

# Face Recognition using Principle Component Analysis for Biometric Security System

Raman Kumar<sup>#1</sup>, Satnam Singh<sup>\*2</sup>

<sup>1</sup>M. Tech Scholar, Department of ECE, SSCET, Badhani, Pathankot, Punjab, India

<sup>2</sup>AP, Department of ECE, SSCET, Badhani, Pathankot, Punjab, India

*Abstract— Face recognition is an application area where computer vision research is utilized in both military and commercial products. It is a process of identifying or verifying a person from an image and comparing the selected features from the image with a given database. This paper provides a critical survey of researches on image-based face recognition. The principle Component Analysis (PCA) technique of face recognition are comprehensively reviewed and discussed. Their strategies, advantages/disadvantages and performances are elaborated.*

*Keywords— PCA, Face Recognition, Eigen face, Eigen value.*

## I. INTRODUCTION

Face recognition is a biometric technique used for surveillance purposes such as search for wanted criminals, suspected terrorists, and missing children. The term face recognition refers to identifying, by computational algorithms, an unknown face image. This operation can be done by comparing the unknown face with the faces stored in database. Face recognition has three stages a) face location detection b) feature extraction c) facial image classification. There are various methods to recognize the faces. Though many face recognition approaches [1-6] reported satisfactory performances, their successes are limited to the conditions of controlled environment, which are unrealistic in many real applications. In recent surveys of face recognition techniques [7-8], pose variation was identified as one of the prominent unsolved problems in the research of face recognition and it gains great interest in the computer vision and pattern recognition research community.

Face recognition across pose refers to recognizing face images in different poses by computers. It is of great interest in many face recognition applications, most notably those using indifferent or uncooperative subjects, such as surveillance systems. For example, face recognition is appealing in airport security to recognize terrorists and keep them from boarding plane. Ideally, the faces of terrorists are collected and stored in the database against which travellers' faces will be compared. The face of everyone going through a security checkpoint will be scanned. Once a match is found, cameras will be turned on to surveil people with a live video feed, and then the authorities will

verify the match and decide whether to stop the individual whose face matches one in the database.

The most natural solution for this task might be to collect multiple gallery images in all possible poses to cover the pose variations in the captured images, which requires a fairly easy face recognition algorithm. Few promising methods have been proposed in tackling the problem of recognizing faces in arbitrary poses, such as tied factor analysis (TFA) [9], 3D morphable model (3DMM)[10], Eigen light-field (ELF)[11], illumination cone model (ICM)[12], etc.

## II. EIGEN-FACE APPROACH

In this approach, the face images are decomposed into a small set of characteristic feature images called “Eigen-faces” (which contain the common features in a face) which are extracted from the original training set of images by means of principal component analysis. An important feature of PCA is that any original image can be reconstructed from the training set by a linear combination of the Eigen-faces. Each Eigen-face represents only certain features of the face. However, the losses due to omitting some of the Eigen-faces can be minimized by choosing only the most important features (Eigen-faces).

The Eigen-face approach involves the following initialization operations:

1. An initial set of images (training set) is acquired.
2. The Eigen-faces from the training set are calculated and only M images that correspond to the highest Eigen values define the face space.
3. By projecting the face images onto the face space, the corresponding distribution in M-dimensional weight space for each individual image is found.

With these weights, any image in the database can be reconstructed using the weighted sum of the Eigen-faces. In order to recognize face images, the following steps are to be followed

1. A set of weights based on the input image and the M Eigen-faces are calculated by projecting the input image onto each of the Eigen-faces.

Nearest neighbour classification is used in order to find out the unknown image in the training set.

A. Initialization

Let the training set of face images be  $T_1, T_2, T_3, \dots, T_M$ . This training data set has to be mean adjusted before calculating the covariance matrix or eigenvectors. The average face is calculated as

$$\Psi = (1/M) \sum_1^M T_i$$

Each image in the data set differs from the average face by the vector  $\Phi = T_i - \Psi$ . This is actually mean adjusted data. The covariance matrix is

$$C = (1/M) \sum_1^M \Phi_i \Phi_i^T = AA^T$$

where  $A = [\Phi_1, \Phi_2, \dots, \Phi_M]$ . The matrix  $C$  is a  $N^2$  by  $N^2$  matrix and would generate  $N^2$  Eigen vectors and Eigen values. With image sizes like 256 by 256, or even lower than that, such a calculation would be impractical to implement. A computationally feasible method was suggested to find out the eigenvectors. If the number of images in the training set is less than the no of pixels in an image (i.e  $M < N^2$ ), then we can solve an  $M$  by  $M$  matrix instead of solving a  $N^2$  by  $N^2$  matrix. Consider the covariance matrix as  $A^T A$  instead of  $AA^T$ . Now the eigenvector  $V_i$  can be calculated as follows,

$$A^T A V_i = \mu_i V_i$$

where  $\mu_i$  is the Eigen value. Here the size of covariance matrix would be  $M$  by  $M$ . Thus we can have  $m$  Eigen vectors instead of  $N^2$ . Premultiplying equation 2 by  $A$ , we have

$$AA^T A V_i = \mu_i A V_i$$

The right hand side gives us the  $M$  Eigen-faces of the order  $N^2$  by 1. All such vectors would make the image space of dimensionality  $M$ . The  $M$  Eigen-faces which have the largest associated Eigen values are selected. These Eigen-faces now span a  $M$ -dimensional subspace instead of  $N^2$ .

