M. Tech. (Computer Science) Dissertation Report

Face Recognition Using Facial Landmarks

A dissertation submitted in partial fulfillment of the requirements for M. Tech. (Computer Science) degree of the Indian Statistical Institute

By

Srinivas Nagamalla

Roll No: CS0614

Under the supervision of

Prof. Bhabatosh Chanda

Electronics and Communication Sciences Unit

Indian Statistical Institute

203, B. T. Road

Kolkata-700108

Indian Statistical Institute

Certificate of Approval

This is to certify that the thesis entitled "**Face Recognition using Facial Landmarks**" by Srinivas Nagamalla towards partial fulfillment for the degree of M. Tech.in Computer Science at Indian Statistical Institute, Kolkata, embodies the work done under my supervision.

(**Prof. Bhabatosh Chanda**)
ECSU- Indian Statistical Institute
Kolkata

Date:

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Srinivas Nagamalla
M.Tech(CS)
Indian Statistical Institute
Kolkata

Date:

Abstract

In today's networked world, the need to maintain the security of information or physical property is becoming both increasingly important and increasingly difficult. Recently, technology became available to allow verification of "true" individual identity. This technology is based on a field called "biometrics". Face recognition is one of the few biometric methods that possess the merits of both high accuracy and low intrusiveness. In this report we have presented a novel approach for Face recognition that works based on facial landmarks/features in a face such as eyes, nose and lips etc. In this approach we, first locate the probable positions of these facial features using gradient technique. Template Matching is used over a predefined area around the probable positions to detect the exact location of these landmarks. We extract statistical and geometrical features for representing the facial landmarks and their relative location. We have used two different similarity/distance measures in recognition process. The algorithm is implemented using VC++ and tested on various databases.

CONTENTS:

Chapter 1. Introduction

A **face recognition system** is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. This is branch of a more wide topic called 'Biometrics' [2].

The rising human population, coupled with advances in technology has introduced new ways by which information is shared and transmitted. This, in turn, creates a demand in security, both of individuals and the integrity of their data. Today, we see different security methods being employed in different places. We need to provide PIN numbers to withdraw money from ATMs, passwords to access the computer or data, and sometimes secret code to access a highly secure building. These are hard coded access permission and may be lost, forgotten, stolen or hacked. To surmount this problem, recent years there is a trend of using biological signature of individual as his/her security code through a system called biometrics. Examples of biometric identification systems include the use of iris [14], DNA [2] and fingerprint recognition systems [1]. While such systems are expensive and require the subject to cooperate, a face recognition system can work without the cooperation of the subject. All it requires is capturing of images of the subject and performing identification. A schematic diagram for face recognition/verification system is shown in Fig.1.

Face recognition systems can operate in two different modes:

Face verification or authentication: involves one-to-one match between the given image and a database image whose identity is being claimed.

Face identification or recognition: involves one-to-many match between the given image and many database images from which the given face has to be identified.

1.1 Issues in Face Recognition

- Illumination variations due to skin reflectance properties and due to the internal camera control.
- Pose changes affect the authentication process, as they introduce projective deformations and self-occlusion.
- Aging is another important factor, as the face changes over time, in a nonlinear fashion over long periods. In general this problem is harder to solve with respect to the others and not much has been done to counter it especially.

