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Face Recognition using Eigenfaces based on Holistic Approach

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Abstract—*Systems that recognize faces are applied to a wide variety of tasks including security systems, image and video processing, human identity recognition and verification and human computer interaction. Different types of approaches to face recognition are holistic approach, feature-based approach and hybrid approach. The holistic approach which uses appearance-based methods takes into account the whole face region as an input to the face recognition system. One such method is generation and analysis of eigenfaces. In this method the local features of eyes, nose and mouth are extracted and fed into a structural classifier. We have applied a combination of PCA with LDA in face recognition in order to improve the overall performance. PCA performs the dimensionality reduction while LDA is used for classification and discrimination. Therefore, both PCA and LDA are combined to reduce the misclassification of the images which occur if only one of technique is used. The performance of this appearance based method of face recognition based on PCA along with LDA is compared which individual performances LDA and PCA subspace. Experiments conducted show that PCA with LDA has higher accuracy in terms of recognition rate as well as higher efficiency in time than either PCA or LDA applied separately.*

Keywords: *Face preprocessing, Principal Component Analysis, Linear Discriminant Analysis, Eigenface, Euclidean Distance.*

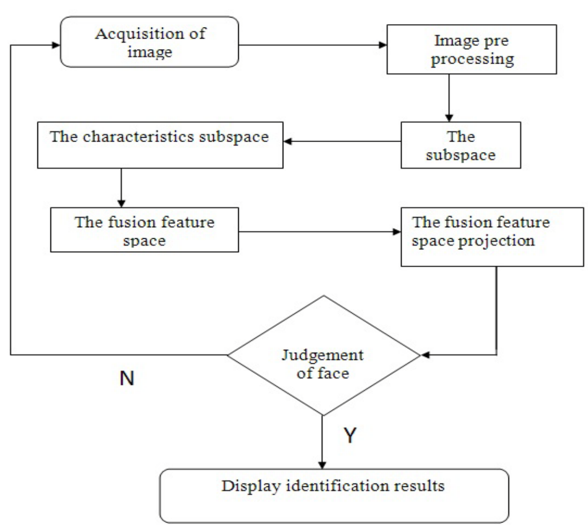
1. INTRODUCTION

The Face is our primary focus of attention in social life playing important role in conveying identity and emotions. We see a number of faces throughout our life and identify them at glance despite of large variations in visual stimuli. Inspired by this ability, face recognition became the important field of biometric and do not require the individual cooperation to perform the identification or recognition. The face recognition technology is a hot technology including face image acquisition, face location, faces preprocessing, identity verification, identity search and many other links. With the continuous development of society, the functional demand for face recognition technology increases continuously and the target functions vary in various fields. The advantages of face recognition technology based on different algorithms are different, so it is particularly important to choose a good algorithm. We have used the holistic based approach for feature extraction of the whole face region, which considers all the pixels of a face image in NxM dimensional space. However these spaces are large, which increases the

computational complexity in recognition system. To overcome this we have used dimensionality reduction and class discrimination methods namely PCA (Eigenface analysis) and LDA (Fisher discriminant analysis). The two methods are merged into one to overcome the drawbacks of one another. PCA is a statistical approach to express the faces as eigen vectors. Eigenface applies Principal Component Analysis to project the data points along the directions of maximal variances. Fisherface applies Linear Discriminant Analysis to project the data points along the directions optimal for discrimination. Both Fisherface and Eigenface consider the global Euclidean distance, but the Eigenface method is unsupervised while the Fisherface method is supervised.

2. PCA PLUS LDA SOLUTION

Face recognition algorithm based on PCA+LDA is the combination of PCA and LDA, two different kinds of algorithms. Through the algorithm combination, the two make up the defects of each other and make full use of the advantages of both to a certain extent.



Flowchart 1: PCA + LDA flow graph.

PCA reduces the dimension of the data and also data redundancy is minimized as components are orthogonal. With help of PCA, complexity of grouping the images can be reduced. LDA is used to preserve as much of the class discriminatory information as possible. The goal of LDA is to maximize the between class scatter matrix measure while minimizing the within class scatter matrix measure. A two-stage PCA+LDA method is used, where PCA is used to project images from the original image space to the low dimensional space.

