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A Real-time Face Recognition System based on BDPCA plus BDDLDA

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Abstract

Holistic-based methods, especially principal component analysis(PCA) and linear discriminant analysis(LDA), are very popularly used in face recognition. In last several years, the direct LDA(D-LDA) method was suggested to overcome the so-call "small simple size" problem. Besides, the researchers suggest bidirectional PCA(BDPCA) method, which may be more real-time and effective than PCA, and proposed BDPCA plus LDA (BDPCA+LDA). In the same way, we suggest bidirectional D-LDA(BDDLDA) should be faster than D-LDA, and proposed BDPCA plus BDDLDA (BDPCA+BDDLDA). In this paper, we present a real-time face recognition system for operating system authentication based on BDPCA+BDDLDA. A face database, which was collected with a CCD camera on the laptop, is used to evaluate this system. Experimental results show that this practical system is real-time and effective.

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Keywords: Face Recognition, Bidirectional Principal Component Analysis (BDPCA), Bidirectional Direct Linear Discriminant Analysis (BDDLDA).

1. Introduction

Face recognition has been an important issue in pattern recognition over the last several decades[2], and the approaches based on appearance have been widely studied in recent years[12][13][14]. Besides, many standard face databases have been build (e.g. the ORL database[5] and the AR database[11]). Researchers conducted a series of experiments, using the standard databases, and the results show that the recognition accuracy has been greatly improved. Many practical systems are also being used. Operating system authentication is one of the most important purposes of face recognition, and it's also our purpose.

A complete face recognition system includes two main steps, i.e., face detection and face recognition. In this paper, both steps will be introduced, and the attention will be focused on face recognition part.

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Holistic-based approaches extract a holistic representation of the whole face region, by extracting the distinctive features of high dimensional data in a lower dimensional subspace. The two main holistic-based face-recognition approaches are the principal component analysis (PCA) and the linear discriminant analysis(LDA). A number of approaches have been proposed based on the PCA method and the LDA method. Yang proposed the two-dimensional PCA(2DPCA)[3], which is based on 2D image matrices rather than 1D image vectors. Compared with the covariance matrix of PCA, the size of the covariance matrix in 2DPCA is significantly reduced. Zuo proposed bidirectional PCA(BDPCA)[7], which can do image feature extraction by reducing the dimension in both column and row directions. Yu proposed the direct LDA(D-LDA) method[10], which can overcome the so-called "small sample size" problem. The combination of the PCA and the LDA was also praised highly by many researchers. Yang proved that LDA can be performed in PCA transformed space, and proposed the complete PCA plus LDA method[4]. Using this achievement, Zuo proposed the BDPCA plus LDA method[8].

Based on all the effective achievement on the above, we suggest bidirectional D-LDA(BDDLDA) should be faster than D-LDA with less storage cost, and proposed the BDPCA+BDDLDA. In this paper, we present a complete practical face recognition system based on BDPCA+BDDLDA used for operating system authentication. The most important factors of a practical face recognition is the real-time and the accuracy. We collect some face images as a database with a CCD camera. The experimental results on this database show that this system is fast and effective.

The organization of the rest of this paper is as follows: Section II proposes the BDPCA+BDDLDA procedure. Section III introduces the structure of the face recognition system and some details. Section IV introduces our face database and presents the results of experiments on this database. Finally, Section V offers our conclusion.

2. BDPCA plus BDDLDA

2.1BDPCA

In the BDPCA, the images of the face region are used as 2D matrices rather than 1D vectors. Given a training set $\{X_1,\ldots,X_N\}$. The size of each image matrix is m×n. We define the column scatter matrix and the row scatter matrix as follows, where $\overline{X}$ denotes the mean matrix of all training images:

$$\mathrm{S_c}=\sum_{i=1}^{N}(X_i-\overline{X})(X_i-\overline{X})^{\mathrm{T}}.. \quad \mathrm{S_r}=\sum_{i=1}^{N}(X_i-\overline{X})^{\mathrm{T}}(X_i-\overline{X})\tilde{} \qquad .(1)$$

The eigenvectors corresponding to the first k_c largest eigenvalues of $\mathrm{S_c}$ construct the column projection $\mathrm{W_c}$. The eigenvectors corresponding to the first k_r largest eigenvalues of $\mathrm{S_r}$ construct the column projection $\mathrm{W_r}$. The size of $\mathrm{W_c}$ is m× k_c and the size of $\mathrm{W_r}$ is n× k_r.

