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Discriminative Binary Descriptor for Finger Vein Recognition

HAIYING LIU[1], LU YANG[2], GONGPING YANG[1], AND YILONG YIN[1]
[1]School of Computer Science and Technology, Shandong University, Jinan 250101, China
[2]School of Computer Science and Technology, Shandong University of Finance and Economics, Jinan 250101, China

Corresponding author: Yilong Yin (ylyin@sdu.edu.cn)

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ABSTRACT In this paper, we propose a new local discriminative feature learning method for finger vein recognition. Unlike most previous finger vein recognition methods, which use hand-crafted descriptors such as local binary pattern, local line binary pattern, and Gabor features, this paper aims to learn a feature mapping to enhance the discriminative ability of local features. To achieve this goal, we first extract multi-directional pixel difference vectors (MDPDVs) for each pixel in a training finger vein image by computing the difference between each pixel and its straight-line neighboring pixels. Second, we learn a feature mapping to project these MDPDVs into low-dimensional binary codes in a supervised manner, where: 1) the loss between the original real-valued codes and learned binary vectors is minimized; 2) the between-class variation of the local binary features is maximized; and 3) the within-class variation of the local binary features is minimized. Last, we represent each finger vein image as a histogram feature by clustering and pooling these binary codes. Experiments on SDUMLA-FV and PolyU databases verify the superior performance of the proposed method over other existing finger vein recognition methods.

INDEX TERMS Finger vein recognition, feature learning, local line binary pattern, discriminative binary descriptor, biometrics.

I. INTRODUCTION

Biometrics is an automatic individual recognition technology that is based on human physiological and/or behavioral characteristics, which satisfies several requirements, such as universality, distinctiveness, permanence, collectability, acceptability, circumvention and performance [1]. Biometric signatures based on DNA, ear, fingerprint, hand geometry, iris, palmprint, signature, face, gait, keystroke, and voice, have been applied to access control, immigration control, and user authentication for financial transactions. Over the past few years, finger vein recognition has attracted increasing attention because it has some advantages other than biometrics, such as living-body identification, noninvasiveness and no-contact image capture [2], [3]. Despite the significant progress made in recent years, finger vein recognition is still a challenging problem due to the low quality of finger vein images, which is caused by pose, occlusion, deformation, illumination variation, and other factors.

To overcome these issues, many approaches have been proposed from different perspectives, such as region of interest (ROI) extraction [4], [35], image restoration [5], [6], image enhancement [7] and representation [21], [22], [25]. Among these possibilities, finger vein representation plays an important role in finger vein recognition. Generally, four major categories of finger vein representation methods have dominated recent research, namely, vein pattern based methods, dimensionality reduction based methods, local binary based methods and bag-of-words based methods.

Vein pattern based methods are based on the segmented blood vessel network and use the geometric shape or topological structure of vein patterns for matching. For example, Miura *et al.* [8] introduced an extraction method based on repeated line tracking (RLT) from various starting positions and demonstrated good extraction performance with regard to image shading. In later research by Miura *et al.* [9], the finger vein region is darker than the skin area, and the intensity of the cross-sectional profile in the finger vein is represented as a valley. Based on this property, the investigators in [9] obtained the vein centerlines by calculating the local maximum curvatures in cross-sectional profiles. Song *et al.* [10]

designed vascular features by mean curvature. Qin *et al.* [11] proposed a vein pattern extraction method by running a region-growing operator based on different seeds. Kumar *et al.* [12] presented a finger vein extraction approach using Gabor filters. However, if the quality of the captured image is low, the network might not be segmented properly. Consequently, the extracted features based on an improper network will make the performance of the recognition degrade dramatically. To alleviate the difficulty of segmentation, many finger vein representation methods without segmentation have been proposed.

Dimensionality reduction based methods, such as principal component analysis (PCA) [13], linear discriminant analysis (LDA) [14], and two directional and two-dimensional principal component analysis ($(2D)^2$PCA) [15], transform an image into low-dimensional space before classification. Although those methods extract global finger vein features without segmenting the network of finger veins, a global feature transformation is usually not robust to local appearance variations that are caused by the pose, rotation, scale, skin scattering, uneven illumination, or other factors. In addition, the training process will be complicated for these methods because of the large finger vein database.

Hence, many finger vein representations based on local binary features have been applied to finger vein recognition. Lee *et al.* [16] proposed a feature fusion method that use simple binarization, local binary pattern (LBP) and local derivative pattern (LDP) for finger vein recognition, which shows improved recognition accuracy and reduced process time. Rosdi *et al.* [17] applied the local line binary pattern (LLBP) approach on finger vein recognition, and their experiment showed that the LLBP method can achieve higher recognition rates compared to LBP and LDP. In addition, there were other variants of LLBP to enhance the discriminative ability of the features, such as poly-directional local line binary pattern (PLLBP) [18], personalized best bit map (PBBM) [19] and generalized local line binary pattern (GLLBP) [20]. These studies also showed that local features are more robust to small variations caused by varying illuminations and make it easy to add prior knowledge. In addition, binary features have faster computational speed and require little memory. However, these features are designed by hand, and it is difficult to obtain optimal binary features manually. For example, extracting LBP can be decomposed into two steps. Pixel difference vectors (PDVs) are first extracted for each pixel by computing the difference between each pixel and its neighboring pixels. Then, LBPs are obtained through encoding the real-valued PDVs to binary codes with a fixed threshold for each pixel, which is related to only the current pixel. During the encoding procedure, although LBP can preserve the direction information of the PDVs and is invariant to monotonic photometric changes, the amplitude information of the PDVs is lost. In addition, the threshold used for encoding is independent of the whole PDVs in the images. Further, these methods are based on pixels that are sensitive to the translation and rotation of the finger in an image.

