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FACE RECOGNITION FOR DIFFERENT FACIAL EXPRISIONS BASED ON PCA, LDA ANALYSIS

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ABSTRACT

The face is our primary focus of attention in social intercourse, playing a major role in identity. We can recognize thousands of faces in our lifetime and identify familiar faces at glance even after years of separation but it is difficult for computer compared with the human brain. In this paper presents comparative study of PCA (Principal Components Analysis) and LDA (Linear Discriminant Analysis) which are most popular appearance-based approaches in face recognition. PCA is recognized as an optimal method to perform dimension reduction. LDA once proposed to obtain better classification by using class information. Disputes over the comparison of PCA and LDA have motivated to study their performance. The Database of Faces which comprises 40 subjects with 10 images each, both recognition results have revealed the superiority of LDA over PCA for this medium-sized database.

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INTRODUCTION

As one of the most successful applications of image analysis and understanding of face recognition has recently received significant attention especially during the past several years. At least two reasons are accounted for this trend; first it is widely used in real life applications and second is the availability of feasible technologies after many years of research (Zhao *et al.,* 2003). The range of face recognition applications are very assorted such as face-based video indexing, multimedia management, human computer interaction, biometric identity authentication, surveillance (Li *et al.,* 2006), image and film processing, and criminal identification. Face recognition is a method of identity authentication on biometrics study (Cho and Moon, 2009). Comparing face recognition with another existing identification technology such as fingerprint and iris recognition. It has several characteristics that are advantageous for consumer applications such as nonintrusive and user-friendly interfaces, low-cost sensors and easy setup, and active identification (Zuo *et al.,* 2005). This method can be divided into the following categorizations such as holistic matching methods, feature-based matching methods and hybrid methods. The holistic methods used the whole face as input, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) belongs to this class of methods (Ye *et al.,* 2009). This paper describes and compares PCA and LDA recognition rate, conducted on several groups of images with various disturbances. PCA and LDA were selected because these methods are most widely used with simple processing steps; this is beneficial to the embedded systems (Cho and Moon, 2009).

PCA Mathematical Approach

Our face recognition system consists of several steps; each of the steps is described in detail in below:

Initialization and Finding Principal Components

At first we take images, these images are nothing but the matrix which has pixel intensity at different rows and columns.

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This image could be viewed as a vector also, if an image has height h and width w, then we could formulate this image as w vectors, where each vector has h dimensions. The rows of the images are placed one after another like the Figure1 below.

Fig. 1. Formation of the face's vector from face's images

The vector which is represents our image and this image has a certain space so this is called image space. If we have N images, we have image space dimension as $N \times w \times h$. In this image space all images are represented by w by h pixels. These images under same image space look like each other. They all have two eyes, a nose, a mouth etc located at the same image space. Now we will build the face space from the image space. The main task of building a face space is to describe the face images. The basis vector of this space is called principal component, the dimension of the face space will be $M \times w \times h$. In the face space all pixel is not relevant and each pixel depends on the neighbors. So the dimension of face space is less than the dimension of the image space. We could find the principle components of the faces by finding the eigenvectors of the covariance matrix of the set of face images. This eigenvectors are basically a set of features which characterize to the maximum variations between face images. Each of this images that comes from the image space contribute more of less to the eigenfaces. So we can display eigenvector as a sort of ghostly faces which we call eigenface,. actually eigenfaces do not exist in real world. We could not say we can build or create eigenface of a particular image face which is in the image space; Eigen face actually is an imaginary face which is a combination of all the images with in a particular image space.

We present the mathematical formulation of eigenfaces below:

- We obtain N training images $I1, I2, \dots .IN$, each of these images has dimensioned $w \times h$. Convert these images into vector space by concatenation. After the concatenation a matrix is converted to a vector.

- Represent each image I_i with its corresponding

Vector λ_{i}.:

$$\begin{bmatrix} B_{11} & B_{12} & \cdot & B_{1h} \\ \vdots & \vdots & \vdots & \vdots \\ B_{w1} & B_{w2} & \vdots & B_{wh} \end{bmatrix} \xRightarrow[concatenation]{} \begin{matrix} B_{11} \\ \vdots \\ B_{1h} \\ \vdots \\ B_{wh} \end{matrix} \quad \lambda_i$$

- Calculate the mean face vector ω by the following equation:

$$\omega = \frac{1}{N} \sum_{i=1}^{N} \lambda_i$$

Subtract the mean face, ϖ from each face vector, λ_i to get a set of vector μ_i:

$$\mu_i = \lambda_i \quad \varpi$$

The purpose of subtracting the mean image from each image vector is to keep only the distinguishing features from each face by removing the common information, Find the covariance matrix *C* by the following equation:

$$C = A^T A$$

Where, $A = [\mu_1, \mu_2, \dots .. \mu_N]$

Find the eigenvalues and eigenvectors for the covariance matrix C, Sort the eigenvectors according to the eigenvalues. Take the first *M* eigenvectors that have higher eigenvalues. Now each eigenvector will have $N \times 1$ dimension. Let us name those eigenvectors as η_i for *i=1, 2…M.*