For an image matrix *X* with the size m×n, we extract the feature matrix *Y* by the transformation

$$Y=\mathrm{W_c^T}X\mathrm{W_r}\tilde{} \qquad .(2)$$

2.2D-LDA

In the D-LDA, the images of the face region are used as vectors. We define the within-class scatter $\mathrm{S_w}$ and between-class scatter $\mathrm{S_b}$ as follow:

$$\mathrm{S_w} = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N_i}(\boldsymbol{x}_{ij} - \overline{\boldsymbol{x}_i})(\boldsymbol{x}_{ij} - \overline{\boldsymbol{x}_i})^{\mathrm{T}}. \tag{3}$$

$$\mathrm{S_b} = \frac{1}{N}\sum_{i=1}^{C} N_i(\overline{\boldsymbol{x}_i} - \overline{\boldsymbol{x}})(\overline{\boldsymbol{x}_i} - \overline{\boldsymbol{x}})^{\mathrm{T}}. \tag{4}$$

where C, N, and $\overline{\boldsymbol{x}}$ are the number of classes, the total number and the mean vector of all the images. N_i, $\overline{\boldsymbol{x}_i}$, and $\boldsymbol{x}_{ij}$ are the number of vectors, the mean vector and the *j*th vector of class *i*.

The traditional LDA aims to find a projection W that maximizes the ratio of $\mathrm{S_w}$ against $\mathrm{S_b}$ (Fisher's criterion):

$$\arg\max_{\mathrm{W}} \frac{\left|\mathrm{W^T S_b W}\right|}{\left|\mathrm{W^T S_w W}\right|} \tag{5}$$

The D-LDA tries to find a matrix to similarly meet the Fisher's criterion. It find a matrix that simultaneously diagonalizes both $\mathrm{S_w}$ and $\mathrm{S_b}$:

$$\mathrm{W^T S_w W} = \Lambda,\ \mathrm{W^T S_b W} = I. \tag{6}$$

where Λ is a diagonal matrix with diagonal elements sorted in increasing order.

The algorithm is outlined as follow:

First, we choose the eigenvectors corresponding to the first k_b largest eigenvalues of $\mathrm{S_b}$ to construct the projection matrix $\mathrm{W_b}$, now

$$\left|\mathrm{W_b^T S_b W_b}\right| = \left|\mathrm{D_b}\right| > 0. \tag{7}$$

where $\mathrm{D_b}$ is a diagonal matrix. Let

$$\mathrm{\tilde{W}_b} = \mathrm{W_b D_b}^{-1/2}. \tag{8}$$

$$\widetilde{\mathrm{S_w}} = \mathrm{\tilde{W}_b^T S_w \tilde{W}_b}. \tag{9}$$

The first k_w smallest eigenvalues of $\mathrm{\tilde{S}_w}$ construct the projection matrix $\mathrm{W_w}$, and the D-LDA matrix is

$$\mathrm{W} = \mathrm{W_w \tilde{W}_b} \tag{10}$$

2.3BDPCA+BDDLDA

In this section, we propose a new BDPCA plus BDDLDA method. Given a train set as

$$\{X_{ij} \mid i = 1, \cdots, C; j = 1, \cdots N_i\}. \tag{11}$$

where C is the number of classes, and N_i is the number of images in *i*th class. The size of each image in the train set is m×n. This method first get the BDPCA projection matrixes $\mathrm{W_{c\_BDPCA}}$ and $\mathrm{W_{r\_BDPCA}}$ as said in section Ⅱ-*A*, and for each image in the train set, we get

$$Y_{ij} = \mathrm{W^T_{c\_BDPCA}} X_{ij} \mathrm{W_{r\_BDPCA}}. \tag{12}$$

The size of the BDPCA features matrix is $k_{c\_BDPCA} \times k_{r\_BDPCA}$.

