Differential Multidimensional Principal Component Analysis Based Face Recognition System against Light Variation

Tomesh Verma[#1], Raj Kumar Sahu[#2], Deepak Sharma [#3]

[#1,2,3]*Department of Electronics & Telecommunication Engg*

Chhatrapati Shivaji Institute Of Technology, Durg, C.G., India

[1]tomeshverma@csitdurg.in

[2]rajkumarsahu@csitdurg.in

[3]deepaksharma@csitdurg.in

***Abstract*— Face recognition system has been reviewed by various techniques. Most of the cases illumination has been a great problem. To increase accuracy light variation is needed to be dominated. In this paper, Face Recognition is performed by vertically dividing facial images under test; into two equal halves and then dimension reduction techniques is employed which is Differential 2-D Principal Component Analysis. As D2DPCA is being separately applied to two halves facial image database, they are normalized by sigmoid function and then fused together by weighted summation technique. Face images for this experiment is taken by Extended Yalle Face Database B+. It is having 64 illumination variant face images each of 38 subjects. Out of these facial images, 5 images are taken for training and remaining images are taken for testing purpose. On applying D2DPCA over this technique, it is found that it is giving 90.27% recognition rate which is around 40.36% greater than 2-D PCA technique. Hence it is shown that this technique works well for illumination variant images and D2DPCA is better dimension reduction tool than 2DPCA.**

***Keywords*—2DPCA, D2DPCA, Illumination variation, Normalization, Fusion.**

I. Introduction

Face recognition is computer based person identification based on arithmetical and numerical features obtained from face images. This identification by human observation is possible with little effort, but building an automatic system this process is very challenging. This task become more intense in case of large variation in illumination conditions, facial expressions, aging, viewing directions or poses , hair, glasses or cosmetics. Recognition implies the tasks of identification or authentication. Identification involves a one-to-many comparison. Authentication involves a one-to-one comparison. Furthermore, closely related to recognition is classification where the problem is to identify a group of individuals as sharing some common features. In a face recognition system, 3 steps includes: Face detection, feature extraction & face recognition.

In face detection, segmentation of faces from background, feature extraction from the face regions, recognition, or verification is used. In identification, the input to the system is an unknown face, and the system identifies it from database, whereas in verification, the system needs to confirm or reject the claimed identity. In feature extraction, face features that are fed into a classification system. Depending on the type of classification system, features can be local features such as lines or facial features such as eyes, nose, and mouth. Feature extraction is also a key to animation and recognition of facial expressions. In face recognition, algorithm train the system to identify individuals using knowledge gained from the face detection / feature extraction phase [2] [16].

Based on various studies and survey work, a face recognition system can be categorized as shown

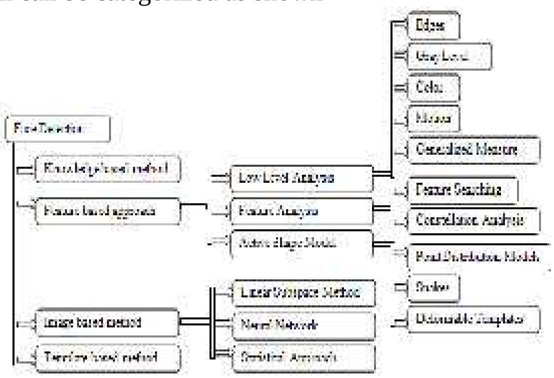

Fig 1. Categories of methods involved in Detection\Recognition system.

In this paper we are adopting face recognition technique by D2DPCA technique. This paper is organized as follows: Section 1 was a brief introduction of this paper. Section 2 is giving an overview of face recognition related works performed by researchers before this work. Section 3 is describing system architecture which is categorized as database acquisition, feature extraction, normalization, fusion and recognition phases. Section 4 is the experimental results section where results obtained from 2DPCA and D2DPCA technique are compared and Finally Section 5 is the conclusion of this work.

