High Performance Iris Recognition Based on LDA and LPCC

Chia Te CHU and Ching-Han CHEN
Institute of Electrical Engineering,I-Shou University,1, Section 1, Hsueh-Cheng Rd., Ta -Hsu Hsiang, Kaohsiung County, Taiwan, 840, R.O.C.
Email: cld123@giga.net.tw, pierre@isu.edu.tw

Abstract

In this paper, the iris recognition algorithm based on LPCC and LDA is first presented. So far, the two algorithms are not found for iris recognition in literature. In addition, a simple and fast training algorithm, particle swarm optimization (PSO), is also introduced for training the Probabilistic Neural Network (PNN). Finally, a comparative experiment of existing methods for iris recognition is evaluated on CASIA iris image databases. The proposed algorithms can achieve 100% recognition rates and the result is encouraging.

Keywords: iris recognition; wavelet transform; probabilistic neural network; particle swarm optimization.

1. Introduction

Iris recognition [1,7,12-14,18] is the process of automatically differentiating people on the basis of individuality information from their iris images. The technique can be used to verify the identity of a person when accessing a system. Due to its reliability and high precision, it is beneficial for biometric authentication system.

An iris recognition system can be decomposed into three modules: an iris detector for detection and location of iris image, a feature extractor and a matcher module.

In this paper, we focus our investigation on a new iris feature extraction and representation approach to further implement an iris recognition system with low complexity and high performance.

Firstly, in order to reduce system complexity, we use 2-D wavelet transform [2-3] to obtain a low resolution image and localize pupil position. By the center of pupil and the radius of pupil, we can acquire the iris circular rings. The more iris circular rings are acquired, the more information is abundant. Secondly, we adopt Sobel operator [4] to extract iris texture. The iris texture is stretched into 1-D array and it is regarded as a 1-D signal. The 1-D discrete wavelet transform is adopted to reduce the dimensionality of the signal. In our experiments, the wavelet permits to further reduce the system complexity. Finally, the LPCC and LDA algorithms are regarded for feature extraction methods. A PNN (Probabilistic Neural Network)[5] is regarded as classifier model that has proved to be effective for classification problems [16,19-21]. The PNN is optimized by PSO. Finally, the combination of the new feature extraction methods and PNN classifier is evaluated on the CASIA iris database [6] for iris recognition

2. Detection of iris region

The iris image, as shown in Fig. 1 (a), contains not only abundant texture information, but also some useless parts, such as eyelid, pupil, etc. The iris is between the pupil (inner boundary) and the sclera (outer boundary). In order to locate the pupil, a simple and efficient method is proposed. The procedure is as following:

1. Take a raw image and apply 2-D wavelet filtering. The size of the resulting image is only quarter of the original image.
2. Compute the histogram to find the maximum peak.

The Fig. 1(b) shows that the maximum peak of histogram is the gray values of pupil region, because the pupil region is concentrated on the lower gray values. The maximum peak is set to P and the threshold T is obtained by PxW. The W is weight and the value of it is set to 1.1 in the paper. The binary image B is obtained by the original image A.

$$B(i,j)=\begin{cases}1, & if \quad A(i,j)>T\\ 0, & if \quad A(i,j)<T\end{cases} \tag{1}$$

Because the binary image B has still some black points outside the pupil region, an estimated point is computed by a function $E(i,j)$:

$$E(i,j)=\sum_{ii=-1}^{1}\sum_{jj=-1}^{1}B(i+ii,j+jj) \tag{2}$$

and

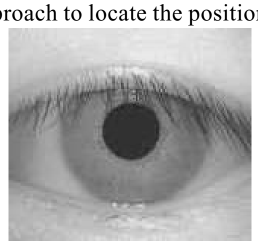
$$B'(i,j)=\begin{cases}B(i,j), & if \quad E(i,j)>=4\\ 1, & otherwise\end{cases} \tag{3}$$

If the value of $E(i,j)$ is greater or equal to 4, there are at least four dark points surrounding the $B(i,j)$. Because the estimated point is located in pupil region, the estimated point is retained. Otherwise the estimated point is removed. Finally, we use the vertical projection and horizontal projection to obtain the center coordinates and the radius of pupil. The extracted pupil region is shown in Fig. 1(c).

