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Face Recognition based on Singular Value Decomposition Linear Discriminant Analysis Method

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Abstract: - In this paper, we are presenting the face recognition techniques based on the linear discriminant analysis method. The recognition of human faces is quite complex. The human face is full of information but working with all the information is time consuming and less efficient. It is better get unique and important information and discards other useless information in order to make system efficient. We implement Fischer face Singular Value Decomposition-Linear Discriminant Analysis (SVD-LDA) method where we have added Singular value decomposition (SVD) in comparison to Eigen-value decomposition (EVD) to reduce the time complexity and Euclidean distance in face space. Recognition is performed by projecting a new face image into the subspace spanned by the Eigen faces and then classifying the face by comparing its position in the face space with the positions of known individuals. The Results reveals that the efficiency of the Singular Value Decomposition-Linear Discriminant Analysis method is better than the other existing face recognition techniques. Results also shows that the time complexity is reduce to a great extant with Linear Discriminant Analysis method for face recognition.

*Keywords:-***Singular Value Decomposition (SVD), Eigen-value decomposition (EVD), linear discriminant analysis (LDA) method, face recognition.**

I. INTRODUCTION

Face recognition has become an important issue in many applications such as security systems, credit card verification and criminal identification. The face recognition's target is to distinguish persons via their facial images which vary with expression, illumination. A face recognition system includes two steps, face detection [1] [2] and face recognition [3] [4]. Feature extraction plays an important role in face recognition. Two of the classical algorithms, principal component analysis (PCA) [5] and linear discriminant analysis (LDA) [6], which are well-known for feature extraction and dimension reduction, have been widely used in face recognition. PCA is a standard statistic technique and it derives an orthogonal projection basis which directly leads to dimensionality reduction, and feature selection. LDA has been widely used in pattern recognition for feature extraction and dimension reduction. LDA is used to find the optimal projection that the ratio of the determinants of the between class and the within-class scatter matrices of the projected samples reaches its maximum. Linear discriminant analysis (LDA)[7] is a well-known scheme for feature extraction and dimension reduction, which has been used widely in many applications such as speech recognition, face recognition, multimedia information retrieval. Linear discriminant analysis (LDA) [8][9] extracts features of the original data in a way which selects the most discriminable features between classes. The aim of LDA [10] is to find the optimal projection in order to maximize the between class scatter matrices and to minimize the within class scatter matrices, which makes the ratio of the determinants of the between class and the within-class scatter matrices of the projected samples reach its maximum. In this paper, we are use the face recognition techniques based on the linear discriminant analysis method. The recognition of human faces is quite complex. The human face is full of information but working with all the information is time consuming and less efficient. It is better get unique and important information and discards other useless information in order to make system efficient. We implement Fischer face Singular Value Decomposition-Linear Discriminant Analysis (SVD-LDA) method where we have added Singular value decomposition (SVD) in comparison to Eigen-value decomposition (EVD) to reduce the time complexity and Euclidean distance in face space. Recognition is performed by projecting a new face image into the subspace spanned by the Eigen faces and then classifying the face by comparing its position in the face space with the positions of known individuals. The rest of the paper is organized as follows: In section II, explain the face recognition techniques are presented. In Section III, Linear discriminant analysis (LDA) is presented. Section IV explains the Face Recognition based on LDA. In Section V, simulation results are presented for the effectiveness of the proposed techniques. Finally, a conclusion is made.

II. FACE RECOGNITION

Face recognition [1] [2] is a type of pattern recognition task where a face classified as either "known" or "unknown" after comparing that face with the images of known individuals stored in the database. Since there is variability in data due to the random variation across people as well as the systematic variations due to pose,

