A Method for Face and Iris Feature Fusion in Identity Authentication

Jun-ying Gan , Yu Liang
School of information, Wuyi University, Jiangmen City, Guangdong Province, P.R.C. 529020

Abstract

Multimodal biometric fusion and identity authentication technique help achieve an increase in performance of identity authentication system. In this paper, combined with the characteristics of 2-Dimensional Fisher Linear Discriminant Analysis (2DFLD), a method for face and iris feature fusion is presented on the basis of feature extraction and fusion. Experimental results on ORL (Olivetti Research Laboratory) face database and CASIA (Chinese Academy of Sciences, Institute of Automation) iris database show that, the problem that within-class scatter matrix maybe singular can be solved by the method, and a higher correct recognition rate can be gained. Results also demonstrate the validity of the method, and a new approach is supplied for multimodal biometric feature fusion and recognition.

1. Introduction

Along with the development of information age, biometric identity authentication has been paid more and more attention to, which is the main means for protecting information security. Because human beings possess unique and measurable physiological or behavioral characteristic information, biometric identity authentication inevitably becomes a trend in the field of identity authentication. Single biometric identity authentication has its own shortage that is hard to be conquered. Up to date, there is no biometric system that could satisfy the requirement perfectly. Therefore, the performance of single biometric system need be improved, and the techniques of multimodal biometric system can offer a feasible method to solve the problems coming from single biometric system [1].

Multimodal biometric system makes use of different biometric traits simultaneously to authenticate a person’s identity. The key technique of multimodal biometric system is information fusion. In multimodal biometric system, there are generally three sorts of fusion levels. The first one is fusion at the feature extraction level; the second one is fusion at the matching score level; and the third one is fusion at the decision level [1, 2]. Many studies about multimodal biometric system mainly focus on fusion at the matching score level and decision level. Fusion at the matching score level means to combine the matching scores coming from different biometric systems, and get classification results. Compared with the other fusion method, fusion at the matching score level draws more attention due to the easier actualization, and its main fusion methods include sum rule, decision trees, linear discriminant and so on [1]. Fusion at the decision level is easiest, because classification results from different biometric systems are integrated to make the final classification by appropriate ways, such as OR rule and AND rule. Fusion at the feature extraction level is to combine biometric features from different biometric systems, and the corresponding original feature vectors are integrated into one higher-dimensional feature vector. At present, there are few studies about fusion at the feature extraction level, because there exist some difficulties on how to integrate single biometric system.

Face recognition is most natural and acceptable in identity authentication; and iris recognition is more accurate. In order to improve the performance of biometric system, face and iris features are selected to construct multimodal biometric system in this paper. Up to now, there is little research work on face and iris feature fusion in identity authentication. Dr. Tieniu Tan proposed a method for combining face and iris biometrics in identity verification in 2003, which studies information fusion at the matching score level [3]. Meantime, comparisons of fusion methods including sum rule, Fisher Linear Discriminant Analysis (FLD) and Radial Basis Function Neural Network (RBFNN) are also discussed deeply.

In this paper, combined with the characteristics of 2-Dimensional Fisher Linear Discriminant Analysis (2DFLD), a method for face and iris feature fusion in identity authentication is presented based on fusion at the feature extraction level. Experiments are done on ORL (Olivetti Research Laboratory) face database and

CASIA (Chinese Academy of Sciences, Institute of Automation) iris database. Results show that a higher correct recognition rate can be gained, and a new approach is supplied for multimodal biometric identity authentication.

2. The model of face and iris feature fusion

The model of face and iris feature fusion is shown in Fig.1. Firstly, face image preprocessing and feature extraction are done to attain face original feature matrix. Then feature standardization (FS) is applied to the face original feature matrix. Meanwhile, iris image preprocessing and feature extraction are realized to gain iris original feature matrix, and feature standardization is done to the iris original feature matrix. Secondly, feature combination (FC) is used to integrate the face standardization matrix and iris standardization matrix into one matrix, and the combined matrix is obtained. Then, feature fusion and extraction are done to the combined matrix by way of 2DFLD. Meanwhile, the optimal discriminating projection matrix is constructed, and the fusion feature matrix is gained. Finally, NND is applied in recognition. Each module of the model is discussed as follows.

