

# FACE RECOGNITION USING LINEAR DISCRIMINANT ANALYSIS

<sup>1</sup>Manju Bala, <sup>2</sup>Priti Singh, <sup>3</sup>Mahendra Singh Meena

<sup>1</sup> Student M.Tech. ECE, Amity University Haryana, India

<sup>2,3</sup> Assistant Professor, Amity University Haryana, India

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**Abstract:** Linear Discriminant Analysis (LDA) has been successfully applied to face recognition which is based on a linear projection from the image space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter. LDA allows objective evaluation of the significance of visual information in different features of the face for identifying the human face. The LDA also provides us with a small set of features that carry the most relevant information for classification purposes. LDA method overcomes the limitation of Principle Component Analysis method by applying the linear discriminant criterion. This criterion tries to maximize the ratio of determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples. Linear discriminant groups the images of the same class and separate images of different classes. Here to identify an input test image, the projected test image is compared to each projected training, and the test image is identified as the closest training image. The experiments in this paper we present to use LDA for face recognition. The experiments in this paper are performed with the ORL face database. The experimental results show that the correct recognition rate of this method is higher than that of previous techniques.

**Keywords:** Lda, Face Recognition, Projection Vector, Eigen Value, Eigen Vector.

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## 1. INTRODUCTION

Nowadays, face recognition has become a popular topic among the researchers because of its broad usage in many applications such as digital cameras, surveillance camera, image editing software, Facebook and many more. In Facebook it implements facial recognition technology that allows all users to semi-automating the photo-tagging process. In this comparative study, face recognition was chosen because it is the most significant human identifier. The face is the most visible part of human anatomy and serves as the first distinguishing factor of a human being. It helps a person to distinguish an individual from one to another. Every individual has his own uniqueness and this could be one of the most transparent and unique feature of a human being.

Face recognition involves comparing an image with a database of stored faces in order to identify the individual of that input image. The image will first be analyzed and faces can then be identified, before it can be recognized. While this process may be a trivial task for the human brain, it has proved to be extremely difficult for the artificial technology to imitate. It is commonly used in applications such as human- machine interfaces and automatic access control systems.

### **Face recognition:**

A facial recognition system is a computer application to automatically identifying a person from a digital image or a video frame. One way to achieve this is by comparing selected facial features from the image to a facial database [2]. It is typically used in security systems and can be compared to other biometrics such as fingerprint or human iris [1].

Currently, developers came up with the design that is capable of extracting and picking up faces from the crowd and have it compared to an image source - database. The software has the ability to know how the basic human face looks like in order for it to work accordingly. Thus, developers designed these programs (by storing commands) to pinpoint a face and measure its features.

Facial recognition software falls into a larger group of technologies known as biometrics. Biometrics uses biological information to verify identity. The basic idea behind biometrics is that our body contains unique properties that can be used to distinguish us from other persons.

Face recognition has a number of advantages over other biometrics. Firstly, it is non-intrusive. While many biometrics require the subject's co-operation and awareness in order to perform identification, such as looking into an eye scanner or placing their hand on a fingerprint reader, face recognition could be performed even without the subject's knowledge. Secondly, the biometric data used to perform recognition is in a format that is readable and understood by humans.

### **Linear Discriminant Analysis:**

Linear Discriminant is a "classical" technique in pattern recognition [4], where it is used to find a linear combination of features which characterize or separate two or more classes of objects or events. The resulting combination may be used as a linear classifier or, more commonly, for dimensionality reduction before it can be classified. In computerized face recognition, each face is represented by a large number of pixel values. Linear discriminant analysis is primarily used here to reduce the number of features to a more manageable number before classification. Each of the new dimensions is a linear combination of pixel values, which form a template. The linear combinations obtained using Fisher's linear discriminant are called Fisher faces, while those obtained using the related principal component analysis are called eigenfaces.

whereas LDA doesn't change the location but only tries to provide more class separability and draw a decision region between the given classes [5].

Data sets can be transformed and test vectors can be classified in the transformed space by two different approaches.

(i) Class-dependent transformation: This type of approach involves maximizing the ratio of between class variance to within class variance. The main objective is to maximize this ratio so that adequate class separability is obtained. The class-specific type approach involves using two optimizing criteria for transforming the data sets independently.

(ii) Class-independent transformation: This approach involves maximizing the ratio of overall variance to within class variance. This approach uses only one optimizing criterion to transform the data sets and hence all data points irrespective of their class identity are transformed using this transform. In this type of LDA, each class is considered as a separate class against all other classes.

