# PCA's Face identification and representation technique: 2D-PCA

A.M. Abhishek Sai
*CSE-AI dept*
*Amrita School of Engineering*
Amritapuri , India
abhisheksai1456@gmail.com

Kalla Likhit Sai Eswar
*CSE-AI dept*
*Amrita School of Engineering*
Amritapuri , India
likhitsaieswar@gmail.com

Koganti Sri Sai Harshith
*CSE-AI dept*
*Amrita School of Engineering*
Amritapuri , India
kogantisaiharshith@gmail.com

Perumalla Raghavendra
*CSE-AI dept*
*Amrita School of Engineering*
Amritapuri , India
Perumallaraghava19@gmail.com

G.Yashwanth Kiran
*CSE-AI dept*
*Amrita School of Engineering*
Amritapuri , India
yashwanthkiran2624@gmail.com

***Abstract*— Face recognition is becoming more popular due to the rapid growth of information and communication technology. Image recognition is an important field of artificial intelligence, and its accuracy is improving rapidly. So to do this, in this paper Facial Identification is performed on ORL Dataset using 2D Principal Component Analysis based dimension reduction technique. Analogous to PCA, 2D-PCA is based on 2D image matrices rather than computing the covariance matrix using a 1D-vector. Feature extraction using 2D principal component analysis is the proposed methodology, in this paper. For the experiment ORL Face database is used. 2D-PCA is the traditional matrix-based feature extraction method. Speculative findings indicate that the proposed method demonstrates a higher recognition rate than conventional methods. Furthermore, we utilized image pre-processing techniques such as cropping, resizing and varying the brightness to increase the rate of recognition.**

***Index Terms*—Face recognition , 2D principal component analysis , dimensionality reduction, Image matrix , ORL Data Set**

## I. Introduction

Principal Component Analysis (PCA) has been widely utilized in dimensionality reduction, pattern recognition and computer vision. Face recognition is performed for unique identification. Two-dimensional principal component analysis (2DPCA), as a state-of-the-art method for dimensionality reduction, has been widely utilized in face recognition. Recognition would imply the tasks of identification or authentication of a person or image. Identification involves a one-to-many comparison. Authentication involves a one-to-one comparison. During a face recognition system, 3 steps include Face detection, feature extraction and face recognition. Feature Extraction Methods involve vector-based and matrix-based methods. In the vector-based method the 2- Dimensional facial image matrix must be transformed into 1- Dimensional vector. PCA and LDA are two well-known vector-based methods for feature extraction.

However, applying PCA to face image representation and recognition, we need to transform each image, which is usually represented as a matrix, into a 1D vector column by column or row by row, so it cannot well exploit the spatial structure information embedded in pixels and their neighbours of image. Moreover, this often leads to a high-dimensional vector space, where it is difficult to evaluate the covariance matrix accurately due to its large size and a relatively small number of training samples. To tackle this problem, Yang et al proposed two-dimensional principal component analysis (2DPCA) which is based on the 2D image directly rather than a 1D vector. It has been successfully applied in the computer vision and signal process community. Unlike PCA, 2DPCA uses 2D matrices rather than 1D vectors. That is, the image matrix does not need to be previously transformed into a vector. The original image matrices can instead be used to calculate a covariance matrix. The size of the image covariance matrix using 2DPCA is much smaller. As a result,2DPCA has two important advantages over PCA. First, it is easier to evaluate the covariance matrix accurately since it is smaller. Second, less time is required to determine the corresponding eigenvectors.

To increase the Recognition rate we use image processing techniques. Image cropping - The image region where the face can be found is cropped and the region cropped is used in the face recognition process. Image Resize - The images used in the analysis are resized in different scales to lower the data size. Change the Brightness - Increasing the brightness will increase the recognition rate.

Section I gives an introduction to 2D PCA, Section II discusses the background and related works of 2D PCA, Section III describes the 2D PCA algorithm, Section IV details the implementation methodology. Section V deals with experimentation. Section VI presents the results and discussion. Section VII summarizes the paper.

## II. LITERATURE REVIEW

Two-dimensional principal component analysis (2D-PCA) has been proposed and has found a huge application in face recognition. 2D-PCA performed on the 2D images is actually like the PCA performed on the rows of the pictures. Only working in the row direction of images makes it a lower compression rate than that of PCA.

To address this problem, some bilateral projection-based approaches have been developed. Kong et al proposed B2DPCA that constructs two subspace to encode the row and column vectors of image matrices respectively.