Recently, the bag-of-words based approach has been applied to finger vein recognition; this approach uses statistical information in images to be resistant to occlusions, geometric deformations, translation, rotation and illumination variations. To enhance the discriminability, Dong *et al.* [21] designed a finger vein verification method through learning a personalized best patches map that was based on bag-of-words, which achieved satisfactory performance on the PolyU database and their self-built rotation and translation databases. In contrast to a rectangular grid with a fixed size and shape, super-pixel can describe local consistency characteristics of an image effectively, and Liu *et al.* [22] proposed a score-level fusion of pixel and super-pixel level features for finger vein recognition and thereby improved the recognition performance greatly. Further, because the spatial pyramid representation can reveal the global spatial layout and the local detail of the finger vein, Liu *et al.* [23] presented an identification framework for finger vein recognition with super-pixel-base features and a weighted spatial pyramid matching (SPM) scheme, and they achieved an inspiring recognition performance. Dong *et al.* [24] proposed a method based on bag-of-words and the spatial pyramid matching (SPM) method, which separately uses LBP, mean curvature and webber local descriptor (WLD) as base features. The limitation of the methods that are based on the bag-of-words scheme is that they treat all patches or super-pixels equally in homologous matching and heterologous matching, and thus, there is a lack of discriminability. In view of this limitaion, Zhou *et al.* [25] presented a finger vein recognition method that is based on stable and discriminative super-pixels. In addition, they designed three types of features for finger veins to further enhance the performance of the system. Despite the successful application of these bag-of-words based recognition methods, most of which adopted LBP or other hand-crafted features as the base features, the shortcomings of hand-crafted feature methods are inherit. Further, the other limitation of hand-crafted features such as the three novel features in [25] designed for finger veins, is that this approach requires strong prior knowledge to engineer the features.

To address the above problems for hand-crafted features, a number of feature learning methods have emerged in recent years, such as, learning-based (LE) descriptor [26], local quantized patterns (LQP) [27], discriminant face descriptor (DFD) [28] and compact binary face descriptor (CBFD) [29]. These studies have demonstrated that the feature learning approach can produce higher recognition rates compared to the hand-crafted feature approach because they exploit more data-adaptive information. In other words, learning-based feature methods can sample a greater diversity of shapes and a larger size than the hand-crafted features. Moreover, the optimization process of learning-based features is dependent on all of the basis features of the training images, which acts in a data-driven way.

In addition to the aforementioned considerations, many methods in the finger vein field utilize class information to enhance their discriminative ability for recognition, such

TABLE 1. Comparison of previous and proposed methods.

Methods	Feature	Segmentation	Bag-of-words	Using class information	Category
[8],[9],[10],[12]	Vein pattern	√	×	×	Vein pattern based methods
[13],[15]	Global finger vein feature	×	×	×	Dimensionality reduction based methods
[14]	Global finger vein feature	×	×	√	Dimensionality reduction based methods
[16],[17],[18],[20]	Hand-crafted local feature	×	×	×	Local binary based methods
[19]	Hand-crafted local feature	×	×	√	Local binary based methods
[21],[22],[23],[24]	hand-crafted local feature	×	√	×	Bag-of-words based methods
[25]	hand-crafted local feature	×	√	√	Bag-of-words based methods
Proposed method	Learned local feature	×	√	√	Bag-of-words based methods

as [19], [21] and [25]. Personalized best bit map (PBBM) [19] eliminates the noise bits and selects the stable bits for each class to match. Personalized best patches map (PBPM) [21] rejects inconsistent patches and uses consistent patches for each class to match. Zhou *et al.* [25] employed a new reversible weight-based fusion method that is based on stable and discriminative super-pixels. However, extracting the local features and utilizing the class information in these methods are separate tasks, which could limit the practical applications.

In addition, many existing feature learning methods use LBP-like PDVs as their base feature for learning, such as [29] and [30]. Compact binary feature descriptor (CBFD) [29] learns a hashing filter to project each PDV into a compact binary vector in an unsupervised manner. Simultaneous local binary feature learning and encoding (SLBFLE) [30] jointly learns binary codes for PDVs and the codebook for feature encoding. However, the larger the pixel's neighborhood size for calculating the PDVs, the larger the amount of information that can be extracted from the image. However, the higher the dimension of the PDV is, the larger the calculation time and the larger the amount of memory that will be required.