Projection of new face to eigenfaces

When a new image is encountered, calculate the set of weights based on the new or input image and the *M* eigenfaces by projecting the input image onto each of the eigenfaces, the mathematical formulation is given below:

Let us consider the new image as $\boldsymbol{I_{new}}$

Find out the *M* eigenface components, Ψ_l, by projecting the new image :

$$\boldsymbol{\Psi_l = \gamma_l^T (I_{new} \quad \varpi)} \text{for l=1,2,…M.}$$

Where,

$$\gamma_l = \sum_{k=1}^{N} \eta_{lk} \, \mu_k \quad \text{for } l=1, 2, \dots .M.$$

Create a new feature vector, $\boldsymbol{\Omega_{new}}$ for the new image by concatenating eigenface components, Ψ_1

$$\Omega_{new} = [\Psi_1, \Psi_2, \dots \dots . \Psi_N]$$

Face Recognition by classification algorithms

The last step of the face recognition system is to identify the new face to be recognized or not recognized, if the face is recognized the system will tell the person's name for which the face has been recognized. In the other word, if we have N persons in the image database, we say that there are N classes where each individual person representing a class. Comparison is done by the Euclidian distance between two features Ω_{new} and Ω_i, if the distance is less than some predefined threshold *t*, we say that the image is recognized. The class of the new image will be one that has the least Euclidian distance with the new image, providing this distance is less than the threshold.

Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis (LDA) or Fisher's Linear Discriminant (FLD) approach is a widely used method for feature extraction in face images. LDA is a dimensionality reduction technique which is used for classification problems. This approach tries to find the projection direction in which, images belonged to different classes are separated maximally. Mathematically it tries to find the projection matrix (the weights) in such a way that the ratio of the between-class scatter matrix and the withinclass scatter matrix of projected images is maximized (Jafri and Arabnia, 2009). In contrast to algorithms based on PCA, LDA considers class membership for dimension reduction. Key idea of LDA is to separate class means of the projected directions well while achieving a small variance around these means. Alike PCA, the derived features of LDA are linear combinations of the original data. As LDA reduces the data efficiently onto a low dimensional space, it is suited for graphical representation of the data sets (Karg *et al.,* 2009). LDA wants to solve an optimal discrimination projection matrix *Wopt* (Ye *et al.,* 2009) as in (5):

$$W_{opt} = \arg\max_{W} \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|}$$

The basic steps in LDA are as follows:

a) Calculate within-class scatter matrix, SW as

$$S_W = \sum_{i=1}^{c} (x_i - \mu_{k_i})(x_i - \mu_{k_i})^T$$

b) Calculate between-class scatter matrix, SB as

$$S_B = \sum_{i=1}^{c} n_i (\mu_i - \mu)(\mu_i - \mu)^T$$

c) Calculate the eigenvectors of the projection matrix

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

d) Compare the test image's projection matrix with the projection matrix of each training image by using a similarity measure. The result is the training image which is the closest to the test image. *SB* is the between-class scatter matrix, *SW* is the withinclass scatter matrix, *ST* = *SB* + *SW* is the total scatter matrix, The notation *c* is the total number of samples in whole image set, *xi* is the feature vector of a sample, and μ*ki* is vector of image class that *xi* belongs to. M *i* is the mean feature vector of class *i,* and *ni* is number of samples in image class *i*. The within-class scatter matrix, also called intra-personal, represents variations in appearance of the same individual due to different lighting and face expression. The between class scatter matrix, also called the extra-personal, represents variations in appearance due to a difference in identity (George, 2008).

Experimental Evaluation

a. ***Database and Experiment Conditions:*** PCA and LDA were evaluated using The Database of Faces provided by AT&T Laboratories Cambridge which is much more renowned by its formal name is the ORL Database of Faces. This database contains 10 different images of 40 distinct subjects. The images vary in terms of lighting, facial expressions including open and closed eyes, facial details such as glass and without glasses, and different time of snapping pictures. In our experiment, these images were separated into training set and testing set and being processed in 56 x 46 pixels, based on Euclidean distance as the classification measurement, identification was performed on every image in testing set using the templates of training images

