Face Recognition Using Eigen Faces and Artificial Neural Network

Mayank Agarwal, Nikunj Jain, Mr. Manish Kumar and Himanshu Agrawal

Abstract—**Face is a complex multidimensional visual model and developing a computational model for face recognition is difficult. The paper presents a methodology for face recognition based on information theory approach of coding and decoding the face image. Proposed methodology is connection of two stages – Feature extraction using principle component analysis and recognition using the feed forward back propagation Neural Network. The algorithm has been tested on 400 images (40 classes). A recognition score for test lot is calculated by considering almost all the variants of feature extraction. The proposed methods were tested on Olivetti and Oracle Research Laboratory (ORL) face database. Test results gave a recognition rate of 97.018%**

Index Terms—**Face recognition, Principal component analysis (PCA), Artificial Neural network (ANN), Eigenvector, Eigenface.**

I. Introduction

The face is the primary focus of attention in the society, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable. A human can recognize thousands of faces learned throughout the lifetime and identify familiar faces at a glance even after years of separation. This skill is quite robust, despite of large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses, beards or changes in hair style.

Face recognition has become an important issue in many applications such as security systems, credit card verification, criminal identification etc. Even the ability to merely detect faces, as opposed to recognizing them, canbe important.

Although it is clear that people are good at face recognition, it is not at all obvious how faces are encoded or decoded by a human brain. Human face recognition has been studied for more than twenty years. Developing a computational model of face recognition is quite difficult, because faces are complex, multi-dimensional visual stimuli. Therefore, face recognition is a very high level computer vision task, in which many early vision techniques can be involved. For face identification the starting step involves extraction of the relevant features from facial images. A big challenge is how to quantize facial features so that a computer is able to recognize a face, given a set of features. Investigations by numerous researchers over the past several years indicate that certain facial characteristics are used by human beings to identify faces.

II. Related Work

There are two basic methods for face recognition. The first method is based on extracting feature vectors from the basic parts of a face such as eyes, nose, mouth, and chin, with the help of deformable templates and extensive mathematics. Then key information from the basic parts of face is gathered and converted into a feature vector. Yullie and Cohen [1] used deformable templates in contour extraction of face images.

Another method is based on the information theory concepts viz. principal component analysis method. In this method, information that best describes a face is derived from the entire face image. Based on the Karhunen-Loeve expansion in pattern recognition, Kirby and Sirovich [5], [6] have shown that any particular face can be represented in terms of a best coordinate system termed as "eigenfaces". These are the eigen functions of the average covariance of the ensemble of faces. Later, Turk and Pentland [7] proposed a face recognition method based on the eigenfaces approach.

An unsupervised pattern recognition scheme is proposed in this paper which is independent of excessive geometry and computation. Recognition system is implemented based on eigenface, PCA and ANN. Principal component analysis for face recognition is based on the information theory approach in which the relevant information in a face image is extracted as efficiently as possible. Further Artificial Neural Network was used for classification. Neural Network concept is used because of its ability to learn ' from observed data.

III. Proposed Technique

The proposed technique is coding and decoding of face images, emphasizing the significant local and global features. In the language of information theory, the relevant information in a face image is extracted, encoded and then compared with a database of models. The proposed method is independent of any judgment of features (open/closed eyes, different facial expressions, with and without Glasses). The face recognition system is as follows:

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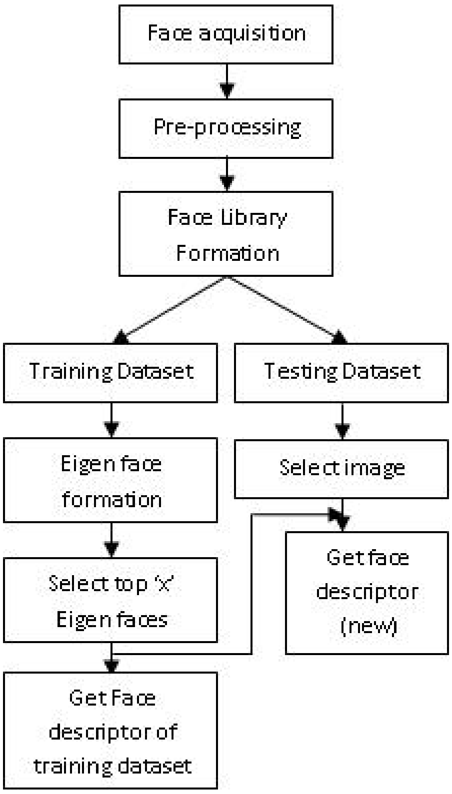

Fig. 1 – Face Library Formation and getting face descriptor

A. *Preprocessing And Face Library Formation*

Image size normalization, histogram equalization and conversion into gray scale are used for preprocessing of the image. This module automatically reduce every face image to X*Y pixels(based on user request), can distribute the intensity of face images (histogram equalization) in order to improve face recognition performance. Face images are stored in a face library in the system. Every action such as training set or Eigen face formation is performed on this face library. The face library is further divided into two sets – training dataset (60% of individual image) and testing dataset (rest 40% images). The process is described in Fig. 1.

