

A New Face Recognition Method using PCA, LDA and Neural Network

A. Hossein Sahoozadeh, B. Zargham Heidari, and C. Hamid Dehghani

Abstract—In this paper, a new face recognition method based on PCA (principal Component Analysis), LDA (Linear Discriminant Analysis) and neural networks is proposed. This method consists of four steps: i) Preprocessing, ii) Dimension reduction using PCA, iii) feature extraction using LDA and iv) classification using neural network. Combination of PCA and LDA is used for improving the capability of LDA when a few samples of images are available and neural classifier is used to reduce number misclassification caused by not-linearly separable classes. The proposed method was tested on Yale face database. Experimental results on this database demonstrated the effectiveness of the proposed method for face recognition with less misclassification in comparison with previous methods.

Keywords—Face recognition Principal component analysis, Linear discriminant analysis, Neural networks.

I. INTRODUCTION

IN the last years, Face Recognition [1] has become one of the most challenging tasks in the pattern recognition field. The recognition of faces is very important for many applications such as: video surveillance, retrieval of an identity from a data base for criminal investigations and forensic applications. Among various solutions to the problem [2] the most successful seems to be those appearance-based approaches, which generally operate directly on images or appearances of face objects and process the image as two-dimensional patterns. These methods extract features to optimally represent faces belong to a class and separate faces from different classes. Ideally, it is desirable to use only features having high separability power while ignoring the rest. Most effort in the literature have been focused mainly on developing feature extraction methods [5]-[7] and employing powerful classifiers such as probabilistic [8], hidden Markov models (HMMs) [9] neural networks (NNs) [10], [16],[19] and support vector machine (SVM) [11].

The main trend in feature extraction has been representing the data in a lower dimensional space computed through a linear or non-linear transformation satisfying certain properties. Statistical techniques have been widely used for

face recognition and in facial analysis to extract the abstract features of the face patterns. Principal component analysis (PCA) [3]-[5] and linear discriminant analysis (LDA) [6] and discrete cosine transform (DCT) [16]-[18] are three main techniques used for data reduction and feature extraction in the appearance-based approaches. DCT, Eigen-faces [5] and fisher-faces [6] built based on these three techniques, have been proved to be very successful.

DCT remove the some high frequency details and in this way reduce the size of images [16]-[18]. LDA algorithm selects features that are most effective for class separability while PCA selects features important for class representation. A study in [12] demonstrated that PCA might outperform LDA when the number of samples per class is small and in the case of training set with a large number of samples, the LDA still outperform the PCA. Compared to the PCA method, the computation of the LDA is much higher [13] and PCA is less sensitive to different training data sets. However, simulations reported in [13] demonstrated an improved performance using the LDA method compared to the PCA approach. When dimensionality of face images is high, LDA is not applicable and therefore we deprive from its advantage to find effective features for class separability.

To resolve this problem we combine the PCA and LDA methods, by applying PCA to preprocessed face images, we get low dimensionality images which are ready for applying LDA. Finally to decrease the error rate in spite of Euclidean distance criteria which was used in [4], we implement a neural network to classify face images based on its computed LDA features.

II. FEATURE EXTRACTION ALGORITHMS

PCA and LDA are two powerful tools used for dimensionality reduction and feature extraction in most of pattern recognition applications. In this section, a brief review of PCA and LDA fundamentals is given.

A. Principal Component Analysis

Let $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$, $\mathbf{x} \in \mathcal{R}^n$ be N samples from L classes $\{\omega_1, \omega_2, \dots, \omega_L\}$, and $p(\mathbf{x})$ their mixture distribution. In a sequel, it is assumed that a priori probabilities $P(\omega_i)$, $i = 1, 2, \dots, L$, are known. Consider \mathbf{m} and $\mathbf{\Sigma}$ denote mean vector and covariance matrix of samples, respectively. PCA algorithm can be used to find a subspace whose basis vectors correspond to the maximum variance directions in the original n dimensional space. PCA subspace can be used for presentation of data with minimum error in

Hossein Sahoozadeh is with the Electrical Engineering Department, Arak Azad University, Arak, Iran (e-mail: Hosein_Sahooli@yahoo.com).