- Occlusions can dramatically affect face recognition performance**s.**

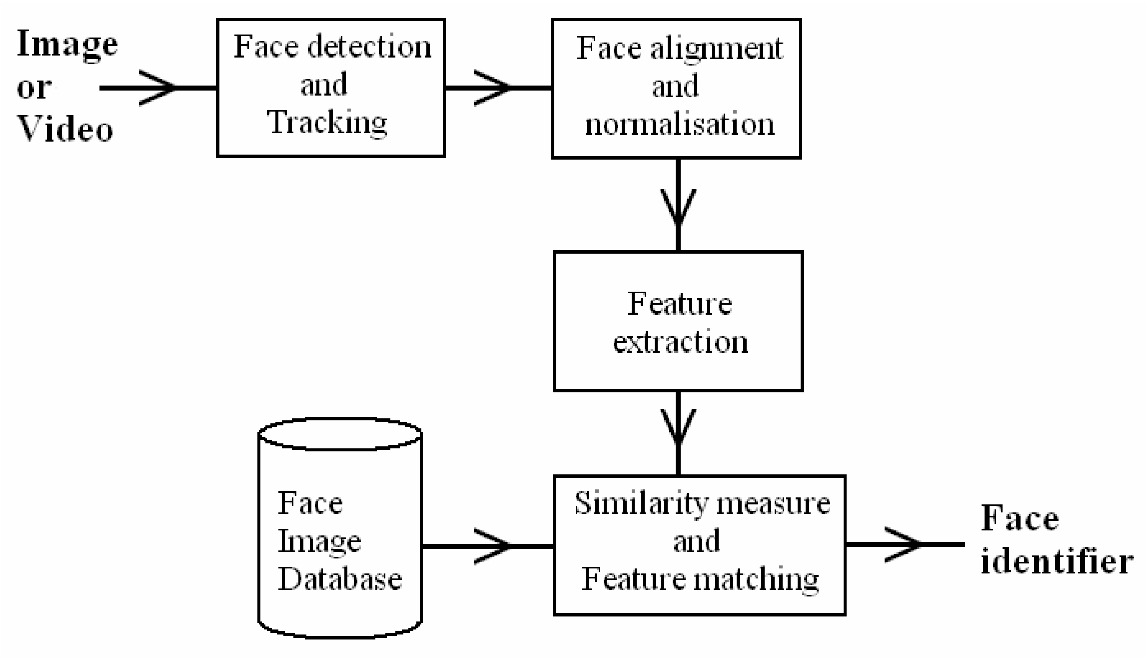


Fig.1.1 Schematic diagram of a face recognition system

1.2 Brief review of related work:

Face recognition is a very high level computer vision task that can be achieved through various techniques. Many techniques have been proposed during the past 20 to 30 years. A single face recognition system usually involves techniques motivated by various principles from many disciplines, making it difficult to accurately categorize them based purely on what kinds of techniques they use. Face recognition techniques are categorized based on the psychological study of how human use holistic and local features. Generally, there are three categories of recognition methods: **holistic matching, feature-based and hybrid methods**. Within each of these categories, further categorization is possible.

The first category of face recognition techniques is the holistic matching methods that use the whole face region as input to the face recognition system. The Eigen face approach by Turk and Pentland [13] is a representative of holistic analysis on faces, where it directly applies the Principal Component Analysis (PCA) method developed by Kirby and Sirovich. [8] Other representations of this approach include Linear Discriminant Analysis (LDA) [6] and Independent- Component Analysis (ICA). [3]

The second type is feature-based or structural matching methods which include classical methods such as the pure geometry methods. The first step in this approach is to extract local facial features such as the eyes, nose and mouth. Then, their locations and local (geometric) statistics are fed into a structural classifier. Examples of this approach are Dynamic Link Architecture [15], graph matching methods and Hidden Markov Models. [9]

The third approach is the hybrid models that use both local features and the whole face region. These methods give a more robust performance as compared to the other two approaches applied individually. Modular Eigen faces [11], Hybrid Local Feature Analysis (LFA) [10] and Component-based 3D Models [4] are examples of hybrid models.

1.3 Objective of the work:

Face Recognition has become an important component of security systems used all around the globe. It is an essential part of video surveillance, and various such other biometric systems. An automated face recognition system is usually faster, efficient and cheaper as compared to a manual system for the same. We have focused on recognizing gray images of faces .We restrict ourselves to images devoid of occlusions, aging variations or variations due to the illumination differences. An efficient and computationally fast algorithm, for face recognition, is proposed. The major part of the algorithm is based on localizing structural facial landmarks. We use statistical and geometrical features for representing facial landmarks. As a result our algorithm would lie on the boundary of structural and holistic methods. The similarity/ distance between feature vectors of two face images is measured using the standard L_2 and Mahalanobis distance.

1.4 Organization of the report

Organization of rest of the report is as follows. We discuss the detection of facial landmarks using gradient and template matching techniques, in detail, in the second chapter. The facial landmarks are represented by statistical and geometrical features. This statistical and geometrical feature representation is presented in the third chapter. The fourth chapter narrates the recognition process using different similarity matching measures. In fifth chapter we have presented the experimental results.

