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Local Derivative Pattern with Smart Thresholding: Local Composition Derivative Pattern for Palmprint Matching

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Abstract

Palmprint recognition is a new biometrics system based on physiological characteristics of the palmprint, which includes rich, stable, and unique features such as lines, points, and texture. Texture is one of the most important features extracted from low resolution images. In this paper, a new local descriptor, Local Composition Derivative Pattern (LCDP) is proposed to extract smartly stronger and more distinguishing texture features from palmprint images by composition of both radial and directional derivative information among local neighbors using a threshold function with an adaptive threshold value which result from local directional derivative information. The distribution of the LCDP is modeled by local spatial histogram and histogram intersection function is used to measure the similarity between spatial histograms of two different palm print images. Then, nearest neighbor classifier is used to classify them. Experiments on the Hong Kong Polytechnic University (PolyU) 2D_3D_palmprint database demonstrate the effectiveness of the LCDP in palmprint recognition versus well-known local pattern descriptors.

Keywords: Palmprint recognition, Texture, Local pattern, Adaptive threshold, Local composition derivative pattern (LCDP).

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1. Introduction

In the modern world, the social development is dependent on the development of personal recognition systems. Nowadays, personal identification and verification systems based on the biometric characteristics have attracted the attention of many researchers and have been developed significantly. A biometric system identifies individuals based on their physiological/behavioral characteristics which are generic, permanent, and unique over the life. Biometric systems are based on the physiological characteristics of people such as fingerprint, iris, retina, face, palm print, palm vein, and hand geometry or their behavioral aspects such as voice, signature, gesture, and keystroke [1].

Because of the competences such as high performance, user acceptability, low cost, low fake, and distinctiveness, palmprint has been studied broadly. There are useful features in a palmprint image such as principal lines, wrinkles, minutiae points, singular points, and texture that can be used for representation and recognition [2], [3]. Extracting different palmprint features need different image resolutions. For minutiae points and singular points, a high resolution image (at least 400 dpi) and for features such as principal lines, wrinkles, and texture, a low resolution palm print image with less than 150/100 dpi is required [4], [5]. In general, for justice and security applications, high resolution images and for civil and commercial applications, low resolution images are suitable [3].

A typical palm print recognition system consists of several units. The data acquisition unit collects palm print images. The preprocessing unit aligns palm print images and segments central part of the palm print image, Region of Interest (ROI), for feature extraction. The feature extraction unit extracts drastic features from ROIs. The matching unit compares two palmprint feature vectors, and the database unit stores registered template models [6], [27].

The existed feature extraction approaches in the palmprint recognition field can be divided into two categories: line-based and texture-based approaches. The line-based approaches extract palm lines and compare palm prints using the lines' type, thickness, location, and orientation of them. Up to now, many researches have been done to develop the line-based approaches to increase recognition accuracy [7], [8], [24], [26]. Texture-based approaches such as the Principal Component Analysis (PCA) [10], the Independent Component Analysis (ICA) [11], the wavelet transformation [12], [13], the Gabor wavelets [14], [15],[9], and the Local Binary Pattern (LBP) [16], [17], have been used already more often in biometric systems.

However, in recent years, strong algorithms to extract texture features using powerful local descriptors such as the Local Directional Pattern (LDP) [19], [22], and the Local Derivative Pattern (LDeriveP) [20] have been proposed in face recognition systems that they are invariant to illumination and pose variations, and are successful to extract detailed information.

Unlike other texture-based approaches, performance of these methods in palmprint recognition systems, have not been studied truly. As a result, in this paper, we done it and propose a new local descriptor, Local Composition Derivative Pattern (LCDP), for palmprint recognition to encode the composition of the radial first-order derivatives and the first-order local directional derivative variations by threshold function with an adaptive threshold value which contains more detailed discriminative features than the other famous local pattern descriptors had suggested.

The histogram intersection is used to measure the similarity of two different palm print images. Comparative experiments are conducted on the Hong Kong Polytechnic University (PolyU) 2D_3D_palmprint database [21] to evaluate the proposed method. The experimental results demonstrate that the LCDP is more powerful than other local texture descriptors.

The rest of this paper is as follows: Section 2 introduces the proposed method elaborately. Section 3 describes the comparative experiments. Section 4 concludes the paper.

2. Proposed Method

In this section, we describe the local binary pattern (LBP), local directional pattern (LDP) and local derivative pattern (LDeriveP) briefly and then introduce proposed method.

A) Local Pattern Descriptors

The original LBP operator is one of the most famous methods to extract texture features from images in face and palm print recognition. In the LBP, the difference between the central pixel Z_0 and eight neighboring pixels are encoded as the binary by a threshold function (Fig.1).

