FACE RECOGNITION TECHNIQUES WITH PERFORMANCE AND COMPARISON

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Abstract
Principle Component Analysis or PCA is widely used for dimension reduction. It has found its use in many applications such as face recognition which use high dimensional data. In this paper, we present a new variant on Principle Component Analysis(PCA) for face recognition by reducing dimensions of input images using matrix form and after that using Singular Value Decomposition(SVD) to get the projection matrix, to assign the high dimension face images a vector in low dimension face space. Linear Discriminant Analysis (LDA) is also a face recognition technique that gives us faster computation but at the cost of a little bit lower accuracy rate than PCA.

Keywords: Face recognition, Principal Component Analysis (PCA), Eigenface, Eigen Value Decomposition (EVD) and Singular Value Decomposition (SVD), Linear Discriminant Analysis (LDA).

I. INTRODUCTION

A Wide range of researchers is being carried out on subjects related to face recognition. This problem is studied in a different field with a different point of views. It has been seen that face recognition is preferred over other biometric methods [1] [2].The biometrics system being used till date involves some voluntary action by the customer such as fingerprinting or detecting the geometry of the hand and has to stand in a particular alert position in front of a camera lens for iris or retina identification. On the other hand, face recognition no participation or particular position has to be maintained on the part of the user since face images can be easily acquired from a distance by a camera, thus serving for security and surveillance purposes. Other daily life applications of face recognition include various purposes like identification of the person using ID cards, door lock security, Law enforcement & surveillance, video games etc.

Also, there are numerous factors that make the appearance of the face to varying. These factors of various variations [3] in the facial look can be classified mainly into two groups: intrinsic factors and extrinsic factors. A) Intrinsic factors are caused due to the physical characteristics of the face and are independent of the observer, for examples age, facial expression, facial hair, facial accessories, gender, glasses, cosmetics, etc. B) Extrinsic factors alter the appearance of the human's face as the interaction of light with the face and the observer tends to highlight or darken some areas. Various such factors include illumination, pose, scale and a range of imaging parameters (e.g., noise, focus, resolution, imaging etc.). PCA & LDA [4][5] are the most widely used appearance based comprehensive techniques and linear methods, in which the entire face region is taken into consideration as input to the face recognition system. Examples of such methods are Eigenfaces & Fisher faces, and therefore PCA is called as Eigenspace Projection which linearly projects the image space to a lower dimensional feature space called as Eigenspace. This technique helps in finding Eigenvectors of the Covariance matrix that matches up to the directions of Principal Component of originally supplied input data. PCA in face recognition is an unsupervised method. Whereas LDA subspace is called as Fisher space. It tries to find a feature subspace that maximizes the discrimination between different classes by increasing the separability between the classes and minimizing in between the classes. In comparison to PCA-LDA is a supervised method. A Supervised method, the trainer provides a category label or cost for each pattern in the training set, or in other words classes of the patterns is already known. In the Unsupervised method, the system tends to forms clusters or groups of the input patterns, or in other words the classes of the patterns not known a prior. The important step in PCA-based face recognition algorithm is based on Karhunen Loeve transformation (KLT) [6]. LDA is advanced to PCA as it provides higher class discrimination by using the class information [7] but the latter one tends to outperform LDA when the number of samples per class is small.

The paper is organized as Section II review of previous approaches. Section III describes the proposed methods PCA with SVD, LDA with EVD and LDA with SVD. The effectiveness of our methods is compared by performing tests using face database. Tests are done; results and comparison have been illustrated in Section IV. Lastly, Section V concludes the proposed algorithms.

II. REVIEW OF THE PREVIOUS APPROACH

This section is about the dimensionality reduction by Principle Component Analysis (PCA) along with Eigen Value Decomposition (EVD).