2.1 Algorithm Used

I. Let D be a Vector of face images where x denotes an image and R is the dataset of images.

$$D = \{x_1, \dots x_n\},\ x_i \in R^d$$

II. Calculation of the mean of all images,

$$m = \frac{1}{n}\sum_i (x_i)$$

III. Calculation of the the covariance matrix,

$$C = \frac{1}{n}\sum_i (x_i - m)(x_i - m)^T$$

IV. Calculation of the eigenvector and eigenvalue of the covariance matrix. Where Φ denotes the principal components or the eigenfaces and σ is the eigenvalue.

$$C = \phi \wedge \phi^T, \wedge = diag(\sigma_1^2, \dots \sigma_n^2)\phi^T\phi = I$$

V. Ordering them by eigenvalue, highest to lowest.

$$\sigma_1^2 > \dots > \sigma_n^2$$

For a certain k, $\sigma_k << \sigma_1$

eliminate the eigenvalues and eigenvectors above k. The eigenvector with the highest eigenvalue is the principle component of the data set.

VI. Given principal components ϕi,

$$i \in 1, \dots, k$$

And a test sample

$$T = \{t_{1,\dots,} t_n\}, t_i \in R^d$$

VII. Subtract mean to each point.

$$t_i' = t_i - m$$

VIII. Project onto eigenvector space.

$$y_i = At_i'$$

where

$$A = \begin{pmatrix} \phi_1^T \\ \vdots \\ \phi_k^T \end{pmatrix}$$

IX. Use $T' = \{y_1, \dots\dots\dots y_n\}$ to estimate class conditional densities and do further processing on y.

X. Merging with LDA

a) Calculation of the within-class scatter matrix.

$$S_W = \sum_{i=1}^{n} C_i$$

where

$$C_i = \sum_{x \in R}^{n} (x - m_i)(x - m_i)^T$$

and $\mathbf{m_i}$ is the mean vector $m_i = \frac{1}{n_i}\sum_{x \in R}^{n} x_k$

b) Calculation of between-class scatter matrix

$$S_B = \sum_{i=1}^{n} N_i (m_i - m)(m_i - m)^T$$

where $\mathbf{m}$ is the overall mean, and $\mathbf{m_i}$ and $\mathbf{N_i}$ are the sample mean and sizes of the respective classes.

c) Computation of the LDA projection

$$\mathrm{invS_w\_by\_S_B} = \mathrm{invS_w} * S_B$$

d) The LDA projection is then obtained as the solution of the generalized eigen value problem where W is projection vector.

$$S_w^{-1}S_B W = \sigma W$$

$$W = eig(S_w^{-1}S_B)$$

e) Euclidean distance is calculated between the mean adjusted input image and the projection onto face space.

f) The matching result is finally given on the basis of nearest k neighbour having minimum distance. If the minimum distance between test face and training faces is higher than a threshold θ, the test face is considered to be unknown otherwise it is known and belongs to a person. The most common way for calculation θ is to first calculate the minimum distance of each image from the training base from the other images and place that distance in a vector. Threshold is taken as 0.8 times of the maximum value of vector.

3. FACE IMAGE DATABASES USED

3.1 ORL (AT&T) Database

10 different images of each of 40 distinct subjects are taken. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position.

3.2 Yalefaces

Contains 165 grayscale images in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad, sleepy, surprised, and wink.

3.3 Face94

Contains 3060 images in color. There are 20 females each having 20 images, 113 males each having 20 images and 20 male staff each having 20 images. The images vary with intensity of light, expression and glasses.

3.4 Jaffe Database

Japenes female facial expression. The database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by 10 Japanese female models. Each image has been rated on 6 emotion adjectives by 60 Japanese subjects.

4. EXPERIMENTAL RESULTS AND ANALYSIS

The experiments are done using PCA+LDA and tested on four famous databases (ORL, Yalefaces, Face94, Jaffe). The performance is compared between PCA, LDA and PCA + LDA. All experiments were conducted on an Intel Core i5 processor with 2.4 GHZ frequency and a 4 GB RAM. The algorithm is tested on the MATLAB platform of version R2011a.

4.1 Experiments on AT&T Database

The size of each 8 bit image is 112 x 92 pixels. Fig. 1.1 below shows sample images from the AT&T database. A total of 400 images are present in this database for 40 individuals, having 10 images of each. 5 images of each individual are taken for training making a total of 200 images, and the other 5 images are used for testing making a total of 200 images. Recognition rate and efficiency (time taken by the CPU) are provided in Table 1.1 and Table 1.2 respectively.

Fig. 1.1: Train database images for four individuals from AT&T database.

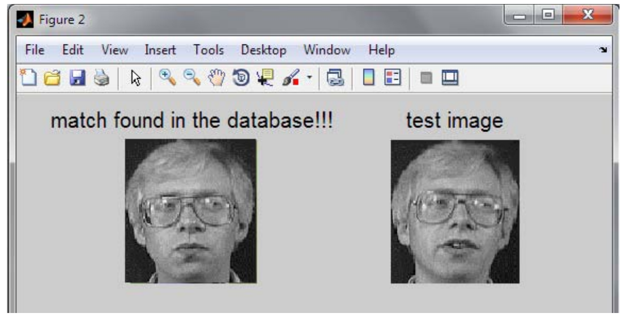


Fig. 1.2: Output window from MATLAB for a tested image from AT&T database.

