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Face Recognition by Using Distance Classifier Based On PCA and LDA

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ABSTRACT— Numerous method have been developed for holistic face recognition with impressive performance. It has become one of the most challenging tasks in Biometrics. Among different biometric traits, face and palm print recognition receive great amount of attention in the past decade. They can get high recognition rate. Feature representation and classification are two key steps for face recognition. This paper deals with a face recognition method using Distance classifier based on Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). A novel method for face recognition was presented based on combination of PCA& LDA. The Principal Component Analysis was used for feature extraction and dimension reduction. Linear Discriminate Analysis was used to further improve the separability of samples in the subspace and extract LDA features. The normalization had been done to eliminate redundant information interference previous to feature extraction. The experiments were implemented by using ORL face database. Comparing PCA, LDA and Distance Classifier, our approach is to improve the face recognition rate.

KEYWORDS- Face recognition, PCA, LDA, Distance Classifier, Recognition rate.

I. INTRODUCTION

Face is a complex multidimensional structure and needs good computing techniques for recognition. The face is our primary and first focus of attention in social life playing an important role in identity of individual. We can recognize a number of faces learned throughout our lifespan and identify that faces at a glance even after years. There may be variations in faces due to aging and distractions like beard, glasses or change of hairstyles .Face recognition is an integral part of biometrics. In biometrics basic traits of human is matched to the existing data and depending on result of matching identification of a human being is traced. Facial features are extracted and implemented through algorithms which are efficient and some modifications are done to improve the existing algorithm models. Face recognition algorithms are used in a wide range of applications viz., security control, crime investigation, and entrance control in buildings, access control at automatic teller machines, passport verification, identifying the faces in a given database [1], [2]. The Eigen face is the first method considered as a successful technique of face recognition. The Eigen face method uses Principal Component Analysis (PCA) to linearly project the image space to a low dimensional feature space [3], [4]. The Fisherfaces is an enhancement of the Eigen face method. The Eigen face method uses PCA for dimensionality reduction, thus, yields projection directions that maximize the total scatter across all classes, i.e. across all images of all faces. In PCA ,preprocessing techniques could be used after that feature extraction . Instead, the Fisherfaces method uses Fisher's Linear Discriminant Analysis (FLDA or LDA) which maximizes the ratio of between-class scatter to that of within-class scatter [5].

At one level, PCA and LDA are very different: LDA is a supervised learning technique that relies on class labels, whereas PCA is an unsupervised technique. LDA has been compared to PCA in several studies [6], [7], [8]. One characteristic of both PCA and LDA is that they produce spatially global feature vectors. In other words, the basis vectors produced by PCA and LDA are non-zero for almost all dimensions, implying this change to a single input pixel, will alter every dimension of its subspace projection. As we know that any image or face has size n x m pixels which require name dimensional space. This space is too large and needs to be reduced for better recognition which is achieved by dimensionality reduction techniques [1]. We have two most popular techniques for these purposes that are principal component analysis (PCA) and linear discriminant analysis (LDA) [7]. For better performance we have implemented these two algorithms with several preprocessing factors such as gray scale conversion and modified histogram equalization before recognition algorithms. The aim of this paper is to study the performance of the PCA and LDA with respect to face recognition rate and dimensionality. Considering for small training data set, we have designed the both algorithms for face recognition.

The organization of this paper is done in six sections. Section II describes the preprocessing methods performed on facial images. Section III Describes introduction to PCA and its mathematical derivation and discuss LDA and the related mathematical analysis and results and conclusion are presented in section V & VI respectively.