Z_1	Z_2	Z_3
Z_8	Z_0	Z_4
Z_7	Z_6	Z_5

Fig. 1. An 8-neighborhood around the central point Z_0.

The Local Directional Pattern (LDP) uses edge response values in different directions rather than pixels' intensity to extract texture feature from an image. The LDP feature is an 8-bit binary code which is computed by using Kirsch masks for pixels in eight orientations [19].

The high-order Local Derivative Pattern ($LDeriveP^n$) is the most powerful local pattern presented in a general form which many new local descriptors have been derived from it. The LDeriveP encodes the high-order derivative information within local neighborhoods along 0˚, 45˚, 90˚, and 135˚ directions to extract more distinctive features [20].

B) Local Composition Derivative Pattern

The Local Composition Derivative Pattern (LCDP) combines the radial and the directional first order derivatives information. Given an image $I(Z)$, Z_0 be a point in $I(Z)$, and Z_i, $i = 1,2,\dots,8$ be the neighboring points around Z_0, the Sum of first-order derivatives along the radial direction SFD_r at Z_0 is defined as

$$SFD_r = \sum_{i=1}^{8} (I(Z_0) - I(Z_i)) \tag{1}$$

In palmprint images, principal lines and most wrinkles have been distributed on the entire surface of the palms and they play an effective and significant role to extract texture features from the palmprint images. According to the conducted experiments in this research, we use local changes of the first-order directional derivatives along 0˚ direction which contain more detailed and discriminative information. The first-order derivative along 0˚ direction at Z_0, $I'(Z_0)$ is defined as

$$I'(Z_0) = I(Z_0) - I(Z_4) \tag{2}$$

The derivative information within local neighborhoods along radial and 0˚ direction at $Z = Z_0$ are shown in Fig.2 by green and blue arrows, respectively. Generally, the Local Composition Derivative Pattern (LCDP) at $Z = Z_0$ is defined as

$$\begin{aligned} LCDP(Z_0) = \\ \{f_T(Sign(SFD_r), I'(Z_1)), \\ f_T(Sign(SFD_r), I'(Z_2)), \dots \\ \dots, f_T(Sign(SFD_r), I'(Z_8)) \end{aligned} \tag{3}$$

where the threshold function $f_T(.,.)$ is defined as

$$f_T(Sign(SFD_r), I'(Z_i)) = \begin{cases} 0 & Sign(SFD_r)\cdot I'(Z_i) > T \\ 1 & Sign(SFD_r)\cdot I'(Z_i) \le T \end{cases} \quad i = 1,2,\dots,8 \tag{4}$$

where T is an adaptive threshold value defined as

$$T = \frac{\sum_{i=1}^{8} I'(Z_i)}{8} \tag{5}$$

The threshold value of the function $f_T(.,.)$ is related to the extracted information of the local neighborhood. T is equal to average of the first-order gradient changes along 0° direction at $Z = Z_0$ within local neighborhood. As a result, for each LCDP micro pattern, a unique threshold value is obtained that compared with uniform and fixed threshold value for all the micro patterns, $f_T(.,.)$ can extract more distinguishing features that reduce the differences intra classes and increase the differences between classes.

Fig.3 illustrates the computation of the LCDP micro-pattern. To get the LCDP, we compute the product's sign of the Sum of first-order derivatives along the radial direction SFD_r and the directional derivatives along 0° direction. Then, we apply the threshold function $f_T(.,.)$ with the threshold value is set to the average of the first-order derivatives along 0° direction. In fact, as will be shown in the results, the proposed algorithm intelligently uses the radial and the directional information to extract the best features. Fig.4 visualizes examples of the LBP, the LDP, the second-order LDeriveP ($\mathrm{LDeriveP}^2$), and the LCDP representations for a palmprint image.

The spatial histogram of the LCDP micro pattern contains important distinguishing information of the local features in an image. The distribution of the LCDP is modeled by the local spatial histogram, because the holistic histogram of the entire image is causing the loss of the structural information. We divide the LCDP image into L non-overlapping square zones and then the spatial histogram for each zone is computed, separately.

The spatial histograms of the zones are concatenated as

$$HLCDP = \{HLCDP(R_i) | i = 1,2,\dots,L\} \tag{6}$$

where $HLCDP(R_i)$ is the histogram feature extracted from the local zone R_i.

Histogram intersection technique is used to measure the similarity between two spatial histograms of the LCDPs as

$$S_{HI}(HLCDP^1, HLCDP^2) = \sum_{j=1}^{B} \min(HLCDP_j^1, HLCDP_j^2) \tag{7}$$

where $HLCDP^1$ and $HLCDP^2$ are the histograms of the query and the model palmprints and B is the number of histogram bins in both histograms.