To overcome the above problems in the existing systems and to utilize the prior knowledge of the finger vein image, in this paper, we propose a discriminative binary descriptor (DBD) feature learning method for finger vein representation. Considering the binary code advantages, we aim to learn the binary code directly from the raw pixels for the finger vein representation. Motivated by the fact that the finger veins in the image have a linear shape, we create new multi-directional pixel difference vectors (MDPDVs) to overcome the shortcomings of traditional PDVs. To use fusion class information into the local feature, we design a discriminative feature mapping method that projects MDPDVs into low-dimensional binary vectors in a supervised manner. Thus, in addition to preserving the information in the original base features, our mapping method simultaneously maximizes the inter-class variation in the local binary features, and minimizes the intra-class variation in the local binary features. Further, considering that the bag-of-words method is a compact global image representation that preserves the information from the set of local descriptors extracted from each image, which is robust to translation and rotation of the finger vein image, we represent every image as a histogram feature descriptor based on the bag-of-words method. Finally, the experimental results on the two standard finger vein databases verify the superior performance of the proposed method compared with other existing finger vein recognition methods. For clarity, we make comparison of previous and proposed methods in Table 1.

The main framework of our method was inspired by the study in [29], however, there are two differences in this aspect. First, to ensure the discriminative proficiency of the learned local features, the intra-class and inter-class variances are formulated into an optimization issue in our method. Hence, the objective function is different between our method and theirs. Second, to reduce the dimensions of the base features, we adopt the MDPDV as the base feature in our method, rather than the LBP-like PDV in [29]. The reason is that there is a larger amount of redundant information in the LBP-like PDV. If the neighborhood size of the sampling increases for each pixel when constructing its PDV, the training time becomes larger. To verify and make our novel ideas effective, we also compare our method with CBFD on two standard finger vein databases. Throughout the experiments, the results demonstrate the discriminability of our objective function and the efficiency of MDPDV for finger vein recognition.

The remainder of this paper is organized as follows. Section II presents our feature learning approach in detail. Section III provides experimental results and comparisons with traditional methods. Section IV states our conclusions and provides suggestions for future work.

II. PROPOSED APPROACH

Our method involves two main stages: the training stage and the testing stage. The training stage and the testing stage using DBD are illustrated in Fig. 1. In the training stage, MDPDVs are extracted from preprocessed finger vein training images, and then, feature filters that can project high-dimensional real-valued MDPDVs into low-dimensional binary code, are learned from all MDPDVs using DBD. Next, binary code can be obtained through projecting all of the MDPDVs by feature filters. Last, these binary codes are clustered to learn a codebook. In the testing stage, after extracting the MDPDVs of the testing image, we encoded these MDPDVs into binary

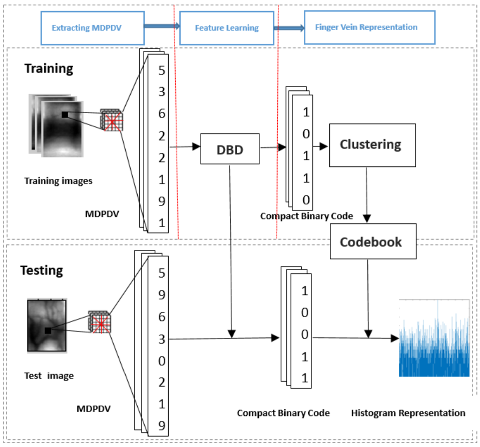

FIGURE 1. The pipeline of our proposed feature learning based finger vein representation and recognition method.

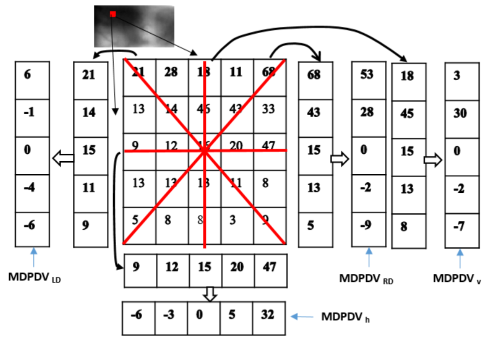

FIGURE 2. Illustration of the MDPDV operator in our method.

codes using the learned feature filters. Then, these binary codes are pooled as a histogram feature descriptor for the test image representation.

In the following part, we first present the DBD feature learning method which includes extracting the MDPDVs and feature learning, and then, we introduce how to use DBD for finger vein representation.

A. EXTRACTING MULTI-DIRECTIONAL PIXEL DIFFERENCE VECTORS

Although LBP-like PDVs have been widely used in feature learning methods [29], [35], this approach suffers from some limitations, such as existing redundancy information and a requirement for a larger amount of calculation time. To address these limitations, we adopt the PLLBP construction method to extract base features because LLBP [31] and PLLBP [18] have shown good performance in many finger vein recognition systems. We call this method for constructing base features the multi-directional pixel difference vector(MDPDV). The main difference between LBP-like PDV and MDPDV is that MDPDV adopts the neighborhood shape with straight lines, instead of the square shape in LBP-like PDV.

Next, we introduce MDPDV in detail.

An illustration of the MDPDV operator is shown in Fig. 2. For every pixel in the image, we calculate the difference between that pixel and its neighboring pixels in a straight line for each direction separately, and then, we concatenate the difference vectors as the MDPDV. The details are described as follows:

Let N represent the number of pixels in the line, and let h_n, v_n, ld_n and rd_n denote the pixel value along the horizontal, vertical, diagonal and anti-diagonal lines, respectively. Here, $c = (N + 1)/2$ is the position of the center pixel, while h_c, v_c, ld_c and rd_c denote the center pixels that are located in the corresponding horizontal, vertical, diagonal and anti-diagonal lines, respectively. $MDPDV_h$, $MDPDV_v$, $MDPDV_{LD}$ and $MDPDV_{RD}$ denote the local line real-valued vectors that are extracted from horizontal, vertical, diagonal and anti-diagonal directions, respectively.

