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PALMPRINT RECOGNITION BASED ON CURVELET AND LOCAL DIRECTIONAL PATTERN

Feifei Liu[1], Lijian Zhou[1], Zheming Lu[2,*] and Kun Zhao[1]

[1]School of Communication and Electronic Engineering
Qingdao University of Technology
No. 11, Fushun Road, Qingdao 266033, P. R. China
{ liufeifei; zhoulijian }@qtech.edu.cn

[2]School of Aeronautics and Astronautics
Zhejiang University
No. 38, Zheda Road, Hangzhou 310027, P. R. China
*Corresponding author: zheminglu@zju.edu.cn

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Abstract. *The principle lines and wrinkles of a palmprint image can be extracted as the features to perform biometric identification in civil and commercial fields usually. Because the principles and wrinkles are almost curves and the curvelet transform has a better performance in representing singularities of the edge along curves, the curvelet transform is chosen to extract the elementary features of a palmprint image. Moreover, it can be seen that the lowest frequency band curvelet information of a palmprint image can present its main information better than the other frequency bands information by analyzing the curvelet features in every frequency band. In addition, the Local Directional Pattern (LDP) can describe the local textures stably and efficiently, so the final features of a palmprint can be further computed using the LDP method for representing its texture changes more effectively. Thus, a palmprint recognition method is proposed, which combines the properties of curvelet transform with the LDP method. First, the lowest frequency band curvelet coefficients of the palmprint image are extracted by the Fast Discrete Curvelet Transform (FDCT) via Wrapping. Then, the LDP computation is performed to extract the final palmprint features further. At last, the Nearest Neighborhood (NN) Classifier is used to recognize the palmprint. The experiments performed on the PolyU 2D Palmprint Database show that the proposed approach is more efficient in the palmprint feature extraction and has a higher recognition accuracy and robustness than the methods using curvelet, curvelet + PCA, LBP or LDP.*
Keywords: Palmprint recognition, Curvelet transform, Local directional pattern

1. **Introduction.** Palmprint has been shown a promising biometric feature because of its stability, uniqueness, acceptability and abundant biometric information; especially the main information of a palmprint image can be contained even if the image resolution is low. Therefore, a number of previous works mainly focus on extracting and recognizing palmprint from low resolution images in the past decade [1,2].

As we all know, palm lines and texture are the main features for identifying the low resolution palmprint image. Considering that there are abundant singular smooth line feature in the palmprint image, the method based on transform domain analysis can highlight the main feature of palmprint images, such as wavelet, ridgelet or curvelet transforms. Kong et al. [3] used the 2-D Gabor wavelet filter to extract the palmprint feature for authentication. Wu et al. [4] proposed using the ridgelet transform to obtain the multiple-scale feature of the palmprint image, and classified the palmprint by a hierarchical matching approach. Compared with the wavelet transform, curvelet, as a more sparse representation algorithm, is a more effective method to represent the curvilinear structure of an image at different scales and angles. Therefore, Dong et al. [5] firstly introduced the 1st generation curvelet transform to extract palmprint features. Xu et al. [6] used the 2nd discrete curvelet transform to obtain the lowest frequency coefficients as the palmprint feature. Liu et al. [7] introduced that the second frequency band curvelet coefficients of the palmprint image could better represent the veins of the palm by analyzing the curvelet coefficients of each frequency band. Moreover, the local texture feature of the palmprint image also helps the recognition of the palm, which is often extracted by some local texture descriptors. Local Binary Pattern (LBP) is one of the effective local texture descriptors in texture representation, for it has insensitivity to monotonic grayscale and illumination changes, good capability to discriminative and simplicity in operation [8,9]. Based on LBP, Local Directional Pattern (LDP) [10] is proposed by Jabid et al., which overcame the LBP weakness in non-monotonic illumination and random noise. And the LDP method was proved to be more efficient than the LBP method in representing the curve, edge and texture of face images [11,12]. By analyzing the characteristics of the palmprint image, we propose a method of palmprint recognition combined the properties of curvelet transform with the LDP method. We firstly decompose the palmprint image by Fast Discrete Curvelet Transform (FDCT) via Wrapping, select the lowest frequency coefficients as the elementary palmprint feature, and then extract the palm feature further by LDP. At last, the Nearest Neighbor (NN) algorithm is used to classify the palmprint. This paper is organized as follows. The key technologies are introduced in Sections 2 and 3. Section 4 presents the implementation of the proposed method. The experiments and performance analysis are performed in Section 5. Section 6 gives the conclusion of this paper.