Chapter 2. Facial Landmarks

Regions of interest in a face may be termed as 'Facial Landmarks' like eyes, lips and nose. The algorithm proposed by us is based on the localizing these landmarks in a face. We, at first locate the probable positions of these landmarks. Template Matching is used over a predefined are around the probable positions to accurately measure the exact location of the Facial Features. The algorithm is divided into 3 parts namely, (i) localizing eyes, (ii) localizing nose, and (iii) localizing lips.

2.1 Detection of facial landmarks:

By the term 'facial landmarks' we mean those features based on which human beings discriminate different faces. Some examples of facial features are eyes, nose lips and their relative positions. In this section we try to extract these features.

2.1.1 *Finding the probable location of eyes*:

The first step of localizing the Facial Features is finding the location of eyes. If we look at an image of a face, an abrupt change of gray values is observed in the neighborhood of eyes. To exactly find the bounding box for eyes, in an image, we first find the probable position of the eyes. To locate the probable position, we first determine an approximate position of the first occurrence of the skin; through a mean comparison based approach. Once the skin position is localized, the probable position of the eyes is localized using a gradient based approach. We have used Sobel operator for finding the horizontal gradient. The horizontal mask is shown in Fig. 2.1. Projection of gray values along rows is computed from skin position to 50% of the distance between the skin position and the image height. This ensures a speedy computation, saving redundant searching. The location of eyes is obtained along the row which gives maximum projection. Fig. 2.2 shows the output of this process.

-1	0	1
-2	0	2
-1	0	1

(a) Horizontal mask

-1	-2	-1
0	0	0
1	2	1

(b) Vertical mask

Fig 2.1 Sobel operator of size 3x3

.

Rest of the chapter, we denote the height of the image by IMAGE_HEIGHT and the width as IMAGE_WIDTH.

Algorithm:-

Step1: Calculate the mean gray value of given image (I).Let the average gray value is AVG_GRAY

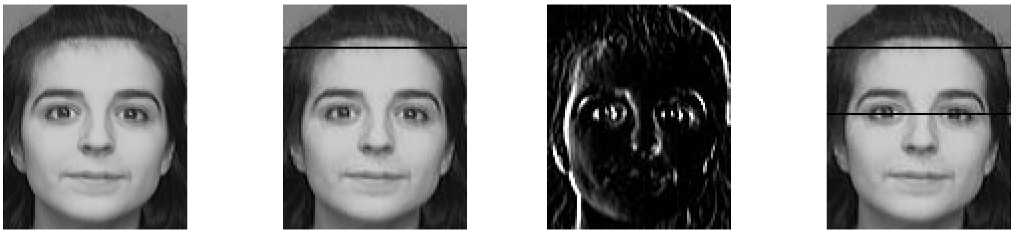
Step2: Starting from the first row of the image find the average gray value for each row.

Step3: Find out the first occurrence of a row such that the average gray value of that row is greater than AVG_GRAY . Let that row as SKIN_ROW.

Step4: Apply sobel operator (in horizontal direction) to the image (I).

Step5: Compute the projection of the gradient image along the rows, starting from the SKIN_ROW to (IMAGE_HEIGHT-SKIN_ROW)*0.5 .

Step6: Find out the position in which row the projection value is maximum. This row corresponds to the position of eyes. Let this position as EYE_ROW.



(a) Face image | (b) SKIN_ROW location of (a) | (c) Gradient of (a) | (d) EYE_ROW location of (a)

Fig 2.2 Result after locating the probable eye position

2.1.2 *Nose detection:*

To detect the nose, we have applied the template matching technique. To apply the template matching we need a template of nose. A nose template is obtained from the sampled images.

To build a nose template, cutout nose from the sampled images. Here all these sample images are frontal images. Resize all of these nose images into the template size. By taking the average of all these resized nose images gives the nose template. The template is shown in Fig. 2.3(b). Let the template size is NOSE_HEIGHT x NOSE_WIDTH. Let, for this nose template nose tip is located at (Nose_Tip_Row, Nose_Tip_Col).

As we know the location of eyes from the above algorithm, we will apply the template matching technique in the region started from the location of eyes to 25% of distance between location of eyes and image height.

