Frontal Human Face Recognition Using PCA Technique

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Abstract- This work deals with Principal Component Analysis (PCA) based technique, to be specific eigen face strategy is considered and implemented on the Faces 94 database. This methodology regards face recognition as a two-dimensional recognition issue. Face images are anticipated onto a face space that encodes best variety among known face images. The face space is characterized by Eigen faces which are eigen vectors of the arrangement of faces, which may not compare to general facial highlights, like; eyes, lips and nose. Face will be arranged as known or obscure face in the wake of coordinating with the present database, Simulation results shows an accuracy of above 98% and this can be recognizes one image approximately within 0.5 sec.

Keywords- *Face recognition, Principal component analysis (PCA), Eigen vectors, Eigen values, Eigen faces.*

I. INTRODUCTION

Human Face Recognition is the capacity to perceive individuals by their facial attributes. Over years it happens to be one of the expanding prominent patterns in picture investigation and preparing. This sort of innovation has numerous advantages which makes it be utilized in a few distinct zones which push more analysts into distinguishing some exceptional issue as yet existing in its present execution as a biometric framework. A biometric is a unique, measurable characteristic of a human being that can be used to recognize an individual or verify an individual's identity. Biometrics can measure both physiological and behavioral characteristics.
Physiological biometrics includes; finger scan, iris scan, faces recognition and so on [1].

Face recognition is an integral part of biometrics and it has a number of strengths to be recommended over its peer in certain circumstances. Automated Face recognition is an intriguing PC vision issue with numerous business and law requirement applications [2]. Face recognition methods can be partitioned into two gatherings in view of the face portrayal they utilize:

(i) Appearance-based, which utilizes surface highlights and is connected to either entire face or particular locales in a face picture and

(ii) Feature-based, which utilizes geometric facial highlights like mouth, eyes, foreheads, cheeks etc. and geometric connections between them.

Face images from a standard database which is auxiliary source information are separated and utilized for this work. There are various standard databases accessible for research purposes which could be utilized to test the execution of face recognition framework. For the motivations behind this task faces 94 database is considered. It contains 152 people with 180 x 200 pixels in goals and in representation organize, 20 of which are female, 112 as guys and 20 as male staff taken at various points and varieties. The analysis is done with Matlab software.

II. METHODOLOGY

A. Principal Component Analysis

The Principal Component Analysis (PCA) is the successful analysis technique. It is used in face recognition and detection and compression. PCA is a statistical approach. The main use of it is to reduce a large dimensional data space to smaller instinctive dimensional feature space (independent variables), which are needed to expound the data parsimoniously. This is the situation when there is a solid connection between observed variables. PCA can do something that is prediction, feature extraction and many more. A vital and to a great extent unsolved problem in dimensional reduction is the choice of the intrinsic dimensionality of the principal doublet. No expository derivation of this number for a complex natural visual signal is available to date. To elucidate this problem, it is common to assume that in the noisy embedding of the signal of interest (in our case, a point sampled from the face space) in a high-dimensional space, the S/N (signal to noise) ratio is high. This assumption relates to the eigen spectrum - the set of the eigenvalues of the data covariance matrix.

The first algebraic solution to PCA could be derived using linear algebra. This solution is based on an important property of eigenvector decomposition. The data set is X, an m×n matrix, where, m is the number of measurement types and n is the number of data trials. The goal is to find some orthogonal matrix P where Y = PX such that $S_Y = \frac{1}{n-1}YY^T$ is diagonaized. The rows of P are the principal components of X. Begin by rewriting SY in terms of our variable of choice P.

$$S_Y = \frac{1}{n-1}YY^T \tag{1}$$

$$S_Y = \frac{1}{n-1}(PX)(PX)^T \tag{2}$$

$$S_Y = \frac{1}{n-1}PXX^TP^T \tag{3}$$

$$S_Y = \frac{1}{n-1}P(XX^T)P^T \tag{4}$$

$$S_Y = \frac{1}{n-1}PAP^T \tag{5}$$

Note that a new matrix $A=XX^T$, is defined, where A is symmetric. The roadmap is to recognize that a symmetric matrix (A) is diagonalized by an orthogonal matrix of its eigenvectors. A symmetric matrix 'A' can be written as EDET, where D is a diagonal matrix and E is a matrix of eigenvectors of A arranged as columns. The matrix A has $r \leq m$ orthonormal eigenvectors where r is the rank of the matrix. We select the matrix P to be a matrix where each Row pi is an eigenvector of XX^T By this selection, $P = E^T$. Hence, $A = P^TDP$. With this relation and the fact that $P^{-1}= P^T$ since the inverse of orthonormal matrix is its Transpose, S_Y can be evaluated as follows;

$$S_Y = \frac{1}{n-1}PAP^T$$

$$S_Y = \frac{1}{n-1}P(P^TDP)P^T \tag{6}$$

$$S_Y = \frac{1}{n-1}(PP^T)D(PP^T) \tag{7}$$

$$S_Y = \frac{1}{n-1}(PP^{-1})D(PP^{-1}) \tag{8}$$

$$S_Y = \frac{D}{n-1} \tag{9}$$

It shows that P diagonalizes S_Y.

