

Face Recognition Based on Two Dimensional Principal Component Analysis (2DPCA) and Result Comparison with Different Classifiers

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Abstract- In this paper, Face Recognition is performed using 2D Principal Component Analysis based dimension reduction technique. 2DPCA is the traditional matrix based feature extraction method. 2DPCA essentially work on the facial image matrixes only in one or two direction. The projection vectors based on eigen values are compared by Euclidean distance, City Block distance, Mahalanobis and Covariance Similarity measures. Face recognition is performed for unique identification. Proposed methodology is fusion of two stages – Feature extraction using 2D principle component analysis and recognition using classifiers. For experiment ORL Face database is used. In this database 10 face images of 40 persons each are provided. So as a whole 400 face images are obtained. This database provides images which vary on the basis of pose, illumination, beard, moustaches, and glasses. 2DPCA with City Block distance is giving best result.

Key words- PCA, 2DPCA, Euclidean distance, City Block distance, Mahalanobis and Covariance

I. INTRODUCTION

In the last years, Face Recognition as the most successful applications of image analysis and computer vision. Biometrics is widely adopted in various applications areas such as access control, remote login, border control, etc, since it provides unique identification. Biometrics is used for privacy and security concern arises. Recognition implies the tasks of identification or authentication. Identification involves a one-to-many comparison. Authentication involves a one-to-one comparison. In a face recognition system, 3 steps includes: Face detection, feature extraction & face recognition.

Feature Extraction Methods involved two based method are vector based and matrix based methods. In the vector based methods the 2D facial image matrix must be transformed into 1D vector. PCA and LDA are two well known vector based methods for feature extraction. This method is very time consuming as well as include a large scale scatter matrix. In matrix based methods directly deals with matrixes do not need the matrix to vector conversion. 2DPCA is matrix based method which work on image matrixes for feature extraction.

2DPCA was proposed by Yang et al. 2DPCA has the lower dimensionality than that of PCA. 2DPCA is more efficient than PCA. 2DPCA directly extract the feature from the matrix by projecting the image matrix along the projection axes that are the eigen vectors of the image scatter matrix.

Based on various studies and survey work, a face recognition system can be categorized as shown in fig 1.

II. RELATED WORKS & BACKGROUND

Two-dimensional principal component analysis (2DPCA)[1] has been proposed and been widely applied in face recognition. Different from the classical PCA, 2DPCA takes a 2D-matrix-based representation model rather than simply the 1D-vector-based one. And image covariance matrix is constructed directly from the 2D image matrixes. Since the size of image covariance matrix is much smaller, 2DPCA can evaluate the matrix accurately and computational more efficiently than PCA[2].

Principal Component Analysis is widely used linear subspace image based dimensionality reduction technique. Eigen features calculated here are eigenfaces. Face image, in the form of image vector, is appended column wise. Then the average vector is computed that represents a mean face. Also, a difference vector is computed for each user to qualify the differences to the mean face. Then the covariance matrix of the difference vectors is computed. Finally, principal axes can be obtained by eigen decomposition of covariance matrix. The first N eigenvectors presenting the highest eigen values will be retained and represents the most significant features of faces. Finally, each user model is represented as a linear combination (weighted sum) of coefficients corresponding to each eigenface [3].

Turk et. al. [4] developed face recognition using eigenface techniques. The term eigenface is used because mathematical algorithms using eigenvectors represent the primary components of the face.

