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Improved PCA Based Face Recognition System

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Abstract – **Face Recognition is a computer based application which detects the faces of different persons for authentication and various other purposes. It has separate applications from the fingerprint and iris recognitions. There are various successful techniques are purposed so far as Holistical methods and Discrete Cosine Transform (DCT). In this paper, we build a simple and fast face recognition system on the basis of feature extraction using Principal Component Analysis (PCA).This paper explains how the faces, having some variations like facial expressions, hairstyles and viewing conditions w.r.t the original faces reserved in the database, are detected with improved accuracy and success rate.**

Index Terms—Face Recognition System, PCA, eigenface, projected images, Euclidian distance, recognition rate.

I. Introduction

Face Recognition is a biometric phenomenon recognizes the faces which are already stored in the database. The face of a person which is to be recognized is compared with the faces present in the database and best matches the face having highest resemblance. Face recognition system detects the different facial expressions, hairstyles and viewing conditions. Initially on preparation of face database, fingerprint and iris recognitions needs the presence of the person but face database can be made by any face image of the person.

Face Recognition System compares the tested face with the various training faces reserved in the database with efficient success rate. The best matching of the tested face with the training faces is an important task. To detect the tested face from the database requires - one to one matching or one to many matching.

In past few years, there are many face recognition algorithms are purposed as Principal Components Analysis(PCA), Discrete Cosine Transform (DCT),Partitioned Iterative Function System(PIFS),Fisher face and Local Feature Analysis which are based on different methodologies with successful results but the accuracy and success rate varies.

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Face of a person is a collection of feature points which contains maximum information about the face. In Principal Component Analysis, we calculate the principal components of the faces by extracting the features from the face space. The extracted feature vectors of different maximum distant face points makes different angles with horizontal and vertical axis using geometrical properties of the face. The different facial lines made by the face points count the principal components and the eigenvectors of the face which in returns are the different projections of the face. These feature variations forms the Eigen faces which contains the highest information of the face as required [2]. Hence, we map the test images to the training images as one to many using Eigen faces for comparing the test image and training images for the recognition of the correct face.

In this work, we use the different no. of Eigen faces for different no. of training images to recognize the test face with improved results by using the face database of 40 different training images which are resized to 200x180 pixels for the simulation process with the help of MATLAB.

II.Background and Related Works

PCA is a method of reducing dimensions of face space by decomposing the high dimensional space into low dimensional space. Kirby and Sirovich represent the faces using PCA in 1990. In 1991, M.A. Turk and A.P. Pentland use the eignface representation of faces for face recognition.

Further, on the basis of face recognition many successful algorithms are developed till now as Hausdorff distances for face recognition, Discrete Cosine Transform (DCT), Linear Discriminant Analysis (LDA), Partitioned Iterated Function System (PIFS) and Wavelet Packet Decomposition (WPD).

DCT technique converts a signal into elementary frequency components and this algorithm compresses the images and related to the discrete Fourier transform. It has strong energy compaction properties. Therefore, it can be used to transform images, compact the variations, allowing an effective dimensionality reduction. DCT executes both geometric and illumination normalization functions by extracting the features. This feature vector contains the low-to-mid frequency DCT coefficients. These feature coefficients are compare the test face and training faces to recognize the face on the basis of Euclidean distance [1].

LDA computes projection vectors which can map high-dimensional samples onto a low-dimensional space. All

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projected samples will form the maximum between-class scatter and the minimum within-class scatter simultaneously in the projective feature space. It maximize the ratio of all classes the between-class scatter matrix and the within-class scatter matrix for face detection [7].

The Independent Component Analysis (ICA) minimizes both second-order and higher-order dependencies in the face image. Independent Component Analysis transforms the images as linear combinations of statistically independent data points. Hence, it provides an independent rather that uncorrelated image representation [10].

Hausdorff distances measures the two binary points sets and defines weighting function which reflect the properties among different face edge images for face recognition [16].

Wavelet Packet Decomposition (WPD)with the classical PCA method for face recognition based upon the WPD which decomposes the training face image into k parts and calculates the k eigenfaces from the smaller training images from the large database using PCA.Using the wavelet decomposition, the image is decomposed into the approximation and details images, the approximation is then decomposed itself into a second level of approximation and details and so on. Wavelet Packet Decomposition (WPD) decomposes both approximations and details into a further level of approximations and details [5].

Barnsley presented a couple of revolutionary ideas based on the hypothesis presented by Mandelbrot, emphasizing the practical aspect of fractals. Partitioned Iterated Function System (PIFS) is an image compression algorithm with the use of fractal geometry for face recognition based upon PIFS transformation codes which calculates the region wise similarity for encoding the facial images [8].

