

Pose & Size Independent Face Recognition Using Advanced PCA Algorithm

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Abstract. This paper mainly addresses the building of not only pose but also size independent face recognition system by using Principal Component Analysis (PCA). Furthermore, This is an illustration of face recognition method including both algorithm as well as schematic diagram where the dimension of testing image need not to be equal with the dimension of database or training images. PCA is a statistical approach used for reducing the number of variables in face recognition. In PCA, every image in the training set is represented as a linear combination of weighted eigenvectors called eigenfaces. These eigenvectors are obtained from covariance matrix of a training image set. The weights are found out after selecting a set of most relevant Eigenfaces. Recognition is performed by projecting a test image onto the subspace spanned by the eigenfaces and then classification is done by measuring minimum Euclidean distance. A number of experiments were done to evaluate the performance of the face recognition system. In this thesis, we used a training database of students of Electronics and Telecommunication Engineering department, Batch-2007, Rajshahi University of Engineering and Technology, Bangladesh.

Keywords: Pose & Size Independent Recognition, PCA, Eigenvalue, Eigenvector, Covariance, Euclidean distance, Eigenface.

1. ALGORITHM

Let a face image $\Gamma(x, y)$ be a two dimensional M by N array of intensity values. In this thesis, we used a set of image by 200×149 pixels as database. An image may also be considered as a vector of dimension $M \times N$, so that a typical image of size 200×149 becomes a vector of dimension 29,800 or equivalently a point in a 29,800 dimensional space.

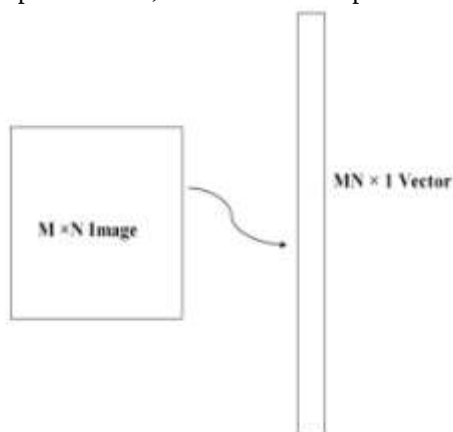


Fig-1: Conversion of $M \times N$ image into $MN \times 1$ vector

Step1: prepare the training faces ie database

Obtain face images $I_1, I_2, I_3, I_4, \dots, I_M$ (training faces). The face images must be centered and of the same size.

Step 2: Prepare the data set

Each face image I_i in the database is transformed into a vector and placed into a training set S .

$$S = \{\Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4, \dots, \Gamma_M\}$$

In My example $M = 34$. Each image is transformed into a vector of size $MN \times 1$ and placed into the set. For simplicity, the face images are assumed to be of size $N \times N$ resulting in a point in N^2 dimensional space. An ensemble of images, then, maps to a collection of points in this huge space.

Step 3: compute the average face vector

The average face vector (Ψ) has to be calculated by using the following formula:

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

Step 4: Subtract the average face vector

The average face vector Ψ is subtracted from the

original faces Γ_i and the result stored in the variable Φ_i ,

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

Step 5: Calculate the covariance matrix

We obtain the covariance matrix C in the following manner,

$$\begin{aligned} C &= \frac{1}{M} \sum_{n=1}^M \Phi_n \Phi_n^T \\ &= AA^T \quad \begin{matrix} (N^2 \times N^2 \text{ matrix}) & \text{Where, } A = [\Phi_1, \Phi_2, \Phi_3, \Phi_4, \dots, \Phi_M] \\ (N^2 \times M \text{ matrix}) \end{matrix} \end{aligned}$$

Step 6: Calculate the eigenvectors and eigenvalues of the covariance matrix

The covariance matrix C in step 5 has a dimensionality of $N^2 \times N^2$, so one would have N^2 eigenface and eigenvalues. For a 256×256 image that means that one must compute a $65,536 \times 65,536$ matrix and calculate 65,536 eigenfaces. Computationally, this is not very efficient as most of those eigenfaces are not useful for our task. In general, PCA is used to describe a large dimensional space with a relative small set of vectors.

Compute the eigenvectors u_i of AA^T

The matrix AA^T is very large - - ► not practical!!!

Step 6.1: consider the matrix

$$L = A^T A \quad (M \times M \text{ matrix})$$

Step 6.2: compute eigenvectors v_i of $L = A^T A$

$$A^T A v_i = \mu_i v_i$$

What is the relationship between u_i and v_i ?

$$A^T A v_i = \mu_i v_i$$

$$A A^T A v_i = \mu_i A v_i$$

$$C A v_i = \mu_i A v_i \quad [\text{since } C = A A^T]$$

$$C u_i = \mu_i A v_i$$

where, $u_i = A v_i$ Thus, $C = A A^T$ and $L = A^T A$ have the

same eigenvalues and their eigenvectors are related as follows: $u_i = A v_i$

Note 1: $C = A A^T$ can have upto N^2 eigenvalues and eigenvectors.

