LEARNING DISCRIMINATIVE FINGER-KNUCKLE-PRINT DESCRIPTOR

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ABSTRACT

Direction information has been intensively investigated for Finger-Knuckle-Print (FKP) recognition. However, most existing direction-based KFP recognition methods are hand-crafted, which are heuristic and require too much prior knowledge to engineer them. In this paper, we propose a discriminative direction binary feature learning (DDBFL) method for FKP recognition. We first propose a direction convolution difference vector (DCDV) to better describe the direction information of FKP images. Then, we learn a feature projection to convert the DCDV into binary codes, which are compact for the intra-class samples and more separable for the inter-class samples. Finally, we concatenate the block-wise histograms of the DDBFL codes to form the final descriptor for FKP recognition. Experimental results on the baseline PolyU FKP database demonstrate the competitive performance of the proposed method.

***Index Terms*—** Biometrics, FKP recognition, Direction feature learning, Discriminative FKP descriptor

1. INTRODUCTION

Biometrics refers to automatically recognizing an individual by using one's distinctive anatomical and behavioral traits [1][2], which has become an important solution for our security applications [3]. In the modern society, various biometrics modalities such as face, iris, fingerprint and palmprint have been developed [4][5]. As a relatively new biometric trait, Finger-Knuckle-Print (FKP) contains rich line and texture features, which are deemed to be unique to a subject [6][7][8] and not easy to be abraded. Due to its high reliability, stability and user acceptability, FKP recognition has been attracting increasing research attention in the past decade [9][10][11].

In recent years, many FKP recognition methods have been proposed [12][13][14][15], which can be roughly classified into two categories: holistic feature-based and local feature-based methods. The holistic-based feature extraction methods use the whole FKP images for recognition and the typical methods include PCA and LDA [11]. For example, Kumar et al. [11] extracted and fused the FKP features by using the PCA and LDA principles. By contrast, more efforts of researchers focused on the local feature extraction of FKP images due to its rich line and texture information. For example, Kumar et al. [12] proposed a KnuckleCode method by using localized Radon transform to characterize random lines and creases of FKP images. Zhang et al. [13] used the Gabor filter-based competitive code to represent the dominant direction features of FKP images. Gao et al. [14] proposed a multiple orientations and multiple levels FKP recognition method by encoding the Gabor filtering responses on multiple orientations. More direction-based FKP recognition methods can be found in [16][17][18][19][20]. It can be seen that the direction-based information serves as one of the most important features for FKP recognition providing encouraging recognition performance. However, most existing direction-based FKP recognition methods are hand-crafted and their performance heavily depends on the prior knowledge.

In this paper, we propose a direction feature learning method for FKP recognition. Fig. 1 shows the basic idea of the proposed method. The main contributions of the proposed method can be summarized as follows. (1) We propose a direction convolution difference vector to better describe the direction information of a FKP image for discriminative direction feature learning; (2) We propose a feature learning method to jointly learn and encode the discriminative direction features for FKP recognition; (3) We conduct comparative experiments on the baseline PolyU FKP database and the experimental results show that our method outperforms state-of-the-art methods.

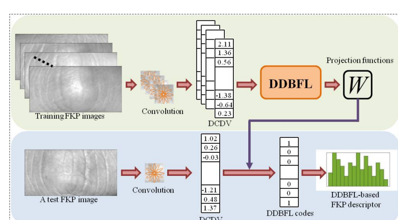

Fig. 1. The basic idea of the proposed DDBFL method.

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2. LEARNING DISCRIMINATIVE FKP DESCRIPTOR

In this section, we first briefly review the direction features of FKP images. Then, we show the extraction of the direction convolution difference vector. Lastly, we present the discriminative direction binary feature learning (DDBFL) method.

2.1. Direction Features of FKP Images

A FKP image contains rich line features such as wrinkles and creases, which carry rich direction features. For this reason, most existing methods extract the direction features for FKP recognition. They usually use a bank of direction-based templates such as Gabor filters to convolve with a FKP image. The dominant direction-based methods such as the competitive code [21] and KunckleCode methods encoded the direction of the template which produces the maximum filtering response as the direction features. However, these kinds of methods that extracted the single dominant direction features may loss the information on other directions such as multiple dominant directions of FKP images. Due to this, some methods such as MoriCode [14] and BOCV [22] encoded the filtering responses between the templates and a FKP image on multiple directions. It can be seen that most existing direction-based methods are hand crafted, which require too much prior knowledge to design them. In this work, we propose a direction feature learning method for FKP recognition.