B. Eigen Face Approach

An image space can be considered as a space that has dimensions equal to the number of a pixel that make up the image and that have values in the range of pixel values. An image can be thought of as a point in the image space by converting the image into a long vector by concatenating each image column one after the other. All facial images are grouped in a certain position in the image space when all face images become vectors because the images have a similar structure and their relative position is related. To start the correlation of the approximation position of the eigen face is the main point. A smaller dimensionality space has found the eigen face method for image representation by eliminating the variance due to images without a face. The implementation of principal components analysis (PCA) on images is performed using the eigen facial method. The characteristics of the images studied are obtained with this method, looking for the maximum deviation of each image of the average image. This variance is obtained by having the eigenvectors of the covariance matrix of all the images.

Eigen facial space is obtained by applying the eigen face method to training images. Next, the training images are projected into the eigen face space. To classify the projected test image in a new space, the distance of the test image projected onto the training images is used. In the standard eigen face procedure suggested by Turk and Pentland, the nearest average classifier is used for the classification of test images. Because of the simplicity, speed and learning ability of the method used in facial recognition, it is an appropriate and efficient method. For the problem of artificial vision of human facial recognition, their faces are used as a set of eigenvectors. Eigen faces are the main components of a face distribution, or equivalently, the eigenvectors of the covariance matrix of the face image set, in which an image with N x N pixels is considered a point in the dimensional space N^2. This suggests that the encoding and decoding of facial images can provide information on facial images that emphasize the importance of features.

These characteristics may or may not be related to facial features such as eyes, nose, lips and hair. Relevant information in a facial image must be extracted, efficiently coded, and compared to a database of similarly encoded faces. In an image of the human face, a simple approach to extracting data content is to capture variation in a collection of facial images. Each position of the image contributes to each eigenvector, so that the eigenvector can be visualized as a sort of face. Each image of the face can be visualized in terms of the linear combination of the Eigen faces. Faces can also be approximated using the very best visuals, which have the largest eigenvalues and thus represent the largest variation in facial image sets. The main reason why fewer Eigen faces are acquired is computational efficiency. The whole recognition process involves two steps:
(i) Initialization process
(ii) Recognition process

III. CALCULATING EIGEN FACES

Let I(x, y) be a two-dimensional M x N array face image with 8-bit intensity values. For simplicity assume size N x N. The image can also be recognized as a vector of dimension N^2, so that an exemplary image of size 256 x 256 becomes a vector of dimension 65,536 or a point in 65,536-dimensional space.

Steps for Calculation:

1. Prepare Training Set
   The image matrix I of size (Nx x Ny) pixels is converted to the image vector Γ of size (P x 1) where P = (Nx x Ny); that is the image matrix is reconstructed by adding each column one after the other. Thus, this two dimensional vector is changed to one dimensional vector.
   Training Set $\Gamma = [\Gamma_1, \Gamma_2 \ldots, \Gamma_{Mt}]$
2. Compute Mean Face Vector
   $\psi = \frac{1}{M_i}\sum_{i=1}^{M_i}\Gamma_i$
   is the arithmetic average of the training image vectors at each pixel point. Its size is (P x 1).
3. Subtract Mean Face Vector
   $\Phi = \Gamma - \Psi$ is the difference of the training image from the mean image (size P x 1). Thus, each face differs from the average by $\Phi = \Gamma - \Psi$ which is also called mean centred image.
4. Difference Matrix $A = [\phi_1, \phi_2, \ldots, \phi_{Mt}]$
   is the matrix of all the mean subtracted training image vectors and its size is (P x Mt).
5. Calculate Covariance Matrix
   $X = A.A^T = \frac{1}{M_t}\sum_{i=1}^{M_i}\phi_1\,\phi_i^T$
6. Calculate the eigenvectors and eigenvalues of the covariance matrix.
7. Instead of using Mt of the Eigen faces, $M' \leq Mt$ of the Eigen faces can be used for the Eigen face projection. This is achieved to eliminate some of the eigenvectors with small Eigen values, which contribute less variance in the data.
8. Eigen vectors can be considered as the vectors pointing in the direction of the maximum variance and the value of the variance the eigenvector represents is directly proportional to the value of the eigenvalue. Hence, the sorting of the eigen vectors can be obtained with respect to their corresponding eigenvalues.

Eigen faces with low eigenvalues can be omitted because they explain only a small part of characteristic features of the faces.

IV. SIMULATION AND RESULTS

This work is done on Matlab software. The result are shown in Figs. 1-2.

Fig.1 The recognition of my test image

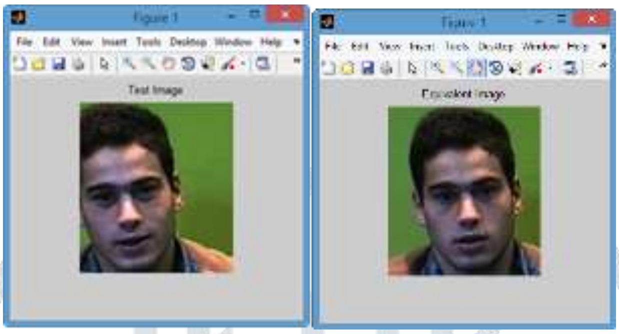

Fig.2 The recognition of database image

V. CONCLUSIONS

In this Paper frontal face recognition based on eigen face approach using PCA is implemented. This recognizes the human face picture successfully. The Eigen face approach provides a very good solution in practical for human face recognition process. It is fast, simple, and well work in constrained atmosphere.

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