Zhang et al presented (2D)2 PCA that simultaneously considering the row and column directions of images.

Xu et al constructed two projection transformation matrices by defining two image covariance matrices and proposed complete 2D-PCA which similar as (2D)2 PCA in

. Kim et al developed a way which obtains the linear transform matrix by using two covariance matrices in 2D-PCA .

Turk et. al developed face recognition using eigenface techniques. The term eigenface is employed because mathematical algorithms using eigenvectors represent the first components of the face.

Recently, Yang et al proposed to use 2D-PCA for face recognition. 2D-PCA has two important advantages over the traditional method:

1. First, it is based on 2D image matrices and easier to gauge the covariance matrix accurately. 2. Second, less time is required to work out the corresponding eigenvectors.

However, 2D-PCA can only reduce the dimension of a matrix on one side, so there are too many feature coefficients for face recognition and representation. Although a feasible alternative to affect this problem is to use PCA after 2D-PCA for further dimensional reduction, it's still unclear how the dimension of 2D-PCA might be reduced directly.

## III. THE 2D-PCA

An image space can be thought of as a space with dimensions equal to the number of pixels comprising the image and values within the range of those pixels. For Grayscale images, the dimension could have a value between 0 and 255. When all the face images are converted into vectors, they will group at a certain location in the image space as they have a similar structure, having eye, nose and mouth in common and their relative position correlated. The correlation is the main starting point for the eigenface analysis. The Eigenface method tries to find a lower-dimensional space for the representation of the face images by eliminating the variance due to non-face images; or, in other words, it tries to focus on the variation just arising from variations between faces. Eigen features calculated here are eigenfaces. The Eigenface method is the implementation of Principal Component Analysis (PCA) over images. Face image, in the form of an image vector, is appended column-wise in PCA, but in 2DPCA images are stacked one on top of the other. The first N eigenvectors presenting the highest eigenvalues will be retained and represent the most significant features of faces.

In this paper, Principal Component Analysis with an improved version i.e. 2DPCA is used for feature extraction. Here dimensionality of a data set is reduced and variations in the data set are altered using some image pre-processing techniques. Here face images are taken as matrices and then all of the vectors are appended to form an array. As a result, the recognition rate increases.

### A. Algorithm for 2D-PCA

Let X denotes an m-dimensional unitary column vector . The idea of 2D-PCA is to project a given image A, an m×n matrix, onto X to get an n-dimensional vector Y, where

$$Y = XA$$

by undergoing linear transformation and we call Y The projected feature vector of A. The total scatters of the projected samples can be introduced to measure the dis- criminatory power of the projection vector X. The total scatters of the projected samples can be characterized by the trace of the covariance matrix of the projected feature vectors. From this point of view, we adopt the following criterion:

$$J(X) = tr(Sx)$$

In this place, Sx denotes the covariance matrix of the projected feature vectors of the training samples and tr(Sx ) denotes the trace of Sx . The physical significance of maximizing the criterion is to find transformation matrices, onto which all samples are projected so that the total scatter of the resulting projected samples is maximized. The covariance matrix Sx can be denoted by

$$S = E(Y - EY)(Y - EY)^T$$

$$= E[AX - E(AX)][AX - E(AX)]^T$$

The IMAGE covariance matrix can be defined as

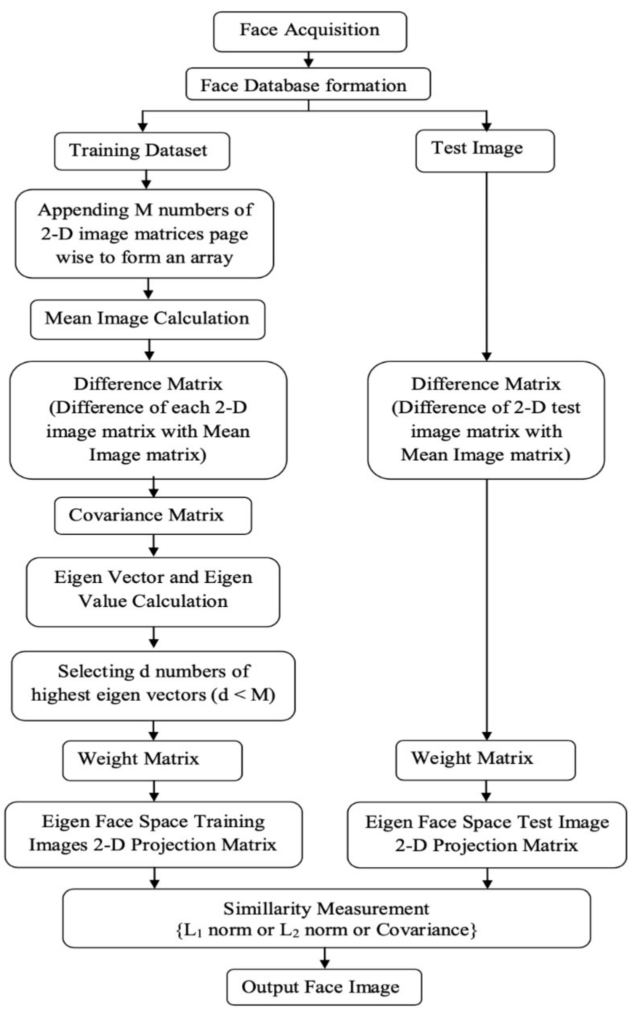
$$G = \frac{1}{M} \sum_{i=1}^{M} (A_i - \bar{A})^T (A_i - \bar{A})$$