In this paper, the work is done using PCA based method with improved results. It is fast, relatively simple, and works well in a constrained environment and rejects the unknown faces during recognition.

III. PURPOSED METHODOLOGY

Figure 1 describes the basic face recognition steps using Principal Components Analysis. The training, testing and the recognition of face are described by following parts which includes the database preparation, reading and normalizing the training images, calculation of principal components, calculations of the projected face images and then recognize the tested face image by calculating the Euclidian distance.

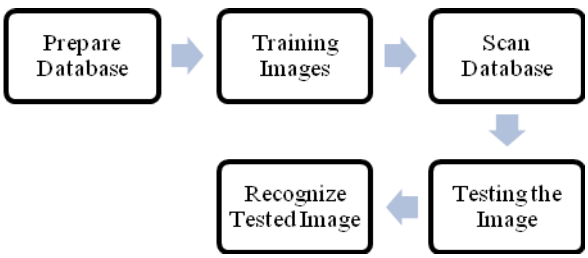

Figure 1: PCA Based Face Recognition

A. Face Database Preparation

In this paper, the database contains colored images under various different facial expressions with cropped and resized images to 200x180 pixels. There are other face databases are also available as AT&T face database also known as ORL database of faces, Yale face database and Feret face database.

B. Training of the Input Face Images

In this work, first read all the training images contained by the database and change the colored images into grey-scale face images. These two dimensional N×M grey-scale images spans the N×M dimensional vector space. The 200x180 pixels face images contained in the database having the 36,000 dimensional image spaces. From this high dimensional image space, there are only few dimensional image space which contains highest information is required because it is very difficult task to deal with that much high dimensional space. PCA method computes the maximum variance in the data by calculating the principal components.

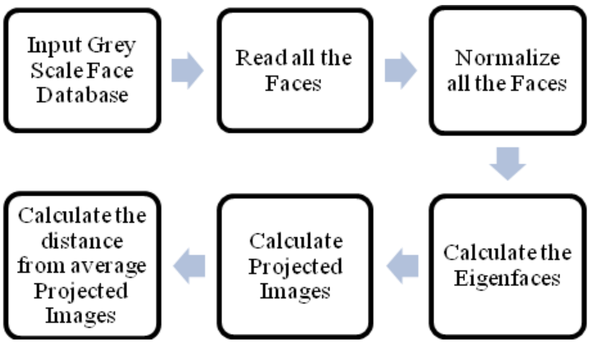

Figure 2: Implementation of Training Images

C. Computing Eigen Faces

Assume the m sample images contained in the database as A_1, A_2, A_3………A_m. All the images are taken as a column vectors with 200x180 pixels and each image having (x,y) co-ordinates with (0,0). The size of column vector of x×y pixels image is (x*y) ×1.The algorithm is as follows:-

1. Calculate the mean face image, **Ø**

As $\boldsymbol{\O = \sum A_l/m}$ where 1< L<m

2. For normalization process, calculate the difference by subtracting mean face from each sample image,

As $\mathbf{O = A_i - \O}$ where 1< i<m

3. Then, merge all the centered images as

$$\mathbf{A = [\, O_1\ O_2\ O_3 \ldots O_m]}$$

Matrix A of size (x*y) × m, which forms the Covariance matrix defined as

$$\mathbf{C = 1/M \sum O_n O_n^T = AA^T} \quad \text{where } 1< n<m$$

For calculating Eigen faces, minimum dimensional space is required. As we know from the linear algebra theory ,for a X×Y matrix the maximum number of non-zero eigenvalues of the matrix is min.(X-1,Y-1).As the no. of training images is less than the no. of pixels of (M×N) image. Since, in X×Y matrix X>Y can only have Y-1 non-zero Eigen values. So, the Co-variance is calculated as:

$\mathbf{L = A^TA}$ **(X×X matrix)** for low dimensional space

As the dimensions of $\mathbf{C = AA^T}$ **(M*N×M*N)** matrix is larger than $\mathbf{A^TA}$. Hence, the dimensions are decomposed.

