FACIAL FEATURE EXTRACTION TECHNIQUES FOR FACE RECOGNITION SYSTEM

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DECLERATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

In this thesis face recognition identification system was designed. A Principal Component Analysis PCA and Fisher Linear Discriminant Analysis FLD are used to obtain the feature of images. Principal components analysis PCA is one of a family of techniques for taking high-dimensional data, and using the dependencies between the variables to represent the image in a more tractable, lower-dimensional form, without losing too much information. PCA is one of the simplest and most robust ways of doing such dimensionality reduction. FLD is the most famous way to search for trends in the data, which has the largest difference and highlight data. This method is used, for lower-dimensional representation of the data, which removes some of the trends "noisy".

Fast Pixel Based Matching FPBM is a method to extract the feature of images on the basis of face matching image areas and sub-pixel displacement estimate using similarity measures. This method was used to compare the results of PCA, FLD and FPBM.

Classifications of image parameters are done by measuring Euclidian distance. The given approach is used to classify the faces to different patterns. The system can identify persons according to these face patterns. The comparative simulation results of described methods have been given. The developed system has a Graphical User Interface GUI that contains many buttons and controls that allow the user to choose the necessary method and drive the results. The system has been designed using Matlab package. Using callbacks, you can make the components do what you want when the user clicks or manipulated with keystrokes.

Key Words: Face Recognition Program, PCA, FLD, Fisher LDA, Euclidean distance, FPBM.

ÖZET

Bu tezde, parmakizi tanıma sistemi dizayn edilmiştir. Görüntü özelliklerini elde etmek için Temel Bileşen Analizi (TBA) ve Fisher Doğrusal Diskriminant Analizi (FDDA) kullanılmıştır. Temel Bileşen Analizi (TBA), yüksek boyutlu veri almak ve aşırı bilgi kaybetmeden değişkenler arasındaki bağımlılıkları kullanarak görüntüyü daha uysal, daha düşük boyutlu formda göstermek için kullanılan teknikler ailesinden biridir. TBA, bu şekildeki boyutluluk indirgemesi yapmanın en basit ve en sağlıklı yöntemlerinden biridir. FDDA, en büyük farkları bulunan verilerin trendlerini araştıran ve verileri vurgulayan en ünlü yoldur. Bu yöntem, verilerin alt boyutlu gösterimi için kullanılmakta ve bazı "sesli" trendleri de kaldırmaktadır.

Hıızlı Piksel Tabanlı Eşleşme (HPTE), eşleşen yüz görüntü alanlarına ve alt piksel yer değişim tahminine dayanan görüntü özelliklerini, benzerlik ölçülerini kullanarak ortaya çıkaran bir yöntemdir. Bu yöntem, TBA, FDDA ve HPTE sonuçlarını karşılaştırmak için kullanılmıştır.

Görüntü parametreleri sınıflandırılması, Öklid mesafesi ölçülerek yapılmıştır. Verilen bu yaklaşım, yüzün farklı şekil düzenlerine sınıflandırılması için kullanılmıştır. Sistem, kişileri bu yüz şekil düzenlerine göre belirleyebilmektedir. Açıklanan yöntemlerin karşılaştırmalı simülasyon sonuçları verilmiştir. Geliştirilen sistemin, kullanıcının gerekli yöntemi seçmesine ve sonuç çıkarmasına olanak tanıyan, ve birçok buton ve denetimi içeren bir Grafik Kullanıcı Arayüzü (GKA) mevcuttur. Sistem, Matlab paket programı kullanarak dizayn edilmiştir. Kullanıcı tıkladığı ve tuş vuruşları ile manipüle edildiği zaman, geri arama kullanılarak bileşenleri sizin istediğinizi yapmaya yönlendirebilirsiniz.

Anahtar Kelimeler: Yüz Tanıma ve Tanıtma Programı, TBA, Fisher DDA, Öklid Mesafesi, HPTE.