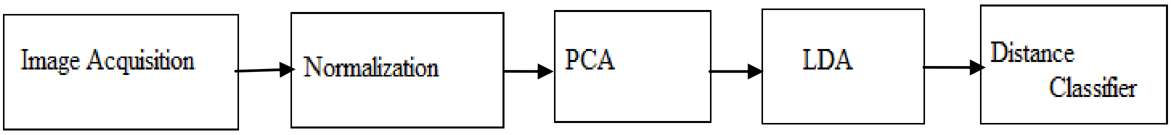

Fig.1 Face recognition block diagram

II. FACE IMAGES NORMALIZATION

In general, the parts of a face image such as hair, neck, shoulders and background are regarded as redundant information for the face recognition system. Furthermore, images are often affected by various factors, such as illumination, image size, face rotation, changes in facial expression, etc. All above factors would cause difficulties for face recognition and lead to the recognition rate dropped, so face normalization must be carried out previous to facial feature extraction. The normalization includes geometric normalization, face image correction, gray balance, etc. Our experiments were completed on ORL face database and only geometric normalization was performed as Fig. 2. Face recognition is mainly for feature extraction and classification and in further form we are going to discuss about PCA and LDA, that's is feature extraction techniques and here I have discussed about distance classification method. After this normalization process the feature extraction and classification will be carried out according to the block diagram shown in figure 1.

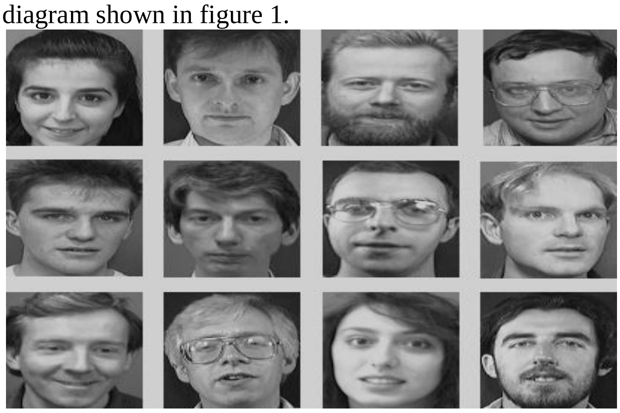

Fig. 2 Some Sample Images From The ORL Database

II. FEATURE EXTRACTION

Here PCA and LDA are used as preprocessing techniques from the original face images. PCA and LDA produce feature vectors in a reduced dimension.

A. Principle Component Analysis

PCA is a feature extraction technique used to approximate the original data with lower dimensional feature vectors. The face image of PCA algorithm is seen as a random vector. When the subspace orthogonal bases are arranged as image array, they will show the shape of faces, so orthogonal bases are called eigenfaces. [1] The Eigen faces of our experiments are shown as Fig. 3. Where 40 largest Eigen value were adopted to form Eigen face. PCA Eigen face is particularly suitable to reconstruct the Images. Principle Component Analysis (PCA) is a dimensionality reduction technique that is used for image recognition and compression. It is also known as Karhunen-Loeve transformation (KLT) or eigenspace projection.

Calculation of Eigenfaces

Let a face image I(x, y) be a two-dimensional N x N array of 8-bit intensity values. So that typical image of size 256 x 256 becomes a vector of dimension 65,536, or equivalently a point in 65,536-dimensional space. An ensemble of images, then, maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principal component analysis (or Karhunen-Loeve expansion) is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space" describes an N x N image, and is a linear combination of the original face images. Because these vectors are the Eigen vectors of the covariance matrix corresponding to the original face images, and they are face-like in appearance, we refer to them as "Eigen faces".

Definitions:

An N x N matrix A is said to have an eigenvector X, and corresponding eigenvalue λ if

$$AX = \lambda X. \quad \text{---------- (1)}$$

Evidently, Eq. (3.1) can hold only if

$$\det \left| A - \lambda I \right| = 0 \quad \text{---------- (2)}$$

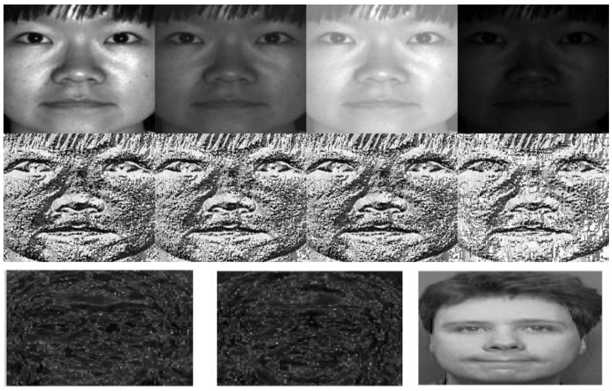

Fig. 3 Standard Eigen Face

Which, if expanded out, is an N^{th} degree polynomial in λ whose root are the eigenvalues. This proves that there are always N (not necessarily distinct) eigenvalues. Equal eigenvalues coming from multiple roots are called "degenerate".