2. **Palmprint Feature Extraction Based on Curvelet.** Candès and Donoho proposed the curvelet transform based on ridgelet [13], which was a new sparse representation method of curves. Because of the complexity of the algorithm, Candès et al. [14] presented the 2nd generation curvelet transform and its fast algorithm. Two Fast Discrete Curvelet Transform (FDCT) algorithms [14] were implemented via USFFT and Wrapping. FDCT via Wrapping is chosen in this paper for its high efficiency. Let us take an original $n \times n$ image $\mathbf{F}$ as an example. First, apply 2D FFT to the original image $\mathbf{F}$ and obtain its 2D discrete Fourier samples $\mathbf{F}_1$, where their rectangular coordinates n_1 and n_2 meet $-n/2 \leq n_1, n_2 \leq n/2$. Second, calculate the product $\tilde{\mathbf{U}}_{j,l} \cdot \mathbf{F}$ for each scale j and angle l, where $\tilde{\mathbf{U}}_{j,l}$ is the discrete area with the size of $L_{1,j} \times L_{2,j}$ corresponding to the window with the scale j. Third, wrap this product around the origin and obtain $\tilde{\mathbf{F}}_{lj} = W\left(\tilde{\mathbf{U}}_{j,l}\right) \cdot \mathbf{F}_1$, where $W\left(\tilde{\mathbf{U}}_{j,l}[n_1 \bmod L_{1,j}, n_2 \bmod L_{2,j}]\right) = \tilde{\mathbf{U}}_{j,l}[n_1, n_2]$, and their rectangular coordinates n_1 and n_2 meet $0 \leq n_1 \leq L_{1,j}$, $0 \leq n_2 \leq L_{2,j}$ separately. At last, apply the inverse 2D FFT to each $\tilde{\mathbf{F}}_{lj}$ and obtain the discrete curvelet coefficients.

Taking a gray-level palmprint image (Figure 1(a)) from the PolyU 2D Palmprint Database [15] as an example, the curvelet transform results are shown in Figures 1(b)-1(d). The original palmprint image (size of 128×128) is decomposed into 4 layers sub-band by FDCT via wrapping. Figure 1(b) shows the lowest frequency band coefficients. Figures 1(c) and 1(d) show the middle and the highest frequency sub-band coefficients. From Figure 1, we can see that the lowest frequency band coefficients contain the most information of the original palmprint image, and other sub-band coefficients contain relatively less curve textures and false information caused by environmental noises.

3. **LDP Feature Extraction.** Like the encoding method of LBP, LDP also uses a matching window to get 8 pixel values around the current pixel firstly. Then 8 edge response values are calculated with a mask in 8 directions, which will be large in a corner or edge. Next, a series of binary results is obtained by comparing these edge response

(a) Original palmprint image (128 × 128) (b) Lowest band image (21 × 21) (c) Middle band image (4400 pixels) (d) Finest band image (128 × 128)

