Face Recognition System Based on PCA and Feedforward Neural Networks

Alaa Eleyan and Hasan Demirel

Department of Electrical and Electronic Engineering,
Eastern Mediterranean University,
Gazimağusa, North Cyprus, Mersin 10, Turkey
{alaa.eleyan, hasan.demirel}@emu.edu.tr

Abstract. Face recognition is one of the most important image processing research topics which is widely used in personal identification, verification and security applications. In this paper, a face recognition system, based on the principal component analysis (PCA) and the feedforward neural network is developed. The system consists of two phases which are the PCA preprocessing phase, and the neural network classification phase. PCA is applied to calculate the feature projection vector of a given face which is then used for face identification by the feedforward neural network. The proposed PCA and neural network based identification system provides improvement on the recognition rates, when compared with a face classifier based on the PCA and Euclidean Distance.

1 Introduction

Much of work done in computer recognition of faces has focused on detecting individual features such as the eyes, nose, mouth, and head outline, and defining a face model by the position, size, and relationships among these features. Such approaches have proven difficult to extend to multiple views and have often been quite fragile, requiring a good initial guess to guide them. Research in human strategies of face recognition, moreover, has shown that individual features and their immediate relationships comprise an insufficient representation to account for the performance of adult human face identification [1]. Bledsoe [2,3] 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. Parameters for the classification were normalized distances and ratios among points such as eye corners, mouth corners, nose tip, and chin point. Fischler and Elschlager [4] 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 [5, 6] 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,

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nose, lips, and hair. In mathematical terms, the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as point (or vector) 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 eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that it is possible to display these eigenvectors as a sort of ghostly face image which is called an "eigenface". Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can also be approximated using only the "best" eigenfaces, those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images. The best *M* eigenfaces span an *M*-dimensional subspace which we call the "face space" of all possible images. The method proposed by M. Turk and A. Pentland [7] uses a PCA based face recognition system which is called the eigenfaces method. In this method, a given face image is transformed into the eigenspace to obtain a feature projection vector. The Euclidean Distance between the projection vector of a given face and the class projection vectors are used to determine a correct or false recognition. In this paper, the projection vectors obtained through the same PCA procedure are used as the input vectors for the feedforward neural network classifier. The proposed PCA and neural network based identification system provides improvement on the recognition rates, when compared with a face classifier based on the PCA and Euclidean Distance introduced by M. Turk and A. Pineland [7].

2 Calculating Eigenfaces

Let a face image I(x,y) be a two-dimensional $N \times N$ array. An image may also be considered as a vector of dimension N^2, so that a typical image of size 112×92 becomes a vector of dimension 10,304, or equivalently a point in a 10,304-dimensional space. 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 relatively low dimensional subspace. The main idea of the principle component 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 of length N^2, describes an $N \times N$ image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, we refer to them as "eigenfaces".

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 principal component analysis, which seeks a set of M orthonormal vectors, U_n , which best describes the distribution of the data. The kth vector, U_k , is chosen such that

$$\lambda_k = \frac{1}{M} \sum_{n=1}^{M} \left(U_k^T \Phi_n \right)^2 \tag{3}$$

is a maximum, subject to

$$U_I^T U_k = \delta_{Ik} = \left\{ \begin{matrix} 1, & if \ I = k \\ 0, & otherwise \end{matrix} \right\} \tag{4}$$

The vectors U_k and scalars λ_k are the eigenvectors and eigenvalues, respectively of the covariance matrix

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T \tag{5}$$

where the matrix $A = [\Phi_1 \ \Phi_2 .... \Phi_M]$. 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.

Fig. 1. First 25 eigenfaces with highest eigenvalues

Consider the eigenvectors v_i of A^TA such that

$$A^T A v_i = \mu_i v_i \tag{6}$$

Premultiplying both sides by A, we have

$$AA^T A v_i = \mu_i A v_i \tag{7}$$

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 $L= A^TA$, 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 .

$$U_I = \sum_{k=1}^{M} v_{Ik}\Phi_k\ , \qquad I = 1,\dots,M \tag{8}$$

Examples of eigenfaces after applying the eigenfaces algorithm are shown in Fig.1.

