얼굴 인식을 위한 개선된 (2D)^2 DLDA 알고리즘

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Improved (2D)^2 DLDA for Face Recognition

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ABSTRACT

In this paper, a new feature representation technique called Improved 2-directional 2-dimensional direct linear discriminant analysis (Improved (2D)2 DLDA) is proposed. In the case of face recognition, thesmall sample size problem and need for many coeffficients are often encountered. In order to solve these problems, the proposed method uses the direct LDA and 2-directional image scatter matrix. Moreover the selection method of feature vector and the method of similarity measure are proposed. The ORL face database is used to evaluate the performance of the proposed method. The experimental results show that the proposed method obtains better recognition rate and requires lesser memory than the direct LDA.

key Words : Linear Discriminant Analysis, Direct LDA, Face Recognition

Ⅰ. Introduction

In the pattern recognition like Face recognition, high dimensional data should be handled. Various methods have been proposed for getting small feature vector or matrix. Especially, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) have been well used. The PCA seeks directions that have the largest variance associated with it.

The PCA based methods have been developed since the eigenfaces methods[1,2] was presented for face recognition. However, in the case that training samples are a lot, the LDA generally outperforms the PCA. But the LDA is faced with small sample size (SSS) problem. The SSS problem arises when the number of training samples is smaller than the dimensionality of the samples[3]. Therefore it is difficult to directly apply the LDA to high dimensional matrix. To escape the problem, Belhumeur et al.[4] proposed Fisherfaces. They proposed PCA plus LDA. However They didn't directly use the LDA to data. To use the LDA to data directly, Yu et al.[5] proposed direct LDA (DLDA) method. the DLDA directly processes data in the original high dimensional vectors. Not to be confronted with SSS, They tried to search the discriminant vector that makes between scatter matrix unit matrix and minimizes projection value of within scatter matrix.

Recently, 2-dimensional based methods are proposed. Yang et al.[6] proposed two dimensional PCA (2DPCA). While previous methods use 1D image vector, the 2DPCA makes directly the scat-

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논문번호 : KICS2006-06-284, 접수일자 : 2006년 9월 29일, 최종논문접수일자 : 2006년 10월 18일

ter matrix from 2D image matrices. The 2DPCA deals with the small size scatter matrix than the traditional PCA-based methods and evaluates the scatter matrix accurately. For example, an image vector of 112×92 forms 10304 dimensional vector and the size of the scatter matrix is 10304×10304. On the other hand, the covariance of the 2DPCA forms only 92×92 matrix. Also, Li et al. [7] proposed 2DLDA. They showed that the 2DLDA is free from SSS problem. because 2-dimensional based scatter matrix is small. But still they have a weakness. They needs more storage and more time for recognition than the traditional PCA and LDA. L. Wang et al.[8] showed that the 2DPCA is equivalent to a special case of the block-based PCA. Specially, the blocks are the row directional lines of the images.

In this paper, we introduce a new low-dimensional feature representation method, Improved $(2D)^2$ DLDA. The proposed method uses 2-dimensional scatter matrix. Because the image scatter matrix is free from the SSSproblem. And then the DLDA algorithm is used for obtaining the feature matrix. To reduce the storage space, It is run the row direction and the column direction, respectively. Moreover the selection method of feature vector and the row based similarity measureare proposed.

The remainder of this paper is organized as follows. In Section 2, the proposed Improved $(2D)^2$ DLDA algorithm is described. Experimental results and comparisons with the DLDA is presented in Section 3. Finally, conclusions are offered in Section 4.

Ⅱ. Improved $(2D)^2$ DLDA

2.1 2D DLDA

Let X denotes a $m \times n$ image, and W is an n-dimensional column vector. X is projected onto W by the following linear transformation

$$Y = XW \tag{1}$$

Thus, we get an m-dimensional projected vector Y, called the feature vector of the image X. Suppose there are C known pattern classes in the training set, and M denotes the size of the training set. The jth training image is denoted by a $m \times n$ matrix X_j $(j = 1, 2, \cdots, M)$ and the mean image of all training sample is denoted by $\overline{X}$ and $\overline{X}_i (i = 1, 2, \cdots, c)$ denoted the mean image of class T_i and N_i is the number of samples in class T_i, the projected class is P_i. After the projection of training image onto W, we get the projected feature vector

$$Y_j = X_j W, \quad j = 1, 2, \cdots, M \tag{2}$$

LDA attempts to seek a set of optimal discriminating vectors to form a transform W by maximizing the Fisher criterion denoted as

$$J(W) = \frac{tr(\widetilde{S}_b)}{tr(\widetilde{S}_w)} \tag{3}$$

Where tr(·) denotes the trace of matrix, $\widetilde{S}_b$ denotes the between-class scatter matrix of projected feature vectors of training images, and $\widetilde{S}_w$ denotes the within-class scatter matrix of projected feature vectors of training images. So,