Employing formula (1), the horizontal component (real-valued vector) of MDPDV based on PLLBP-like features extracts $N - 1$ real-valued differences for each pixel. The same numbers of real-valued differences can be extracted for the vertical, diagonal and anti-diagonal component of MDPDV using formula (2), formula (3) and formula (4), respectively. Then, we obtain whole MDPDV by concatenating the real-valued from $MDPDV_h$, $MDPDV_v$, $MDPDV_{LD}$ and $MDPDV_{RD}$ as formula (5). The total length of the whole MDPDV based on LLBP for each pixel is $4(N - 1)$.

$$MDPDV_h(x, y) = [h_1 - h_c, \cdots, h_N - h_c] \tag{1}$$
$$MDPDV_v(x, y) = [v_1 - v_c, \cdots, v_N - v_c] \tag{2}$$
$$MDPDV_{LD}(x, y) = [ld_1 - ld_c, \cdots, ld_N - ld_c] \tag{3}$$
$$MDPDV_{RD}(x, y) = [rd_1 - rd_c, \cdots, rd_N - rd_c] \tag{4}$$
$$MDPDV(x, y) = [MDPDV_h, MDPDV_v, MDPDV_{LD}, MDPDV_{RD}] \tag{5}$$

Compared with traditional PDV in [29] and [30], MDPDV has two merits. First, MDPDV has a higher ability to capture more information in the finger vein pattern than traditional PDV since the veins are located inside the finger in a piecewise-linear style [17]. Second, MDPDV saves more memory and requires less computational time in the training and testing stage than traditional PDV. The reason is that if the neighborhood size is the same, then the dimensions of MDPDV for any pixel in the image are less than the traditional PDV dimensions. For example, when the neighborhood size is 3 and 6, the dimensions of the traditional PDV are 48 and 178, while the MDPDV dimensions are 24 and 48, respectively.

However, MDPDV is the real-valued and high-dimensional data. How to obtain compact and discriminative binary code is our main problem. Hand-crafted features such as LBP and LLBP use a fixed threshold to binarize, which is not optimal for local feature representation. In addition, reducing the dimension is not included. Therefore, in the next part we will introduce our method on how to learn a discriminative mapping that can transform the high-dimensional and real-valued MDPDVs to low-dimensional binary features.

B. DBD FEATURE LEARNING

In this section, we elaborate the details of the proposed binary feature learning for finger veins. As mentioned above, our feature learning method aims to learn a discriminative mapping. Suppose that we are given a training set $X = [X_1, \cdots, Xc]$ from C classes. Each MDPDV set X_i is extracted from the i-th class training images, which is represented as $X_i = [x_{i1}, \cdots, x_{in_i}]$, where $x_{ij} \in R^d$ is the j-th MDPDV of the i-class images, $i = 1, \cdots, C, j = 1, \cdots, n_i$, and n_i is all MDPDVs of the i-class in the training set. We denote $N = \sum_{i=1}^{c} n_i$ as the total number of MDPDVs from the training images. Our main goal here is to learn K hash functions to map and quantize X into the binary matrix $B = [B_1, B_2, \cdots, B_c] \in \{-1, 1\}^{K \times N}$, where $B_i = [b_{i1}, b_{i2}, \cdots, b_{in_i}] \in \{-1, 1\}^{K \times n_i}$, $b_{ij} = [b_{1ij}, b_{2ij}, \cdots, b_{Kij}]^T \in \{-1, 1\}^{K \times 1}$. Let $W = [w_1, \cdots, w_K] \in R^{d \times K}$ be the projection matrix, where $w_k \in R^d$ is the projection vector for the kth hashing function, and then, the kth binary code b_{kij} can be calculated as follows:

$$b_{kij} = sgn(w_k^T x_{ij}) \tag{6}$$

where $sgn(a)$ equals 1 if $a \geq 0$ and -1 otherwise in the learning procedure. In particular, $sgn(a)$ equals 1 if $a \geq 0$ and 0 otherwise in the testing procedure.

To make every b_{ij} discriminative and compact, we enforce only two important criteria to learn W. First, the learned compact binary descriptor should preserve the energy of the original base feature. In other words, the quantization loss should be as small as possible after mapping. Second, we require the binary descriptor to be more discriminative. To obtain this goal, we attempt to make the inter-class variation of the local binary feature maximized while the intra-class variation is minimized.

