FACE RECOGNITION USING PCA AND EIGEN FACE APPROACH

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ABSTRACT:

In this paper an approach to the detection and identification of human faces is presented and then recognizes the person by comparing characteristics of the face to those of known individuals is described.A face recognition system using the Principal Component Analysis (PCA) algorithm was implemented.

The algorithm is based on an eigen faces approach which represents a PCA method in which a small set of significant features are used to describe the variation between face images. Experimental results for different numbers of eigen faces are shown to verify the viability of the proposed method.

Keywords:

Face recognition, PCA ,Eigen face.

1. INTRODUCTION :

Face is a complex multidimensional structure and needs good computing techniques for recognition. To find out exact identity of any person ,face recognition is very essential technology. We can recognize a number of faces learned throughout our lifespan and identify that faces at a glance even though that persons became old in age. There may be variations in faces due to aging and distractions like beard, glasses or change of hairstyles.

Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching identification of a human being is traced. Facial features are extracted and implemented through algorithms which are efficient and some modifications are done to improve the existing algorithm models. Computers that detect and etc.

Face detection and recognition is used in many places nowadays, in websites hosting images and social networking sites. Face recognition and detection can be achieved using technologies related to computer science. Features extracted from a face are processed and compared with similar faces which are existing in our database.

If input face image matches with the image present in the databases then it is known as person is recognized otherwise it is known as person is unrecognized. In surveillance system if a unknown face appears more than one time then it is stored in database for next recognition procedure. This all face recognition procedures are having number of advantages such as information security, personal security, access management, biometrics entertainment etc. In general, face recognition techniques divided into two types, based on the face representation they use appearance-based, which requires large set of training samples, it uses statistical analysis techniques to learn the characteristics of a face from a large set of face images and feature-based, which uses geometric facial features (mouth, eyes, brows, cheeks etc), and geometric relationships between them.

Principal component analysis (PCA) is a variable reduction procedure and useful when obtained data have some redundancy[1]. This will result into reduction of variables into smaller number of variables which are called Principal Components which will account for the most of the variance in the observed variable. Problems arise when we wish to perform recognition in a high-dimensional space. Goal of PCA is to reduce the dimensionality of the data by retaining as much as variation possible in our original data set.

PCA can supply the user with low dimensional picture by using only the first principal components so that dimensionality of the transformed data is reduced. By using principal component analysis it becomes possible to get reduced set which is much easier to analyze and interpret. The major advantage of PCA is using it in eigen face approach which helps in reducing the size of the database for recognition of a test images[2].

The images are stored as their feature vectors in the database which are found out projecting each and every trained image to the set of Eigen faces obtained. PCA is applied on Eigen face approach to reduce the dimensionality of a large data set. Eigen face approach is efficient method to be used in face recognition due to ease of implementation, low processing steps and no knowledge of geometry or any specific feature of face is required.

Eigen faces are principal components of the distribution of faces which seeks to capture the most important characteristics of face images which are further useful for face recognition[2]-[3]. They refer to an appearance based approach to face recognition that seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces in a holistic manner. The Eigen faces[3]-[5] are Principal Components which extract facial information to reduce computation and space complexity representing the face images, where an image with N by N pixels is considered a point in N 2 dimensional space.

Previous work on face recognition ignored the issue of face stimulus, assuming that predefined measurement were relevant and sufficient. Eigen face approach contains coding and decoding of face images extracts the relevant information in a face image, encode it and compare it with database of similarly encoded faces. But it is no necessary that these feature be related to facial features such as eyes, brows, nose, lips and hairs.

Eigen face approach used to extract the relevant information in a face image, encode it efficiently and compare one face encoding with a database of faces encoded similarly. In short this approach is very useful to capture the information content in an image of a face which are further useful for face recognition efficiently.

2. PRINCIPAL COMPONENT ANALYSIS:

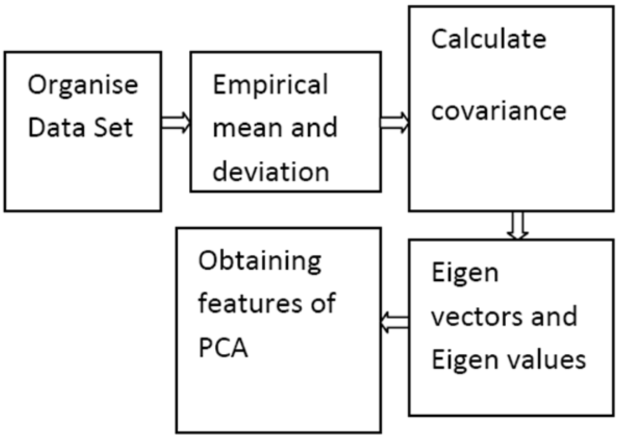

Figure 1: Steps Involved In Principal Component Analysis.