Algorithm:-

Step1: row_ no = EYE_ROW .

Step2: col _no = 1

Step3:

Step3.1: Build a new image (I') from given image (I) of size nose template by cropping the image I starting from (row_no, col_no) up to size of the template.

Step 3.2: Calculate the correlation between nose template and new image (I').

Step4: Increment col_no by 1 and go to step 3 until col_no >IMAGE _WIDTH

Step5: Increment row_no by 1 and go to step 2 until row_no> (IMAHE_HEIGHT-EYE_ROW)*0.25.

Step 6: Find the max correlation value.

Step 7: Find from which I' we have got the max correlation value. Let it be I'_ MAX

Step 8: Add Nose _Tip_ Row and Nose_ Tip_ Col value to the first row and first col value of image I'_MAX . And the resultant pixel position corresponds to the nose tip of image(I). Let the nose tip of image I is located at (NOSE_ROW , NOSE_COL).

(a) Probable eye location (b) Nose template (c) Nose detection of (a)

Fig 2.3 Result of Nose detection

2.1.3 *Bounding box for EYES:*

This step is followed by the determination of the exact location of the nose in the image. It is important to exactly locate the nose. An exact determination of the nose will give an area to search for the exact location of eyes. This information is collectively used in the process of Template Matching for an exact determination of the location of eyes.

For template matching technique an eye template is obtained by cutout the eye from the sample images. As we know the position of eyes (EYE_ROW), we can find the bounding boxes to the eyes by using template matching technique, by searching for the eyes in the region starting from the position (EYE_ROW-EYE_WIDTH) to NOSE_ROW location. Finding the probable position of the eye, followed by the exact measurement over a predefined area, reduces the localization time considerably. This is the novelty of our algorithm. The results are shown in Fig.2.4.

Algorithm:-

Left Eye:

Step1: row_ no = EYE_ROW-EHEIGHT.

Step2: column _no = 1.

Step3:

Step3.1: Build a new image (I') from given image (I) of size left eye template by cropping the image I starting from (row_no, col_no) up to size of the left eye template.

Step 3.2: Calculate the correlation between left eye template and new image (I').

Step4: Increment col_no by 1 and go to step 3 until col_no > (NOSE_COL-EWIDTH/2).

Step5: Increment row_no by 1 and go to step 2 until row_no>NOSE_ROW

Step 6: Find the max correlation value.

Step 7: Find from which I' we have got the max correlation value.

Right Eye:

Step1: row_ no = EYE_ROW-EHEIGHT.

Step2: column _no = NOSE_COL.

Step3:

Step3.1: Build a new image (I') from given image (I) of size right eye template by cropping the image I starting from (row_no, col_no) up to size of the template

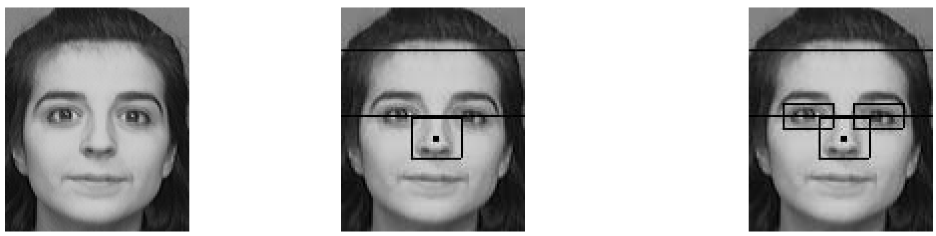
Step 3.2: Calculate the correlation between right eye template and new image (I').

Step4: Increment col_no by 1 and go to step 3 until col_no >(IMAGE_WIDTH-EYE_WIDTH)

Step5: Increment row_no by 1 and go to step 2 until row_no>NOSE_ROW

Step 6: Find the max correlation value.

Step 7: Find from which I' we have got the max correlation value.



(a)Original image (b) Result of nose detection (c) Bounding box for eyes

Fig. 2.4 Result of bounding box for eyes.

2.1.4 *Finding the probable lips position*:

The purpose of this step is to locate the lips position in a face image. We can see an abrupt change of gray values at the lips of a face image. Once the nose is detected, the probable position of the lips is localized using a gradient based approach. We have used Sobel operator for finding the vertical gradient. Fig. 2.1(b) shows the vertical mask used for finding the vertical gradients. Projection of gradient values along rows is computed from NOSE_ROW to 90% of the image height. The location of lips is obtained along the row which gives maximum projection. The result of this process is shown in Fig. 2.5.

