

## FACE RECOGNITION USING EIGENVECTORS FROM PRINCIPAL COMPONENT ANALYSIS

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### ABSTRACT :

*Face recognition is one amongst the foremost challenges and is that the hottest analysis areas within the pc vision. folks in sustaining pc vision and pattern recognition are performing on direct recognition of human faces for the last twenty years. pc will perform several face recognition through the event technique "eigenfaces". Since, giant information of faces should be searched. we have a tendency to use principal part analysis with "Eigenface" approach because of its simplicity, speed and learning capability. the planning of the face recognition system is predicated upon "eigenfaces"& its approaches. The propose work is predicated on the renowned approach of eigenvalues. the initial pictures of the coaching set ar remodeled into a group of eigenfaces E. Then, the weights of pictures ar calculated for every image of the coaching set and keep within the set W. Upon observant associate unknown image Y, the weights ar calculated for that exact image and keep within the vector American state. The results indicate the projected recognition strategy through eigenfaces works sophisticatedly.*

**Keywords—** Feature vector, eigenfaces, eigenvalues, eigenvector, PCA

### INTRODUCTION :

Face recognition system is kind of tough as a result of human faces ar quite advanced, dimensional and corresponding on atmosphere changes. the popularity of human faces may be a difficult drawback due the changes within the face identity and variation between pictures of an equivalent because of illumination and viewing direction. PCA technique that is provided by Kirby and Sirovich not solely resulted during a technique that with efficiency represents photos of bound faces, however conjointly arranged the inspiration for the event of the "Eigenface" technique of Turki and Pentland [1]. Such patterns, which may be discovered all told signals, that might be in domain of face recognition - the presence of some objects (eyes, nose, mouth) in any face additionally as relative distances between these objects. Since this are some characteristic options are known as Eigen faces within the face recognition domain out of original image information these characteristics will be extracted with the assistance of a mathematical tool known as Principal part Analysis (PCA). The eigen faces is renowned methodology for face recognition. we have a tendency to develop a way to extract options from associate intensity image of human frontal face to represent the options mistreatment eigen faces .The face area is represented by a group of eigenfaces. By jutting a face onto the area expanded by eigen faces is diagrammatical. Principal part analysis is applied to search out the aspects of face that ar vital for identification. Eigenvectors (eigenfaces) ar calculated from the initial face image set. New faces ar projected onto the area expanded by eigenfaces and diagrammatical by weighted add of the eigenfaces. to spot faces we have a tendency to build uses of those weights.

**PRINCIPAL COMPONENT ANALYSIS :**

Principal component analysis (PCA) may be a spatiality reduction technique that is employed for compression and face recognition issues. it's conjointly referred to as eigenspace projection or karhunen-loeve transformation [11]. PCA calculates the eigenvectors of the variance matrix, and comes the initial information onto a lower dimensional feature area, that is outlined by eigenvectors with giant eigenvalues. PCA has been employed in face illustration and recognition wherever the eigenvectors calculated ar stated as eigenfaces. PCA may be a helpful applied math technique that found application in fields for face recognition and compression, and may be a common technique for locating patterns in information of high dimension. it's one amongst the additional winning techniques of face recognition [11]. The good thing about PCA is to scale back the dimension of the info. No information redundancy is found as parts ar orthogonal. With facilitate of PCA, quality of grouping the pictures will be reduced. the applying of PCA is formed in criminal investigation, access management for pc, on-line banking, post workplace, passport verification, medical records etc.

Methodology to search out the principal part uses the subsequent methodology [7].