## **2. ALGORITHM USED IN LDA**

In Linear discriminant analysis we provide the following steps to discriminant the input images:

### **Step-1**

We need a training set composed of a relatively large group of subjects with diverse facial characteristics. Database should contain several examples of face images for each subject in the training set and at least one example in the test set. These examples should represent different frontal views of subjects with minor variations in view angle. They should also include different facial expressions, different lighting and background conditions, and examples with and without glasses. It is assumed that all images are already normalized to  $m \times n$  arrays and that they contain only the face regions and not much of the subjects' bodies.

### **Step-2**

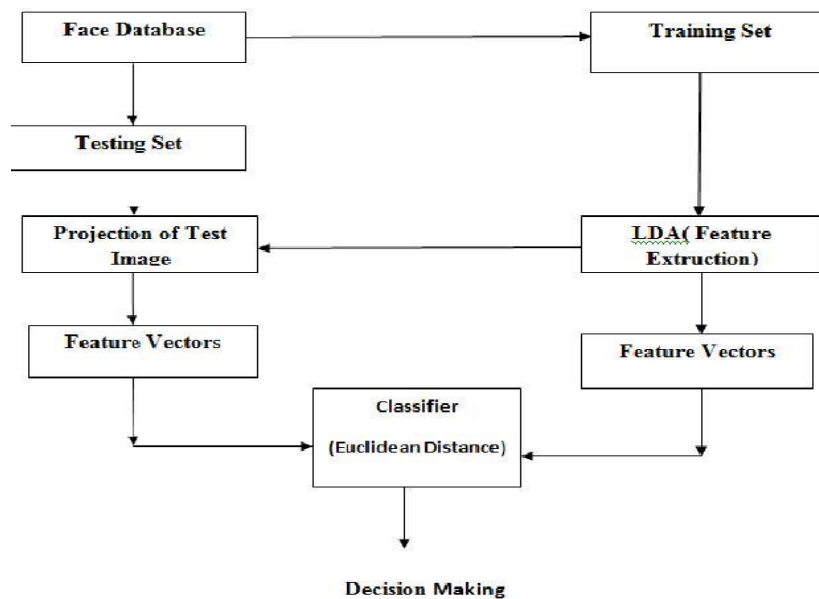
For each image and sub image, starting with the two dimensional  $m \times n$  array of intensity values  $I(x, y)$ , we construct the vector expansion  $\Phi_R$   $m \times n$ . This vector corresponds to the initial representation of the face. Thus the set of all faces in the feature space is treated as a high-dimensional vector space.

### **Step-3**

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.

The testing phase of the Linear Discriminant Analysis is as shown as in figure below:

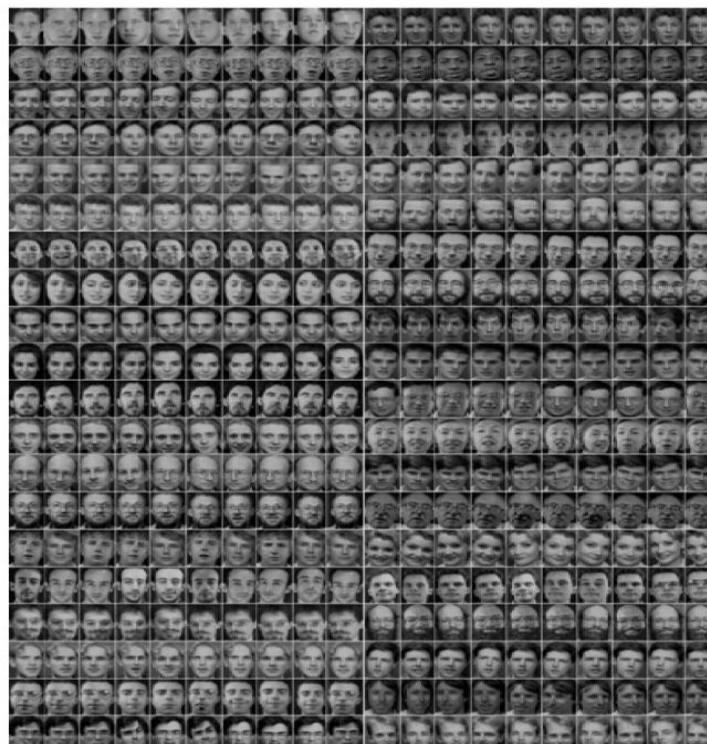


The testing phase of the LDA approach

### 3. DATABASE USED

Here database of face used AT & T "The Database of Faces" which is also known as "The ORL Database of Faces". There are ten different images of each of 40 distinct subjects. For some subjects the images were taken at different times, varying the lighting facial expressions not smiling) and facial details such as glasses or without glasses. All the images were taken against a dark homogeneous background with the subjects in an up right, frontal position.