2.2. Direction Convolution Difference Vector

Unlike most direction-based methods which use direction-specific convolution results, we introduce a new and informative direction convolution difference vector for discriminative FKP direction feature learning and extraction. We first define twelve Gabor filters [5][21] with the directions of $(j-1)\pi/12 (j = 1, 2, ..., 12)$ and then convolve them with a FKP image as follows:

$$c_j(x, y) = G_j * I(x, y), \tag{1}$$

where G_j represents the Gabor filter with direction of $(j-1)\pi/12$. I is a FKP image and "*" is the convolution operation. c_j is the convolution result, which is referred to as direction convolution. After that, we calculate the direction convolution difference between each pair of the neighboring directions to form the DCDV, as follows:

$$DCDV = [c_{12}-c_{11}, ..., c_j-c_{j-1}, ..., c_2-c_1, c_1-c_{12}]. \tag{2}$$

Fig. 2 shows an example of how to calculate the DCDV of a pixel in a FKP image. DCDV measures the convolution difference between two neighboring directions so that it can better describe how the direction convolution change and implicitly denote the significance of a direction feature. Moreover,

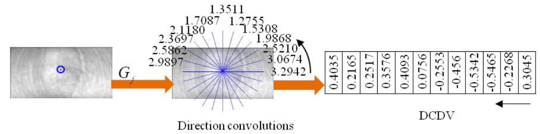


Fig. 2. An illustration of how to obtain a DCDV.

a DCDV can clearly denote the multiple dominant direction features of a point in a FKP image. For example, a positive direction convolution followed a negative direction convolution usually denotes a dominant direction in a local patch of a FKP image. Therefore, DCDVs contain informative direction information of a FKP image. In addition, a DCDV has a zero mean, which is suitable for feature learning without performing zero-normalization.

2.3. DDBFL

DCDVs contain informative direction information of a FKP image. We aim to learn the most discriminative features from the DCDVs. Motivated by the fact that binary features are effective and robust to local changes such as illumination variations, our DDBFL method aims to learn K hash functions to map a DCDV into a binary feature vector. Suppose $x_{p,i} \in R^{d\times 1}$ is the DCDV of the pth pixel of the ith FKP image, the kth binary code $b_{p,i,k}$ of $x_{p,i}$ is computed as follows:

$$b_{p,i,k} = \frac{1}{2} \times (sgn(w_k^T x_{p,i}) + 1), \tag{3}$$

where $sgn(u)$ equals to 1 when $u > 0$ and -1 otherwise. $w_k (k = 1, 2, ..., K)$ is the kth projection function.

To make the learned feature discriminative, for the training samples, we maximize the variance of all the learned binary codes so that the learned feature codes are separable. Moreover, the inter-class distance of them is maximized and the intra-class distance is minimized, making the feature codes compact for the same class and more separable for different classes of the FKP images. To this end, we formulate the following optimization objective function:

$$\begin{aligned} \max_{w_k} J(w_k) &= \max_{w_k} J_1(w_k) + 2\lambda J_2(w_k) \\ = \max_{w_k} \sum_{p=1}^{P}\sum_{i=1}^{N} ||b_{p,i,k} - \bar{\mu}_{p,k}||^2 &+ 2\lambda \sum_{p=1}^{P}\sum_{i=1}^{N} \Big(\sum_{j\notin\Upsilon(i)} ||b_{p,i,k} \\ &- b_{p,j,k}||^2 - \sum_{j\in\Upsilon(i)} ||b_{p,i,k} - b_{p,j,k}||^2 \Big), \end{aligned} \tag{4}$$

where $\bar{\mu}_{p,k}$ is the mean of the kth binary codes extracted from the DCDVs of the pth pixels of all samples. N is the number of the training FKP images and P is the pixel number of a FKP image. $\Upsilon(i)$ is the index set of the samples that are from the same class as the ith sample. It is seen that the objective function has two terms, which are trade off by a balance parameter, i.e., λ. The first term is to ensure that the variance of the learned binary codes of all samples is maximized in an unsupervised manner. The objective of the second term is to maximize the inter-class difference and the intra-class similarity of the feature codes in a supervised manner.