To achieve these objectives, we formulate the following optimization objective function to learn a linear projection:

$$\begin{aligned} minJ(w_k) &= \lambda_1 J_1(w_k) + \lambda_2 J_2(w_k) - \lambda_3 J_3(w_k) \\ &= \lambda_1 \sum_{i=1}^{C} \sum_{j=1}^{n_i} \sum_{k=1}^{K} ||b_{kij} - w_k^T x_{ij}||^2 \\ &\quad + \lambda_2 \sum_{i=1}^{C} \sum_{j=1}^{n_i} (b_{ij} - \mu_i)(b_{ij} - \mu_i)^T \\ &\quad - \lambda_3 \sum_{i=1}^{C} n_i (\mu_i - \mu)(\mu_i - \mu)^T \end{aligned} \tag{7}$$

where $\mu_i = \frac{1}{n_i} \sum_{j=1}^{n_i} b_{ij}$ is the mean of the training binary features of the ith class, and $\mu = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{n_i} b_{ij}$ is the total mean of the binary features of all of the training images.

The objective of J_1 is to ensure that the quantization error between the projection of the original MDPDVs and the encoding binary codes is minimized. We can write J_1 in a matrix form, as $J_1 = \lambda_1 ||B - W^T X||_F^2$. The objective of J_2 and J_3 is to ensure that the intra-class variation of the local binary feature is minimized and the inter-class variation of the local binary feature is maximized, respectively. Thus, the learned binary features have discriminative ability, and are robust to translation, image rotation and illumination variation to a certain degree.

Due to the non-linear $sgn(\cdot)$ function, the whole objective function is an NP-hard problem. To solve this problem, we relax it with the signed magnitude. We can write formula (7) in the following matrix form:

$$\begin{aligned} minJ(W) &= \lambda_1 ||B - W^T X||_F^2 + \lambda_2 tr(W^T S_w W) \\ &\quad - \lambda_3 tr(W^T S_b W) \end{aligned} \tag{8}$$

$$S_w = \sum_{i=1}^{C} \sum_{j=1}^{n_i} (x_{ij} - m_i)(x_{ij} - m_i)^T \tag{9}$$

$$S_b = \sum_{i=1}^{C} n_i (m_i - m)(m_i - m)^T \tag{10}$$

where S_w and S_b are intra-class and inter-class scatter matrix of MDPDVs in the training data, respectively. Here, $m_i = \frac{1}{n_i} \sum_{j=1}^{n_i} x_{ij}$ is the mean of all of the MDPDVs of the i-th class over all of the training images, and $m = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{n_i} x_{ij}$ is the total mean of the MDPDVs of all of training images.

While formula (8) is not convex, but we can use the work in [32] to iteratively optimize W and B by the following method:

1) fix W and update B: let B be a given matrix, and then, formula (8) can be written as

$$minJ(B) = ||B - W^T X||_F^2 \tag{11}$$

According to [29], the solution to formula (11) is

$$B = sgn(W^T X) \tag{12}$$

2) fix B and update W: let B be a given matrix, and then, formula (8) can be written as

$$\begin{aligned} minJ(W) &= tr(W^T (\lambda_1 X X^T + \lambda_2 S_w - \lambda_3 S_b) W) \\ &\quad - 2\lambda_1 tr(B X^T W) \\ Subject\ to\ & W^T W = I \end{aligned} \tag{13}$$

According to [29], this problem can use the gradient descent method with the curvilinear search algorithm in [33] to solve W. The detailed procedure of the proposed DBD can be summarized as Algorithm 1.

C. DBD-BASED FINGER VEIN REPRESENTATION

Since the bag-of-words based methods [21], [22], [29] can utilize statistical information in images to give resistance to occlusions, geometric deformations, translation, rotation and illumination variations, we adopt the bag-of-words method to represent the finger vein image. The following describes the details of the finger vein representation and the matching score calculation.

Having the learned feature mapping matrix W, we first map each MDPDV into a low-dimensional binary descriptor in the training images. Then we apply the K-means method

Algorithm 1 DBD Algorithm

Require:

X: training set; T: number of iterations; λ_1, λ_2 and λ_3: parameters; K: the length of the binary code; ϵ: the convergence parameter;

Ensure:

Optimal W

1: Initial W as the top K eigenvectors of XX^T that correspond to the K largest eigenvalues; initialize t as one;
2: **repeat**
3: Update t as $t+1$;
4: Update B with fixed W using formula (12);
5: Update W with fixed B using formula (13);
6: **until** $|W^t - W^{t-1}| < \epsilon$ and $t > 2$
7: **return** W.

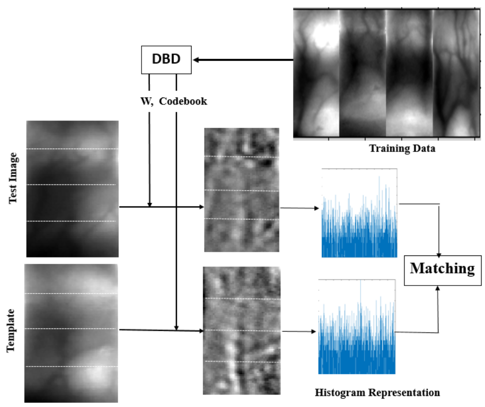

FIGURE 3. The flow-chart of the DBD-based finger vein representation and recognition method.

to learn a codebook from the obtained binary descriptor. Finally, each binary descriptor is pooled as a bin and all MDPDVs within the same finger vein image are represented as a histogram feature for the finger vein representation.

