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Evaluation of PCA and LDA techniques for Face recognition using ORL face database

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Abstract-- **In this paper, we present a face recognition system that identifies a person from the input image given, for authentication purposes. As a feature extraction technique, Linear Discriminant Analysis (LDA) is used. After the generation of features, the classification is performed using Euclidean Distance classifier. Recognition rates are calculated for varying sizes of training data and corresponding test data. The data set is the ORL face database which is a standard face database for face recognition systems. The database consists of 400 images of 40 people with 10 different poses for each individual. Towards the end, experimental results show a high recognition rate of 93.7% obtained by the use of LDA feature set**.

Keywords-- Face recognition, Liner Discriminant Analysis, Principal Component Analysis, Image processing

I. INTRODUCTION

Face recognition is a universally important paradigm under pattern recognition with many applications moving towards the use of facial features for authorization and authentication. This is due to the fact the facial features are simpler to obtain than that of other biometrics such as the iris or fingerprints. The algorithms in face recognition systems extract the set of facial features to be projected on to a feature space for comparison and recognition. Some algorithms normalize and compress the images and store only the useful information for recognition. Other techniques involve three dimensional sensors to capture the shape of facial features in addition to size and relative position. Face recognition can be used in two kinds of application: 1) Identification and 2) Authentication. Since people can hide their faces or undergo surgeries for facial alteration, it is more beneficial to use face recognition system for authentication where the image taken from the subject can be compared against images in a database to allow access to the system. However Face recognition is susceptible to changes in the environment such as lighting and problems of blur. The problem of Gender recognition is particularly challenging, as many females are falsely identified as males in face recognition. Improving gender recognition rates will help the overall efficiency of the face recognition system.

The paper is organized as follows. In Section II, a brief note on face recognition systems and the background studies undertaken is presented. In Section III, the feature extraction techniques of PCA and LDA the second of which is used in the proposed system are discussed. In Section IV the classification methods are defined. In Section V, the experiments and results are described. Finally, in Section IV, the conclusion and future research direction are discussed.

II. BACKGROUND STUDIES

Face recognition system consists of four steps, as shown in Fig.1 Image acquisition, pre-processing, feature extraction and classification as known or unknown [18].

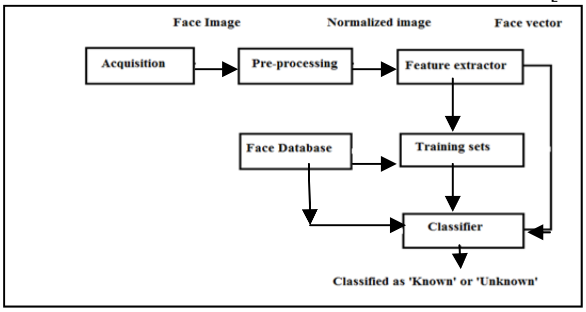

Fig.1 Face recognition system

Many methods have been developed and presented to improve face recognition systems. K.C.Lee et al.[2] presented a paper that shows how to arrange physical lighting so that the acquired images of each object can be directly used as the basis vectors of a low-dimensional linear space and that this subspace is close to those acquired by the other methods. R.Gopalan et al.[4] show that the corresponding subspaces created from a clean image and its blurred versions are equal under the ideal case of zero noise and some assumptions on the properties of blur kernels. Masashi Nishiyama et al.[5] constructed a feature space such that blurred faces degraded by the same PSF (Point Spread Function) are similar to one another and learn statistical models that represent prior knowledge of predefined PSF sets in this feature space. Timo Ojala et al.[6] derive a generalized gray-scale and rotation invariant operator presentation that allows for detecting the ªuniformº patterns for any quantization and presents a method for combining multiple operators for multi-resolution analysis. Soma Biswas et al.[9] presented a non stationary stochastic filtering framework for the task of albedo estimation from a single image. Margarita Osadchy et al.[10] show that the surface characteristics determine the type of image comparison method that should be used. Anat Levin et al.[11] presented a paper that analyzed and evaluated recent blind de-convolution algorithms both theoretically and experimentally. Blind de-convolution is the recovery of a sharp version of a blurred image when the blur kernel is unknown. Turk and Pentland [12] presented face recognition by eigenfaces which are the eigenvectors of the set of faces; they do not necessarily correspond to isolated features such as eyes, ears, and noses. The framework provides the ability to learn to recognize new faces in an unsupervised manner. Jian Yang et al.[13] presented a new technique, coined two-dimensional principal component analysis (2DPCA) based on 2D image matrices rather than 1D vectors so the image matrix does not need to be transformed into a vector prior to feature extraction. Ahonen. T et al.[14] presented a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. Wright. J, Yang et al. [15] used sparse representation computed by C^1-minimization to propose a general classification algorithm for (image-based) object recognition. Wiskott.L et al [16] presented a system where Image graphs of new faces are extracted by an elastic graph matching process and can be compared by a simple similarity function to identify human faces. Xiaofei He et al. [17] proposed an appearance-based face recognition method called the Laplacianface approach. By using Locality Preserving Projections (LPP), the face images are mapped into a face subspace for analysis. The Laplacianfaces are the optimal linear approximations to the eigenfunctions of the Laplace Beltrami operator on the face manifold. In this way, the unwanted variations resulting from changes in lighting, facial expression, and pose may be eliminated or reduced.

