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Iris Recognition Using Curvelet Transform Based on Principal Component Analysis and Linear Discriminant Analysis

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Abstract. *The iris texture curve features play an important role in iris recognition. Although better performance in terms of recognition effectiveness can be attained using the recognition approach based on the wavelet transform, the iris curve singularity cannot be sparsely represented by wavelet coefficients. In view of the better approximation accuracy and sparse representation ability of the Curvelet transform, an iris recognition method based on Curvelet, Principal Component Analysis (PCA) and Linear Discriminant Analysis(LDA) is proposed. First, the iris image is preprocessed including iris localization, elimination of the eyelash shading and iris normalization. Next, the preprocessed iris image is decomposed into the N layers Curvelet coefficients by the Curvelet transform. The highest frequency coefficients are filtered directly because they mainly contain the false information caused by some environmental noises. And then the iris Curvelet features are mapped by PCA and LDA to extract the further features, in which we use the Curvelet coefficients of the former N-1 layers and only the first layer coefficients as the iris Curvelet features respectively. At last, the nearest neighbor classifier is adopted for iris recognition. Experimental results show that the iris recognition methods using the former N-1 layers Curvelet coefficients and only using the first layer Curvelet coefficients both can recognize iris effectively and get the higher recognition rate with minor difference. But the method only using the first layer Curvelet coefficients can effectively reduce the feature dimension and improve the recognition speed.*
Keywords: Iris Recognition, Curvelet Transform, PCA, LDA.

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1. **Introduction.** The iris recognition has become one of the most reliable biometric recognition technologies because of the iris's stability. Daugman and Downling [1,2] coded

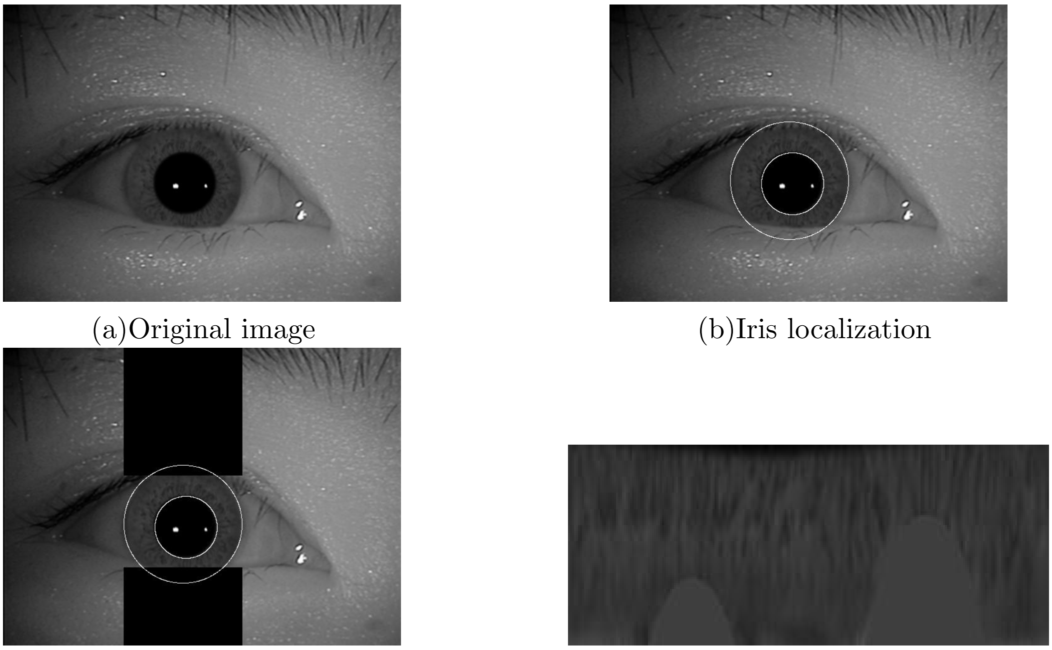
iris using the multi-scale Gabor filter and computed the Hamming distance between two iris by XOR, but this method does not consider using the direction information in the feature extraction. Wildes et al. [3] decomposed the iris image in different resolutions using the Gaussian-Laplacian pyramid and matched the decomposed iris images, but this method was complicated in calculation. Boles and Boashash[4] proposed an iris recognition method based on wavelet zero crossing detection. However, this method is sensitive to the change of image grayscale, and thus the recognition rate is not high. Lim et al. [5] used the two-dimensional Haar wavelet transform to decompose the input iris image into 4 layers and made use of the fourth layer as the iris feature. Zhu et al. [6] adopted the multichannel Gabor filter and Daubechies-4 wavelet transform texture analysis methods to extract features. The wavelet transform cannot accurately express curve singularity in the image, although it can effectively express point singularity of the image. But the iris image contains many curve information such as iris crypt, fold and pigment spots, the wavelet coefficients cannot sparsely represent them effectively. Curvelet transform is a new generation multi-scale collection analysis tool, which takes into account the size, position and angle information of the image, so the Curvelet transform is better than the wavelet transform of the input image [7][8]. Najafi and Ghofrani[9] provided feature extraction methods based on the ridgelet transform and Curvelet transform for identifying iris images. Rahulkar et al. [10] computed the directional iris texture features based on the two-dimensional fast discrete curvelet transofrm. Ahamed and Bhuiyan [11] proposed a low complexity technique for iris recognition in the Curvelet transform domain. In addition, the statistics feature extraction algorithm is more and more attended by researchers recently, such as PCA, LDA, ICA and the related algorithm. Shi and Gu [12] compared the feature extraction algorithm based on PCA, ICA and Gabor wavelets for a compact iris code. Duan et al.[13] proposed a remote image fusion method based on PCA and dual tree compactly supported shearlet transform. Zhang et al. [14] adopted optimizing matrix mapping with data dependent kernel for image classification.