Previous studies [17] have shown that partitioning the figure vein image could improve the performance of the system because different regions have different structural information, and therefore, we divided each finger vein image into multiple non-overlapping regions, and we learn the projection matrix and cluster for each local region. Last, the histogram features from all of the regions within a finger vein image are concatenated as the feature representation of the whole finger vein image.

After obtaining the histogram feature representation of each finger vein image, we use whitened PCA (WPCA) to reduce the feature dimension into 500 and calculate the matching score with cosine similarity. Fig. 3 illustrates how to use the DBD for finger vein representation.

III. EXPERIMENTS AND RESULTS

In this study, all of the experiments are implemented in MATLAB R2013a and conducted on a PC with 3.60 GHZ i7-4790 CPU and 16 GB RAM. Several experiments are designed to evaluate the proposed DBD method: 1) the first experiment determinates the binary length on SDUMLA-FV database; 2) the second experiment validates the effectiveness of our MDPDV and the objective function on SDUMLA-FV and PolyU databases; 3) the third experiment evaluates the performance of the DBD method in comparison with different categories of state-of-the-art finger vein recognition methods on the SDUMLA-FV and PolyU databases.

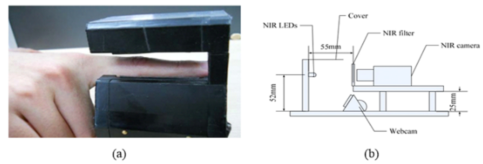

FIGURE 4. Imaging devices: (a) SDUMLA-FV database; (b) PolyU database.

A. DATABASES

To make the experimental results more persuasive, we perform rigorous experiments on two different databases: one is the finger vein image database constructed by our MLA Lab, called the SDUMLA-FV database [34]; and the other is the finger vein image database constructed by Hong Kong Polytechnic University, called the PolyU database [12].

The SDUMLA-FV database was acquired from 34 volunteers over a period of 20 days using the imaging device manufactured by the Joint Lab for Intelligent Computing and Intelligent System of Wuhan University, China, which is shown in Fig. 4(a). There are 106 individuals. Each individual provided six fingers. Thus, there are 3816 (106 subjects $\times$ 6 fingers $\times$ 6 samples) finger vein images in the SDUMLA-FV database. In our experiment, all of the images, i.e., 636 (106 subjects $\times$ 6 fingers) in the SDUMLA-FV database, are used.

The PolyU database was acquired from 156 volunteers over a period of eleven months using the imaging device shown in Fig. 4(b), and each of the subjects provided six image samples from the index finger to the middle finger. In our experiments, we employ all of the finger vein images acquired in the first session, i.e., 156 subjects with 6 images per subject. Because the finger veins are believed to be quite unique between different fingers of the same individual [12], different finger vein images from an individual are regarded as belonging to different classes, i.e., 312 classes with 6 samples per class.

The SDUMLA-FV and PolyU databases were preprocessed by the methods proposed in [12] and [35], respectively. In addition, in all of the images in the two databases, we extracted the region of interest(ROI) and normalized it into 96 $\times$ 64 pixels. Some of the preprocessed images are shown in Fig. 5. The first row comes from the SDUMLA-FV database, and the second row comes from the PolyU database.

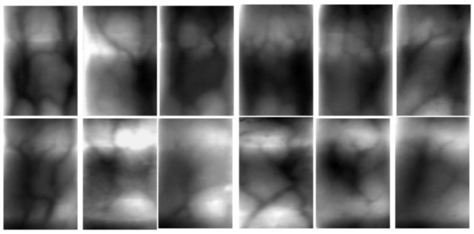

FIGURE 5. Example preprocessed images from the SDUMLA-FV database and the PolyU database.

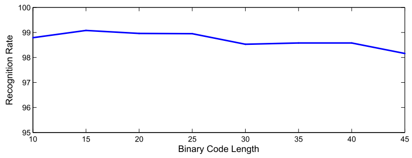

FIGURE 6. Recognition rates (%) of binary codes with varied length on the SDUMLA-FV database.

B. PARAMETER DETERMINATION

Here, we try to find the best value for the binary code length K. The recognition performance of different code lengths are evaluated on SDUMLA-FV database. The recognition rates are reported in Fig. 6. From the experimental results, we can see that, the best recognition rate can be achieved with the code length is 15. This value will be used in the following experiments.

C. EVALUATION OF OUR MDPDV AND THE OBJECTIVE FUNCTION

In this part, we investigate the efficiency of MDPDV and the effectiveness of our objective function. First, we use LBP-like PDV as the base features and our objective function for learning the feature mapping, which is denoted as DBD-LBP. Second, we apply MDPDV and our objective function jointly.

On the SDUMLA-FV database, we use the first three images as training samples, and the other three images are used as testing samples. Three-fold cross-validation is adopted in the experiment. Consequently, there are 1089 (363×3) intra-class matchings and 1,211,580 $(636 \times 3 \times 635)$ inter-class matchings. We set the length of MDPDV at each direction to eight, and MDPDVs are extracted from eight directions; therefore, a 64-dimensional MDPDV is obtained for each pixel in the image and is projected into K-bit binary codes by using the learning mapping functions. In all of our experiments, K was empirically set to 15. Through the cross-validation strategy on the training sample of the SDUMLA-FV database, we determined the parameters λ_1, λ_2 and λ_3 as 1, 0.08 and 1, respectively. The codebook size was set to 500, and we also determined the local region to be 4×1 through experimentation. As a result, each finger vein image was represented as a 2,000-dimensional feature vector after using DBD $(2,000 = 500 \times 4 \times 1)$. Then, we utilized whitened PCA (WPCA) to reduce the feature dimension into 500 and applied the nearest neighbor classifier with cosine similarity for the finger vein matching.