III. Feature Extraction Methods

The image based face recognition has classified into Appearance-based face recognition and Model-based face recognition[18]. Model based approaches involve 2D or 3D models; under which is the creation of 3D morphable model that is constructed to capture facial variations [3]. Appearance based face recognition further classified into linear and non-linear analysis. Linear analysis methods, the face vectors can be projected to the basis vectors. Through the projecting from a higher dimensional input image space to a lower dimensional space, dimensionality of original input image space is reduced [18].

PCA is a linear transformation also known as Karhunen-Lo`eve transformation which captures the variance of the input data. In PCA, the first-axis will contain highest variance, the second-axis contain the second highest, and so on. PCA is an unsupervised method that does not have any knowledge of class labels. PCA is used for dimensionality reduction and is a preferred tool for data analysis. It removes redundancy and compresses data

This paper involves the use of Linear Discriminant Analysis for the feature extraction. LDA is also a linear transformation technique that is similar to PCA except that LDA implicitly also finds within and outside class differences. i.e. it is a supervised method .

i. Computation of the n- dimensional mean values $\varphi_1 \ldots\ldots \varphi_n$ for the different classes
ii. Computation of differences in (a) within class and (b) outside class
iii. Computation of eigenvectors and eigenvalues
   a. If A is a square matrix, a non-zero vector **v** is an eigenvector of A if there is a scalar λ (eigenvalue) such that $Av=\lambda v$
iv. Formation of n x m dimensional matrix K that consist of m eigenvectors that have the largest eigenvalues.
v. The matrix K transforms the samples on to the new subspace.
   a. It is given by the equation

$C = K^T$ x d where d is a n x 1 – dimensional vector representing a sample (1)

IV. Classification Methods

A. The nearest distance criteria

The nearest distance criterion is the simplest form of classification criteria. According to this criterion, the distance between the test sample y and its training sample y_i is given by

$$\text{Distance} = \sum_{n=1}^{m} |y(n) - y_i(n)| \quad (2)$$

B. The Euclidean distance criteria

According to the Euclidean distance criteria, the distance between, the test sample y and its training sample y_i is given by

$$\text{Distance} = \sum_{n=1}^{m} (y(n) - y_i(n))^2 \quad (3)$$

This paper applies the Euclidean distance criteria for the classification in the face recognition system that gives a better classification than nearest distance criteria

V. Experimental Results

The face recognition system is developed in MatLab 7.0 and implemented in a desktop PC consisting of Intel (R) Core (TM) i3 processor of 2.13GHz CPU and 2 GB RAM. The ORL face database which is the standard database for face recognition system is used to analyze the performance of the developed system. The ORL face database consists of 400 images of 40 people/classes with 10 poses for each individual. The dataset is divided into that of training and test images. The varying sizes of the testing dataset involves 360 images with 1 pose count for training, 320 images with 2 post counts for training and 280 images with 3 pose counts for training. The recognition rates are calculated and summarized in the table I. This is compared against the data summarized for PCA feature selection by Ergun Gumus et al [1]. We have calculated the weighted mean for the Recognition Rate and arrived at 85.9% for LDA feature set. Fig.2 gives the output of the system depicting the input/test image and the recognized image.

Table I. Recognition Rates According To Pose Count In Training

Technique	Pose Count for training images / Number of testing images			Weighted Mean (%)
	1/360 (%)	*2/320 (%)*	*3/280 (%)*	
PCA- ND	54.7	71.2	82.1	69.3
LDA - ED	82.5	85	90.3	85.9

The Fault Rejection Rate (FRR) is the rejection of an image when an image not present in the database is given as the input. Table II gives the comparison between the FRR of PCA and LDA.

Test Image

recognized Image

Fig.2 Face recognition system output

TABLE II. FRR OF PCA AND LDA

Technique	Fault Rejection rate *(%)*
PCA- ND	82
LDA - ED	100

Table III below gives the recognition rates obtained for larger number of training data of sizes 280, 320 and 360 images. Calculating the weighted mean, we arrive at a recognition rate of 93.7% using LDA feature set.

TABLE III. RECOGNITION RATES ACCORDING TO TRAINING IMAGES

Technique	Number of training images			Weighted Mean (%)
	360 (%)	*320 (%)*	*280 (%)*	
LDA - ED	95	93.75	92.5	93.7

Test Image

recognized Image

Fig.3 False drop of female image (ID= 35)

VI. CONCLUSION

The face recognition system developed in this paper using MATLAB 7.0 identifies a person from the input image given for authentication purposes. As a feature extraction technique, Linear Discriminant Analysis (LDA) is used. After the generation of features, the classification is performed using Euclidean Distance classifier. Recognition rates are calculated for varying sizes of training data which involves 280, 320 and 360 training images and corresponding test images. The data set is the ORL face database which is a standard face database for face recognition systems. The database consists of 400 images of 40 people with 10 different poses for each individual. Experimental results show a high recognition rate of 93.7% obtained by the use of LDA feature set.

As future work, we can build a system that recognizes an image from input images where only certain parts of the face are visible such as just above the nose. Hybridization of feature extraction techniques and classification techniques may be applied to bring about high recognition rates and gender recognition rates. Our results indicate that the use of LDA feature set provides better recognition rates than that of PCA feature set.

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