Journal of Information Hiding and Multimedia Signal Processing ©2017 ISSN 2073-4212
Ubiquitous International Volume **8**, Number **3**, May **2017**

Palmprint Feature Extraction based on Multi-wavelet and Complex network

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Received August, 2016; revised January, 2017

Abstract. *A new palmprint feature extraction method is proposed by analyzing the characteristics of palmprint images, multi-wavelet analysis and complex network. As we all know, the main lines of a palmprint image is a key to recognize a palmprint, and the other thin and small lines usually may influence the recognitions results relatively small. Motivated by this, the principle line feature extraction is preferred in the palmprint recognition. Multi-wavelet analysis can not only extract the coarse information, but also give the detail information in horizontal and vertical direction. By analyzing the multi-wavelet features of palmprint images, it can be seen that the low frequency sub-band image with a multi-wavelet decomposition can present the principle lines very well. So the low frequency component is selected first. By observing the 4 components of the low frequency sub-image, three components except for the diagonal component contain almost all information, so these components are extracted as the elementary feature of a palmprint image. Furthermore, the binarization computation is performed on the 3 extracted features with different thresholds to extract the secondary feature of a palmprint image. Instead of directly using the binary features, the connectivity of the points in the principle line is considered because the relative correlation of the principal lines is also a key factor to recognize a palmprint image. Therefore, a series of dynamic evolution small-world networks of the feature points in the principal line are built and the final complex network features are extracted, which contain maximum degree, average degree, standard deviation of the degree and contrast. Experimental results on the CASIA Palmprint Image Database show that the proposed method is effective, especially for the little training sample number.*

Keywords: Palmprint feature; Multi-wavelet; Complex network; Recognition.

1. **Introduction.** The palmprint recognition technology has been widely applied to our daily life because it needs not directly contact and does not involve privacy information. It is more important that it does not require the complex and expensive acquisition equipment and strict acquisition environment because the low-resolution image can provide enough information to recognize palmprint. The palmprint feature is a key to recognize the identification. The time-frequency feature is often used because it can represent the palmprint texture and line properties effectively. KONG et al. [1] used 2-D Gabor filters to extract people's palmprint features. WANG et al. [2] extracted the palmprint feature on different curvelet transform scales. ZHANG et al. [3] decomposed the palmprint image using the wavelet first, and then calculate the statistics of each sub-band image as the palmprint feature. The multi-wavelet [4] can have symmetry, orthogonality, compact support and high vanishing moments, which can effectively extract face feature[5]. Moreover, the main lines and wrinkles are mainly contained in the low frequency components. So the multi-wavelet low frequency component is selected first, in which the low, vertical and horizontal components obtained by pre-filtering are extracted as the elementary feature of a palmprint.

At present, complex networks have been applied to various fields in recent years such as computer vision and image processing. Backes A R et al.[6] proposed a novel texture analysis method using the complex network theory, which can represent a texture image effectively using degree measurements. And it is valid to identify different texture types, which overcomes the shortcomings of the traditional methods. Backes A R et al.[7] proposed a new method to extract boundary characteristics by constructing the dynamic evolution small world network, in which replaces the image boundary by a node, and describes the shape feature by using degree correlation of the network in different thresholds. Because the complex network features can describe not only the texture and line feature of a palmprint image, but also their correlations, the complex network feature is chosen as the final feature of a palmprint image based on the multi-wavelet low frequency feature.

A new palmprint recognition method is proposed, which combines the properties of the multi-wavelet analysis and complex network. First, the multi-wavelet low frequency components is extracted, in which the three lower frequency sub-images are selected for filtering the noise. And then, the extracted three sub-images are converted to binary image using the average window method. Third, dynamic evolution complex networks models are constructed. Fourth, the maximum degree, average degree, standard deviation of degree and Contrast of the network are calculated as the features of palmprint image. Finally, the palmprint image is recognized using Nearest Neighbor Classifier (NNC).

The main work of this paper is as follows: Section 2 introduces the proposed feature extraction method based on muliti-wavelet analysis and complex network. Section 3 presents the implementation of the proposed palmprint recognition method. In the Section 4, the performance of the method is verified by experiments. Section 5 gives the conclusion of this paper.