Then, we define the column within-class scatter S_{wc}, the column between-class scatter S_{bc}, the row within-class scatter S_{wr}, and the row between-class scatter S_{br} as

$$S_{wc} = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N_i}(Y_{ij} - \overline{Y}_i)(Y_{ij} - \overline{Y}_i)^{T}. \tag{13}$$

$$S_{bc} = \frac{1}{N}\sum_{i=1}^{C} N_i(\overline{Y}_i - \overline{Y})(\overline{Y}_i - \overline{Y})^{T}. \tag{14}$$

$$S_{wr} = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{N_i}(Y_{ij} - \overline{Y}_i)^{T}(Y_{ij} - \overline{Y}_i). \tag{15}$$

$$S_{br} = \frac{1}{N}\sum_{i=1}^{C} N_i(\overline{Y}_i - \overline{Y})^{T}(\overline{Y}_i - \overline{Y})\tilde{} \tag{16}$$

Finally, we get the column D-LDA projection W_{c_BDDLDA} and row D-LDA projection W_{r_BDDLDA} by the method outlined in section Ⅱ-*B*.

For an image matrix *X* with the size m×n, we extract the feature matrix *Z* by the transformation

$$Z=W_{c\_BDDLDA}^{T} W_{c\_BDPCA}^{T} X W_{r\_BDPCA} W_{r\_BDDLDA}. \tag{17}$$

hence, the final column projection matrix W_c and row projection W_r are defined as

$$W_c = W_{c\_BDPCA} W_{c\_BDDLDA}.\ W_r = W_{r\_BDPCA} W_{r\_BDDLDA}\tilde{} \tag{18}$$

The size of the BDDLDA features matrix is $k_{c\_BDDLDA} \times k_{r\_BDDLDA}$.

3. The system structure

As introduced on the above, A complete face recognition system includes two main steps, i.e., face detection and face recognition. Our system works as follow:

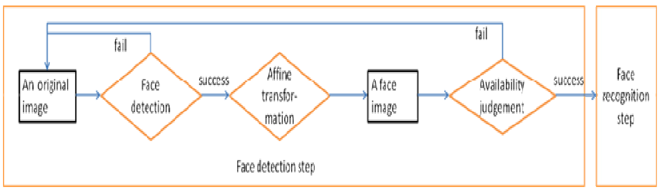

Figure 1 The system structure

First, we get an original image by the camera or from a file, like the example in Fig. 2.

Figure 2 An example of the original image

The detectors based on the Haar like features are used to detect the general region of the face and eyes. Then, we do an affine transformation on the general face region to get a face image. The size of the face image is d×d, and the center of the left eye and right eye are located at (0.25d, 0.25d) and (0.25d, 0.75d) respectively, as shown in Fig.3.

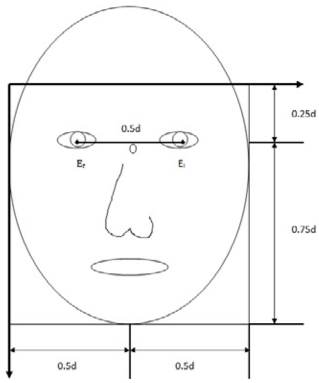

Figure 3 The structure of the face image

To reduce the influence of the clothes or some other background features, we cut the bottom-left corner and the bottom-right corner of the face image. For the image shown in Fig.2, we finally get a face image as shown in Fig.4.

In the availability judgement step, we try to discard the images which may make bad influence to the recognition. Several simple standards are used in this step, such as the mean value of the image matrix is too large or too small, the number of 0-value pixels in the face image exceeds the threshold, etc.