I) Get the data: Suppose  $X_1, X_2, \dots, X_M$  is  $N \times M$  one Vectors

$$M \times X = \text{one}/M \sum X_i \quad i = 1$$

II) reckon the Mean:

$$\Phi_i = X_i - X$$

III) calculative the variance matrix: type of matrix  $A = [\Phi_1, \Phi_2, \dots, \Phi_M]$  ( $N \times M$  matrix) then figure  $M \times T$

$$C = \text{one}/M \sum \Phi_n \Phi_n = A A^T \quad n = 1$$

IV) calculative the eigenvector and eigenvalue of the variance matrix

V) selecting parts and forming a feature vector: Once eigenvectors ar found from the variance matrix, ensuing step is to get them organized by eigenvalue, highest to lowest. this offers the parts so as of significance. The eigenvector with the best eigenvalue is that the principle part of the info set. opt for the best eigenvalue and forming a feature vector.

VI) explanation the new informationsets: Once chosen the parts (eigenvectors) that want to stay within the data and shaped a feature vector, imply take the transpose of the vector and multiply it on the left of the initial information set, transposed. Final information = row feature vector \* row information alter the higher than formula obtaining the options of images; the geometer distance is calculated between the mean adjusted input image and also the projection onto face area. The low values indicate that there's a face and show the face

**ALGORITHM FOR FACE RECOGNITION :**

The projected is predicated on the well-known eigenfaces. In mathematical terms, we have a tendency to want to search out the principal parts of the distribution of faces, or the eigenvectors of the variance matrix of the set of face pictures, treating a picture as some extent (or vector) during a high dimensional area. The eigenvectors ar ordered, every one accounting for a unique quantity of the variation among the face pictures. These vectors will be thought of as a group of options that along characterize the variation between face pictures. every image location

contributes additional or less to every eigenvector, so we are able to show the eigenvector as a kind of phantasmal face that we have a tendency to decision associate eigenfaces.

The eigenfaces algorithmic program and projected changes are represented below:

### A. Eigenfaces Algorithm:

we have a tendency to assume the coaching sets of pictures are:  $\Gamma_1, \Gamma_2, \dots, \Gamma_m$  with every image is  $I(x, y)$ . Convert every image into set of vectors and new life-sized matrix  $(m \times p)$ , wherever  $m$  is that the range of coaching pictures and  $p$  is  $x * y$

realize the typical by:-

$$\psi = (\sum_{i=1}^m \Gamma_i) / m$$

Calculated the mean-subtracted face:

$$\phi_i = \Gamma_i - \psi, \quad i = 1, 2, \dots, m$$

And a group of matrix is obtained with

$A = [\phi_1, \phi_2, \dots, \phi_m]$  is that the mean-subtracted matrix vector

realize the variance matrix as:-

$$C = A^T A$$

Compute the Manfred Eigen values from the variance  $M$

$$U_i = A v_i$$

$$U_1 = A * v_1$$

$$U = [U_1 \ U_2 \ U_3]$$

A Face image will be projected into this face area by

$$\Omega_k = U^T (\Gamma_k - \psi), \quad k = 1, \dots, M$$

$$\Omega_1 = U^T \phi_1$$

### B. Projected Improved Recognition Strategy

The take a look at image,  $\Gamma$  is projected into the face area to get a vector  $\Omega$

$$\Omega = U^T (\Gamma - \psi)$$

the gap of  $\Omega$  to every face category is outlined by

$$k_2 = \|\Omega - \Omega_k\|^2, \quad k = 1, \dots, M$$

A Distance threshold  $\theta_c = 1/2 \max_j k \|\Omega_j - \Omega_k\|$ ,  $k = 1, \dots, M$

realize the gap  $\varepsilon$  between the initial image  $\Gamma$ , and its reconstructed image from the Manfred Eigen area,

$$\varepsilon^2 = \|T - TF\|^2, \quad \text{wherever } TF = U\Omega + \psi$$

### C. Recognition method.

$$\text{If } \varepsilon \geq \theta_c$$

Then input image isn't a face image

$$\text{If } \varepsilon < \theta_c \text{ AND } \varepsilon_k \geq \theta_c, \text{ for all } k$$

Then input image contains associate unknown face

$$\text{If } \varepsilon < \theta_c, \text{ AND } \varepsilon_k = \min_k \varepsilon_k < \theta_c \text{ Then input image contains the face of individual } K.$$

Where  $\theta_c$  may be a appropriate threshold based mostly quality and noise gift within the pictures.

