Palmprint Recognition Using Learning Discriminant Line Direction Descriptors

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Abstract. Palmprint-based biometrics has received a lot of attention for personal identification. The paper proposes a novel learning discriminant feature technique for palmprint recognition, called the Learning Discriminant Line Direction Descriptor (LDLDD), that learns separately all three kind of directional pattern code. The dominant direction number (DDN) map is calculated first in this method. Then, this technique computes direction pattern maps with three multi-direction encoding methods based on the DDN map, where pixels with the same DDN values will use the same encoding strategy and belong to the same feature map. Finally, $(2D)^2$LDA is used to train new feature subspaces that project these maps from a high-dimensional space to a discriminant space with lower dimensions. Experiments on Hong Kong Polytechnic University's (PolyU and IITD) public databases show that the proposed method outperforms existing techniques in terms of accuracy.

Keywords: Palmprint recognition · Dominant direction number · Multi direction pattern · Biometrics

1 Introduction

In the past, people utilized identity cards, keys, and passwords for individual recognition. Due to the rapid development of information technology and online financial activities, personal authentication based on biometrics is growing in popularity today. Biometrics based on the physiological and behavioral characteristics of a human offer various advantages including high security, high efficiency, and user friendliness. Biometric features include signatures, gaits, voices, faces, fingerprints, palmprints, etc. The palmprint has some advantages over other biometric features because it contains so much distinguishing information, including principal lines, wrinkles, and texture [1]. Region of

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interest (ROI) segmentation, feature extraction, and matching are the three main stages of palmprint processing. A sub-region in the palm's center that contains discriminative information is segmented during the ROI segmentation stage and used for feature extraction [2]. A palmprint extraction stage is needed in order to build a description with multiple subject separations [3, 4].The local direction feature is the main attribute used to extract palmprint since it is not changed by fluctuations in illumination [1–3]. Several strategies for constructing palmprint descriptors that take advantage of this local direction feature have been recommended for several decades, and they can be categorized into four general groups: one-direction based approach, local direction statistics-based approach, multiple-directions based approach and fusion discriminant representation approach [1, 3].

The one-direction technique frequently employs a particular type of line shape filter to measure lines in a specific direction and encode the results into a feature code [4–11]. For extracting of palmprint features, a 2D Gabor phase encoding approach with a fixed orientation is proposed [4]. Kong et al. obtained line responses using a Gabor filters and compared the hamming distance between two palmprint images [5]. CompCode is computed using six different Gabor filters with different directions and based on determining the most dominating direction of palm lines using the winner-take-all rule [6]. The Robust Line orientation code (RLOC) methodology employs twelve Radon-based filters to generate the dominant direction features [7].

The multiple-direction based technique makes use of the magnitudes of various direction filters. Sun et al. compute three orthogonal direction codes for palmprint representation using three orthogonal Gaussian filters [8]. Guo et al. [9] develop the binary orientation co-occurrence vector from palmprint images by applying six Gabor filters and concatenating the normalized responses into six directions. BOCV is more resistant to image rotation and accurately describes local direction features. In order to determine the delicate direction points, E-BOCV, acting as the BOCV, created six direction code maps [10]. To encode the results of comparing the six directions, Fei et al. proposed a discriminatory neighboring direction indicator. The indicator is not affected by noise or rotation [11].

The approach based on local direction statistics displays direction features as encoded vectors based on the statistics of one or more direction features. Jia et al. [12] propose the histogram of oriented lines (HOL), which is light-insensitive and forgiving of minor changes. Luo et al. [13] proposed the local line directional patterns (LLDP) technique, which uses palm lines to encode two dominant directions using either the real component of Gabor filters or the modified finite radon transform (MFRAT). Fei et al. propose a local multiple directional pattern (LMDP) [14] to accurately characterize the multiple directions information. Li et al. [15] propose the Local Micro-structure Tetra Pattern (LMTrP) for extracting palmprint features, which captures the local region histograms after effectively removing redundant features and then uses kernel linear discriminant analysis to minimize dimension. Zhang et al. [16] propose collaborative representation (CR)-based method that builds the feature vectors for the palmprint using the competing code's blockwise histograms. Fei et al. [17] present a novel double-layer direction extraction technique that uses latent direction information from the apparent direction's magnitude layer map.

