REAL TIME FACE RECOGNITION BY VARING NUMBER OF EIGENVALUES

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ABSTRACT

Face recognition have been fast growing, challenging and interesting area in real-time applications. A large number of face recognition algorithms have been developed from decades. The present paper primarily focuses on principal component analysis, for the analysis, the software is implemented using Mat lab and C#.net This face recognition system detects the faces in a picture taken by web-cam, and these face images are then checked with training image dataset based on Eigen features. Eigen features are used to characterize images. 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 are obtained for different numbers of Eigen faces and different numbers of training set images.

Keywords—Eigen faces, eigenvalues PCA, face recognition, face classification,

I. INTRODUCTION

One of the simplest and most effective PCA approaches used in face recognition systems is the so-called Eigen face approach. This approach transforms faces into a small set of essential characteristics, Eigen faces, which are the main components of the initial set of learning images (training set).

Face recognition systems have been grabbing high attention from commercial market point of view as well as pattern recognition field. Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities. The face recognition systems can extract the features of face and compare this with the existing database. The faces considered here for comparison are still faces. Machine recognition of faces from still and video images is emerging as an active research area. The present paper is formulated based on still or video images captured by a web cam.

The face recognition system extracts the Eigen features from trainee set. It later compares with the database of faces, which is collection of faces in different poses. The present system is trained with the database shown in Figure (1), where the images are taken in different poses like head variation , light variation, scale variation , feature variation means with glasses, with and without beard. Experimental results are obtained by different numbers of Eigen faces and different numbers of training set images.

II. PCA Approach to Face Recognition

Principal component analysis transforms a set of data obtained from possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of components can be less than or equal to the number of original variables. The first principal component has the highest possible variance, and each of the succeeding components has the highest possible variance under the restriction that it has to be orthogonal to the previous component. We want to find the principal components, in this case eigen vectors of the covariance matrix of facial images. The first thing we need to do is to form a training data set. 2D image Ii can be represented as a 1D vector by concatenating rows. Image is transformed into a vector of length N = mn.

$$\boldsymbol{I} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}_{m\times n} \xrightarrow{CONCATENATION} \begin{bmatrix} x_{11} \\ \vdots \\ x_{1n} \\ \vdots \\ x_{2n} \\ \vdots \\ x_{mn} \end{bmatrix}_{1xN} = \boldsymbol{x} .$$

Let M such vectors xi (i = 1, 2, ..., M) of length N form a matrix of learning images, X. To ensure that the first principal component describes the direction of maximum variance, it is necessary to center the matrix. First we determine the vector of mean values Ψ, and then subtract that vector from each image vector.

$$\boldsymbol{\Psi} = \frac{1}{M}\sum_{i=1}^{M} \boldsymbol{x}_i ,$$

Averaged vectors are arranged to form a new training matrix (size N×M);

$$A = (\phi_1, \phi_2, \ldots, \phi_M)$$

The next step is to calculate the covariance matrix C, find its eigenvectors ei and Eigen values λi:

$$C = \frac{1}{M}\sum_{n=1}^{M} \varphi_n \varphi_n^T = AA^T,$$

Covariance matrix C has dimensions N×N. From that we get N Eigen values and eigenvectors. For an image size of 128×128, we would have to calculate the matrix of dimensions 16.384×16.384 and find 16.384 eigenvectors. It is not very effective since we do not need most of these vectors. Rank of covariance matrix is limited by the number of images in learning set — if we have M images, we will have M–1 eigenvectors corresponding to non-zero eigenvalues.

Once the Eigen faces are created, identification becomes a pattern recognition task. The Eigen faces span an N^2-dimensional subspace of the original A image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues.

The Euclidean distance between two weight vectors d(i,j) provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between Test and Trainee faces exceeds some threshold value, then Test face is not present.

$$d(\boldsymbol{A},\boldsymbol{B}) = \sqrt{\sum_{i=1}^{D}(a_i - b_i)^2} = \|\boldsymbol{A}-\boldsymbol{B}\|$$

III. EXPERIMENTAL RESULTS

The experiment was conducted own database of faces shown in fig.1 The training database contains 120 images of 12 persons (10 images per each person),a test database has 40 images of different individuals (35 known and 5 unknown). All photos have dimensions 92×112 and grayscale (intensity levels of gray are taken as image features).

