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Palmprint Feature Extraction Based on Curvelet Transform

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Abstract. *An approach of palmprint feature extraction based on the second frequency band curvelet coefficients is proposed in this paper. As we all know, the veins of the palmprint are the important factors to recognize the palmprint. Because curvelet transform can effectively presents the lines and curvilinear structure, we perform the curvelet transform to the palmprint image. By analyzing the features, amplitude spectrum and energy statistics of the curvelet coefficients for each frequency band, we can see that the curvelet coefficients in the second frequency band can represent the veins of the palm better, so we choose them as the palmprint features. Firstly, the palmprint image is transformed by the fast discrete curvelet transform via wrapping to extract the second frequency band coefficients as the palmprint features. Then, the PCA method is used to reduce the dimension of the extracted features and get a more representative palmprint features. Finally, we use the nearest neighbor method to classify the palmprint. The results of the experiments performed in PolyU 2D palmprint database show that our approach has the high effectiveness and robustness in palmprint recognition.*
Keywords: palmprint recognition, feature extraction, curvelet transform, the second frequency band.

1. **Introduction.** Biometrics recognition is a science of recognizing individuals based on the specific physiological and behavioral characteristics. The palmprint recognition has become one hotspot in the field of identity recognition because it has rich texture information, stable characteristics, low-resolution image, low-cost collection, easy acceptability and high accuracy recognition rate.

The inner surface of the hand between the wrist and the fingers is often used as the palmprint to extract biometric feature, such as principal lines, wrinkles, geometry feature, delta points, datum points feature and texture (Fig. 1) [1]. All the above features can be extracted at least 400 dpi (dots per inch)in the high-resolution images, while some main features like principal lines and wrinkles can be obtained with less than 100 dpi from a low-resolution palmprint image. In civil and commercial fields, the recognition accuracy of a low resolution palmprint can meet the application needs sufficiently. Therefore, the palmprint feature extraction approach discussed in this paper is based on the low resolution images.

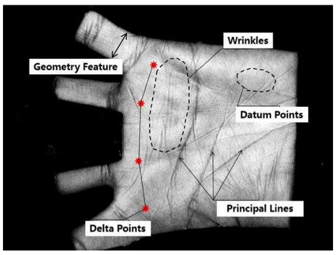

Figure 1. Features in a Palmprint

The main steps of palmprint verification are described below:

Step 1: Preprocessing. Align the palmprint images and select the ROI (Region of Interest).

Step 2: Feature extraction. Obtain discrimination feature information.

Step 3: Classification. Use the extracted features to classify palmprint.

Feature extraction is a key step of the palmprint recognition. Researches on feature extraction and matching methods can be classified into 4 categories [3]: (1) Structural-based approaches. These approaches mainly use the position and direction of palm-lines as the features, which are researched early. Shu et al. [4, 5] presented two approaches to recognize palmprint based on line feature matching and datum point invariance. The palm-lines were firstly traced and linked. Then each palm-line was presented approximately by several straight-lines and the palm was recognized by matching these straight-line segments. (2) Subspace-based approaches. These approaches usually reduce the dimension of features by projecting and transforming to get the more representative palmprint features. Principal Component Analysis (PCA), two-dimensional Principal Component Analysis (2DPCA) and Linear Discriminant Analysis (LDA) etc. are commonly used. Lu et al. [6] used PCA to transform the original palmprint images into a small set of feature space, called EigenPalm, which were the eigenvectors of the training set and could represent the principle components of the palmprint quite well. Wu et al. [7, 8] proposed a two stage PCA+LDA method, which was known as Fisherpalm. Yang et al. [9] introduced the concept of 2DPCA for face recognition, and showed that it provides better results than PCA. Lu et al. [10] used wavlet+2DPCA method to recognize the palmprint. (3) Statistical-based approaches. They transform images into another domain and then divide the transformed images into small regions [11-13]. Statistics such as mean and variance of each small region are calculated as the palmprint features. (4) Coding-based approaches. They encodes the palmprints transform domain coefficients as features [14, 15], where Gabor filters, wavelets and Fourier transforms are commonly applied to extract the information of palmprint.