In order to consider the iris texture curve features and better resolve the high dimension of the feature, this paper proposes an iris recognition method based on the second generation Curvelet transform, PCA and LDA. First, the iris image is preprocessed by iris localization, elimination the shading of eyelash and iris normalization. Next, the preprocessed image is decomposed by Curvelet and the lowest frequency Curvelet coefficients of the preprocessed iris images are used as the iris features. Then the PCA and LDA are performed to extract the feature and reduce the feature dimension. At last, a dictionary is established using Curvelet, PCA and LDA algorithms. During the recognition process, the test iris images are preprocessed. And then the lowest frequency Curvelet coefficients are projected onto the dictionary. Experimental results show that our method can not only improve the recognition rate, but also reduce the feature dimension and the computational complexity.

2. **Iris Image Pre-processing.** In general, there are three important factors that influence the iris recognition result. First, the size and location of the iris in the images are different. Second, the eyelashes can shade the iris. At last, the iris image grayscale is variable because of non-uniform illumination. In order to reduce these influences, the pre-processing of the iris localization, removal of eyelash shading and image normalization should be done before iris feature extraction.

2.1. **Iris Localization.** After acquiring the iris image, the first step is to segment the iris. We take an iris image with a resolution of 480×640 from CASIA-Iris-Syn of CASIA-IrisV4 for example, it is shown in Fig.1(a). The texture of the iris is contained between the inner and outer approximate circle boundary parts, so the inner and outer boundaries should be extracted. The iris inner boundary is approximately circular with a large gray gradient. According to this characteristic, the pupil is separated through the thresholding method and the iris inner boundary is extracted. Then the outer edge is detected by using the Canny edge detector[9]. The iris localization image is shown in Fig.1 (b). From Fig.1 (b), we can see that the iris can be located accurately in the iris image. Further, the eyelash shading will influence the recognition result, so it is necessary to be eliminated as shown in Fig.1(c). We can see that the shading of eyelash can be eliminated effectively from Fig.1(c).

2.2. **Iris Image Normalization.** The iris location, size and gray are different with different acquisition environments, so the iris location, size and gray normalization is necessary. Because the structure of the iris is ring, the normalized iris image can be expanded into a rectangle form by polar coordinates. Thus, the size of the iris image is zoomed uniformly after normalization, we can extract its feature in the future. The normalization result of Fig.1(a) is shown in Fig.1(d), and the size of the normalized image is100×240.



(a)Original image (b)Iris localization

(c)Elimination influence of eyelash shelter (d)Iris image normalization

FIGURE 1. Results of image pre-processing.

3. **Discrete Curvelet Transform.** The Curvelet transform is a multiscale geometrical transform with frame elements as scale, location and orientation parameters. In 1999, Candes and Onoho introduced the first generation Curvelet transform. Over the past few years, Curvelet construction has been redesigned in order to make it simpler to understand and use. Then Candes et al.[15] proposed the second generation Curvelet transform in 2002. The second generation Curvelet transform is better than the first generation Curvelet transform because of its simpler concept, faster operation and smaller redundancy. Thus, the second generation Curvelet transform is used in this paper.

