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A Mixed Two-dimensional Linear Discriminate Method

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Abstract

Feature extraction is one of key technologies of the palmprint identification. In the light of the characteristics subspace palmprint identification technology, the two-dimensional principal component analysis, two-dimensional fisher linear discriminant and two-way two-dimensional principal component analysis algorithm is deeply analyzed. Based on two-dimensional subspace palmprint identification algorithm is a direct projection of the palmprint image matrix and is achieved very good results for dimension reduction. This paper proposed a mixed two-dimensional linear discriminant dimension reduction algorithm which can eliminate the relevance of rows and columns to get the best projection vector and extract optimal discriminant information. Experimental results show that the proposed method has faster extraction speed, higher recognition rate and better robustness.

Keywords: *feature extraction, palmprint identification, two-dimensional linear discriminant*

1. Introduction

Feature extraction is one of key technologies for palmprint recognition [1]. The measure of a good or bad feature extraction methods should take into account the best description feature and the best classification feature, but also should consider the method to extract low-dimensional feature. The most typical feature extraction method is subspace feature extraction method of principal component analysis (PCA) and linear discriminant analysis (LDA), which convert the image matrix into vector to realize feature extraction [2].

Extractting the main features to PCA method is the description of the image feture, while extracting the main features to LDA method is the image classification feature. However, PCA method exists overfitting problem, and LDA method will cause within-class scatter matrix singularity problem when the number of training samples is less than the dimension of the feature vector, which is the so-called small sample size problem. In order to solve such problems, the first PCA is used to dimensionality reduction, and then LDA techniques is adopted in the main low-dimensional molecular space. This is a PCA+LDA framework under subspace linear discriminant analysis techniques of dimension reduction [3] .

However, when the number of training samples N is too excessive, PCA and LDA need convert palmprint image matrix into vector, resulting in solving large matrix computationally intensive. So recognition need to consume a lot of computing resources to train discriminant vectors, which affect the speed of classification and identification efficiency. Two-dimensional principal component analysis (2DPCA) and two-dimensional Fisher linear discriminant (2DFLD) [4,5] have solved the problem of image matrix projection vector. They are directly projection to palmprint image matrix, therefore, computing resources consumption and feature loss are small. 2DFLD is also known as the two-dimensional linear discriminant analysis (2DLDA) [6].

2DFLD method is directly obtained from the image matrix within-class scatter matrix and between-class scatter matrix image matrix, which does not need to be converted into a one-dimensional vector. It can be better than the LDA method classification characteristics [6]. 2DPCA method is to extract the image compression features, eliminate the correlation of the image columns. But, there is still a high feature dimension without taking into account the redundancy row. In order to solve the above mentioned problems, it can eliminate the image column correlation while eliminating the correlation of the image lines, i.e. bidirectional 2DPCA method [7, 8]. This method can speed up the recognition speed, reduce the feature dimension , improve generalization ability and reduce the computational storage resources.

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PCA method, 2DPCA method or derived bidirectional 2DPCA method are based on principal component analysis method. Extracting feature based on principal component analysis is mainly descriptive feature of the images, while classification feature is used in the recogintion phase. Thus on the basis of the in-depth study and solve the small sample size problem PCA + LDA, this paper propsoed A Mixed Two-dimensional Linear Discriminate Method (TDLD) The content can be summarized as the following two aspects:

(1) To construct the overall scatter matrix of the columns and the overall scatter matrix of the rows to solve row projection matrix and a column projection matrix, eliminate the correlation of the columns and rows, and extract bidirectional 2DPCA subspace feature information.

(2) To construct a new within-class scatter matrix and between-class scatter matrix in bidirectional 2DPCA subspace to,define a new criterion function biaxial compression on the row and column directions, and extract discriminant features of bidirectional 2DPCA subspace .