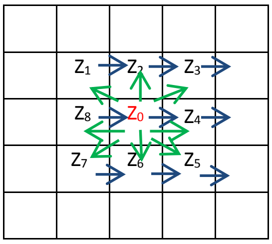

Fig. 2. The first-order derivatives along the radial direction and along 0° direction at $Z = Z_0$.

6	0	3	1	4
2	9	7	3	2
0	6	**3**	5	1
4	1	9	8	7
7	8	5	3	1

(a)

2	4	1
3	**-2**	4
-8	1	1

(b)

$SFD_r = -28$

$T = 1$

1	1	1
1		1
0	1	1

$(11111101)_2$

(c)

Fig. 3. Computing the LCDP micro-pattern at $Z_0 = 3$. (a) 3 × 3 neighborhood in the original image. (b) The first-order derivatives along 0° direction. (c) LCDP code.

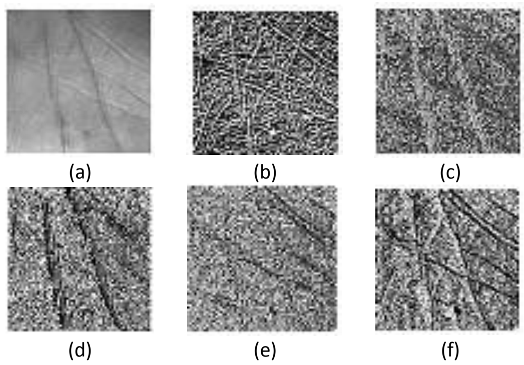

Fig. 4. The LBP, the LDP, the LDeriveP2, and the LCDP representations. (a) Original palmprint image, (b) the LBP, (c) the LDP, (d) the LDeriveP2 ($\alpha = 0^\circ$), (e) the LCDP (T = 0), (f) the LCDP.

3. Results

The comparative experiments between the LCDP, the LBP, the LDP, and the second-order

LDeriveP (LDeriveP^2) are conducted on the Hong Kong Polytechnic University (PolyU) 2D_3D_palmprint database [21]. This database includes two sets: 2D and 3D palm print images. Each set contains 8,000 palm print images from 200 volunteers, including 136 males and 64 females. The original size of an image is 128 × 128 pixels. There are two separated sessions and the average time interval between the two sessions is one month. In each session, there are 20 samples (10 samples of right palm and 10 samples of left palm) for each subject. We use the 2D palm print images of the database in our experiments.

A) Verification Scenario

In the verification scenario, each query palm print image in the database is compared with all palm print models. If the dissimilarity between the query and the model is below a certain threshold, the matching is correct/genuine and if not, the matching is incorrect/imposter. There are 8,000 × 7,999 ÷ 2 = 31,996,000 matches, while the number of genuine matching is 400 × 20× 19 ÷ 2 = 76,000.

Table.1 lists the Equal Error Rates (EER) of the proposed method and the benchmarks. Among the LBP, the LDP, the LDeriveP^2, the LCDP (T = 0), and the LCDP, the LCDP performs the best (EER=1.08%) followed by the LCDP (T = 0) (1.43%), the LDeriveP^2 (1.6%), the LBP (2.1%), and the LDP (3.3%). The results show that the LCDP contains more discriminative features and reduces the EER, significantly. However, in comparison with latter orientation and line based approaches [25], results indicate that these local pattern descriptors are much less verification accurate.

Table.1.
The Equal Error Rate (EER) of the LCDP and the benchmarks on the PolyU 2D_3D_palmprint database [21].

Method	EER (%)
LBP	2.1
LDP	3.3
LDeriveP^2	1.6
LCDP(T=0)	1.43
LCDP	1.08

B) Identification Scenario

In the identification scenario, the users' identities are recognized by comparing their images with the gallery images in the database without any prior knowledge. One sample per palm of subject is selected as the gallery and the other samples are used as the probes. Therefore, there are 7,600 probes and 400 galleries. To compute the rank-1 recognition rate of the proposed method, the probes are matched with all the galleries using the histogram intersection.

Table.2 illustrates the comparative rank-1 recognition rates of the proposed method and the benchmarks on the PolyU 2D_3D_database [21]. In this experiment, we use sub-regions with the size of 8 × 8 pixels and 32-bin histograms in each sub-region. This experiment properly reveals that the highest rank-1 recognition belongs to the LCDP.

Table.2.
The rank-1 Recognition Rate (%) of the LCDP and the benchmarks on the PolyU 2D_3D_palmprint database [21].

Method	Recognition Rate (%)
LBP	97.29
LDP	95.98
LDeriveP^2	97.66
*Derivative Variation Pattern (DVP) [23]	98.32
LCDP(T=0)	98.12
LCDP	98.83

*The result is from [23].