TABLE 2. Performance of CBFD, DBD-LBP and DBD on the two databases.

Methods	Recognition rate on the SDUMLA-FV database	Recognition rate on the PolyU database
CBFD	98.32%	99.25%
DBD-LBP	98.95%	99.89%
DBD	99.08%	99.98%

TABLE 3. Computational time on the SDUMLA-FV database.

Methods	Training time	Matching time per image
CBFD	557.066s	52.0ms
DBD-LBP	1317.468s	51.6ms
DBD	680.459s	42.8ms

On the PolyU database, we use the first three images as training samples, and the other three images are used as testing samples. Three-fold cross-validation is adopted in the experiment. Consequently, there are $936(312 \times 3)$ intra-class matchings and $291{,}096(312 \times 3 \times 311)$ inter-class matchings on the PolyU database. The parameter settings and experimental process are the same as on the SDUMLA-FV database.

Additionally, to make a fair comparison with CBFD on the finger vein databases, we tuned the parameters for CBFD on the SDUMLA-FV database. Through these experiments,we determined that when the dimension of PDV is 169 and the local region is 4×1, the performance of CBFD is maximized.

The performance is evaluated using the recognition rate and computational time for the key operations, which are the most common benchmarks in biometrics. In this paper, the training time includes the time interval from the input of the training images (after preprocessing) to obtaining the projection mapping and computing the template representation; and the matching time interval is from the input of the testing image to obtaining the final matching result. For the sake of brevity, the computational time was calculated only on the SDUMLA-FV database.

Tables 2 and 3 illustrate the comparison results. We can analyze the results with regard to four main aspects.

First, DBD-LBP are compared with CBFD in the recognition accuracy and training time. The difference between DBD-LBP and CBFD only is the objective function in the learning process. DBD-LBP utilizes the class information, while CBFD is unsupervised. Table 2 shows that DBD-LBP outperforms CBFD on the two databases. This finding occurs because DBD-LBP uses an inter-class scatter matrix and intra-class scatter matrix in the learning process to explore the discriminative information for the finger vein recognition. However, Table 3 shows that the training time for DBD-LBP is larger than that for CBFD on the SDUMLA-FV database. This finding arises because constructing the inter-class scatter matrix and intra-class scatter matrix consumes a large amount of computing time. Therefore, we can conclude that our objective function is highly discriminative but has a low efficiency compared with that of CBFD.

Second, DBD-LBP was compared with DBD in the recognition accuracy and training time. The difference between DBD-LBP and DBD only is the base feature. LBP-like PDV is used in DBD-LBP while MDPDV is used in DBD. Table 2 shows that DBD slightly outperforms DBD-LBP in terms of the recognition accuracy on the two databases, but Table 3 shows that the training time for DBD is much less than that for DBD-LBP on the SDUMLA-FV database. These results are due to the following reasons: 1) the length of MDPDV in DBD is shorter than that of PDV in DBD-LBP; and 2) the neighborhood shape in MDPDV could be more suitable to capture the vein shape information. Hence, these results validate that using MDPDV as the base features for the learning feature methods can largely reduce the computational time and slightly enhance the accuracy of the recognition system.

Third, DBD was compared with CBFD in terms of the recognition accuracy and training time. The differences between CBFD and DBD are the base features and the objective function. Tables 2 and 3 show that DBD achieves better recognition performance than CBFD on the two databases and that the training time of DBD is slightly larger than that of CBFD on the SDUMLA-FV database. The main reason for these results is that we jointly use the MDPDV and our objective function in DBD. Using the MDPDV can reduce the dimension of the base features and enhance the rate of the recognition system. Using our objective function in the learning process can enhance the discrimination of local learning features and increase the recognition performance. Therefore, using the MDPDV and our objective function jointly can not only increase the recognition accuracy but also improve the computational efficiency.

Last, DBD was compared with DBD-LBP and CBFD in terms of the matching time. Table 3 shows the following: 1) the difference in the matching time per image between CBFD and DBD-LBP is very small; 2) the matching time per image for DBD is less than that for DBD-LBP; and 3) the matching time per image for DBD is less than that for CBFD. The main reason for these results is that MDPDV is used as the base feature in DBD, rather than LBP-like PDV in DBD-LBP and CBFD. The dimensions of MDPDV are lower than those for LBP-like PDV when the optimal performance is achieved.

D. COMPARISON WITH THE EXISTING FINGER VEIN RECOGNITION METHODS

The key target of this set of experiments is to evaluate the finger vein recognition performance of our proposed method in comparison with some state-of-art finger vein recognition methods, i.e., LBP [36], LLBP [31], LDP [16], LDC [37], PBBM [19], SPF [23], SPCF [25] and DBC [38]. The experimental settings are the same as the previous settings. The performance is evaluated using the equal error rate (EER). EER is the value at which the false acceptance rate (FAR) is equal to the false rejection rate (FRR).