Recently, researchers have been interested in developing several discriminant features learning techniques to learn specific mapping functions that transform raw data in discriminant features subspace. Sub-space learning [18], dictionary learning [19], metric learning [20], and deep learning [22, 23] are examples of these techniques. Principal component analysis (PCA) and linear discriminant analysis (LDA) are the most widely used discriminant feature learning techniques. Ribaric et al. [24] propose a multimodal biometric identification system that uses the PCA to extract the eigenfinger and eigenpalm. Hoang et al. [25] apply 2DLDA to both positive and negative orientations maps to find class separability features for palmprint recognition. Rida et al. [26] present a new ensemble classifier for palmprint recognition based on the Random Subspace Method, which employs 2DPCA to generate nearly incoherent random subspaces. Hoang et al. [27] propose a palmprint recognition method that combines a Local line direction pattern technique with (2D) 2LDA to achieve high discrimination features. Fei et al. [3] propose a palmprint recognition technique that computes the convolution difference between neighboring directions before using the LDA to generate the discriminative code.

In general, some learning discriminating feature-based methods have recently achieved good palmprint recognition accuracy [3, 25]. This paper proposes a novel learning discriminant feature technique for palmprint recognition, called the direction pattern Learning Discriminant Line Direction Descriptor (LDLDD), that learns separately all three kind of directional pattern code. The technique starts by calculating the dominant direction number (DDN) map. Then, based on the DDN map, LDLDD will calculate three direction pattern maps with three multi-direction encoding methods, where pixels with the same DDN values will have the same LLDP encoding strategy and belong to the same feature map. Finally, $(2D)^2$LDA is utilized to train new feature subspaces that project these maps from a high-dimensional space to a lower-dimensional, discriminant space. Experiments using the public datasets of Hong Kong Polytechnic University (PolyU and IITD) demonstrate that our proposed technique outperforms existing methods in terms of accuracy.

The remaining article is arranged as follows. Section 2 details our proposed the method. Section 3 presents the experimental results. The conclusion is provided in Sect. 4.

2 Our Proposal Method

A pixel in a palmprint image can have one of three scenarios: (1) a ridge runs across it, (2) two intersecting ridges connect at the consideration point, or (3) more than two crossing ridges intersect at that pixel. As a result, a technique for describing the three types of palm line patterns at the pixel is required. Various patterns are represented by distinct maps at the same time to avoid pattern matching ambiguity. Fei et al. [3] proposed the dominant direction number value (DDN), which allows the number of palmlines passing through a point to be determined. Therefore, we propose the Learning Discriminant Line Direction Descriptor (LDLDD) for palmprint recognition that performs the following steps: (1) estimate ridges in various directions using Gabor filters; (2) compute the DDN value of the LDDBP feature at each pixel; (3) compute Multiple line directions descriptors (MLDD) based on DDN map. The results are three direction coding maps without the ambiguity in matching; (4) Finally, apply the $(2D)^2LDA$ method for each map in order to learn the feature space with high discriminant in classification and feature size reduction. The results are three feature matrices for each sample type, each with a small number of dimensions for classification using Euclid distance. Figure 1 illustrates the scheme of the proposed algorithm. The following are specific formulas for implementing the proposed method.

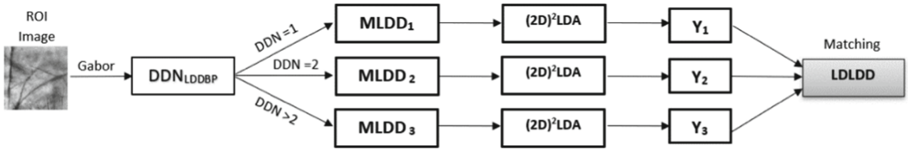


Fig. 1. The scheme of the proposal method

2.1 Gabor Filter for Detecting Line of Palmprint

The proposed method needs measure the appearance of the palm line in different directions. The 2D-Gabor filter is an effective tool for this goal. The 2D-Gabor filter is defined as the followings [4, 13]:

$$G(x, y, \theta, \mu, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left\{-\frac{x^2 + y^2}{2\sigma^2}\right\} exp\{2\pi i(\mu x \cos\theta + \mu y \sin\theta)\} \quad (1)$$

where $i = \sqrt{-1}$, μ denotes the frequency of the sinusoidal wave, θ is used to control the direction, and σ denotes the standard deviation of the Gaussian envelope. Then, the convolution of the Gabor filter is conducted on the palmprint image to obtain line response as follows:

$$r_j = (I * G(\theta_j))_{(x,y)} \quad (2)$$

where I is the palmprint image, $G(\theta)_j$ denotes the real part of the Gabor filter with the orientation of θ_j, '*' is the convolutional operator, r_j is the convolution result, and (x, y) denotes the position of a pixel in I, and the orientation of θ_j is computed as follows:

$$\theta_j = \frac{\pi(j-1)}{n} j = 1, 2, \ldots n \quad (3)$$

2.2 DDN

There are several crossing lines in a palmprint image, therefore, each pixel could has multiple dominant direction. The dominant direction number (DDN) is can be computed as follows [3]:

$$DDN = \frac{1}{2} \sum_{j=1}^{N_\theta} \left| s\left(r_j - r_{\varphi(j)}\right) - s\left(r_{\varphi(j)} - r_{\varphi(\varphi(j))}\right) \right| \quad (4)$$

where N_θ ($N_\theta = 12$) is the direction number of Gabor functions; j is the corresponding direction index; r_j represents the convolved result on the *jth* direction; *s(x)* equals to 1 if $x > 0$ and 0 otherwise; $\varphi(j)$ denotes the adjacent clockwise direction index of j. $\varphi(j)$ equals to N_θ if $j = 1$ and $(j - 1)$ otherwise, and it can be directly calculated as follows:

$$\varphi(j) = mod(j - 2, N_\theta) + 1 \tag{5}$$

DDN is used to determine the type of directional pattern used to represent the feature at each pixel. The next sub-section describes the use of DDN in representing this feature.

2.3 Multiple Line Directions Descriptor Using DDN

Multiple line directions descriptor (MLDD) is proposed for representing multiple dominant directions patterns in which pixels with a DDN value of 1 are represented by respectively the first and last dominant direction indices, pixels with a DDN value of 2 are represented by the first and second dominant direction indices, and pixels with a DDN value more than 2 are represented by DDN dominant direction indices and placed in a separate result maps. MLDD is defined as follows:

$$D^1 = \begin{cases} 0, \textit{if } DDN \neq 1 \\ m_f \times N_\theta + m_l, \textit{if } DDN = 1 \end{cases} \tag{6}$$

$$D^2 = \begin{cases} 0, \textit{if } DDN \neq 2 \\ m_f \times N_\theta + m_s, \textit{if } DDN = 2 \end{cases} \tag{7}$$

$$D^3 = \begin{cases} 0, \textit{if } DDN \leq 2 \\ \sum_{i=0}^{N_\theta - 1} s(r_i - r_{DDN})2^i, \textit{if } DDN > 2 \end{cases} \tag{8}$$

where the index numbers m_f, m_s and m_l are respectively the first, second and last dominant direction indices with the maximum, second maximum and minimum filtering responses; r_k is the k-th minimum directional response (k = DDN).

After applying the MLDD technique to each input image I, the output will be three feature matrices, each of which represents the patterns of pixels with the same characteristic (that have 1 line, 2 lines or more lines at the pixel). These matrices are utilized as features for pattern matching between various objects with no ambiguity. However, because these images are large and include redundant information, the following part will describe how to use $(2D)^2$LDA to extract image features with the goal of reducing the number of dimensions and increasing recognition discrimination (Fig. 2).

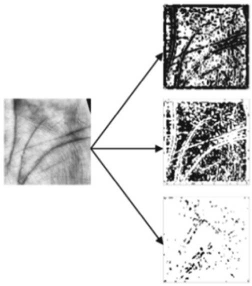


Fig. 2. Three feature matrices of the patterns of pixels.

2.4 2DLDA

Suppose $\{A_k\}$, $k = 1 \ldots N$ are the MLDD matrices which belong to C classes, and the *ith* class C_i has n_i sample ($\sum_{i=1}^{C} n_i = N$). Let $\overline{A}$ and $\overline{A}_i$ denote the means of *ith* class and the whole training set, respectively. 2DLDA attempts to seek a set of optimal discriminating vectors to form a transform $X = \{x_1, x_2, \ldots, x_d\}$ by maximizing the 2D Fisher criterion denoted as:

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

where T denotes matrix transpose, G_b and G_w respectively are between-class and within-class scatter matrices:

$$G_b = \frac{1}{N} \sum_{i=1}^{C} n_i \left(A_i - \overline{A}\right)\left(A_i - \overline{A}\right)^T \tag{10}$$

$$G_w = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{n_i} \left(A_i - \overline{A}\right)\left(A_i - \overline{A}\right)^T \tag{11}$$

Equation (9) can be obtained by computing orthonormal eigenvectors of $G_w^{-1} G_b$ corresponding to the d largest eigenvalues thereby maximizing function J_x. The value of d can be controlled by setting a threshold as follow:

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

where $\lambda_1, \lambda_2, \ldots, \lambda_n$ is the n biggest eigenvalues of $(G_w)^{-1} G_b$ and θ is a pre-defined threshold.