Example of images from the training base is given in Fig. 1. And Fig. 2 shows some Eigen faces which carry high 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.

In Figs. 1 and 2 shows, first three and last three Eigen faces are shown, respectively. While the figure in Fig. 1 resembles the faces, those in Fig. 2 do not carry important information about the images from the training base.

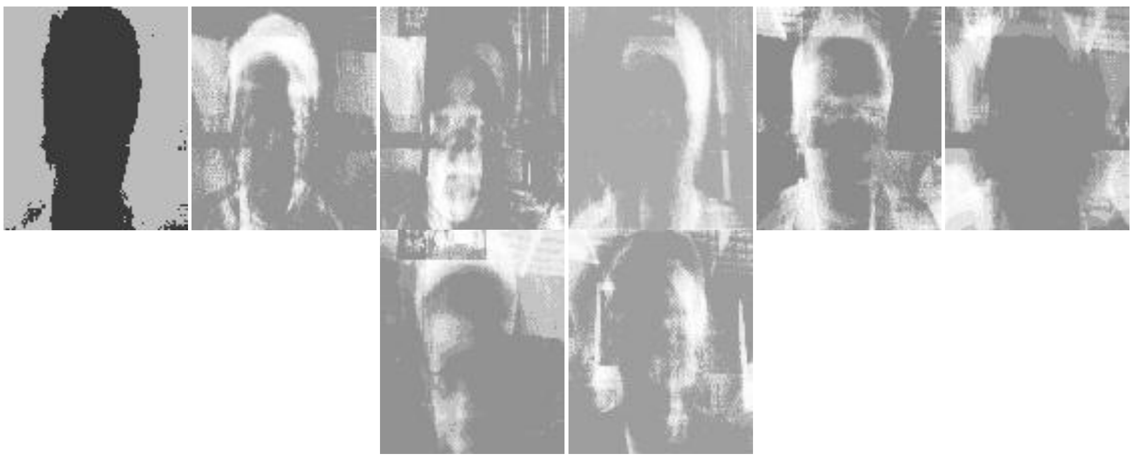


FIG.1 FIRST 8 EIGEN FACES

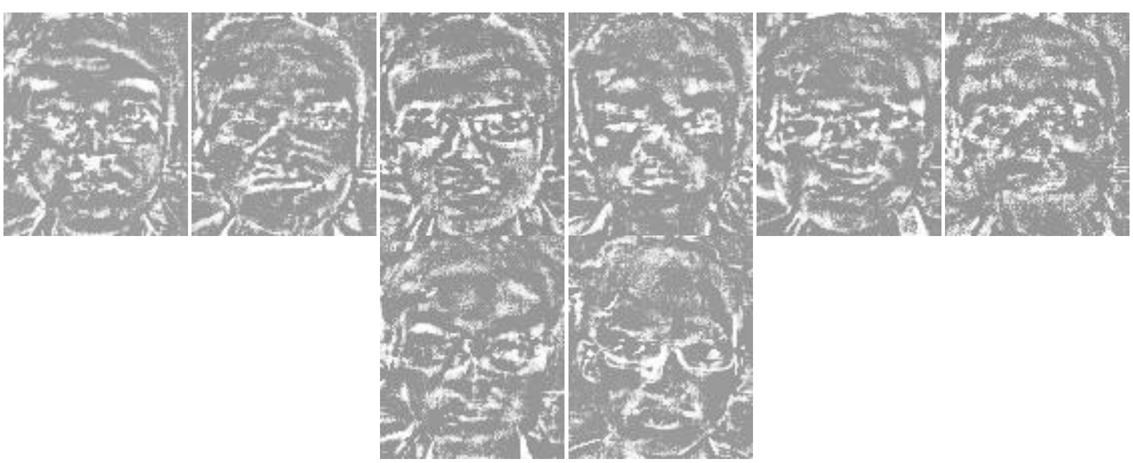
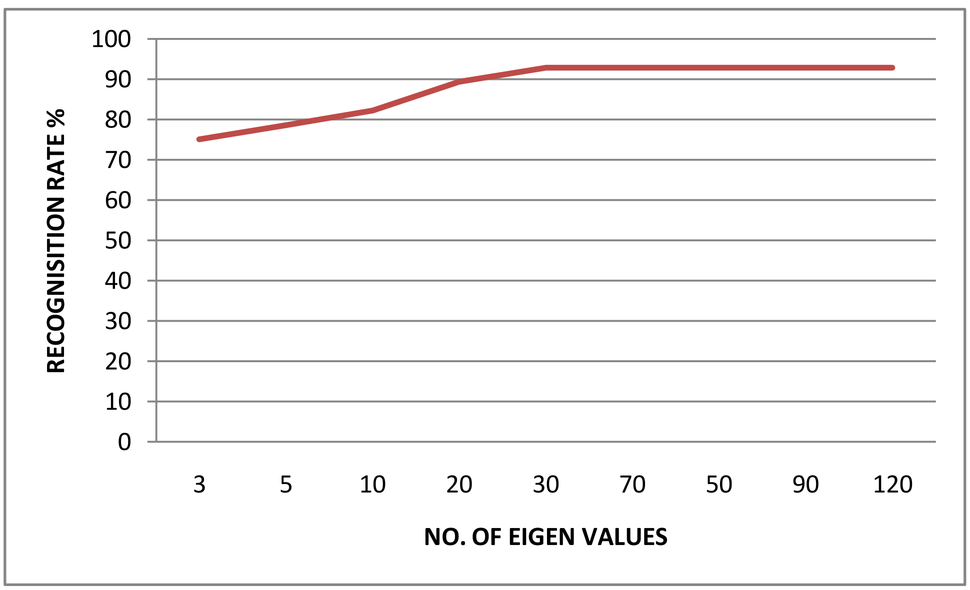