Although wavelet transform has obvious advantages in dealing with point singularities, it fails to efficiently represent objects with highly anisotropic elements, such as lines and curvilinear structure. Motivated by the need of representation the lines, curves and edges, Candes and Donoho developed curvelet multi-resolution analysis in 2000[16, 17]. Curvelet transform is not only a multi-scale transform, but also directionally sensitive and highly anisotropic, which are more efficiently than those traditional transforms in representing singularities and edges along curves. Curvelet transform have had an important success in a wide range of image processing and pattern recognition [18-22]. Because the palmprint image involves lots of curves, Dong et al. [20] firstly presented a palmprint recognition method using digital curvelet transform for palmprint recognition. And the recognition rate of the experiment carried on in the PolyU database was up to 95.25%, which is approximate to the method of wavelet transform. Amayeh et al. [21] proposed a fingerprint enhancement method in fast discrete curvelet domain, which showed the promising performance comparing with Gabor-based and Wavelet-based methods. A simple application of curvelet transform in palmprint recognition can be found in [22]. The authors used Support Vector Machine (SVM) classifier directly on the curvelet decomposed palmprint. The recognition rate up to 98.5%, which indicated that this method had better performance than wavelet-based method and other classical method.

The above methods used all frequency band curvelet features except the highest frequency band information without considering the characters of each frequency band. Motivated by this, the curvelet coefficients of the palmprint image in each frequency band are analyzed from themselves, their amplitude spectrum and energy statistical characters. We find the curvelet coefficients in the second frequency band can represent the palmprint more efficiently. So we first choose them as the elementary feature to recognize the palmprint in this paper. Next, the PCA method is used to reduce the dimension of the features. At last, we use the nearest neighbor method to recognize the palmprint. The results of the experiments performed in PolyU 2D palmprint database show that our approach has better performance not only in the recognition accuracy, but also in the speed and efficiency, especially for the small training sample number situations.

In the second part of this paper, the theory of curvelet transform will be discussed in brief. In part 3, the palmprint image is decomposed into the curvelet components via the wrapping method to extract different layer coefficient sets, and their features, amplitude spectrum and energy statistics are analyzed in detail. Then, Part 4 illustrates the procedures of our approach. In Part 5, the experiments results are presented. Based on the analysis above, the conclusions are given in last part.

2. **Curvelet Transform.** The first generation curvelet transform is a ridgelet transform in nature [23, 24]. It decomposes the image into different blocks at fine scales, where the curved edges are subdividing into some approximate straight lines, and then analyze each block by a local ridgelet transform. However, it is complex in realization and has bigger data redundancy in transform. For solving this, the initial construction of curvelet was redesigned later and was reintroduced as Fast Digital Curvelet Transform (FDCT) [16, 17], namely, the second generation curvelet transform, which can be calculated faster and less redundancy.

2.1. **Continuous Curvelet Transform.** Like other sparse multidimensional analysis, continuous curvelet transform is one of sparse theories, and can be represented by the inner product of basis function and input signal.

$$c\,(j,l,k) = \langle f, \varphi_{j,l,k} \rangle \tag{1}$$

where $\varphi_{j,l,k}$ is curvelet, j, l, k is scale, direction and orientation parameters.

A continuous two dimensional (2D) curvelet transform can be represented by a pair of radial and angular windows $W\,(r)$ and $V\,(t)$ as 'corner window', where $r \in (1/2, 2)$,

$t \in [-1,1]$. These windows will always obey the following admissibility conditions:.

$$\sum_{j=-\infty}^{\infty} W^2\left(2^j r\right) = 1, r \in (3/4, 3/2) \tag{2}$$

$$\sum_{l=-\infty}^{\infty} V^2\left(t-1\right) = 1, r \in (-1/2, 1/2) \tag{3}$$

For all scales $j \geq j_0$, define its Fourier frequency domain window.

$$U_j\left(r,\theta\right) = 2^{-3j/4} W\left(2^{-j} r\right) V\left(\frac{2^{\lfloor j/2 \rfloor}\theta}{2\pi}\right) \tag{4}$$

where $\lfloor j/2 \rfloor$ denotes the integer part of $j/2$. U_j is a wedge window determined by the radius window $W\left(r\right)$ and corner window $V\left(t\right)$, which are the support space of continuous curvelet transform.