Principal Component Analysis (PCA) is a dimensionality reduction technique based on extracting the desired number of principal components of the face data images. The use of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically[4]-[12]. This is the case when there is a strong correlation between observed characteristics of images .The principal component is the linear combination of the original dimensions that has the maximum variance; the n-th principal component is the linear combination with the highest variance ,subject to being orthogonal to n-1 first principal component[13]-[19].

There are several ways of deriving the principal components mathematically. The simplest one is by finding the projections which maximize the variance. The first principal component is the direction in feature space along which projections have the largest variance. The second principal component is the direction which maximizes variance among all directions orthogonal to the first. The kth component is the variance-maximizing direction orthogonal to the previous k - 1 components. There are p principal components in all.

This theory relates to the eigen spectrum - the set of the eigen values of the data covariance matrix. The i-th eigen value is equal to the variance along the i-th principal component; thus, it is proper algorithm for detecting k is to search for the location along the decreasing eigen spectrum where the value of drops significantly. Since the basis vectors constructed by PCA[20]-[24] had the same dimension as the input face images, they were named "Eigen faces".
PCA is an information theory approach of coding and decoding face images may give insight into the information content of face images, describing the significant local "features".

PCA can be described by following figure:

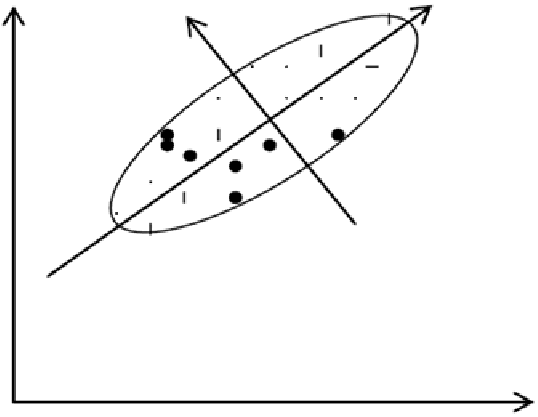

Figure2:PCA Representation

Eigen Vectors shows the direction of axes of a fitted ellipsoid. Eigen Values show the significance of the corresponding axis. The larger the Eigen value, the more separation between mapped data. For high dimensional data, only few of Eigen values are significant.

There are two phases to represents PCA in face recognition procedure:

1. Learning Phase: A training set is used for learning phase, it consist of applying PCA to training data to form a new coordinate system defined by significant Eigen vectors representing each data in PCA coordinate system (weights of Eigen vectors)

2. Testing Phase: A test set is used for testing phase. Same PCA coordinate system is used. Each new data is represented in PCA coordinates. New data is recognized as the closest training data (Euclidean distance)

3. FACEIMAGE REPRESENTATION:

Each image is represented as a 1-D data i Feature vector of a face is stored in a N By N matrix. This two dimensional vector is changed to one dimensional vector. Images of faces, being similar in overall configuration, will not be randomly distributed in the huge space and thus can be distributed by a relatively low dimensional subspace. The main idea of principal component 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, which we call "face space".

3.1 EIGEN FACE RECOGNITION:

In Eigen face recognition we need to obtain a set S with M face images. Each image is transformed into a vector of size N and placed into the set as follows:

$S = \Gamma 1 + \Gamma 2 + 3, \ldots\ldots\ldots\ldots. \Gamma m$ (1)
After you have obtained your set,
you will obtain the mean image
$\Psi = 1/M\ \Gamma n$ (2) Mn1
Then you will find the difference Φ between
The input image and the mean image.
$\Phi i = \Gamma i - \Psi$ (3)
Next we seek a set of M orthonormal vectors,
UK which best describes the distribution of the data.
The kth vectoruk, is chosen such that
k =1/M (ukΦn) 2 (4) □ Mn1

Once we have found the eigenvectors, a new face is transformed into its eigenface components. First we compare our input image with our mean image and multiply their difference with each eigenvector of the L matrix. Each value would represent a weight and would be saved on a

Vector Ω.
Ωt={w1, w2 ...wm} (5)

For Eigen face recognition we now need to find out the result about which face class provides the best description for the input image. This is done by minimizing the Euclidean distance.