2.5 $(2D)^2$LDA

$(2D)^2$LDA apply 2DLDA on the row-wise direction of MLDD matrices to learn an optimal matrix X and on the column-wise direction of MLDD matrices to learn optimal projection matrix Z. Suppose we have obtained the projection matrices X and Z, projecting the MLDD matrix $D_{m\times n}$ onto $X_{n\times d}$ and $Z_{m\times q}$ simultaneously, yielding a matrix $C_{q\times d}$ [27]:

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

The matrix C is also called the learning discriminant line direction descriptor (LDLDD) for recognition.

2.6 LDLDD for Palmprint Recognition

The region of interest (ROI) for rotation and translation alignment is initially identified in palmprint images [4]. The ROI images are used as input in our proposed method. The processing steps of the proposed methods for obtaining LDLDD feature are as follows:

- Step 1: Applying Gabor filters to estimate palm lines different directions using formulas (5).
- Step 2: With each image I, computing the DNN value feature at each pixel using formulas (4).
- Step 3: Computing MLDD features: D^1, D^2, D^3 using formulas (6), (7), (8).
- Step 4: Applying $(2D)^2$LDA to MLDD feature: D^1, D^2, D^3 using formulas (9)–(11) and obtain the feature matrix: Y^1, Y^2, Y^3 using formulas (13).
- Step 5: The combined feature matrix $\{Y^1, Y^2, Y^3\}$ is LDLDD of input image.

Given a test palmprint image A, use our proposed method to compute LDLDD feature Y: $\{Y^1, Y^2, Y^3\}$, and apply our method to all the training images to get the

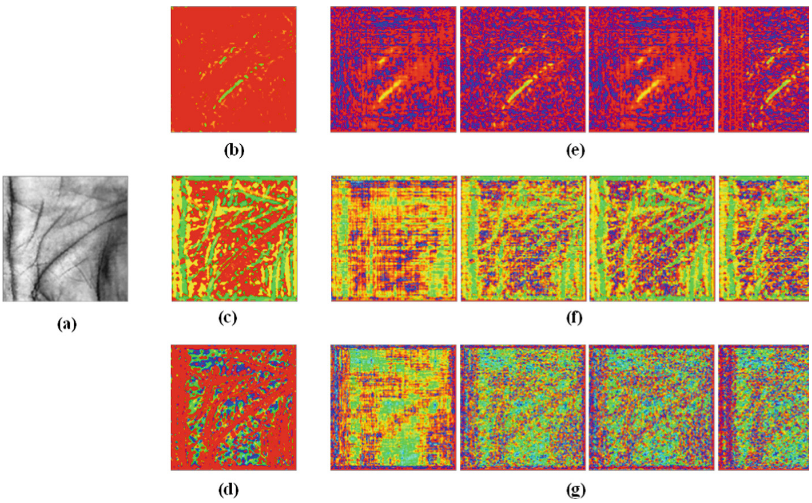


Fig. 3. Results of MLDP and $(2D)^2$LDA: (a) original palmprint image, (b–d) MLDP image, (e–g) some reconstructed images of the MLDP image of (a–d) with (d, q) = (50, 50), (100, 100), (128, 100), (100, 128), respectively.

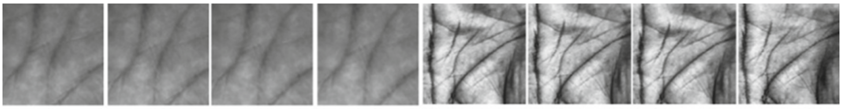
LDLDD feature matrix Y_k(k = 1, 2, …, N). Then, the nearest neighbor classifier is used for classification. Here, the distance between Y and Y_k is defined by: $d(\mathrm{Y}, Y_k) = \|\mathrm{Y} - Y_k\|$. The distance $d(\mathrm{Y}, Y_k)$ is between 0 and 1. The distance of perfect match is 0 (Fig. 3).