B. Recognition

A new image  $T$  is transformed into its Eigen-face components by a simple operation,

$$w_k = u_k^T (T - \Psi)$$

where  $k = 1, 2, \dots, M$ . The weights obtained as above form a vector  $\Omega T = [w_1, w_2, w_3, \dots, w_M]$  that describes the contribution of each Eigen-face in

representing the input face image. The Euclidean distance of the weight vector of the new image from the face class weight vector can be calculated as follows,

$$\epsilon_k = \|\Omega - \Omega_k\|$$

where  $\Omega_k$  is a vector describing the  $k$ th face class. The face is classified as belonging to class  $k$  when the distance  $\epsilon_k$  is minimum. The Eigen Faces of images is shown in Figure 1.

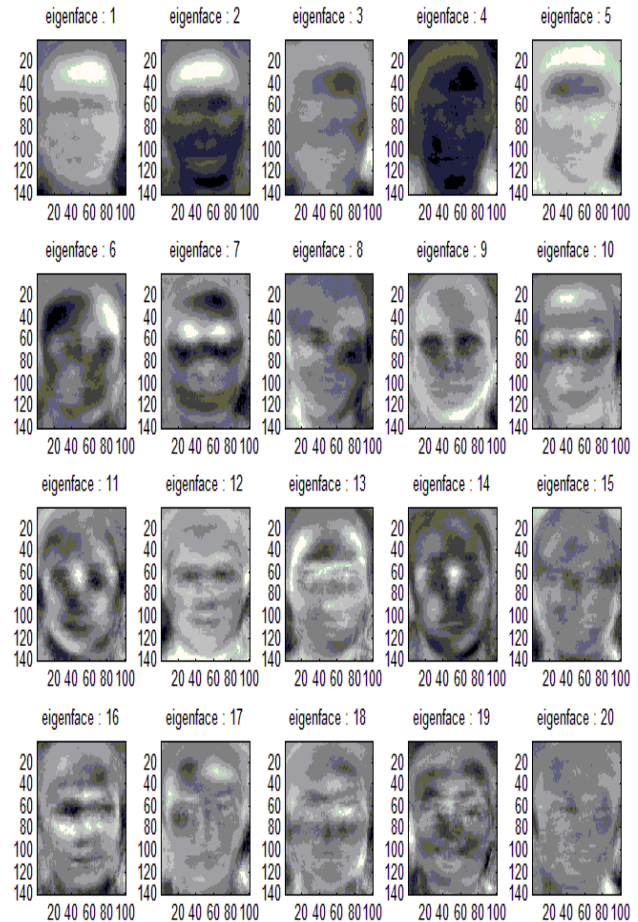


Fig. 1: Eigen Faces

III. RESULTS

In this paper for experimentation, 60 images are taken for training. One of the images as shown in fig 2(a) is taken as the Input image and corresponding retrieve image is shown in figure 2 (b). The mean image and reconstructed output image by PCA, is as shown in fig (b) and 3(c). Eigen faces are as shown in fig 3(d).

