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Improving Gender Recognition Rate in Face Recognition System Based On Linear Discriminant Analysis Technique

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Abstract: In this paper, we present a face recognition system that is used for identity authentication. An image is given as input to the system by the user; this is matched against the images in the database and identity is resolved. The main metric for the system is the Gender recognition rate calculated for varying sizes of testing and training dataset. This metric is determined for the identification female individuals of the ORL face database that consists of 400 images of 40 people in 10 poses. The Euclidean distance classifier is used for matching the features that are generated by Linear Discriminant Analysis technique of feature extraction. The system is tested under problems of blur and illumination. Towards the end, experimental results show a recognition rate of 72% and 96.1% for female and male individuals respectively. Experimental results also show a recognition rate of 91.5% for real time images.

Keywords: Face recognition; Gender recognition rate; Liner Discriminant Analysis; Real time images; Image processing; ORL face database

I. INTRODUCTION

Face Recognition is an extensively researched area in pattern recognition primarily due to its many commercial applications. The acquisition of the image can be non intrusive in the case of an face verification system such as video-surveillance and is easy to obtain. Face identification systems deal with problem of identity authentication. The user submits to the system, a real time image of their face and declares their identity. This is checked against the data in the database through feature matching. Many popular techniques for face recognition systems exist. These face recognition algorithms are basically classified as 2D and 3D technique. The 2D algorithms encompass linear techniques of Principal Component Analysis, Linear Discriminant Analysis, Incremental component Analysis non linear techniques of Kernal Principal Component Analysis and IsoMap. 3D techniques are based on 3D morphable model were a 3D image of the person's face is constructed for recognition applicationsPage Layout

The paper is organized as follows. In Section II, the background studies undertaken are presented. In Section III, gives the methodology followed for development of the system including notes on the feature extraction technique of LDA and the Euclidean distance classification method. In Section IV, the experiments and results are described. Finally, in Section V, the conclusion and future research direction are discussed.

II. BACKGROUND STUDIES

This section presents the background studies conducted for this paper. As described earlier, Face recognition is extensively researched area and many techniques exist. Some of them involve the use of multi-resolution wavelet transform for the extraction of features as presented by Jen-Tzung Chien et al.[1]. The nearest feature plane (NFP) and nearest feature space (NFS) classifiers are explored for robust decisions in presence of wide facial variations [1]. Ming-Hsuan Yang investigated the use of Kernel Eigenface and kernel Fisherface methods that provide generalizations which take higher order correlations into account [2]. Li et al. proposed classification method called Nearest feature Line (NFL) for face recognition that generalizes any two feature points of the same class by a feature line passing through the points to capture more variations of face images [2]. Wenyi Zhao et al. proposed a method that combines PCA and LDA for classification. The method consists of two steps: first we project the face image from the original vector space to a face subspace via PCA, second we use LDA to obtain a linear classifier. The basic idea of combining PCA and LDA is to improve the generalization capability of LDA when only few samples per class are available [3]. Lawrence et al. presented a hybrid neural-network for human face recognition that combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. They presented results using the Karhunen-Loeve transform in place of the SOM, and a multilayer perceptron (MLP) in place of the convolutional network for comparison [4].

Jianxin Wu et al. suggested the use of one training image per person by applying an extension of the eigenface technique, i.e. projection-combined principal component analysis, $(PC)^2A$. This technique combines the original face image with its horizontal and vertical projections and then performs principal component analysis on the enriched version of the image. It requires less computational cost than the standard eigenface technique and experimental results show that on a gray-level frontal view face database where each person has only one training image, $(PC)^2A$ achieves 3–5% higher accuracy than the standard eigenface technique through using 10–15% fewer eigenfaces [5]. Baback Moghaddam et al. proposed a technique for direct visual matching of images for the purposes of face recognition and image retrieval, using a *probabilistic* measure of similarity, based primarily on a Bayesian (MAP) analysis of image differences [6]. G. C. Feng et al. proposed a sub-band approach in using PCA—apply PCA on wavelet sub-band. Here wavelet transform is used to decompose an image into different frequency sub-bands, and a midrange frequency sub-band is used for PCA representation. In comparison with the traditional use of PCA, the proposed method gives better recognition accuracy and discriminatory power [7].