A matrix is called *symmetric* if it is equal to its transpose,

$$A = A^{T} \text{ or } a_{ij} = a_{ji} \quad \text{----------- (3)}$$

It is termed *orthogonal* if its transpose equals its inverse,

$$A^{T} A = AA^{T} = I \quad \text{----------- (4)}$$

Finally, a real matrix is called *normal* if it commutes with is transpose,

$$A^{T} A = AA^{T} \quad \text{----------- (5)}$$

Eigenvalues of a real symmetric matrix are all real. Contrariwise, the eigenvalues of a real nonsymmetrical matrix may include real values, but may also include pairs of complex conjugate values. The eigenvalues of a normal matrix with no degenerate eigenvalues are complete and orthogonal, spanning the N dimensional vector space. After giving some insight on the terms that are going to be used in the evaluation of the Eigenfaces, we can deal with the actual process of finding these Eigenfaces. Let the training set of face images be $\Gamma_1\ \Gamma_2 \ldots\ldots\ldots\ldots \Gamma_{M,}$ then the average of the set is defined by each face differs from the average by the vector. This set of very large vectors is then subject to principal component analysis. The evaluation of the eigenvalues and eigenvectors of the real symmetric matrix L that is composed from the training set of images.

B. Linear Discriminant Analysis

Linear Discriminant analysis or Fisherfaces method applies the fisher's linear discriminant criterion to overcome the limitations of eigenfaces method, which tries to maximize the ratio of determinant of between classes to the determinant of the within-class scatter matrix of the projected samples. Grouping images of the same class, while separating the images of different classes take place due to the fisher discriminant. Projection of face images on fisher space converts its dimension from N2-dimensional space to C dimensional space (where C is the number of classes of images). For example, two sets of points are considered in 2-dimensional space projected onto a single line hence depending on the direction the points are either mixed (Fig. 4a) or separated (Fig. 4b). The fisher discriminate to find the line which best separates the points i.e., in order to identify the input test image, the comparison of the projected test image with each training image takes place after which the test image as the closest training image can be identified [5], [6], [14].

Along with eigenspace projection, the training images are also being projected into a subspace. The test images being projected at the same subspace can be identified using a similarity measure and the only difference is the way in the subspace calculations take place. The PCA method is used to extract features which represents face image and the LDA method discriminates different face classes in order to find the subspace. It is based on with in class and between class matrix values. By defining all instances of the same person’s face as being in one class and the faces of different subjects as being in different classes for all subjects in the training set, we establish a framework for performing a cluster separation analysis in the feature space. Also, having labeled all instances in the training set and having defined all the classes, we compute the within-class and between-class scatter matrices. Now with-in class scatter matrix ‘S_w’ and the between class scatter matrix ‘S_b’ is defined as follows: Calculate Within-Class Scatter Matrix S_W, Calculate Between-Class Scatter Matrix S_b, Calculate the Eigen vectors of the projection matrix.

Calculate Within-Class Scatter Matrix S_W:

$$S_B = \sum_{i=1}^{c} N_i (\square_i - \square)(\square_i - \square)^T \quad \text{----- (6)}$$

The with class scatter matrix represents how face images are distributed closely with-in classes and between class scatter matrix describes how classes are separated from each other. When face images are projected into the discriminant vector W