Note 2: $L = A^T A$ can have upto M eigenvalues and eigenvectors.

Note 3: The M eigenvalues of $C = A A^T$ (along with their corresponding eigenvectors) correspond to the M largest eigenvalues of $L = A^T A$ (along with their corresponding eigenvectors).

Where v_i is an eigenvector of $L = A^T A$. From this simple proof we can see that $A v_i$ is an eigenvector of $C = A A^T$. The M eigenvectors of $L = A^T A$ are used to find the M eigenvectors u_i of C that form our eigenface basis:

$$u_i = \sum_{i=1}^M v_i \Phi_i$$

Where, u_i are the Eigenvectors i.e. Eigenfaces.

Step 7: keep only K eigenvectors (corresponding to the K largest eigenvalues)

Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of Characteristic features of the faces.

2. PROJECTION OF TRAINING SAMPLES INTO THE EIGENFACE SPACE

Next we have to project the training sample into the Eigenface space. The feature weight for the training images can be calculated by the following formula:

$$\omega_i = u_i^T (\Gamma_i - \Psi)$$

Where, u_i is the i^{th} Eigenfaces and $i=1, 2, 3, \dots, K$. The weight is obtained as above form a vector as follows

$$\Omega^T_i = [\omega_1, \omega_2, \omega_3, \dots, \omega_K]$$

3. TESTING SAMPLE CLASSIFICATIONS

- a) Read the test image and separate face from it.
- c) Equalize the dimension of test image to database image
- b) Calculate the feature vector of the resized test face.

The resized test image is transformed into its eigenface components. First we compare line of our input image with our mean image and multiply their difference with each eigenvectors. Each value would represent a weight and would be saved on a vector Ω^T

$$\omega_{test} = u_i^T (\Gamma_{test} - \Psi)$$

Where, u_i is the i^{th} Eigenfaces and $i=1, 2, 3, \dots, K$.

$$\Omega^T_{test} = [\omega_1, \omega_2, \omega_3, \dots, \omega_K]$$

- c) Compute the average distance (Euclidean distance) between test feature vector and all the training feature vectors.

Mathematically, recognition is finding the minimum Euclidean distance ε_k , between a testing point and a training point given in the following equation

$$\varepsilon_k = \sqrt{\|\Omega_{test} - \Omega_i\|^2}$$

Where, $i = 1, 2, 3, \dots, K$. The Euclidean distance between two weight vectors thus provides a measurement of similarity between the corresponding images.

- d) The face class with minimum Euclidean distance shows similarity to test image.