B. *Calculating Eigenfaces*

The face library entries are normalized. Eigenfaces are calculated from the training set and stored. An individual face can be represented exactly in terms of a linear combination of eigenfaces. The face can also be approximated using only the best M eigenfaces, which have the largest eigenvalues. It accounts for the most variance within the set of face images. Best M eigenfaces span an M-dimensional subspace which is called the "face space" of all possible images. For calculating the eigenface PCA algorithm [5], [8], was used.

Let a face image I(x, y) be a two-dimensional N x N array. An image may also be considered as a vector of dimension N2, so that a typical image of size 92 x 112 becomes a vector of dimension 10,304, or equivalently a point in 10,304-dimensional space. An ensemble of images, then, 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 principal component analysis (or Karhunen- Loeve expansion) is to find the vectors that best account for the distribution of face images within the entire image space.

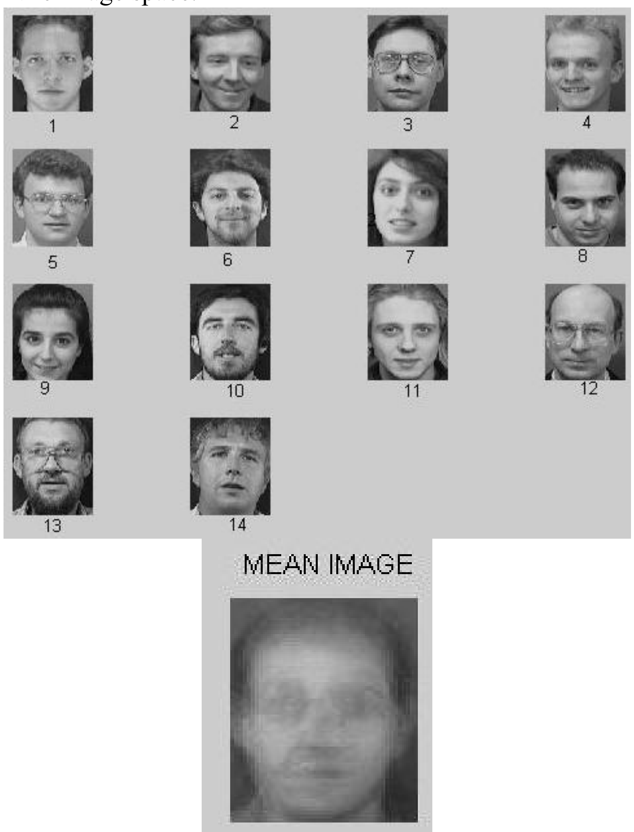

Fig – 2 Eigen Faces and their mean Image

These vectors define the subspace of face images, which we call "face space". Each vector is of length N2, describes an N x 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". Some examples of eigenfaces are shown in Figure 3.

Let the training set of face images be Γ1, Γ2, Γ3... ΓM then the average of the set is defined by

$$\Psi = \frac{1}{M}\sum_{n-1}^{M}\Gamma_n \quad (1)$$

Each face differs from the average by the vector

$$\Phi i = \Gamma i - \Psi \quad (2)$$

An example training set is shown in Figure 2, with the average face Ψ.

This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors, un , which best describes the distribution of the data. The kth vector, uk , is chosen such that

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

is a maximum, subject to

$$u_l u_k = \delta_{lk} = \begin{cases} 1, & if\ l = k \\ 0, & otherwise \end{cases}$$

The vectors uk and scalar λk are the eigenvectors and eigen values, respectively of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T = A A^T \quad (4)$$

where the matrix A = [Φ1, Φ2,........ΦM] The covariance matrix C, however is N2 x N2 real symmetric matrix, and determining the N2 eigenvectors and eigen values is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors.