To our knowledge, Eq. (4) is NP-hard due to the nonlinear sgn function. According to [23][24], we relax the sign function to its signed magnitude. Hence, the first term of Eq. (4) can be rewritten as:

$$\begin{aligned} J_1(W) &= \sum_{p=1}^{P} ||W^T X_p - W^T M_p||^2 \\ &= tr(W^T(\sum_{p=1}^{P}(X_p X_p^T - 2X_p M_p^T + M_p M_p^T))W), \end{aligned} \tag{5}$$

where $X_p \in R^{d\times N} = [x_{p,1}, x_{p,2}, ..., x_{p,N}]$ is the DCDV matrix extracted from the pth pixels of all the training samples. $M_p \in R^{d\times N} = [m_p, m_p, ..., m_p]$ is the pth DCDV mean matrix, where $m_p \in R^{d\times 1}$ is the mean vector of the pth DCDVs extracted from the pth pixels of the samples. $W = [w_1, w_2, ..., w_K] \in R^{d\times K}$ is the projection matrix. d is the size of a DCDV, i.e., 12.

For the second term, we replace the $l_2 - norm$ distance metric with the sign multiplication and rewrite it as follows:

$$\begin{aligned} J_2(w_k) = \sum_{p=1}^{P}\sum_{i=1}^{N}(&\sum_{j\in\Upsilon(i)} sgn(w_k^T x_{p,i})\times sgn(w_k^T x_{p,j}) \\ &- \sum_{j\notin\Upsilon(i)} sgn(w_k^T x_{p,i})\times sgn(w_k^T x_{p,j})). \end{aligned} \tag{6}$$

We relax the sgn function to its magnitude and the second term of Eq. (4) can be rewritten as follows:

$$\begin{aligned} J_2(W) &= \frac{1}{2}\sum_{p=1}^{P} tr(W^T X_p S X_p^T W) \\ &= \frac{1}{2} tr(W^T(\sum_{p=1}^{P} X_p S X_p^T)W), \end{aligned} \tag{7}$$

where $S \in R^{N\times N}$ is defined as follows:

$$S_{i,j} = \begin{cases} 1, & \text{if } i\in\Upsilon(j), \\ -1, & \text{else.} \end{cases} \tag{8}$$

By combining Eq. (5) and Eq. (7), we rewrite the objective function $J(W)$ as follows:

$$\begin{aligned} J(W) &= J_1(W) + 2\lambda J_2(W) \\ &= tr(W^T(\sum_{p=1}^{P}(X_p X_p^T - 2X_p M_p^T + M_p M_p^T))W \\ &+ \lambda W^T(\sum_{p=1}^{P} X_p S X_p^T)W) = tr(W^T Q W), \end{aligned} \tag{9}$$

where $Q = \sum_{p=1}^{P}(X_p X_p^T - 2X_p M_p^T + M_p M_p^T + \lambda X_p S X_p^T)$. Therefore, our optimization function becomes a typical eigenproblem, and W can be solved by calculating the eigenvectors corresponding to the top-K eigenvalues of Q [23].

2.4. DDBFL-based Descriptor for FKP Recognition

To better represent the position-specific direction features of FKP images, we use the block-wise statistics of the DDBFL codes as the final features. Specifically, having learned the projection matrix W, we map the DCDVs of a FKP image into DDBFL binary codes. Then, we divide the feature map into non-overlapped local blocks, such as 16×16 pixels, and calculate the histograms of the DDBFL codes within each block. Lastly, we concatenate the block-wise histograms to form the final FKP feature descriptor. After that, we can use the simple and efficient chi-square distance to calculate the similarity of two DDBFL-based descriptors for FKP recognition.

3. EXPERIMENTS

In this section, we conduct experiments on the widely used PolyU FKP database [13] to evaluate the proposed method.

3.1. Database

The PolyU FKP database contains 7,920 FKP images collected from 165 volunteers. A subject was asked to provide 12 images in two sessions for the index and middle figures of each hand. Therefore, the PolyU FKP database consists of 7,920 samples from 660 different fingers. In our experiment, we used the enhancement method [13] to extract the ROIs of these FKP images and resized them into 55×110 pixels.

3.2. FKP Recognition

In this subsection, we first conducted FKP identification and then FKP verification experiments. FKP identification is a one-against-many comparison procedure to identify a query FKP image. In this study, we selected the first n(n=2,...,6) images for each finger as the training samples and used the rest as the query samples. The average rank-one identification accuracy on different training sets was calculated to evaluate the identification performance of the proposed method. For better comparison, the conventional representative FKP recognition methods such as MoriCode [14], ImCompCode [13] and ImCompCode&MagCode [13], and the popular direction-based palmprint recognition methods such as the competitive code [21] and BOCV [22] were also implemented. For the proposed DDBFL method, we empirically set λ to 0.01 and the number of DDBFL codes for a pixel to 6. Table 1 tabulates the identification results of different methods.

Furthermore, we divided the PolyU FKP database into the index FKP dataset and middle FKP dataset and each dataset contains 3,960 FKP images from 330 different fingers. We conducted identification experiments on both the index and middle FKP datasets, as reported in Table I. From the table, we can see that the proposed method achieves obviously better performance with the smallest gain of approximately 4% in accuracy than the state-of-the-art methods on each dataset.