Where $\bar{A}$ is the whole average matrix of training samples.

Defining criterion function J(X)is as follows:

$J(X) = X^T G X$

Calculating the maximal value of the expression, then unitary vector X which corresponds to the maximal value was called an optimal projected vector. The projection result in the direction of vector X scatters from each other at the largest degree. The vector X is the namely unitary eigenvector corresponding to the maximal eigenvalue of G. The optimal projection axis Xopt is the unitary vector that maximizes J ( X ). Generally speaking, choosing a single optimal projected direction isn't enough in the complex background for detection images, so we need to find a set of optimal projected vectors X1 , X2, ,Xd , which accord with the maximal condition of J(X) The optimal vector set X1 , X2,... ,Xd should be the eigenvectors of G corresponding to previous the largest eigenvalues.Let P=[ X1 , X2,... ,Xd ] ,then P is called optimal projected matrix.




## IV. METHODOLOGY

In this paper, an Improved version of Principal Component Analysis,2D-PCA, is used for feature extraction. Here dimensionality of a data set is reduced and variations in the data set are altered using some image pre-processing techniques. Here face images are taken as matrices and then all of the image vectors are stacked to form an array, recognition rate shoots up through this.

Let X denote an m-dimensional unitary column vector and A denotes an m×n image matrix. The optimal projection vectors of 2D-PCA, X1, X2...Xm, are used for feature extraction. For a given image sample D, let

$Y_m = X_K A, k = 12.......m$

The principal component vectors obtained are used to form an mxn matrix

B = Y1, Y2....Yn called the feature matrix of the training image set A. All 360 training faces(images) from ORL

## Feature Extraction technique :

### Step-1:

All the 360 training facial images which are under the training database are of size 92x112 pixels. Which are now cropped into 48x42 pixels, then all the images are page-wise annexed to form an array.

### Step-2: (Face Mean Calculation)

Now mean of the array is calculated as

$\bar{A} = \frac{1}{N} \sum_{K=1}^{N} A_k$

This two dimensional matrix $\bar{A}$ is the arithmetic average of the training images at each pixel point of size (48x42).

### Step-3:(Mean subtracted image)

Now each training images is subtracted from mean image so as to obtain the variance matrix.

M = (A $-\bar{A}$ )

### Step-4:(Variance Matrix)

All of these mean subtracted images (variance of each image), are annexed to form an array represented by S. Its size is (48x42x320).

## Step-5:(Scatter Matrix)

Covariance of each variance matrix is calculated which is the product of variance matrix with itself with transpose.

$G = S^T S$

$G = \frac{1}{N} \sum_{i=1}^{N} (M)^T (M)$

Then covariance matrices of all facial images are added. Hence face image covariance matrix size will be off (42x42).

## Step-6:(Eigen values and Eigen vectors)

Eigen vectors $vi$ and eigenvalues $\mu i$ of G are calculated as

$Gvi = \mu ivi$

$S^T Svi = \mu ivi$

The null space of this $(G - \mu i)$ gives the eigen vector matrix.

$S^T.S.S.v = \mu i.S.vi$

After replacing $S.vi$ with $ui$,

$i$ is one of the eigen vector of G and its size is same as G $(42 \times 42)$.

There will be 42 numbers of eigen values and it will be of form $(42 \times 42)$ diagonal matrix. Eigen vectors corresponding to highest eigen values are to be choosed.

## Step-7:(Eigenface Matrix calculation)

The product of variance of each face image with d numbers of highest eigen vectors is the eigen face matrix.