FIG.2 LAST 8 EIGEN FACES

Table 1 shows the matched and unmatched percentage of system for different number of eigenvectors Recognition rate is increases as number of eigenvectors increases up to some extend then it becomes constant, because higher feature information present in first 20-30 eigenvectors , remaining vectors having less information nearly zero.

Table-1 shows the matched and unmatched percentage for different number of eigenvalues for 28 Test Images

EIGEN VALUES	MATCHED IMAGES	RECOGNISATION RATE %
3	21	75
5	22	78.57
10	23	82.14
20	25	89.28
30	26	92.85
50	26	92.85
70	26	92.85
90	26	92.85
120	26	92.85



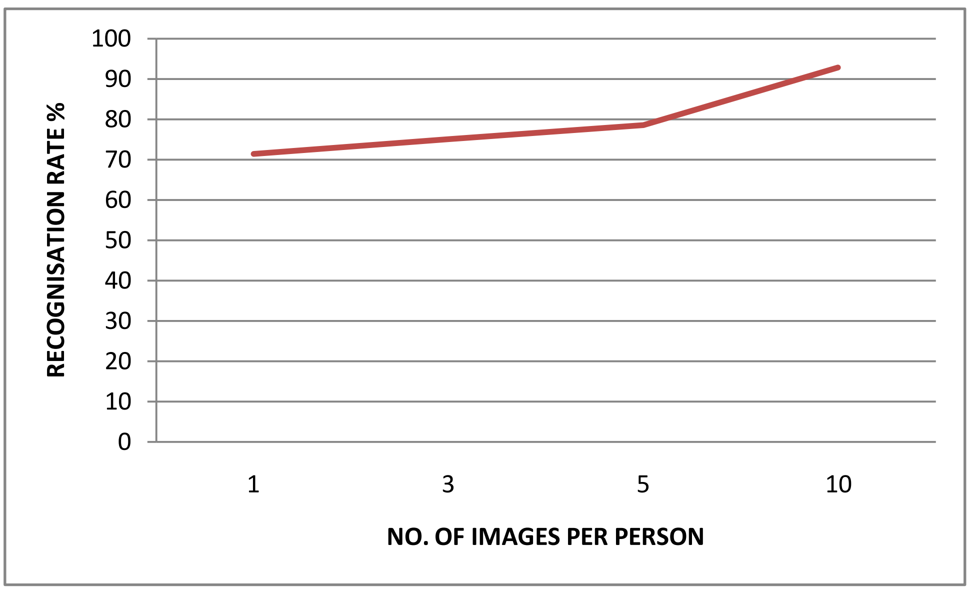
GRAPH 1 EIGEN VECTORS VS MATCHED PERCENTAGE

In practice, only a few images per person are available for the training base, so it is important to note the effect of a number of images per subject on the rate of recognition. The corresponding recognition rates for different number of training images per subject are given in Table 2. For comparison, we selected the 120 principal components in each case.

