IRIS RECOGNITION USING 2D-LDA + 2D-PCA

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ABSTRACT

This paper presents a biometric iris recognition using 2D-LDA with embedding 2D-PCA. A new approach that the 2D-PCA is embedded into the 2D-LDA to improve its performance is proposed. The approach first finds the most concentrated training samples in each class, and uses the sample mean to represent the class. Then the 2D-PCA is adopted to find the projection matrix which can scatter the variance between classes. The results show that the new approach has an encouraging performance. The recognition rate up to 99.20% can be achieved.

Index Terms—*Biometric Recognition, Iris, Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA).*

1. INTRODUCTION

The recent advances of information technology and the increasing requirement for security have led to a rapid development of intelligent personal authentication techniques based on biometric recognition. Biometrics [1] employs physiological or behavioral characteristics to accurately identify each subject. The human iris, a thin circular diaphragm lying between the cornea and the lens, has an intricate structure with many minute characteristics, such as furrows, freckles, crypts and coronas. These visible characteristics, generally called the texture of the iris, are unique to each subject [2]. The iris recognition algorithms can be grouped into three main categories:

(1) Filter-based methods: Daugman [2] made use of multiscale Gabor filters to demodulate texture phase structure information of the iris. Filtering an iris image with a family of filters resulted in 1,024 complex-valued phasors which denote the phase structure of the iris at different scales. The resulting 2048-component iriscode was used to describe an iris. Tan *et al*. [3] developed a texture analysis-based iris recognition.

(2) Transform-based methods: Wildes *et al*. [4] represented the iris texture with a Laplacian pyramid constructed with four different resolution levels and used the normalized correlation to determine whether the input image and the model image are from the same class. Lim *et al*. [5] decomposed an iris image into four levels using 2D Haar wavelet transform and quantized the fourth-level high-frequency information to form an 87-bit code. Boles and Boashash [6] calculated a zero-crossing representation of 1D wavelet transform at various resolution levels of a concentric circle on an iris image to characterize the texture of the iris.

(3) Projection-based analysis: Bae *et al.* [7] projected iris signals onto a bank of basis vectors derived by independent component analysis and quantized the resulting projection coefficients as features. Sepehr *et al.* [8] use the real term of 1D Gabor filter, and reduce the dimensionality of the extracted features by 2D-PCA.

2. SYSTEM OVERVIEW

The proposed system consists of three modules: image pre-processing, feature extraction, and recognition. The entire system flow is briefly described as follows. First, the pre-processing employs some image processing algorithms to demarcate the region of interest (i.e., iris zone) from the input image containing an eye. It performs three major tasks: localization/segmentation, normalization/transformation, and enhancement, as shown in Fig. 1. Next, the feature extraction performs a 2D-LDA with embedding 2D-PCA to compute the projection matrices. Using these projection matrices projects iris images to lower dimension, and generates the iris feature vectors. Finally, the pattern recognition employs a minimum distance classifier according to Euclidean distance metric to recognize the iris pattern by comparing the iris features with the enrolled iris features in the database.

3. THE MODIFIED 2D-LDA

3.1. LDA and IM-LDA

The original linear discriminant analysis (LDA) [9] is a supervised learning approach by seeking to preserve the discriminant information. The LDA finds a subspace projected onto which the data points of different classes are as far as possible while the data points of the same class are as compact as possible. The optimal projections are obtained by minimizing the matrix-norm of within-class scatter matrix and maximizing the matrix-norm of between-class scatter simultaneously. Since LDA is vector-oriented;

that is, an original 2D image is reshaped into a 1D long vector before using LDA. The vectorization may bring on some drawbacks. First, the intrinsic 2D structure of an image matrix is broken, thus the spatial information contained therein is not used effectively. Second, the operation is very time consuming. To remedy the critical drawbacks of LDA, image matrix-based linear discriminant analysis (IM-LDA) [10] was proposed. Different from classical LDA, IM-LDA is directly performed on 2D image matrices rather than 1D vectors.

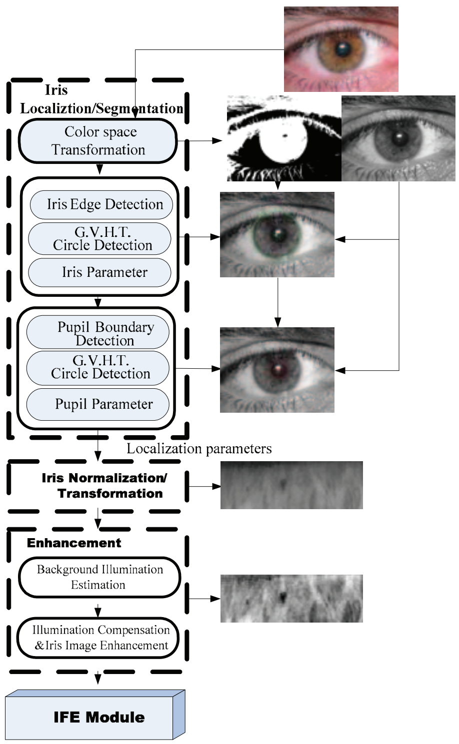


Fig. 1: Pre-processing module.