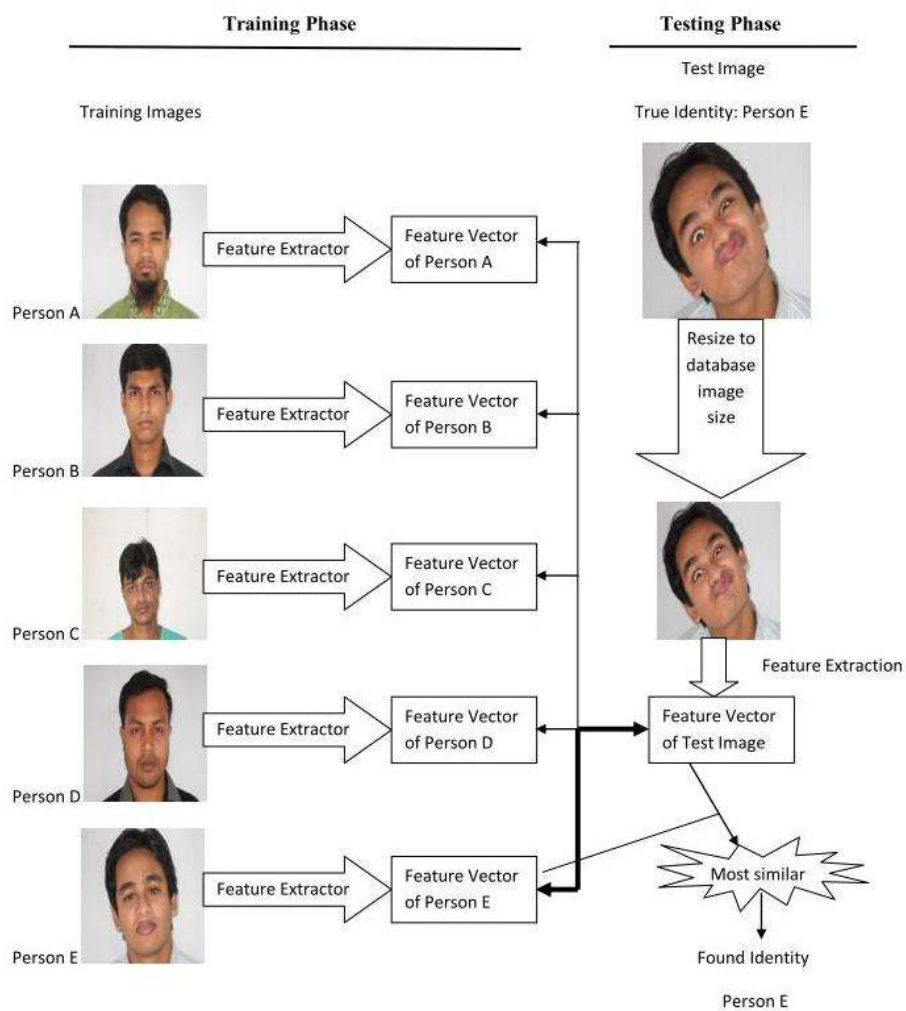
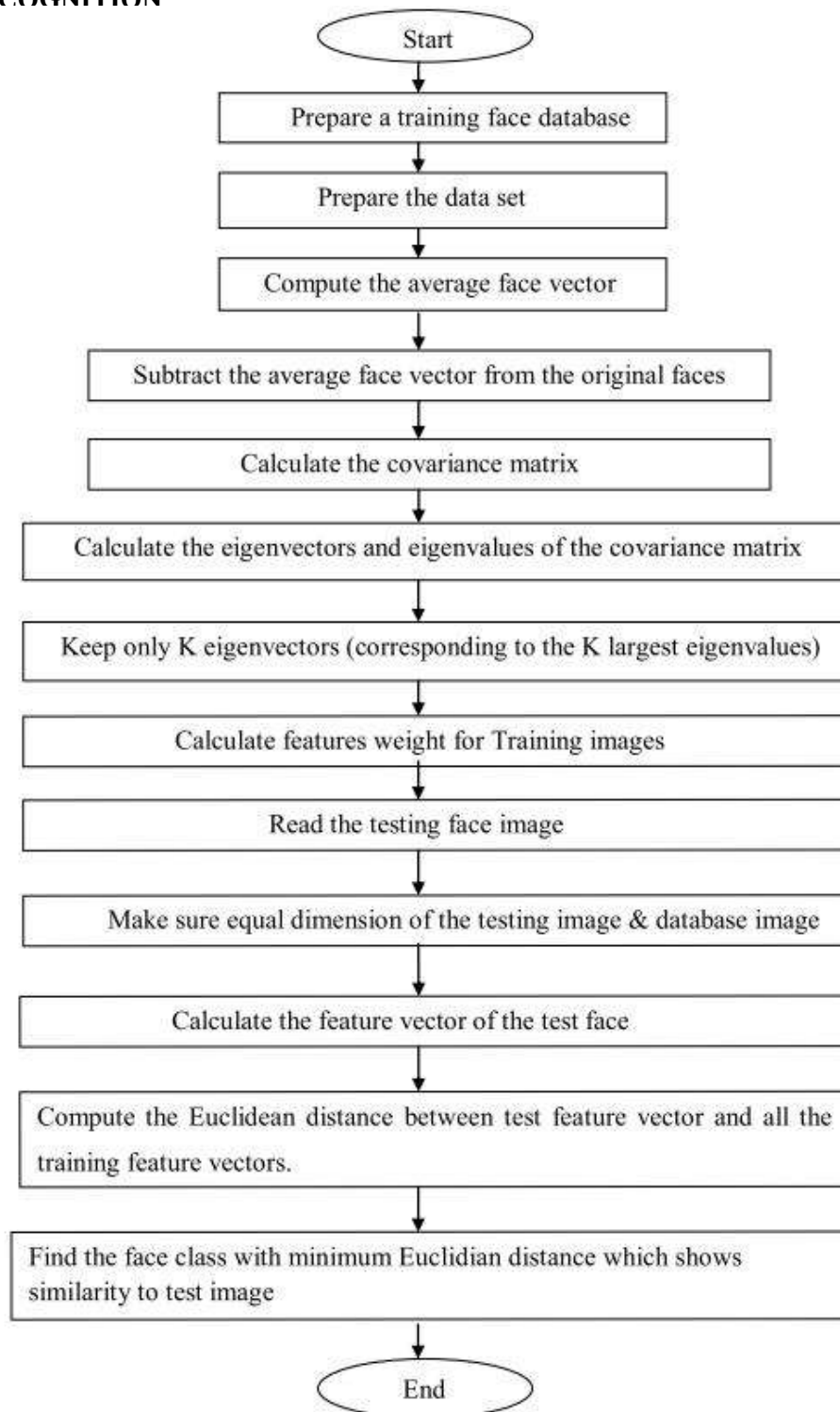