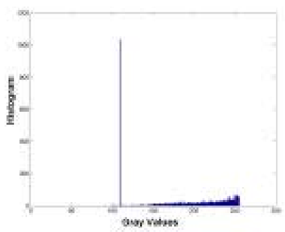
3. Because the center coordinates and the radius of the pupil are multiplied by two, the center coordinates and the radius of the pupil are obtained in original eye image.

4. The iris circular ring (such as seen in Fig. 1 (d)) is obtained by giving a radius from the center of the pupil.

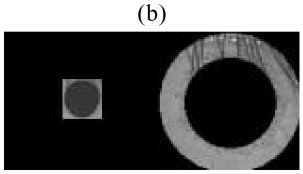
In the above procedure, the first step reduces the dimensionality of image to improve the efficiency of iris image extraction. The second and third steps provide an approach to locate the position of the pupil.



(a)



(b)



(c) (d)

Fig 1. Iris location:

(a) Original image (b) The histogram of the gray values of eye image (c) Segmented pupil (d) Iris image

We give different radius to get iris circular rings of different size. The more iris circular rings are extracted, the more information is used as features. The recognition performance is much better, but the efficiency is slightly affected. The proposed method is different from the traditional methods. The traditional methods extract a complete iris image, but the proposed method only extracts parts of the iris image for recognition. This will result in lower computational demands. In the next section, the detailed description of the iris feature extraction method will be presented.

3. Iris texture feature extraction

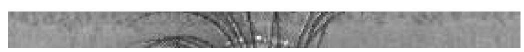
We extract consecutive circular rings using step 4 of iris location procedure. These circular rings then are stretched horizontally and accumulated, and construct a rectangular-type iris block image, shown as in Fig. 2 (a).

Iris texture has abundant texture information for iris identification or matching. Here we elaborate a very simple and fast algorithm to extract iris feature for iris recognition. The idea comes from that the iris features exist in high frequency. It is different from traditional 2-D iris feature extraction method. Firstly, The extracted iris image is normalized (see Fig. 2 (b)) and the Sobel operator is used to extract iris texture. The texture information is represented as 1-D energy profile signal, and the 1-D wavelet transform is applied in the profile signal [16] for generating the iris feature vector.

3.1 Sobel operator

The iris image is captured in different size from different people. It is not convenient for iris recognition, and the recognition performance is also affected. In the cause of the convenience of computation and achieving the high recognition performance, the number of captured iris circular ring from different iris image is the same. In order to enhance the texture of iris, the iris image is normalized. We adopt the Sobel operator to analyze texture shown as in Fig. 2(b) and (c) and the vertical Sobel mask S_x is as following:

$$S_{x=}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad (4)$$



(a)

(b)

(c)

(d)

Fig.2 (a) stretched iris block image; (b) normalized iris image; (c) iris image after Sobel operator (d) filtered iris image

So as to reduce the affection of noise, the smooth filter is adopted to filter the iris image as shown 2(d).

Finally, in order to extract the iris feature, a matrix I is constructed by all the filtered iris images according to the following equations:

$$\mathrm{I} = \begin{bmatrix} I_{1xn} & \cdots & I_{1xn} \\ \vdots & \ddots & \vdots \\ I_{mx1} & \cdots & I_{mxn} \end{bmatrix} \tag{5}$$

where m is denotes the total number of iris images, and n is the size of the iris image. If the image is 21x280 in our experiments, n is 5880(21x280). That is, each iris image is regarded as a 1-D signal.

3.2 LPCC

The LPCC [19] is a well-known algorithm and widely used to extract feature in speech signal. The advantage of feature extraction is for the dimension reduction and representation of original signal. In the paper, the LPCC is firstly presented for iris recognition.

The LPC generates prediction errors e(n).If the all-pole model was good, e(n) would be very small. Thus, e(n) can be stated as the ideal excitations of the all-pole mode. The LPC coefficients will be transformed into LPCC as feature vectors, because the robust and reliability of the LPCC coefficients is better that LPC ones.