Algorithm:-

Step1: Apply sobel operator (In vertical direction) to the image (I).

Step2: Compute the projection of the gradient image along the rows, starting from the NOSE_ROW to (IMAGE_HEIGHT)*0.9.

Step3: Find out the position in which row the projection of gradient value is maximum. This corresponds to the position of lips . Let this position as LIPS_ROW.

(a) Face Image (b) Gradient of (a) (c) Probable lips position

Fig 2.5 Locating the probable lips position

2.1.5 *Bounding box for Lips*:

This step followed by the locating the lips position. We apply template matching technique to exactly localize the lips. A lips template has made from sample images. The lips template is shown in Fig. 2.6 (b). The result after applying the template matching technique is shown in Fig 2.6 (c).

Algorithm:-

Step1: row_ no = NOSE_ROW .

Step2: column _no = 1 .

Step3:

Step3.1: Build a new image (I’) from given image (I) of size lips template by cropping the image I starting from (row_no, col_no) up to size of the lips template.

Step 3.2: Calculate the correlation between lips template and new image (I’).

Step4: Increment col_no by 1 and go to step 3 until col_no >NOSE_COL

Step5: Increment row_no by 1 and go to step 2 until row_no>LIPS_ROW

Step 6: Find the max correlation value.

Step 7: Find from which I’ we have got the max correlation value.

(a) Face image (b) Lips template (c) Bounding box for lips

Fig 2.6 Result of bounding box for lips

Chapter 3. Statistical and geometrical Features

In this section we discuss about the statistical and geometrical features, which we have used in our recognition system.

3.1 Statistical features:

We have adapted two approaches to measure statistical features based on the pixel intensity. In the following section we have discussed about this features in detail.

3.1.1 *Spatial Moments*:

The idea is borrowed straightway from physics [12], [5]. The gray level at a pixel is considered as the mass at point of an object. Thus (i,j)th moment of an image f(r,c) is defined as

$$m(i,j) = \sum_{c} \sum_{r} r^i c^j f(r,c)$$

m (0,1) and m(1 , 0) are simply called moments with respect to r-axis and c-axis, respectively. We see m (0, 0) is the mass of the object represented by f, and

{ m(1,0)/m(0,0) , m(0,1)/m(0,0)}

is the coordinate of the centriod of that object.

The normalized (i,j)th moment of an image f(r,c) is defined as

$$m^*(i,j) = \frac{\sum_{c} \sum_{r} r^i c^j f(r,c)}{\sum_{c} \sum_{r} r^i c^j}$$

3.1.2 *Co-occurrence matrix based features:*

A co-occurrence matrix, also referred to as a co-occurrence distribution, is defined over an image to be the distribution of co-occurring values at a given offset. Mathematically, a co-occurrence matrix **C** is defined over an n x m image I, parameterized by an offset **(Δx,Δy)**, as:

$$C(i,j) = \sum_{p=1}^{n} \sum_{q=1}^{m} \begin{cases} 1, & \text{if } I(p,q) = i \text{ and } I(p+\Delta x, q+\Delta y) = j \\ 0, & \text{otherwise} \end{cases}$$

Here we consider **Δx= Δy =1.**

The co-occurrence matrix can measure the texture of the image. Because co-occurrence matrices are typically large and sparse, various metrics of the matrix are often taken to get a more useful set of features. For a given image of size n x m the relative frequency of co-occurrence $P_{i,j}$=C(i,j)/nm represents approximately the joint probability mass of the discrete variables i and j. Here i,j varies from 0 to L , where L is the max gray value in the image. The commonly used features [7] from co-occurrence matrix are:

Energy: $$\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{i,j}^2$$

Entropy: $$-\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{i,j} \log p_{i,j}$$

Contrast: $$\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} (i-j)^2 p_{i,j}$$

Homogeneity: $$\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{p_{i,j}}{1+|i-j|}$$

3.2 Geometrical features:

The geometrical features include the Euclidean distance between (i) CG (Centre of Gravity) of nose and CG of lips (ii) CG of nose and CG of left eye (iii) CG of nose and CG of right eye.