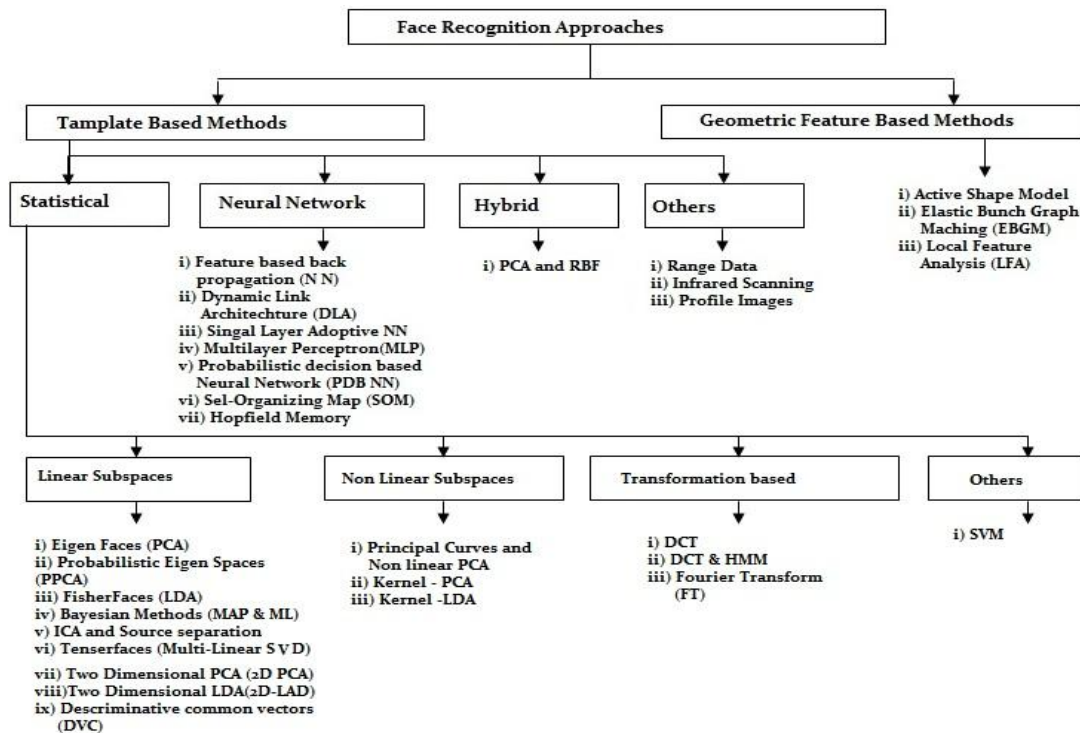


Fig.1 Categories of methods involved in Detection/Recognition system.

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.

Lee et al. [5] proposed a method using PCA to detects and recognize the head of an individual in a complex background.

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.

Kanade et. al. [10] proposed system in which all steps of the recognition process were automated, using a top-down control strategy under a generic model of expected feature characteristics. His system calculated a set of facial parameters from a single.

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. Test image is compared with training images for smallest distance.

Chung et al. [12] suggested the use of PCA and Gabor Filters together. Their method consists of two parts: In the first part, Gabor Filters are used to extract facial features from the original image on predefined fiducially points. In the second part, PCA is used to classify the facial features optimally.

Sahoolizadeh et. al. [13] fused PCA and LDA for maximizing 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] used 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.

Moghaddam et. al. [15] used the Eigenface Method on human faces for applications such as video telephony, database image compression and face recognition.

III. METHODOLOGY

An image space can be thought of as a space having dimensions equal to the number of pixels making up the image and having values in the range of the pixels values. For gray scale images, dimension could have a value in 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 similar structure, having eye, nose and mouth in common and their relative position correlated. This correlation is the main point to start 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; that is, it tries to focus on the variation just coming out of the variation between the face images.

Eigenface method is the implementation of Principal Component Analysis (PCA) over images. Fig. 2 shows the flow chart of PCA Algorithm. In this method, the process of PCA each block is explained by mathematical

expression and calculation in below. The features of the studied images are obtained by looking for the maximum deviation of each image from the mean image. This variance is obtained by getting the eigenvectors of the covariance matrix of all the images [5].

The eigenface space is obtained by applying the eigenface method to the training images. Later, the training images are projected into the eigenface space. Next, the test image is projected into this new space and the distance of the projected test image to the training images is used to classify the test image [12].