The waveform $\varphi_j\left(x\right)$ is defined by its fast Fourier transform $\hat{\phi}_j\left(\omega\right) = U_j\left(\omega\right)$. Thus, all the curvelets can be obtained by translation and rotation of the mother curvelet $\varphi_j\left(x\right)$ at the scale 2^{-j}, orientation θ_l, and position $x_k^{(j,l)} = R_{\theta_l}^{-1}\left(k_1 \cdot 2^{-j}, k_2 \cdot 2^{-j/2}\right)$. The curvelet coefficients can be represented as

$$\varphi_{j.l.k}\left(x\right) = \varphi_j\left(R_{\theta_l}\left(x - x_k^{(j,l)}\right)\right) \tag{5}$$

where R_{θ_l} is the rotation by θ_l .θ_l is the equal-spaced sequence of rotation angles $\theta_l = 2\pi \cdot 2^{-\lfloor j/2 \rfloor} \cdot l, l = 0, 1, \cdot\cdot\cdot, 0 \leq \theta_1 \leq 2\pi$. $k = (k_1, k_2) \in Z^2$ is the sequence of translation parameters. The expression of continuous curvelet transform is

$$c\left(j,l,k\right) = \frac{1}{2\pi^2}\int F\left(\omega\right)\overline{\varphi_{j,l,k}\left(\omega\right)}d\omega = \frac{1}{2\pi^2}\int F\left(\omega\right)U_j\left(R_{\theta_l}\omega\right)e^{j\left\langle x_k^{(j,l)},\omega\right\rangle}d\omega \tag{6}$$

2.2. **Discrete Curvelet Transform.** The 2-dimension discrete function $f\left[t_1,t_2\right], 0 \leq t_1, t_2 < n$ is defined on a Cartesian coordinate as the input data, the expression of its discrete curvelet transform is

$$C^D\left(j,l,k\right) = \sum_{0 \leq t_1, t_2 < n} f\left[t_1,t_2\right]\overline{\varphi_{j,l,k}^D\left[t_1,t_2\right]} \tag{7}$$

where $C^D\left(j,l,k\right)$ represents the discrete curvelet coefficients, j, l, k is scale, direction and orientation parameters.

There are two different digital implementations for fast discrete curvelet transform (FDCT): curvelets via USFFT (Unequally Spaced Fast Fourier Transform) and curvelets via Wrapping (Wrapping of specially selected Fourier samples) [16]. Two implementations both provide an outputs of discrete coefficients, only differ in choosing the spatial grid to translate curvelets at each scale and angle. We choose FDCT via wrapping as the transform method. The curvelet transform procedures are as follows for a $n \times n$ image $f\left[i_1,i_2\right], 0 \leq i_1, i_2 < n$.

Step 1: Perform the 2D FFT to the input image $f\left[i_1,i_2\right]$ and obtain its Fourier samples $F\left[n_1,n_2\right], n/2 \leq n_1, n_2 \leq n/2$.

Step 2: Compute the product $F\left[n_1,n_2\right]\hat{U}_{j,l}\left[n_1,n_2\right]$ for each scale j and angle l .

Step 3: Wrap the product F around the origin to obtain

$$F_{j,l}\left[n_1,n_2\right] = W\left(\hat{U}_{j,l}F\right)\left[n_1,n_2\right] \tag{8}$$

Step 4: Apply the inverse 2D FFT to the wrapped data to get discrete curvelet coefficients $C^D\left(j,l,k\right)$.