Zargham Heidari is with the Electrical Engineering Department, Islamic Azad University of Iran, Khormoj branch, Boushehr, Iran (e-mail: Nariman_azma@yahoo.com).

Hamid Dehghani is with Electrical Engineering Department, Maleke Ashtar University of Technology, Tehran, Iran (e-mail: Hamid_deh@yahoo.com).

reconstruction of original data. Let Φ_{PCA}^p denote a linear $n \times p$ transformation matrix that maps the original n dimensional space onto a p dimensional feature subspace where $p < n$. The new feature vectors $\mathbf{y}_i \in \mathfrak{R}^p$ are defined by:

$$\mathbf{y}_i = (\Phi_{PCA}^p)^t \mathbf{x}_i \quad i = 1, 2, \dots, N \quad (1)$$

It is easily proved that if the columns of Φ_{PCA}^p are the eigenvectors of the covariance matrix corresponding to its p largest eigenvalues in decreasing order, the optimum feature space for the representation of data is achieved. The covariance matrix can be estimated by:

$$\hat{\Sigma} = \left(\sum_{i=1}^N (\mathbf{x}_i - \hat{\mathbf{m}})(\mathbf{x}_i - \hat{\mathbf{m}})^t \right) / (N - 1) \quad (2)$$

Where $\hat{\mathbf{m}}$ in (2) can be estimated by:

$$\mathbf{m}_k = \mathbf{m}_{k-1} + \eta (\mathbf{x}_k - \mathbf{m}_{k-1}) \quad (3)$$

Where \mathbf{m}_k is estimation of mean value at k -th iteration and \mathbf{x}_k is a the k -th input image. PCA is a technique to extract features effective for representing data such that the average reconstruction error is minimized. In the other word, PCA algorithm can be used to find a subspace whose basis vectors correspond to the maximum variance directions in the original n dimensional space. PCA transfer function is composed of significant eigenvectors of covariance matrix. The following equation can be used for incremental estimation of covariance matrix:

$$\Sigma_k = \Sigma_{k-1} + \eta_k (\mathbf{x}_k \mathbf{x}_k^t - \Sigma_{k-1}) \quad (4)$$

Where Σ_k is the estimation of the covariance matrix at k -th iteration, \mathbf{x}_k is the incoming input vector and η_k is the learning rate.

B. Linear Discriminant Analysis

LDA searches the directions for maximum discrimination of classes in addition to dimensionality reduction. To achieve this goal, within-class and between-class matrices are defined. A within-class [14] scatter matrix is the scatter of the samples around their respective class means \mathbf{m}_i :

$$\Sigma_w = \sum_{i=1}^L P(\omega_i) E[(\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^t | \omega_i] = \sum_{i=1}^L P(\omega_i) \Sigma_i \quad (5)$$

where Σ_i denotes the covariance matrix of i -th class. The between-class scatter matrix is the scatter of class means \mathbf{m}_i around the mixture mean \mathbf{m} , and is given by:

$$\Sigma_b = \sum_{i=1}^L P(\omega_i) (\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^t \quad (6)$$

Finally, the mixture scatter matrix is the covariance of all samples regardless of class assignments, and is defined by [14]:

$$\Sigma = E[(\mathbf{x} - \mathbf{m})(\mathbf{x} - \mathbf{m})^t] = \Sigma_w + \Sigma_b \quad (7)$$

