Palmprint Recognition Using Discriminant Local Line Directional Representation

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Abstract. Palmprint is a new biometric feature for personal identification with a high degree of privacy and security. In this paper, we propose the palmprint feature extraction method which combines the direction-based method (Local line direction pattern) and learning-based method (two-directional two-dimensional linear discriminant analysis ($(2D)^2$LDA)) to get the high discriminant direction based features, so-called Discriminant local line Directional Representation (DLLDR). First, the algorithm computes the LLDP features with two strategies of encoding multi-directions. Then, $(2D)^2$LDA is applied to extract DLLDR features with higher discriminant and lower-dimensional from the LLDP matrix. The experimental results on the public databases of Hong Kong Polytechnic University demonstrate that our method is effective for palmprint recognition.

Keywords: Biometrics · 2DLDA · Palmprint · Discriminant local line directional pattern (DLLDP)

1 Introduction

Recently, palmprint has been increasingly studied and applied for personal recognition because of its advantages such as high performance, cost-effectiveness, user-friendliness, and etc. [1]. Low resolution Palmprint image could be used for recognition. The low resolution refers to 100 pixels per inch (PPI). Low resolution palmprint images contain features such as: principal lines (longest lines), wrinkles (weaker lines), and texture [2]. There are many methods exploiting these features, grouped into two categories such as subspace-based approaches and local feature based approachs [3–7].

Subspace-based approaches (PCA, LDA, ICA, …) project palmprint images from high dimensional space to a lower dimensional feature space. The subspace coefficients are considered as features [8]. To overcome illumination, contrast, and position changes,

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inputs are directional images [9–11]. Rida et al. [12] used both 2D-PCA and 2D-LDA for feature extraction and identification.

Local feature representations commonly use dominant direction features and texture because that are insensitive to illumination changes [25]. Zhang et al. [13] used Gabor phase in a fixed orientation to encode the palmprint, called palmcode for palmprint recognition system. Kong and Zhang [14] proposed the dominant direction feature extraction method for palmprint recognition by using Gabor filters with different directions. Then, the improved dominant direction based methods are fusion code [15], DRCC code [16], and etc. Jia et al. proposed RLOC feature which is computed by using line-shape filter (MFRAT based filter) [17]. Sun et al. [18] used three grouped Gaussian filters with three orthogonal directions with the aim that describes multiline at each pixel. Fei et al. [20] computes a double orientation code by using two dominant orientations for palmprint recogntion. BOCV feature were proposed for palmprint recogntion, in which orientation features were encoded with all six orientations by using six Gabor filters [19]. The local line direction pattern representation jointly encoded by two optional directions is also proposed for palmprint recognition [21]. Zheng et al. [22] proposed DoN of palmprint to build the direction feature descriptor for recognition. Many orientation based methods were investigated in [23]. In general, the direction features are robust and discriminant for palmprint recognition [24]. Li et al. [29] proposed Local Microstructure Tetra Pattern (LMTrP) for extracting palmprint features. Moreover, the modern deep convolutional neural network is also studied for palmprint recognition [26–28]. Recently, the approaches combined direction features and subspace based methods are deemed to be promising methods because of the following reasons: (1) Direction feature could be stable and robust against illumination. (2) Subspace-based methods compute the global discriminative features with low dimensions. Hoang et al. [9–11] have proposed some methods of combining the global and local features using the local directional feature and the linear discriminant analysis method. However, the local line directional pattern is reported to be distinctive and gives higher accuracy than the dominant directional feature [1, 21].

This paper proposes a novel Discriminant local line Directional Representation for palmprint recognition by combining local line discriminant pattern (LLDP) and two-directional two-dimensional linear discriminant analysis ($(2D)^2$LDA), so-called DLLDR. First, the algorithm computes the LLDP features with two strategies of encoding multi-directions. Then, $(2D)^2$LDA is applied to compute DLLDR features with lower-dimensional and higher discriminant. The experiments on the public databases from Hong Kong Polytechnic University demonstrate that DLLDR is a complete and robust direction representation for palmprint recognition.

In the following sections, we present in detail our proposed algorithm of palmprint recognition. Section 2 presents our proposed method. Experimental results are presented in Sect. 3. Finally, the paper conclusions are drawn in Sect. 4.