2. Operation Mode and Evaluation Performance of Palmprint Recognition

2.1. Operation Mode of Palmprint Recognition

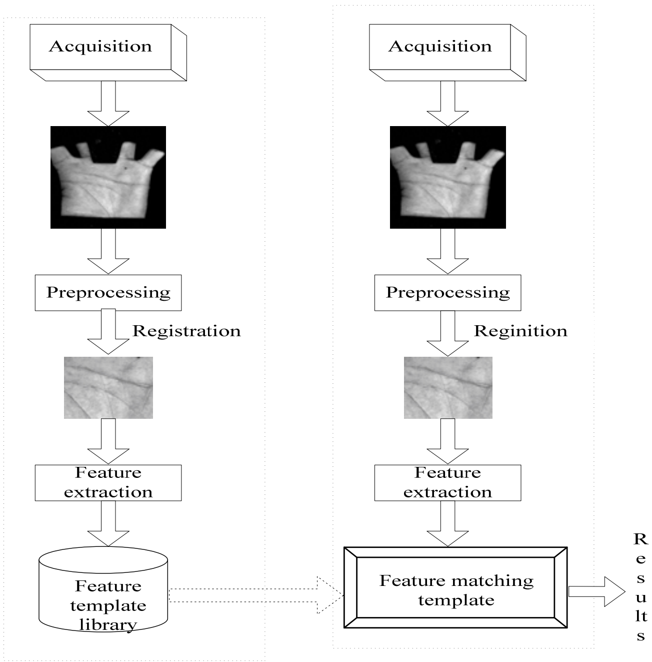

Figure 1. Structural Diagram of Palmprint Recognition System

Structural diagram of palmprint recognition system is shown in Figure 1. Any biometric identification systems include registration and regnition stages, and palmprint identification system also includes two stages. In the registration stage, first user name is registered to obtain the palmprint image through the palmprint acquisition. Then it is to preprocessing to obtain the effective ROI of palmprint image. Finally, a user template is created in the database after extracting the feature of the user. In the recognition stage, firstly, palmprint feature information of the user's is accquired, and various palmprint feature information is extracted. Then the extracted feature information is matched with the feature information in the template library to identify user identity. Finally, a final recognition result is obtained.

2.2. Evaluation Performance of Palmprint Recognition

Palmprint acquisition process will be subject to many uncertainties, so the palm of the same person at different times, in different locations which collected palmprint image is not exactly the same. Therefore there should be an evaluation metrics of palmprint recognition algorithm which is good or bad. It usually includes three arguments indicators which are False Reject Rate (FRR), False Accept Rate (FAR) and Genuine Accept Rate (GAR) to evaluate the various algorithms.

Input palmprint features will do not exactly match the registered palmprint features during the palmprint recognition. If the matching degree is greater than a selected threshold value, the user will be seemed legitimate user which is accepted. When the matching degree is smaller than the selected threshold, the user will be considered to be impersonator which is rejected. FRR is the probability which legitimate user is rejected as an impostor. FAR is the probability refers to an impostor as the legitimate user is accepted. GAR is the percentage of the correct number of samples and the total test sample in the match. They can be calculated using the following formula:

$$FRR = \frac{NFR}{NGA} \times 100\% \quad (1)$$

$$FAR = \frac{NFA}{NIA} \times 100\% \quad (2)$$

$$GAR = \frac{NCR}{NTA} \times 100\% \quad (3)$$

NGA represents the Number of Genuine Accesses which is the total number of the legitimate user. NIA represents the Number of Impostor Accesses which is the total number of the imposter user. NTA represents the Number of Test Accesses which is the total number of the test samples. NFR stands for the Number of False Rejection. NFA stands for Number of False Accesses Number of False Rejection. NCR stands for the Number of Correct Recognition.

FRR and FAR in the palmprint identification algorithm can be as small as possible, while GAR should be as large as possible. FAR is lower and GAR is higher, so the safety of the system is the higher. FRR is lower and GAR is higher, so the usability of the system is the better. However, the decrease of the FRR in the actual application system, will lead to the increase of the FAR, to the contrary, the decrease of the FAR will also accompanied the increase in the FRR. Thus FRR and FAR cannot be simultaneously reduced and will be always mutually restricting. Therefore, the system is designed to be trade-offs FAR and FRR relationship. For systems with high security requirements, such as military systems, should usually reduce the FAR, and ease of use is more important systems, access control systems such as civil should be appropriate to reduce the FRR.

In this paper for a comprehensive evaluation of the overall performance of the palmprint identification algorithms, using the following measure:

(1) To compare different palmprint identification algorithms correct recognition rate, that the accuracy of the recognition algorithm;

(2) System response time of a variety of algorithms, which the ease uses of the recognition algorithm;

(3) ROC (Receiver Operating Characteristic) curve of one of the criteria for the evaluation of biometric technology which the curve can reflect the GAR and FAR relations. ROC curve of the GAR and FAR is nearer the top of the figure, the system performance is the better. In ROC curves of the GAR-FAR, abscissa coordinates of the FAR generally are used logarithmic to represent, which can more significantly reflect FAR acceptable performance near zero. The indicator reflects the acceptability of the recognition algorithm.