2. The proposed feature extraction method.

2.1. Multi-wavelet elementary feature extraction.

Multi-wavelet is a vector wavelet which is constructed by two or more functions. Multi-wavelet analysis not only preserve the good local characteristics in time and frequency domain, but also can have symmetry, orthogonality, compact support and high vanishing moments at the same time. The pre-filter should be performed before an image is transformed using multi-wavelet because the multi-wavelet filter is a vector filter [4]. The repeated row pre-filtering and approximation order pre-filtering [8] methods are usually used. The repeated row pre-filtering is used in this paper. A palmprint image of CASIA Palmprint Image Database is taken as an example to illustrate the multi-wavelet feature extraction using the CL multi-wavelet [9] proposed by Chui and Lian, as shown in Fig. 1. First, the original palmprint image is pre-filtered using the CL repeated row pre-filter. the result is shown in Fig. 1 (b). For illustrating the preprocessing results clearly, 4 components is denoted as 1, 2, 3, 4, which is represented as the subscript in the multi-wavelet decomposition. And then the pre-filtered image is decomposed using CL multi-wavelet. 4 frequency components is denoted as LL, LH, HL and HH, as shown in Fig.1(c). It is clearly that the main information is contained in the LL component. So the LL component is studied in this paper. For analyzing every corresponding pre-filtered component in the LL component better, every component is processed using the histogram equalization, as shown in Fig.1(d). It can be seen that the LL_1, LL_2, LL_3 components can represent the palmprint well, and LL_4 contains the palmprint information little relatively. Therefore, the LL_1, LL_2, LL_3 components are chosen as the elementary feature of the palmprint image. In general, the decomposition level is set 1 because the lower resolution palmprint images are usually used and the size of the palmprint image is small. For example, the size of the images in the test palmprint databases is 128×128 in this paper, so the decomposition level is set to 1. If the size of the image is bigger, the decomposition level can be set to a higher value. It is enough that the size of the lowest frequency band is kept as 64×64.

2.2. **Principal line feature extraction of the multi-wavelet palmprint sub-images.** As we all know, lines are the main feature in a palmprint, so the principal lines are extracted as secondary features further. In general, the key pixel point will be thought as a point of a principal line if its value is apparently lower than other neighbor points and their difference is greater than a threshold. For determining the principal line in a palmprint image, we assume that $G(x, y)$ is the gray value at the pixel point (x, y), the mean value in a $(2l + 1) \times (2l + 1)$ window with the center point (x, y) is denoted as $A(x, y)$, which can be calculated as follows [10]. l=8 in this paper.

$$A(x, y) = \sum_{i=-l}^{i=l} \sum_{j=-l}^{j=l} G(x + i, y + j)/(2 \times l{+}1)^2 \tag{1}$$

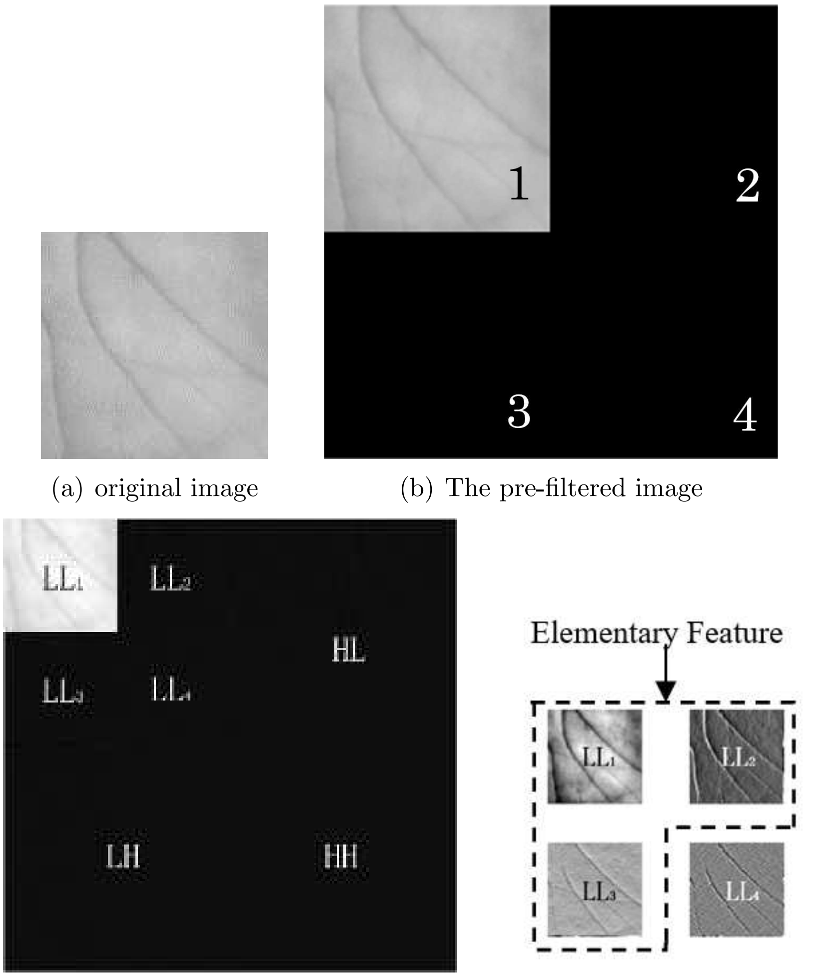
Thus, the difference between the pixel value at (x, y) and their neighbor points is defined as:

$$D(x, y) = G(x, y) - A(x, y) \tag{2}$$

The binary pixel value at (x, y) can be obtained by comparing the difference value with the threshold T. Thus the points of the principal lines can be set to 255, the others are set to 0, which can be used easily for the next complex network feature extraction.

$$B(x, y) = \begin{cases} 255, & D(x, y) < -T \\ 0, & D(x, y) \geq -T \end{cases} \tag{3}$$

the threshold T is usually chosen mainly by analyzing the mean and standard of the corresponding image. T is chosen as a bigger value if the mean and standard is bigger. The principle lines are extracted for the 3 extracted elementary multi-wavelet components in section 2.2 respectively with the parameters l=8, T_{LL1}=5, T_{LL2}=2 and $T_{LL3} = 2$. The results are shown in Figure 2. It can be seen that the extracted principle lines in the 3



(a) original image (b) The pre-filtered image

(c) The 1^{th} decomposition image (d) All LL components after histogram equalization

FIGURE 1. The original palmprint image and its Multi-wavelet decomposition analysis

component features can represent the main palmprint features well. Therefore the binary sub-images extracted principle line are seen as the secondary features.

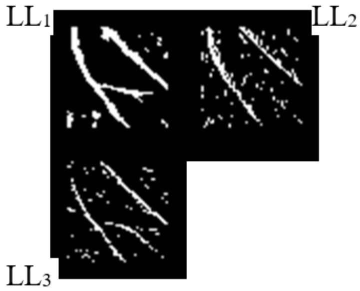


FIGURE 2. The extracted principal line binary sub-images of LL_1, LL_2 and LL_3

2.3. **Feature extraction based complex network.** By observing the binary sub-images with the line feature obtained in section 2.2, it can be seen that the points in the lines and their relations between them can provide the main information in palmprint recognition. For quantity analyzing these points and their correlations in the lines, the complex network models are constructed first. And then, the secondary palmprint features can be extracted by calculating the statistics characteristics of the complex network.

2.3.1. *Complex network modeling method.* Because the lines feature has been presented in the binary images in section 2. A pixel point with the value 255 can be taken as a network node, denoted by s_i, whose coordinate is denoted by (x_i,y_i) at the same time. The Euclidean distance between two network nodes s_i and s_j is defined as E.

$$E(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

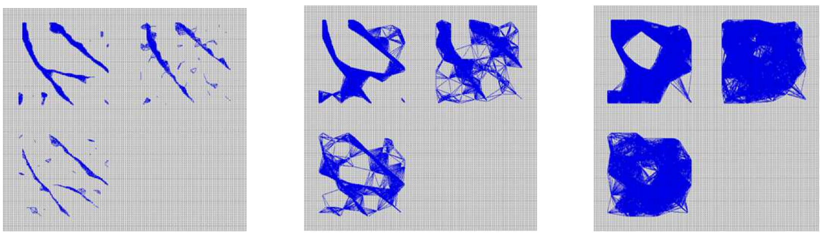
For determining whether an edge is connected between two nodes, a weight w_{ij} between them is calculated by

$$w_{ij} = \frac{E(s_i, s_j)}{L} \tag{5}$$

where L is the possible maximum distance of image edge. So $0<w_{ij} \leq 1$. An edge can be connected between two nodes s_i and s_j when the weight w_{ij} is less than a threshold T. A complex network model can be constructed by connecting the edges between each two nodes whose weight is less than a threshold T. For representing the relations between nodes better, a series of dynamic evolution complex network models can be constructed by choosing different thresholds. The thresholds can be generated according to the equation (6).