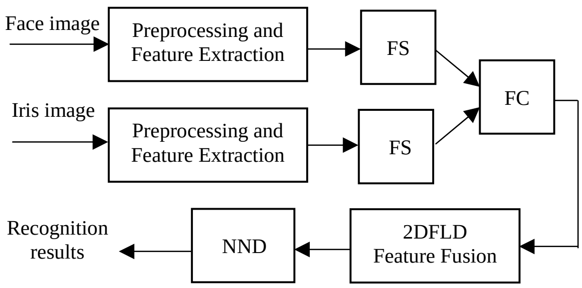

Fig.1 The model of face and iris feature fusion

2.1. The work before feature standardization

Face feature extraction and iris feature extraction belong to two separate modules. Any approach of face preprocessing and feature extraction can be used in its corresponding module, while any method suits iris preprocessing, and feature extraction can be used in the corresponding module too. In this paper, the methods of face preprocessing and feature extraction can refer to the literature [4], and the approach utilized in the module of iris preprocessing and feature extraction can refer to the literature [5]. Then, Face original feature matrix $F \in R^{b\times d}$ and iris original feature matrix $I \in R^{p\times q}$ can be obtained respectively, as shown in Fig.1.

2.2. Feature standardization and feature combination

There exist differences between face original feature matrix F and iris original feature matrix I because of the differences of feature extraction methods and measurement, so data proportion between matrix F and I may lose balance if the two matrixes are integrated directly. In order to eliminate the influence of unbalance, face original feature matrix F and iris original feature matrix I need be standardized apart.

Suppose C is the number of training samples, and the original feature matrix of training samples is denoted by A_j, $j = 1, 2, \cdots, C$. Thus the procedure of feature matrix standardization can be described as

$$\mu = \frac{1}{C}\sum_{j=1}^{C} A_j \tag{1}$$

$$\sigma = \frac{1}{C}\sum_{j=1}^{C} \left|A_j - \mu\right| \tag{2}$$

$$B_j = \frac{A_j - \mu}{\sigma}, \quad j = 1, 2, \cdots, C \tag{3}$$

Where μ and σ are respectively called as average matrix and average variance matrix from original feature matrix of training samples; B_j expresses the standardized feature matrix. After feature standardization, face original feature matrix F and iris original feature matrix I are converted into matrix $F' \in R^{b\times d}$ and $I' \in R^{p\times q}$ respectively. The two matrixes F' and I' can be combined as matrix $FI = [F', I']$. If b is not equal to p, one of the matrixes F' and I', whose row is lower, need be added by zeros according to the value of $|b - p|$. Therefore, the combined feature matrix FI is acquired, where $FI \in R^{\max(b,p)\times(d+q)}$.

2.3. Feature fusion and recognition based on 2DFLD

Based on 2-Dimensional Principal Component Analysis (2DPCA) by Jian Yang [6], 2-dimensional fisherface method is proposed by Ming Li et al [7]. Compared with traditional FLD, the problem, that within-class scatter matrix maybe singular when training samples are insufficient, can be solved, and the computation cost is decreased greatly because image matrix is directly used in calculation. In this paper, feature fusion and extraction are discussed according to the characteristics of 2DFLD.

Let $\overline{FI} \in R^{m\times n}$ denotes the average combined feature matrix of training samples; $\overline{FI}_i \in R^{m\times n}$ is the average combined feature matrix of class i of training samples; L_i is the combined feature matrix set of class i of training samples; $FI_k \in R^{m\times n}$ is the combined feature matrix belonging to element set L_i; M is the class number of training samples; and M_i is the number of class i of training samples. Then between-class scatter matrix S_B and within-class scatter matrix S_W from 2DFLD can be calculated respectively as follows

$$S_B = \sum_{i=1}^{M} M_i (\overline{FI}_i - \overline{FI})(\overline{FI}_i - \overline{FI})^{\mathrm{T}} \tag{4}$$

$$S_W = \sum_{i=1}^{M} \sum_{FI_k \in L_i} M_i (FI_k - \overline{FI}_i)(FI_k - \overline{FI}_i)^{\mathrm{T}} \tag{5}$$

Then the eigenvalues and eigenvectors of the matrix $S_W^{-1}S_B$ can also be computed, and the corresponding eigenvectors to the r larger eigenvalues can be chosen to construct the optimal discriminating projection matrix, represented by $W_{\mathrm{opt}} = [w_1,\ w_2,\ \cdots,\ w_r]$, where $r \le d + q$. The combined feature matrix FI of training samples is projected to W_{opt}, denoted by

$$v_j = w_j^{\mathrm{T}} FI, \qquad j = 1,2,\cdots,r \tag{6}$$

After projection conversion, each combined feature matrix FI corresponds to the projected feature matrix $V = [v_1,\ v_2,\ \cdots,\ v_r]^{\mathrm{T}}$, which demonstrates face and iris fusion feature matrix. Finally, NND rule is utilized in recognition.

3. Experimental results and analysis

3.1. Experimental data

At present, there is no public multimodal database that includes both face image and iris image from the same person. Due to the independence of face and iris biometric traits, it is allowed that face data of some one is assigned to iris data of the same person [3]. In this paper, experiments have been done on ORL face database and CASIA iris database.