II. Related Works And Background

An Principal Component Analysis is a famous dimensionality reduction technique used for calculating eigenfeatures. Turk et. al. [4] developed eigenface techniques for face recognition. The term eigenface is used because mathematical algorithms using eigenvectors represent the primary components of the face. Weights are used to represent the eigenface features so a comparison of these weights permits identification of individual faces from a database. Against performance degradation due to uncentered face image, head orientation and rotation is performed. Kohonen et. al. [6][7] describe an associative network with a simple learning algorithm that can recognize face images and recall a face image from an incomplete or noisy version input to the network. Fischler et. al. [8] gave algorithm that used local feature template matching and a global measure of fit to find and measure facial features automatically. Fleming et. al. [19] extends these ideas using nonlinear units, training the system by back propagation. Yuille et. al. [9] proposed deformable templates techniques, where models of the face and its features are determined by interactions with the face image. Connectionist approaches to face identification seek to capture the configurationally nature of the task. Moghaddam et. al. [11] suggested Bayesian PCA in which the Eigenface Method based on simple subspace-restricted norms is extended to use a probabilistic measure of similarity. Also, this method uses the image differences in the training and test stages. The intrapersonal difference and extra personal differences are calculated. Chung et al. [12] used of PCA and Gabor Filters together. Gabor Filters are used to extract facial features from the original image on predefined fiducially points. PCA is used to classify the facial features optimally. Sahoolizadeh et. al. [13] combined PCA and LDA for mximizing between class separability. For improving the capability of LDA when a few samples of images are available and neural classifier is used to reduce number misclassification caused by not-linearly separable classes. Baek et. al. [14] concatenated PCA and ICA over FERET face database and found that when a proper distance metric is used, PCA significantly outperforms ICA on a human face recognition task. Zhang et al. [20] proposed a subspace method called diagonal principal component analysis (DiaPCA). It extracts optimal projective vectors from diagonal face images without image-to-vector transformation. This method is found more accurate than both PCA and 2DPCA. Su et al. [21] adapts a multi-feature extraction technique that includes PCA and LDA, radius basis function network (RBFN). They also acquired features in both special and frequency domains.

Face recognition in two dimensional domains is more efficient than one dimensional. Vijay kumar et. al. [18] proposed $(2D)^2$PCA for face representation where images are treated as matrices instead of vector. They adopted a least squares solution for super-resolution with reduced computational cost as compared to a similar algorithm with a 1D model. Their technique improved the performance of the super-resolution algorithms at high magnification factors. Lee et. al. [19] adopted differential 2DPCA for achieving good result in case of large illumination variation. They divided whole-face images into two sub-images to minimize illumination effects and the D2D-PCA is applied to each of these sub-images. Features obtained from two separate half faces are normalized and fused before recognition.

In this paper we are adopting D2DPCA technique for face recognition for domination light variation over face image.

III. System Architecture

All The face recognition system adopted in this paper is having five phases-

1. Face Database Acquisition
2. Feature Extraction
3. Normalization Technique
4. Fusion Technique
5. Recognition

Description of all these phase is explained below.

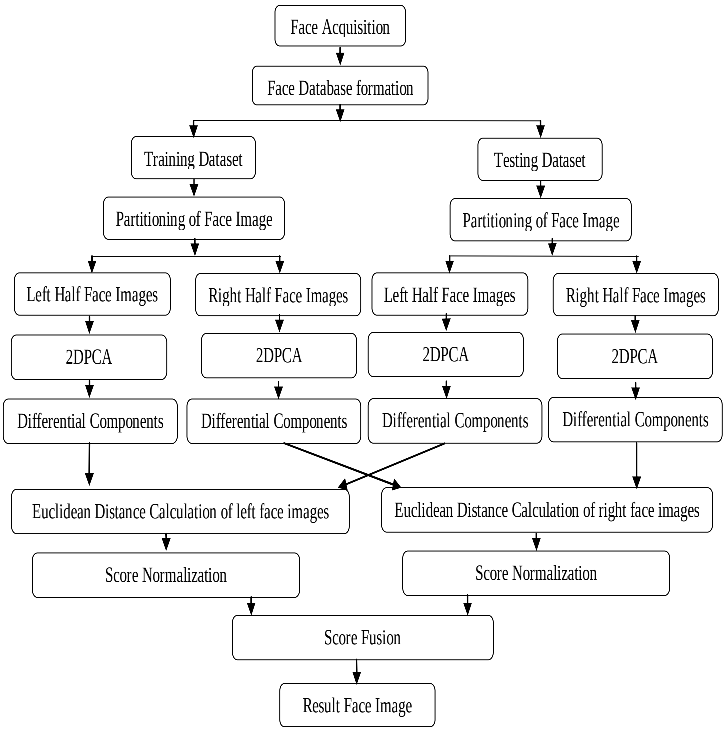

Fig.2 Flowchart of D2DPCA based Face Recognition Technique

A. *FACE IMAGE DATABASE ACQUISITION*

The facial images for this experiment are collected from the publicly available database called Extended Yalle Face Database B+ [22]. The database provided facial images of 38 different persons having 64 images under different illumination condition and different gesture. For some subjects, the images were taken at varying the lighting, facial expressions (open / closed eyes) and facial details. All the images were taken in an upright, frontal position. The size of each image is 168x192 pixels, with 256 grey levels per pixel. These images are first resized to 48x42 pixels. Out of 64 illumination variant facial images, 5 images are taken for training while rest of 59 images is taken for testing. Training images have more or less same illumination intensity. After which they are divided into two equal halves by vertical line passing through nose tip. Both of these half images are then histogram equalized.