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To Ramadan the father and son, Osama,

Mother Om Rami,

My dear wife Samar, Om Ramadan

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LIST OF ABBREVIATIONS

PCA	Principal Component Analysis
FLD	Fisher Linear Discriminant
FPBM	Fast Pixel Based Matching
1 D	1 Dimensional
2 D	2 Dimensional
T	Vector of reshaped database images
Sw	The Within Scatter Matrix
Sb	The Between Scatter Matrix
eig(A, B)	MATLAB function returns a vector containing the eigenvalues, that satisfy the equation $A \times X = B \times X$
Min	Minimum
M	The mean vector
A	The deviation vector
C	Covariance matrix
L	The surrogate of the covariance matrix
BMP	Bitmap image file
RR	Recognition Rate
ATM	Automated teller machine
LDA	Linear discriminant analysis
GUI	Graphical user interface

1. INTRODUCTION

Since the last century several biometric techniques were used for identification of humans. These techniques are: Iris recognition, Face recognition, Fingerprint recognition, Voice recognition, etc. Each of these techniques has number of real life applications [1].

Face recognition or face authentication refers to the automated method of verifying a match between two human faces. Faces are one of many forms of biometrics used to identify individuals and verify their identity [1].

The aim of this thesis is design face recognition system using principal component analysis and fisher linear discriminant analysis. Face recognition system is divided into two main stages. The first one is used to extract the features from the face image, and the second stage is used for classification of patterns. Feature extracting is a very important step in face recognition system. This thesis touches on two major classes of algorithms used for extraction of the features of face images. The recognition rate of the system depends on the meaningful data that are extracted from the face image. So, important feature should be extracted from the images. If the features belong to the different classes and the distance between these classes are big then these features are important for given image. The flexibility of the class is also important. There is no 100% matching between the images of the same face even if they were from the same person.

Nowadays there have been designed a number of methods for feature extraction. These are Principal component analysis, linear discriminant analysis, Fisher method, Multifactor dimensionality reduction, nonlinear dimensionality reduction, Kernel PCA, independent component analysis etc. The PCA and FLD are efficient methods used for image feature extraction. In the thesis the application of PCA and FLD methods are considered for extraction the features of face images. The classification of the images can be implemented using different classification algorithms: Euclidean Squared Distance, Hidden Markov Model (HMM), vector quantization, k-means algorithm, or Artificial Neural Network (ANN) [2]. In this thesis, Face recognition system was developed, and two techniques were used for feature extraction. These techniques are PCA and FLD.

Each of these techniques was implemented on MATLAB and they are combined by using Graphical User Interface (GUI). The algorithm that was used for classification of face images uses Euclidean Distance. If there is matching between the trained database images and the tested image, the recognized image will be shown in GUI. But if there is no matching between them, a message will appear to inform the user that this images in not recognized.

In this thesis the design of face recognition system using PCA and FLD feature extraction methods has been considered. The thesis includes introduction, five chapters, conclusion, references and appendices.

Chapter 2 is devoted to the descriptions of biometric systems using fingerprint, eye, face, voice, DNA and hand recognition techniques used in real life.

Chapter 3 describes the basic stages of face identification. The minute characteristics of the images, the basic important meaningful features of the face images have been described. The extraction properties, advantages and disadvantages faces have been presented.

Chapter 4 explains the features extraction methods of PCA and FLD. The basic steps of PCA, FLD and the recognition process using Euclidean distance are described.

Chapter 5 presents the design stages of face recognition system. General structure of the system, the flowcharts of feature extraction methods are described. The thesis based on two feature extraction techniques: PCA and FLD. The face recognition system is designed in Matlab 2012a package using Graphical User Interface (GUI).

Finally, Chapter 6 contains the important simulation results obtained from the thesis.

2. BIOMETRIC SYSTEMS

2.1 Overview

In this chapter the review of human identification systems is presented. The various biometric techniques are described. The physiological and behavioral characteristics of human which can be used as a biometric identifier to identify the person are presented.

2.2 Biometric Systems

Due to the large number of swindling and fraud methods and the increasing incidence of crime and the spread of terrorism went many studies

To develop the technical means relating to disclosure or minimize or protection from these risks and one of the most important techniques and studies that have helped in the protection of the individual and society from these dangers and techniques oriented studies on the vital features of the human being.