Different objective functions have been used as LDA criteria mainly based on a family of function of scatter matrices. For example, the maximization of the following objective functions have been previously proposed [14]:

$$J_1 = \text{tr}(\Sigma_w^{-1} \Sigma_b) \quad (8)$$

$$J_2 = \ln |\Sigma_w^{-1} \Sigma_b| = \ln |\Sigma_b| - \ln |\Sigma_w| \quad (9)$$

$$J_3 = \text{tr}(\Sigma_b) - \mu [\text{tr}(\Sigma_w) - c] \quad (10)$$

$$J_4 = \text{tr}(\Sigma_b) / \text{tr}(\Sigma_w) \quad (11)$$

In LDA, the optimum linear transform is composed of p ($p \leq n$) eigenvectors of $\Sigma_w^{-1} \Sigma_b$ corresponding to its p largest eigenvalues. Alternatively, $\Sigma_w^{-1} \Sigma$ can be used for LDA, simple analysis shows that both $\Sigma_w^{-1} \Sigma_b$ and $\Sigma_w^{-1} \Sigma$ have the same eigenvector matrices. In general, Σ_b is not full rank and therefore not a covariance matrix, hence we shall use Σ in place of Σ_b . The computation of the eigenvector matrix Φ_{LDA} of $\Sigma_w^{-1} \Sigma$ is equivalent to the solution of the generalized eigenvalue problem $\Sigma \Phi_{LDA} = \Sigma_w \Phi_{LDA} \Lambda$ where Λ is the generalized eigenvalue matrix. Under assumption of positive definite matrix Σ_w , there exists a symmetric $\Sigma_w^{-1/2}$ such that the problem can be reduced to a symmetric eigenvalue problem:

$$\Sigma_w^{-1/2} \Sigma \Sigma_w^{-1/2} \Psi = \Psi \Lambda \quad (12)$$

where $\Psi = \Sigma_w^{1/2} \Phi_{LDA}$.

III. PROPOSED FACE RECOGNITION METHOD

The proposed face recognition method consists of four separate parts:

- i) Pre processing
- ii) Dimensionality reduction using PCA
- iii) Feature extraction for class separability using LDA
- iv) Classification using neural network

In the next sections, we describe role of each part.

A. Preprocessing

In this part, at first we manually cut the input images to 40×40 images in order to remove the background information and have only face details (face images in most databases contain background information that is not useful for recognition, Figure (1) shows some face images with background information)



Fig. 1 Sample Face images that used in our experiment

After that we histogram equalize all input images in order to spread energy of all pixels inside the image and then normalize them to equalize amount of energy related to each face image.

As a next step, we subtract mean images from face images to mean center all of them. Fig. 2 shows mean images of face images that used in our experiments.



Fig. 2 Mean images related to our selected faces.

Finally all preprocessed face images change to a vector (1600×1 vector) and go to the next step. Fig. 3 shows block diagram of operation made in this section. For complexity and memory size reduction, mean image is computed adaptively using (3) [15].

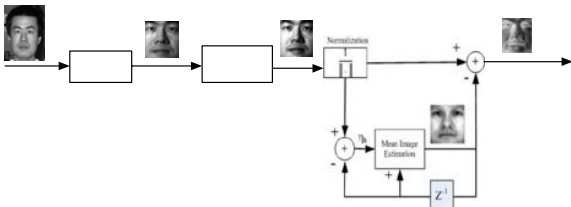


Fig. 3 Preprocessing Block diagram

B. Dimensionality Reduction

As mentioned in the previous section, we cropped every input image to 40×40 image; as a result the input of this stage is a preprocessed 1600×1 vector. We used these vectors to estimate the covariance matrix [14]. After estimation of the covariance matrix, significant eigenvectors of the covariance matrix are computer.

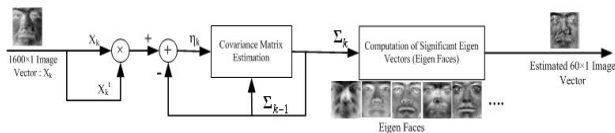


Fig. 4 Dimension reduction Block diagram

Number of eigen-vector depend to our application and accuracy that we need, it is clear that if we compute large number of eigen-vectors accuracy of the method improved but computational complexity increased in this step and next step. In this stage, we computed 100 most significant eigen-vectors and related eigen-faces. By projection of every input image on these eigenafeces, they will convert to reduce size 100×1 vectors which will be go to LDA feature extraction part. Fig. 4 demonstrated operation done in this stage (covariance estimation and computation of the eigen-faces). We repeated our experiment with different values of significant eigen-vectors and choose them equal to 20, 40, and 60 and 80 and compared the performance of the proposed face recognition method.