$E = S.u$

If we consider d to be 20 ,eigen face matrix will be of size $(48 \times 20 \times 320)$

## Step-8:(Projected train matrix)

By selecting and appending only projected training matrix will be the Projected train matrix and

$\bar{A}i = E^T Ai$

where i= 1, 2, 3......320

## Testing Phase:

Test images from the ORL Dataset ,the Facial images which are under test ,of size 92x112 pixels, are to be cropped into 48x42 pixels.

From the cropped test face images, mean image of database has to be subtracted from the cropped image of (48x42) pixels

Projected Test image is calculated from eigen face matrix as

$\bar{A}t = E^T.A$

Which is of size (20x42),

The extracted options of all matrix images that are to be detected is calculated as

$Y_k = AX_K$

B = [Y1 , Y2, ... ,Yd]

Let P=[X1,....Xd],then P is called optimal projected matrix of highest d eigen vectors.

# Pre-processing Technique:

## Technique 1 - Increasing Brightness

Changing the brightness of the image is one of the easiest pre-processing techniques. Brightness is a measure of the overall lightness or darkness of the image. The value of brightness is usually from -255 to +255. To increase brightness, some constant values like 100 should be added to each pixel. In this analysis, we found that when 100 or 150 are added to each pixel image brightness increases and so the recognition rate is increased.

In order to reduce the brightness, some constant values must be subtracted from each pixel. Positive values will brighten the image, while negative values will darken it. Deducting 100 or 140 from each pixel darkens the images and decreases recognition rates.

## Technique 2 - Resize

.The main purpose of image resizing is to produce a lower data size, which hastens the processing time The resize scale randomly varies from 0.1 to 0.9 value, which produces different image sizes Resizing the image to a small scale can lead to the loss of many important features, especially if the image texture is used during classification Image resizing scales range from 0.3 to 0.9.

When resizing using the 0.5 scales, the images become 56 x 46 pixels, and when resized using the 0.8 scales, the images become 100 x 86 pixels. Image resizing according to the image resolution can be efficient and increases the recognition rate

### Technique 3 - Reshape

The selection of a specific set of pre-processing steps differs according to the particular application concerned. All images of faces from the database are manually aligned by adjusting the eye location. Consequently, all faces are rotated at first to position the eye centres on particular pixels.

Afterwards, the region that shows the face is cropped from the image and only this region is used in the face recognition process. The face is cropped from the whole image manually depending on the position of the left and right eyes as well as the mouth. The face can be detected using face detection, and unwanted details can be cropped out with cropping.

## V. Experimentation.

In this paper, Olivetti and Oracle Research Laboratory (ORL) face database base is used. The ORL database contains pictures from 40 individuals, every providing 10 different images. All the images are in grayscale. So totally there are 400 images. Out of 10, 8 face images of each person are taken for training and 2 images are taken for testing.

Fig 1 : some of ORL Database faces

In Some samples, the images are taken at different times. First, an experiment is performed using the first eight image samples per class for training, and the remaining images for the test. Thus, the total number of training samples are 320 and the testing samples are 80. We have used different parameters and samples to compare the performance of the two algorithms standard PCA and 2DPCA. Initially, we used the first 8 images of each class for training and the last 2 images for testing. We have taken an accuracy of 90 percent.

We have even calculated the number of eigenvalues required to achieve this accuracy.

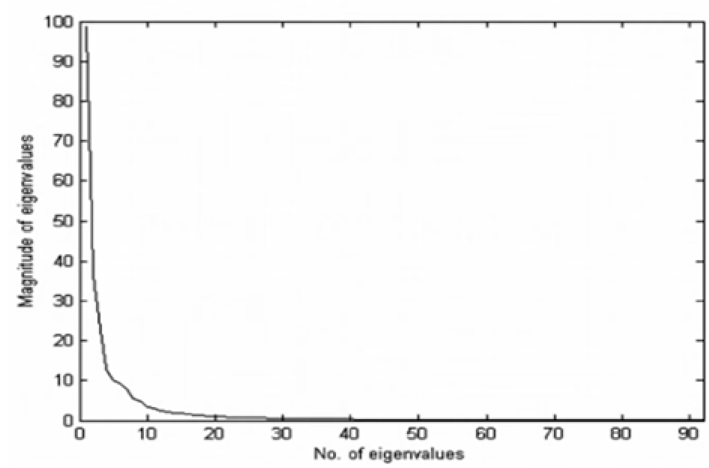



Fig 2 : Plot of No. of Eigen values to obtain an Accuracy of 90

We see that to obtain that accuracy of 90. The top 10-20 eigenvectors contribute to it, and the rest others contribute to a total of 10 . As the value of d increases, the information contained in d becomes gradually weaker. Fig 2 shows the magnitude of the Eigenvalues quickly converges to zero. Eigenfaces should be constructed using the top ‘d’ number of Eigenvectors together. The reconstructed images become clearer as the number of sub-images is increased.