If the number of data points in the image space is less than the dimension of the space (M < N2), there will be only M-1, rather than N2 , meaningful eigenvectors. The remaining eigenvectors will have associated eigen values of zero. We can solve for the N2 dimensional eigenvectors in this case by first solving the eigenvectors of an M x M matrix such as solving 16 x 16 matrix rather than a 10,304 x 10,304 matrix and then, taking appropriate linear combinations of the face images Φi.

Consider the eigenvectors vi of ATA such that

$$A A^T A v_i = \mu_i v_i \quad (5)$$

Premultiplying both sides by A, we have

$$A A^T A v_i = \mu_i A v_i \quad (6)$$

from which we see that Av_i are the eigenvectors of C = AA^T.

Following these analysis, we construct the M x M matrix L = A^TA, where Lnm = $\Phi m^T \Phi n$, and find the M eigenvectors, vi , of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces ui.

$$\mu_i = \sum_{k=1}^{M} V_{lk}\Phi_k \quad (7)$$

where i = 1,2 ... M

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 eigen values allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

The success of this algorithm is based on the evaluation of the eigen values and eigenvectors of the real symmetric matrix L that is composed from the training set of images.

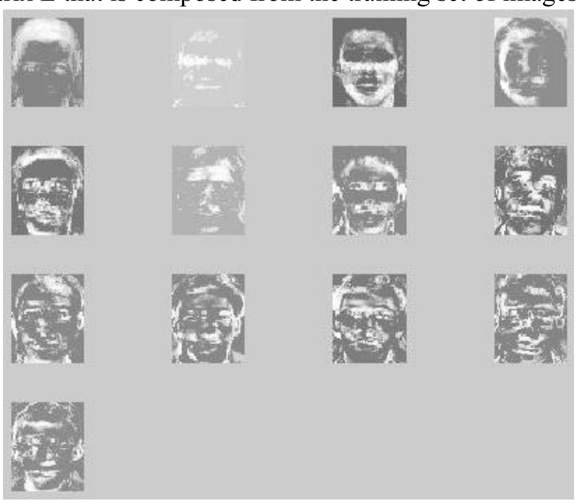

Fig 3 – Eigen faces

C. *Using Eigenfaces to classify the face image and get the face descriptor*

The eigenface images calculated from the eigenvectors of L, span a basis set with which to describe face images. Sirovich and Kirby evaluated a limited version of this framework on an ensemble of 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. With M' = 40 eigenfaces, RMS pixel by pixel errors in representing cropped versions of face images were about 2%.

In practice, a smaller M' can be sufficient for identification, since accurate reconstruction of the image is not a requirement and, 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. But for maximum accuracy, the number of eigenfaces should be equal to the number of images in the training set.

In this framework, identification becomes a pattern recognition task. The eigenfaces span an M' dimensional subspace of the original N2 image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated eigen values.

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

$$W_k = U_k^T(\Gamma - \varphi) \quad (8)$$

for k = 1,2,… …*M'*

The weights W_k formed a feature vector or face descriptor,

$$\Omega^T = [W_1 W_2 \dots\dots W_{M'}] \quad (9)$$

Ω^T 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/face descriptor is then used in a standard pattern recognition algorithm.

In the end, one can get a decent reconstruction of the image using only a few eigenfaces (M).

D. *Training of Neural Networks*

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems.

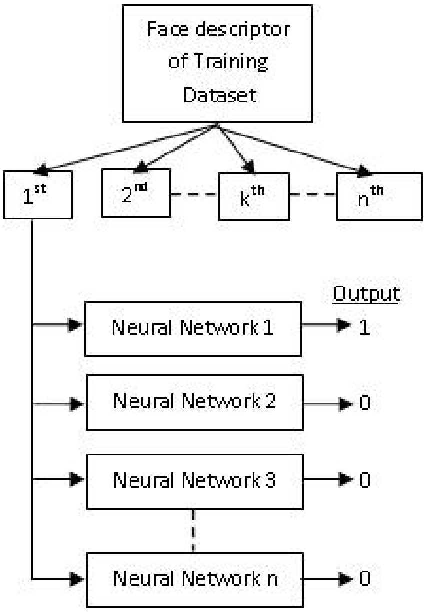

Fig. 5 – Training of Neural Network

One ANN is used for each person in the database in which face descriptors are used as inputs to train the networks [3]. During training of the ANN's, the faces descriptors that belong to same person are used as positive examples for the person's network (such that network gives 1 as output), and negative examples for the others network. (such that network gives 0 as output). Fig.5 shows schematic diagram for the networks training.