C. LDA Feature Extraction

Outputs of dimension reduction part are 100×1 vectors which are used to construct within class scatter matrix and covariance matrix. As mentioned in section II, significant eigenvectors of $\Sigma_w^{-1}\Sigma$ can used for separability of classes in addition to dimension reduction. Using 100×1 vectors, $\Sigma_w^{-1}\Sigma$ computed and then eigenvectors related to the greater eigenvalues are selected. In our experiment we considered 10 classes, therefore there are 9 major eigenvectors (Fisher faces) associated with non-zero eigenvalues which have separability capability. It is clear that extracting all of 9 LDA features increase the discriminatory power of the method. Therefore, this section produce 9×1 vectors which are used as input of MLP three layer neural network. Fig. 5 demonstrate operation of this part, at first covariance and within class scatter matrices are estimated and then significant eigenvector of $\Sigma_w^{-1}\Sigma$ are computed (Fisher Faces).

D. Neural Network Classifier

We used a three layer perceptron neural network with 40 neurons in the input layer, 20 neurons in the hidden layer and 10 neurons in the output layer, for classification of the input data. A simple back propagation algorithm is used to update weights according to desired values. Three layers MLP neural network will train using training face images and at its output layer, it produces a 10×1 vector that each elements of that vector is a number between zero and one representing similarity of input face images to each of ten classes. Training face image enter the neural network and according to their class, a back propagation error, spread on the network and correct the weights toward the right values. The input face image will classified to the class which has the greatest similarity to it. For example if for a test input face image, row 3 of network's output be greater than other rows, that test face images will classified to class 3. Fig. 6 demonstrate process classification using three layer neural network.

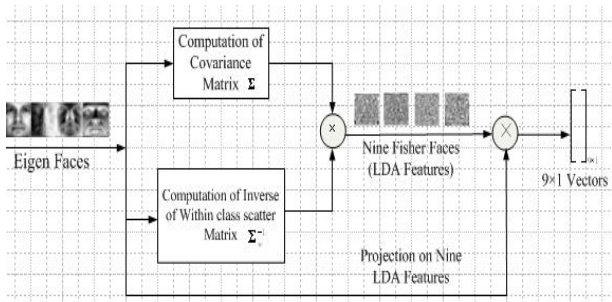


Fig. 5 LDA feature extraction (Fisher faces) Block diagram



Fig. 8 50 most significant eigen-faces

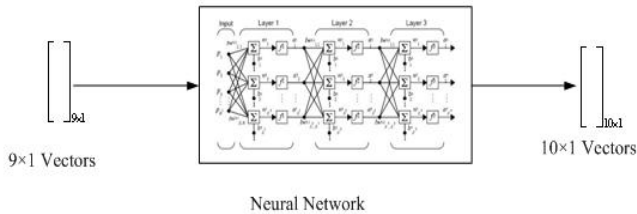


Fig. 6 Classification using three layer MLP neural Network

IV. EXPERIMENT RESULTS

We applied the proposed new face recognition method on YALE face datasets for separation of ten classes. For all experiments, we used Matlab code running on a PC with Intel Pentium 4, 2.8-GHZ CPU and 1024-Mb RAM. Before doing any experiment, we cropped the input images to reduce their size to 40x40.



Fig. 7 Preprocessed Sample face Images

Our selected database contains grayscale images of 10 subjects in GIF format. In these experiments, we considered 60 images per each subject (total 600 images) containing different illumination and different poses, which 40 images of each used for training and remaining 20 images used for testing the method. Fig. 7 shows some of selected preprocessed subjects in different position and illumination. Then 100 significant eigen faces are computed in stage 2, where Fig. 8 shows first 50 of them.

As mentioned we repeat the same experiment by extracting 80, 60, 40 and 20 eigen faces and compared the identification rate of the proposed method, in that cases.