Autocorrelation sequence $R(k)$ is obtained in the analysis of the signal from the equation 5.

$$R(k) = \sum_{n=-\infty}^{\infty} I(n)I[n+k]R(k) \quad k = 0,\cdots,p+1 \tag{6}$$

Where n is the sample index, and k is a time shift.

The Levinson-Durbin algorithm is an iterative method of computing the LPC coefficients.

$$\begin{aligned}
& E^{(0)} = R(0) \\
& for \quad i = 1:p \\
& k_i = R(i) - \sum_{j=1}^{i-1} \alpha_j^{(i-1)} R(i-j) \quad \alpha_i^{(i)} = k_i \big/ E^{(i-1)} \\
& for \quad j = 1 : i-1 \\
& \alpha_j^{(i)} = \alpha_j^{(i-1)} - k_i \alpha_{i-j}^{(i-1)} \\
& end \\
& E^{(i)} = \left(1 - k_i^2\right) E^{(i-1)} \\
& LPC \quad coefficients = a_i = \alpha_i^{(p)} \quad 1 \le i \le p
\end{aligned} \tag{7}$$

After LPC coefficients was obtained, we will obtain LPCC coefficients through transform:

$$c_m = a_m + \sum_{k=1}^{m-1} \left(\frac{k}{m}\right) c_k a_{m-k} \quad 1 \le m \le p \tag{8}$$

Since the LPCC coefficients can improve the robust and reliability of feature vector.

3.3 LDA

The basic idea of LDA [22] finds a linear transformation such that feature clusters are most separable after the transform. For a C-class problem and M images in each class, the between-class and within-class scatter matrices S_{b_x} and S_{w_x} are defined as:

$$S_{b_x} = \sum_{c=1}^{C} \left(\bar{I}^c - \bar{I}\right)\left(\bar{I}^c - \bar{I}\right)^T \tag{9}$$

$$S_{w_x} = \sum_{c=1}^{C} \sum_{m=1}^{M} \left(I_m^c - \bar{I}^c\right)\left(I_m^c - \bar{I}^c\right)^T \tag{10}$$

where $\bar{I}$ is a overall mean vector and $\bar{I}^c$ is the average vector of class C.

The class separability can be measured by a certain criterion. A commonly used one is the ratio of the determinant of the between-class scatter matrix of the projected samples of the within-class scatter matrix of the projected images:

$$A_{opt} = \arg\max_A \frac{\left|A^T S_{b_y} A\right|}{\left|A^T S_{w_y} A\right|} \tag{11}$$

The basic idea of the LDA is to find a matrix A that can simultaneously diagonalize both S_{b_x} and S_{w_x}, i.e.,

$$S_{w_x}^{-1} S_{b_x} A = A\left(A^T S_{w_x} A\right)^{-1}\left(A^T S_{b_x} A\right) \tag{12}$$

If we want to reduce dimension of the matrix from m to n, we can simply use first n rows of A as the transformation matrix, which corresponds to the largest n eigen values of $\left(A^T S_{b_x} A\right)$.

4. Learning algorithm

PSO is a new bio-inspired optimization method developed by Kenney and Eberhart [23] in 1995. PSO exploits cooperative and social behavior's heuristics, such as shoal of fishes, flock of birds and swarm of insects. The basic algorithm involves the start from a population of distributed individuals, named particles, which tend to move toward the best solution in the search space. These particles will remember the individual best solution encountered and the swarm population's best solution. At each iteration, every particle adjusts its velocity vector, based on its momentum and the influence of both its individual best solution and the swarm population's best solution.

At time unit t, the position of ith particle x_i, $i = 1,2...M$, (M is the number of particles) moves by adding a velocity vector v_i. v_i is the function of the best position p_i found by that particle, and of the best position g found so far among all particles of the swarm. The movement can be formulated as:

$$v_i = w(t)v_i(t-1) + c_1u_1(p - x_i(t-1)) + c_2u_2(g - x_i(t-1)) \tag{13}$$

$$x_i(t-1) = x_i(t) + v_i(t) \tag{14}$$

Where $w(t)$ is the inertia weight, c the acceleration constants, and $\mu \in (0,1)$ the uniformly distributed random variables.