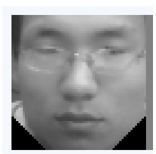

Figure 4 The face image get from the original image in Fig.2

In the face recognition step, first, we get a train set from the face detection step. In the experiments below, we choose the images for training by hand. However, in practical application, the train set should be choosed by computer with little assist from users. Then, we get the projection matrixes W_c and W_r by the method introduced in section Ⅱ-*C*. For each image in the train set, we extract a feature matrix. Then, for each face image to be recognized, we also extract a feature matrix. We use the weighted KNN algorithm to classify, with the Euclidean distance between this matrix with the feature matrix of each image in the train set used as the factor. There should be a refusing threshold. If the minimum of the distance exceeds this threshold, the system should refuse to recognize.

4. Experiments and analysis

4.1The experiment scenario and database construction

Our system is purposed to work for Operating system authentication. The general experiment scenario is the following: 1)The number of users should be no more than 10; 2)the original images are collected by a CCD camera with the size 320×240; 3)the images should be indoor, and the light should be uniform with no great change.

So that, in our face image database, there are 10 individuals, and for each individual, there are about 10 images used for train and 20 images used for test. The size of each face image is 60×60. Some example images of one individual are shown in Fig. 5.

We consider that the interference between classes should reduce as the number of classes reduce. Hence, in all the following experiments, the number of classes is 10. As a matter of convenience for comparing, we don't consider the refusing threshold in the following experiments.

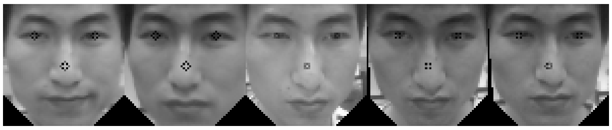

Figure 5 Some example images of one individual in our database

4.2The results and analysis

First, we want to compare BDPCA+BDDLDA with BDPCA. Let the size of the feature matrix is 6×8. The maximum recognition accuracy rate is shown in Table I. We used NN algorithm for classfication in these experiments.

We study the effect of parameter on the recognition accuracy rate of the BDPCA+BDDLDA. The most import parameters in the BDPCA+BDDLDA are the number of column eigenvectors in BDPCA k_{c_BDPCA}, the number of row eigenvectors in BDPCA k_{r_BDPCA}, the number of column eigenvectors in BDDLDA k_{c_BDDLDA} ,and the number of row eigenvectors in BDDLDA k_{r_BDDLDA}. We used NN algorithm for classfication in these experiments. As shown in Fig. 6, the maximum accuracy rate(90%) is obtained when

$$[k_{c\_BDPCA}, k_{r\_BDPCA}, k_{c\_BDDLDA}, k_{r\_BDDLDA}] = [8,11,6,8]^{\sim} \tag{19}$$

Table 1 Comparisons of the BDPCA and the BDPCA+BDDLDA

Method	BDPCA	BDPCA+BDDLDA
Parameters	$[k_c, k_r]$	$[k_{c\_BDPCA}, k_{r\_BDPCA}],[k_{c\_BDDLDA}, k_{r\_BDDLDA}]$
Values	[6,8]	[9,12],[6,8]
Accuracy rate(%)	76.3%	88.9%

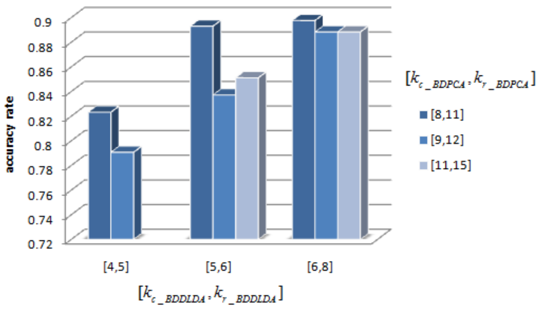

Figure 6 Comparisons of the accuracy rates with different parameter values

We also study the weighted KNN algorithm for classification. We compare NN, weighted 3-NN, and weighted 5-NN. As shown in Table II, the maximum accuracy rate(91%) is obtained when classification algorithm is weighted 3-NN or weighted 5-NN, and

$$[k_{c\_BDPCA}, k_{r\_BDPCA}, k_{c\_BDDLDA}, k_{r\_BDDLDA}] = [9,12,6,8]^{\sim} \quad (20)$$