In our simulations, we considered 10 subjects. For each selection of eigen faces we also change the number of selected LDA significant features. We changed number of LDA features from 3 to 9 for each selection of eigen faces. It means that for example for the case, eigen faces equal to 60, we repeated the experiment by LDA features equal to 3 to 9 and compared the error rate. Fig. 9 shows 9 estimated fisher faces in the situation that all nine available LDA features are selected. In this case face image projected to nine dimensional spaces.

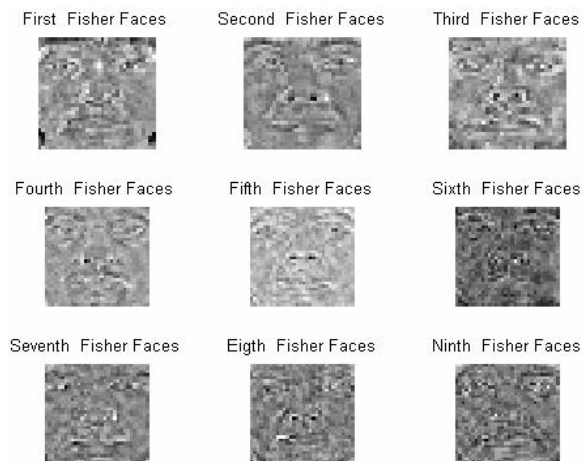


Fig. 9 Computed nine Fisher faces

Fig. 10 demonstrate distribution of the face images in the 3 dimensional LDA subspace, some classes are linearly separable and there are overlapping between some other classes. It is clear that overlapped classes may be are separable in remaining (not shown) 6 dimensional subspaces (it is not possible to demonstrate face images in nine dimensional space and only to get a sense about performance of the method we show them in three dimensional space). In Fig. 10 each

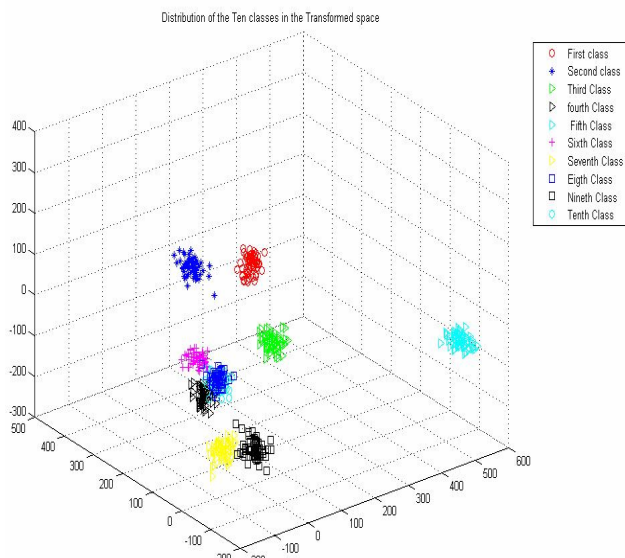


Fig. 10 Distribution of classes in three dimensional LDA feature space

color represents a class. To improve the accuracy of the method for face classification, projected face images are given to a neural network. This neural network consists of three layers, 40 neurons in the first layer, 20 neurons in the hidden layer and 10 neurons in the output layer. Tangent sigmoid function is used as activation function in the first and second layers and pure linear function is used in the output layer and simple back-propagation learning rule is used for training the weights. Output of the neural network is a 10×1 vector that each element of that vector represents similarity of the input image to one of 10 available classes. For example the first element of the output vector represents similarity to the first class and the other element represents the similarity to other classes. Similarity is between zero and one and the input image is classified to the class that has the greatest similarity to it. 40 images from each class (totally 400 images) are used for network training and remaining 15 images from each class (totally 200 images) are used for testing the proposed method. As mentioned before, the above experiment repeated for different values of PCA eigenvectors and LDA eigenvectors. As the number of selected PCA features increase the reconstruction error of a face images decrease and we get a more precise estimation of it and as the number of LDA features increase separability power raise and error rate reduce.