TABLE-2 Recognition Rates for Different Number Of Training Images per person for 28 Test Images

NO.OF IMAGES /PERSON	MATCHED IMAGES	RECOGNISATION RATE %
1	20	71.42857
3	21	75
5	22	78.57143
10	26	92.85714

GRAPH 2 Images Per Person Vs. Recognition Rate



Following figures show the Output of software which is implemented using mat lab when threshold is 0.3, Fig 3 shows the Test image is exactly matches with one of the trainee images when Euclidian distance is zero. Fig 4 shows the Test image is matches with one of the trainee images when Euclidian distance is greater than zero and less than threshold. Fig 5 shows the Test image is not matches with one of the trainee images when Euclidian distance greater than threshold.

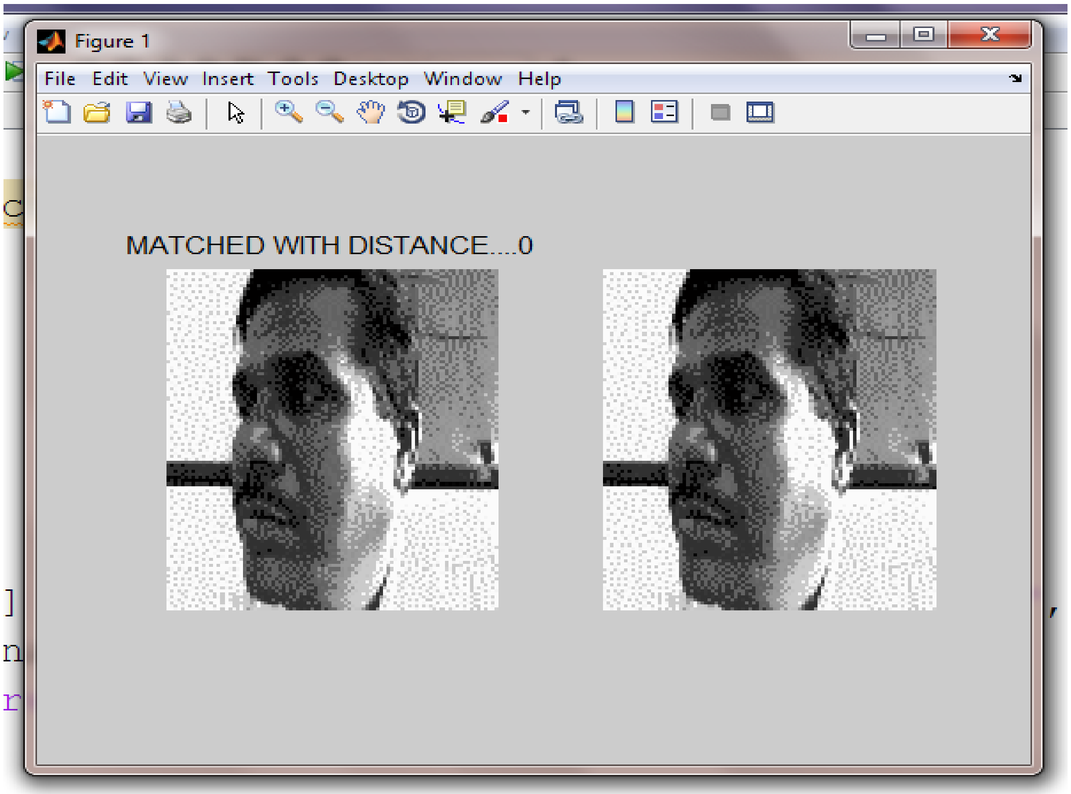


Fig-3 output of software implemented in MATLAB when distance is zero