The second generation Curvelet transform is defined by applying the inner product of basis functions and signal. The continuous Curvelet transform can be expressed as follows

$$c(j,l,k) = \langle f, \varphi_{j,l,k} \rangle = \int_{R^2} f(x)\, \overline{\varphi_{j,k,l(x)}} dx \tag{1}$$

where $\varphi_{j,l,k}$ are Curvelet functions, andj,l,k denotes the variables of scale, orientation and position respectively; $c\,(j,l,k)$ denote Curvelet coefficients.

Set the input $f\,[t_1,t_2]\,(0 \le t_1,t_2 < n)$ in the spatial Cartesian, then the discrete form of above continuous Curvelet transform can be defined as

$$c^D\,(j,l,k) = \sum_{0 \le t_1,t_2 < n} f\,[t_1,t_2]\,\overline{\varphi^D_{j,l,k}\,[t_1,t_2]} \tag{2}$$

where the superscript D denotes the discrete form. There are two kinds of algorithms to implement the Curvelet transform, USFF algorithm and Wrap algorithm. The same result can be obtained by these two algorithms, but the USFF algorithm equipped with faster operation and higher efficiency, so the USFF algorithm is used in this paper.

A preprocessed iris image (Fig.1(d)) is transformed by Curvelet transform, and we can get three layers sub band images. The resulting images except the highest frequency band are shown in Fig.2(a). The highest frequency information is shown in Fig.2(b). From Fig.2, we can see that the primary information of the image focuses on the lowest frequency band and the false information caused by environment noise focuses on the highest frequency band.

(a)Low and bandpass frequency band images (b)Highest frequency band image

Figure 2. The Curvelet transformed images.

4. **Iris Recognition Based on Curvelet, PCA and LDA.** Considering the curve information of Iris such as iris crypt, fold and pigment spots, in order to extract the curve feature of the iris, reduce the feature dimension and improve the lower recognition rate caused by environment noise, an iris recognition method by combining Curvelet, PCA and LDA is proposed. The flow chart is shown in Fig.3.

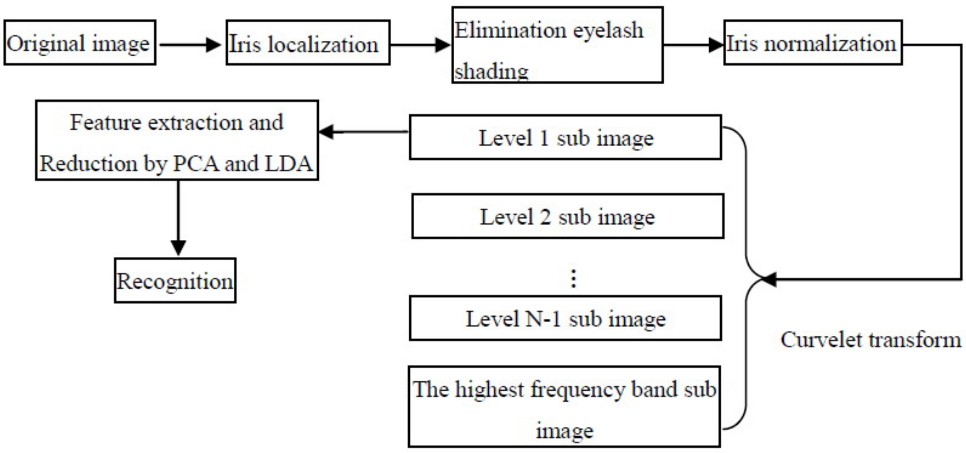


Figure 3. The flow chart of iris recognition based on Curvelet+PCA+LDA.

The specific algorithm steps are as follows:

Step 1. Preprocess all training images by localization, elimination of the eyelash shading and normalization.

Step 2. Transform the preprocessed images $X_1, X_2, \cdots X_M$ by Curvelet and obtain the first,second,$\cdots$, N-th layers Curvelet coefficients of the images. Generally, $N = \lfloor \texttt{log}_2(\texttt{min}(A, B)) - 3 \rfloor$ where $A \times B$ denotes the size of image, $\lfloor\rfloor$ is the floor rounding function. We adopt $N = 3$ in this paper. The second to the $(N-1)\,th$ layers are fine scales, which represent the detailed feature of the iris image. If iris recognition adopts the fine scales as the features, the result shows that the feature dimension is very high. So we only choose the first layer Curvelet coefficients as the feature.