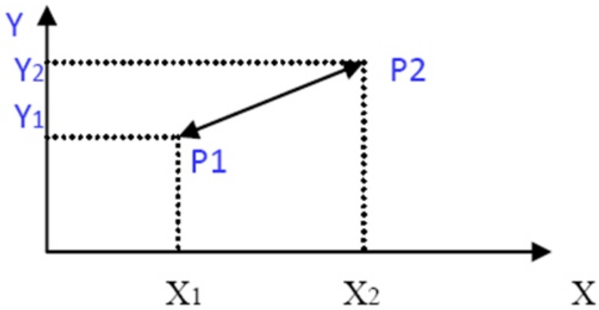

Figure 3. Euclidean distance, d12, for two points in two dimensions

The Euclidean distance between points P1 and P2 is
d12 = sqrt(dx2 + dy2) (6)
where dx = x2-x1, and dy = y2-y1.

The input face is consider to belong to a class if εk is bellow an established threshold θε. Then the face image is considered to be a known face.

If the difference is above the given threshold, but bellow a second threshold, the image can be determined as a unknown face. If the input image is above these two thresholds, the image is determined NOT to be a face.If the image is found to be an unknown face, you could decide whether or not you want to add the image to your training set for future recognitions.

You would have to repeat above all steps to incorporate this new face image

4. TRAINING IMAGES FROM ORL DATABASE:

The ORL face database -This directory contains a set of faces taken between April 1992 and April 1994 at the Olivetti Research Laboratory. There are 10 different images of 40 different persons. There are images taken at different times, varying lightings lightly, facial expressions .

All the images are taken against a dark homogeneous background and the subjects are in up-right, frontal position (with tolerance for some side movement). The files are in PGM format and can be conveniently viewed using the 'xv' program. The size of each image is 92x112, 8-bit grey levels. The images are organised in 40 directories.

Figure 4:Pictures from training database

5. RESULTS:

The experiment is conducted using ORL database of faces . The training database contains 400 images of 40 persons (10 images per each person), I also used my personal database which contains 10 images of each person. All photos have dimensions 92×112 and a dark homogeneous background and the subject is photographed in an upright, frontal position. All images are grayscale (intensity levels of gray are taken as image features).

Each eigen value corresponds to a single eigenvector and tells us how much images from training bases vary from the mean image in that direction. It can be seen that about 10% of vectors have significant eigen values,while those for the remaining vectors are approximately equal to zero. We do not have to take into account eigenvectors that correspond to small eigen values because they do not carry important information about the image.

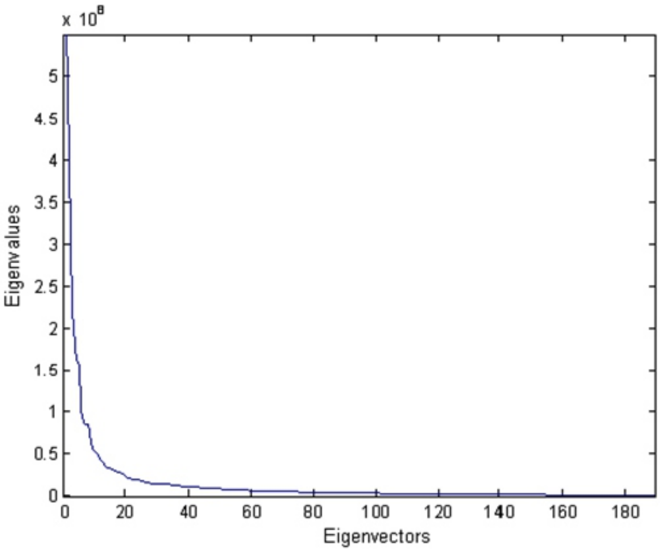

Figure 5: Eigen values

Figure 4:First three eigenfaces

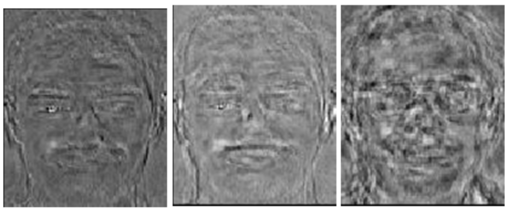

Figure 6: Last three Eigen face

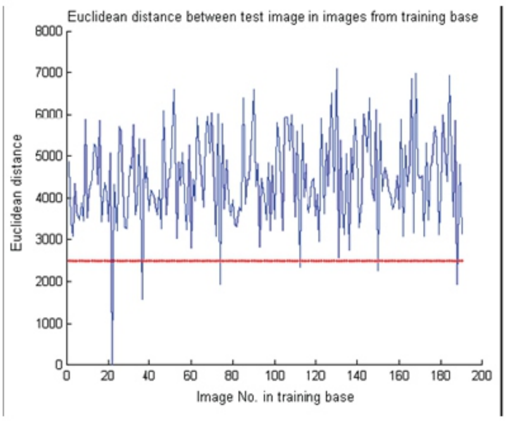

Figure 7.– Euclidean distance between the test image and images from the database