5. Decision rule

In experiments, the feature vectors of iris image are extracted by LPCC and LDA. The two feature vectors are feed into the PNN. We use PSO to adjust the smooth parameter and obtain an optimized PNN. When the best smooth parameters are obtained, the PSO stop training. The output of PNN has two output probabilistic values P_{LPCC} and P_{LDA}. Therefore the average output of P_{LPCC} and P_{LDA} is P_{av}. The P_{av} will determine that the enrolled image belongs to.

6. Experimental procedure and results

In this section, the proposed method is evaluated on CASIA iris database and the results are reported. The database contains 756 iris images of 108 individuals (7 images per individual).

Experiments are divided into iris identification and iris verification. In the following experiments, a total of 324 iris images (three iris images of each person is extracted) were randomly selected as the train set and the rest of them as the test set. Such procedure was carried out 100 times. The experimental platform is the AMD K7 Athlon 2.2 GHz processor, 1G SDRAM, Windows XP, and the software is Matlab 6.5.

We use LPCC and LDA to extract the feature vector of iris images and the experimental results are shown in Table 1.

Table 1. Comparison of performance in LPCC and LDA

Methods	LPCC	LDA
Average recognition rates (%)	93.66	96.88
Best recognition rates (%)	97.45	99.31
Feature dimension	546	80

In Table 1, the best recognition rate is 99.31% in LDA and the best recognition rate is 97.45% in LPCC. The feature dimension of LDA is less than LPCC. Hence, We know LDA is better than LPCC.

In next experiment, the integration of LDA and LPCC is proposed for improvement of performance. The proposed method is expected to achieve a higher accuracy.

Table 2. Comparison of performance in CASIA iris database

Methods	The proposed method without PSO	The proposed method with PSO
Average recognition rates (%)	98.38	99.14
Best recognition rates (%)	100.0	100.0
Recognition time (ms)/per image	<1ms	<1ms

In table 2, we know the proposed method indeed improves the accuracy of iris recognition. The recognition performance of the proposed method without and with PSO training is compared. In the first case, the average recognition rate of PNN without PSO is 98.38%. With PSO training, the average recognition rate is 99.14%. Experimental results have shown that the proposed method with PSO possesses the best recognition performance.

The previous methods [7-15] for iris recognition mainly focus on feature extraction and matching. Mayank Vatsa [17] implemented four algorithms based on Iris Code. The proposed method is based on feature extraction. Their algorithms are evaluated in CASIA iris database. In the same standard of experiment procedure, the proposed method will be compared with the four algorithms. The experimental results in Table3 are cited from Mayank Vatsa. Thus, we only analyze and compare the performance of feature representation of these methods. Here, the results will be presented in Table 3.

Table 3. The recognition performance of comparing with existing methods

Algorithms	FAR/FRR (%)	Overall Accuracy (%)
Avila [18]	0.03/2.08	97.89
Li Ma [15]	0.02/1.98	98
Tissue [14]	1.84/8.79	89.37
Daugman [10]	0.01/0.09	99.9
The proposed method	0.0/0.69	99.14

From the results shown in Table 3, we can find the proposed method performs a satisfactory efficiency in high performance. The above results show that the proposed method is only inferior to Daugman's method and much better than the others. So far, all researchers extract a complete iris image for recognition. We only need partial iris image for recognition. We extract characteristics of iris from the viewpoint of signal analysis, whereas the Daugman's method is based on the phase information. In fact, our current method achieves also the satisfied accuracy in high efficiency.

7. Conclusions

In the paper, we proposes a novel pupil located method and feature extraction method. Finally, the proposed method is combined with an optimized PNN. Each iris image is regarded as a 1-D signal. We use LPCC and LDA to extract feature vectors from each iris image. The combination of the proposed feature extraction methods and the optimized PNN is evaluated in CASIA iris database. The PNN optimized by PSO is better than the PNN without PSO. This shows the optimized PNN possesses better recognition performance. The experimental results show the superior of the proposed method. We show the LPCC and LDA are feasible in iris recognition. The experimental results show the superior of the proposed method.