A. *PCA with EVD*

The PCA using EVD is used for dimensionality reduction to locate the feature vectors which are best suited for the distribution of face images within the whole image space. These vectors help in defining the face images subspace called face space. All faces in the training image set are projected to a low dimensional face space in order to find a set of weights that details the contribution of each vector in the face space. To identify a test image from a group of other images one needs to project the test image onto the face space to obtain the equivalent weights. By comparing the Euclidean distances between the weights of the test image provided along with the set of weights of the faces present in the training set, the face present in the test image can be easily recognized.

The number of eigenfaces that can be possible is equal to the number of face images in the training set. However, the eigenfaces can also be estimated using the best of the eigenfaces based upon those who have the largest eigenvalues, and which thus account for the most variance within the given set of face images. The main important reason for using fewer eigenfaces is computational efficiency. This idea of using eigenfaces was motivated by a technique developed by Sirovich and Kirby [8] for representing pictures of faces using principal component analysis with great efficiency.

B. *Algorithm*

1) Training: Steps to follow at the time of training.

a) First, we start with select a training set which includes a number of face images. Let a face image $I(x, y)$ of N^2 dimension $(N \times N)$ is represented as a column vector of $N^2 \times 1$ dimension. An input data set consisting of M images, therefore be easily mapped to a group of points in the high dimension space called the "face space" as $I_1, I_2, \ldots, I_M$.

b) Next step is to compute the mean of the training set and then normalize the set by subtracting the mean from each face image in the training set.

$$A = \frac{1}{M}\sum_{n=1}^{M} I_n$$

$$\emptyset_i = I_i - A$$

$$C = \frac{1}{M}\sum_{n=1}^{M} \emptyset_n \emptyset_n{}^T$$

where,

$$X = [\emptyset_1, \emptyset_2, \ldots, \emptyset_M]$$

c) Eigen Value Decomposition (EVD): Factorize covariance matrix C in order to compute the Eigenvalues and Eigenvectors of the images, which has a dimension of $N^2 \times N^2$, for typical image size, this size would be an extremely high value. Therefore, we need a more proficient method to find out 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 $(M\text{-}1)$ meaning full eigenvectors, and rest of the eigenvectors will have eigenvalues to be zero and thus can be neglected.

$$(C - \Delta_i I)v_i = 0$$

d) Next choose the eigenvectors corresponding to the highest value in terms of eigenvalues (Λ), which can be done by combining these after sorting from higher to lower we get feature or projection vector.

e) At last, we can now project the each face in the set of the lower dimension and thus reconstruct it as eigenfaces. Each of these

centered training images $\emptyset_i$ is projected onto the eigenspace. In order to project an image onto the eigenspace, calculate the dot product of the image with sorted eigenvectors.
Therefore, the dot product of the image and the eigenvectors will serve as the new vector.

2) Testing: Steps to follow at the time of testing-

a) Each of the test images is first to mean centered by subtracting the mean image.

$$\overline{t_i} = t_i - A$$

b) Then, they are projected into the same eigenspace defined by V.

$$\hat{t_i} = V^T \overline{t_i}$$

We thus get the feature vector of the testing image face.

c) Now, we calculate the Euclidean distance to measure the distance between the projected feature vectors of the test image with projected feature vector of each face image in the training set in "face space".

$$\hat{\Phi}_i = V^T \Phi_i$$

d) Finally, we compare the Euclidean distance, thus showing the face image which has minimum Euclidean distance.

III. Proposed Algorithms

A. PCA Using SVD (Singular Value Decomposition)

Instead of using EVD (Eigenvalue Decomposition), in proposed system we replace step.3 of the previous algorithm with SVD [9] for matrix factorization and to get the feature vectors, to reduce the time of execution without affecting its accuracy percentage so much.