Suppose there are c known classes. S is the total number of training samples and S_i is the numbers of training samples in class i. In class i, the j-th training image is denoted by an $(m \times n)$ matrix $A_j^{(i)}$. The mean image of training samples in class i is denoted by $\bar{A}^{(i)}$ and the mean image of all training sample is $\bar{A}$. Based on the given training image matrices, the image between-class scatter matrix G_b and image within-class scatter matrix G_w can be constructed by

$$G_b = \frac{1}{S}\sum_{i=1}^{c} S_i \left(\bar{A}_i - \bar{A}\right)^T \left(\bar{A}_i - \bar{A}\right) \tag{1}$$

$$G_w = \frac{1}{S}\sum_{i=1}^{c}\sum_{j=1}^{S_i} \left(A_j^{(i)} - \bar{A}^{(i)}\right)^T \left(A_j^{(i)} - \bar{A}^{(i)}\right) \tag{2}$$

The generalized Fisher criterion can be defined by

$$J(\Phi) = \frac{\Phi^T G_b \Phi}{\Phi^T G_w \Phi} \tag{3}$$

It is easy to find a set of optimal discriminating vectors $\Phi_d = [\varphi_1, \varphi_2, \cdots, \varphi_d]$ by maximizing the Fisher criterion $J(\Phi)$, where $\Phi_d = [\varphi_1, \varphi_2, \cdots, \varphi_d]$ is the set of generalized eigenvectors of G_b and G_w corresponding to the d largest generalized eigenvalues, i.e., $G_b\varphi_i = \lambda_i G_w \varphi_i$, where $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_d$. The obtained eigenvectors Φ_d are used for image feature extraction. Let

$$B = A\Phi_d, \tag{4}$$

where $\Phi_d = [\varphi_1, \varphi_2, \cdots, \varphi_d]$, the resulting feature matrix **B** is used to represent image **A**. The transform is called the uncorrelated IM-LDA in horizontal direction.

After transformation in horizontal direction, we get the feature matrix **B** of sample **A** using Eq.(4). Constructing the image between-class and within-class scatter matrices H_b and H_w based on B^T, we have

$$H_b = \frac{1}{S}\sum_{i=1}^{c} S_i \left(\bar{B}_i - \bar{B}\right)^T \left(\bar{B}_i - \bar{B}\right) \tag{5}$$

$$H_w = \frac{1}{S}\sum_{i=1}^{c}\sum_{j=1}^{S_i} \left(B_j^{(i)} - \bar{B}^{(i)}\right)^T \left(B_j^{(i)} - \bar{B}^{(i)}\right) \tag{6}$$

where $\bar{B}^{(i)} = \bar{A}^{(i)}\Phi_d$ and $\bar{B} = \bar{A}\Phi_d$. Similarly, it is easy to find a set of optimal discriminating vectors $\Omega_e = [\omega_1, \omega_2, \cdots, \omega_e]$ by maximizing the Fisher's criterion,

$$J(\Omega) = \frac{\Omega^T H_b \Omega}{\Omega^T H_w \Omega} \tag{7}$$

We obtain the IM-LDA feature matrix of B^T by

$$C^T = B^T \Omega_e. \tag{8}$$

Thus

$$C = \Omega_e^T B = \Omega_e^T A \Phi_d. \tag{9}$$

The resulting feature matrix **C** is an $e \times d$ matrix, which is arranged into a feature vector for classification.

3.2. 2D-LDA

The 2D-LDA [11] is based on 2D matrices rather than 1D vectors. The initial idea of 2D-LDA is to perform the uncorrelated IM-LDA twice: the first is in horizontal direction and the second is in vertical direction. After performing two sequential IM-LDA transforms, the discriminant information is compacted into a small matrix.

The 2D-LDA method has been one of the most useful face recognition [12] and gait recognition [13], however, in the literature, has not ever been used in iris recognition.