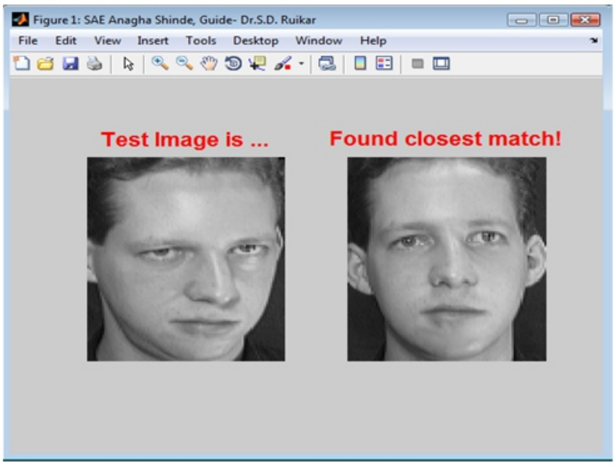

Figure8:Test image and recognized image from the training base

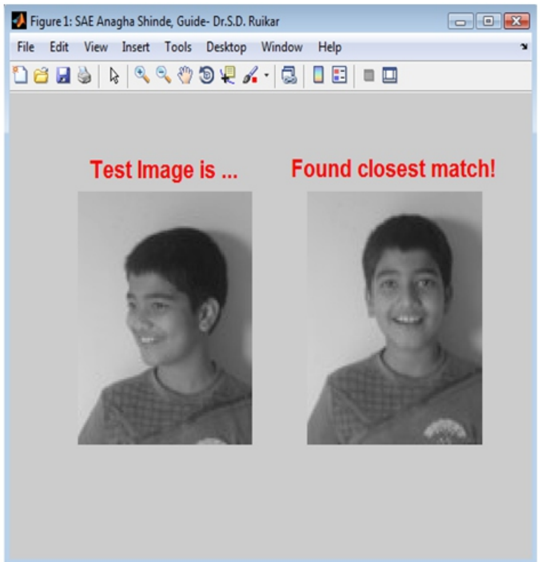

Figure 9:Test image and recognized image from the training base.

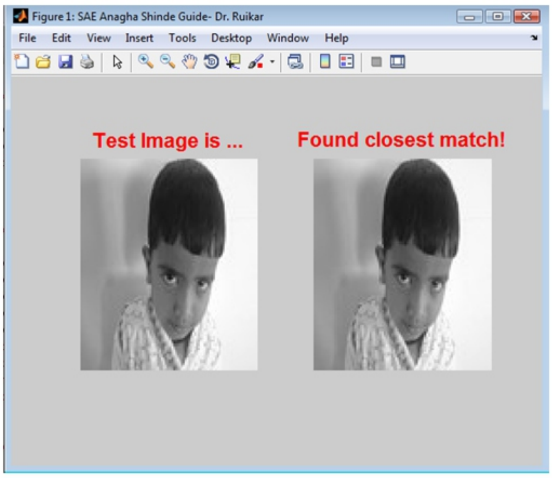

Figure 9:Test image and recognized image from the training base.

Table1:The Result Of Face Recognition Using Eigenface Contains Number Of Principal Components With Recognition Rate

Number of principle components	RECOGNITION RATE	
	Euclidean distance	Manhattan distance
5	77.5%	80%
10	92.5%	95%
20	97.5%	97.5%
190	97.5%	97.5%

6. CONCLUSION :

Face recognition method using eigen faces is proposed. We used database of face images which contains 190 images of 38 different persons (5 images per person). From the results, it can be concluded that, for recognition, it is sufficient to take about 10% eigen faces with the highest eigen values. It is also clear that the recognition rate increases with the number of training images per person. It is obvious that if the minimum distance between the test image and other images is zero, the test image entirely matches the image from the training base.

7. ACKNOWLEDGMENT:

This work is carried out with the help of face images from database which contains a set of faces taken between April 1992 and April 1994 at the Olivetti Research Laboratory in Cambridge, UK.
The project is successfully tested and obtained.

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