3. **Feature Extraction from the Curvelet Coefficients of Palmprint.** For analyzing the characters of every frequency band curvelet coefficients, we take a palmprint image of size 128×128 from the PolyU 2D Palmprint Database as an example, which is shown in Fig. 2. We decompose it to 4 levels by FDCT via wrapping. 4 sets of curvelet transform coefficients are obtained corresponding to 4 frequency bands, whose situations are shown in Table 1. The first (1^{st}) frequency band is coarse layer, which mainly includes low frequency coefficients. The second and third frequency band $\left(2^{nd}\ and\ 3^{rd}\right)$ are both detail layers, which mainly includes middle frequency coefficients; the forth frequency band $\left(4^{th}\right)$ is fine scale, which mainly includes high frequency coefficients. Fig. 3 shows the images of lowest and middle frequency curvelet coefficients. The lowest frequency coefficients are indicated at the center of the image, which is enlarged as shown in Fig. 3(d) for observing better. The Cartesian concentric coronae shows the coefficients at different detail scales, the outer coronae are correspond to higher frequencies, as shown in Fig. 3(b) and (c); the highest frequency coefficients are shown in Fig. 4. From Fig. 3 and 4, it is clearly that the lowest frequency coefficients (Fig.3(d)) is the coarse image of the original image, the middle frequency coefficients retain the curved edge characteristics, the highest frequency coefficients reflect the subtle edge characteristics and background noise.

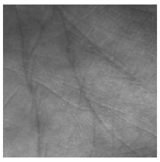

Figure 2. Original palmprint image

Table 1. Analysis of the curvelet coefficients

Layer (Frequency band)	Scale coefficients	No. of the direction parameters	Dimension of the matrix			
Coarse(1^{st})	C{1}	1	21×21			
Detail(2^{nd})	C{2}	4×4	18×22	16×22	22×18	22×16
Detail(3^{rd})	C{3}	4×8	34×22	32×22	22×34	22×32
Fine(4^{th})	C{4}	1	128×128			

In order to observe the image features better, we perform the inverse curvelet transform for each frequency band coefficients. The reconstructed image of every frequency band is shown in Fig. 5. We can see the reconstructed image of 1^{st} frequency band coefficients shown in Fig. 5(a) is obscure, which retains the main grey information but loses the detail. Fig. 5(b) and (c) show the reconstructed images of two middle frequency coefficient sets contained less grey information and more edge features, which correspond to 2^{nd} and 3^{rd} frequency bands. The 2^{nd} frequency band reflects the main edge feature, and the 3^{rd} frequency band retains not only the edge feature of palmprint, but also the edge of the palmprint shadow. Some subtle detail of the edge information and high frequency noise can be seen in the reconstructed image of the Fine layer, as shown in Fig. 5(d). For understanding the effect of every frequency band to represent the palmprint characters, on one hand, the amplitude spectrum is computed for every frequency band reconstructed image, as shown in Fig. 6, on the other hand, the energy ratio of the different frequency band is calculated, as shown in Table 2. From Table 2, we can see that the strongest energy is in the coarse layer, and the energy wears off from the coarse layer to the fine

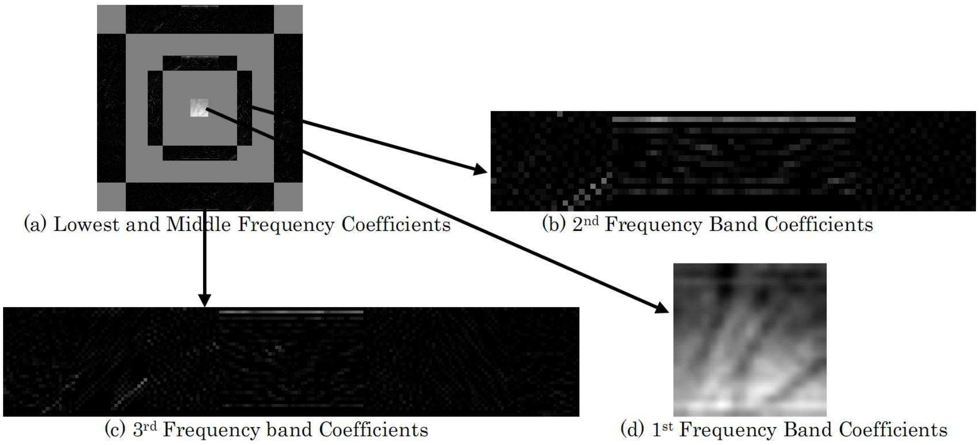

FIGURE 3. Curvelet coefficients in coarse and detail layers

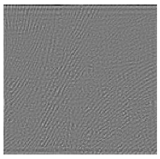

FIGURE 4. 4^{th} Frequency band Ccoefficients

layer. Therefore, it is more likely to extract image feature from low frequency coefficients or together with the low and middle frequency coefficients [19-22]. Moreover, we can find that the 2^{nd} frequency band coefficients cover the main edge feature information from Fig.6, and it has a bigger energy proportion at same time, so we choose them as the elementary feature.