We also change the algorithm's parameters such as the square zone size and the number of the histogram bins. The results using three different square zone sizes (4 × 4, 8 × 8, and 16 × 16) and the same 32 histogram bins in each square zone are shown in Fig.5. The figure shows that both increasing and reducing of the square zone size will reduce the recognition accuracy except for the LBP in which increasing the square zone size will increase the recognition accuracy.

The recognition rates with three different histogram bins (16, 32, and 64) and the same 8 × 8 square zone size are shown in Fig.6. As can be seen, the recognition accuracy is increased from 16 bins to 64 bins. The results again prove that the proposed method is more powerful than the other local descriptors.

The LCDP captures the changes of the directional derivatives within local neighborhoods along 0˚ direction to extract more detailed discriminative derivative features. In this experiment, we generalize the directional derivatives information along 0˚ direction to other directions (45˚, 90˚, and 135˚) and compute the rank-1 recognition rate of the Generalized Local Composition Derivative Pattern (GLCDP) along 0˚, 45˚, 90˚, and 135˚ directions, separately.

Fig.7 illustrates the comparative rank-1 recognition rates of the GLCDP (T=0) and the GLCDP. The square zone with 32 histogram bins and the size of 8 × 8 pixels in each sub-region are used. This experiment demonstrates that the discriminated feature extraction of the first-order derivatives information along 0˚ direction is the best compared to other directions.

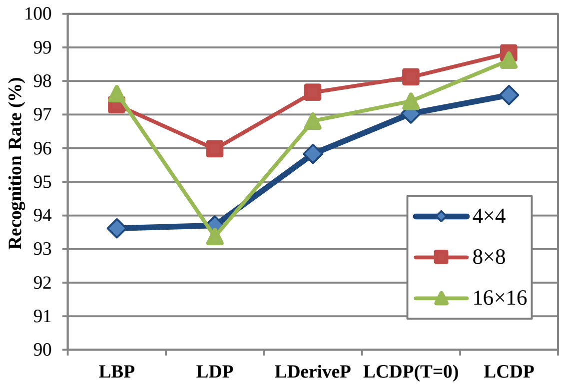

Fig. 5. Rank-1 recognition rates of the proposed method and the benchmarks with different square zone sizes.

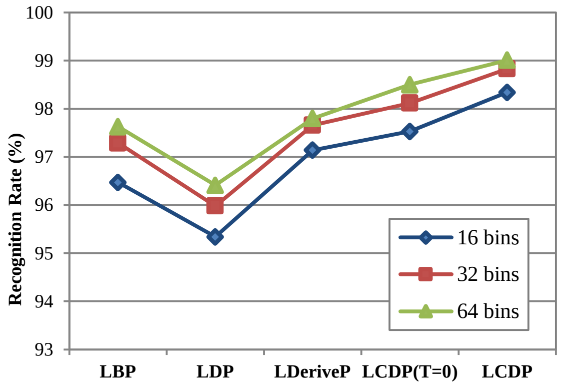

Fig. 6. Rank-1 recognition rates of the proposed method and the benchmarks with different histogram bins.

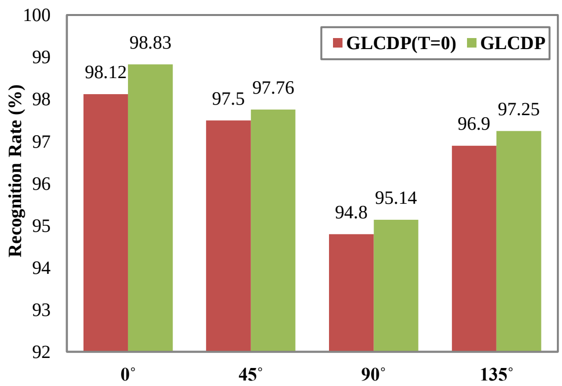

Fig. 7. Rank-1 recognition rates of the GLCDP and the GLCDP (T = 0) along 0˚, 45˚, 90˚, and 135˚ directions.

4. Conclusion

This paper presented a novel local descriptor for palmprint recognition which extracted the effective texture features from gray level images. The Local Composition Derivative Pattern (LCDP) combines the first-order gradient changing information over a local neighborhood in a specific direction and the first-order gradient changing information along the radial direction at the central point of a neighborhood by using a threshold function with a threshold value is set to the average of the same first-order derivative information over local neighborhood along the specific direction.

The comparative experiments on the Hong Kong Polytechnic University 2D_3D_palmprint database demonstrate that the LCDP by using special modeled threshold function extracts the important information and smartly combines them. Also the use of adaptive threshold value for each neighborhood is significant role in increasing the recognition accuracy of the proposed algorithm and compared to other local pattern descriptors is more powerful.

Research on high order version and improved accuracy of LCDP are interesting future aims. Due to the eligible performance and the capability of the LCDP, we expect that it can be applied to other biometric recognition systems.

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