PCA and LDA Based Face Recognition Using Feedforward Neural Network Classifier

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Abstract. Principal component analysis (PCA) and Linear Discriminant Analysis (LDA) techniques are among the most common feature extraction techniques used for the recognition of faces. In this paper, two face recognition systems, one based on the PCA followed by a feedforward neural network (FFNN) called PCA-NN, and the other based on LDA followed by a FFNN called LDA-NN, are developed. The two systems consist of two phases which are the PCA or LDA preprocessing phase, and the neural network classification phase. The proposed systems show improvement on the recognition rates over the conventional LDA and PCA face recognition systems that use Euclidean Distance based classifier. Additionally, the recognition performance of LDA-NN is higher than the PCA-NN among the proposed systems.

1 Introduction

The development in the multimedia applications has increased the interest and research in face recognition significantly and numerous algorithms have been proposed during the last decades [1]. Research in human strategies of face recognition, has shown that individual features and their immediate relationships comprise an insufficient representation to account for the performance of adult human face identification [2]. Bledsoe [3,4] was the first to attempt to use semi-automated face recognition with a hybrid human-computer system that classified faces on the basis of fiducially marks entered on photographs by hand. Fischler and Elschlager [5] described a linear embedding algorithm that used local feature template matching and a global measure of fit to find and measure the facial features. Generally speaking, we can say that most of the previous work on automated face recognition [6, 7] has ignored the issue of just what aspects of the face stimulus are important for face recognition. This suggests the use of an information theory approach of coding and decoding of face images, emphasizing the significant local and global features. Such features may or may not be directly related to our intuitive notion of face features such as the eyes, nose, lips, and hair. In mathematical terms, the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of a face images, treating an image as point in a very high dimensional space is sought. The eigenvectors are ordered, each one accounting for a different amount of the variation among the face images. These

B. Gunsel et al. (Eds.): MRCS 2006, LNCS 4105, pp. 199 – 206, 2006.

eigenvectors can be thought of as a set of features that together characterize the variation between face images.

Principal Component Analysis (PCA) method [8, 9], which is called eigenfaces in [10, 11] is widely used for dimensionality reduction and recorded a great performance in face recognition. PCA based approaches typically include two phases: training and classification. In the training phase, an eigenspace is established from the training samples using PCA method and the training face images mapped it for classification. In the classification phase, an input face is projected to the same eigenspace and classified by an appropriate classifier such as Euclidean distance [10] or Bayesian [12].

Contrasting the PCA which encodes information in an orthogonal linear space, the Linear Discriminant Analysis (LDA) method encodes discriminatory information in a linear separable space of which bases are not necessarily orthogonal. Researchers have demonstrated that the LDA based algorithms outperform the PCA algorithm for many different tasks [13, 14].

In this paper, the PCA and LDA methods are used for dimensionality reduction and feedforward neural network (FFNN) classifier is used for classification of faces. The proposed methods are called PCA-NN and LDA-NN respectively. The methods consist of two phases which are the PCA or LDA preprocessing phase, and the neural network classification phase. The proposed systems show improvement on the recognition rates over the conventional LDA and PCA face recognition systems that use Euclidean Distance based classifier. Furthermore, the recognition performance of LDA-NN is higher than the PCA-NN among the proposed systems.

2 PCA Method - Calculating Eigenfaces

Let a face image Γ be a two-dimensional $N \times N$ array. An image may also be considered as a vector of dimension N^2. An ensemble of images maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a low dimensional subspace. The main idea of the PCA is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each vector is a linear combination of the original face images. Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$ then the average of the set is defined by

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n \tag{1}$$

Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

This set of very large vectors is then subject to PCA, which seeks a set of M orthonormal vectors, U_m , which best describes the distribution of the data. Then the covariance matrix C can be defined as

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T \tag{3}$$

where the matrix $A = [\Phi_1\ \Phi_2 \ldots \Phi_M]$. The covariance matrix C, however is $N^2 \times N^2$ real symmetric matrix, and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors.

Consider the eigenvectors v_i of $A^T A$ such that

$$A^T A v_i = \mu_i v_i \tag{4}$$

Premultiplying both sides by A, we have

$$A A^T A v_i = \mu_i A v_i \tag{5}$$

where we see that Av_i are the eigenvectors and μ_i are the eigenvalues of $C = A\,A^T$.