2 Our Proposed Method

The local line directional pattern (LLDP) is insensitive to illumination change and is more discriminative than the dominant directional code. However, this feature has two ways to represent the potential directional code: (1) using the direction of the brightest and darkest lines, (2) using the direction of the darkest line and the second darkest line. To exploit the distinctiveness of these two features, our proposed method first computes LLDP features with these two encoding strategies. Then, we apply the $(2D)^2$LDA method to reduce the dimensional number of two LLDP feature maps and eliminate the less distinctive information. Therefore, in this section, we present the proposed method in detail including LLDP, $(2D)^2$LDA method and combination scheme.

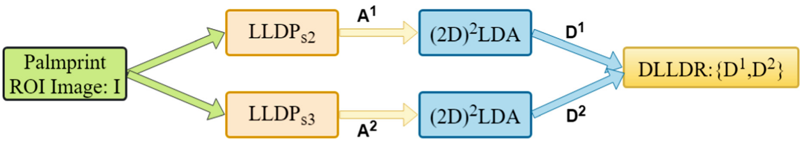

Fig. 1. The scheme of the proposal method.

2.1 LLDP

LLDP descriptor uses the index numbers of line directions to compute the feature code. There are three ways to build LLDP code [21].

S1: The directional bits of minimum k line magnitudes $\{m_i\}$, $(i = 0, 1, \ldots, K)$ are set to 1 and the remaining bits are set to 0, as:

$$LLDP_k = \sum\nolimits_{i=0}^{K} b_i\left(m_i - m_j\right)/2^i, b_i(a) = \begin{cases} 0, a \geq 0 \\ 1, a < 0 \end{cases} \tag{1}$$

where m_k is the *k-th* minimum magnitude. K is the number of consider directions.
S2: The indexes of the first and the second minimum line magnitudes, t_{12} and t_{11} are used as:

$$LLDP = t_{12} \times K^1 + t_{11} \times K^0 \tag{2}$$

S3: The index numbers of the minimum line response t_{12} and the maximum line response t_1 are used as follows:

$$LLDP = t_{12} \times K^1 + t_1 \times K^0 \tag{3}$$

The lines could be computed by MFRAT or Gabor filter bank. In an image, given a square local area Z_p, whose size is $p \times p$, MFRAT computes magnitues of different lines $\{m_i\}$, $(i = 0, 1, ..K)$ at the pixel (x_0, y_0) as:

$$m_i = \sum\nolimits_{x,y \in L_i} f(x, y) \tag{4}$$

$$L_i = \{(x, y) : y = S_i(x - x_0) + y_0, x \in Z_P\} \tag{5}$$

where $f(x, y)$ is gray value at (x, y), L_i is the set of points built a line on the Z_P, and i means the index number of a slope of S_i.

Given an image *I*, Gabor filter bank can be applied for detecting the lines $\{m_i\}$, $(i = 0, 1, \ldots, 12)$, located in (x, y) as follows:

$$\begin{aligned} m_i &= \langle I * G(x, y, \theta_i, \mu, \sigma)\rangle, \\ \theta_i &= \tfrac{\pi(i-1)}{12}, i = 1, 2, .., 12, \\ G(x, y, \theta, \mu, \sigma) &= \tfrac{1}{2\pi\sigma^2} exp\left\{-\tfrac{x^2+y^2}{2\sigma^2}\right\} f(x, y, \theta, \mu), \\ f(x, y, \theta, \mu) &= exp\{2\pi j(\mu x cos\theta + \mu y sin\theta)\} \end{aligned} \tag{6}$$

where $j = \sqrt{-1}$, μ is the frequency of the sinusoidal wave, θ controls the orientation of the function and σ is the standard deviation of the Gaussian envelop.

LLDP has three strategies for coding line directional patterns. However, strategy 2 can represent strategy *1* with $k = 2$, so we only choose two strategies to get the candidate patterns in order to fully exploit the distinctiveness of the palm lines. That is strategy 2 and strategy 3. With these two strategies, LLDP created by the darkest, second darkest and least dark lines which are stable and clear lines, and effect to the accuracy of recognition.

2.2 (2D)^{2}LDA

(2D)^{2}LDA is applied for reducing the dimension of LLDP matrix. Suppose $\{A_k\}, k = 1 \ldots N$ are the LLDP matrices compute by formula (2) with strategy s2 (or s3) which belong to *C* classes, and the j^{th} class C_i has n_i templates $\left(\sum_{i=1}^{C} n_i = N\right)$. Let $\overline{A}$ is the means of the registration set, and $\overline{A}_i$ is the means of i^{th} class.