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lighting conditions, and so on, face recognition becomes a challenging task. Computational models of face recognition must address several difficult problems. These difficulties arise from the fact that faces must be represented in a way that best utilizes the available face information to distinguish a particular face from all other faces in the database. The system starts with the Acquisition Module where images are captured with a digital camera or any image capturing device. In the second phase, captured images are sent through the pre-processing Module to meet the standards required by a given recognition system. The pre-processing Module may perform tasks such as color-to-grayscale conversion, image resizing, and illumination and background removal in order to normalize the input image. Then the normalized images are added to the Face Database. Some of the images in the face database are used as the Training Set of the system and the rest will be the Test Set. The Feature Extraction Module takes as input a normalized image and outputs a mathematical model of that input image that expresses the most important features in that image, thereby reduce its dimensionality. For example, techniques such as Principal Components Analysis [5] (PCA) and the Linear Discriminant Analysis [6] (LDA) can be used as feature extractors. Finally, the Classifier Module compares the feature vectors between a test image and all the training images and decides which training image is closest to that test image.

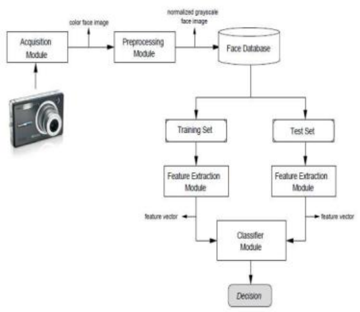

Fig: 1 Stages of Face Recognition System

III. LINEAR DISCRIMINANT ANALYSIS (LDA)

Linear discriminant analysis (LDA) [8]-[12] is a well-known scheme for feature extraction and dimension reduction, which has been used widely in many applications such as speech recognition, face recognition, multimedia information retrieval, and so on. Given a set of high-dimensional data grouped into classes, LDA aims to find an optimal transformation that tries to maximise the ratio

$$J_{\mathrm{LDA}}(W) = \arg\max_{\mathrm{W}} \frac{|W^{\mathrm{T}} S_{\mathrm{B}} W|}{|W^{\mathrm{T}} S_{\mathrm{W}} W|} \qquad (1)$$

Where S_B is the between-class scatter matrix and S_W is the within-class scatter matrix. Thus, by solving a generalised Eigen values problem, the projection vector W can be found as the eigenvectors of $S_W^{-1} S_B$ corresponding to the largest Eigen values. When the sample size is smaller than the dimensionality of samples, however, S_W becomes singular and we cannot compute $S_W^{-1}S_B$ directly. There are two fundamental problems with the linear discriminant analysis (LDA) for face recognition. First one is LDA is not stable because of the small training sample size problem. The other is that it would collapse the data samples of different classes into one single cluster when the class distributions are multimodal.

Face Recognition based on LDA

A. Training for LDA

1. Select a training set that includes a number of leaf images. Let a leaf image $I(x; y)$ of N^2 dimension ($N \times N$) represent as a column vector of $N^2 \times 1$ dimension. A data set of M images can therefore be mapped to a collection of points in this high dimension "leaf space" as $I_1, I_2 \ldots\ldots, I_M$.
2. Compute the mean of the training set and normalized the set by subtracting the mean from each leaf image in the training set.

$$A = \frac{1}{M}\sum_{n=1}^{M} I_n \qquad (2)$$

$$\Phi_i = I_i - A \qquad (3)$$

$$C = \frac{1}{M}\sum_{n=1}^{M} \Phi_n \Phi_n^T = X X^T \qquad (4)$$

Where

$$X = [\Phi_1, \Phi_2, \ldots., \Phi_M] \qquad (5)$$

3. **Eigen Value Decomposition (EVD):** Factorize covariance matrix C to compute the Eigen values and Eigenvectors of, which has dimension of $N^2 \times N^2$, for typical image size, this size would be a very high value. Therefore, we need a computationally feasible method to determine these eigenvectors. If the number of data points in the image space is less than of the space $M << N^2$ there will be only M-1 meaning full eigenvectors, and rest of the eigenvectors will have Eigen values zero.

$$(C - \Lambda_i I)v_i = 0 \qquad (6)$$

4. Choose the eigenvectors corresponding to the highest Eigen values, by combining these after sorting from higher to lower we get feature or projection vector.