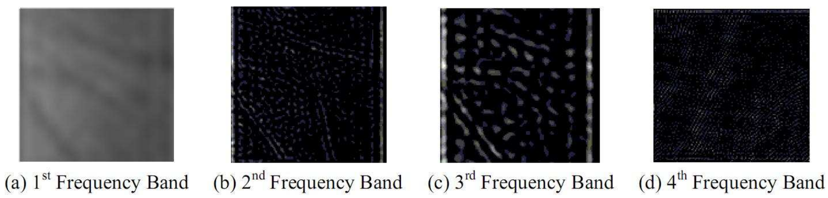

FIGURE 5. Reconstructed image of each frequency band based on inverse curvelet transform

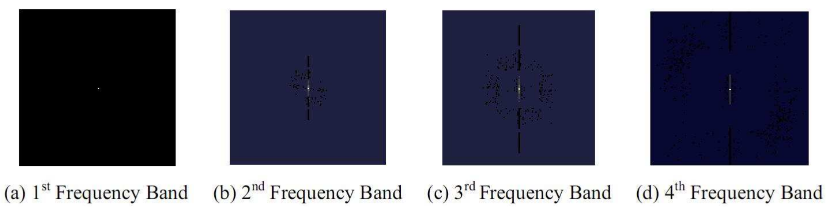

FIGURE 6. Amplitude spectrum of the restored image of different frequency band

4. **The proposed method.** Based on the above analysis, this paper proposes a novel approach for palmprint feature extraction. And the total steps of the palmprint recognition is as follows.

TABLE 2. Energy Ratio of the Restored Image of Different Frequency Band (%)

Frequency Band	**1^{st}**	**2^{nd}**	**3^{rd}**	**4^{th}**
Energy Ratio	99.78	0.078	0.054	0.053

Step1: Curvelet features extraction. The 2nd frequency band palmprint curvelet coefficients are extracted using FDCT via wrapping for the training images and test images. Reshape the coefficient matrixes of each palmprint to a row vector. All the row vectors of training images form a new matrix, denoted as the training sample feature space.

Step 2: Dimensionality reduction. The size of the row vector of each palmprint usually is very large, which lead to a high-dimensional vector space, so we perform PCA to reduce the dimension and obtain a more representative feature, called Curvelet-PCA(CP) Feature.

Step 3: PCA Projection. Project the test image into the subspace spanned by the corresponding CP Feature obtained from Step 2 to get the test image feature.

Step 4: Palmprint classification. Use nearest neighbor method to classify the test palmprint image.

5. **Experiment and Analysis.** In order to test our proposed method of palmprint recognition, we perform experiments on the PolyU 2D Palmprint Database, which contains 8000 samples collected from 400 different palms. Twenty samples from each of these palms were collected in two separated sessions, where 10 samples were captured in each session, respectively. 2D ROI of each sample is recorded by a 128×128 BMP format grey image file in the database.

Our experiments are programmed and tested by Matlab 2012. We choose 1000 samples of 100 different palms (10 samples of each palm) as the experimental database from the PolyU 2D Palmprint Database. Four and five levels curvelet decomposition are performed to extract the palmprint feature.

The training samples are randomly chosen from the selected experimental database, and the rest images are taken as the test samples. For evaluating the experimental results, We choose the sample numbers from 1 to 9 for every person randomly, perform 10 times for each situation and calculate their average recognition (AR) and standard deviation(SD). Table 3 shows the recognition results of the methods using CP feature of different frequency bands based on 4 levels decomposition, in which N presents the number of training samples of each person. For comparison, we give the recognition rate (RR) using the Curvelet-SVM method(CS)[22], which used the low frequency coefficients based on discrete curvelet transform and Radial Basis Function (RBF)-SVM classifier to recognize. We set the parameters of RBF ($\sigma = 29$) like [22]. Because the runtime of CS is long, we only randomly choose training samples once in every sample space. As shown in Table 3, the average accuracy using feature of the second frequency band CP coefficients is higher than the accuracy using other frequency band coefficients, especially in the situation of small sample space. The standard deviations also indicate the higher robustness and stability of the approach we proposed. It can be obtained the same conclusion in Table 4, which shows the compared results corresponding to the experiments carried on with curvelet transform at 5 scales. It is evident whether in the small sample space or large sample space, the recognition accuracy of the proposed approach using the 2^{nd} frequency band coefficients as the main feature is much higher.