3 Experimental Results

All experiments are test on on the commonly used palmprint databases, including Palmprint PolyU and IITD. These methods were conducted using C# on PC with Intel(R) i5 core(TM) i5-4300U CPU @ 1.90 GHz (4 CPUs) ~ 2.5 GHz and Windows 10 Professional operating system. The PolyU palmprint database [28] contains 7,752 images obtained from 386 palms belonging to 193 people. The images are captured over the duration of around 60 days in two sessions. The IITD palmprint database contains 2,601 contactless palmprint images from 460 palms corresponding to 230 persons [29]. For each palm, five to six samples are collected. In our experiments, we use the ROI images with the sizes of 128 × 128 pixels. The parameters of the IITD and PolyU datasets in our experiments are listed in Table 1. Palmprint identification is a one-to-many matching process for determining the class label of a query palmprint image. The rank-1 identification rate, which compares a query sample to all of the training samples and uses the label of the most similar sample as the query sample's class label, is used to calculate identification accuracy. Verification is a one-to-one comparison that determines whether the person is who he claims to be. To generate incorrect and correct distances, each palmprint image in the testing set is compared to all palmprint images in the training set. Because a training palmprint has some templates in the training set, a palmprint query in testing set is matched with its templates in the training set to produce correct distances. The minimum of these distances is taken as correct distance. Similarly, a query in testing set is compared all templates of the other palms in training set to produce incorrect distances. We take the minimum of these distances as the incorrect distances. If the matching distance between two images from the same palm is less than the threshold, the match is genuine acceptance. Similarly, if the matching distance between two images from different palms is less than the threshold, the match is a false acceptance. EER (Equal Error Rate) was calculated using the statistical pairs of False Reject Rate (FRR) and False Accept Rate (FAR). Tables 2 and 3 show the average rank-1 identification rates and EERs of our proposed method in comparison with the state of art methods with the PolyU database and the IITD (Figs. 4 and 5).

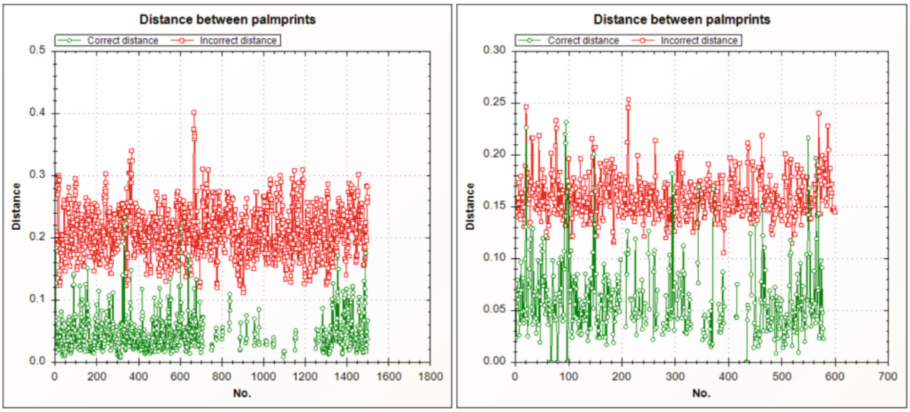
Table 1. Parameters of the PolyU and IITD Datasets.

Dataset	Each class			All class		Number of scores	
	Training set	Testing set	Training set	Training set	Testing set		
		Registration set	Unregistration set			Correct distance	Incorrect distance
IITD	3	3	3	$450(3 \times 150)$	$450(3 \times 150) + 150\ (3 \times 50) = 600$	450	600
PolyU	5	5	5	$1000(5 \times 200)$	$1000(5 \times 200) + 500(5 \times 100) = 1500$	1000	1500



(a) (b)

Fig. 4. Palmprint ROI samples from (a) PolyU, and (b) IITD databases.



(a) (b)

Fig. 5. Correct and incorrect distances of our proposed method on (a) PolyU, and (b) IITD datasets, respectively.

Table 2. Average performance with POLYU Dataset.

Matcher	EER (%)	Recognition rate (%)	Time of feature extraction (s)
HOL [12]	2.73	97.9	0.020
LLDP [13]	1.27	99.1	0.074
PalmNet [21]	3.87	91.2	1.610
LDDBP [4]	1.06	99.4	0.075
Our proposed method	0.87	99.8	0.350

Table 3. Average performance with IITD Dataset.

Matcher	EER (%)	Recognition rate (%)	Time of feature extraction (s)
HOL [12]	7.33	83.33	0.016
LLDP [13]	5.11	86.45	1.287
Palmnet [21]	7.78	77.56	1.710
LDDBP [4]	5.56	88.45	0.076
Our proposed method	4.45	91.22	0.431

4 Conclusion

Direction feature and the discriminability of multiple direction patterns are important in palmprint recognition. In this paper, the Learning Discriminant Line Direction Descriptor (LDLDD) is proposed for palmprint recognition that learns separately all three kind of directional pattern code. The dominant direction number (DDN) map is calculated first in this method. LDLDD will then create three MLDD maps with three multi-direction encoding methods based on the DDN map, where pixels with the same DDN values will use the same encoding strategy and belong to the same feature map. Finally, $(2D)^2$LDA is used to train new feature subspaces that project LLDP maps from a high-dimensional space to a discriminant space with lower dimensions. The promising effectiveness of the proposed method has been validated using Hong Kong Polytechnic University's (PolyU and IITD) public databases. In the future, we will expand the current approach to other biometric recognition applications.

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