A New Era of Face Recognition

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***Abstract*— Face detection and recognition has many applications in a variety of fields such as security system, videoconferencing and identification. This document demonstrates how a face recognition system can be designed with artificial neural network using Eigen faces A face authentication system based on principal component analysis and neural networks is proposed to developed in this paper . The system consists of three stages; preprocessing, principal component analysis, and recognition. In preprocessing stage, normalization illumination, and head orientation were done. Principal component analysis is applied to find the aspects of face which are important for identification. Eigenvectors and eigenfaces are calculated from the initial face image set. New faces are projected onto the space expanded by eigenfaces and represented by weighted sum of the eigenfaces. These weights are used to identify the faces. Neural network is used to create the face database and recognize and authenticate the face by using these weights. In this work, a separate network was build for each person.**

Keywords* — *Face recognition, Face Authentication 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, can be 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.

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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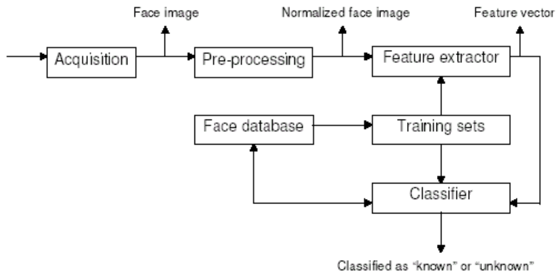

Figure 1. Face Recognition System

IV Eigenvectors and Eigenvalues,

An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding Eigen value of the eigenvector. This relationship can be described by the equation $M \times u = \lambda \times u$, where u is an eigenvector of the matrix M and λ is the corresponding Eigen value.

Eigenvectors possess following properties:

• They can be determined only for square matrices

• There are n eigenvectors (and corresponding eigenvalues) in a $n \times n$ matrix.

Algorithm is follows shown in figure 2.:

V Principle Component Analysis

In this section, the original scheme for determination of the eigenfaces using PCA will be presented. The algorithm described in scope of this paper is a variation of the one outlined here. A detailed (and more theoretical) description of PCA can be found as below

Step 1: Prepare the data

In this step, the faces constituting the training set (Γ_i) should be prepared for processing.

Step 2: Subtract the mean

The average matrix Ψ has to be calculated, then subtracted from the original faces (Γ_i) and the result stored in the variable Φ_i :

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

$$\Phi_i = \Gamma_i - \Psi$$

Step 3: Calculate the covariance matrix

In the next step the covariance matrix C is calculated according to

$$C = \frac{1}{M}\sum_{n-1}^{M}\Phi_n\Phi_n^T$$

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix

In this step, the eigenvectors (eigenfaces) ui and the corresponding eigenvalues should be calculated. The eigenvectors (eigenfaces) must be normalized so that they are unit vectors, i.e. of length 1. The description of the exact algorithm for determination of eigenvectors and eigenvalues is omitted here, as it belongs to the standard arsenal of most math programming libraries.

Step 5: Select the principal components

From M eigenvectors (eigenfaces) ui, only M' should be chosen, which have the highest eigenvalues. The higher the Eigen value, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces. After M' eigenfaces ui are determined, the "training" phase of the algorithm is finished.
The original algorithm ,We Can use following techniques for calculation of C, L, Ui

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

$$L = A^T A \quad L_{n,m} = \Phi_m^T\Phi_n$$

$$u_l = \sum_{k-1}^{M} v_{lk}\Phi_k \quad l = 1,\ldots,M$$

where L is a M × M matrix, v are M eigenvectors of L and u are eigenfaces. Note that the covariance matrix C is calculated using the formula $C = AA^T$, the original (inefficient) formula is given only for the sake of explanation of A. The advantage of this method is that one has to evaluate only M numbers and not N^2. Usually, $M<<N^2$ as only a few principal components (eigenfaces) will be relevant. The amount of calculations to be performed is reduced from the number of pixels ($N^2 \times N^2$) to the number of images in the training set (M).

Step 6: Classifying the faces

The process of classification of a new (unknown) face to one of the classes (known faces) proceeds in two steps.
First, the new image is transformed into its eigenface components. The resulting weights form the weight vector T new

$$\omega_k = u_k^T(\Gamma_{\text{new}} - \Psi) \quad k = 1\ldots M'$$

$$\Omega_{\text{new}}^T = [\ \omega_1 \quad \omega_2 \quad \ldots \quad \omega_{M'}\ ]$$

The Euclidean distance between two weight vectors d(i,j) provides a measure of similarity between the corresponding images i and j.

Step 7:A Euclidean Distance

Let1 an arbitrary instance x be described by the feature vector $x = [a_1(x), a_2(x), \ldots, a_n(x)]$
where $a_r(x)$ denotes the value of the rth attribute of instance x. Then the distance between two instances xi and xj is defined to be d(xi, xj):

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n}(a_r(x_i) - a_r(x_j))^2}$$

•

All eigenvectors are perpendicular, i.e. at right angle with each other.