4. Compute the kth Eigen values of Covariance matrix **L:** $\lambda_1, \lambda_2, \lambda_3 \ldots\ldots \lambda_k$

5. The Eigen vectors of the covariance matrix L are the Eigen faces of the face images which are the linear combinations of m training face images. The k principal components are the Eigen vectors w.r.t k Eigen values. This k Eigen vectors are calculated as

$$\mathbf{u}_k = \frac{\sum_{l=1}^{M} \ddot{\mathrm{O}}_l \mathrm{X}_{lk}}{\sqrt{\lambda_k}}$$

D. Calculating the Projected Images

After the calculation of the Eigen faces, all the centered images are projected into face space by multiplying on the Eigen face basis. Projected vector of each face is its corresponding feature vector. For this, first calculate the weights of vectors by multiplying Eigen Vectors $\mathbf{U^T}$ with a vector **O** calculated above as

$$\mathbf{w = U^TO = U^T(A_i - Ø)} \quad \text{where } 1< i<m$$

These weights forms a vector, which describe the contribution of Eigen vectors of Covariance matrix in the input face image, as:

$$\mathbf{W^T = [w_1, w2\ldots..w_m]}$$

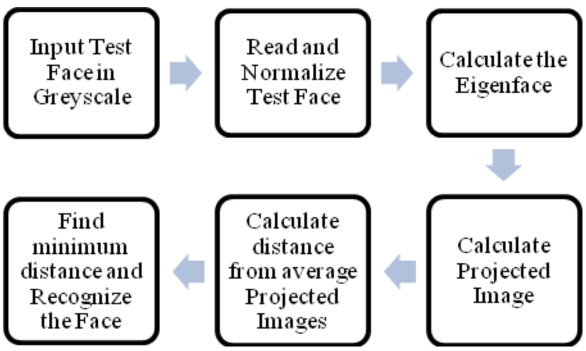

Figure 3: Implementation of Test Image

E. Recognition of the Tested Face Image

For this, calculate the Euclidian distance between the projected test face and the projections of all the training faces stored in the database. Euclidian distance is the minimum distance between the projected test face and the projections of all the training faces. The face image in the database, having the minimum distance below some threshold value from the test face, is detected as output. Euclidian distance is calculated as:

$$\mathbf{e^2_k = ||(W - W_k)||^2}$$

where W_K is the kth face class. If the test image does not belong to the kth face class, then test face is taken as unknown face class. If the test image belongs to the kth face class, then Euclidian distance $\mathbf{e_k}$ will lies below some threshold value q_e and the test face is treated as known face and recognized.

IV. Experimental Results

In this works simulation is completed by using MATLAB. The database used contains the different colored training face images with 200×180 pixels as two images are shown in the figure 4.

Figure 4: Training Images taken from the database

For feature extraction, these images are converted to grey-scale and normalized as shown in figure 5.

Figure 5: Grey-scale converted Training Images

A. Computing Eigen Faces

After normalization, the features are extracted from the decomposed dimensional space and the Eigen faces of these face images is extracted by calculating the eigenvectors of the Covariance matrix as described above and shown in figure 6.There are two grey-scale face images and their corresponding Eigen faces.

Figure 6: Eigen Faces of Training images

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Similarly, the same work is done with the tested face image and compares the projected training images with the projection of test face for finding the Euclidian distance.

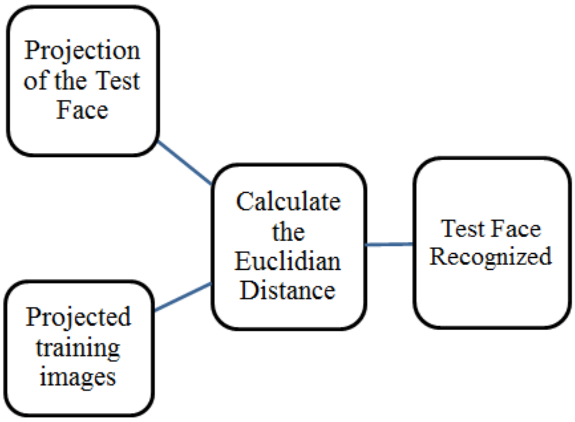

Figure 7: Face Recognition on the basis of minimum Euclidian Distance

B. Computation of Resulted Recognition Rate

The success rates are shown by using three tables and corresponding graphs via increasing the number of Eigen face and training images for improved results using PCA based face recognition system. Tables and corresponding graphs are formed by using the number of training images and the number of Eigen faces as shown below in Table 1, 2, 3 and figures 8,9,10.