B. FEATURE EXTRACTION

In this paper, Principal Component Analysis with improved version ie. D2DPCA is used for feature extraction. It is a well-known feature extraction and data representation technique where dimensionality of a data set is reduced and variations in the data set is unaltered. Here face images are converted into a single column vectors and then all face vectors are appended column wise. To increase efficiency images are not converted into vector and facial images are concatenated as matrices page by page. Feature Extraction technique is described as below-

1) Training Phase

a) Image

All 190 facial images which are under training database are of size 168x192 pixels. These images are then cropped into 48x42 pixels. Now all cropped images are vertically divided into two halves and each halves of all divided images are appended to form array. Size of left and right half face image array will be (48x21x190).

b) Face Mean Calculation

Now mean of the array is calculated

$$\Psi = \frac{1}{N}\sum_{i=1}^{N}\Gamma_i \tag{1}$$

This 2D matrix is the arithmetic average of the training images at each pixel point and its size is also (48x21) pixels.

c) Mean subtracted image

Then each of the left and right half training images is subtracted from mean image.

$$\Phi = \Gamma - \Psi \tag{2}$$

Its size is (48x21).

d) Variance Array Calculation

All of these mean subtracted images for left and right halves, i.e. variance of each image, are appended to form an array represented by A. Its size is (48x21x190).

e) Covariance Matrix

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

$$X = A^T A = \frac{1}{N}\sum_{i=1}^{N}\Phi_i^T\ \Phi_i \tag{3}$$

Then covariance matrices of all facial images are added. Hence for both halves face image covariance matrix size will be (21x21).

f) Eigen values & Eigen vectors calculation

Eigenvectors v_i and eigenvalues μ_i of X are calculated as

$$X \cdot v_i = \mu_i \cdot v_i \tag{4}$$

The value of X is put in this equation,

$$A^T .A.\ v_i = \mu_i \cdot v_i \tag{5}$$

The necessary matrix arrangements are made,

$$A^T .A \cdot A \cdot v_i = \mu_i \cdot A \cdot v_i \tag{6}$$

$$X \cdot A \cdot v_i = \mu_i \cdot A \cdot v_i \tag{7}$$

Now replace $A \cdot v_i$ with υ_i

Hence $\upsilon_i = A \cdot v_i$ is one of the eigen vector of X and its size is same as X i.e (21x21).

Also there will be 21 numbers of eigen values and it will be in the form of (21x21) diagonal matrix.

Eigen vectors corresponding to highest eigen values are selected.

g) Eigenface Matrix calculation

It is product of variance of each face image with d numbers of highest eigen vectors.

$$\Phi = A.\ \upsilon \tag{8}$$

It will be of size (48x20x190). Here we are taking 20 highest eigen values.

h) Projected train matrix calculation

$$\omega_k = \varphi^T.\ A_i \tag{9}$$

where i= 1, 2, 3……190

And on selecting and appending only projected training matrix will be of size (20x21x190).

i) Differential 2-D PCA calculation

$$d\omega_K - \omega_{K\,i+1\,j} - \omega_{K\,i,j} \tag{10}$$

Where, i=1, 2…..47, j=1, 2…..20

2) Testing Phase:

a) Test image

Facial images which are under test is also of size 168x192 pixels. This image is then cropped into 48x42 pixels. Now cropped image is vertically divided into two halves. Size of left and right half face image will be (48x21).

b) Mean subtracted image

The cropped left and right half test face image, Γ_t is subtracted with respective left and right mean image of database,

$$\Phi_t = \Gamma_t - \Psi \quad (11)$$

Its Size will be (48x21).

c) Projection test matrix calculation

Projected Test image of both left and right halves are calculated from eigen face matrix.

$$\omega_t = \varphi^T . \Phi_t \quad (12)$$

It will be of size (20x21)

3) Classification

Testing image can be classified with training images by calculating the distance between the projected train matrix and projected test matrix. In this paper it is performed by Euclidean distance calculation also known as L_2 norm,

$$\delta_k = \sqrt{\sum_{i=1}^{m-1} \sum_{j=1}^{d} (\omega_{k\,i,j} - \omega_{t\,i,j})^2} \quad (13)$$

Where k=1, 2…190, i=1, 2…..20 and j=1, 2…..21

C. NORMALIZATION TECHNIQUE

Distance Score between each of left and right half projected training image and projected test image is then normalized. By normalization, distance scores of each of left and right half face image are mapped between 0 and 1. In this paper it is performed by sigmoid function.

$$s_{i,new} = \frac{1}{1 + \exp(-v_i(s_{i,old}))} \quad (14)$$

where $$v_i(s_{i,old}) = \frac{[s_{i,old} - (\mu_i - 2\sigma_i)]}{2\sigma_i} \quad (15)$$

V_i is normalized score, $S_{i,old}$ is raw score, μ_i is mean and σ_i is standard deviation of i^{th} half face image

These left half and right half normalized scores are then fused in next stage.