1) SVD Algorithm to find Feature Vectors (Eigenfaces)

These are the following steps:

a) Compute the X^T and X^TX.

b) Determine eigenvalues of X^TX and sort these in the descending order, in the absolute sense. Square roots of these are used to obtain the singular values of X.

c) Construct diagonal matrix S by placing singular values in descending order along its diagonal. Compute its inverse S^{-1}.

d) Use the ordered eigenvalues from the second step and compute the eigenvectors of X^TX. Place these eigenvectors along the columns of V and compute its transpose V^T.

e) Compute $U = XVS^{-1}$ where X is the normalized training set of the order of $M \times N$, V is the Eigenvectors of the order of $N \times N$ and S is the singularity matrix of the order of $M \times N$. Apply SVD on $X = USV^T$. X is expanded into the product of the matrices U, S and V where the columns of U are the eigenvectors of matrix XX^T, the columns of V are the eigenvectors of X^TX and the diagonals S contains the square root of the eigenvalues of both XX^T and X^TX, which are called the singular values of X. For $m < n$ only the first m columns of V are computed and then S is $m \times m$, V is $n \times m$ and U is $m \times m$.

B. LDA Using EVD (Eigen Value Decomposition)

1. Assume we have N samples of m dimensions $x^1, x^2, ..., x^N$, N_1 of which belongs to class ω_1 and N_2 belongs to ω_2. In other words, Each class has Ni m-dimensional samples, where $i = 1, 2, \cdots C$, where C is denoting the number of classes.

2. We seek to obtain a scalar Y by projecting the samples X onto a line (C-1 space, C=2). $Y=W^TX$, where

$$X = [x_1, x_2, \dots x_m]^T$$

and

$$W = [\omega_1, \omega_2, \dots \omega_m]^T$$

3. The mean vector of each class in x and y feature space is:

$$\mu_i = \frac{1}{N_i} \sum_{x \in \omega_i} x$$

4. However, the distance between the projected means is not a very good measure since it does not take into account the standard deviation of the classes. The solution proposed by Fisher is to maximize a function that represents the difference between the means, normalized by a measure of the within-class variability or the so-called scatter.

5. For each class we define the scatter, an equivalent of the variance, as;

$$(s_i)^2 = \sum_{y \in \omega i} (y - \tilde{\mu_i})^2$$

6. Thus this measures the variability within the two classes at hand after projection, hence it is called within-class scatter of the projected samples.

7. The Fisher linear discriminant is defined as the linear function W^TX that maximizes the criterion function:

$$J(\omega) = \frac{|\mu_1 - \mu_2|^2}{((s_1)^2 + (s_2)^2)}$$

8. Therefore, we will be looking for a projection where samples from the same class are projected very close to each other and, at the same time, the projected means are as farther apart as possible.

IV. EXPERIMENT AND RESULTS

In our experiments, we have used a 2.40 GHz Intel i-5 Core computer with 4 GB RAM and the MATLAB version 7.11. We test our algorithms on faces 96 databases. It has a data set of 8 faces each have a size of 80x80 illustrated in Fig 1. And the eigenfaces corresponding to the algorithms by EVD and SVD are shown in Fig 2. & Fig 3, while the fisher-faces by EVD and SVD are shown in Fig 4. & Fig 5. Recognition based on Euclidean distance shown in table 1, we get our recognized image labeled as image 3 for a test image is shown in Fig 6 & Fig 7. respectively.