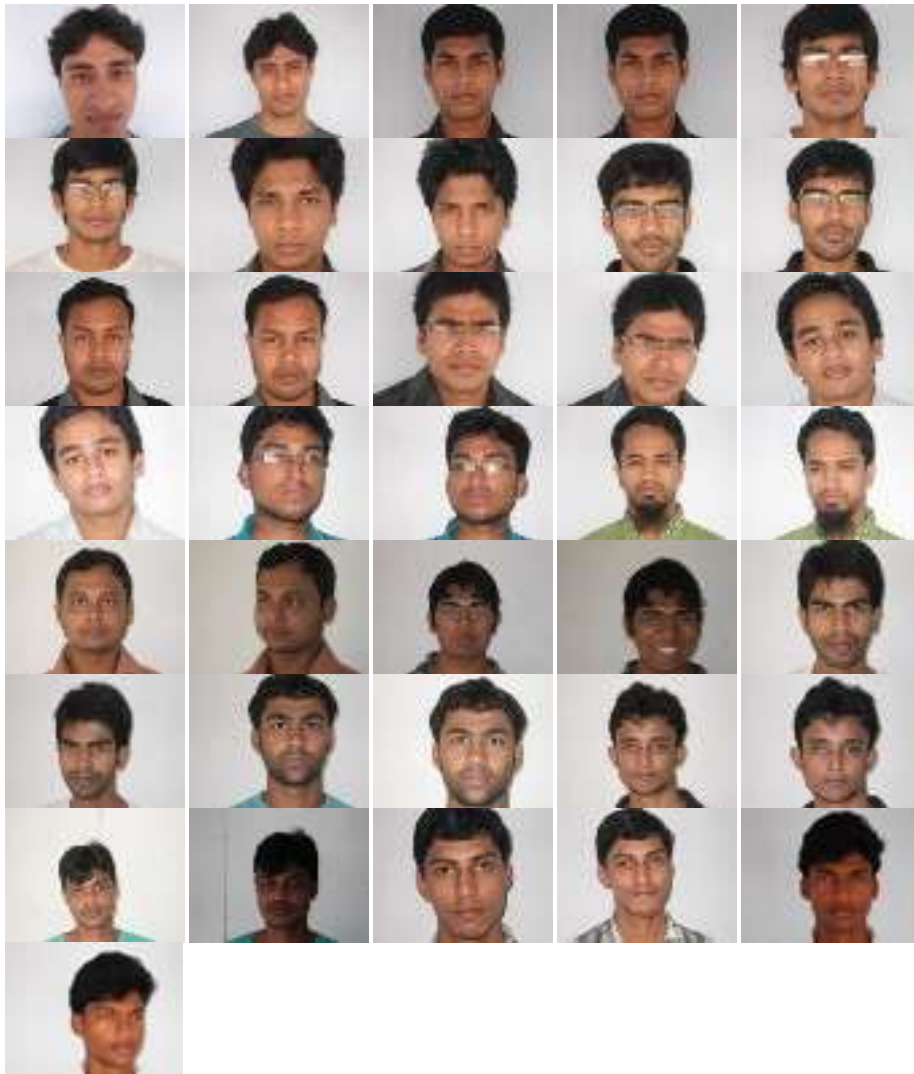