D. FUSION TECHNIQUE

In this paper, fusion is being performed by weighted summation method.

It is given by

$$s = \sum_{i=1}^{N} s_N \omega_N \quad (16)$$

E. RECOGNITION

At this stage, test image is recognized with training image. To carry out this task, simply minimum value of fused score s is found.

$$\text{output} = \min(s) \quad (17)$$

Its location reflects the facial image under test.

IV. Experiments And Results

These face recognition system is implemented on a 2.67 GHz PC with 3 GB RAM and software used is MATLAB version R2010a. The face database has been obtained from Extended Yalle Face Database B+. Experiment consists of two sections. In first part, recognition is performed by 2DPCA and results have been obtained. In second part, same training database is operated with D2DPCA. The result, being obtained from D2DPCA system is then compared with that of 2DPCA system. Out of 64 images of each subject, 5 illumination invariant images are taken for training and rest are taken for testing database.

Fig.3 Training Face Database Images

Fig.4 Testing Face Database Images

Each of these facial images are divided into two halves by a vertical line.

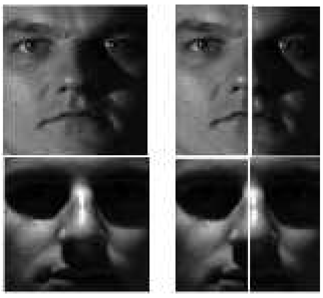

Fig. 5 Original Image and Partitioned Image

After which mean of partitioned facial images are taken

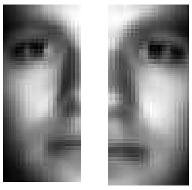

Fig.6 Left half and Right half mean face image

During testing phase, recognition is performed by both 2DPCA and D2DPCA techniques. It is found that D2DPCA is giving good result than 2DPCA. Moreover by varying number of principal components, recognition rates also vary. Recognition rate reduces with its reduction.

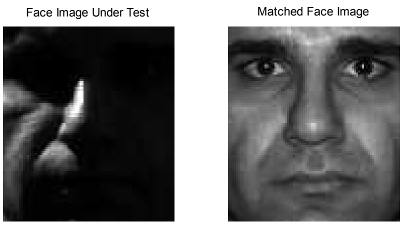

Fig.7 Image under testing and output image

Subject wise recognition by both D2DPCA and PCA is shown below.