All the files are in PGM format. The size of each image is  $92 \times 112$  pixels, with 256 grey levels per pixel. The images are organized in 40 directories (one for each subject), which have names of the form m sx, where x indicates the subject number (between 1 and 40). In each of these directories, there are ten different images of that subject, which have names of the form Y.pgm, where Y is the image number for the subject between 1 and 10



**A. Test Data Sets:**

Here we take one images from each subject and form test data set. So i n the test data set have 40 i mages for the 40 person. All the images are converted in bitmap (.bmp) image for mat.

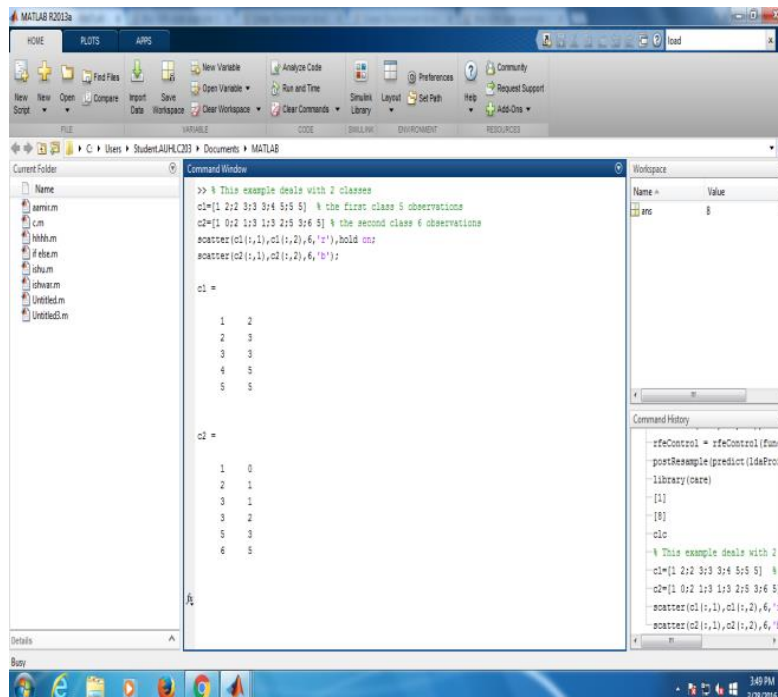


**Figure.2: ORL Test Database**

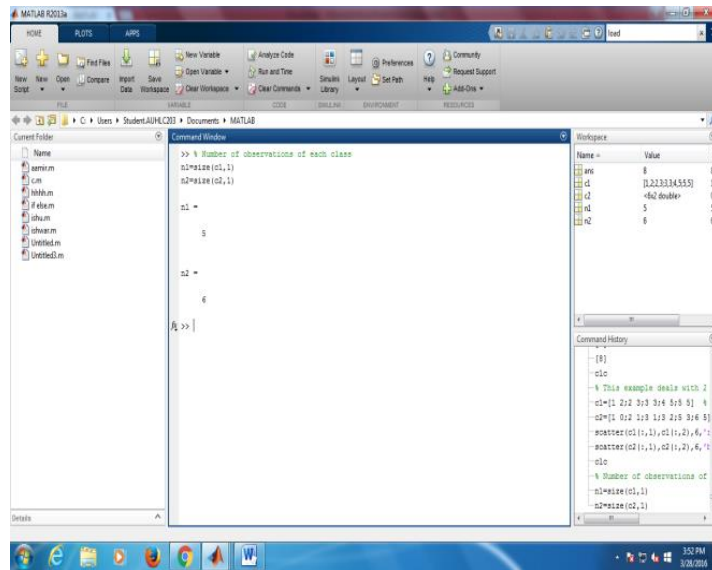
**B. Training Data Sets:**

After forming the test data set we form training data set from the ORL database by extracting 40 images which are present in the test data set. So for the each person w e have now 9 different in ages in all the 40 directories. Total 360 images present in our training dataset. All the images are converted into bitmap (.bmp) in mage format.

