Analysis of Covariance Based Face Recognition Algorithms

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***Abstract*-- In this paper we have discussed low dimensional representation in the context of face recognition using Principle Component Analysis (PCA). First the eigenspace is generated and all the training images are projected onto this subspace. They are called as eigenfaces. Each test image is projected onto this subspace, compared with all the training images by a similarity or distance measure. The computational time of eigenspace projection is directly proportional to the number of eigenvectors used to generate the eigenspace. The effectiveness of PCA is tested on BioId database and ORL database. We were able to design a prototype system, which provides user authentication via facial features. The proposed system of face recognition may be applied in identification systems, document control and access control.**

***Index Terms*-- Eigen value, Face Recognition, Pattern Analysis, Principle Component Analysis (PCA),**

I. Introduction

FACE recognition [1] is a form of biometric identification. A biometrics is, "Automated methods of recognizing an individual based on their unique physical or behavioral characteristics." The process of facial recognition involves automated methods to determine identity, using facial features as essential elements of distinction. The automated methods of facial recognition, even though work very well, do not recognize subjects in the same manner as a human brain. The way we interact with other people is firmly based on our ability to recognize them. One of the main aspects of face identification is its robustness. Least obtrusive of all biometric measures, a face recognition system would allow a user to be identified by simply walking past a surveillance camera.

Robust face recognition scheme require both low dimensional feature representation for data compression purposes & enhanced discrimination abilities for subsequent image retrieval. The representation methods usually start with a dimensionality reduction procedure since the high dimensionality of the original visual space makes the statistical estimation very difficult & time consuming [2,5]

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II. PRINCIPLE COMPONENT ANALYSIS

PCA is also known as Karhunen Loeve (KL) Transform or Eigenspace, in pattern recognition or principle component analysis in the statistical literature. Principle Component Analysis (PCA) is an orthogonal transformation of the coordinate system in which we describe our data. The new coordinate values by which we represent out data are called as principal components. We demonstrate that any particular face can be economically represented in terms of best coordinate system called as eigenpictures. These are the eigenfunctions of the several covariance of ensembles of faces which is an information theory approach of coding & encoding face images, emphasizes on the significant local & global features. The original space of an image is just one of infinitely many spaces in which the image can be examined. The specific subspace is the subspace created by the eigenvectors of the covariance matrix of training data. Eigenspace optimizes variance among the images. First the eigenspace is generated and all the training images are projected onto this subspace. They are called as eigenfaces. Each test image is projected onto this subspace, compared with all the training images by a similarity or distance measure. [3,4,6,7]. Eigenspace projection projects images into a subspace such that the first orthogonal dimension of this subspace captures the greatest amount of variance among the images and the last dimension of this subspace captures the least amount of variance among the images [8].

The computational time of eigenspace projection is directly proportional to the number of eigenvectors used to create the eigenspace. Therefore by removing some portion of eigenvectors, computation time is decreased. Furthermore, by removing additional eigenvectors that do not contribute to the classification of image, performance can be improved.

Let the face image I (x, y) be a two dimensional N by N array of 8 bit intensity values. An image may also be considered as a vector of dimension of N^2. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and this can be described by a relatively low dimensional subspace. The main idea of PCA analysis 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, called as face image. Each vector is of length N^2, describes NXN 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.

A Creating the eigenspace

The following steps are used to create an Eigenspace: -

Distribution of face images are within the entire image space. These vectors define the subspace of face images, which we called as "face space". Each vector is of length N^2, describes NXN image and is a linear combination of the original face images, termed as eigenfaces.

