8, it can be seen that the proposed method has made the obvious improvement of recognition performance, which validates the effectiveness of the proposed GLDP feature representation.

Table 1. The EER Performance Comparisons between the Proposed Approach and Other Existing Approaches

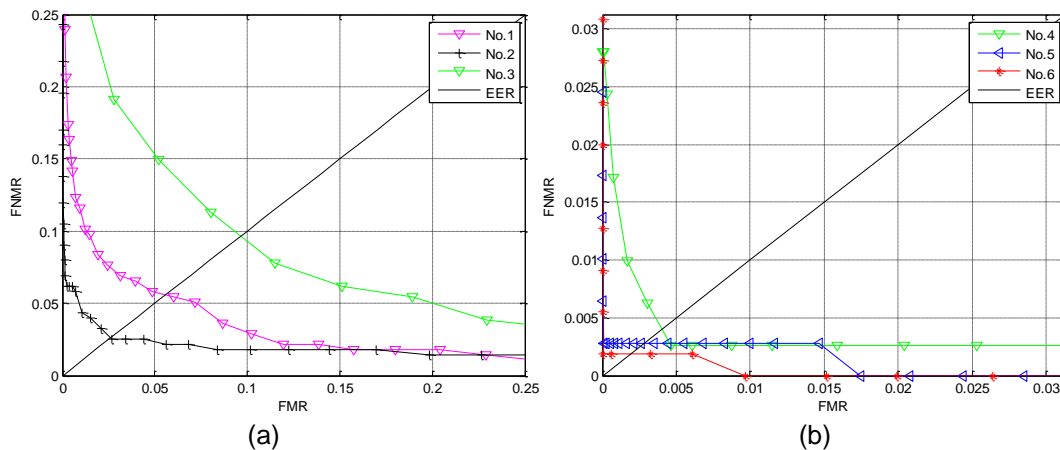| No.	1	2	3	4	5	**6**
Method	The repeated line tracking [2]	The maximum curvature [3]	The minutia [4]	The Gabor filters [5]	The GLBP [6]	**The proposed method**
EER	5.57%	2.59%	9.50%	0.43%	0.30%	**0.20%**

(a)

(b)

Figure 8. ROC Curves of Different Recognition Methods : (a) The Approaches with Lower Performance (b) The Approaches with Higher Performance

5. Conclusion

In this paper, a novel method for finger vein recognition method based on Log Gabor filter and Local Derivative Pattern are proposed. This method is composed of two main steps: GLDP feature extraction and BPCA. With LDP encoding technique, Log Gabor filters can generate more distinctive features in finger vein recognition. In addition, BPCA method is applied to reduce the dimensionality of the GLDP feature vector and improve recognition performance. Experimental results show that the proposed method has made significant improvements over other existing approaches. In future, we plan to fuse multiple features from the finger vein images to enhance the accuracy of finger vein recognition.

Acknowledgements

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