In general, the physiological properties do not vary with the passage of time or for the most part are subject to small changes while affected by the behavioural characteristics of the psychological state of the individual. For this reason, identity verification systems based on behavioural characteristics need frequent updates. The main task of a biological system is to identify the individual [3].
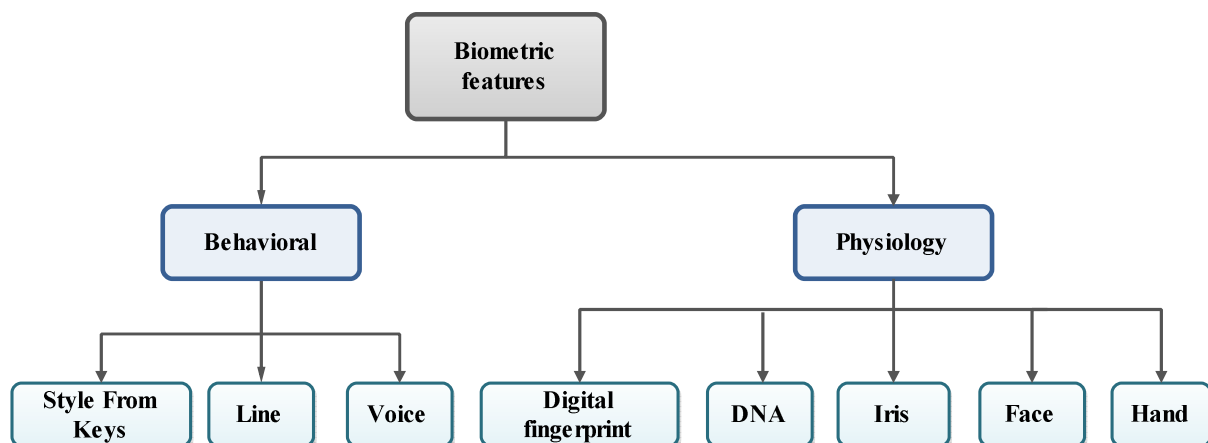
Figure 2.1: Biometric features.

2.3 Biometric Classifications

Science of biometrics is the science of forensic evidence in human bodies because it includes means of identification for people automatically on the basis of anatomical and physiological characteristics of each person. The most common fingerprint evidence and computers can match them in seconds. You can also identify your identity through facial features or voice or hand geometry or iris. Each biometric device that use both general principles. These standards address through programming and encryption of the unique attributes of each person and stored in the database to match them with the features characteristic of the suspects. For this, we find that in the information systems and means of biometrics is a quick and accurate can be used as more than a way to get to know the identity of the person 100% [4].
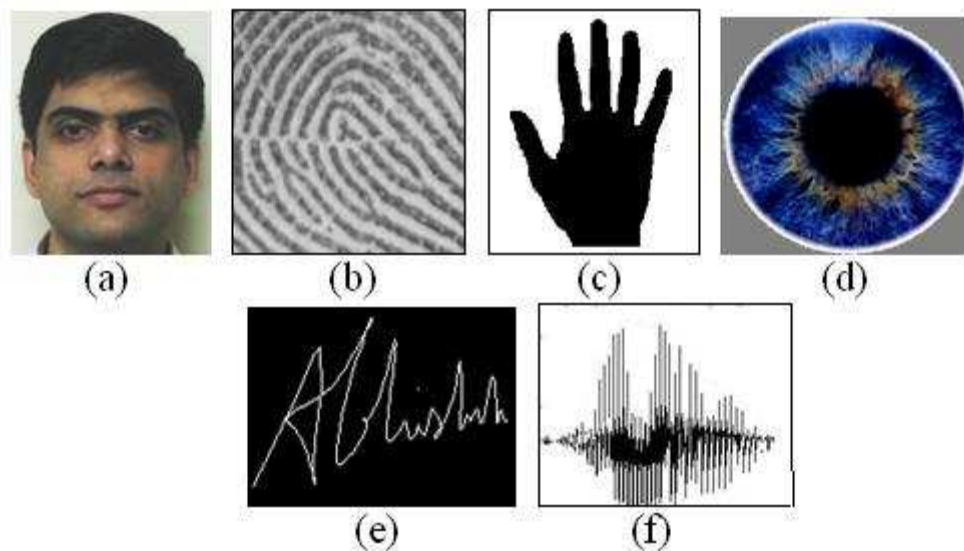
Figure 2.2: Examples of biometric characteristics that are commonly used: (a) face, (b) fingerprint, (c) hand geometry, (d) iris, (e) signature, and (f) voice [5].