Eigenspace is calculated from the vectors of covariance matrix derived from a set of training images. The eigenvector corresponding to non-zero eigenvalues of the covariance matrix form an orthonormal basis that rotates and / or reflects the images in the N-dimensional space. Specifically, each image is stored in a vector of size N X 1, where N is no of pixels in the image and P are the total number of images in the training set (database) [11,12].

$$X^i = [X_1^i, \text{-------}, Xp^i]\ T \quad \text{--------} \quad (1)$$

1. Center data**:** Each of the training images must be centered by subtracting the mean image from each of the training images as shown in equation (2). The mean image is a column vector such that each entry is the mean of all corresponding pixels of the training images.

$$X^{-} = [X_i - m] \text{ where } m = 1/p \sum_{i=1}^{p} X_i \quad \text{---------} \quad (2)$$

2. Create data matrix**:** Once the training images are centered, they are combined into data matrix of size N x P, where P is the number of training images and each column is a single image as shown in equation 3. [2]

$$X_i^{-} = [X_1^{-} \mid X_2^{-} \mid \quad .X_p^{-}] \quad \text{--------} \quad (3)$$

3. Create covariance matrix**:** Find covariance matrix of size P X P, instead of N^2 X N^2 .In the original method, covariance matrix has been calculated by the expression **Ω**= X $X^{T.}$ which results into N^2 X N^2 matrix. A common theorem in linear algebra states that the eigenvalues of X X^T & X^T.X are the same.

$$\Omega' = X^T.X \quad \text{--------------------} \quad (4)$$

4. Compute the eigenvalues and eigenvectors**:** The eigenvalues and corresponding eigenvectors are computed for the covariance matrix from equation 5.

$$\Omega' V = \Lambda V \quad \text{---------------------} \quad (5)$$

Where V is eigenvalues of an image.

5. Compute the eigenvectors of XX^T. Multiply data matrix by normalized eigenvectors to calculate eigenvectors.

$$V_{new} = X .V \quad \text{-----------------} \quad (6)$$

$$V_i = V_{n`ew} / \| V_{new} \|$$

6. Order eigenvectors**:** Order the eigenvectors v_i **ε** ***V*** according to their corresponding eigenvalues λ_i from high to low. Keep only the eigenvectors associated with non-zero eigenvalues. This matrix of eigenvector is the eigenspace *V*, where each column of *V* is an eigenvector as shown in equation 7.

$$V = [\ v_1 \mid v2 \mid \ldots\ldots \mid vp] \quad \text{----------------}(7)$$

Projection of an image into face space will be discussed in the next section.

B Projection of an image to face space

1. Project training images**:** Each of the centered training images (xi^{-}) is projected into the eigenspace. To project an image into an eigenspace, calculate the dot product of the image with each of the ordered eigenvectors from equation 8.

$$X_{\tilde{a}} = V^T .x_i^{-} \quad \text{-------------------}(8)$$

Therefore, the dot product of the images and the first eigenvector will be the first value in the new vector. The new vector of the projected image will contain as many values as eigenvectors.

2. Projecting test image**:** Each test image is first mean centered by subtracting the mean image y_i^{-} = [yi – m], and then projected into the same eigenspace defined by V as given by equation 9.

$$Y_{\tilde{a}} = V^{T} y_i^{-} \quad \text{------------------} \quad (9)$$

The projected test image is compared with every projected training image and distance measures using Euclidean Distance is calculated for every training image. use automatic hyphenation and check your spelling. Additionally, be sure your sentences are complete and that there is continuity within your paragraphs. Check the numbering of your (figures and tables) and make sure that all appropriate references are included.

III. RESULT AND ANALYSIS

Data preparation: We have used BioId database [15] and ORL database as our testbed to compare algorithm. The frontal face images of the 20 subjects in BioId database each with 5 different expression provide variation in views of the individual such as lighting, facial features (such as glasses) and slight changes in head orientation[13] and the frontal face images of the 20 subjects in ORL database each with 10 different expression provide variation in views of the individual such as lighting, facial features (such as glasses) and slight changes in head orientation are of size 92×112 are used for evaluation are as shown in figure 1 [14]. Performance evaluation of proposed algorithm on different databases is given in table-I.