$$\begin{gathered} A_k = \left[\left(A_k^{(1)}\right)^T, \left(A_k^{(2)}\right)^T, \ldots, \left(A_k^{(m)}\right)^T\right]^T, \overline{A}_i = \left[\left(\overline{A}_k^{(1)}\right)^T, \left(\overline{A}_k^{(2)}\right)^T, \ldots, \left(\overline{A}_k^{(m)}\right)^T\right]^T, \\ \overline{A} = \left[\left(\overline{A}^{(1)}\right)^T, \left(\overline{A}^{(2)}\right)^T, \ldots, \left(\overline{A}^{(m)}\right)^T\right]^T, \end{gathered} \tag{7}$$

where $A_k^{(j)}, \overline{A}_k^{(j)}, \overline{A}^{(j)}$ are the j^{th} row vector of A_k, $\bar{A}_k$ and $\bar{A}$, respectively. 2DLDA compute a set of optimal vectors to find the optimal projection matrices:

$$X = \{x_1, x_2, \ldots, x_d\} \tag{8}$$

by maximizing the criterion as follows:

$$J(X) = \frac{X^T G_b^X}{X^T G_w^X} \tag{9}$$

$$G_b = \frac{1}{N} \sum\nolimits_{i=1}^{C} n_i \sum\nolimits_{j=1}^{m} \left(\overline{A}_i^{(j)} - \overline{A}^{(j)}\right)^T \left(\overline{A}_i^{(j)} - \overline{A}^{(j)}\right) \tag{10}$$

$$G_w = \frac{1}{N} \sum\nolimits_{i=1}^{C} \sum\nolimits_{k \in c_i} \sum\nolimits_{j=1}^{m} \left(A_i^{(j)} - \overline{A}_k^{(j)}\right)^T \left(A_i^{(j)} - \overline{A}^{(j)}\right) \tag{11}$$

where T is matrix transpose, G_b is between-class matrix, G_w is within-class scatter matrix. Therefore, X is the orthonormal eigenvectors of $G_w^{-1}G_b$ corresponding to the d largest eigenvalues $\lambda_1, \ldots, \lambda_d$. The value of d is selected based on the predefined threshold θ as follow:

$$\frac{\sum_{i=1}^{d} \lambda_i}{\sum_{i=1}^{n} \lambda} \geq \theta \tag{12}$$

2DLDA described above works in the row-wise direction to learn an optimal matrix X from a set of training LLDP matrices, and then project an LLDP matrix $A_{m \times n}$ onto X, yielding m by d matrix, i.e. $Y_{m \times d} = A_{m \times n}.X_{n \times d}$. Similarly, the alternative 2DLDA learns optimal projection matrix Z reflecting information between columns of LLDP matrices and then projects A onto Z, yielding a q by n matrix, i.e. $B_{q \times n} = Z_{m \times q}^{T}.A_{m \times n}$. Suppose we have obtained the projection matrices X and Z, projecting the LLDP matrix $A_{m \times n}$ onto X and Z simultaneously, yielding a q by d matrix D:

$$D = Z^T.A.X \tag{13}$$

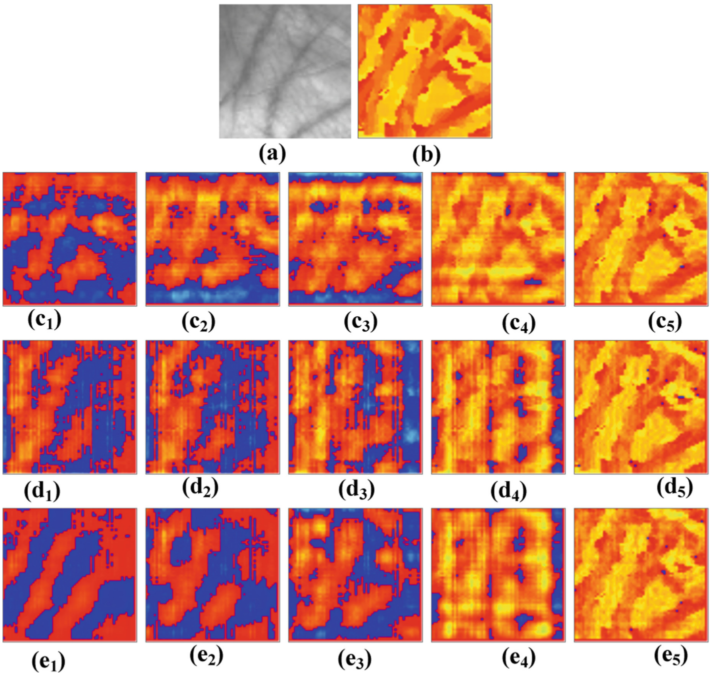

Fig. 2. Results of LLDP with strategy 2 and (2D)^{2}LDA: (a) original palmprint image, (b) LLDP image, (d1)–(d5), (e1–e5) some reconstructed images of the LLDP image with (c1)–(c5) d = 10, 15, 20, 25, 50 and q = 64, (d1)–(d5) d = 64, q = 10, 15, 20, 25, 50, (e1)–(e5) q = d=10, 15, 20, 25, 50, respectively.