VI EXPERIMENT OF EIGNVALUE & EIGNVECTORS

Figure 3.Sample Faces

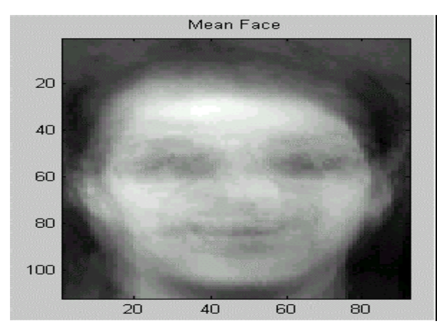

Figure 4.Mean Face

VII. TRAINING AND SIMULATION OF NEURAL NETWORKS FOR RECOGNITION

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

In this paper, there is one neural network for each person in the database. After calculating eigenfaces, the feature vectors are calculated for the faces in the database. These feature vectors are used as inputs to train the each person's networks. In training algorithm, the faces feature vectors 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), Figure shows schematic diagram for the networks training.

When the new image is come for recognition, its feature vectors are calculated from the eigenfaces found before, and this image gets its new descriptors. These new descriptors are inputted to every network and the networks are simulated with these descriptors.. The network outputs are compared. If the maximum output exceeds the predefined threshold level, then this new face is decided to belong to person with this maximum output.

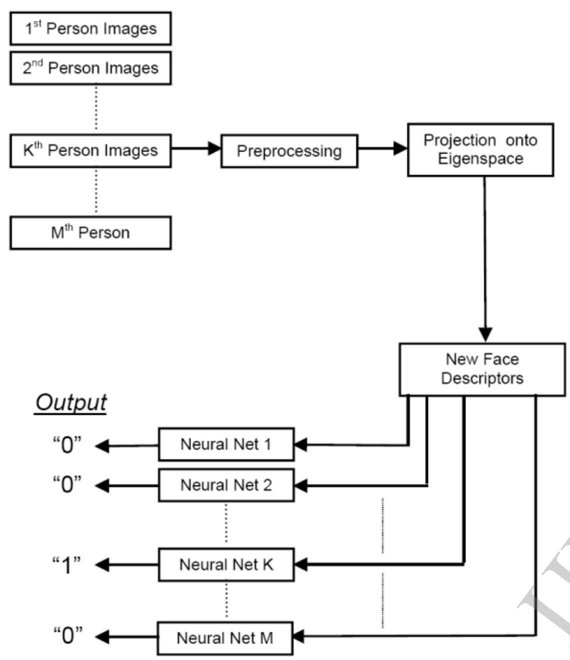

Figure 8.Training of Neural Network

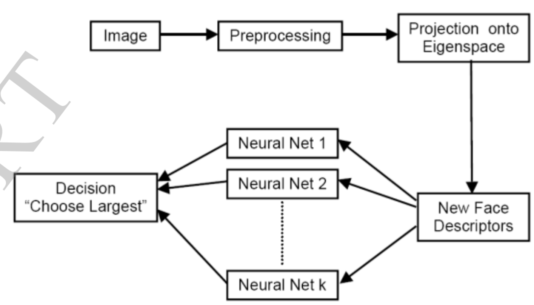

Figure9. Simulation of Neural Networks

Number of Images/Eigenfaces	Number of Neurons in Hidden Layer	Recognition Rate (%)
50	5	60
	10	68
	15	82
	20	96.7
75	5	50
	10	81.8
	15	88.5
80	5	48.8
	10	81.3
	15	89.5
	20	92.8
90	5	52
	10	81.8
	15	91.5
	20	94.3

Table 1. Performance Comparison

Above table represents that how the recognition rate varies as number of neuron in hidden layers varies. It is to be concluded that if no of neurons in hidden layer are more then recognition rate is more. The system gives good recognition rate at 20 no of neurons in hidden layer.

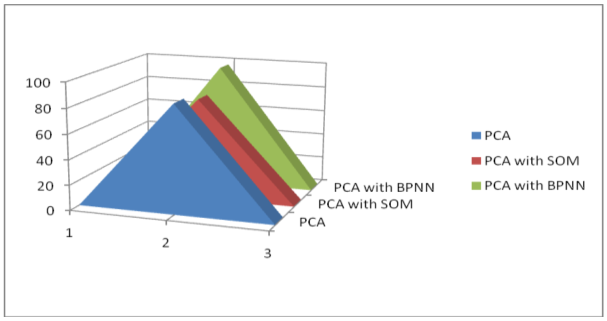

Figure 11. Performance Graph

Figure 11 gives how the PCA with ANN is best as compared to other face recognition techniques like PCA,PCA & SOM.

Performance Analysis: Face Recognition Using Eigenfaces & BPNN

No of Input Images/Eigenfaces	Recognition Rate (%)			
	Result	Result	Result	Average of
	1	2	3	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	94.86
70	94.643	96.031	95.556	95.41
80	94.95	94.837	95.212	95

Table 2. Performance Analysis : Input vs Recognition

Table 2 represents the average recognition rate with respect to input varies. As it concluded that if no of Input Images are 5o then recognition rate is 97.018%., Which is better as compared to other techniques.

VIII CONCLUSION

This paper presents the eigenfaces to represent the features vectors for human faces. The features are extracted from the original image to represents unique identity used as inputs to the neural network to measure similarity in classification and recognition. The eigenfaces has the capability to provide the significant features and reduces the input size for neural network. Due to this the network speed for recognition is raised up to 97.018%.

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