## APPLICATION OF PCA IN FACIAL RECOGNITION

### A. Generating Eigenfaces

Assume a face image  $I(x,y)$  be a two-dimensional  $M$  by  $N$  array of intensity values, or a vector of dimension  $M \times N$ . The coaching set used for the analysis is of size  $110 \times 129$ , leading to fourteen,190 dimensional areas. A typical image of size  $256$  by  $256$  describes a vector of dimension sixty five,536, or, equivalently, a degree in sixty five,536-dimensional house. For simplicity the faces pictures ar assumed to be of size  $N \times N$  leading to a degree in  $N^2$  dimensional house. associate ensemble of pictures, then, maps to a group of points during this Brobdingnagian house. pictures of faces, being similar in overall configuration, won't be willy-nilly distributed during this Brobdingnagian image house and therefore are often delineate by a comparatively low dimensional mathematical space. the most plan of the principal element analysis (or Karhunen Loeve transform) is to search out the vectors that best account for the distribution of face pictures inside the complete image house. These vectors outline the mathematical space of face pictures, that we have a tendency to decision "face space". every vector is of length  $N^2$ , describes associate  $N$  by  $N$  image, and may be a linear combination of the first face pictures. as a result of these vectors ar the eigenvectors of the variance matrix akin to the first face pictures, and since they're face like in look, we have a tendency to ask them as "eigenfaces".

The coaching set pictures used for the analysis purpose ar shown within the Figure (1) and therefore the corresponding eigenfaces for the coaching sets ar shown within the Figure (3).

Let the coaching set of face pictures be  $\Gamma_1 \Gamma_2 \dots \Gamma_M$ . the typical face of the set is outlined by

$$\Psi = 1/M \sum \Gamma_k$$

Each face differs from the typical by the vector  $\Phi = \Gamma_i - \Psi$ . associate example coaching set is shown in Figure (1), with the typical face  $\Psi$  shown in Figure (4). This set of terribly giant vectors is then subject to principal element analysis, that seeks a collection of  $M$  orthonormal vectors,  $U_k$ , that best describes the distribution of the info. The  $k$ th vector is  $U_k$  chosen such,

$$\lambda_k = 1/M ( \sum_{n=1}^M \Phi_n^T U_k )^2 \quad (1)$$

The vectors  $U_k$  and  $\lambda_k$  scalars ar eigenvectors and eigenvalues,

Respectively, of the variance matrix

$$C = 1/M \sum_{n=1}^M \Phi_n \Phi_n^T$$

Where the matrix  $A = [\Phi_1, \Phi_1, \Phi_1, \dots, \Phi_M]$

The matrix  $C$ , however, is  $N^2 \times N^2$  a pair of by  $N$ , associated decisive the  $N$  eigenvectors and eigenvalues is an recalcitrant task for typical image sizes. A Computationally possible methodology is to be funded to calculate these eigenvectors. If the quantity of knowledge points within the image house is  $M$ .

The matrix  $C$ , however, is  $N^2 \times N^2$  by  $N$ , and determining the  $N$  eigenvectors and eigenvalues is an intractable task for typical image sizes. A Computationally feasible method is to be funded to calculate these eigenvectors. If the number of data points in the image space is  $M$  ( $M < N^2$ ), there will be only  $M-1$  meaningful eigenvectors, rather than  $N^2$ . The eigenvectors can be determined by solving much smaller matrix of the order  $M^2 \times M^2$  which reduces the computations from the order of  $N^2$  to  $M$ , pixels. Therefore we construct the matrix  $L$