3.3. 2D-PCA

The two-dimensional principal component analysis (2D-PCA) [14] is used to eliminate the correlation between images. We can derive it by following the procedure of IM-LDA but modify the formula as follows. Based on the given training image samples (image matrices), the image total scatter matrix can be calculated by

$$\mathrm{G}_T = \frac{1}{S}\sum_{i=1}^{c}\sum_{j=1}^{S_i}\left(\mathrm{A}_j^{(i)} - \bar{\mathrm{A}}\right)^T \left(\mathrm{A}_j^{(i)} - \bar{\mathrm{A}}\right) \tag{10}$$

$$\mathrm{H}_T = \frac{1}{S}\sum_{i=1}^{c}\sum_{j=1}^{S_i}\left(\mathrm{B}_j^{(i)} - \bar{\mathrm{B}}\right)\left(\mathrm{B}_j^{(i)} - \bar{\mathrm{B}}\right)^T \tag{11}$$

The generalized criterion can be modified and defined by

$$J(\Phi) = \Phi^T \mathrm{G}_T \Phi \tag{12}$$

$$J(\Omega) = \Omega^T \mathrm{H}_T \Omega \tag{13}$$

Finally, we also compute $\Phi_d = \left[\varphi_1, \varphi_2, \cdots, \varphi_d\right]$ and $\Omega_e = \left[\omega_1, \omega_2, \cdots, \omega_e\right]$ to compact an image into a small matrix. The 2D-PCA has been applied to face recognition [15], palmprint recognition [16] and iris recognition [8].

3.4. The Proposed Method: 2D-LDA + 2D-PCA

Based on the 2D-LDA, our proposed method, as shown in Fig. 2, is divided into two parts instead of directly using the Fisher criterion method. Our main idea is to prevent the outliers in each class since the representation of each class derived from training image set which contains outliers may be misleading. We construct 2D-PCA model to compact original images to small matrices. The matrices are reshaped to column vectors, and normalize them. According to inner product (cosine similarity) of every pair of them, we extract a subset concentrated more than training samples set. The larger number calculated implies the more similar they are.

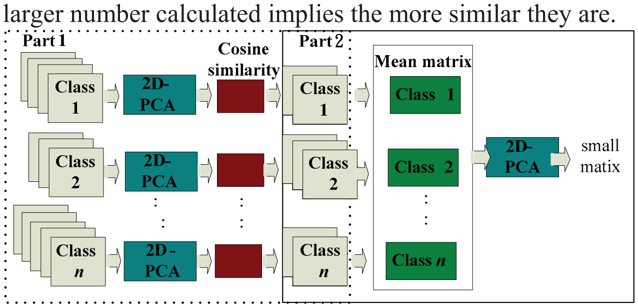


Fig. 2: Illustration of the proposed method.

After getting the result subset of training image from part 1, we adopt the mean matrix as a class representation. At part 2, our method is of a sort similar to 2D-PCA but embed the concept of "class" in it. Actually, we employ the mean matrix instead of total images as the input data of 2D-PCA. Accordingly, we modify Eq.(11) and Eq.(12) as follows:

$$\mathrm{G}_P = \frac{1}{c}\sum_{i=1}^{c}\left(\hat{\mathrm{A}}^{(i)} - \bar{\mathrm{A}}\right)^T \left(\hat{\mathrm{A}}^{(i)} - \bar{\mathrm{A}}\right) \tag{14}$$

$$\mathrm{H}_P = \frac{1}{c}\sum_{i=1}^{c}\left(\hat{\mathrm{B}}^{(i)} - \bar{\mathrm{B}}\right)\left(\hat{\mathrm{B}}^{(i)} - \bar{\mathrm{B}}\right)^T \tag{15}$$

where $\hat{\mathrm{A}}^{(i)}$ and $\hat{\mathrm{B}}^{(i)}$ denote the mean matrices of subset training samples in class i.

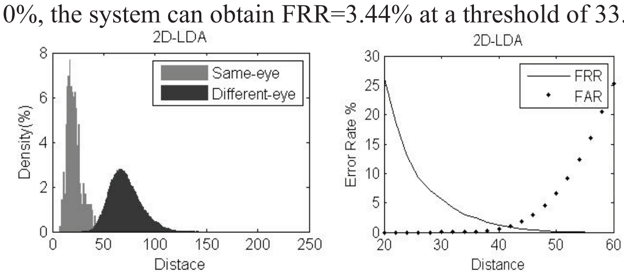
4. EXPERIMENTAL RESULTS

To evaluate the performance, we tested the proposed schemes on the UBIRIS iris image database. It comprises 1,205 iris images captured from 241 different eyes (i.e., 241 classes). Each image has the resolution of 600×800 in color. For each class, 5 images are captured. The proposed system has the rate (each class at least 3 images) of 94.02% (1,133 images) from 1,205 images by passing pre-processing procedure. We regard 220 classes as legal users and the rest as impostors. We train the system by selecting 3 images to be the training images for each person (total 660 images) from the authorized users in the enrollment phase. Hence, there are 473 images for testing (416 images from the authorized users and 57 images from the impostors).