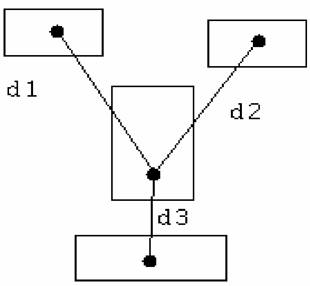


Fig. 3.1 A diagram, which illustrates the geometrical features

3.3 Feature vector:

From each facial landmark we are finding 9 spatial moments (up to 2^{nd} order) .From co-occurrence matrix we are finding 9 moments, energy, entropy, contrast and homogeneity. In this way we are getting 22 features from each facial landmark. Since there are 4 facial landmarks totally we get 88 statistical features. We also have 3 geometrical features. The dimension of feature vector is 91.

Chapter 4. Recognition Process

In this chapter we will discuss about the recognition process. This recognition algorithm will help us to recognize a particular face image from a given set of images. This algorithm will process the feature vectors which we have got from feature extraction. From a given query image the recognition system first compute the feature vector. By using similarity/distance measure the recognition system reports a face image from the database, which is matched with the query image. In our recognition system we have used minimum distance classifier.

4.1 Distance/Similarity measure:

We have used two approaches to measure the distance /similarity measure between two feature vectors.

Euclidean distance: Euclidean distance between two vectors X and Y is defined as

$$D(X,Y) = \sqrt{(X-Y)^T(X-Y)}$$

Mahalanobis distance: The Mahalanobis distance between two vectors X and Y is defined as:

$$D(X,Y) = \sqrt{(X-Y)^T\Sigma^{-1}(X-Y)}$$ where Σ is covariance matrix.

4.2 Reduction of Feature vector's dimension

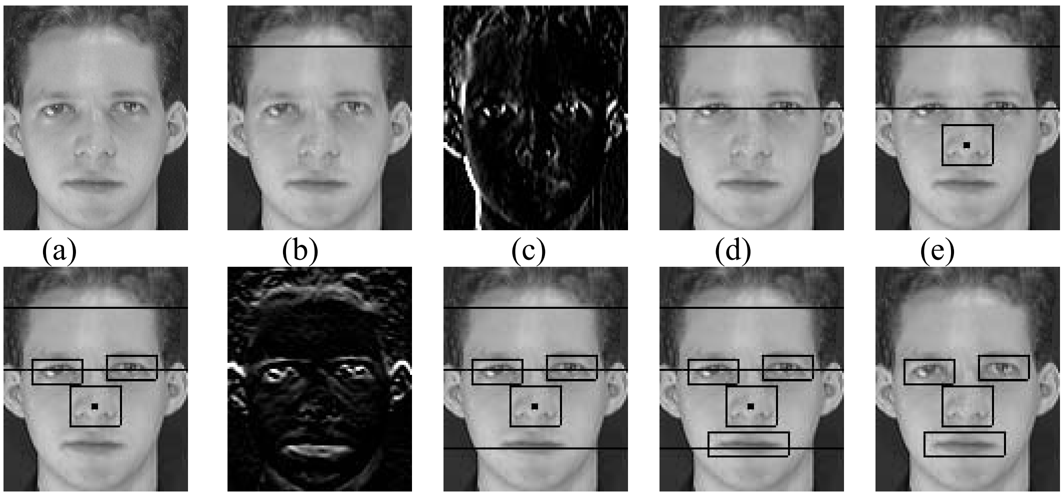
Since the dimension of feature vector is high, it will take more time to compute the distance between two vectors and require more space to store the feature vectors. . If we can reduce the dimension of the vector, in such way that the distance between two vectors is preserved, before and after reduction of dimension. To achieve this we can project the feature vector into low dimension space by using PCA. For this first we have to extract the feature vector from each image of database .Then apply PCA to these feature vectors. Now project the feature vectors into low dimension space. Now these vectors will represents a descriptor of each image.

Chapter 5. Experimental Results

The performance of our recognition system is verified on **ORL Database**. [16] In this database, 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 (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). . The size of each image is 92x112 pixels, with 256 grey levels per pixel.