Figure 2 gives a graph between number of eigen values versus % recognition rate, train time per model, test time per image on ORL database. Series1 gives % recognition rate. series 2 gives train time per model ,series3 gives test time per model .From the graph as number of eigen values goes on increasing the recognition rate is also goes on increasing. But computational time goes on increasing.

Figure3, 4 and 6 show the intermediate results for one test image.

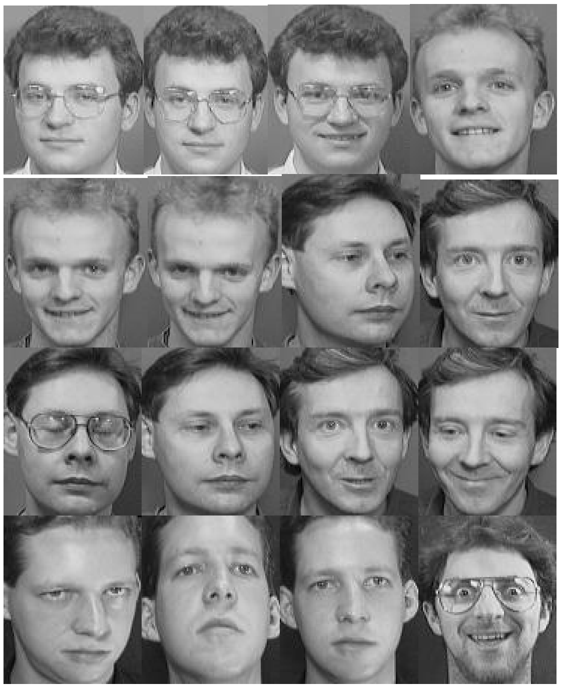

Fig. 1. Sample images from ORL Database

TABLE I
PERFORMANCE EVALUATION OF PROPOSED ALGORITHM

Sr. No.	Parameters	BioID Database	ORL Database
1	No of subjects	20	20
2	No of different expressions per subjects	05	10
3	Total no of images	100	200
4	Recognition Rate	95 %	80 %
5	False Acceptance Rate	Nil	Nil
6	False Rejection Rate	5 %	20 %

The method is fast, relatively simple and work well in constrained environment.

Linear PCA is being used in numerous technical and scientific applications, including noise reduction, density estimation, image indexing and retrieval systems & the analysis of natural image statistics.

IV. CONCLUSION AND FUTURE SCOPE

A method for the identification of human faces based on PCA has been proposed

This method has following advantages:

As PCA selected the most discriminate features, the good recognition results by PCA recognition implies that despite having no 3D surface information, smaller facial structures still contributes as key factors for frontal face recognition.

As there are 10 different expression variations in views of the individual such as lighting, facial features (such as glasses) in ORL database the percentage recognition rate is slightly lower. Though some problems are still to be experimented (such as effect of a more tilting of the head etc) and the algorithm needs to be tested for large variations of pose.

We are also investigating the face recognition using wavelet coefficients. The prototype face recognition system using wavelet coefficient cascaded with proposed PCA system is developed and experimented. We are trying to work on the images rejected by PCA system so as to improve the percentage recognition rate.

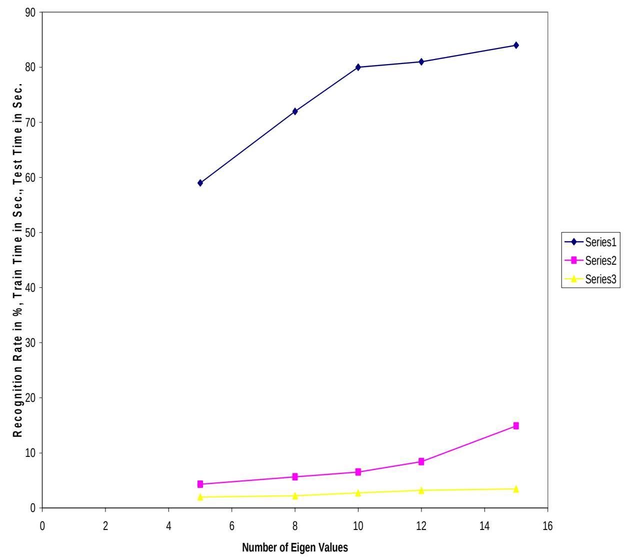

Fig. 2: No. of eigen values verses % recognition rate, train time per model, test time per image on ORL Database.