$$L = A \cdot A^T \quad (3)$$

$$A^T \cdot A$$

Where  $L_{mn} = \Phi_m \cdot \Phi_n$



And find the  $M$  eigenvector  $u_l$  of  $L$ . These vectors determine linear combination of the  $M$  training set face images to form the eigenfaces  $v_l$

$$v_l = \sum u_{lk} \cdot \phi_k, \text{ Where } l = 1 \dots M \quad (4)$$

### CLASSIFICATION AND IDENTIFICATION OF FACE

Once the eigenfaces are created, identification becomes a pattern recognition task. The eigenfaces span an  $N^2$ -dimensional subspace of the original image space. The  $M'$  significant eigenvectors of the  $L$  matrix are chosen as those with the largest associated eigenvalues. In the test number of eigenfaces to be used is chosen heuristically based on the Eigenvalues. A new face image ( $I$ ) is transformed into its eigenface components (projected into "face space") by a simple operation,

$$Q_k = v_k^T (I_k - \Psi)$$

$$\text{Where } k = 1 \dots M' \quad (5)$$

This describes a set of point-by-point image multiplications and summations. Figure 3 shows three images and their projections into the seven-dimensional face space, the weights form a vector

$$\Omega^T = [\Omega_1, \Omega_2 \dots \Omega_{M'}] \quad (6)$$

That describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The vector is used to find which of a number of predefined face classes, if any, best describes the face. The simplest method for determining which face class provides the best description of an input face image is to find the face class  $k$  that minimizes the *Euclidean distance*

$$\varepsilon_k = \|\Omega - \Omega_k\| \quad (7)$$

Where  $\Omega_k$  is a vector describing the  $k$ th face class.

A face is classified as belonging to class  $k$  when the minimum  $\varepsilon_k$  is below some chosen threshold  $\theta_\varepsilon$ . Otherwise the face is classified as "unknown". The distance threshold,  $\theta_\varepsilon$ , is *half the largest distance between any two face images*, Mathematically can be expressed as,

$$\theta_\varepsilon = \frac{1}{2} \max_{j,k} \{ |\Omega_j - \Omega_k| \}$$

Where  $j, k=1$

Recognition process can be formulated as:

If

$\varepsilon \geq \theta_\varepsilon$  then input image is not a face

$\varepsilon < \theta_\varepsilon$ ,  $\varepsilon \geq \theta_\varepsilon$  then input image contains an unknown face

$\{ \} \varepsilon < \theta_\varepsilon$ ,  $\varepsilon = \min \{ \varepsilon_k \} < \theta_\varepsilon$

Then image contains face of individual  $k'$

- In the first case, an individual is recognized and identified.
- In the second case, an unknown individual is present.
- In the first case, the image is not a face image. Case one typically shows up as a false positive in most recognition

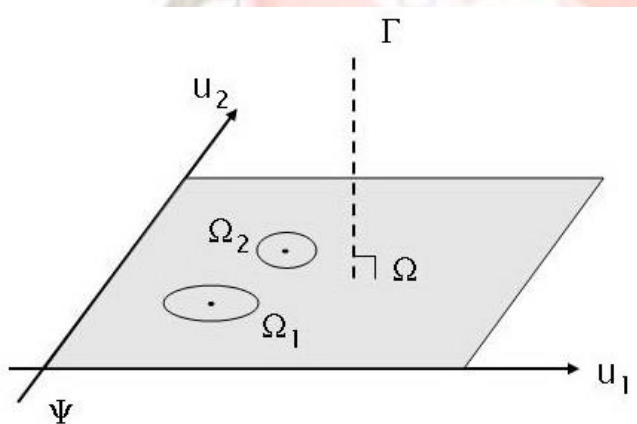
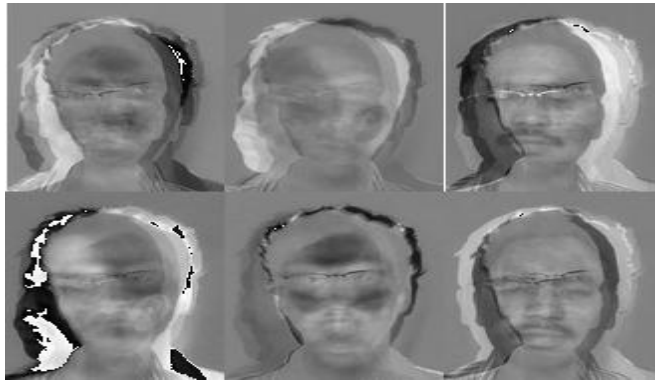