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). In practice, the training set of face images will be relatively small ($M << N^2$), and the calculations become quite manageable. The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

3 Using Eigenfaces to Classify a Face Image

The eigenface images calculated from the eigenvectors of L span a basis set with which to describe face images. Sirovich and Kirby [8, 9] evaluated a limited version of this framework on an ensemble of 115 images (M = 115) images of Caucasian males digitized in a controlled manner, and found that *40 eigenfaces* were sufficient for a very good description of face images. In practice, a smaller M' can be sufficient for identification, since accurate reconstruction of the image is not a requirement. Based on this idea, the proposed face recognition system lets the user specify the number of eigenfaces (M') that is going to be used in the recognition. For maximum accuracy, the number of eigenfaces should be equal to the number of images in the training set. But, it was observed that, for a training set of fourteen face images, seven eigenfaces were enough for a sufficient description of the training set members. In this framework, identification becomes a pattern recognition task. The eigenfaces span an M' dimensional subspace of the original N^2 image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues.

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

$$w_k = U_k^T(\Gamma - \Psi) \tag{9}$$

for k = 1,...,M'. This describes a set of point by point image multiplications and summations, operations performed at approximately frame rate on current image processing hardware, with a computational complexity. The weights form a feature vector,

$$\Omega^T = \left[w_1 \; w_2 .... w_M \right] \tag{10}$$

that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The feature vector is then used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The face class Ω_k can be calculated by averaging the results of the eigenface representation over a small number of face images of each individual. Classification is performed by comparing the feature vectors of the training face images with the feature vector of the input face image. This comparison is based on the *Euclidean Distance* between the faces classes and the input face image. This is given in Eq. (11). The idea is to find the face class k that minimizes the Euclidean Distance.

$$\varepsilon_k = \left\| \left(\Omega - \Omega_k \right) \right\| \tag{11}$$

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

4 Neural Networks for Classification

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 [10] 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 [11] 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 of 40 persons, where half of images are used for training and the other half are used for testing (see Table 1).

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.

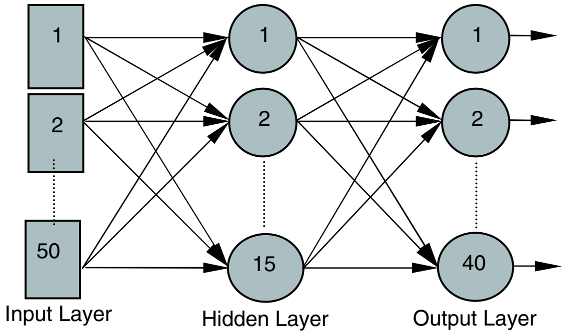

Fig. 2. Architecture of the proposed Neural Network

4.2 Training and Simulation of Neural Network

A large neural network for all people in the database of 40 persons was implemented. After calculating the eigenfaces, the feature projection vectors are calculated for the faces in the database. These feature projection vectors are used as inputs to train the neural network. Fig.3 shows the schematic diagram for the NN training phase.