$$\widetilde{S}_b = \sum_{i=1}^{C} N_i (\overline{Y}_i - \overline{Y})(\overline{Y}_i - \overline{Y})^T = \sum_{i=1}^{C} N_i [(\overline{X}_i - \overline{X})W][(\overline{X}_i - \overline{X})W]^T, \tag{4}$$
$$\widetilde{S}_w = \sum_{i=1}^{C} \sum_{Y_k \in P_i} (Y_k - \overline{Y}_i)(Y_k - \overline{Y}_i)^T = \sum_{i=1}^{C} \sum_{X_k \in T_i} [(X_k - \overline{X}_i)W][(X_k - \overline{X}_i)W]^T$$

So,

$$tr(\widetilde{S}_b) = W^T \left(\sum_{i=1}^{C} N_i (\overline{X}_i - \overline{X})^T (\overline{X}_i - \overline{X}) \right) W,$$
$$tr(\widetilde{S}_w) = W^T \left(\sum_{i=1}^{C} \sum_{X_k \in T_i} (X_k - \overline{X}_i)^T (X_k - \overline{X}_i) \right) W \tag{5}$$

Let us define the following matrix

$$R_b = \sum_{i=1}^{C} N_i (\overline{X}_i - \overline{X})^T (\overline{X}_i - \overline{X}),$$
$$R_w = \sum_{i=1}^{C} \sum_{X_k \in T_i} (X_k - \overline{X}_i)^T (X_k - \overline{X}_i) \tag{6}$$

The matrix R_b is called the row directional image between-class scatter matrix and R_w is called the row directional image within-class scatter matrix.

Alternatively, the criterion can be expressed by

$$J(W_r) = \frac{W_r^T R_b W_r}{W_r^T R_w W_r} \quad (7)$$

Now, we try to find a matrix that simultaneously diagonalizes both R_b and R_w.

$$AR_w A^T = I,\ AR_b A^T = \Lambda_r \quad (8)$$

Where Λ_r is a diagonal matrix with diagonal elements sorted in decreasing order.

First, we find eigenvectors V_r that diagonalizes R_b

$$V_r^T R_b V_r = \Lambda_r \quad (9)$$

Where $V_r^T V_r = I$. Λ_r is a diagonal matrix sorted in decreasing order, i.e. each column of V_r is an eigenvector of R_b, and Λ_r contains all the eigenvalues.

Let Y_r be the first l columns ($l \le n$) of V_r (a $n \times n$ matrix, n being the column numbers of image).

$$V_r^T R_b Y_r = D_b \quad (10)$$

Where D_b is the $l \times l$ principal sub-matrix of Λ_r.

Further let $Z_r = Y_r D_b^{-1/2}$ to unitize R_b,

$$(Y_r D_b^{-1/2})^T R_b (Y_r D_b^{-1/2}) = I \Rightarrow Z_r^T R_b Z_r = I \quad (11)$$

Next, we find eigenvectors U_r to diagonalize $Z_r^T R_w Z_r$.

$$U_r^T Z_r^T R_w Z_r U_r = D_w \quad (12)$$

Where $U_r^T U_r = I$. D_w may contain zeros in its diagonal.

To maximize $J(W_r)$, we can sort the diagonal elements of D_w and discard some high eigenvalues with the corresponding eigenvectors by following proposed method.

$$\frac{\sum_{i=1}^{t} \lambda_i}{\sum_{j=1}^{n} \lambda_k} \le \theta \quad (13)$$

Let the optimal projection matrix, W_r

$$W_r = (D_w^{-1/2} U_r^T Z_r^T)^T \quad (14)$$

Also, W_r unitizes R_w.

2.2 Column directional 2D DLDA

Let us define the following matrix

$$C_b = \sum_{i=1}^{C} N_i (\overline{X}_i - \overline{X})(\overline{X}_i - \overline{X})^T,$$

$$C_w = \sum_{i=1}^{C} \sum_{X_k \in T_i} (X_k - \overline{X}_i)(X_k - \overline{X}_i)^T \quad (15)$$

The matrix C_b is called the column directional image between-class scatter matrix and C_w is called the column directional image within-class scatter matrix.

Alternatively, the criterion can be expressed by

$$J(W_c) = \frac{W_c^T C_b W_c}{W_c^T C_w W_c} \quad (16)$$

Now, we try to find a matrix that simultaneously diagonalizes both C_b and C_w.

$$BC_w B^T = I,\ BC_b B^T = \Lambda_c \quad (17)$$

Where Λ_c is a diagonal matrix with diagonal elements sorted in decreasing order.