Fig-2: Schematic diagram of a pose & size independent face recognizer

5. MODIFIED FLOWCHART FOR POSE & SIZE INDEPENDENT FACE RECOGNITION



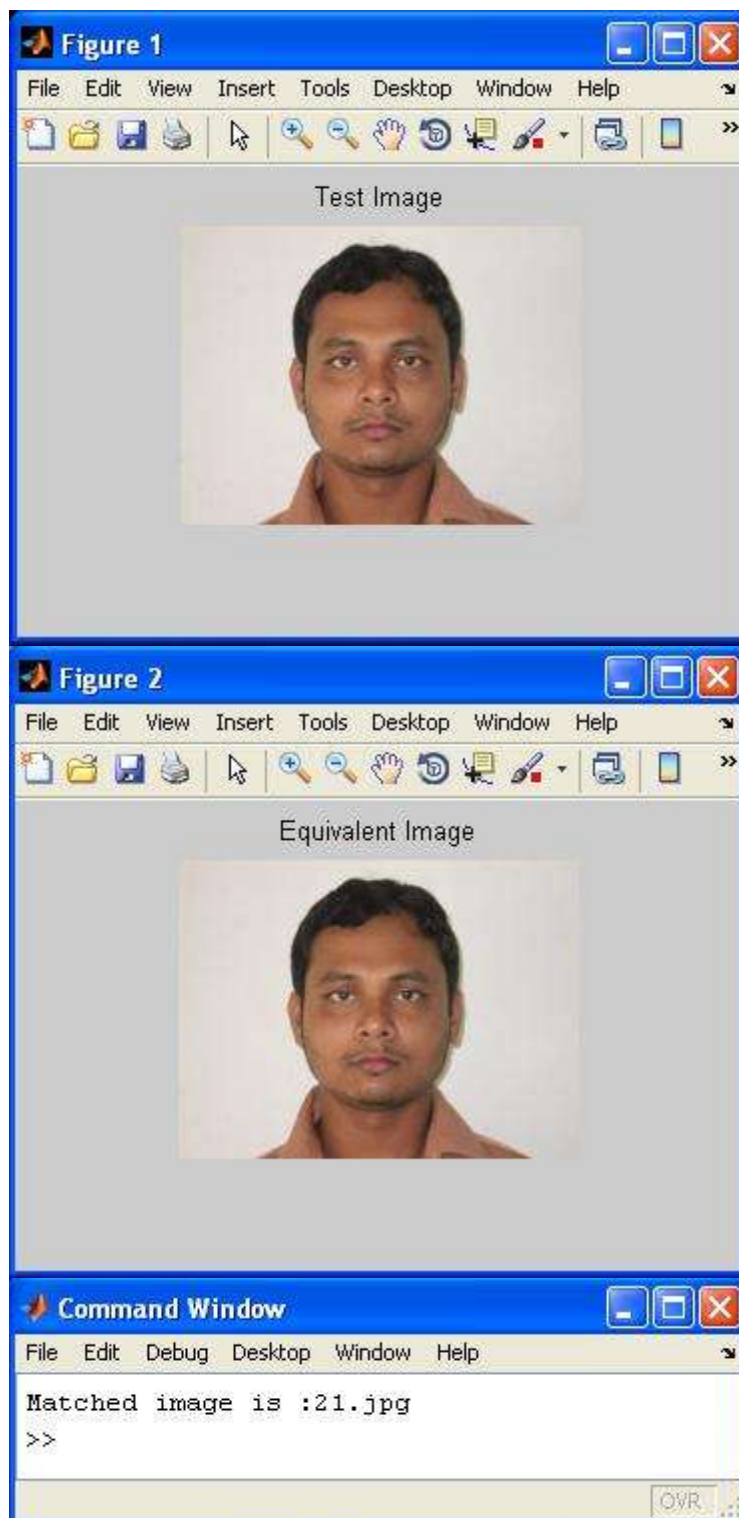
6. TRAINING IMAGES OR DATABASE



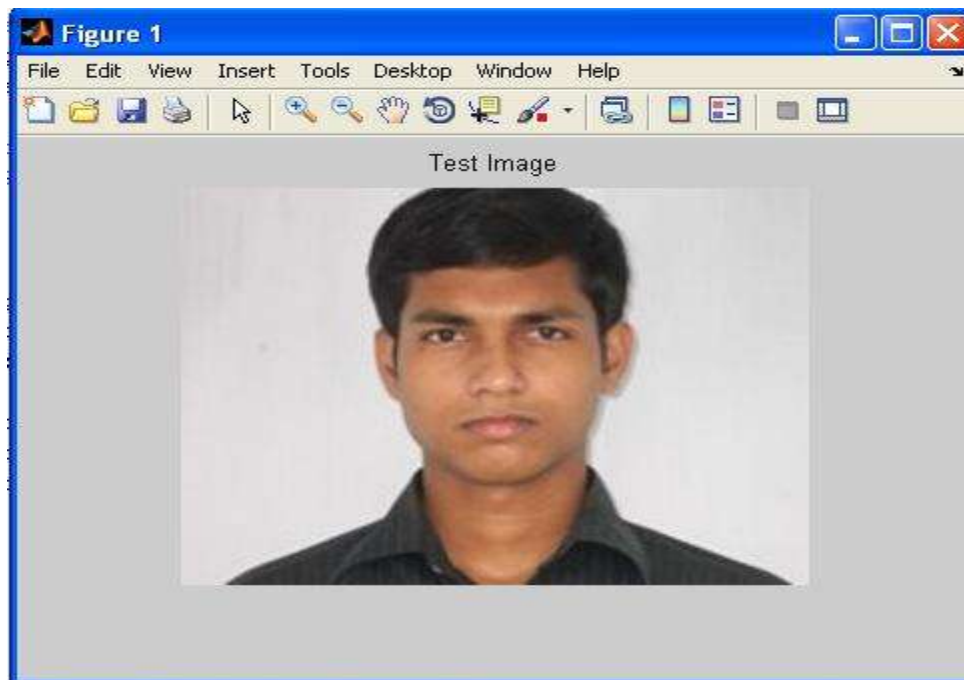
7. EXPERIMENTAL RESULT

This article represents some computational results of my program. In Experimental result-1, both test