$$T_n = T_0 + nT_{inc}\,, \qquad 0 < T_0, T_{inc}, T_f < 1 \tag{6}$$

where T_0 is initial threshold, T_f is final threshold, T_{inc} is the step of threshold evolution, T_n is the n-th threshold. A series of networks are constructed for the image in figure 2 according to the different thresholds(T_0=0.025, T_f=0.075, T_{inc}=0.05), as shown in figure 3. It can be seen that the number of the edges are more and more with the increasing thresholds, and the connection range expands also from the inner to outer of the lines.



(a) T=0.025 (b) T=0.075 (c) T=0.125

FIGURE 3. The network in different thresholds

2.3.2. *Complex networks connectivity analysis.* Each network has its own unique topology, so different networks can be distinguished according to their network topological features. In general, the topology of the network usually is its connectivity or shape. Because the connectivity can represent the edge of a palmprint image well, it is used to extract the palmprint image features. The connectivity of the network usually can be described by the degree of its node, which refers to the number of edges which connects with the node n, denoted as $deg(n)$.

$$deg(n) = |\{n \in N|\{n, n'\} \in E\}| \tag{7}$$

where N is the set of network nodes, and E is the set of network edges. $|A|$ is defined as the elements number of a set A.

2.3.3. *Palmprint feature extraction based on complex network.* The three components are combined to a big image like in figure 2 in constructing the extracted complex network models of the palmprint. The degree average of the nodes and the degree difference between nodes can represent the connectivity of the complex network well. Therefore, maximum degree, average degree, standard deviation of the degree and contrast are selected as the secondary features of the palmprint image.

(1) Maximum degree

$$deg_{\max} = \max\ (deg(n_i)) \quad n_i \in N \tag{8}$$

It shows the maximum edge number of the nodes in the network.

(2) Average degree

It shows the concentration of the network.

$$deg_{\mu} = \sum_{i=0}^{k} ip(i) \tag{9}$$

where $p(i)$ is the probability density function of degree, which can be calculated by

$$p(i) = \frac{h(i)}{\sum\limits_{j=0}^{deg_{\max}} h(j)} \qquad i = 0, 1, 2, \ldots, deg_{max} \tag{10}$$

where $h(i)$ is the number of degree i in a network.

(3) Standard deviation of degree

It shows the network discrete levels.