The proposed algorithm mainly does performance evaluation around palmprint recognition system accuracy, ease of use and acceptability.

3. The Proposed Method

2D dimension reduction method includes 2DPCA, 2DFLD and bi-dimensional PCA. These methods are directly to extract feature to the image matrix, which can have good dimensionality reduction effect.

3.1. Bi-directional 2DPCA Method

Bi-directional 2DPCA method is to solve row projection matrix and column projection matrix by row total scatter matrix and column total scatter matrix. Let $X_i (i = 1, 2, \ldots, N)$ denotes the image feature matrix $(m \times n)$, where m is the number of pixels in the images after down sampling and n is the number of Gabor wavelets masks which is the product of the number of orientations and scales.

The row total scatter matrix C_i^{row} is defined as follows:

$$C_i^{row} = \frac{1}{Nm} \sum_{i=1}^{N} (X_i - \bar{X})(X_i - \bar{X})^T \tag{4}$$

Where $\bar{X} = \frac{1}{Nn} \sum_{i,\mu,\nu} X_{\mu,\nu}^{i}$ is the global mean. The vector that maximizes (4) is the eigenvector w of C_i^{row} corresponding to the largest eigenvalue. We need to select a set of projection directions, $W_{row} = [w_1^{row}, w_2^{row}, \ldots, w_{d_{row}}^{row}]$, which are orthonormal. In fact, the projection directions, $W_{row} = [w_1^{row}, w_2^{row}, \ldots, w_{d_{row}}^{row}]$, are the orhtonormal eigenvectors of C_i^{row} corresponding to the first d_{row} largest eigenvalues $d_{row} \le n$.

The column total scatter matrix C_i^{col} is defined as follows:

$$C_i^{col} = \frac{1}{Nn} \sum_{i=1}^{N} (X_i - \bar{X})(X_i - \bar{X})^T \tag{5}$$

The orthonormal projection matrix is $W_{col} = [w_1^{col}, w_2^{col}, \ldots, w_{d_{col}}^{col}]$ and d_{col} is the number of the largest eigenvalue to C_i^{col}.

From which the images can be efficiently represented along the rows using the W_{row} eigenvector and the columns using the W_{col} eigenvector as:

$$Y = W_{col}^T X W_{row} \tag{6}$$

Where Y is a $d_{row} \times d_{col}$ feature matrix. Therefore, the bi-directional compressed 2DPCA is a principal component of row projection and column projection at the same time.

3.2. MTDLD Method

There are L known pattern classes of training sample set and M training samples, where M_i the number of training sample is set in classes *i*. Let the training sample set is $X = \{x_{ij} \,|\, i = 1, 2, ..., L; j = 1, 2, ..., M_i\}, x_{ij} \in R^{m \times n}$, and x_{ij} is the jth training sample in classes *i*. Let bi-directional 2DPCA subspace mapping set is $Y = \{Y_{ij} \,|\, i = 1, 2, ..., L; j = 1, 2, ..., M_i\}, Y_{ij} \in R^{d_{col} \times d_{row}}$, where $Y = W_{col}^T X W_{row}$.

The between-class scatter matrix S'_B and the within-class scatter matrix S'_W in the directional 2DPCA subspace are described by

$$\begin{aligned} S'_B &= \frac{1}{M} \sum_{i=1}^{L} M_i (\tilde{\mu}_i - \bar{\mu})^T (\tilde{\mu}_i - \bar{\mu}) \\ &= \frac{1}{M} \sum_{i=1}^{L} M_i W_{col}^T W_{row} (\mu_i - \mu)^T (\mu_i - \mu) W_{col} W_{row}^T \\ &= W_{col}^T W_{row} S_B W_{col} W_{row}^T \end{aligned} \tag{7}$$

$$\begin{aligned} S'_W &= \frac{1}{M}\sum_{i=1}^{L}\sum_{j=1}^{M_i}(Y_{ij}-\tilde{\mu}_i)^T(Y_{ij}-\tilde{\mu}_i) \\ &= \frac{1}{M}\sum_{i=1}^{L}\sum_{j=1}^{M_i}W_{col}^T W_{row}(x_{ij}-\mu_i)^T(x_{ij}-\mu_i)W_{col}W_{row}^T \\ &= W_{col}^T W_{row} S_W W_{col} W_{row}^T \end{aligned} \tag{8}$$

The optimal projection vectors $J(\xi)$ of 2DFLD should meet the following Fisher criterion.