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$$v_i = V \quad (7)$$

5. Now we can project the each face in the set into lower dimension and reconstruct it as a Eigen faces as shown in flow chart Fig. 2. Each of the centred training images Φ_i is projected onto the Eigen space. To project an image onto the Eigen space, calculate the dot product of the image with sorted eigenvectors.

$$\hat{\Phi}_i = V^T \Phi_i \quad (8)$$

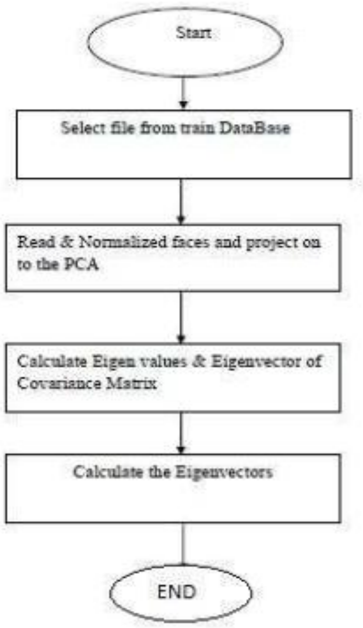

Fig. 3 Flow Chart for Training

B. Testing for LDA

1. Each test image is first mean centered by subtracting the mean image.

$$\bar{t}_i = t_i - A \quad (9)$$

2. Then, projected into the same Eigen space defined by V

$$\hat{t}_i = V^T \bar{t}_i \quad (10)$$

3. Now, calculate the Euclidean distance to measure the distance between the projected feature vector of the test image with projected feature vector of each leaf image in the training set.

$$\epsilon = \|\hat{t}_i - \hat{\phi}_i\|^2 \quad (11)$$

4. At the last compare the Euclidean distance, and showing the leaf image which has minimum Euclidean distance.

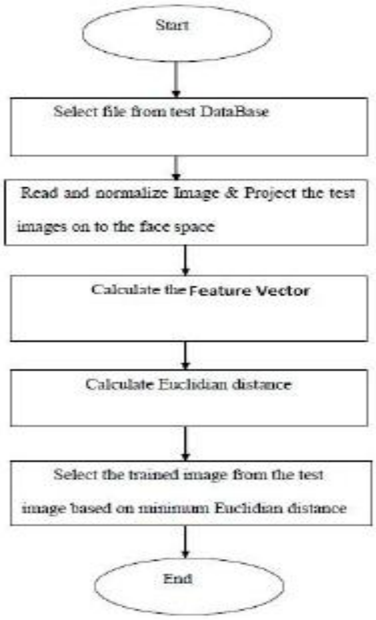

Fig. 3 Flow Chart for Testing

IV. SIMULATION RESULTS

In this section, face recognition using Eigen value Decomposition-Linear Discriminant Analysis Algorithm is explained. All the images are cropped and resized to a resolution of 80 × 100 pixels. In the vector-based algorithms, we randomly grouped the image samples of each individual into two parts. One part is used for training and the other part is used for testing. Fig. 4 shows the input faces for face recognition algorithm. Fig. 5 shows the corresponding fisher faces for SVD-LDA algorithm. Fig.6 shows the test image. Fig. 7 shows the identified face using SVD-LDA algorithm. In case of SVD-PCA algorithm the identified image is more accurate or same as that of Test image where as in SVD-LDA algorithm identified image is not accurate as that of test image. SVD-PCA algorithm gives better result if we compare with SVD-LDA.

Fig. 4 Input faces

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Fig. 5 Eigen faces

Fig. 6 Test image

Fig. 7 Identified image

V. CONCLUSIONS

We have proposed an algorithm for face recognition, called LDA. Most of traditional linear discriminant analysis (LDA)-based methods suffer from the disadvantage that their optimality criteria are not directly related to the classification ability of the obtained feature representation. In this paper, we propose a algorithm that deals with both of the shortcomings in an efficient and cost effective manner. The result compared, in terms of classification accuracy, to other commonly used face recognition methods on two face databases. Results indicate that the performance of the LDA method is overall superior to those of traditional face recognition approaches, such as the Eigen faces, Fisher faces. Results also shows that the time complexity is reduce to a great extant with Linear Discriminant Analysis method for face recognition.

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