TABLE 4. Performance of different traditional methods on the two databases.

Method	EER(SDUMLA-FV database)	EER(PolyU database)
LBP[36]	0.1027	0.0744
LLBP[31]	0.1096	0.1577
LDP[16]	0.2289	0.2361
LDC[37]	0.0887	0.0331
PBBM[19]	0.0336	0.0278
SPF[23]	0.0262	0.0181
SPCF[25]	0.0194	0.0075
DBC[38]	0.0200	0.0132
DBD(Proposed)	0.0189	0.0069

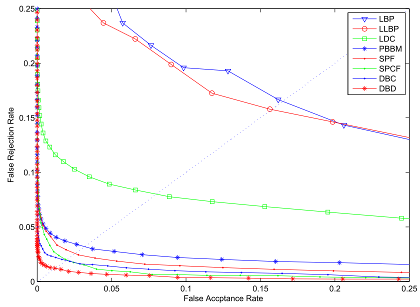

FIGURE 7. ROC curves of different methods on the SDUMLA-FV database.

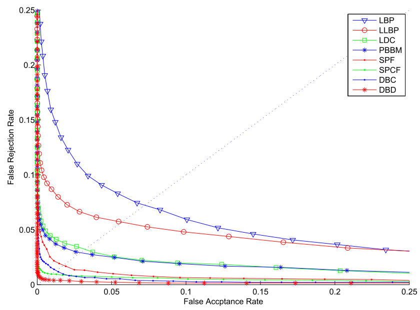

FIGURE 8. ROC curves of different methods on the PolyU database.

Table 4 lists the finger vein recognition performance of the proposed DBD compared with state-of-the-art descriptors on the two databases, and Fig. 7 and Fig. 8 show the ROC curves of our proposed DBD compared with the state-of-the-art methods on the SDUMLA-FV database and the PolyU database, respectively. From the results, we can draw the following conclusions:

First, DBD achieves much better performance than local hand-crafted feature methods such as LBP, LLBP, LDP, LDC and PBBM on finger vein recognition. This finding occurs because our DBD is a feature learning method and adopted the bag-of-words framework to effectively organize the local features.

Second, DBD achieves better performance on the two databases than the bag-of-words based methods, such as SPF and SPCF. The reason for these results lies in two aspects: 1) the proposed method is based on learning the features, which is more data-adaptive than the other methods; 2) using the intra-class scatter and inter-class scatter in the objective function makes the learning features more discriminative than the base features in SPF and SPCF.

Third, compared with recently proposed leaning discriminative binary codes (DBC) [38] on two databases, our DBD obtains better performance. This finding occurs because DBD is a local feature learning method and adopts the bag-of-words framework to represent the image, while DBC is based on dimensionality reduction methods. Our DBD can demonstrate stronger robustness to local variations. Therefore, a low EER can be obtained.

IV. CONCLUSIONS AND FUTURE WORKS

This paper proposes a novel feature learning method called the discriminative binary descriptor (DBD) for finger vein recognition. It enhances the finger vein recognition performance by introducing MDPDV and our discriminative objective function into feature learning. The main contributions of this work are summarized as follows: 1) we adopt a new way to construct the base features for the feature learning method. With a new base feature, the computational time is reduced and more useful information that is helpful for finger vein recognition is explored; 2) a discriminant feature mapping learning method is proposed. The intra-class and inter-class variances are considered in the objective function during the feature learning procedure. This step provides fusion of the label information into the learned local features, and thus, our learned binary features are more discriminative; 3) by incorporating our proposed base feature and feature mapping, a discriminant finger vein descriptor is proposed with a formulation and solution. It is also worthwhile to note that the time saved from our proposed base feature can offset the computational cost in our proposed feature learning process. Moreover, DBDs are learned for different regions of finger vein images to improve the discriminative ability and obtain a more precise image representation. Extensive experimental results show that our approach performs better than most state-of-the-art finger vein recognition algorithms on two figure vein databases. In future work, we plan to apply the proposed algorithm to address other visual recognition applications.

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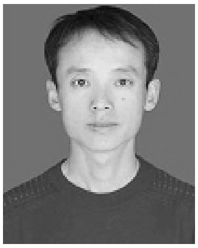

HAIYING LIU received the master's degree from Xinjiang University in 2007. He is currently pursuing the Ph.D. degree with Shandong University. His main research interests are biometrics and machine learning.

LU YANG received the Ph.D. degree from Shandong University in 2016. She is currently a Lecturer with the School of Computer Science and Technology, Shandong University of Finance and Economics. Her main research interests are finger vein recognition and biometrics.

GONGPING YANG received the Ph.D. degree in computer software and theory from Shandong University, China, in 2007. He is currently a Professor with the School of Computer Science and Technology, Shandong University. His research interests are biometrics and medical image processing.

YILONG YIN received the Ph.D. degree from Jilin University, China, in 2000. From 2000 to 2002, he was a Post-Doctoral Fellow with the Department of Electronics Science and Engineering, Nanjing University, China. He is currently the Director of the MLA Group and a Professor with the School of Computer Science and Technology, Shandong University, China. His research interests include machine learning, data mining, and computational medicines.