The matrix D is also called the discriminant local line directional representation matrix (DLLDR) for recognition.

2.3 Discriminant Local Line Directional Representation

The input of our proposed algorithm is palmprint ROI image: *I*. Figure 1 demonstrates the proposed the method. The processing steps for extracting DLLDR feature are summarized as follows:

- Step 1: Compute the LLDP with strategies 2 to get A^1 matrix by using formula (2).
- Step 2: Compute the LLDP with strategies 3 to get A^2 matrix by using formula (3).
- Step 3: Based on $(2D)^2$LDA, compute the DLLDR feature D^1 by applying Eq. (13) to the A^1 feature matrix to get D^1.
- Step 4: Based on $(2D)^2$LDA, compute the DLLDR feature D^2 by applying Eq. (13) to the A^2 feature matrix to get D^2.
- Step 5: The combined feature matrix $\{D^1, D^2\}$ is DLLDR of the input image: *I*.

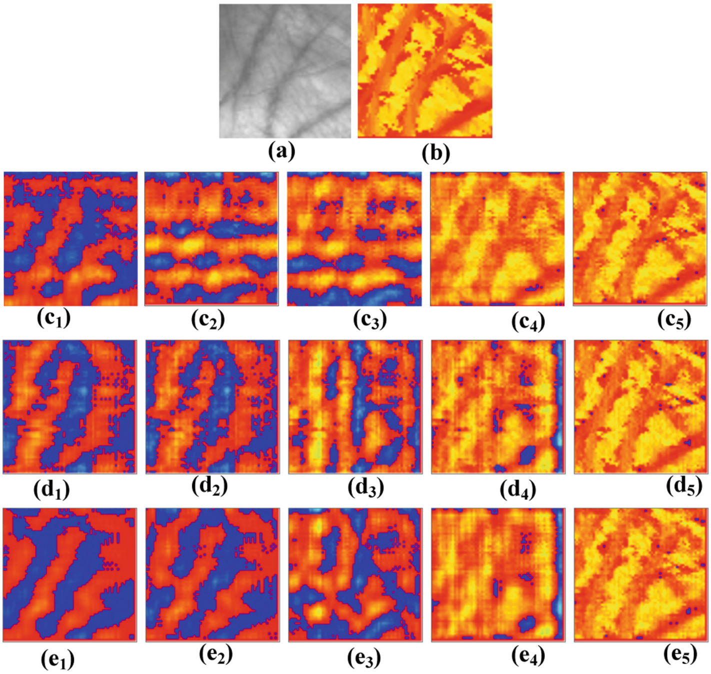

Fig. 3. Results of LLDP with strategy 3 and $(2D)^2$LDA: (a) original palmprint image, (b) LLDP image, (d1)–(d5), (e1–e5) some reconstructed images of the LLDP image with (c1)–(c5) d = 10, 15, 20, 25, 50 and q = 64, (d1)–(d5) d = 64, q = 10, 15, 20, 25, 50, (e1)–(e5) q = d=10, 15, 20, 25, 50, respectively.

Given a query image *I*, apply the proposed method to get DLLDR feature $D{:}\{D^1, D^2\}$, and apply our method to all the training images to get the DLLDR feature matrix $D_k (k = 1, 2, \ldots, N)$. The Euclidean distance is used to compare two features.

The distance between D and D_k is defined by:

$$\begin{aligned} d(D, D_k) &= \|D - D_k\| \\ score(D, D_k) &= 1 - d(D, D_k) \end{aligned} \tag{14}$$

The $d(D, D_k)$ is between 0 and 1. The score of perfect match is 1.