- **Hand Geometry:** Is one of the test methods and biological measurement. This method measures the characteristics of several of the hand, including the height and the spaces between the fingers. The person being scanned and examined carefully. The survey delicate hand to a reasonable degree of order in the verification of the individual compared with the template saved the file, but not accurate enough to identify an anonymous survey [6].
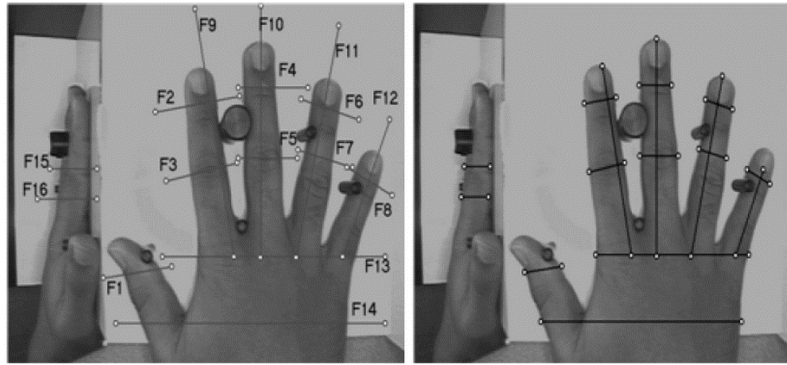
Figure 2.3: Hand geometry biometric devices [6].

- **Iris:** The identification by the iris of the eye in a way more accurate than relying on the footprint that may be damaged, or passport that can forge, as the iris is unique, where the right iris differs from the left with the same person. The experiments showed that the different irises even among identical twins. The process of examining the iris of the most accurate methods for identification because it is fast and very accurate. The rapidly growing biometrics technologies, which is where the use of computers to identify the unique advantages of a person such as palms, or edition facial expressions and installation of the eye [7].
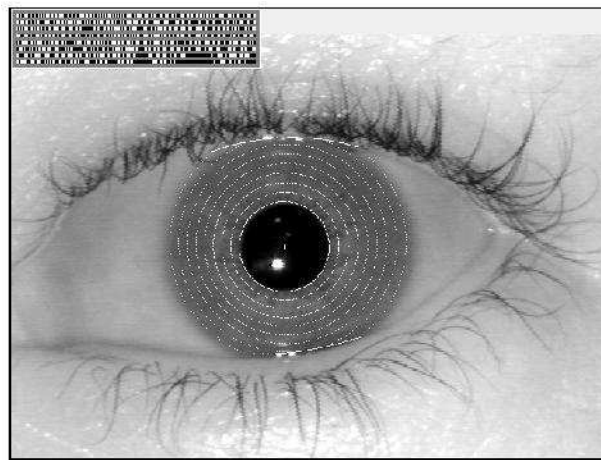
Figure 2.4: Iris geometry biometric [7].

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- **Face:** Analyzes the characteristics of the face and identify them requires this system a digital camera to photograph facial image of the user for the purpose of documentation, and have this test feature that compares with other systems, verification of identity that does not require direct interaction with people and do fingerprints or iris scan. But the main problem that occurs when you use this type of system is the lighting that can change the color of the face and also the passage of time because as a person grows older and face exposure to changes such as weight gain or frequent and wrinkles that could prevent identification [8].
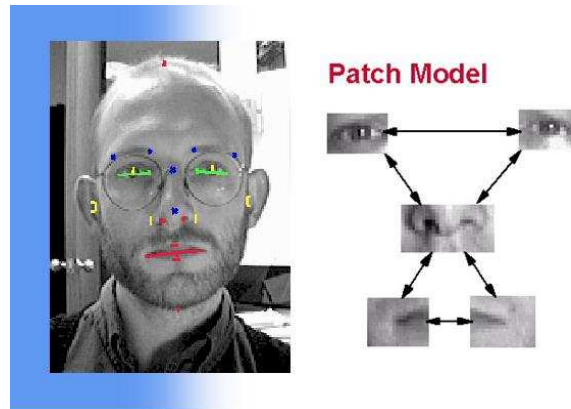
Figure 2.5: Recognition faces [8].