$$J(\xi)=\frac{\xi^T S'_B \xi}{\xi^T S'_W \xi} \tag{9}$$

Substituting into the above equation by (7) and (8):

$$J(\xi)=\frac{\xi^T W_{col}^T W_{row} S_B W_{col} W_{row}^T \xi}{\xi^T W_{col}^T W_{row} S_W W_{col} W_{row}^T \xi}=\frac{\xi^T \phi^T S_B \phi\xi}{\xi^T \phi^T S_W \phi\xi} \tag{10}$$

In above formula $\phi = W_{col} W_{row}^T$, the formula (9) is described as:

$$J(\psi)=\frac{\psi^T S_B \psi}{\psi^T S_W \psi} \tag{11}$$

Therefore, there is mapped to:

$$\psi=\xi\phi=\xi W_{col} W_{row}^T \tag{12}$$

Assumed to be the optimal projection matrix $\psi=[\psi_1,\psi_2,\cdots,\psi_k]$, the projector feature matrix ψ for a given palmprint image μ is followen as:

$$\Gamma=[\Gamma_1,\Gamma_2,\cdots,\Gamma_k]=\mu[\psi_1,\psi_2,\cdots,\psi_k]=\mu\xi\phi=\mu\xi W_{col}W_{row}^T \tag{13}$$

4.2. Feature Classification

In the testing phase, the test samples is projected in the feature subspace, which the projection of the test samples X is named as Γ , and the projection of the training sample points X_i in the feature subspace is recorded as Γ_i , then the normalized distance d_i is calculated between the test samples and all the training sample points, d_i can be expressed as:

$$d_i=\sum_{m=1}^{k}\left\|\frac{\Gamma_m^i-\Gamma_m}{\Gamma_m}\right\|_2, \qquad i=1,2,\cdots,M \tag{14}$$

Find the minimum distance of the normalized distance d_i between the test sample X and all of the training sample points X_i is expressed as:

$$D_{\min 1}=Min(d_i), \quad i=1,2,\cdots,M \tag{15}$$

Similarly, the second category normalized distance d_j between the test sample and the training samples and the same sample point can be expressed as:

$$d_j=\sum_{m=1}^{k}\left\|\frac{\Gamma_m^j-\Gamma_m}{\Gamma_m}\right\|_2, \qquad j=1,2,\cdots,M_i \tag{16}$$

Obtain the minimum distance d_j between the test sample and the training samples from the same sample point is expressed as:

$$D_{\min 2} = Min(d_j), \quad j = 1, 2, \cdots, M_i \tag{17}$$

Comparing two types of minimum distance, if $D_{\min 1} = D_{\min 2}$, the result is correct for palmprint recognition; if $D_{\min 1} \neq D_{\min 2}$, the result is false for palmprint recognition.

4. Results and Analysis

To reduce the computational cost and the computational complexity, the resolution of the palmprint images cropped is decreased to 128 × 128. During the experiments, the features are extracted by using the proposed method with different lengths. The weighted Euclidean distance is employed to cluster those features. All experiments were carried out under the Matlab7.0/PIV2.80GHz/1.99GBRAM experimental platform.

Table 1. Comparison Result of Characteristics Dimension, Recognition Rate and Testing Time to a Varity of Methods

Method	Feature demision	Number of correct	Number of error	Recognition rate	Test time(s)
PCA	120×1	221	79	73.67	13.26
2DPCA	128×12	285	15	95.00	18.23
Bi-directional 2DPCA	10×10	290	10	96.67	5.25
PCA+LDA	96×1	283	17	94.33	8.64
2DPCA+LDA	256×1	292	8	97.33	15.11
TDLD	12×5	297	3	99.00	3.42

In PolyU-I palmprint database, using the first stage 300 palmprint image as a training sample set and the second stage 300 palmprint image as the test samples set, the recognition rate, test time and feature dimensions to achieve high recognition rate are obtained. The experimental results are shown in Table 1. Simulation results show that the feature dimension of the proposed method is lowest relative to other method, which has only $12 \times 5 = 60$ dimensions; highest recognition rate reached 99.00%, and shortest test time is just 3.42 seconds.