Table 1: Recognition Rate for Training Images= 1

Number of Training images	**Number of Eigen Faces**	**Recognition Rate**
1	5	43.33
	6	53.66
	7	58.00
	8	65.66
	9	73.33
	10	85.00
	11	93.33
	12	100
	13	100
	14	100
	15	100

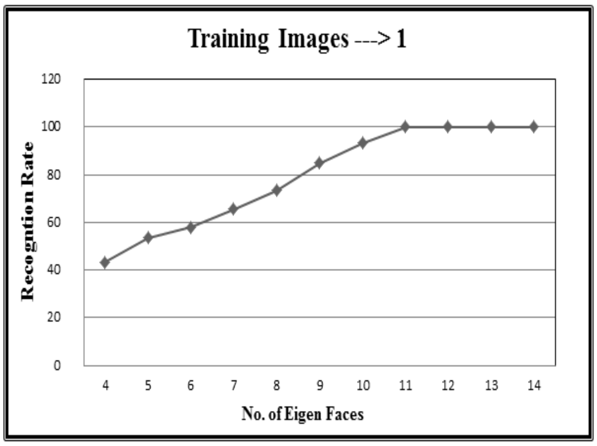

Figure 8: Recognition Rate for Training Images= 1

The same procedure implemented taking number of training images as 3.

Table 2: Recognition Rate for Training Images= 3

Number of Training images	**Number of Eigen Faces**	**Recognition Rate**
3	5	63.33
	6	73.66
	7	78.33
	8	85.00
	9	93.66
	10	100
	11	100
	12	100
	13	100
	14	100
	15	100

The following graph for the number of training images as 3.

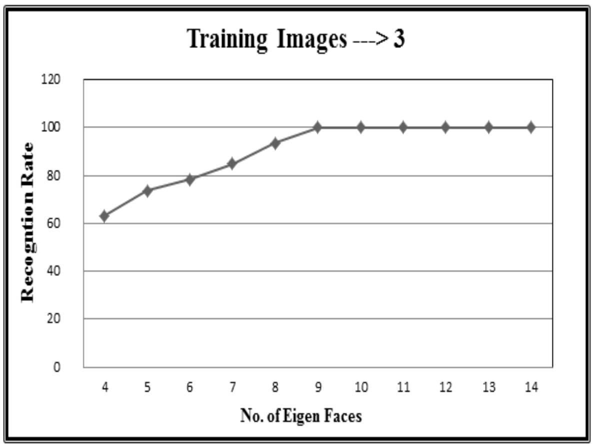

Figure 9: Recognition Rate for Training Images= 3

The same procedure implemented taking number of training images as 5.

Table 3: Recognition Rate for Training Images= 5

Number of Training images	Number of Eigen Faces	Recognition Rate
5	5	83.66
	6	88.33
	7	93.33
	8	95.00
	9	99.33
	10	100
	11	100
	12	100
	13	100
	14	100
	15	100

The following graph for the number of training images as 5.

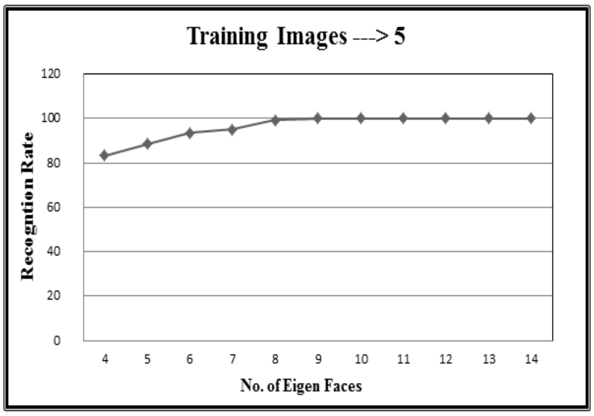

Figure 10: Recognition Rate for Training Images= 5

The following graphical representation shown in the figure.11 is the comparison of above three graphical representations.

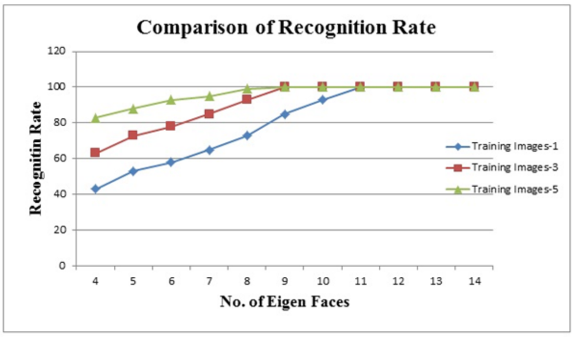

Figure 11: Comparison of Recognition Rate for Training Images= 1, 3, and 5

V. Conclution

In this paper, we purposed the face recognition system by using colored images database. This method for face recognition is based on PCA using Eigen faces and projected images concept. In this work, we purposed the face detection by varying the number of Eigen faces for different number of training face images. Results shows that the accuracy decreases with three dimensional poses .The purposed face recognition performs quickly and provides better success rates. This work is purposed not only for known face images but also rejects the unknown face images otherwise every unknown image counts some minimum Euclidian distance and will be detected as one of the training face image. In future we can combine this algorithm with Neural Networks to provide further improvements.

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