4.1. Results of the 2D-LDA Method

In this experiment, we test the recognition performance for the 2D-LDA method. To obtain a threshold separating FRR and FAR, we perform two tests: one is for false rejection test (416 times) and the other is for false acceptance rate test (248,184 times). For the case of FRR, we can obtain the distribution of non-matching distance between the unknown classes and the registered classes. For the case of FAR, we also obtain the distribution of non-matching between the unknown classes for impostors and the registered classes. Fig. 3(a) shows the distributions of the above two experiments. In this figure, the *x*-axis and *y*-axis indicate the number of data and the degree of distance, respectively.

Fig. 3(b) shows the plot of the variation of FRR and FAR according to the distribution of non-matching distance by selecting a proper distance threshold. When we set the threshold to 43, the system obtains the recognition performance of about EER=0.95%. When the FAR is set to 0%, the system can obtain FRR=3.44% at a threshold of 33.

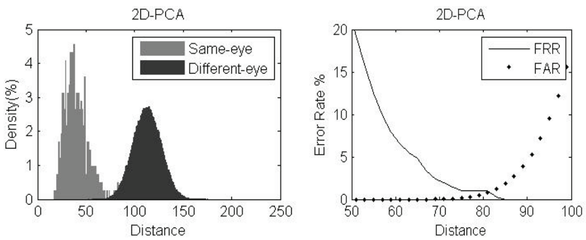


(a) (b)

Fig. 3: Results of the 2D-LDA method: (a) Distribution of non-matching distance, (b) variation of FRR and FAR.

4.2. Results of the 2D-PCA Method

We test the performance for the 2D-PCA separately as the previous method. In the 2D-PCA, we obtain the distribution of non-matching distance for FRR and FAR, shown in Fig. 4(a). Fig. 4(b) shows the plot of the variation of FRR and FAR in the 2D-PCA by selecting a proper distance threshold. By selecting the threshold of 78, the system obtains the performance of EER=0.78%. Similarly, if the FAR is set to 0%, the system obtains FRR=2.64% at a threshold of 67.

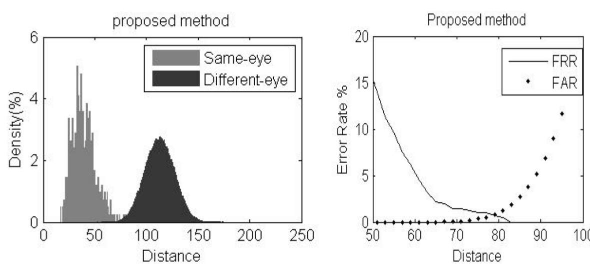


(a) (b)

Fig. 4: Results of the 2D-PCA method: (a) Distribution of non-matching distance, (b) variation of FRR and FAR.

4.3. Results of the Proposed Method

We perform the same experiments for our proposed method. We obtain the distribution of non-matching distance for FRR and FAR, as shown in Fig. 5(a). Fig. 5(b) shows the plot of the variation of FRR and FAR in the proposed method by selecting a proper distance threshold. The performance is about EER=0.74% by selecting the threshold of 78. Similarly, if FAR is set to 0%, the system obtains FRR=2.16% at a threshold of 65. The results show that the proposed method can perform slightly better than the 2D-PCA. We claim that the superiority of our proposed method gains from considering the relationship between classes.



(a) (b)

Fig. 5: Results of the proposed method: (a) Distribution of non-matching distance, (b) variation of FRR and FAR.

We make a summary of the experimental results in Table 1. The results show that our proposed method has a superior performance to the 2D-LDA and 2D-PCA methods by comparing the EER performance. On the other hand, the proposed method can perform superiorly in the case of FAR=0%. Consequently, the proposed method provides a securer system than the other two methods.

Table 1 Recognition accuracy comparison

Mode	**IFE Module**	**Features**	**RA (%)**	**AA (%)**	**AF (%)**	**RF (%)**
ERR	2D-LDA	65	0.95	99.05	0.95	99.05
	2D-PCA	65	0.78	99.22	0.78	99.22
	Proposed	65	0.74	99.26	0.74	99.26
FAR = 0%	2D-LDA	65	3.44	96.56	0	100
	2D-PCA	65	2.64	97.36	0	100
	Proposed	65	2.16	97.84	0	100

5. CONCLUSION

In this paper, a human iris recognition system using 2D-LDA with embedding 2D-PCA has been proposed. Our method surpasses 2D-LDA and 2D-PCA though all the methods can obtain a good recognition rate.

6. REFERENCES

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