- **Voice:** This technique is based on sound waves so that the sound is recorded and analyzed and then converted to graphs showing spectral frequency, intensity and time of speech and other characteristics of the waves to speak. It is then compared to determine whether the sound is the same as that recorded in order to give the correct results should be a quiet environment, this system [9].
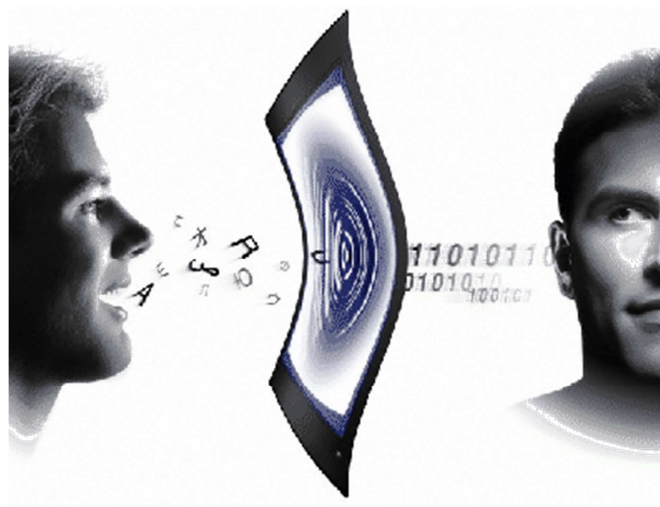
Figure 2.6: Vocal apparatus [9].

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- **Fingerprints:** Biometric technology spread dramatically in the past few years, and the large number of applications in airports in particular. And turned a lot of countries passports and entry visas to biometric shape. As well as many use different technologies to monitor, or as a basis for access control systems specific places, but those applications now become significantly widespread even reached the personal computer to be used as a means to protect the information [10].

Figure 2.7: Fingerprint minutiae [10].

- **Signature:** Use the signature proof of identity so that solves focuses on the characteristics of the signature to the signature itself and signature recipes, speed signing and hand shaking during the sign and the pressure on the pen. The way lies in the signature of the person on the touch-sensitive screen, and then the signature is converted to digital form or representation, which is compared with pre-stored in the system to make sure of the identity [11].

Figure 2.8: Electronic tablet [11].

- **DNA:** Deoxyribonucleic Acid (DNA) is the one-dimensional ultimate unique code for one's individuality, except for the fact that identical twins have identical DNA patterns. It is, however, currently used mostly in the context of forensic applications for person recognition [12].
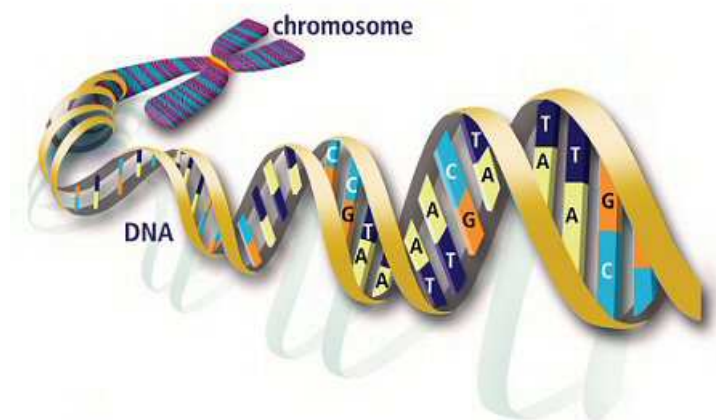
Figure 2.9: DNA recognition [12].

Table 2.1: Comparison of biometric technologies, the data is based on the perception of the authors. High, Medium, and Low are denoted by H, M, and L, respectively [13].

Factors → Biometric identifier ↓	Universality	Distinctiveness	Permanence	Collectable	Performance	Acceptability	Circumvention
Hand Geometry	M	M	M	H	M	M	M
Iris	H	H	H	M	H	L	L
Face	H	H	M	H	L	H	H
Voice	M	L	L	M	L	H	H
Fingerprint	M	H	H	M	H	M	M
Signature	L	L	L	H	L	H	H
DNA	H	H	H	L	H	L	L

3. FACE IDENTIFICATION

3.1 Overview

Due to the increased use of computer technologies in modern society, the growing number of objects and the flow of information that must be protected from unauthorized access, the information security problem become more and more urgent. In such circumstances the use of biometrics technology for personal identity to protect access to sources of information is required.