$$S = \sqrt{p(i) \sum_{i=0}^{k} (i - deg_{\mu})^2} \tag{11}$$

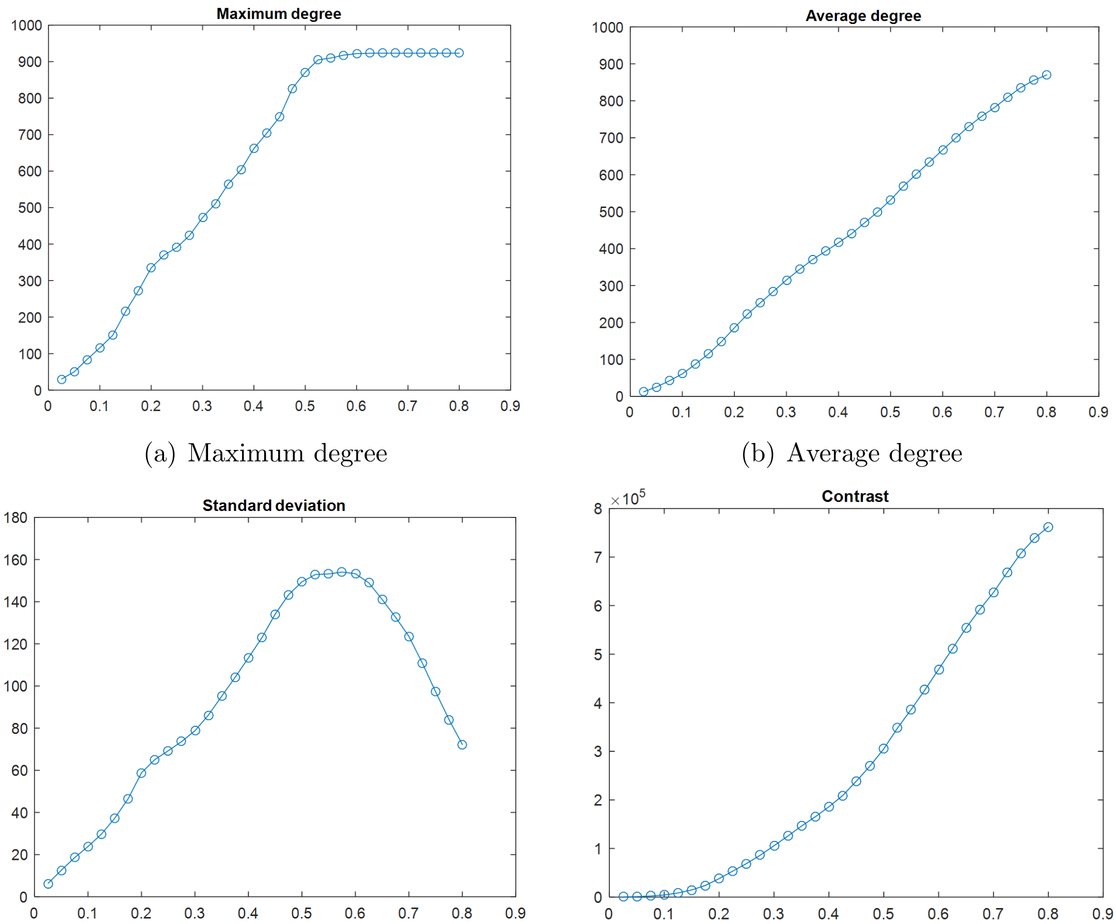
(4) Contrast

It shows the energy level of the network[4].

$$C = \sum_{i=0}^{k} p(i) i^2 \tag{12}$$

The maximum degree , average degree , standard deviation of degree and contrast are calculated for a series of dynamic evolution networks with different thresholds to form the secondary feature of an palmprint image, as shown in equation (13). The secondary features are calculated for the networks generated from the image in figure 2 with the different thresholds, as shown in figure 4. It can be seen that the maximum degree and the standard deviation of degree obviously changes when the threshold is between 0.5 and 0.7.

$$\varphi = [deg_{\max}(T_0), deg_{\max}(T_1), \ldots, deg_{\max}(T_f), deg_{\mu}(T_0), deg_{\mu}(T_1), \ldots, deg_{\mu}(T_f), \\ S(T_0), S(T_1), \ldots, S(T_f), C(T_0), C(T_1), \ \ldots \ , C(T_f)] \tag{13}$$



(a) Maximum degree (b) Average degree

(c) Standard deviation of degree (d) Contrast

FIGURE 4. The features in different thresholds

3. **The proposed plamprint recognition approach.** As is analyzed above in Section 2, A palmprint feature extraction method combining Multi-wavelet and Complex network is proposed. The palmprint recognition approach is given in Fig. 5. First, the multi-wavelet sub-images LL_1, LL_2 and LL_3 features are extracted. Second, the corresponding binary features are obtained using different adaptive thresholds. Third, the three components are mosaiced. Fourth, a series of dynamic evolution small world networks are constructed. Fifth, the complex network features are extracted. Sixth, the LDA method is used to reduce the feature dimension. Finally, the NNC is used to recognize the palmprint. The detail process is as follows.

Step 1: The training palmprint images are decomposed using the CL multi-wavelet to obtain the lower frequency sub-images of their low frequency components.

Step 2: The average image of every sub-image is computed using equation (1) and the deviation image between every sub-image and its average image is obtained using subtraction. The point is selected as the feature point if the pixel value is less than threshold T, which is set to 255. The others are set to 0. Usually, T is set to 5 for the sub-image LL_1, 2 for the sub-images LL_2 and LL_3.