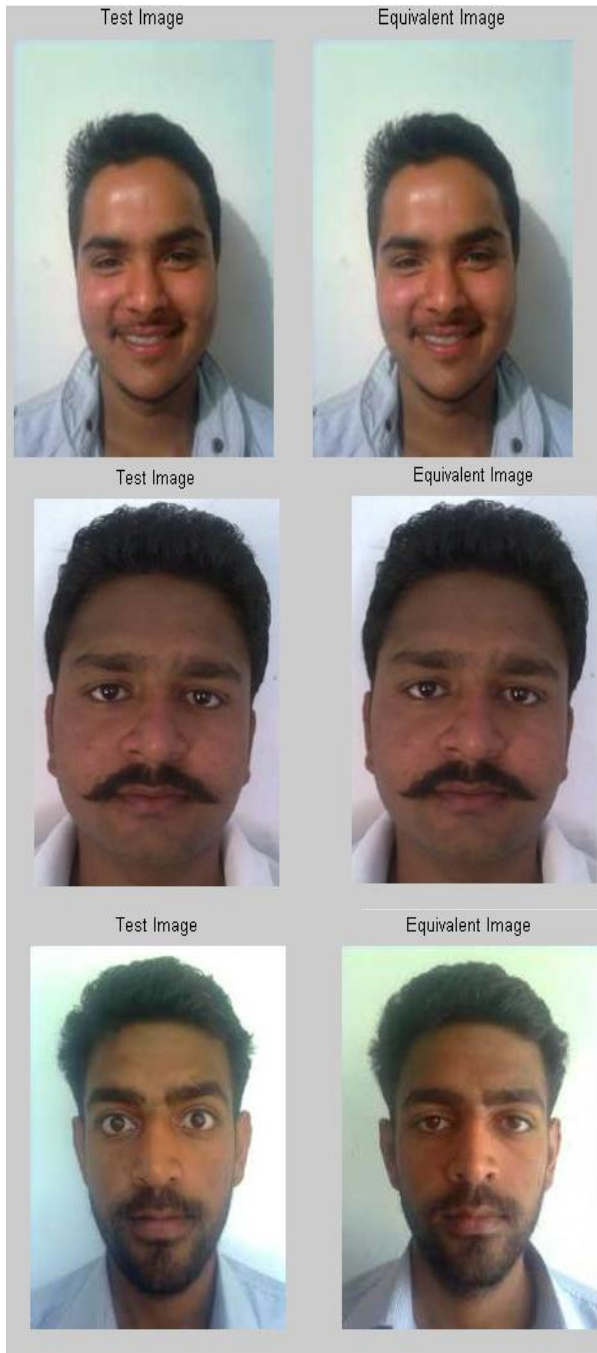


Fig. 2 (a) Test images (b) Equivalent images

#### IV. CONCLUSIONS

Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities. In this paper, Face recognition using Eigen faces has been shown to be accurate and fast, nonlinear face images can be recognized easily. This method has the Acceptance ratio is more than 90 % and execution time of only few seconds.

TABLE I  
ACCEPTANCE & REJECTION RATE

No. of Test Images = 30		
S No.	Parameters	%age
1	Acceptance Rate	91
2	False Acceptance Rate	6.27
3	False Rejection Rate	3.73

#### REFERENCES

- [1] M.S. Bartlett, J.R. Movellan, T.J. Sejnowski, Face recognition by independent component analysis, *IEEE Trans. Neural Network* 13 (6) (2002) 1450–1464.
- [2] P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, Eigenfaces vs. Fisherfaces: recognition using class specific linear projection., *IEEE Trans. Pattern Anal. Mach. Intell.* 19 (7) (1997) 711–720.
- [3] X. He, S. Yan, Y. Hu, P. Niyogi, H.-J. Zhang, Face recognition using Laplacian faces, *IEEE Trans. Pattern Anal. Mach. Intell.* 27 (3) (2005) 328–340.
- [4] Y. Gao, M.K.H. Leung, “Face recognition using line edge map”, *IEEE Trans. Pattern Anal. Mach. Intell.* 24 (6) (2002) 764–779.
- [5] M. Kirby, L. Sirovich, “Application of the Karhunen–Loève procedure for the characterization of human face”, *IEEE Trans. Pattern Anal. Mach. Intell.* 12 (1) (1990) 103–108.
- [6] S.-H. Lin, S.-Y. Kung, L.-J. Lin, Face recognition/detection by probabilistic decision-based neural network, *IEEE Trans. Neural Network* 8 (1) (1997) 114–132.
- [7] S. Chen, X. Tan, Z.-H. Zhou, F. Zhang, Face recognition from a single image per person: a survey, *Pattern Recognition* 39 (9) (2006) 1725–1745.
- [8] W. Zhao, R. Chellappa, P.J. Phillips, A. Rosenfeld, Face recognition: a literature survey, *ACM Comput. Surv.* 35 (4) (2003) 399–459.
- [9] S.J.D. Prince, J. Warrell, J.H. Elder, F.M. Felisberti, Tied factor analysis for face recognition across large pose differences, *IEEE Trans. Pattern Anal. Mach. Intell.* 30 (6) (2008) 970–984.
- [10] V. Blanz, T. Vetter, Face recognition based on fitting a 3D morphable model, *IEEE Trans. Pattern Anal. Mach. Intell.* 25 (9) (2003) 1063–1074.
- [11] R. Gross, I. Matthews, S. Baker, Appearance-based face recognition and light-fields, *IEEE Trans. Pattern Anal. Mach. Intell.* 26 (4) (2004) 449–465.
- [12] A.S. Georghiades, P.N. Belhumeur, D.J. Kriegman, From few to many: illumination cone models for face recognition under variable lighting and pose, *IEEE Trans. Pattern Anal. Mach. Intell.* 23 (6) (2001) 643–660.