ORL face database includes 400 face images. There are 10 different face images for each one of 40 distinct subjects. All the face images were taken with the subjects in an upright frontal position and with tolerance for some tilting and rotation of up to about 20. There are some variations in scales of up to about 10%. The images are grayscale with a resolution of 112×92. The gray level is 256. National Laboratory of Pattern Recognition (NLRP) offers CASIA iris database. This database (Version 1.0) includes 756 iris images from 108 eye classes altogether. The images are grayscale with a resolution of 320×280. The gray level is 256. For each eye, 7 images are captured in two sessions, where three samples are collected in the first session and the other four in the second session.

In this paper, the front 7 face images for each class in ORL face database are chosen, and 280 face images are used in experiments altogether; whereas 40 eye classes in CASIA iris database are selected, and 280 iris images are used in experiments altogether. Then two kinds of biometric data chosen are assigned to match each other to form a new experimental database, called as original database in this paper.

3.2. Experimental results and analysis

In this paper, after the module of face preprocessing and feature extraction, each face image can be described as face original feature matrix with a resolution of 5×28. And through the module of iris preprocessing and feature extraction, iris original feature matrix with a resolution of 5×16 is acquired. Generally, the resolution of the original feature matrix lies on the method used in the module.

Face original feature matrix and iris original feature matrix need be standardized apart, and the two standardized matrixes are combined to form a combined feature matrix with a resolution of 5×44. In the meantime, between-class scatter matrix S_B and within-class scatter matrix S_W of the combined feature matrix of training samples are used to compute the eigenvalues and eigenvectors of the matrix $S_W^{-1}S_B$, where $S_W^{-1}S_B \in R^{5\times 5}$. Then the 5 eigenvectors corresponding to 5 largest eigenvalues are selected to construct the optimal discriminating projection matrix. After the combined feature matrix is projected to the optimal discriminating projection matrix, face and iris fusion feature matrix is acquired and regarded as the final recognition feature matrix. NND is utilized in recognition.

In order to demonstrate the validity of face and iris feature fusion based on 2DFLD, training samples and testing samples are both changed in experiments. Several front samples for each class are chosen as training samples, and the remainder samples for each class are chosen as testing samples. In addition, sample order for each class in original database is randomly produced to form a new database. Random sequence $[5\ 6\ 4\ 7\ 1\ 3\ 2]$ means that 7 samples for each class in original database are rearranged according to random sequence number 5, 6, 4, 7, 1, 3, and 2 to form a new database. Compared with original database, the samples in the new database are no changed but only sample order for each class is changed. Random sequence [1 3 5 4 7 5 2] means that the samples for each class in original database are rearranged according to random sequence number 1, 3, 5, 4, 7, 5, and 2 to form another new database. Experiments on the three databases are done respectively, as shown in Table 1.

Table 1 Correct recognition rate of face and iris feature fusion based on 2DFLD

Database	6_1	5_2	4_3	3_4	2_5
Original Database	100%	100%	96.67%	97.5%	98%
[5 6 4 7 1 3 2]	100%	100%	94.17%	95%	93%
[1 3 5 4 7 5 2]	100%	100%	100%	96.88%	90.5%

Table 1 shows correct recognition rate of face and iris feature fusion based on 2DFLD. In Table 1, the number '6_1' denotes that the front 6 samples for each class are chosen as training samples; whereas the remainder one for each class is chosen as testing sample. It is the same to the others. From Table 1, it can be seen that correct recognition rate based on the three databases reaches 100% entirely, when the front 5 samples for each class are chosen as training samples with 200 training samples in all, and the remainder 2 samples for each class as testing samples with 80 testing samples in all. When the front 2 samples for each class are chosen as training samples with 80 training samples in all, and the remainder 5 samples for each class as testing samples with 200 testing samples in all, correct recognition rate based on original database and the other two random databases reaches 98%, 93% and 90.5% respectively.

From Table 1, it can be known that different selection of the number of training samples and testing samples results in the variation of correct recognition rate; whereas random sample order for each class in original database can also lead to the variation of correct recognition rate. Experimental results show that a higher correct recognition rate can be gained. Moreover, because image matrix is directly utilized to calculate between-class scatter matrix and within-class scatter matrix, computation cost is decreased greatly. Furthermore, the shortcomings that within-class scatter matrix may be singular when training samples are insufficient can be overcome. It also demonstrates that the model of face and iris feature fusion in this paper is effective.

4. Conclusions and outlook

In this paper, 2DFLD is utilized in face and iris feature fusion on the basis of feature extraction and fusion, and the model of face and iris feature fusion in identity authentication is presented. Experiments are done on original database and the database with random sample order for each class. Results show that the method for face and iris feature fusion in identity authentication is valid, and a new approach is supplied for multimodal biometric identity authentication. In the future, the methods for more biometric fusion should be probed into for multimodal biometric identity authentication.

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6. References

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