Table 1. The identification accuracies (average accuracies $\pm$ standard deviations) obtained by different methods.

	PolyU FKP	Index FKP	Middle FKP
CompetiveCode	78.26±1.83	79.35±1.85	80.00±1.43
BOCV	82.28±1.09	83.21±0.93	83.20±0.96
MoriCode	74.79±2.27	75.10±2.24	77.23±2.07
ImCompCode	84.05±1.37	85.16±1.13	85.59±1.41
ImCompCode&MagCode	87.43±1.33	88.29±1.08	88.75±1.27
DDBFL	**92.21±0.85**	**93.19±1.30**	**92.74±0.59**

FKP verification is a one-by-one matching procedure to verify whether two FKP images are from the same finger. In this experiment, we matched each FKP image with all the other samples of the PolyU FKP database and calculated the false rejection rate (FRR) and false acceptance rate (FAR) [13][21]. Then, we drew the Receiver Operating Characteristic (ROC) curve, which is a curve of FRR versus FAR against all possible operating points, to estimate the performance of FKP verification. Fig. 3 shows the ROC curves of the proposed method in comparison with several representative FKP recognition methods. It can be seen that the proposed method always obtains a lower FRR than the five compared methods under each FAR setting. Compared with the existing hand-crafted methods, our DDBFL method and DCDV are elaborately designed for discriminative FKP direction feature learning. More discriminative and data-adaptive direction features of FKP images can be exploited so that a better recognition rate can be obtained.

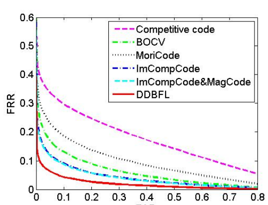
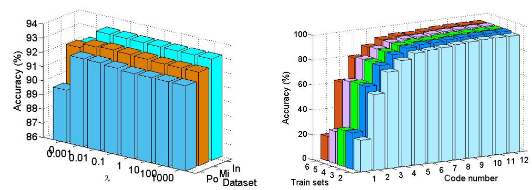


Fig. 3. The ROC curves of different methods.

3.3. Parameter Analysis

The proposed DDBFL contains a balance parameter, i.e. λ. Fig. 4(a) shows the identification rate of the DDBFL with different values of λ on the PolyU FKP (Po), Index FKP (In) and middle FKP (Mi) datasets. It is seen that the proposed method achieves the best when λ is set to 0.001 and 0.01. In this paper, we empirically set λ to 0.01 for the DDBFL method.

The proposed DDBFL method learns the discriminative direction binary codes from the DCDVs. The size of a DCDV is 12 and thus one to at most twelve DDBFL binary codes can be learned for a DCDV. Fig. 4(b) depicts the average identification accuracies of the proposed method versus different numbers of DDBFL codes based on the different training sets. It can be seen that the accuracy increases rapidly as the number of DDBFL codes increases from 1 to 6 and then increases slowly from 6 to 12. It demonstrates that learning more DDBFL codes for a DCDV can achieve a higher identification rate. In addition, the DDBFL method can achieve a very close accuracy to the best one when the number of DDBFL codes is 6. To balance the feature size and the recognition performance, our method extracts 6 DDBFL codes for a DCDV.



(a) (b)

Fig. 4. (a) The accuracies of the proposed method with different values of λ; (b) The accuracies of the proposed method versus different numbers of the DDBFL codes.

3.4. Computational Time Analysis

Different from most existing methods that directly extract direction features, the proposed method needs to first learn a feature mapping and then extract the direction features. It is seen that the DDBFL optimization function has a close-form solution so that it has a high computational efficiency. In addition, after learning a feature mapping, the proposed method can simply yet efficiently convert a DCDV into feature codes. For example, the average time of feature extraction for a FKP image is about 0.03 s under a PC with a double-core Intel(R) i7-7700 (3.60GHz) CPU and 16 GB RAM, which is fast for real-world applications.

4. CONCLUSION

In this paper, we first propose a direction convolution difference vector to better describe the direction information of FKP images. Then, we propose a feature learning method to jointly learn and encode the discriminative direction features for FKP recognition. Experimental results on the benchmark FKP database show that the proposed method outperforms the state-of-the-art FKP recognition methods, which also validate the effectiveness of the hash learning-based methods on FKP recognition. For future work, it would be interesting to apply the DDBFL method to other biometrics tasks such as finger-vein and palmprint recognition to further demonstrate its effectiveness.

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