Fig. 11 compares average recognition rates by changing the number of PCA and LDA features, it is clear that in the case of PCA features equal to 100 and LDA feature equal to 8 or 9, we get the recognition rate equal to 99.5% (in average one misclassification for 200 test face images). The top line in the Fig. 11 related to the case that all nine LDA feature are computed and as we expected in this case we get the highest recognition rates in comparison with cases that less LDA features are selected. It is also obvious that as number of selected PCA features (Eigen faces) increase (for a fixed

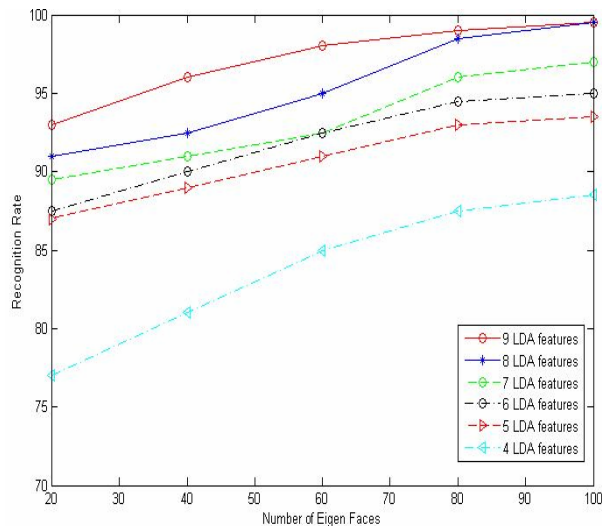


Fig. 11 Comparison of recognition rate for choosing different values of PCA and LDA features

number of LDA features) again accuracy of recognition rate improve. Table I compare recognition rate for selection of different values of LDA features in the case of PCA features equal to 100, 80, 60, 40 and 20. Although choosing 100 PCA features and 8 or 9 LDA features improve the recognition rate in comparison in previous method, but it also increase the computational cost. Table II; compare the recognition rate of the proposed method (highest recognition rate) with algorithms introduced in [4]-[6], [16], [18], [19].

V. CONCLUDING REMARKS

In this paper, a new Face recognition method is presented. The new method was considered as a combination of PCA, LDA and neural networks. We used these algorithms to construct efficient face recognition method with a high recognition rate. Proposed method consists of four parts: i) image preprocessing that includes histogram equalization, normalization and mean centering, ii) dimension reduction using PCA that main features that are important for representing face images are extracted iii) feature extraction using LDA that significant features for class separability are selected and iv) neural network classifier that classify input face images into one of available classes. Simulation results using YALE face datasets demonstrated the ability of the proposed method for optimal feature extraction and efficient face classification. In our simulations, we chose 10 persons and considered 40 training image and 20 test image for each person (totally 400 training and 200 test face images). Experimental results show a high recognition rate equal to 99.5% (in average one misclassification for each 200 face images) which demonstrated an improvement in comparison with previous methods. The new face recognition algorithm can be used in many applications such as security methods.

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TABLE I
COMPARISON OF RECOGNITION RATE BY CHOOSING DIFFERENT NUMBER OF PCA AND LDA FEATURES

	4 LDA features	5 LDA features	6 LDA features	7 LDA features	8 LDA features	9 LDA features
20 PCA features	77%	84%	87.5	87.5%	92%	94.5
40 PCA features	81%	86%	89.5%	90%	93.5%	96.5%
60 PCA features	85%	90.5%	93%	93%	95%	98%
80 PCA features	87.5	92%	94.5	96	98.5%	99%
100 PCA features	88.5%	92.5%	95%	97%	99.5%	99.5%

TABLE II
COMPARISON OF RECOGNITION RATE OF THE PROPOSED METHOD WITH THE AVAILABLE PREVIOUS METHODS

	DCT+LDA+RB Ref. [16] - 2005	DCT+LDA+Short Dist (Euclidean)- Ref. [18] - 2004	DCT – Ref. [20] - 2004	PCA+LDA+ Short Dist (Euclidean) – Ref. [4,6] -1997	PCA+ Short Dist (Euclidean) – Ref. [5]- 1991	Proposed Method
Recognition Rate	98.1	97.7	84.5	94.8	84	99.5