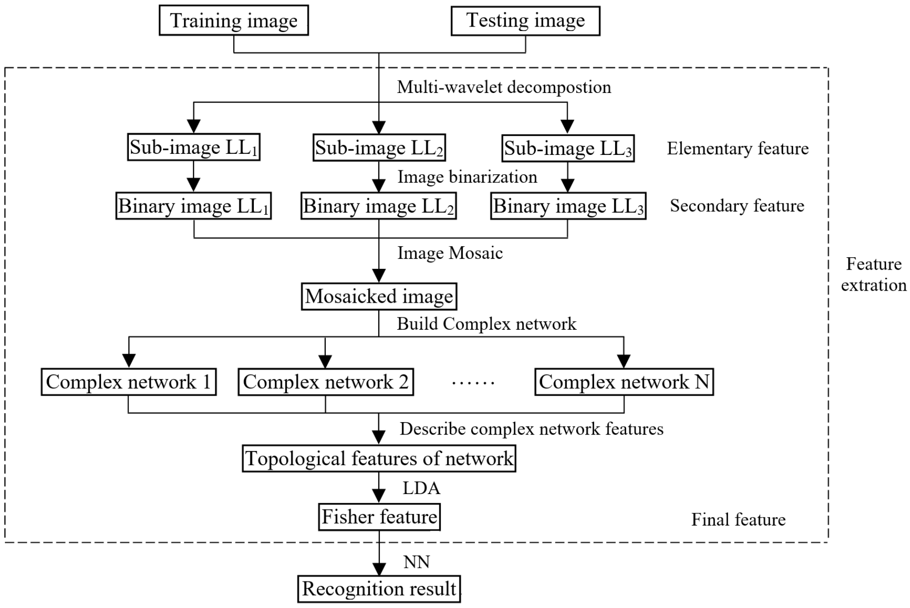


FIGURE 5. palmprin recognition block diagram

Step 3: The binary sub-images are mosaiced according to the original relative position. The others are set to 0.

Step 4: according to equation (4) and (5), the weight w_{ij} between any two nodes is calculated. A series of thresholds are generated using equation (6). The network is constituted by connecting the nodes if the weight is less than the threshold. Every network is corresponding to a threshold. Thus, a series of the dynamic evolution small world complex networks can be obtained by selecting the different thresholds.

Step 5: The complex network features are computed by equation (8)-(12). The final features are formed by connecting the features corresponding to different thresholds.

Step 6: The LDA method is used to extract the fisher feature .

Step 7: The testing image is processed using step 1 to step 6 and recognized using NNC.

4. **Experimental results and analysis.** The CASIA Palmprint Image Database is used to evaluate the proposed method, in which there are 310 different palms with 8 images per palm, These images are the preprocessed ROI images (size of 128×128).

4.1. **Threshold selection in complex network.** In order to achieve the optimal effect of the algorithm, different sets with different thresholds are selected to test. For evaluating the test results. The 10 tests are performed for every test with random 2-6 training samples. The Average Recognition (AR)(%) and their Standard Deviations (SD) are shown in Table 1, in which the numbers T_{min}, T_{inc} and T_{max}, present the beginning threshold, the step and the stop threshold, denoted as T_{min}_T_{inc}_T_{max}. we can see that from table 1, when T_{min}=0.025, T_{inc}=0.025 and T_{max}=0.8, the performance is better than 0.05_0.05_0.8 and 0.025_0.025_0.7, and the efficiency is better than 0.02_0.02_0.8 and 0.025_0.025_0.9.

4.2. **Methods comparison.**

TABLE 1. Comparison of results with different thresholds

	0.02_0.02_0.8		0.025_0.025_0.8		0.05_0.05_0.8		0.025_0.025_0.7		0.025_0.025_0.9	
N	AR	SD	AR	SD	AR	SD	AR	SD	AR	SD
2	89.58	0.44	**89.94**	0.85	86.91	0.90	89.98	0.62	**89.51**	0.79
3	94.03	0.57	**94.14**	0.63	91.49	0.60	93.97	0.56	**94.14**	0.56
4	95.93	0.49	**95.83**	0.55	93.70	0.64	95.66	0.57	**95.96**	0.62
5	97.47	0.46	**97.41**	0.31	95.51	0.64	97.35	0.35	**97.53**	0.30
6	98.04	0.31	**97.85**	0.60	95.93	0.52	97.87	0.41	**97.90**	0.53

4.2.1. *The comparisons with traditional methods.* For evaluating the effectiveness of the proposed method, we perform the experiments using the Gabor filters, Local Binary Patterns (LBP) and Multi-block Local Binary Patterns(MLBP) methods at the same time. The simple description of the methods is as follows.