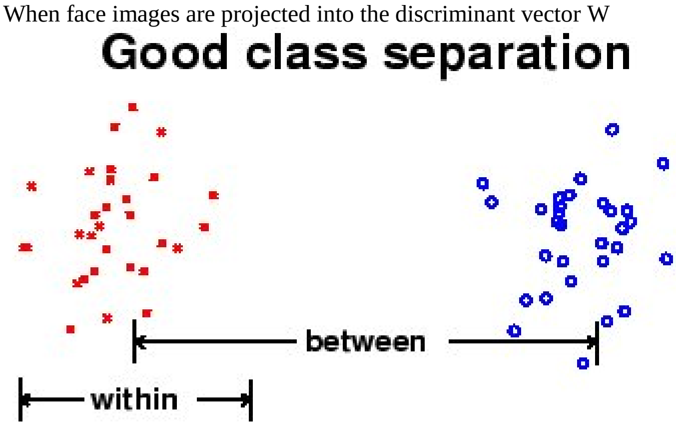

Fig. 4 Class Separations in LDA

Calculate Between-Class Scatter Matrix S_b:

$$S_W=\sum_{i=1}^{c} \sum_{Xk \in Xi}^{c} (X_K - \square_i)(X_K - \square_i)^T \text{------ (7)}$$

S_b is the between-class scatter matrix, representing the scatter..The between-class scatter matrix also called the extra personal represents variation in appearance due to difference in identity of the conditional mean, vectors around the overall mean vector m. The LDA approach being similar to the Eigenfaces method uses projection of training images into subspace. The test images are projected into the same subspace and identified using a similarity measure. The only difference is the method of calculating the subspace characterizing the face space. The face which has the minimum distance with the test face image is labeled with the identity of that image. The minimum distance can be calculated using the Euclidian distance method as given in earlier Equation.

$$S_B=\lambda\, S_W W \qquad \text{----------- (8)}$$

Then,

$$W= \text{eig}\,(S_W^{-1} S_B) \qquad \text{------------ (9)}$$

It is a class specific method LDA maximizes the between – class scattering matrix measure while minimizes the within – class scatter matrix. It makes it more reliable for classification.

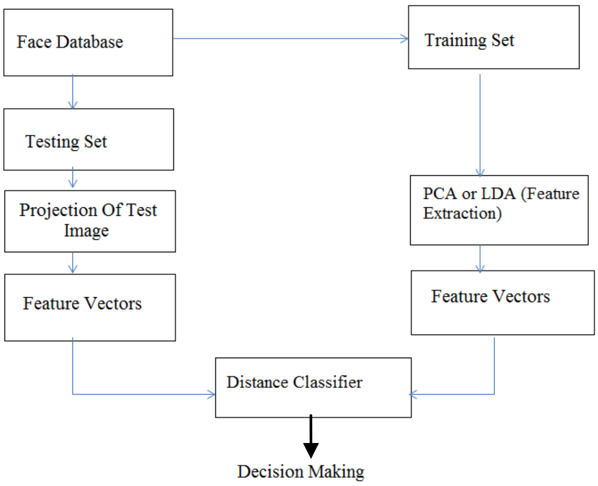

Fig.5 Flowchart for PCA and LDA approach for face Recognition

III. PROPOSED METHOD

The performance of PCA and LDA is limited. First of all, the image preprocessing steps are carried out on the images for improving performance of algorithms. Then by applying principle component analysis and linear discriminant analysis, face recognition is done. Further the performance of PCA and LDA based algorithms was evaluated with respect to face recognition rate and dimensionality. Now we propose the distance classifer to get better recognition rate By Using Trained & Tested Feature Values in PCA and LDA, Distance Calculation is Carried Out.

$$D = - (x*y)/(\text{norm\_x}*\text{norm\_y}) \qquad \text{----------------(10)}$$

V. RESULTS AND DISCUSSION

The ORL database contains images from 40 individuals, each providing 10 different images. For some Subjects, the images were taken at different times. The facial expressions (open or closed eyes, smiling or non smiling) and facial details (glasses or no glasses) also vary.. All images are grayscale and normalized to a resolution of 92 x 112 pixels. are tabulated on Table 1, First of all the image preprocessing steps are carried out on this database and then PCA and LDA are implemented simultaneously, PCA+LDA algorithms and various feature dimension. Remaining 5 images for testing in this experiment we are vary on class 5-40 class, according to this experiment results ORL is a face database of 40 individuals, 10 face images for everyone. 5 images among the 10 images of every one were In this experiment we are used 40 subjects each subject have 10 different images for a same person, during first experiment we give 5 images for train the system, that is train data set, taken to compose training samples and the rest 5 ones. We presented a face recognition method based on Distance classifier combined with PCA+LDA feature extraction. We implemented experiments on ORL face database. First, face images normalization had been done, then PCA for dimension reduction, LDA for feature extraction and distance for classification. The experimental results showed that PCA+LDA+ distance classifier method had a higher recognition rate than the other methods for face recognition. Table 1, 2 illustrates about various feature dimension based on their recognition rate