image and equivalent image which is stored in database have same pose & same size. In result-2, the testing image & equivalent image have same pose but different size. But test image and equivalent image are both different in pose & size which are shown in Experimental result-3, 4, 5 & 6.

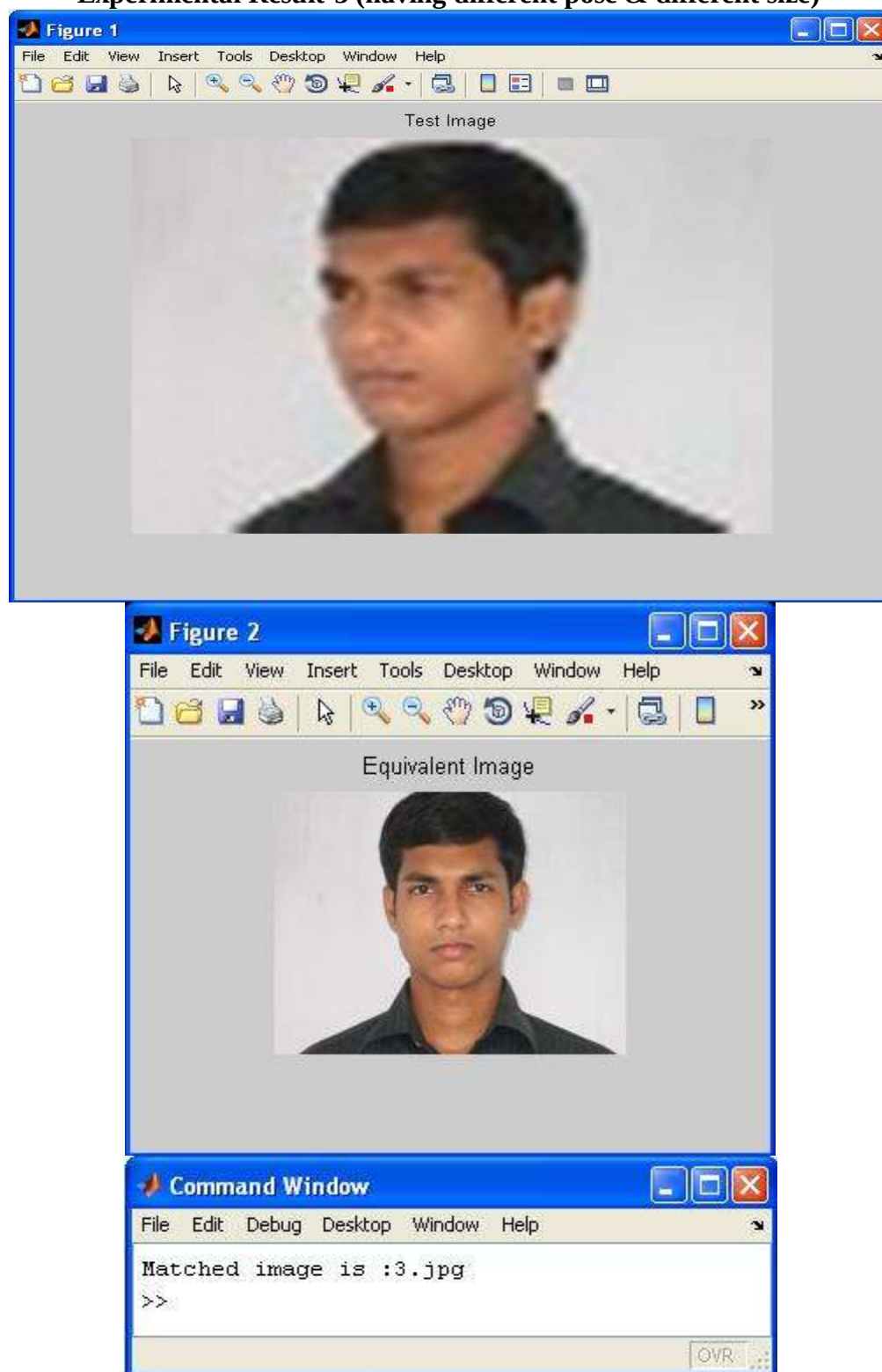
Experimental Result-1 (having same pose & same size)