b. ***Identification Performance of PCA and LDA:*** Our experiment first investigate the performance of PCA and LDA from the effect of varying size of database, *M* and number of training samples, *P*. Size of database is the amount of subject involved in experiment. 5 testing images per subject were fixed at certain set for each different *P* to ensure fair comparison. Figure 3 is an example showing 10 images of a subject in database. The increasing *P* employs some/all images at the first row (1-5); while all images in second row (6-10) belong to testing set. Thus there were (*M* x 5) times of identification performed for each *M*. Experiments were repeated with training set and testing set swapped, be noted that LDA had 2≤*P*≤5 due to the requirement that at least 2 training images needed. Average recognition rate for PCA and LDA are recorded in Figure 4 and Figure 5 respectively. Both algorithms bear performance deterioration when they are to support more subjects which increased from *M*=10 to 20, 30, and 40. Thus large database again proved to inflict more recognition difficulty to algorithms. On the other hand, significant improvement is observed when more training samples are applied, especially from *P*=1 to 3 for PCA. However, it is surprised to find that, recognition rate of *M*=10 and *M*=20 achieve highest accuracy during *P*=3, deviating from our normal expectation. Thus an initial assumption could be drawn is that, more training samples does not guarantee higher recognition rate.

c. ***Identification Performance Comparison of PCA and LDA:*** It has been shown empirically by A.M. Martinez et al., that the performance of algorithms is regarding different ways of selecting images for training set and testing set. Thus in order to compare PCA and LDA in a fairer and reliable manner we examined the recognition rates of 40 subjects by both algorithms in 6 different ways as shown in the table. In the table, number 1-10 under the column of train set and test set refer to 10 images of single subject, which is depicted in Figure 1, The results obtained are plotted in Figure 2 where the performance of PCA and LDA are compared with increasing *P*. Be noted that *P*=1 is omitted because of LDA restriction. From the figure, LDA outperforms PCA even when there are only 2 training samples per subject. From Table LDA is found to be outperformed slightly by PCA at certain comparison especially when there are few training samples. Nevertheless as shown in Figure 2, LDA obviously performs better in overall. This finding is inconsistent with the conclusion drawn by (http://vision.ucsd.edu/extyaleb/CroppedYaleBZip/CroppedYale.zip) which claims the superiority of PCA for small training dataset.

d. ***Verification Performance Comparison of PCA and LDA:*** To evaluate PCA and LDA on verification task, this experiment employed 20 subjects in database as clients.

Figure 1. Example of a subject in the Database of Faces

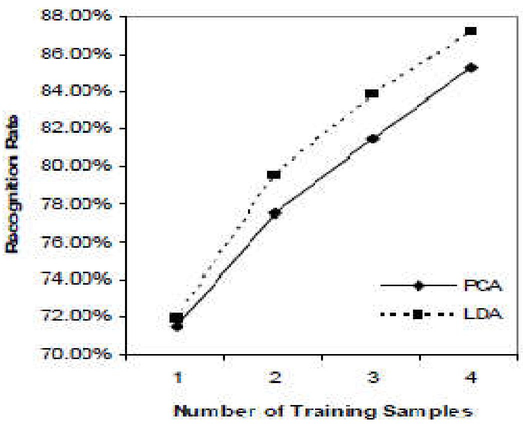

Figure 2. Comparison of PCA and LDA for 40 subjects with varying number of samples per Person

Table 1. Codnition rate of PCA and LDA for 40 Subjects under permutation of trainings set and Testing set

Traln Set	Test Set	Recognition Rate	
		PCA	LDA
1,2	6,7,8,9,10	71.00%	70.00%
1,2,3		75.00%	76.00%
1,2,3,4		78.00%	78.00%
1,2,3,4,5		82.00%	82.00%
2,3	1,7,8,9,10	71.00%	71.50%
2,3,4		75.50%	77.50%
2,3,4,5		80.50%	81.00%
2,3,4,5,6		89.00%	87.50%
3,4	1,2,8,9,10	74.00%	77.00%
3,4,5		81.00%	84.00%
3,4,5,6		91.50%	91.50%
3,4,5,6,7		90.00%	91.50%
4,5	1,2,3,9,10	66.00%	65.00%
4,5,6		70.50%	02.50%
4,5,6,7		81.00%	85.50%
4,5,6,7,8		83.00%	87.00%
5,6	1,2,3,4,10	75.50%	78.00%
5,6,7		80.50%	79.50%
5,6,7,0		02.00%	04.50%
5,6,7,8,9		85.00%	88.00%
6,7	1,2,3,4,5	71.00%	70.00%
6,7,8		74.50%	77.50%
6,7,8,9		76.00%	82.50%
6,7,0,9,10		02.50%	06.50%

Conclusion

In this paper, Face Recognition using PCA and LDA are investigated using The Database of Faces. To enhance original PCA method's discrimination ability, LDA is applied on PCA face subspace for classification. Results have shown the superiority of LDA over PCA even when the training dataset is small. Besides significant improvement is observed when there are more training samples employed for both algorithms. However amount of training samples should consider other factor such as size of database because it consumes more computational time to increase training samples. PCA and LDA achieves recognition rate of 85.25% and 87.08% respectively, 16% percentage of improvement is gained by LDA over PCA for verification task.

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