Fig. 2

Visualization of a 2D face space, With the axes representing two Eigenfaces

A simplified version of face space to illustrate the four results of projecting an image into face space. In this case, there are two eigenfaces ( $u_1, u_2$ ) and three known individuals ( $\Omega_1, \Omega_2, \Omega$ ).



**Fig. 3** Eigenfaces of the corresponding training images shown in Figure (1)

## CONCLUSION :

In this work we introduced a slightly different solution for face recognition. It is one of the best practical solutions for the problem of face recognition. Many applications which require face recognition do not require perfect identification but just low error rate. So instead of searching large database of faces, it is better to give small set of likely matches. By using Eigenfaces approach, this small set of likely matches for given images can be easily obtained. By using eigenfaces approach, we try to reduce this dimensionality. The eigenfaces are the eigenvectors of covariance matrix representing the image space. More research needs to be done on choosing the best value of threshold. This value of threshold may vary depending on the application of Face Recognition. Further, this approach can be applied to show good results on other databases as well.

## REFERENCES :

- [1] Matthew Turk and Alex Pentland , "Eigenfaces for Recognition," Massachusetts Institute of Technology, JCNS Vol 3, No 1, pp. 71-86, 1991.
- [2] Bledsoe, W.W, "The model method in facial recognition & facial expression," Panoramic Research Inc., Palo Alto, CA, Rep. PRI:15, August 1966.
- [3] Bledsoe, W.W, "Man machine facial recognition, Panoramic Research Inc., Palo Alto, CA, Rep. PRI:22, August 1966.
- [4] Goldstein, Harmon, & Lesk, "Identification of human face", Proceedings IEEE, 59, 748. 1971.
- [5] Fisher, M.A., & Eschlager, R.A, "The Representation and matching of pictorial structures. IEEE Transactions on computers, c-22(1).
- [6] Kohonen, T, "Self organization and associate and associative memory", Berlin: Springer-Verlag 1989.
- [7] Kohonen, T. & Lethio, P, "Storage and processing of information in distributed associative memory systems", in G.E. Hinton & J. A. Anderson (Eds.), Parallel models of associative memory hillsdale, NJ: Erlbaum, pp. 105-143, 1981.
- [8] Matthew A. Turk and Alex P. Pentland, "Face Recognition using Eigenfaces", CVPR'91, pp. 586-591 IEEE Computer Society, 1991.

[9] Navneet Jindal, Vikas Kumar, “Enhanced Face Recognition Algorithm using PCA with Artificial Neural Network,” IJARCSSE Vol 3:6, pp. 864-872, June 2013

[10] Kshirsagar, V.P. ;Baviskar, M.R. ; Gaikwad , M.E,“Face Recognition using Eigenfaces” ICCRD, International Conference on Digital object identifier,pp. 302-306, 2011.

[11] karhunen-loeve, “It is one of the more successful techniques of face recognition”.

[12] R .F. Gonzalez, and R. E. Wood, Digital Image Processing, Singapore, Pearson Education, 2001

[13] AL Bovik, “The essential guide to image processing,” 2009.

[14] Rajkiran Gottumukkal, VijayanK. Ansari, “An improved face recognition technique based on modular PCA approach,” Pattern Recognition Letters , 2003.

[15] L. Sirovich and M. Kirby (1987)“Low-dimensional procedure for the characterization of human faces”.Journal of the Optical Society of America a 4: 519–524.