3 Experimental Results

We evaluate the proposed method in comparison some methods (LLDP [21], RDORIC [10]) on the PolyU 3D database of Hong Kong Polytechnic University [30]. These methods were implemented using C# on a PC with a CPU Intel(R) Core(TM) i3-3110 M @ 2.4 GHz and Windows 7 Professional. In the PolyU 3D database, there are *400* different palms. The twenty images from each of palms were captured in each session. The time interval between the two sessions is about 30 days. Each sample contains a 3D ROI (region of interest) and 2D ROI at a resolution of 128 × 128 pixels. In our experiments, we use 2D-ROI database in which the resolution of these ROI images is *64* × *64* pixels. In identification, a query compares to all templates in training set to select the most similar template as result. In verification, each image in the query set is compared with all templates in the registered set to generate incorrect scores and correct scores. The correct score is the maximum of the scores created by the query and templates from the same registered palm. Similarly, the incorrect score is the maximum of the scores created by the query and all templates of the different registered palms. If the query does not have any registered images, we only obtain the incorrect score. If we have N queries of registered palms and M queries of unregistered palms, we obtain N correct scores and $N + M$ incorrect score. We get the verification results: the receiver operating characteristic (ROC) curve. Similar to the number of employees in small and medium-sized companies, we set up two experiments with dataset 1 and dataset 2 with N = 100 and 200. In dataset 1, the training database contains *500* templates from *100* random different palms, where each palm has five templates. The testing database contains *1000* templates from *200* different registered palms. In dataset 2, the training database contains *1000* templates from *200* palms registered. The testing database contains *1000* templates from *200* registered palms. Therefore, there are *500*, *1000* correct identification distances and *1000, 2000* incorrect identification scores for $N = 100$, *200*, respectively. None of samples in the testing datasets is contained in any of the training datasets. Table 1 presents these parameters of our experiments. Table 2 represents the recognition accuracy of our method in comparison with others. The ROC curve illustrating the verification performances of our method and others are shown in Fig. 4. From this group of figures and tables, we can see that the recognition accuracy rate of our method is higher than the state of art methods (RDORIC [11], LLDP [21]).

Table 1. Parameters of databases in recognition experiments.

Dataset	Each class			All class		Number of identification	
	Training set	Testing set		Training set	Testing set		
		Registration set	Unregistration set			Correct distance	Incorrect distance
1	5	5	5	500	500 + 500 = 1000	500	500 + 500 = 1000
2	5	5	5	1000	1000 + 1000 = 2000	1000	1000 + 1000 = 2000

Table 2. Rank one identification in our experiments.

Method	Dataset 1		Dataset 2	
	Recognition rate (%)	Test time for a query image (ms)	Recognition rate (%)	Test time for a query image (ms)
RDORIC [10]	97.80	147	97.67	204
LLDP [21]	98.80	352	98.70	526
Our method (DLLDR)	99.60	153	99.30	275

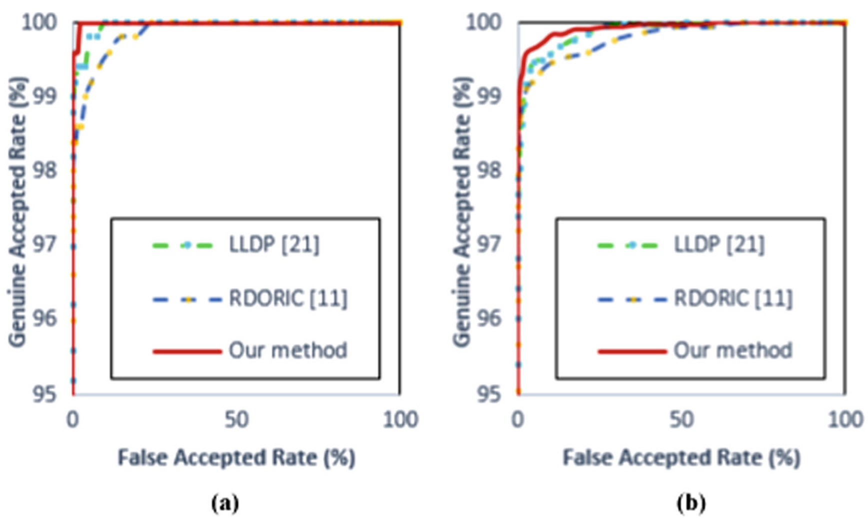

Fig. 4. The ROC curves of our proposed method and other methods with dataset 1 (a), dataset 2 (b), respectively.

4 Conclusion

This paper proposes a novel technique called Discriminant local line Directional Representation for palmprint recognition which combines LLDP and $(2D)^2$LDA. First, the algorithm computes the LLDP features with two strategies of encoding multi-directions. Then, $(2D)^2$LDA is applie to extract the DLLDR features with lower dimension and higher discriminant. Experimental results on two palmprint datasets of 3D PolyU database show that the proposed method achieves the best results in comparison to the state of art methods.

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