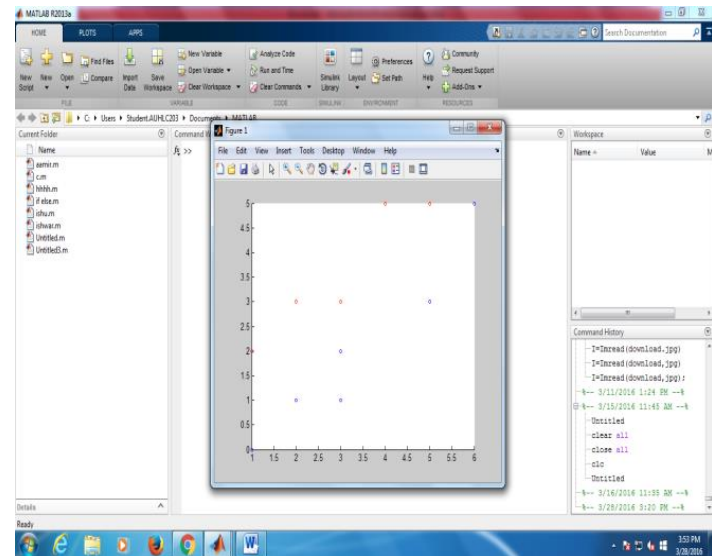
**4. THIS EXAMPLE DEAL WITH 2 CLASSES**



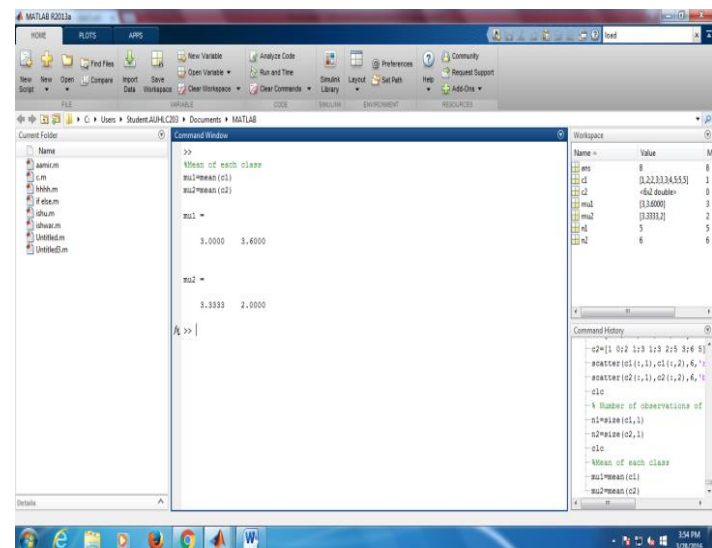
Number of observations of each class:



Output:



Mean of each class:





**Within Class Variance:**

```

>> % This example deals with 2 classes
c1=[1 2 3 3 4 5 5 5] % the first class 8 observations
c2=[1 0 2 1 3 1 3 2 5 3 6 8] % the second class 10 observations
scatter(c1(1,:),c1(1,2),4,'r'),hold on;
scatter(c2(1,:),c2(1,2),4,'b');

% Number of observations of each class
n1=size(c1,1)
n2=size(c2,1)

% Mean of each class
m1=mean(c1)
m2=mean(c2)

% Average of the mean of all classes
mu=(m1+m2)/2

% Center the data (data-mean)
d1=c1-repmat(m1,size(c1,1),1)
d2=c2-repmat(m2,size(c2,1),1)

% Calculate the within class variance (SB)
s1=m1'*d1
s2=m2'*d2
sm=s1+s2
lsv=1/sv(sv)

% In case of two classes only use v
v=lsv*(m1-m2)

% If more than 2 classes calculate between class variance (SB)
sb1=m1*(m1-mu)**(m1-mu)
sb2=m2*(m2-mu)**(m2-mu)
SB=sb1+sb2
v=lsv*(m1-mu)

% find eigen values and eigen vectors of the (v)
[erec,eval]=eig(v)

% Sort eigen vectors according to eigen values (descending order) and
% neglect eigen vectors according to small eigen values
% v=erec(greater eigen value)
% or use all the eigen vectors
% project the data of the first and second class respectively
y2=m2'*v
y1=m1'*v
    
```