E. Simulation of ANN for Recognition

New test image is taken for recognition (from test dataset and its face descriptor is calculated from the eigenfaces (M found before. These new descriptors are given as an input to every network; further these networks are simulated. Compare the simulated results and if the maximum output exceeds the predefined threshold level, then it is confirmed that this new face belongs to the recognized person with the maximum output (fig. 6).

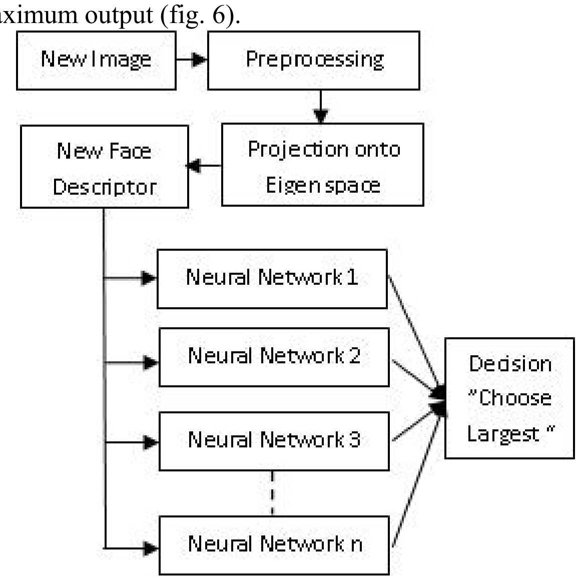

Fig. 6 – Testing of Neural Network

F. Reconstruction of face Image using the extracted face descriptor

A face image can be approximately reconstructed (rebuilt) by using its feature vector and the eigenfaces as

$$\Gamma' = \Psi + \Psi f \tag{10}$$

Where-

$$\Phi_j = \sum_{k=1}^{M} w_j u_j \tag{11}$$

is the projected image.

Eq. (10) tells that the face image under consideration is rebuilt just by adding each eigen face with a contribution of wi Eq. (11) to the average of the training set images. The degree of the fit or the "rebuild error ratio" can be expressed by means of the Euclidean distance between the original and the reconstructed face image as given in Eq. (12).

$$Rebuild\ Error\ ratio = \frac{\|\Gamma' - \Gamma\|}{\|\Gamma\|} \tag{12}$$

It has been observed that, rebuild error ratio increases as the training set members differ heavily from each other.

This is due to the addition of the average face image. When the members differ from each other (especially in image background) the average face image becomes more messy and this increases the rebuild error ratio.

IV. Experiment

The proposed method is tested on ORL face database. Database has more than one image of an individual's face with different conditions. (expression, illumination, etc.) There are ten different images of each of 40 distinct subjects. Each image has the size of 112 x 92 pixels with 256 levels of grey. 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 (with tolerance for some side movement). A preview image of the Database of Faces is available (Fig. 4). The original pictures of 112 x 92 pixels have been resized to 56 x 46 so that the input space has the dimension of 2576.

Eigenfaces are calculated by using PCA algorithm and experiment is performed by varying the number of eigenfaces used in face space to calculate the face descriptors of the images.

The numbers of network used are equal to number of subjects in the database. The initial parameters of the Neural Network used in the experiment are given below:

- Type: Feed forward back propagation network
- Number of layers: 3 (input, one hidden, output layer)
  - Number of neurons in input layer : Number of eigenfaces to describe the faces
  - Number of neurons in hidden layer : 10
  - Number of neurons in output layer : 1
- Transfer function of the ith layer: Tansig
- Training Function: Trainlm
- Number of epochs used in training: 100
- Back propagation weight/bias learning function: learngdm
- Performance function: mse

Since the number of networks is equal to the number of people in the database, therefore forty networks, one for each person was created. Among the ten images, first 6 of them are used for training the neural networks, then these networks are tested and their