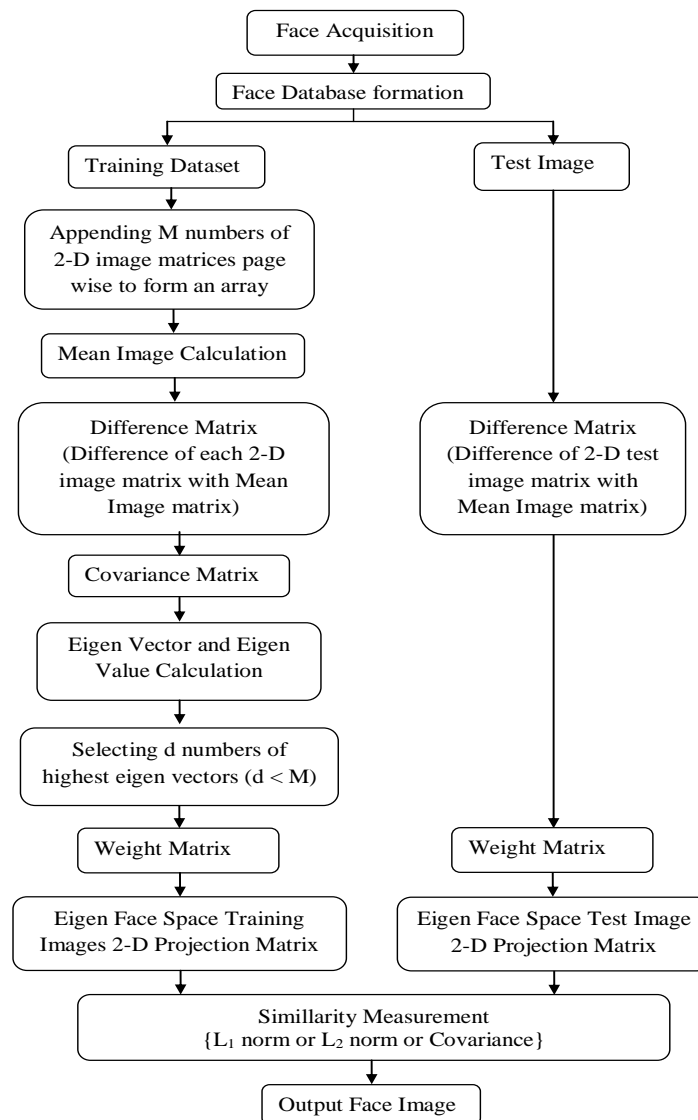


Fig. 2 Flow chart of 2DPCA Algorithm

3.1 Mathematical Expression for Feature Extraction By using 2DPCA

In this paper, Principal Component Analysis with 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 unaltered. Here face

images are taken as matrices and then all of them vectors are appended to form array. It increases recognition rate also. Feature Extraction technique is described as below-

- 1) Training Phase
- a) Image



All 320 training facial images which are under training database are of size 92x112 pixels. These images are then cropped into 48x42 pixels. Now all cropped images are page wise appended to form array.

b)Face Mean Calculation

Now mean of the array is calculated

$$\Psi = \frac{1}{N} \sum_{i=1}^N \Gamma_i \quad (1)$$

This 2D matrix is the arithmetic average of the training images at each pixel point and its size is also (48x42) pixels.

c)Mean subtracted image

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

$$\Phi = \Gamma - \Psi \quad (2)$$

Its size is (48x42).

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 (48x42x320).

e)Covariance Matrix

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

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

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

f) Eigen values & Eigen vectors calculation

Eigenvectors v_i and eigenvalues μ_i of X are calculated as

$$X \cdot v_i = \mu_i \cdot v_i \quad (4)$$

The value of X is put in this equation,

$$A^T \cdot A \cdot v_i = \mu_i \cdot v_i \quad (5)$$

The necessary matrix arrangements are made,

$$A^T \cdot A \cdot v_i = \mu_i \cdot A \cdot v_i \quad (6)$$

$$X \cdot A \cdot v_i = \mu_i \cdot A \cdot v_i \quad (7)$$

Now replace $A \cdot v_i$ with v_i

Hence $v_i = A \cdot v_i$ is one of the eigen vector of X and its size is same as X i.e (42x42).

Also there will be 42 numbers of eigen values and it will be in the form of (42x42) 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.

$$\Phi = A \cdot v \quad (8)$$

It will be of size (48x20x320). Here we are taking 20 highest eigen values.

h)Projected train matrix calculation

$$\omega_k = \phi^T \cdot A_i \quad (9)$$

where $i= 1, 2, 3, \dots, 320$

And on selecting and appending only projected training matrix will be of size (20x42x190).