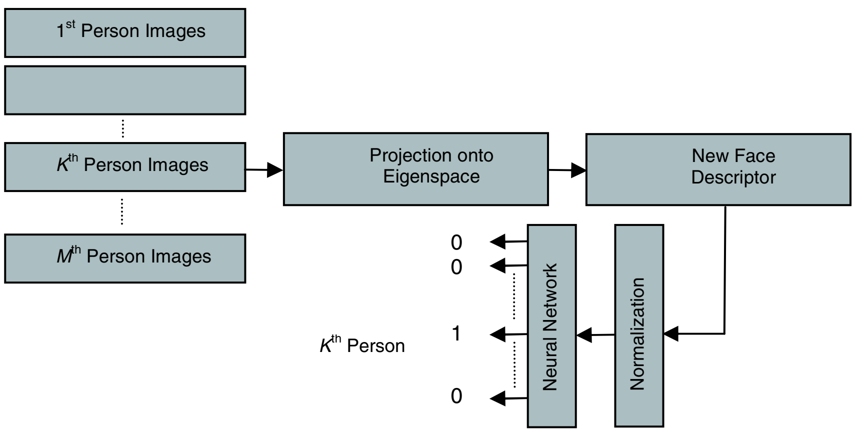

Fig. 3. Training phase of the Neural Network

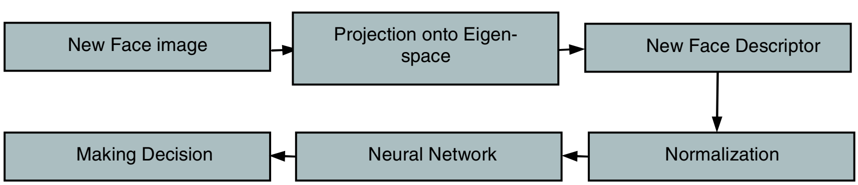

Fig. 4. Simulations of Neural Network for Classification

When a new image is considered for recognition, its feature projection vector is calculated from the eigenfaces, and this image gets its new descriptors. These descriptors are fed to the neural network and the network is simulated with these descriptors, where the network outputs are compared. By looking at the maximum output the new face is decided to belong to the class of person with this maximum output.

5 Experimental Results

In ORL database there are 10 different images for each 40 distinct persons. The neural network is trained with the first *n* poses of the 40 persons in the database. After the training the remaining 10-*n* poses of the persons have been used for the testing. As expected the recognition performance increases with the increasing number of faces used to train the neural network (Table 1). However the real improvement is due to the use of the FFNN as the classifier instead of the Euclidean Distance based classifier. Table 1 clearly shows that, in all cases, the FFNN based face recognition system performs better than the Euclidean Distance based system.

Table 1. Performances of Euclidean Distance and Neural Networks

Training Images	Testing Images	Euclidean Distance performance	Neural Networks preformance
2	8	71	75
3	7	73	76
4	6	77	80
5	5	78	85
6	4	89	90
7	3	92	94
8	2	94	95

6 Conclusion

In this paper, a face recognition system, based on the PCA preprocessing followed by a FFNN based classifier is proposed. The feature projection vectors obtained through the PCA method are used as the input vectors for the training and testing of the FFNN architecture. The face recognition performance of the system using FFNN is better than the Euclidean Distance based classification system for changing number of training images. The performance of the FFNN based system with 5 training faces from each subject gives highest performance improvement which is 7% over the Euclidean Distance based system.

References

1. Carey, S., and Diamond, R., "From Piecemeal to Configurational Representation of Faces", *Science 195*, pp. 312-313, 1977.
2. Bledsoe, W. W., "The Model Method in Facial Recognition", *Panoramic Research Inc.* Palo Alto, CA, Rep. PRI:15, August 1966.

3. Bledsoe, W. W., "Man-Machine Facial Recognition", *Panoramic Research Inc*. Palo Alto, CA, Rep. PRI:22, August 1966.
4. Fischler, M. A., and Elschlager, R. A., "The Representation and Matching of Pictorial Structures", *IEEE Trans. on Computers*, c-22.1, 1973.
5. Harmon, L. D., and Hunt, W. F., "Automatic Recognition of Human Face Profiles", *Computer Graphics and Image Processing,* Vol. 6, pp. 135-156, 1977.
6. Kaufman, G. J., and Breeding, K. J, "The Automatic Recognition of Human Faces From Profile Silhouettes", *IEEE Trans. Syst. Man Cybern*., Vol. 6, pp. 113-120, 1976.
7. Turk, M., and Pentland, A., "Eigenfaces for Recognition", *Journal of Cognitive Neuroscience*, Vol. 3, pp. 71-86, 1991.
8. Kirby, M., and Sirovich, L., "Application of the Karhunen-Loeve Procedure for the Characterization of Human Faces", IEEE PAMI, Vol. 12, pp. 103-108, 1990.
9. Sirovich, L., and Kirby, M., "Low-Dimensional Procedure for the Characterization of Human Faces", *J. Opt. Soc*. Am. A, 4, 3, pp. 519-524, 1987.
10. Lawrence, S., Giles, C. L., Tsoi, A. C., Back, A. D., "Face Recognition: A Convolutional Neural-Network Approach", *IEEE Trans. Neural Networks*, Vol. 8, No. 1, January 1997.
11. Zhujie, Yu, Y. L., "Face Recognition with Eigenfaces", *Proc. of the IEEE Intl. Conf.*, pp.434 - 438, December, 1994.