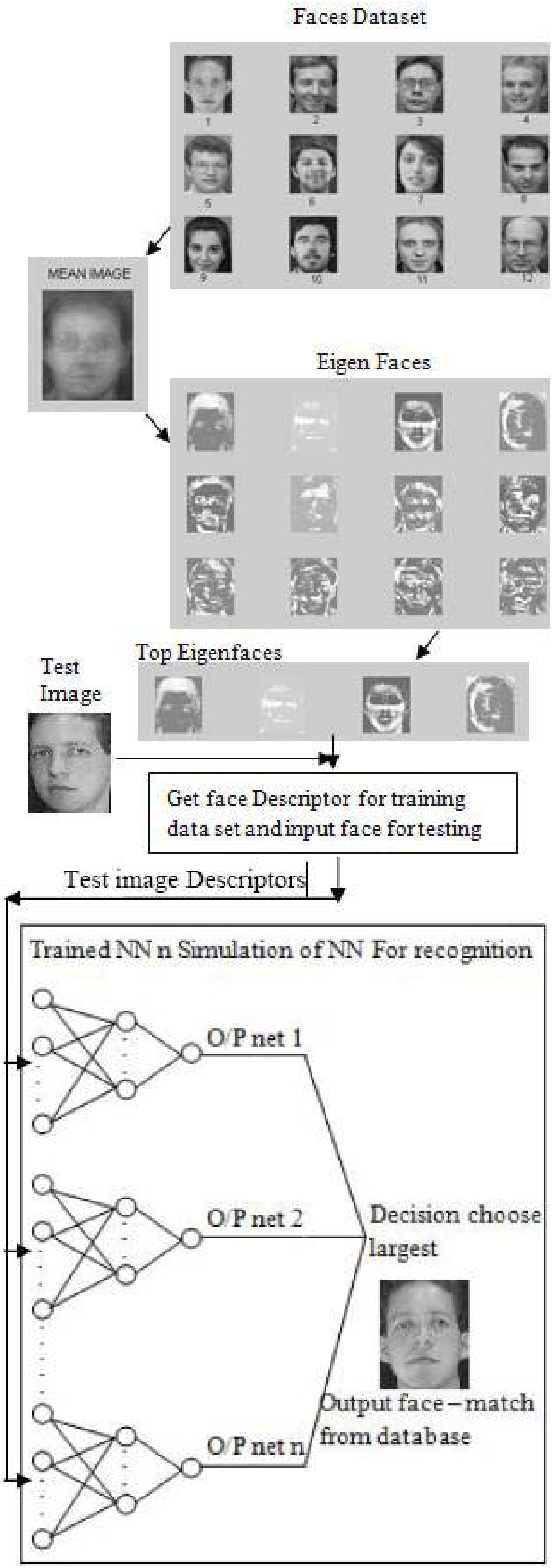

Fig. 4 – A complete process of PCA, Eigenface and ANN based faced recognition system

properties are updated. The trained networks would be used later on for recognition purposes.

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For testing the whole database, the faces used in training, testing and recognition are changed and the recognition performance is given for whole database.

THE COMPLETE FACE RECOGNITION PROCESS IS SHOWN IN FIG. 4

V. Analysis

The proposed technique is analyzed by varying the number of eigenfaces used for feature extraction. The recognition performance is shown in Table I.

The result derived from proposed method is compared with the other techniques which are 1. K-means [2], 2. Fuzzy Ant with fuzzy C-means.[2] Comparison of the result has been tabulated in Table II.

TABLE I: RECOGNITION SCORE OF FACE RECOGNITION USING PCA AND ANN.

No of Eign Facs	Recognition Rate (%)			
	Result 1	Result 2	Result 3	Average of Result 1-3
20	98.037	96.425	96.487	96.983
30	96.037	96.581	96.581	96.399
40	96.506	96.45	97.012	96.656
50	**96.525**	**97.231**	**97.3**	**97.018**
60	94.006	94.987	95.587	94.860
70	94.643	96.031	95.556	95.410
80	94.950	94.837	95.212	95
90	93.356	94.431	93.439	93.742
100	95.250	93.993	93.893	94.379

TABLE II: COMPARISON OF THE RESULT

Method	Recognition Rate
K-means	86.75
Fuzzy Ant with fuzzy C-means	94.82
Proposed	**97.018**

VI. Conclusion

The paper presents a face recognition approach using PCA and Neural Network techniques. The result is compared with K-means, Fuzzy Ant with fuzzy C-means and proposed technique gives a better recognition rate then the other two.

In the Table I one can see the recognition rate by varying the eigenfaces and the maximum recognition rate obtained for the whole dataset is 97.018. Eigenfaces □□□□ of highest eigenvalue are actually needed to produce a complete basis for the face space, As shown in Table I, maximum recognition rate is for M =50.

In the Table II one can see the advantage of using the proposed face recognition over K-means method and Fuzzy Ant with fuzzy C-means based algorithm.

The eigenface method is very sensitive to head orientations, and most of the mismatches occur for the images with large head orientations.

By choosing PCA as a feature selection technique (for the set of images from the ORL Database of Faces), one can reduce the space dimension from 2576 to 50 (equal to no. of selected eigenfaces of highest eigenvalue).

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