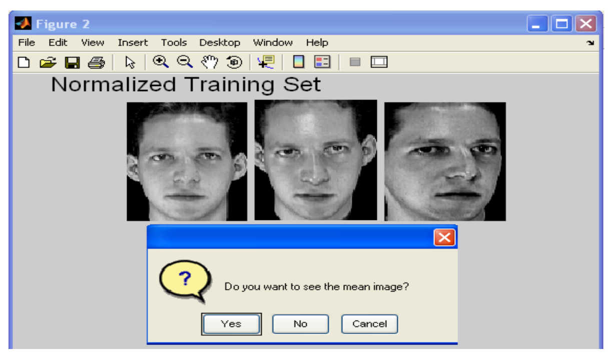

Fig.3: Normalized Training image

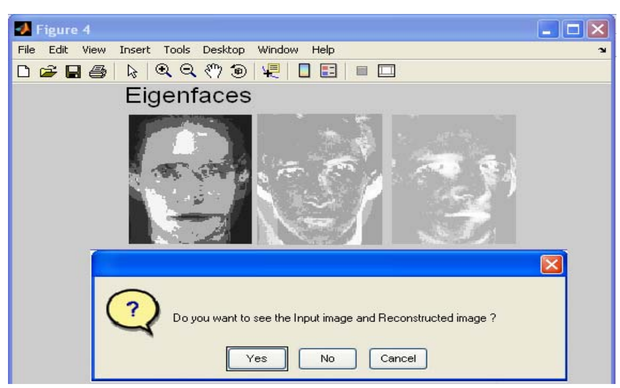

Fig. 4 Eigen values of Training image

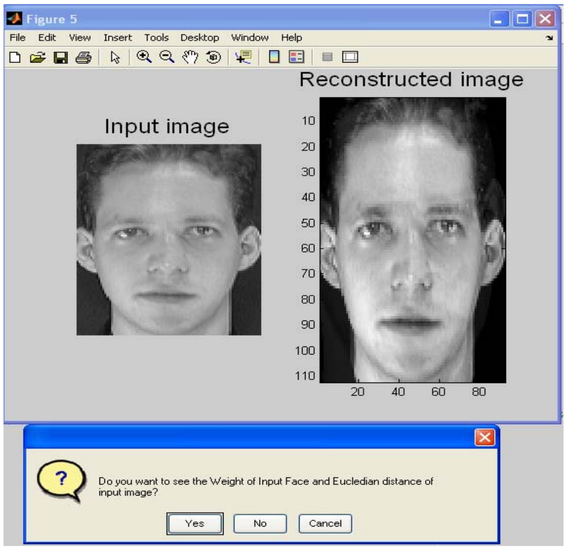

Fig. 5 Result

The proposed system of face recognition may be applied in identification systems, document control and access control. The face similarity meter was found to perform satisfactorily in adverse conditions of exposure, illumination and contrast variations, and face pose. Biometric technologies are found application in four broad application categories: surveillance, screening, enrollment identification, and identity verification.

General security tasks, such as access control to buildings, can be accomplished by a face recognition system. Banking operations and credit card transactions could also be verified by matching the image encoded in the magnetic strip of the card with the person using the card at any time. Finally, a robust system could be used to index video-documents (video-mail messages, for example) and image archives indexed in such a way would be useful for criminal identification by the investigation department.

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VI. Biographies

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