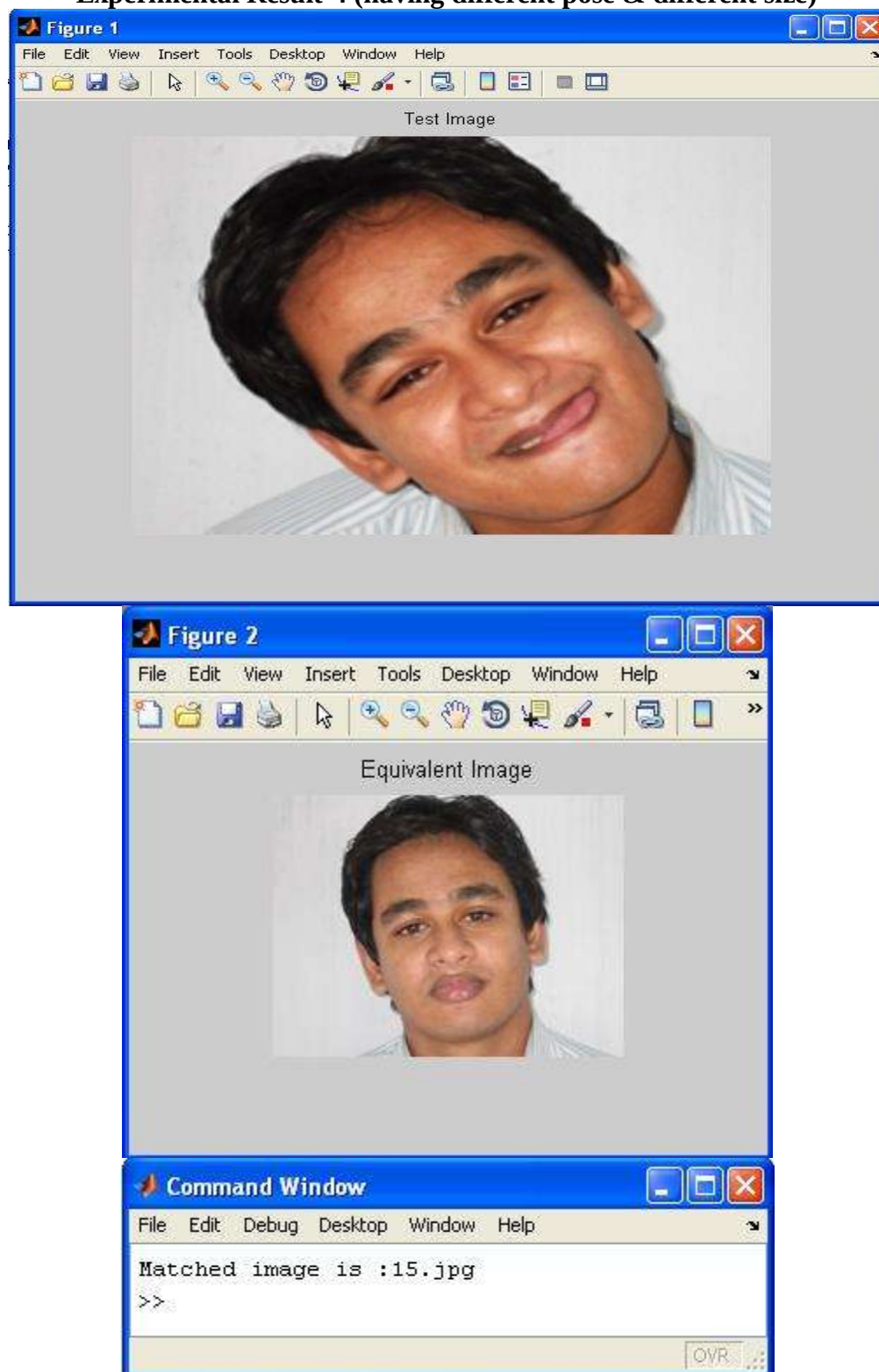
Experimental Result-2 (having same pose but different size)



Experimental Result-3 (having different pose & different size)