2) Testing Phase:

a)Test image

Facial images which are under test is also of size 92x112 pixels. This image is then cropped into 48x42 pixels.

b)Mean subtracted image

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

$$\Phi_t = \Gamma_t - \Psi \quad (10)$$

Its Size will be (48x42).

c)Projection test matrix calculation

Projected Test image is calculated from eigen face matrix.

$$\omega_t = \phi^T \cdot \Phi_t \quad (11)$$

It will be of size (20x42)

3) Classification

Testing image can be classified with training images by calculating the distance or similarity measures between the projected train matrix and projected test matrix. In this paper it is performed by below mentioned four techniques,

Euclidean Distance
$$\delta_k = \sqrt{(\omega_{k \ i,j} - \omega_{t \ i,j})^2} \quad (12)$$

CityBlock Distance
$$\delta_k = (\omega_{k \ i,j} - \omega_{t \ i,j}) \quad (13)$$

Mahalano-bis Distance
$$\delta_k = (\omega_{k \ i,j} - \omega_{t \ i,j})X^{-1}(\omega_{k \ i,j} - \omega_{t \ i,j})' \quad (14)$$

Covariance Similarity
$$\delta_k = \frac{\omega_{k \ i,j}}{\|\omega_{k \ i,j}\|} \cdot \frac{\omega_{t \ i,j}}{\|\omega_{t \ i,j}\|} \quad (15)$$



Where $k=1, 2, \dots, 320$, $i=1, 2, \dots, 20$ and $j=1, 2, \dots, 42$.
 And X is covariance in this method.

4) *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 in case of first 3 measures which are distance measurement. And find maximum value for last measure which is similarity measurement.

$$\text{output} = \min(s) \quad (16)$$

Its location reflects the facial image under test



Eigenface Data base mean image



Fig. 3.1 ORL Face Database

Fig. 3.2 Mean Image



Face Image Under Test



Matched Face Image

Fig 3.3 Test Image and Output Image

Table 4.1

Comparison of Recognition Rate on ORL Face database.

Distance Measurement	No. of Training	No. of test	Correct Outputs	Recognition Rate
Euclidean	320	80	76	95%
City Block	320	80	77	96.25%
Covariance	320	80	51	63.75%
Mahalanobis	320	80	42	52.5%

IV. EXPERIMENT AND RESULT

In this paper, Olivetti and Oracle Research Laboratory (ORL) face database base is used. The database contains 400 images, 40 persons with 10 images each shown in fig. 3.1. Out of 10, 8 face images of each person are taken for training and 2 images are taken for testing. Above mentioned all three, Euclidean distance, City Block distance, Covariance and Mahalanobis to perform classification is incorporated. The mean image, test and finally reconstructed output image by 2DPCA, is as shown in fig 3.2, fig. 3.3 & fig. 3.4. On the basis of results table 4.1 is drawn, comparing results of four modes of classification techniques. And Table 4.2 is comparison of recognition rates by varying eigen values.

Table 4.2

Comparison of Recognition rate by varying eigen values

D	Euclidean	City Block	Covariance	Mahalanobis
20	95%	96.25%	63.75%	52.5%
30	95%	96.25%	16.25%	52.5%
40	95%	96.25%	2.5%	51.25%
50	95%	96.25%	3.25%	51.25%
60	95%	96.25%	3.25%	51.25%

V. CONCLUSION

The paper presents a face recognition approach using 2DPCA and various classification techniques. ORL face database has been used for face database. The result is compared for City Block distance, Euclidean distance, Covariance and Mahalanobis distance. Results are compared for varying number of training images. It is found that as number of training images increased recognition rate increases. Moreover each time City Block distance calculation give best results than other three measures for same number of training images.

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 two-dimensional.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. Zargham Heidari, and C. Hamid Dehghani, "A New Face Recognition Method using PCA, LDA and Neural Network", World Academy of Science, Engineering and Technology 41008
- [16] Kyungim Baek, Bruce A. Draper, J. Ross Beveridge, Kai She, "PCA vs. ICA: A comparison on the FERET data set".
- [17] B. Moghaddam, and A. Pentland, "An Automatic System for Model-Based Coding of Faces", pp. 362- 370, IEEE, 1995.
- [18] Fleming, M., and Cottrell, G., "Categorization of faces using unsupervised feature extraction", Proc. of IJCNN, Vol. 90(2), 1990.
- [19] T. Yahagi and H. Takano, "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, 1994.

BIOGRAPHIES



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