FIGURE 1. Original palmprint image and its curvelet decomposed images

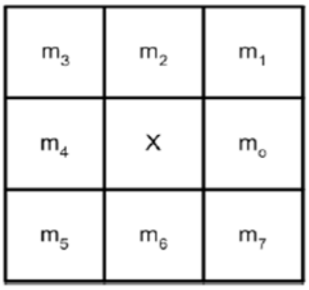

FIGURE 2. 8 directional edge response values

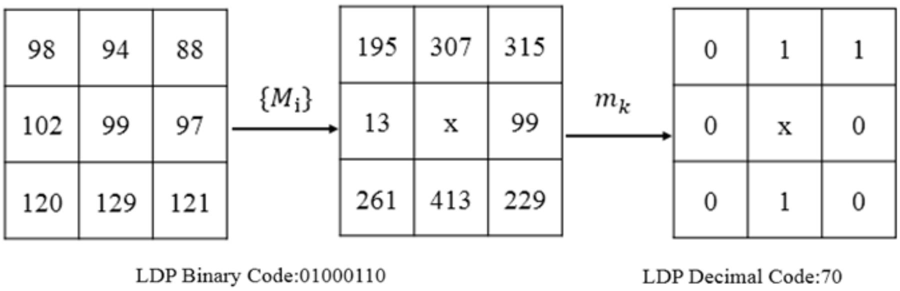

FIGURE 3. LDP code with $k = 3$

values with the given threshold. At last, the binary results are put together to compose an 8 bit binary code in a certain sequence, namely the LDP code of the current pixel.

The Krisch edge masks are often chosen to compute the edge response values [10]. Take a point X in an image as an example, as shown in Figures 2 and 3; $\{m_i\}$, $i = 0, 1, \cdots, 7$ is the 8 edge response values in 8 directions. To facilitate the encoding of LDP, the top k values are often set to 1 and other response values to 0. Finally, the 8 bit binary LDP code can be generated by Equation (1), where m_0 is the low-order bit.

$$\mathrm{LDP}_k = \sum_{i=0}^{7} b_i(m_i - m_k) \cdot 2^i, \quad b_i(a) = \begin{cases} 1 & a \geq 0 \\ 0 & a < 0 \end{cases} \tag{1}$$

From the LDP coding process, it can be observed that the LDP descriptor is unaffected by the variations of the image grey level, and it is also robust to the random noise. On the other hand, the LDP descriptor can well reflect the local image textures and their location and space relationship, such as edges, corners, curves and junctions [10]. Therefore, we use the LDP algorithm to obtain the palmprint feature further based on the lowest frequency band curvelet coefficients of the palmprint image. The LDP texture features of the lowest frequency band curvelet coefficients in Figure 1(b) are computed

Figure 4. The LDP pattern of the lowest frequency band coefficients in Figure 1(b)

using the LDP method. The result is shown in Figure 4. It can be seen that the edges, corners, curves and junctions can be presented well.

4. **The Proposed Method.** As is analyzed above in Sections 2 and 3, a palmprint recognition method combining curvelet and LDP is proposed. Figure 5 shows the whole process of palmprint recognition. First, the palmprint image, which should have been pre-processed to a Region of Interest (ROI) image, is decomposed by the curvelet transform and the lowest frequency band coefficients are obtained as the elementary feature. And then, the LDP method is used to obtain the final palmprint feature for reducing unnecessary information and noise. Finally, the testing palmprint image is recognized by the Nearest Neighbor (NN) classifier. The detail algorithm is given below.

Step 1: Extract the lowest sub-band curvelet feature of the image. All palmprint images, including the training images and the testing images are decomposed by FDCT via Wrapping. Generally, the default number of the decomposed layers of the curvelet transform is $\lceil \log_2(\min(M, N) - 3\rceil$, where M, N are the number of rows and columns of the image, and $\lceil\ \rceil$ represents rounding towards plus infinity.

Step 2: Take the LDP computation to the elementary feature image. Reshape the LDP pattern of each image to form a row vector which will be used as the final feature.

Step 3: Classify the testing palmprint by the NN method.

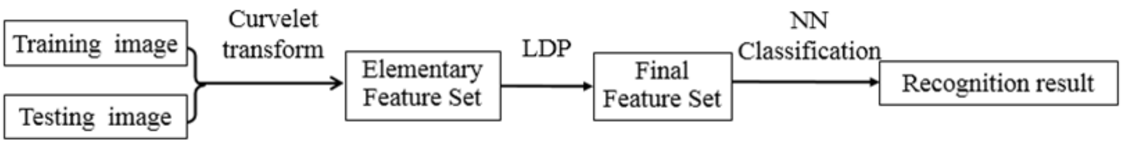

Figure 5. The framework of the proposed method

5. **Experimental Results and Analysis.** We use the PolyU 2D Palmprint Database [15] to implement the proposed method in the experiment, in which there are 400 different palms with 20 images per palm. These 20 samples per palm were collected in two separated sessions, in which 10 samples were captured in each session. And we choose 10 samples per palm from one of the two sessions as the experiment database. Thus, 4000 samples are selected. The palmprint images in this database have already been pre-processed into ROI images (size of 128×128). In experiments, 1 to 9 samples selected randomly are assigned to the training set, and the rest are taken as the testing set. In order to evaluate the experimental results well, we conduct the recognition experiments 10 runs on the same set and take the average recognition accuracy and the standard deviation as the evaluation criteria.