References

1 P.W. Hallinan, "Recognizing Human Eyes," Geometric Methods Comput. Vision. Vol. 1570, pp. 214-226, 1991.

2 C. Sidney Burrus Ramesh A.Gopinath Hai ta Guo, "*Introduction to Wavelets and Wavelet Transforms: A Primer"*, 1998.

3 Jaideva C.Goswami and Andrew K. Chan "*Fundamentals of Wavelets*" 1999.

4 A. Rosenfeld, A.C. Kak, *Digital Picture Processing, Academic Press*, New York, 1976.

5 D.F.Specht,"Probabilistic Neural Network for Classification, Map, or Associative Memory", *Proceeding of the IEEE International Conference on Neural Network*, vol.1, pp525-532, 1988.

6 CASIA iris database. Institute of Automation, Chinese Academy of Sciences, [Online].http://www.sinobiometrics.com/casiairis.htm.

7 J. Daugman, *Biometric Personal Identification System Based on Iris Analysis*, United States Patent, no. 5291560, 1994

8 J. Daugman, "High Confidence Visual Recognition of Person by a Test of Statistical Independence," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp1148-1151, Nov. 1993

9 J. Daugman, "Demodulation by Complex-Valued Wavelets for Stochastic Pattern Recognition," *Int' l J, Wavelets, Multiresolution and Information Processing*, vol. 1, no. 1, pp. 1-17, 2003.

10 J. Daugman, "Statistical Richness of Visual Phase Information: Update on Recognition Persons by Iris Patterns," Int' l J. Computer Vision, vol. 45, no. 1, pp. 25-38 2001.

11 Li Ma, Tieniu Tan, Yunhong Wang, and Dexin Zhang, " Personal Identification Based on Iris Texture Analysis", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1519-1532, Dec. 2003

12 R.Wildes, J.Asmuth, G. Green, S. Hsu, R. Kolczynski, J. Matey, and S. McBride, "A Machine-Vision System for Iris Recognition," *Machine Vision and Application*, vol. 9, pp. 1-8, 1996.

13 R.Wildes, "Iris Recognition: An Emerging Biometric Technology," *Proc. IEEE*, vol. 85, pp. 1348-1363, 1997.

14 Christel-Loic Tisse, Lionel Torres,Michel Robert, "Person Identification Based on Iris Patterns," *Proceedings of the 15 th International Conference on Vision Interface*, 2002.

15 L. Ma, Tan, Tieniu, Wang, Yunhong, " Iris Recognition Using Circular Symmetric Filters", *Processing of THE 16Th International Conference on Pattern Recognition*, vol.2, pp. 414-417, 2002.

16 Chia-Te CHU and Ching-Han CHEN, "The Application of Face Authentication System for Internet Security Using Object-Oriented Technology", *Journal of Internet Technology.* (Accepted)

17 Mayank Vatsa, Richa Singh, and P.Gupta, "Comparison of Iris Recognition Algorithms", *Proceedings of ICISIP'04*, India, pp.354-358, 2004.

18 Sanchez-Avila C., Sanchez-Reillo R.; de Martin-Roche D., "Iris Recognition for Biometric Identification Using Dyadic Wavelet Transform Zero-Crossing", *Proceedings of the IEEE 35th International Carnahan Conference on Security Technology*, pp. 272-277, 2002.

19 Ching-Han CHEN, Chia-Te CHU, "An High Efficiency Feature Extraction Based on Wavelet Transform for Speaker Recognition", *2004 International Computer Symposium (ICS2004)*, Taipei, Dec 2004.

20 Ching-Han CHEN, Chia-Te CHU, " Combining Multiple Features for High Performance Face Recognition System ", *2004 International Computer Symposium (ICS2004)*, Taipei, Dec 2004.

21 Ching-Han CHEN and Chia-Te CHU, "Real-Time Face Recognition Using Wavelet Probabilistic Neural Network", J*ournal of Imaging Science and Technology*. (Accepted)

22 Juwei Lu, Kostantinos N. Plataniotis, and Anasios N. Venetsanopoulos, " Face Recognition Using LDA-Based Algorithms," *IEEE Trans. Neural Networks*, vol.14, no.1, Jan 2003.

23 J.Kennedy et al., "Particle Swarm Optimization", Proc of *IEEE Int. Conf. Neural Networks,* vol. IV, pp.1942-1948, 1995.