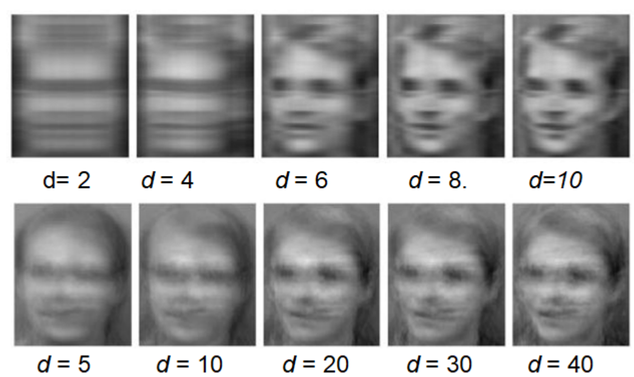
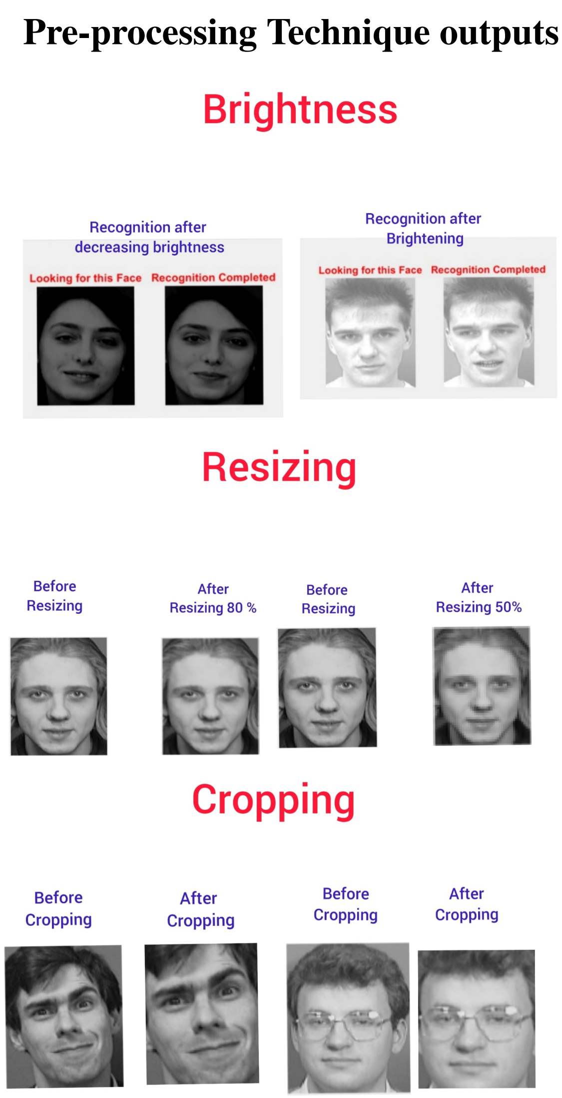



Fig.3. Comparison of the reconstructed images using 2D-PCA (upper) and 1D-PCA (lower)


Fig 4: Some inputs and outputs of the ORL Database using 2D-PCA.




| **Number of Testing images** | **Number of Training images** | **Recognization rate** | Recognization rate after preprocessing |
|---|---|---|---|
| 9 | 1 | 63.8 % | 67.3 % |
| 8 | 2 | 71.4 % | 75.32 % |
| 7 | 3 | 72.93 % | 80.78 % |
| 6 | 4 | 78 % | 85 % |
| 5 | 5 | 80 % | 87 % |
| 4 | 6 | 91.2 % | 93.4% |
| 3 | 7 | 93.71 % | 96.7 % |
| 2 | 8 | 95 % | 97.5 % |
| 1 | 9 | 96 % | 98 % |

## VI. RESULTS

To compare the performance of both standard PCA and 2D-PCA, we have evaluated some of the parameter like correct matches, wrong matches, recognition accuracy, total time taken for recognition process, time taken to recognise one sample, total training time.

All these parameters are calculated by varying the training samples.