**Between Class Variance and Project the Data:**

```

% Calculate the within class variance (SB)
s1=m1'*d1
s2=m2'*d2
sm=s1+s2
lsv=1/sv(sv)

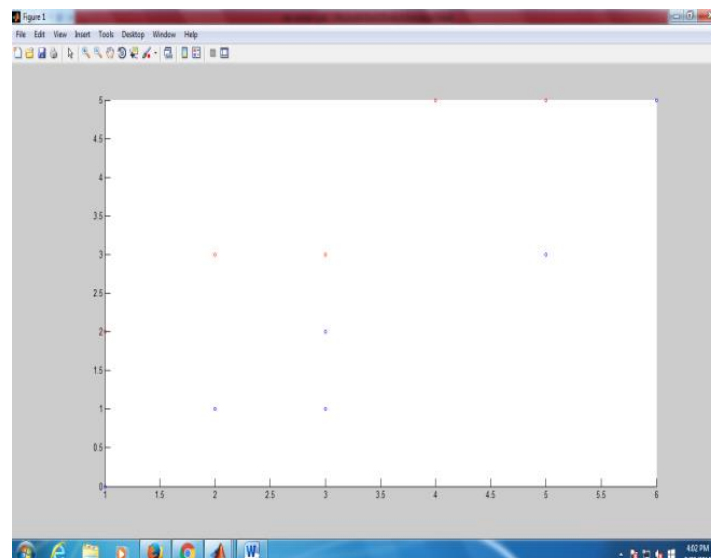
% In case of two classes only use v
v=lsv*(m1-m2)

% If more than 2 classes calculate between class variance (SB)
sb1=m1*(m1-mu)**(m1-mu)
sb2=m2*(m2-mu)**(m2-mu)
SB=sb1+sb2
v=lsv*(m1-mu)

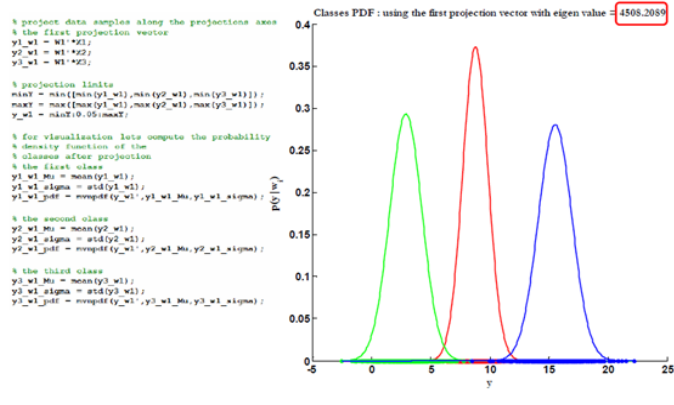
% find eigen values and eigen vectors of the (v)
[erec,eval]=eig(v)

% Sort eigen vectors according to eigen values (descending order) and
% neglect eigen vectors according to small eigen values
% v=erec(greater eigen value)
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% project the data of the first and second class respectively
y2=m2'*v
y1=m1'*v
    
```

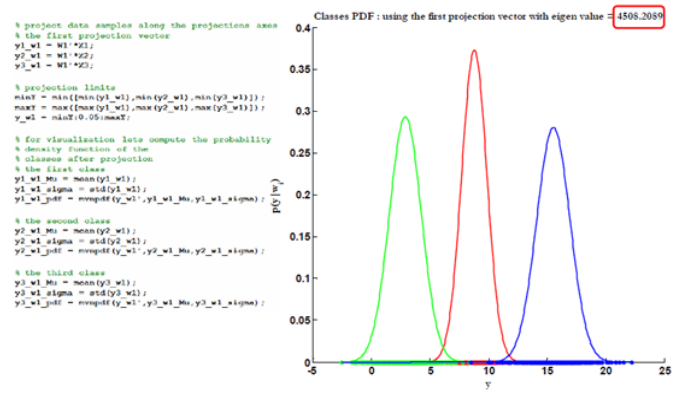
**Output:**



## Projection ... $y = W^T x$ Along first projection vector

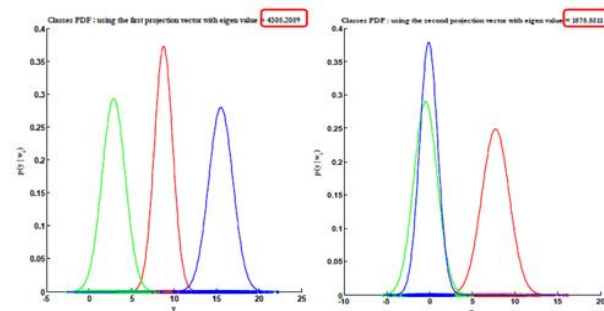


## Projection ... $y = W^T x$ Along first projection vector



## Which is Better?!!!

- Apparently, the projection vector that has the **highest eigen value** provides higher discrimination power between classes



## 5. 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.

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