Table 2. Comparison Result of the Recognition Rate to Different Training Samples in PolyU-I Database

Method	Training samples					
	1	2	3	4	5	Average
PCA	53.33	59.67	73.67	78.67	81.00	69.27
2DPCA	77.33	84.67	90.33	93.33	95.00	88.13
2DFLD	76.00	80.00	90.33	93.00	94.67	86.80
Bi-directional 2DPCA	87.33	90.67	95.00	97.33	98.67	93.80
PCA+LDA	83.33	89.00	94.33	96.00	96.67	91.87
2DPCA+LDA	89.00	92.67	96.67	98.33	99.00	95.13
TDLD	90.33	94.00	99.00	99.00	99.33	96.33

Tabble 3. Comparison Result of the Recognition Rate to Different Training Samples in PolyU-II Database

Method	Training samples					
	1	2	3	4	5	Average
PCA	65.40	74.25	78.45	81.60	85.00	76.94
2DPCA	80.00	85.25	91.65	94.20	96.00	89.42
2DFLD	79.85	84.60	90.95	94.00	95.35	88.95
Bi-directional 2DPCA	89.65	91.60	95.35	97.00	98.15	94.35
PCA+LDA	82.80	90.75	93.85	96.25	97.40	92.21
2DPCA+LDA	91.00	93.40	95.65	97.80	99.00	95.37
TDLD	93.95	95.40	99.00	99.50	99.65	97.50

Palmprint recognition is a small sample problem. A different algorithm to select a different number of training samples in the PolyU-I palmprint database identification results are given in Table 2. Table 3 shows recognition result to the different algorithms 2000 image samples to select a different number of training samples in the PolyU-II palmprint database. Simulation results show that the more the number of training samples, the recognition rate is the higher. Compared with other algorithms, the proposed algorithm has the highest recognition rate in different number of training samples.

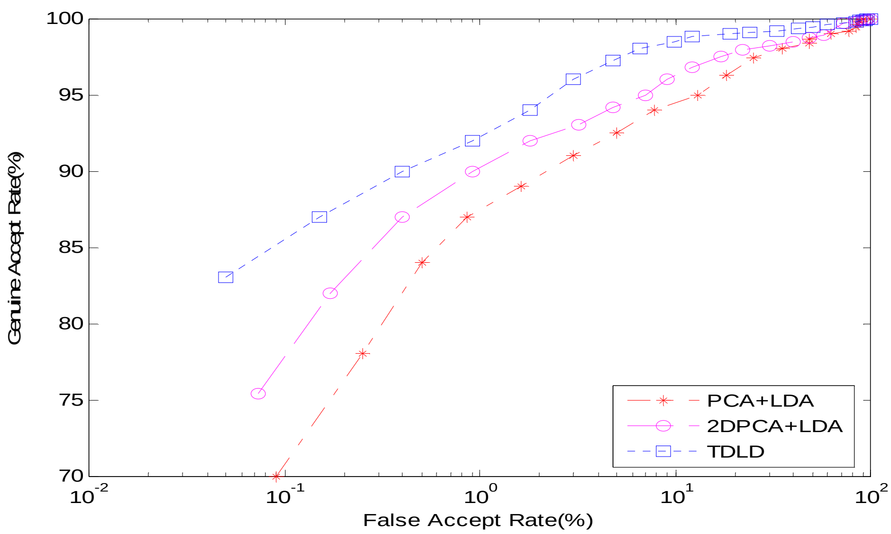

Figure 2. ROC Diagram of TDLD Method

The experiment further compared the PCA+LDA, 2DPCA+LDA, TDLD to identify performance. Figure 2 reflects the ROC characteristic curves of GAR and FAR relations. The comparison is selected 5 training samples in the PolyU-II database. During the matching process, each sample in the test sample set will be compared with all samples so for each sample for test sample set there will be 5 correctly matched and 495 mismatched. There will be 2500 correct matches and 247500 false matches for all the test samples to complete the entire experiment. Correct match is correctly received GAR, while error match is false received FAR. It can be seen from Figure 2, in the same false acceptance rate correct received rate of TDLD is always higher than PCA+LDA, 2DPCA+LDA. Therefore the charactertics to receive for TDLD is better.

In summary, the experimental results show that the proposed method has faster recognition speed, can reduce the feature dimension requirements and achieve high recognition rate under low feature dimension.

5. Conclusion

In terms of small sample problems which exist in the subspace palmprint identification technology and the direct irrelevance to optimize linear discriminant analysis criterion function and the maximization of the recognition rate, this paper proposed a two-dimensional linear discriminant dimension reduction algorithm which merges two dimisional principal component analysises. This algorithm is a direct projection of the palmprint image matrix and is achieved very good results for dimension reduction which can eliminate the relevance of rows and columns to get the best projection vector and extract optimal discriminant information.

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