To compare 2D-PCA and PCA , the PCA (Eigenfaces) is also used to reconstruct the same face image.

| **Parameters** | **2D - PCA** | **PCA** |
|---|---|---|
| Correct Matches | 96/100 | 92/100 |
| Wrong Matches | 4/100 | 8/100 |
| Accuracy | 96.0 | 92.0 |
| Recognition time per sample | 0.0004 | 0.0006 |
| Total time | 0.04 | 0.06 |
| Training time | 0.45 | 7.3 |

The 2D-PCA is performing well in the reconstruction of this image. Furthermore the error between reconstructed facial image and original image is high.The 2D PCA technique is also superior to PCA in terms of calculated efficiently for feature extraction. We see that feature extraction by 2D PCA takes much less time as the number of training samples per class is increased, the relative gain between 2D PCA and PCA becomes more apparent.

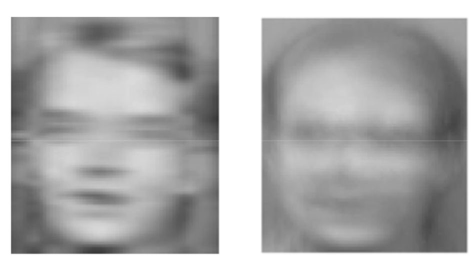


Figure 5: the comparison of reconstructed face images for both cases 2D PCA) and 1D PCA (right) for d = 10.

## VII. CONCLUSION

This paper furnishes a face recognition technique using 2D-PCA and analysing through variousmethods. ORL face database has been used for face database. It is found that as number of training images increases so does the recognition rate.

2D PCA is much faster and accurate than the standard PCA or the Eigen faces. In standard PCA, the image pixel matrix is converted into a vector.For 2D PCA, the Eigen vectors required for computation remain constant.But for standard PCA, the number of Eigen vectors for computation, changes with the change in the numberof input images or the number of training images.2D PCA is much faster in feature extraction.

## References


[1] Vo Dinh Minh Nhat, Sungyoung Lee. Improvement On PCA and 2DPCA algorithms for face recognition [C].CIVR 2005, LNCS 3568,Pp:568-577

[2] D.Q. Zhang, Z.H.Zhou.(2D)2PCA,Two-directional twodimensional.PCA for efficient face representation and recognition .Nerocomputig

[3] Zhao W., Chellappa R, Phillips and Rosenfeld, “Face Recognition: A Literature Survey”, ACM Computing Surveys, Vol. 35, No. 4, December 2003, pp. 399–458.

[4] Patil A.M., Kolhe S.R. and Patil P.M, 2D Face Recognition Techniques: A Survey, International Journal of Machine Intelligence, ISSN: 0975–2927, Volume 2, Issue 1, 2010, pp-74-8

[5] G. H. Dunteman. “Principal Components Analysis”. Sage Publications, 1989.

[6] Turk M. And Pentland A. Eigenfaces for recognition. J. Cogn. Neurosci. 3, 72–86, 1991

[7] S. J. Lee, S. B. Yung, J. W. Kwon, and S. H. Hong, “Face Detection and Recognition Using PCA”, pp. 84-87, IEEE TENCON, 1999.

[8] Kohonen, T., ”Self-organization and associative memory”, Berlin: Springer- Verlag,, 1989.

[9] Kohonen, T., and Lehtio, P., ”Storage and processing of information in distributed associative memory systems”, 1981.

[10] Fischler, M. A., and Elschlager, R. A., ”The representation and matching of pictorial structures”, IEEE Trans. on Computers, c-22.1, 1973.

[11] Yuille, A.L., Cohen, D. S., and Hallinan, P. W., ”Feature extraction from faces using deformable templates”, Proc. of CVPR, 1989.

[12] Kanade, T., ”Picture processing system by computer complex and recognition of human faces”, Dept. of Information Science, Kyoto University, 1973.

[13] B.Moghaddam, and A. Pentland, “Probabilistic Visual Learning for Object Representation”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 19, No. 7, July 1997

[14] K. C. Chung, S. C. Kee, and S. R. Kim, “Face Recognition using Principal Component Analysis of Gabor Filter Responses”, p. 53- 57, IEEE, 1999. [15] Hossein Sahoolizadeh, B. ZarghamHeidari and C. Hamid Dehghani, “A New Face Recognition Method using PCA, LDA and Neural Network”, World Academy of Science, Engineering and Technology 41008

[15] Improve Face Recognition Rate Using Different Image Pre-Processing Techniques Nawaf Hazim Barnouti Baghdad, Iraq