5.1. **Elementary curvelet feature selection.** First, we decompose the image into 4 layers by curvelet transform, and respectively select the lowest frequency band coefficients and 2 middle frequency coefficients as the elementary feature. Then, we compute the LDP features of this two elementary feature sets as the palmprint feature. The recognition results are shown in Table 1, in which N represents the number of the training samples of each palm. From Table 1, we can see that the results of these two experiments are close. However, the computation cost differs greatly. The dimensions of feature vector of each palmprint image are 441 and 28864, respectively. Therefore, we choose the lowest frequency band curvelet coefficients as the elementary feature.

Table 1. Recognition results with different frequency band features (%)

N	Lowest frequency band coefficients + LDP		2 Middle frequency sub-band coefficients + LDP	
	AR	SD	AR	SD
1	96.93	0.42	97.26	0.32
2	98.98	0.21	99.15	0.15
3	99.59	0.08	99.61	0.09
4	99.68	0.07	99.77	0.09
5	99.79	0.07	99.82	0.09
6	99.86	0.06	99.86	0.08
7	99.95	0.07	99.85	0.07
8	99.90	0.01	99.91	0.08
9	100	0	99.95	0.11

5.2. **Method comparison.** The palmprint recognition experiments are performed using curvelet + LDP (the proposed), curvelet, curvelet + PCA, LBP and LDP method respectively, in which we select the lowest frequency band coefficients as the curvelet feature. 10 experiments are also done on the same set as above. The results are illustrated in Table 2, in which it is evident that the average recognition rate using the proposed method is obviously higher than other related methods, especially in the condition with small sample space. Meanwhile, the proposed method is more robust and stable because its standard deviations are less than those of the other methods.

Table 2. Recognition results with different palmprint recognition methods

N	Curvelet + LDP		Curvelet		Curvelet + PCA		LBP		LDP	
	AR	SD	AR	SD	AR	SD	AR	SD	AR	SD
1	**96.93**	**0.42**	76.19	0.52	76.12	0.79	59.34	1.01	59.26	1.05
2	**98.98**	**0.21**	87.95	0.59	87.36	0.67	69.43	0.92	75.98	0.56
3	**99.59**	**0.08**	92.20	0.56	92.27	0.54	73.85	0.86	83.77	0.55
4	**99.68**	**0.07**	94.32	0.47	94.56	0.49	77.81	0.59	87.73	0.58
5	**99.79**	**0.07**	95.90	0.37	95.50	0.46	79.26	0.80	90.68	0.58
6	**99.86**	**0.06**	96.51	0.45	96.48	0.47	80.58	0.97	92.43	0.68
7	**99.95**	**0.07**	96.87	0.37	97.07	0.41	82.09	0.87	93.84	0.53
8	**99.90**	**0.01**	97.67	0.32	97.56	0.83	83.10	1.15	94.43	0.53
9	**100**	**0**	97.75	0.55	98.03	0.69	84.35	1.31	94.80	1.44

6. Conclusions. This paper proposes a novel palmprint recognition approach combining the advantages of the curvelet transform and LDP. The lowest frequency band curvelet coefficients of the palmprint image as the elementary feature are selected first. And then, its LDP feature is computed as the final feature. At last, the NN classifier is used to recognize the palmprint image. The experiment results on the PolyU 2D Palmprint Database show that our approach is more efficient, robust and stable in palmprint recognition than other related methods using curvelet transform, curvelet + PCA, LBP or LDP respectively. In the future, we will study the recognition of palmprint images with more complex conditions.

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