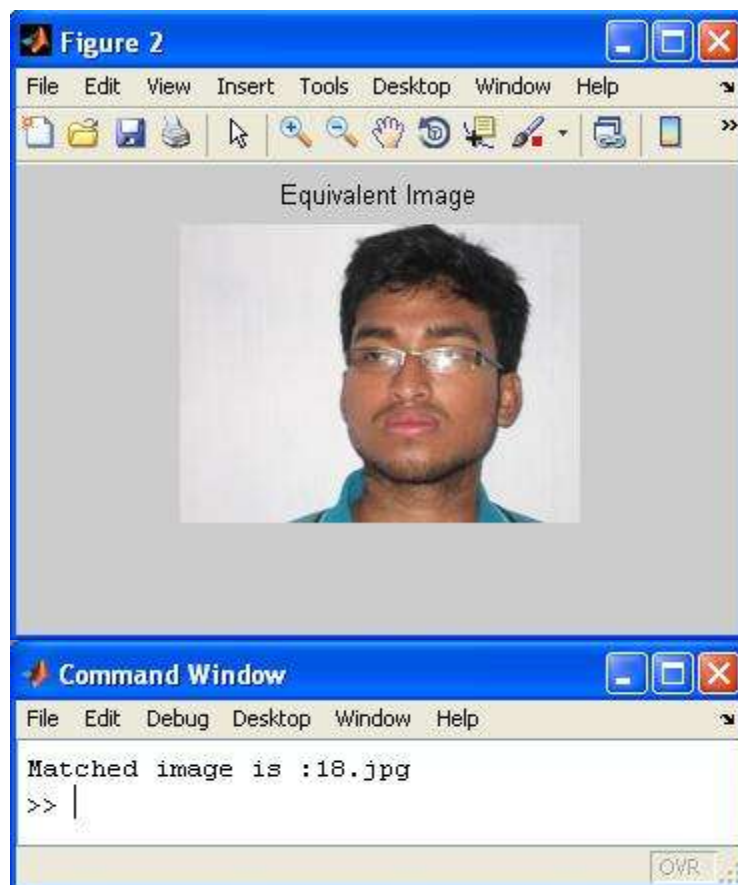


Experimental Result-4 (having different pose & different size)



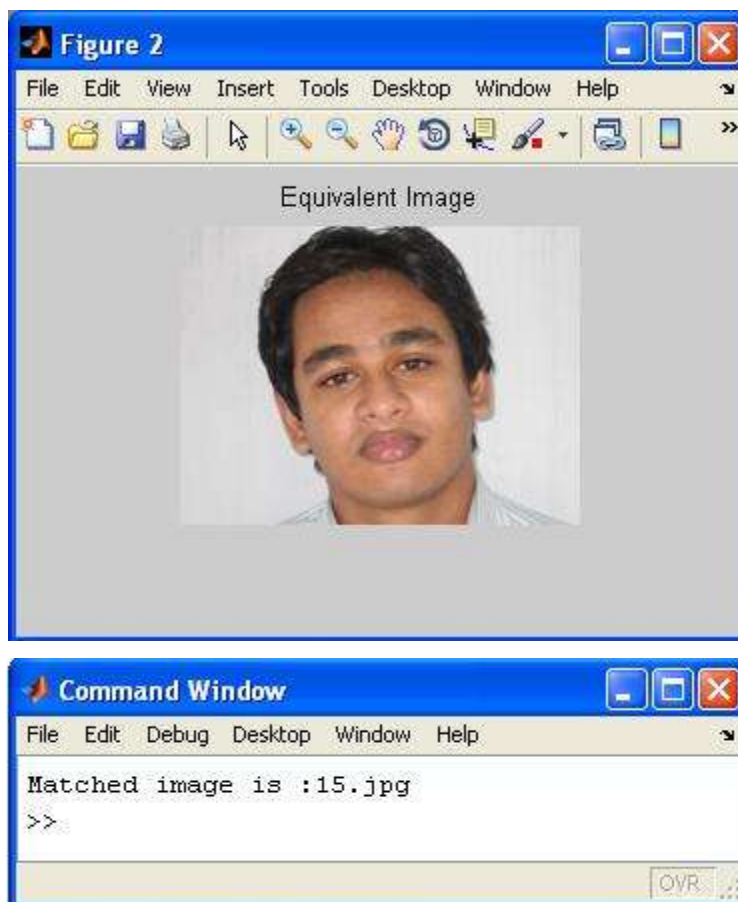
Experimental Result-5 (having different pose & different size)





Experimental Result-6 (having different pose & different size)





8. CONCLUSION

In this research, we implemented the face recognition system using Principal Component Analysis and Eigenface approach. The system successfully recognized the human faces and worked better in different conditions of face orientation. The algorithm has been tested for the image database ETE-07 series, RUET and implemented using MATLAB. The algorithm developed in a generalized one which works well with any format of images but testing image & training image must be in same format. The tests conducted on Bitmap images, PNG images and JPEG images of various subjects not only in different poses but also different in size showed that this method gave very good classification of faces. The main achievement of this work is that the proposed face recognition system is a pose & size independent face recognition system. In future, we want to work with real time face recognition.

9. REFERENCES

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