Step 3. Normalize the first layer Curvelet coefficients of all images to form row vectors $X_{i\mathtt{L}}$.

Step 4. Extract the feature of the training sample sets and reduce the feature dimensions by using PCA and LDA.

Step 5. Preprocess the test sample sets and then extract the feature and reduce the dimension of the feature by PCA and LDA.

Step 6. Adopt the nearest neighbor algorithm to recognize the iris.

5. **Experimental Results.**

We can get three layers Curvelet coefficients when the preprocessed images are transformed by the Curvelet transform. The first layer coefficients are the low frequency information which is the primary information of the image. The second to the $(N-1)\,th$ layers Curvelet coefficients are band pass frequency information which are fine scales of the image. So we should consider whether choosing the different Curvelet frequency band coefficients as feature will influence the recognition rate or not. Besides, we also consider whether the different feature extraction ways will affect the recognition rate or not. So firstly, we use only the first layer Curvelet coefficients or the former $(N-1)$ layers Curvelet coefficients as feature. The experiment results show that only using the first layer Curvelet coefficients as feature is better than using the former $(N-1)$ layers Curvelet coefficients as feature in the convergence speed. Next, we compare the recognition rate of other feature extraction ways with our method when only the first layer Curvelet coefficients are chosen as the feature in this paper. In the following experiments, we adopt 270 iris images from 27 persons with 10 iris images per person from CASIA-Iris-Syn as our testing database.

5.1. **Curvelet Feature Selection.**

In this experiment, we randomly select 1 to 9 images from each person respectively in the CASIA-Iris-Syn database as the training set, and take the rest as the test set. Then, we perform two schemes to form feature vectors in this experiment. The specific steps of these two schemes are as follows

Step 1. The feature vector X_{iL} is composed of low frequency band only, then $X_{iL}$is normalized, and last it is extracted feature and reduced the feature dimension by PCA and LDA.

Step 2. Scheme (a) We normalize the low frequency information to form vectors $X_{i\mathtt{L}}$, and then normalize the second to the $(N-1)\,th$ layers Curvelet coefficients to form vectors $X_{i\mathtt{H}}$.

Scheme (b) One row vector corresponding to one image is formed as $M_i = [X_{i\mathtt{L}} X_{i\mathtt{H}}]$,then we extract the feature from M_i and reduce the feature dimension by PCA and LDA.

To better evaluate the experimental results, we perform 10 runs for each experiment, and then calculate the average recognition rate. The comparison results are shown in Table 1.

From Table 1, we can see that both schemes of choosing Curvelet coefficient as feature can improve the iris recognition rate. But the low+bandpass frequency Curvelet coefficients as feature cannot get the better recognition rate. On the contrary, the speed of convergence is slow compared with the method that only uses the low frequency Curvelet coefficients as feature. The reason is that the bandpass frequency Curvelet coefficients are added into the feature vector which contain the unnecessary detailed information that will influence the recognition result. So the second scheme is inferior to the first. In this paper, we only select the lowest frequency Curvelet coefficient as feature in order to obtain a higher recognition speed.

TABLE 1. Average recognition rates of different runs with different frequency band Curvelet coefficients(%)

Number of samples of each person	Low frequency band feature	Low+bandpass frequency band feature
1	23.87	28.81
2	81.48	74.54
3	79.89	76.72
4	85.93	80.86
5	90.74	89.63
6	96.30	90.74
7	96.30	91.36
8	96.30	94.44
9	96.30	96.30

5.2. **Algorithm Comparisons.** In this experiment, we only select the first frequency Curvelet coefficients as feature. Then, we perform the Curvelet+PCA+LDA, Gabor filter, Haar wavelet, Curvelet+PCA and Curvelet+LDA iris recognition methods respectively on the same set. To better evaluate the experimental results, we perform 10 runs for each experiment, and then calculate the average recognition rate. The comparison results are shown in Table 2.

From Table 2, we can see that the recognition rate of normalized iris images which are transformed and extracted feature by Curvelet, PCA and LDA is higher than the other methods.