TABLE 1
RECOGNITON RATE WITH DIFFERENT TRAINING SAMPLES AND VARIOUS FEATURE DIMENSION

Dimension \ **Training Samples**		2	3	4	5	6	7	8
PCA+LDA	20	0.759	0.814	0.835	0.835	0.869	0.933	0.938
	40	0.684	0.879	0.917	0.930	0.956	0.983	0.950
PCA	20	0.638	0.714	0.721	0.820	0.825	0.86	0.875
	40	0.65	0.732	0.738	0.85	0.856	0.867	0.9

TABLE 2
RECOGNITON RATE WITH VARIOUS FEATURE DIMENSION

Feature Dimension	5	10	15	20	25	30	35	40
PCA+LDA	0.635	0.780	0.845	0.835	0.890	0.895	0.900	0.930
LDA	0.605	0.740	0.800	0.820	0.830	0.840	0.845	0.850

5 Training Sample Face Images per person

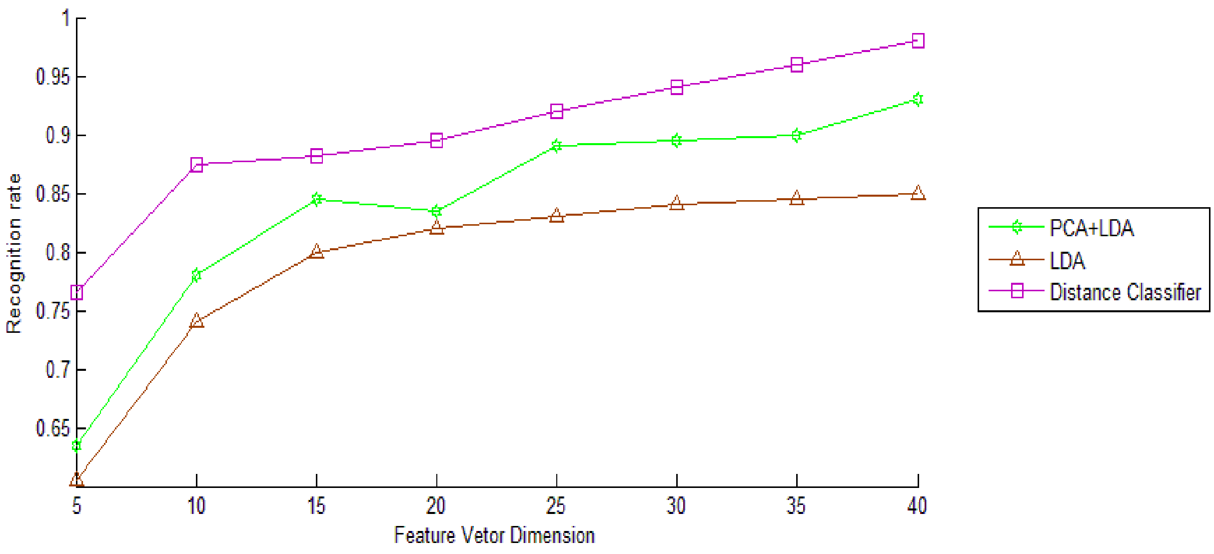

Fig. 6 Curves of Recognition Rate against Feature Vector Machine

VI. CONCLUSION

Judging from Table I the recognition rate increases with the training sample size for both the PCA method and LDA method. That shows that the more the number of training samples, learning more fully, the higher the recognition rate. It is shown from Table 2 and the Figure 6 that the recognition rate increases with the feature vector dimension too. When the dimension change, the recognition rate increases slowly. At the same time we can conclude that the PCA and LDA combination method improved recognition rate compared with alone PCA method and also by using distance classifier the recognition rate will be increased .so,in future work by comparing with other classifiers. we are trying to improve the recognition rate and their performance metrics.

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