Gabor filters. The 2D Gabor filter is a Gauss kernel function modulated by a sinusoidal plane wave, we used the Gabor filters with 5 scales and 8 orientations. The filtered image is reduced to 10×11 dimension by bilinear interpolation, A Palmprint image can be extracted for 4400 dimensional features.

Local Binary Patterns (LBP). We set the radius=1, neighborhood=8, and reduce the histogram to 59 dimensions as features.

Multi-block Local Binary Patterns(MLBP). We divided the image into 64 blocks, compute LBP features for each block.

The results are shown in Table 2.It can be seen that the proposed methods is obviously better than the other three methods.

TABLE 2. Recognition results using the proposed methods and the traditional methods

	Gabor		LBP		MLBP		Proposed approach	
N	AR	SD	AR	SD	AR	SD	AR	SD
2	85.50	1.23	62.39	1.48	86.36	1.16	**89.53**	0.86
3	92.05	0.54	76.99	1.33	92.70	0.43	**94.20**	0.86
4	94.37	0.82	81.81	3.94	94.99	0.69	**96.20**	0.39
5	95.92	0.83	83.51	8.46	96.32	0.67	**97.03**	0.53
6	96.80	0.74	88.32	1.58	96.80	0.41	**97.96**	0.57

4.2.2. *The comparisons with the methods using different elementary features.* The different elementary features can be obtained using the different filters. For evaluating the proposed method better, the elementary features are extracted using Curvelet, GHM, Haar wavelet transforms. And then, the corresponding complex network feature are extracted using the models with thresholds T_{min}=0.025, T_{inc}=0.025 and T_{max}=0.8. At the same time, the same complex network features are also extracted for the original images to test. The detailed parameters are as follows.

Original Image, l=8, T=5 in the average window methods.

Curvelet: the lowest frequency band is extracted by decomposing the palmprint images 3 times. l=8, T=5 in the average window methods.

GHM multi-wavelet: the 4 sub-images are used in the LL frequency band. l=8, T_{LL1}=5, T_{LL2}=5, T_{LL3}=5 and T_{LL4}=5 in the average window methods.

Haar wavelet: the LL, LH and HL components are extracted as the elementary features. l=8, T_{LL}=5, T_{LH}=2, T_{HL}=2 in the average window methods.

The results are shown in Table 3. It can be seen that the proposed methods is obviously better than the methods using the original and curvelet elementary features and slightly better than the methods using the GHM multi-wavelet and haar wavelet elementary features. But the effectiveness is more obvious for the little number of training samples.

TABLE 3. Recognition results with different elementary features

	Original image		Curvelet		GHM		Haar		Proposed approach	
N	AR	SD	AR	SD	AR	SD	AR	SD	AR	SD
2	83.44	0.60	84.77	0.80	88.30	0.64	85.69	0.93	**89.85**	0.64
3	90.32	0.75	91.15	0.77	93.47	0.51	92.70	0.60	**94.28**	0.59
4	94.08	0.70	93.62	0.65	95.50	0.74	95.01	0.92	**96.05**	0.69
5	95.45	0.55	95.47	0.84	96.89	0.68	96.25	0.90	**97.23**	0.71
6	96.46	0.37	96.16	0.65	97.50	0.68	97.32	0.73	**98.02**	0.61

5. **Conclusion.** A palmprint recognition method based on complex network is proposed in this paper. First, Multi-wavelet analysis and image enhancement technology are used to extract principal lines and wrinkles. And then the feature points are selected as the nodes. A series of dynamic small-world network models are constructed to extract the complex network features. Fourth, the LDA method is used to reduce feature dimension. At last, the NNC is used to recognize the palmprint image. This proposed method can improve the recognition rate and reduce the influence caused by the region of interest of cutting is not accurate to some extent comparing with the other methods. In future, the feature extraction of complex networks in palmprint recognition will be studied further.

Acknowledgement. This work was supported by Natural Science Foundation of China under grant 61572269, a Project of Shandong Province Higher Educational Science and Technology Program: J14LN25, Shandong Province Natural Science Foundation, China: ZR2014FP003 and ZR2016FQ14..

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