Following these analysis, we construct the $M \times M$ matrix $L = A^T A$, where $L_{mn} = \Phi^T{}_m \Phi_n$, and find the M eigenvectors, v_i , of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces U_I .

$$U_I = \sum_{k=1}^{M} v_{Ik} \Phi_k \ , \qquad I = 1, \ldots, M \tag{6}$$

With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M).The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

A new face image (Γ) is transformed into its eigenface components (projected onto "face space") by a simple operation,

$$w_k = U_k^T (\Gamma - \Psi) \tag{7}$$

for $k = 1, \ldots, M'$. The weights form a projection vector,

$$\Omega^T = \left[w_1\ w_2 \ldots w_M \right] \tag{8}$$

describing the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The projection vector is then used to find which of a number of predefined face classes that best describes the face. Classification is performed by comparing the projection vectors of the training face images with the projection vector of the input face image based on the *Euclidean Distance* between the faces classes and the input face image. This is given in Eq. (9). The idea is to find the face class k that minimizes the Euclidean Distance.

$$\varepsilon_k = \left\| (\Omega - \Omega_k) \right\| \tag{9}$$

Where Ω_k is a vector describing the k^{th} faces class.

3 LDA Method – Calculating Fisherfaces

Fisherfaces method overcomes the limitations of eigenfaces method by applying the Fisher's linear discriminant criterion. This criterion tries to maximize the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples.

Fisher discriminants group images of the same class and separates images of different classes. Images are projected from N^2-dimensional space (where N^2 is the number of pixels in the image) to C-1 dimensional space (where C is the number of classes of images). For example, consider two sets of points in 2-dimensional space that are projected onto a single line. Depending on the direction of the line, the points can either be mixed together (Fig. 1a) or separated (Fig. 1b). Fisher discriminants find the line that best separates the points. To identify a input test image, the projected test image is compared to each projected training image, and the test image is identified as the closest training image.

As with eigenspace projection, training images are projected into a subspace. The test images are projected into the same subspace and identified using a similarity measure. What differs is how the subspace is calculated. the LDA method tries to find the subspace that best discriminates different face classes as shown in Fig. 1.

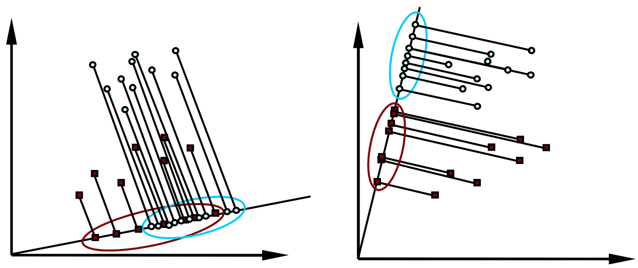

Fig. 1. (a) Mixed when projected onto a line. (b) Separated when projected onto another line.

The separation of classes is achieved by maximizing the between-class scatter matrix S_b, while minimizing the within-class scatter matrix S_w in the projective subspace. S_w and S_b are defined as

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{Nj} (X_i^j - \mu_j)(X_i^j - \mu_j)^T \tag{10}$$

Where X_i^j is the i^{th} sample of class j, μ_j is the mean of class j, C is the number of classes, N_j is the number of samples in class j.

$$S_b = \sum_{j=1}^{C} (\mu_j - \mu)(\mu_j - \mu)^T \tag{11}$$

Where μ represents the mean of all classes. The subspace for LDA is spanned by a set of vectors $W = [W_1, W_2, \ldots\ldots, W_d]$, satisfying

$$W = \arg\max = \left| \frac{W^T S_b W}{W^T S_W W} \right| \tag{12}$$

The within class scatter matrix represents how face images are distributed closely within classes and between class scatter matrix describes how classes are separated.

When face images are projected into the discriminant vectors W, these discriminant vectors should minimize the denominator and maximize the numerator in Eq. (12).

W can therefore be constructed by the eigenvectors of S_w^{-1} S_b There are various methods to solve the problem of LDA such as the pseudo inverse method, the sub-space method, or the null space method.

The approach is similar to the eigenface method, which makes use of projection of training images into a subspace. The test images are projected into the same subspace and identified using a similarity measure. What differs is how subspace is calculated. The face which has the minimum Euclidean distance with the test face image is labeled with the identity of that image.

4 Neural Network – Classification Phase

Neural networks can be trained to perform complex functions in various fields of applications including pattern recognition, identification, classification, speech, vision, and control systems.

In [15] a hybrid neural-network solution is presented which is compared with other methods. The system combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. Zhujie and Y.L. Yu [16] implemented a system to face recognition with eigenfaces and Back propagation neural network using 15 person database from Media Laboratory of MIT. In order to improve their system, Gaussian smoothing was applied where the system performance reached to 77.6%. This performance is almost the same performance with the Euclidean Distance based approach that we used for ORL Face Database, where half of images are used for training and the other half are used for testing (see Fig.4.).