Table 2 Comparisons of the classification algorithms

parameters / method	[8,11,6,8]	[9,12,6,8]	[11,15,6,8]
NN	0.90	0.89	0.89
weighted 3-NN	0.87	0.91	0.87
weighted 5-NN	0.87	0.91	0.89

The accuracy rate in our experiments may be lower than some results obtained by predecessors. We believe that some reason is on our database. The test images are not selected by person, and some of them are unsatisfactory, such as blurry image caused of moving. However, this case may happen in the practical application. As said above, we don't consider the refusing threshold in the experiments. If we consider this threshold, the accuracy rate should be much higher than 90%. In practical application, this system can recognize the right user in less than one second. We consider that the performance of this system can meet the requirements of practical application.

5. Conclusions

In this paper, we proposed BDPCA+BDDLDA for face recognition. And we present a complete face recognition system. We use our own face database, which was collected with a CCD camera on the laptop, to evaluate this system. We compare the BDPCA and the BDPCA+BDDLDA. The BDPCA+BDDLDA performs much better than BDPCA on the accuracy rate. We also suggest the reference values of the parameters in the method. Experimental results show that this practical system is real-time and effective.

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References

[1]L. Sirovich and M. Kirby, “Low-dimensional procedure for characterization of human face,” J. Opt. Soc. Amer., vol. 4, no. 3, pp. 519–524, Mar. 1987.

[2]W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, “Face recognition: A literature survey,” ACM Comput. Surv., vol. 35, no. 4, pp. 399–458,Dec. 2003.

[3]J. Yang, D. Zhang, A. F. Frangi, and J.-Y. Yang, “Two-dimensional PCA: A new approach to appearance-based face representation and recognition,” IEEE Trans. Pattern Anal.Mach. Intell., vol. 26, no. 1, pp. 131–137, Jan. 2004.

[4]——, “Why can LDA be performed in PCA transformed space,” Pattern Recognit., vol. 36, no. 2, pp. 563–566, Feb. 2003.

[5]The ORL Face Database, Cambridge, U.K.: AT&T (Olivetti) Research Laboratories. [Online]. Available: http://www.uk.research.att.com/ facedatabase.html.

[6]M. Turk and A. Pentland, “Eigenfaces for recognition,” J. Cogn. Neurosci., vol. 3, no. 1, pp. 71–86, 1991.

[7]W. Zuo, D Zhang, K Wang, “Bidirectional PCA with assembled matrix distance metric for image recognition”, IEEE Trans. on Systems, Man, And Cybernetics—Part B36(4)(2006)862–872.

[8]W. Zuo, D Zhang, J Yang, K Wang, “BDPCA plus LDA: a novel fast feature extraction technique for face recognition”, IEEE Trans. on System, Man, And Cybernetcs–PartB36(4)(2006)946–952.

[9]Aleix M. MartõÂnez, Avinash C. Kak, “PCA versus LDA”, IEEE Trans. Pattern Anal.Mach. Intell., vol. 23, no. 2, pp. 228-233, 2001

[10] H. Yu, J. Yang, “A direct LDA algorithm for high-dimensional data – with application to face recognition”, Pattern Recognit., vol. 34, pp. 2067-2070, 2001

[11] A.M. Martinez, “Recognizing Imprecisely Localized, Partially Occluded, and Expression Variant Faces from a Single Sample per Class,” IEEE Trans. Pattern Anal.Mach. Intell., vol. 24, no. 6, pp. 748-763, June 2002.

[12] X. Jiang, B. Mandal, A. Kot, “Eigenfeature Regularization and Extraction in Face Recognition”, IEEE Trans. Pattern Anal.Mach. Intell., vol. 30, no. 3, pp. 383-394, 2008

[13] Q. Gao, L. Zhang, D. Zhang, “Sequential row-column independent component analysis for face recognition”, Neurocomputing, vol. 72, pp. 1152-1159, 2009

[14] W. Yang, C. Sun, L. Zhang, K. Ricanek, “Laplacian bidirectional PCA for face recognition”, Neurocomputing, vol. 74, pp. 487-493, 2009