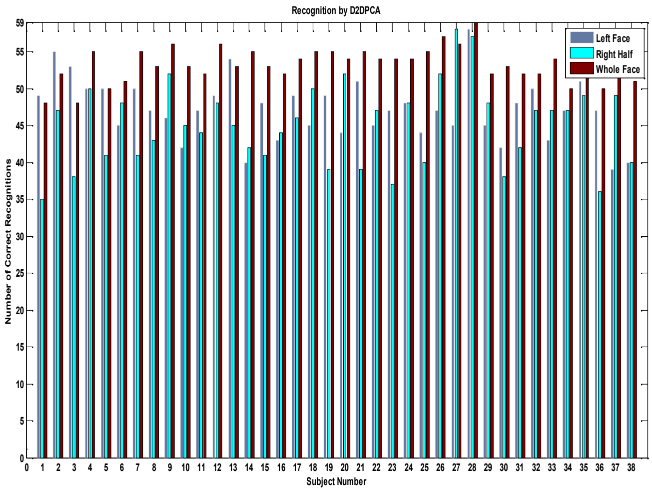

Fig.8 Recognition of each subject by D2DPCA

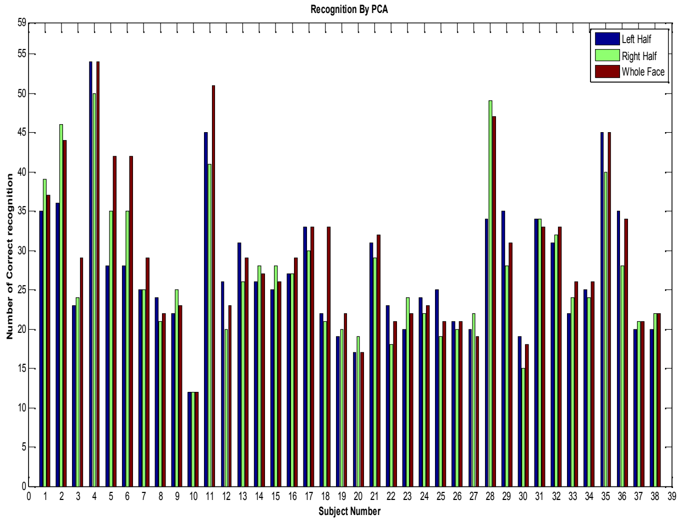

Fig.9 Recognition of each subject by 2DPCA

TABLE I

RECOGNITION RATES OF 2DPCA AND D2DPCA TECHNIQUES FOR LEFT HALF, RIGHT HALF AND WHOLE FACE IMAGE

Dimension Reduction Technique	**Left Half**	**Right Half**	**Whole Face Image**
2DPCA	46.47%	46.52%	49.91%
D2DPCA	79.92%	76.36%	90.27%

Hence it is found that recognition of illumination variant face images are obtained by both 2DPCA and D2DPCA where differential 2DPCA is providing good result than simple 2DPCA. Recognition rate of left half face images of database is being obtained 79.92% by D2DPCA which is around 33.35% greater than 2DPCA and recognition rate of right half face image is 76.36% which is around 29.16% greater than that of 2DPCA. Moreover an improved result is again obtained, if both of these halves are fused together. Recognition rate by D2DPCA is 90.27% which is around 40.36% better than 2DPCA technique.

V. CONCLUSIONS

This paper presents a face recognition approach using D2DPCA followed by normalization and fusion of two separate features. In this system, database face images are divided into two halves and D2DPCA is applied to each halves. These left and right halves scores are then normalized and fused together. Extended Yale face database B has been used for face database. Technique followed by D2DPCA is giving around 90.27% recognition rate while 2DPCA is giving only 49.91% recognition rate. It is also found that as number of training images increased recognition rate increases. As this technique is giving good results than traditional methods so this approach can be used for security system, defence system and real time database management.

ACKNOWLEDGMENT

We would like to express our sincere thanks to complete staff of Deptt. of E&TC Engg., CSIT Durg for extending their technical support for completion of this work.

REFERENCES

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

[2] 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

[3] Dunteman G. H., " Principal Components Analysis". Sage Publications, 1989.

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

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

[6] Kohonen, T., "Self-organization and associative memory", Berlin: Springer- Verlag, (1989).

[7] Kohonen, T., and Lehtio, P., "Storage and processing of information in distributed associative memory systems", (1981).

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

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

[10] Kanade, T., "Picture processing system by computer complex and recognition of human faces", Dept. of Information Science, Kyoto University, (1973).

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

[12] Chung K. C., Kee S. C., and Kim S. R., "Face Recognition using Principal Component Analysis of Gabor Filter Responses", p. 53- 57, IEEE, 1999.

[13] Sahoolizadeh H., Zargham H., and Hamid D., "A New Face Recognition Method using PCA, LDA and Neural Network", World Academy of Science, Engineering and Technology 41 2008

[14] Baek K., Bruce A. Draper, J. Ross Beveridge, Kai She, "PCA vs. ICA: A comparison on the FERET data set".

[15] Moghaddam B., and Pentland A., "An Automatic System for Model-Based Coding of Faces", pp. 362-370, IEEE, 1995.

[16] Fleming, M., and Cottrell, G., "Categorization of faces using unsupervised feature extraction", Proc. of IJCNN, Vol. 90(2), (1990).

[17] Yahagi T. and Takano H., "Face Recognition using neural networks with multiple combinations of categories," International Journal of Electronics Information and Communication Engineering., vol.J77-D-II, no.11, pp.2151-2159. 2011

[18] Vijay Kumar B.G., Aravind R., "Computationally efficient algorithm for face super-resolution using $(2D)^2$ -PCA based prior", IET Image Processing, Volume 4, Issue 2, pp. 61–69, 2010

[19] Lee S.H., Kim D.J. and Cho J.H., "Illumination-Robust Face Recognition System Based on Differential Components", IEEE Transactions on Consumer Electronics, August 2012

[20] D.Q.A. Zhang, and Z.H. Zhou, and S.C. Chen, "Diagonal principal component analysis for face recognition", Pattern Recognition, 39, 2006, pp. 140-142.

[21] H. Su, D. D. Feng, and R. Zhao, "Face Recognition Using Multi-feature and Radial Basis Function Network" VIP2002