Table 1.1 Comparison of face recognition algorithm PCA+LDA with PCA and LDA for the AT&T(ORL) database.

Algorithm	Total images	Images tested	Recognition Rate
PCA	400	75	94
LDA	400	75	95
PCA+LDA	400	75	97

Table 1.2: Time taken by the CPU for AT&T DATABASE

Algorithm used	Recognition time (sec)
PCA	1.713
LDA	0.925
PCA+LDA	0.721

4.2 Experiments on Yale Face Database

The Fig. 2.1 below shows the sample images of Yale database which consists of 165 images. 15 individuals with 11 images per person are present. 5x15 are used in training and 6x15 images are used in testing. Recognition rate and efficiency are provided in Table 2.1 and Table 2.2 respectively.

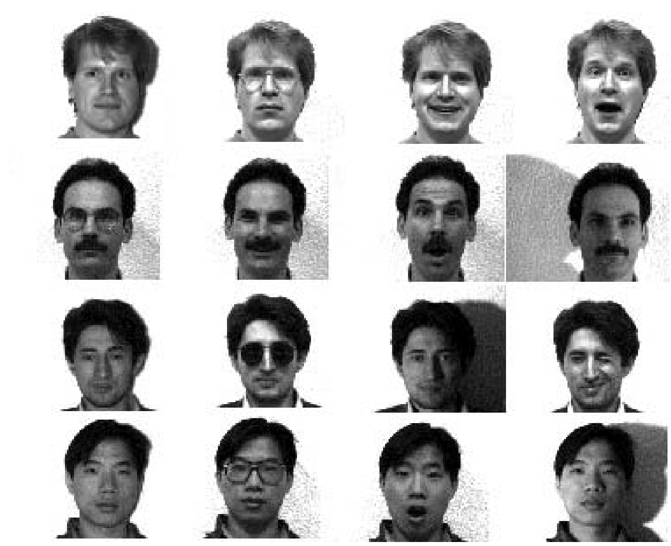


Fig. 2.1: Train database images for four individuals from Yalefaces.

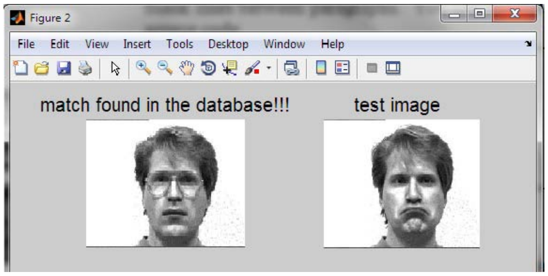


Fig. 2.1: Output window from MATLAB for a tested image.

Table 2.1: Comparison of face recognition algorithm PCA+LDA with PCA and LDA for the Yaleface database.

Algorithm	Total images	Images tested	Recognition Rate
PCA	165	60	71.5
LDA	165	60	72.6
PCA+LDA	165	60	93.2

Table 2.2: Time taken by the CPU for Yalefaces.

Algorithm used	Recognition time (sec)
PCA	0.706
LDA	0.381
PCA+LDA	0.297

4.3 Experiments on Jaffe Database

The Fig. 3.1 below shows the sample images of Jaffe database which consists of 213 images. 10 individuals with 21 images per person are present. 10 images per female are used in training i.e, training set consists of 100 images, and 11 images per person are used in testing i.e, testing set consists of 110 images. Recognition rate and efficiency are provided in Table 3.1 and Table 3.2 respectively.

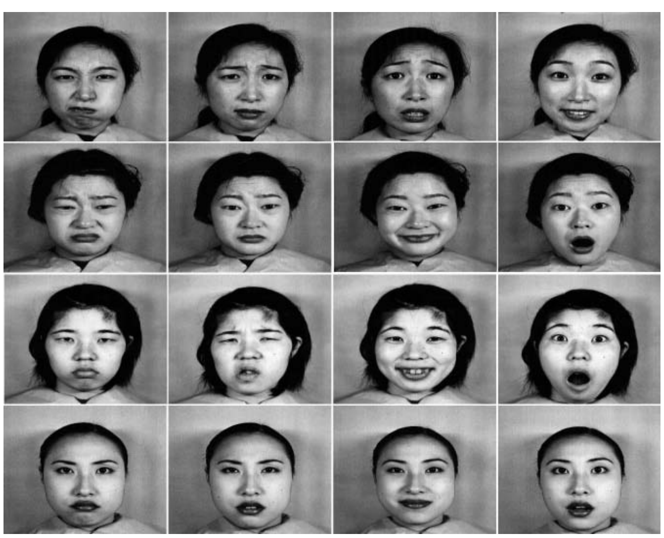


Fig. 3.1 Train database images for four individuals from Jaffe database.