TABLE 2. Average recognition rates of different runs with different iris recognition methods(%)

Number of samples of each person	Curvelet+PCA +LDA	Gabor Filter	Haar Wavelett	Curvelet +PCA	Curvelet +LDA
1	23.87	64.16	23.87	68.72	23.87
2	81.48	74.07	75.00	78.70	77.31
3	79.89	77.78	76.52	81.48	81.48
4	85.93	81.48	83.60	82.72	80.25
5	90.74	84.44	84.57	83.70	87.41
6	96.30	87.04	86.19	87.04	92.59
7	96.30	86.42	88.41	86.42	93.12
8	96.30	85.19	89.63	83.33	94.13
9	96.30	92.59	91.51	92.59	95.26

6. **Conclusions.** In this paper, we propose an iris recognition method based on Curvelet, PCA and LDA. First, we preprocess the iris images by iris localization, elimination of eyelash shading and iris normalization. Then, we adopt the Curvelet transform to decompose the normalized images into 3 layers and only choose the first layer Curvelet coefficients as their features. Lastly, we further extract the feature and reduce the feature dimension

by PCA and LDA. The proposed iris recognition algorithm not only considers the iris texture curve features and eliminates the influence of environment noise, but also reduces the feature dimension. The experimental results show that our method can recognize the iris effectively.

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REFERENCES

[1] J. G. Daugman, Uncertainty relation for resolution in space, spatial frequency and orientation optimized by two-dimensional visual cortical filters, *Journal of the Optical Society of America*, vol. 2, no. 7, pp. 1160-1169, 1985.

[2] J. G. Daugman, and C. J. Downing, Demodulation, predictive coding, and spatial vision, *Journal of the Optical Society of America*, vol. 12, no. 4, pp. 641-660, 1995.

[3] R. P. Wildes, J. C. Asmuth, G. L. Green, S. C. Hsu, R. J. Kolczynski, J. R. Matey, and S. E. McBride, A machine-vision system for iris recognition, *Machine Vision and Applications*, vol.9, no. 1, pp. 1-8, 1996.

[4] W. W. Boles, and B. Boashash, A human identification technique using images of the iris and wavelet transform, *IEEE Trans. Signal Processing*, vol. 46, no.4, pp. 1185-1188, 1998.

[5] S. Lim, K. Lee, O. Byeon and T. Kim, Efficient iris recognition through improvement of feature vector and classifier, *ETRI Journal*, vol. 23, no. 2, pp.61-85, 2001.

[6] Y. Zhu, T. N. Tan, and Y. H. Wang, Biometrics personal identification based on iris pattern, *Acta Automatica Sinica*, vol. 28, no.1, pp. 1-10, 2002.

[7] J. L. Starck, F. Murtagh, E. J. Candes, and D. L. Donoho, Gray and color image contrast enhancement by the curvelet transform. *IEEE Trans. Image Processing*, vol. 12, no. 6, pp. 706-717, 2003.

[8] Y. Q. Zhang, P. L. Zhang, C. Xu, and G. D. Wang, Study on image feature extraction using singular value decompositon and curvelet transform, *Computer Simulation*, vol. 29, no. 12, pp. 303-306, 2012.

[9] M. Najafi, and S. Ghofrani, Iris recognition based on using ridgelet and curvelet transform, *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 4, no. 2, pp. 7-18, 2011.

[10] A. D. Rahulkar, D. V. Jadhav, and R. S. Holambe, Fast discrete curvelet transform based anisotropic iris coding and recognition using k-out-of-n: a fused post-classifier, *Machine Vision and Applications*, vol. 23, no. 6, pp. 1115-1127, 2012.

[11] A. Ahamed, and M. I. H. Bhuiyan, Low complexity iris recognition using curvelet transform, *Proc. of International Conference on Informatics, Electronics & Vision (ICIEV)*, pp. 548-553, 2012.

[12] J. X. Shi, and X. F. Gu, The comparison of iris recognition using principal component analysis, independent component analysis and gabor wavelets, *Proc. of The 3rd IEEE International Conference on Computer Science and Information Technology*, pp. 61-64, 2010.

[13] C. Duan, Q. H. Huang, X. G. Wang, and S. Wang, Remote image fusion based on PCA and dual tree compactly supported shearlet transform, *Journal of Information Hiding and Multimedia Signal Processing*, vol. 5, no. 3, pp. 485-496, 2014.

[14] D. L. Zhang, J. Q. Qiao, J. B. Li, L. Y. Qiao, S. C. Chu and J. F. Roddick, Optimizing matrix mapping with data dependent kernel for image classification, *Journal of Information Hiding and Multiedia Signal Processing*, vol. 5, no. 1, pp. 72-79, 2014.

[15] E. J. Candes, L. Demanet, D. Donoho, and L. Ying, Fast discrete curvelet transform, *Multiscale Modeling and Simulation*, vol. 5, no. 3, pp. 861-899, 2006.