Results of Facial landmarks detection:

In the following figures we have shown the results obtained after extracting all the facial landmarks.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Fig. 5.1 Step wise results of facial landmarks detection. Figures (a) to(j) are arranged in left-to-right and top-to bottom fashion.(a)original image (b)detection of starting location of skin (c)horizontal gradient image of (a) (d) Result of probable eye location detection (e)result of nose detection (f) result of bounding box for eyes (g) vertical gradient image of (a) (h)result of probable lips location detection(i)result of bounding box for lips (j)final result obtained after extracting all the facial landmarks.

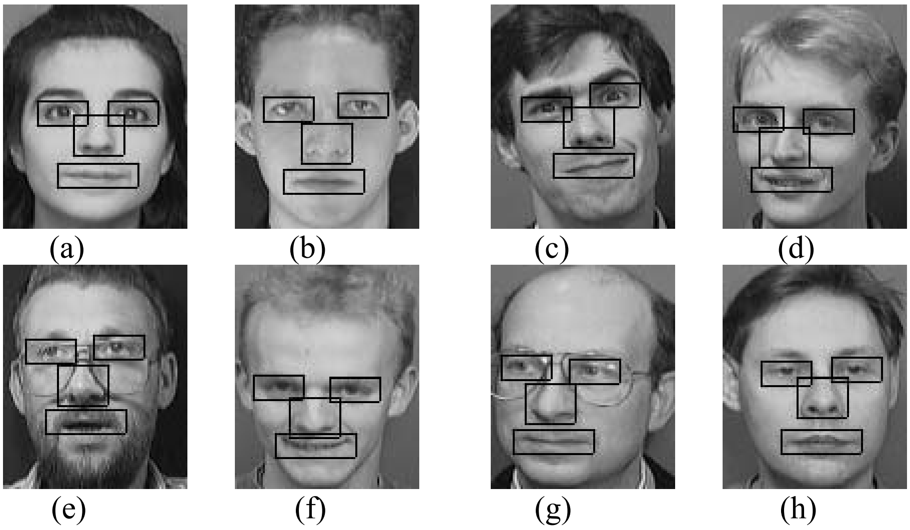


Fig .5.2 Face images with detected facial landmarks

Fig 5.2 shows the results obtained after extracting all the facial landmarks from face images. Here in this figure, (a),(b),and (h) are frontal face images whereas(c),(e) show some expressions , (d),(g) show different poses and (g) contains the glasses.

Our approach gives 89% success rate for facial landmarks detection, tested on ORL database.

Results of Recognition Process:

In Table 5.1, we have shown the performance rates of recognition process using two different distance measurements. Here we have considered all the features to represent an image, i.e. the dimension of feature vector is 91.

Distance metric	No of. Query images	Success Rate
Mahalanobis	400	90%
Euclidean	400	76%

Table 5.1 Performance of recognition process

After reducing the feature vector's dimension using PCA, the results are shown in Table 5.2. Here the dimension of the feature vector is 40.

Distance metric	No of. Query images	Success Rate
Mahalanobis	400	90%
Euclidean	400	76%

Table 5.2 Performance of recognition process after reducing the feature vector's dimension

Selection of principal components: The Fig 5.3 and Fig. 5.4 show the performance of recognition process for varying number of principal components using two different distance metrics namely the Euclidean distance and Mahalanobis distance.