First, we find eigenvectors V_c that diagonalizes C_b

$$V_c^T C_b V_c = \Lambda_c \quad (18)$$

Where $V_c^T V_c = I$. Λ_c is a diagonal matrix sorted in decreasing order, i.e. each column of V_c is aneigenvector of C_b, and Λ_c contains all the eigenvalues.

Let Y_c be the first k columns ($k \le m$) of V_c (a $m \times m$ matrix, m being the row numbers of image).

$$V_c^T C_b Y_c = \widetilde{D}_b \tag{19}$$

Where $\widetilde{D}_b$ is the $k \times k$ principal sub-matrix of Λ_c.

Further let $Z_c = Y_c \widetilde{D}_b^{-1/2}$ to unitize C_b,

$$(Y_c \widetilde{D}_b^{-1/2})^T C_b (Y_c \widetilde{D}_b^{-1/2}) = I \Rightarrow Z_c^T C_b Z_c = I \tag{20}$$

Next, we find eigenvectors U_c to diagonalize $Z_c^T C_w Z_c$.

$$U_c^T Z_c^T C_w Z_c U_c = \widetilde{D}_w \tag{21}$$

Where $U_c^T U_c = I$. $\widetilde{D}_w$ may contain zeros in its diagonal.

To maximize $J(W_c)$, we can sort the diagonal elements of $\widetilde{D}_w$ and discard some high eigenvalues according to constraint condition of (13).

Let the optimal projection matrix, W_c

$$W_c = (\widetilde{D}_w^{-1/2} U_c^T Z_c^T)^T \tag{22}$$

Also, W_c unitizes C_w.

2.3 Improved $(2D)^2$ DLDA

As we discussed in Section 1 and 2, row directional 2D DLDA and column direction 2D DLDA produce optimal projection matrix W_r and W_c, respectively. To project an $m \times n$ image X onto W_r yields m by l matrix $Y_{m \times l} = X_{m \times n} \cdot W_{n \times l}$. Similarly, to project an $m \times n$ image X onto W_c yields a k by n matrix $Y_{k \times n} = W_{m \times k}^T \cdot X_{m \times n}$.

Suppose that we project the $m \times n$ image X onto W_r and W_c simultaneously, we obtain a k by l matrix X^*,

$$X^* = W_c^T (X - \overline{X}) W_r. \tag{23}$$

The row based similarity measure to classify two matrices is proposed. The distance between $X_1^* = (x_{ij}^1)_{k \times l}$ and $X_2^* = (x_{ij}^2)_{k \times l}$ is defined by

$$D(X_1^*, X_2^*) = \sum_{i=1}^{k} \left(\sum_{j=1}^{l} \left(x_{ij}^1 - x_{ij}^2 \right)^2 \right)^{1/2} \tag{24}$$

Ⅲ. Experimental results

The proposed method is tested on the ORL face image database (http://www.cam-orl.co.uk/facedatabase). There are 40 classes. Each class is made up of 10 mages. The images are taken at different times and contain various facial expressions (open/closed eyes, smiling/ not smiling) and facial details (glasses or no glasses). The size of image is 112×92 matrix with 256 gray values.Fig. 1 depicts some sample images in the ORL database. Five sets of experiments are conducted. In all cases the five images per class are randomly chosen for training from each person and the other five images are used for testing. Thus the total number of training images and testing images are both 200. To simulate algorithm, matalb 6 platform is used.

Table 1 compares the average recognition rates and the dimension size obtained using the Improved $(2D)^2$ DLDA, 2D DLDA, and DLDA. In the 112×92 image matrix, the size of the row directional image scatter matrix and the size of the column directional image scatter matrix is 92×92 and 112×112, respectively. SSS problem is not appeared. In the Improved $(2D)^2$ DLDA, the row directional image scatter matrix and the column directional image scatter matrix is used, simultaneously. As a result, the feature matrix size is equivalent to DLDA and the recognition rate is nearly equivalent to 2D DLDA.

Fig. 1. Some face samples of ORL face database

Table 1. Comparison of average recognition rates of different methods

Methods	Average Recognition rate(%)	Dimension
Improved (2D)2 DLDA	94.9	8×5
2D DLDA	94.1	112×7
DLDA	90.6	40×1

Ⅳ. Conclusion

In this paper, the Improved $(2D)^2$ DLDA algorithm is proposed. The method combines the merits of the image scatter matrix and the DLDA approaches. Since 2-dimensional image scatter matrix is used, SSS problem is avoided. Furthermore the selection method of feature vector is proposed. Therefore the number of feature vectors is decided automatically. Also, to obtain the low dimensional feature matrix, we project image matrix onto the row directional and the column directional projection matrix, simultaneously. Lastly, the row based similarity measure raise up the recognition rate.

The experimental results show that the feature matrix size is small like DLDA and the average recognition rate is nearly equivalent to 2D DLDA.

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