Fig.1. Training Face Images

Fig.2. Eigen Faces using EVD

Fig.3. Eigen Faces using SVD

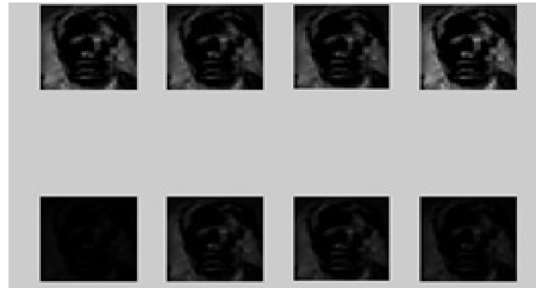

Fig.4. Fisher Faces using EVD

Fig.5. Testing Face

Fig.6. Recognized Face

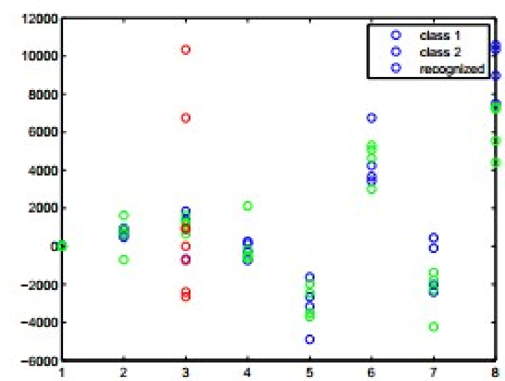

Fig.7. Class discrimination using PCA

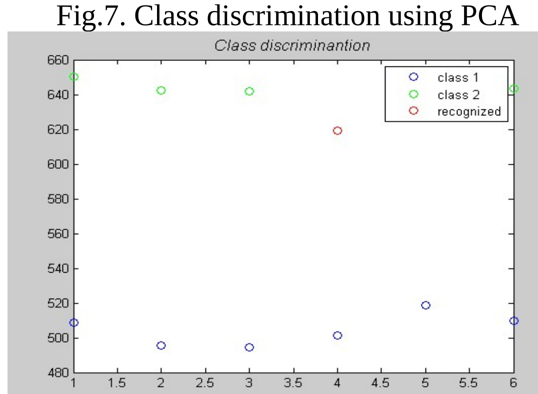

Fig.8. Class discrimination using LDA

Table 1: Euclidean Distances

Image No.	EVD	SVD	LDA
Image 1	1831.8	2951.7	398.4
Image 2	1999.9	3281.5	81.80
Image 3	1397.5	2265.1	15.7
Image 4	1920.4	3132.2	294.7
Image 5	1764.6	2861.6	1014.5
Image 6	3158.5	5112.4	1744.9
Image 7	2353.1	4123.9	1485.9
Image 8	3454.7	5569.8	1230.4

Table 2: Time for execution (in sec)

EVD	SVD	LDA
455.4520	4.4170	400.11

Table 3: Accuracy

EVD	SVD	LDA
87.5	75	37.5

V. Conclusion

In this paper work, we concluded that PCA using SVD is much faster than other approaches at the cost of some accuracy rate by judging table 2 and 3.

Thus, we have the following two plots:-

A. Execution time required in seconds Fig.10, to successfully run the face recognition algorithm.

B. Accuracy Fig.11.

These two plots show graphically how one technique is superior to other and in what terms, thus giving us a better overall picture of different face recognition Techniques.

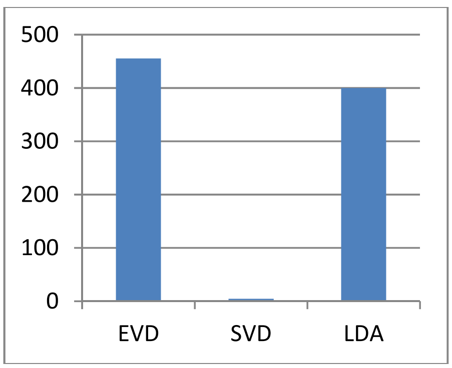

Fig.9. Plot of execution time

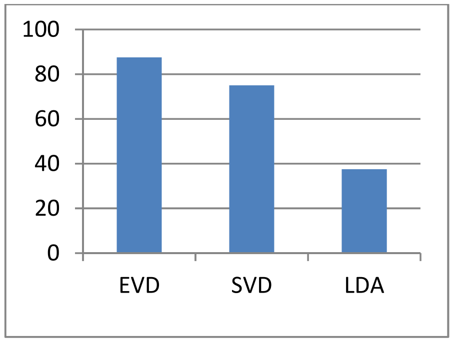

Fig.10. Plot of accuracy

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