Guodong Guo et al. proposed the use of Support Vector Machines (SVM) with a binary tree recognition strategy to tackle the face recognition problem. They illustrated the potential of SVM on the Cambridge ORL face database, which consists of 400 images of 40 individuals, containing quite a high degree of variability in expression, pose, and facial details [8]. Imran Naseem et al. presented a novel approach of face identification by formulating the pattern recognition problem in terms of linear regression. Using a fundamental concept that patterns from a single-object class lie on a linear subspace, they develop a linear model representing a probe image as a linear combination of class-specific galleries [9]. Zhiming Liu et al. presented a recognition method by means of fusing color, local spatial and global frequency information. Specifically, the proposed method fuses the multiple features derived from a hybrid color space, the Gabor image representation, the local binary patterns (LBP), and the discrete cosine transform (DCT) of the input image [10]. Brendan Klare et al. proposed a method of heterogeneous face recognition that uses a common feature-based representation for both NIR images as well as VIS images. Linear discriminant analysis is performed on a collection of random subspaces to learn discriminative projections. NIR and VIS images are matched (i) directly using the random subspace projections, and (ii) using sparse representation classification [11]. Baochang Zhang et al. proposed an object descriptor, histogram of Gabor phase pattern (HGPP) for robust face recognition [12].

III. METHODOLOGY

a) Face Recognition System

Face recognition involves input detection, preprocessing, feature extraction and classification. The input to the system is taken from the standard ORL face database consisting of 400 images of 40 people in 10 poses These images were collected from April 1992 and April 1994, a project in collaboration with Cambridge University. Fig.1. gives sample images from the ORL face database.

Fig 1. Sample images from the ORL face database

Another input to the system are a dataset of 100 real times images of 10 people in 10 poses collected to test the real time application of the system. Fig.2. gives a sample shot of the images in the real time dataset.

Fig 2. Sample images from real time dataset

To evaluate the performance of the system under problems of blur and illumination, the input images are given to the system in a blur or illuminated manner. These images are normalized in the preprocessing step. The input images/ test data are taken from the standard ORL face database for initial evaluation followed by the use of images taken in real time for evaluation. The system is then developed and evaluated with the combination of Linear Discriminant Analysis in the feature extraction step and Euclidean Distance classifier in the feature matching step.

b) Linear Discriminant Analysis

Title Linear Discriminant Analysis is used for the extraction of features from the image. LDA is a supervised linear feature extraction technique. LDA is similar to PCA except that it computes differences within the class and also outside the class. LDA is primarily used for dimensionality reduction.

LDA involves the computation of the following matrices for a given image. These include

- m- dimensional mean values of different classes
- Scatter matrices. These highlight the differences between various classes. Used for computing within and outside class differences.
- Eigen vectors and their corresponding Eigenvalues
- m x n dimensional matrix X that consists of n eigenvectors that have the largest eigen values.
- $C = X^T \text{ x } y$ (1)

, where y is a *n* x *1* – dimensional vector for transformation of samples on to a new space.

c) Euclidean Distance Classifier

Euclidean distance classifier is used for the classification step in the face recognition system that is developed in this paper. The formulae are presented below.

$$\text{Distance} = \sqrt{\sum_{i=1}^{j}(f(i) - f_m(i))^2} \quad (2)$$

Alternatively this distance can be calculated as the squared Euclidean distance given below.

$$\text{Distance}^2 = \sum_{i=1}^{j}(f(i) - f_m(i))^2 \quad (3)$$

The Euclidean distance can also be calculated for more than one dimension.