In addition, we compute the average training running time for the our method and the method [22], as shown in Table 5. In addition, we compute the average testing time for these two methods. It only takes 0.022s using our method, but 136.66s using the method [22]. we can see that our CP method is much more efficient and faster.

Table 3. The Recognition Results of Different methods

	CP (1^{st})		**CP (2^{nd})**		**CP (3^{rd})**		**CP (4^{th})**		**CS**
N	**AR**	**SD**	**AR**	**SD**	**AR**	**SD**	**AR**	**SD**	**RR**
1	76.32	1.50	**81.06**	1.76	41.60	2.76	14.10	2.24	45.67
2	88.21	1.49	**91.93**	0.50	58.14	1.52	20.44	2.27	86.50
3	92.79	1.12	**94.87**	0.84	68.91	1.96	25.36	3.69	92.57
4	94.93	0.94	**96.83**	0.75	74.75	1.19	30.10	3.04	96.17
5	96.34	0.65	**97.66**	0.70	79.96	1.18	33.72	2.30	98.60
6	96.60	0.88	**98.15**	0.52	82.98	2.01	35.75	2.83	98.75
7	97.67	0.54	**98.60**	0.84	86.17	1.81	40.23	2.98	98.67
8	97.20	1.09	**98.55**	0.80	87.55	2.39	41.55	3.47	98.00
9	97.90	1.29	**98.80**	1.03	90.10	2.18	45.20	5.20	99.00

Table 4. The Results of AR and SD with Different Feature Extraction methods (Curvelet Transform at 5 scales)

	CP (1^{st})		**CP (2^{nd})**		**CP (3^{rd})**		**CP (4^{th})**		**CP (5^{th})**	
N	**AR**	**SD**	**AR**	**SD**	**AR**	**SD**	**AR**	**SD**	**AR**	**SD**
1	72.18	2.64	**96.00**	1.15	81.39	1.24	41.91	1.46	14.02	1.84
2	85.45	1.54	**98.54**	0.50	91.33	1.38	58.88	1.86	21.88	2.17
3	90.14	1.28	**99.09**	0.14	95.34	0.79	68.10	1.97	26.39	2.55
4	92.10	1.15	**99.38**	0.14	96.58	0.74	74.32	1.49	31.85	2.32
5	94.74	0.60	**99.68**	0.25	97.58	0.60	79.84	1.14	35.06	3.52
6	95.63	0.66	**99.78**	0.25	98.00	0.51	83.40	1.53	37.75	2.58
7	96.63	1.29	**99.60**	0.21	98.37	0.62	86.47	2.14	40.33	2.66
8	97.60	0.91	**99.60**	0.39	98.45	0.44	87.35	2.45	43.35	4.01
9	97.80	1.55	**99.90**	0.32	98.70	0.67	88.90	3.28	45.00	3.20

Table 5. Comparison of Trainning Time in CP and CS methods(s)

N	1	2	3	4	5	6	7	8	9
CP	0.19	0.41	0.64	1.22	1.89	2.56	3.15	4.08	4.67
CS	32.52	36.47	41.20	45.56	49.14	50.95	54.78	57.85	61.88

6. **Conclusions.** Curvelet transform is good at approximating curve singularities, so it is more suitable to extract crucial edge-based features from palmprint than wavelet transform. In this paper, we propose a novel approach of palmprint feature extraction based on fast discrete curvelet transform. The novelty of the approach is that we select the 2nd frequency band coefficients as the palmprint feature and apply PCA on the selected feature space to get an more lower dimensional representation, which not only reduces computational cost, but also increases recognition accuracy. Experimental results carried on in PolyU 2D Palmprint Database show that our approach has higher performance in terms of efficiency and robustness.

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