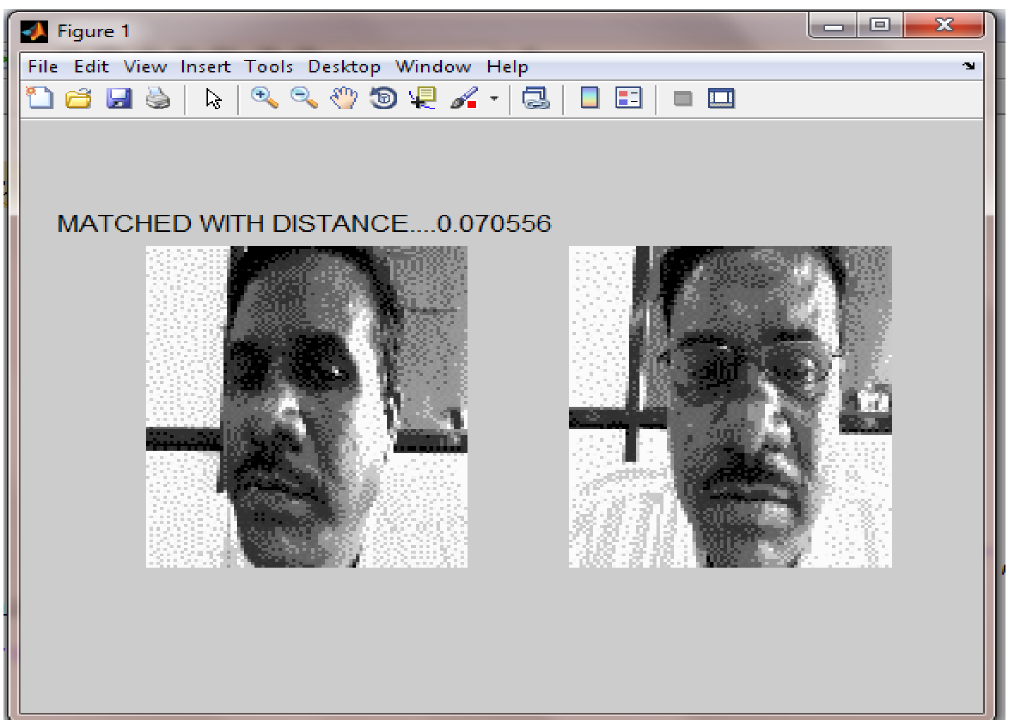


Fig-4 output of software when distance greater than zero and less than threshold

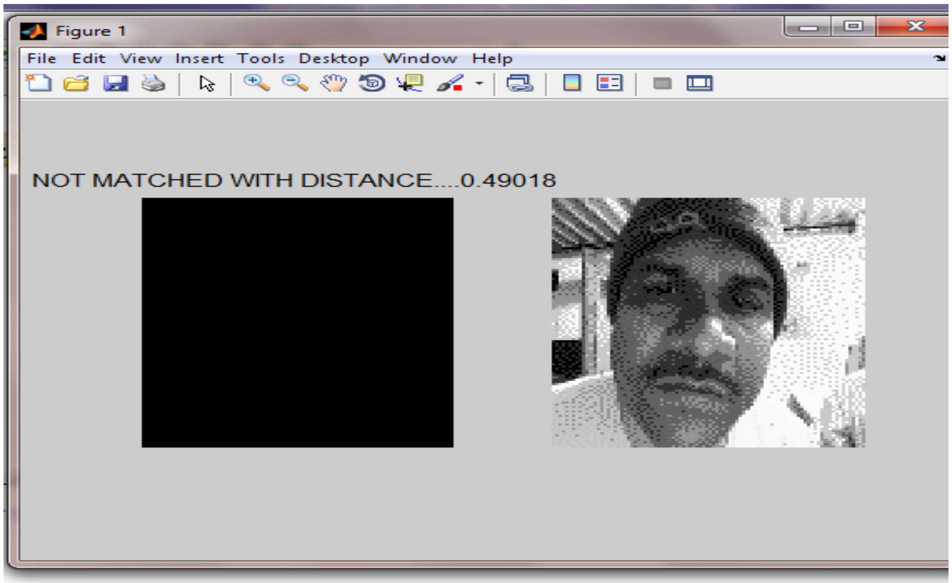


Fig-5 output of software when distance greater than threshold

IV. CONCLUSION

In Face recognition method using Eigen faces, we used database of face images which contains 120 images of 12 different persons (10 images per person). From the results, it can be concluded that, for recognition, it is sufficient to take about 20% Eigen faces with the highest eigenvalues. 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. If the distance is greater than zero but less than a certain threshold, it is a known person with other facial expression, otherwise it is an unknown person.

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