IV. Experimental Results

The 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 consists of images of 40 people, out of which images 4, 5, 31, 34 are that of women. Fig.3. Gives the output of the face recognition system for woman with ID: 4 and man with ID: 2

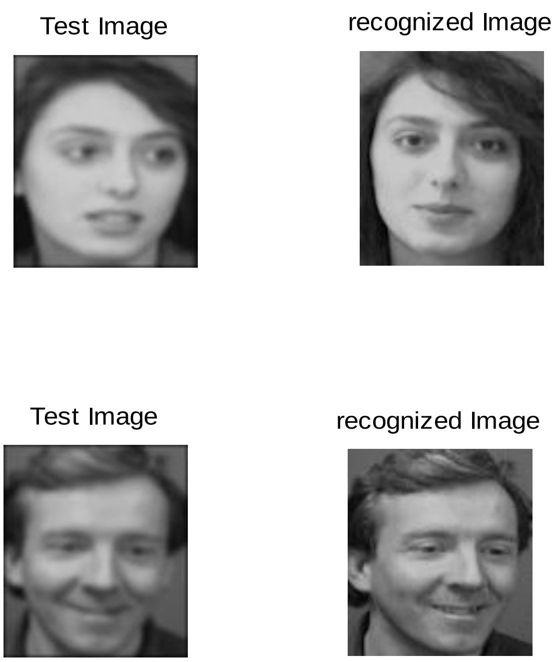

Fig 3. Face recognition system output for female (ID: 4) and male (ID:2)

Face recognition of women may lead to false drops where in the input image of the women is recognized as that of a man from the image database. This false drop is summarized in the table I below and depicted in Fig.4 The notation used is X^y where X is the image ID and y is the number of times that image X is obtained as the recognized image. For the women with image ID 10 as the input image the recognized image for 280 training images is image 2 and image 37 each occurring once. The leads to the gender recognition rates as summarized in table II for the varying number of training images. The Gender recognition obtained by the system is 72% for female individuals and 96.1% for male individuals.

Fig 4. False drop of female (ID: 34) with male (ID: 39)

TABLE I
False drops of female individuals according to number of training images

Image ID	**Number of training images**		
	360	***320***	***280***
4	-	-	-
5	2^1	2^1	2^1, 37^1
31	-	-	-
34	7^1	7^1	7^1 ,39^1

TABLE II
Gender Recognition rate according to number of training images

Recognition Rates	**Number of training images**			**Weighted Mean (%)**
	360 (%)	***320 (%)***	***280 (%)***	
Female Recognition Rate	75	75	66.6	72
Male Recognition Rate	97.2	95.8	95.3	96.1

Real time images can be submitted to the face recognition system which recognizes the identity of the person by feature matching with those images in the database. For this experiment, images of 10 students in 10 poses totaling 100 images were collected. The input image is presented to the system which employed LDA feature extraction technique. Fig.5. gives the output of the system for real time images. The results are summarized in table III. Use of normalized images in training helped to improve the recognition rates. The weighted average obtained was 91.5%.

TABLE III
Recognition rates of real time images

Technique	**Number of testing images**		**Weighted Mean (%)**
	80 (%)	***90(%)***	
LDA - ED	93	90	91.5

Test Image

recognized Image

Fig 5. Output (right) of real time images for test image (left)

V. CONCLUSION

The face recognition system is developed for identity authentication using MATLAB 7.0. An image is given as input to the system via webcam by the user; this is matched against the images in the database and identity is resolved. The Gender recognition rate calculated for 360, 320 and 280 training images. This metric is determined for the identification female individuals and the male individuals of the ORL face database that consists of 400 images of 40 people in 10 poses. The Euclidean distance classifier is used for matching the features that are generated by Linear Discriminant Analysis technique of feature extraction. The system is tested under problems of blur and illumination. Experimental results show a recognition rate of 72% and 96.1% for female and male individuals respectively. Experiments with real time images show a recognition rate of 91.5%

As future work, the system can be incorporated and tested under real time scenario of attendance maintenance. Hybridization of techniques can be applied to obtain better Gender recognition rates. The system can also be extended to identify a person from a part of his facial features.

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