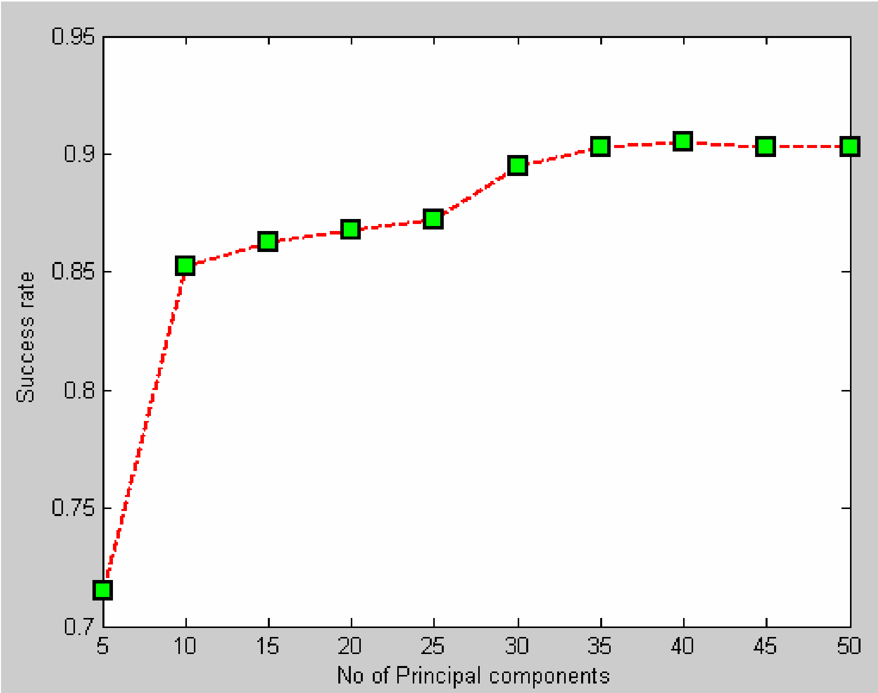


Fig. 5.3 Performance of recognition process with Mahalanobis distance

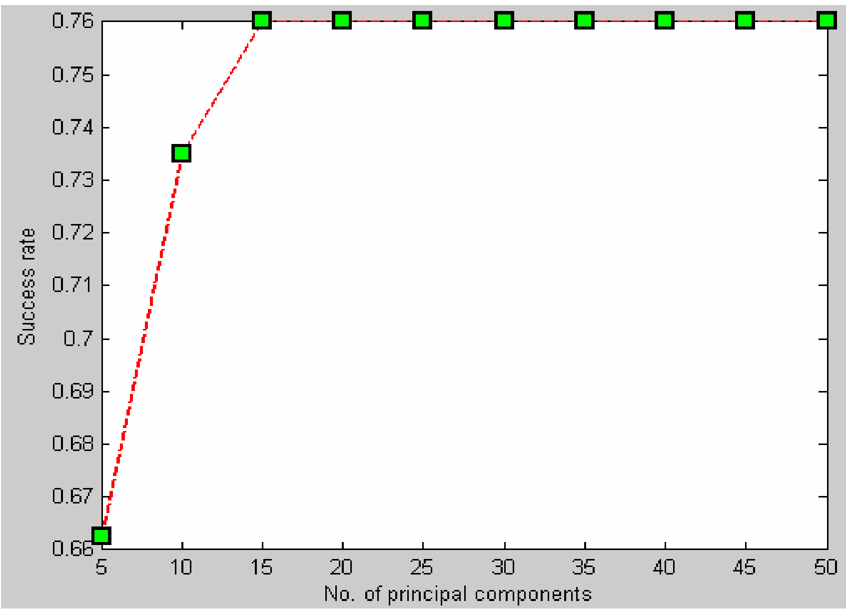


Fig. 5.4 Performance of recognition process with Euclidean distance

Energy: The amount of energy for K principal components is computed by

$$E = {\sum_{i=1}^{k} \lambda_i} \Big/ {\sum_{i=1}^{N} \lambda_i}$$

Where N is the total number of principal components and λ is eigen value.

In Table 5.3 we have shown the energy for different number of principal components.

No.of principal components	Amount of Energy preserved
10	98%
20	99.92%
30	99.99%
40	99.99%

Table 5.3

We have compared our result with the Eigen face method. For the purpose we have implemented the eigen face method and have applied on the ORL database. The success rate for ORL database is 97.5%, by considering the 400 principal components.

Chapter 6. Conclusion and Future work

In this thesis we have presented an approach, which can efficiently extract the facial landmarks like eyes, nose and lips from a face image. Statistical and geometrical features extracted from these facial features are used as a descriptor for a face. The results of experiments show that the method is effective. Though our method is lagging behind eigen face method (tested for ORL database) in terms of success rate, but it is computationally much more efficient. Second, our method has adopted a more general approach combining both structural and statistical features; it is expected to better on a lager class of face images.

The proposed method can be further improved, if we use some robust techniques for exactly localize the facial features. If we will consider more statistical features the method can be improved.

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