4.1 Feedforward Neural Networks (FFNN)

In FFNN the neurons are organized in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this type of networks connections to the neurons in the same or previous layers are not permitted. Fig. 2 shows the architecture of the proposed system for face classification.

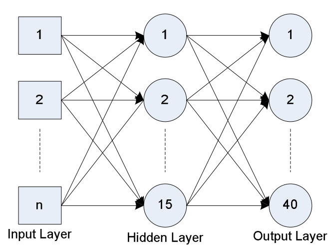

Fig. 2. Architecture of the proposed Neural Networks

4.2 Training and Testing of Neural Networks

Two neural networks, one for PCA based classification and the other for LDA based classification are prepared. ORL [18] face database is used for training and testing.

The training is performed by n poses from each subject and the performance testing is performed by 10-n poses of the same subjects.

After calculating the eigenfaces using PCA the projection vectors are calculated for the training set and then used to train the neural network [17]. This architecture is called PCA-NN. Similarly, after calculation of the fisherfaces using the LDA, projection vectors are calculated for the training set. Therefore, the second neural network is trained by these vectors. This architecture is called LDA-NN. Fig.3 shows the schematic diagram for the neural network training phase.

When a new image from the test set is considered for recognition, the image is mapped to the eigenspace or fisherspace. Hence, the image is assigned by a projection vector. Each projection vector is fed to its respective neural network and the network outputs are compared.

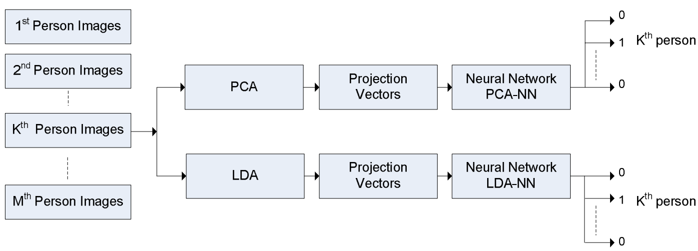

Fig. 3. Training phase of both Neural Networks

5 Results and Discussions

The performances of the proposed systems are measured by varying the number of faces of each subject in the training and test faces. Table 1 and Fig. 4 show the performances of the proposed PCA-NN and LDA-NN methods based on the neural network classifiers as well as the performances of the conventional PCA and LDA based on the Euclidean Distance classifier. The recognition performances increased due to the increase in face images in the training set. This is obvious, because more sample images can characterize the classes of the subjects better in the face space. The results clearly shows that the proposed recognition systems, PCA-NN and LDA-NN, outperforms the conventional PCA and LDA based recognition systems. The LDA-NN shows the highest recognition performance, where this performance is obtained because of the fact that the LDA method discriminate the classes better than the PCA and neural network classifier is more optimal classifier than the Euclidean Distance based classifier. The performance improvement in PCA versus PCA-NN is higher than the LDA versus LDA-NN. For example, when there are 5 images for training and 5 images for testing, the improvement is 7% in PCA based approach and 4% in the LDA based approach. These results indicate that the superiority of LDA over PCA in class separation in the face space leaves less room for improvement to the neural network based classifier.

Table 1. Recognition rates of conventional PCA and LDA versus PCA-NN and LDA-NN

Training Images	Testing Images	PCA	PCA-NN	LDA	LDA-NN
2	8	71	75	78	80
3	7	73	76	82	84
4	6	77	80	87	89
5	5	78	85	87	91
6	4	89	90	93	93
7	3	92	94	95	95
8	2	94	95	96	97

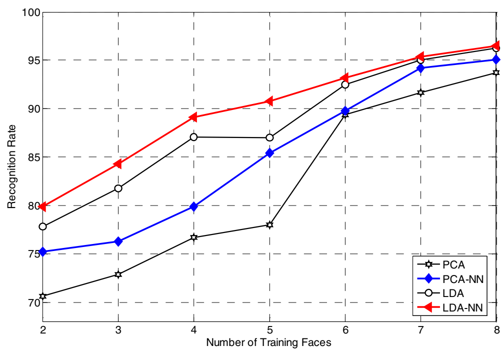

Fig. 4. Recognition rate vs. number of training faces

6 Conclusion

In this paper, two face recognition systems, the first system based on the PCA preprocessing followed by a FFNN based classifier (PCA-NN) and the second one based on the LDA preprocessing followed by another FFNN (LDA-NN) based classifier, are proposed. The feature projection vectors obtained through the PCA and LDA methods are used as the input vectors for the training and testing of both FFNN architectures. The proposed systems show improvement on the recognition rates over the conventional LDA and PCA face recognition systems that use Euclidean Distance based classifier. Additionally, the recognition performance of LDA-NN is higher than the PCA-NN among the proposed systems.

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