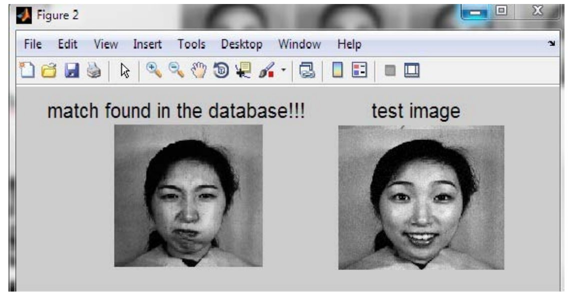


Fig. 3.2: Output window from MATLAB for a tested image for Jaffe database.

Table 3.1: Comparison of face recognition algorithm PCA+LDA with PCA and LDA for the Jaffe database.

Algorithm	Total images	Images tested	Recognition Rate (%)
PCA	213	35	96
LDA	213	35	95
PCA+LDA	213	35	98

Table 2.2: Time taken by the CPU for Jaffe database.

Algorithm used	Recognition time (sec)
PCA	0.911
LDA	0.491
PCA+LDA	0.384

4.4 Experiments on Face94 Database

The Fig. 4.1 below shows the sample images of Face94 database which consists of 3060 images. 153 individuals with 20 images per person are present. 10 images per individual are used in training i.e, training set consists of 1530 images, and 10 images per person are used in testing i.e, testing set consists of 1530 images. Recognition rate and efficiency are provided in Table 3.1 and Table 3.2 respectively.

Fig. 3.1: Train database images for four individuals from Jaffe database.

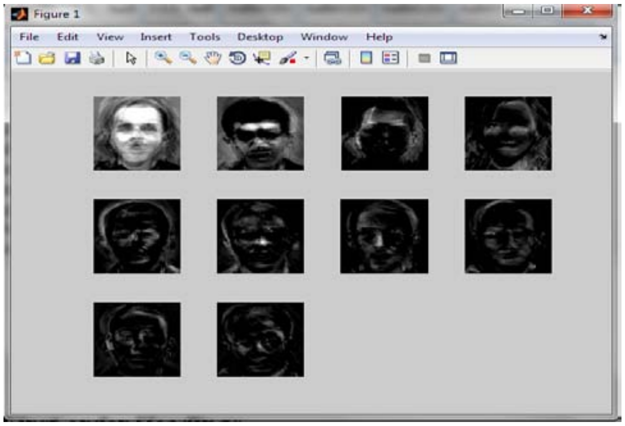


Fig. 3.1: Eigenfaces with respect to the FACE94database.

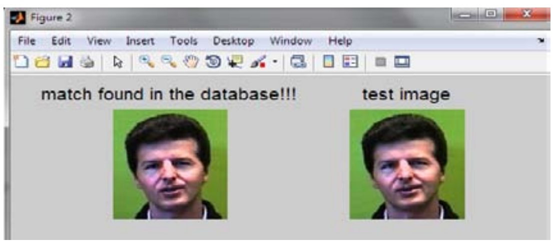


Fig. 3.2: Output window from MATLAB for a tested image for Face94 database.

Table 3.1: Comparison of face recognition algorithm PCA+LDA with PCA and LDA for the Yaleface database.

Algorithm	Total images	Images tested	Recognition Rate
PCA	3060	250	97
LDA	3060	250	97.9
PCA+LDA	3060	250	99

Table 2.2: Time taken by the CPU for Face94 database.

Algorithm used	Recognition time (sec)
PCA	2.562
LDA	1.385
PCA+LDA	1.08

5. CONCLUSION

This paper introduces PCA, LDA and PCA+LDA algorithm and compares the result on the basis of recognition rate and time taken by each method. We have calculated an accuracy of 96.8% for PCA+LDA, 89.6% for PCA and 90.1% for LDA. The time taken by the algorithms are 1.7, 0.7, 0.9, 2.5 for PCA; 0.9, 0.3, 0.4, 1.3 for LDA; 0.7, 0.2, 0.3, 1.1 for PCA+LDA in seconds. From the results, it can be concluded that PCA+LDA has better performance than either PCA or LDA taken separately. It is obvious that if the minimum distance between the test image and other images is zero, the test image entirely matches the image as in case of Face9 database Fig. 3.2 from the training base. If the distance is greater than zero but less than a certain threshold, it is a known person, otherwise it is an unknown person.

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