The use of biometrics to verify the identity involves the use of physical characteristics such as face, voice or fingerprint, for the purpose of identification. Facet matching is the most successful biometric identification technology for its ease of use, and the absence of any interference reliability. The basic characteristics of faces, their representation, minute characteristics and feature extractions stages are considered in this chapter.

3.2 Face as a Biometric

Face recognition has a number of strengths to recommend it over other biometric modalities in certain circumstances, and corresponding weaknesses that make it an inappropriate choice of biometric for other applications. Face recognition as a biometric derives a number of advantages from being the primary biometric that humans use to recognize one another. Some of the earliest identification tokens, i.e. portraits, use this biometric as an authentication pattern [14].

Furthermore it is well-accepted and easily understood by people, and it is easy for a human operator to arbitrate machine decisions in fact face images are often used as a human-verifiable backup to automated fingerprint recognition systems.

Face recognition has the advantage of ubiquity and of being universal over other major biometrics, in that everyone has a face and everyone readily displays the face (Whereas, for instance, fingerprints are captured with much more difficulty and a significant proportion of the population has fingerprints that cannot be captured with quality sufficient for recognition.) Uniqueness, another desirable characteristic for a biometric, is hard to claim at current levels of accuracy. Since face shape, especially when young, is heavily influenced by genotype, identical twins are very hard to tell apart with this technology.

3.3 Know the Identity Using Physiological Characteristics

Enjoy human several physiological characteristics allow the identifying common with behavioral characteristics can say that it is the footprint, has identified these characteristics are as follows: face, fingerprint, hand size and detail, voice, eye and hand signature. The arrangement also provided for these properties based on the recognition rate of existing systems where we find that the face is the best properties, was adopted in Ranked on several things, such as: ease of application, the requirements of the gear drive, when the public acceptance and others [16].

Figure 3.1: How using physiological to know the identity [17].

It also mediated by facial recognition has many beauties, namely:

- It is a property of any normal human being can be carried out, unlike some recognition processes, such as know the iris. Where END known to human mainly depends on the face to get to know all the characters that offset.

- Ease of implementation and tested and used, as the recognition systems do not require special equipment, but all you need is a good camera High Resolution.

3.4 How to Work the System Faces Discrimination

The system known faces to recognize all of the faces in the picture or video automatically, and such a system has a work pattern may work either one or both at the same time, namely:

- Authentication of the face Authentication: This is in some environments and selected on the basis of (1:1) For example, this pattern is applied in exchange ATM devices, the system compares the face of the person who pulls the coins with a face that person has in the existing data base, where the system has a picture of a person's face, and compares the image with the outcome. But until now has been the use of specific applications in this area [15].

- Identify Recognition: Unlike the previous pattern, people do not know about themselves, but the system will recognize them. This includes the style process of comparing (1: M), where he owns a system database for people , and is recognized as everyone 's collected are monitoring public places where gatherings such as football stadiums , airports, railway stations and often take place in places in which there are cameras imaging and audio devices [15, 18].

Depends permission recognition systems databases, contain images of persons desired to identify them by investors, for example, interested in security agencies to identify the criminals, the system base data contains images of suspects, and the computer program comparing the images captured by surveillance cameras database to find out what If one is located in the desirable location or not here that the first step to face fingerprint system work is to get the picture.

We recall an example of the recognition systems currently used system facet the developed by the company Identic; for this system to work it must distinguish between himself and dorsal face they rely on facial recognition and then measure the properties of this face. This system is in place at all airports in Malaysia. The recall of the companies that produce such systems: Company Animatic Inc., the company FACE Engine ID, Set Light and Sensible Vision and other companies [15, 19].

Each face has many distinctive features, are in various curves on the face. Each face has about 80 contract months, these nodes that can be measured using the software are:

1. The distance between the eyes.

2. View the nose.

3. The depth of the eye.

4. The form of the cheekbones.

5. The length of the jaw line.

These features measured by the software specialist to identify the face and fingerprint translated into digital codes called face print face and fingerprint used to represent the face in the database.

In the past, custom programs based on two - dimensional images to compare images in the database, which are also two-dimensional and the image must be taken of the person and is almost the opposite of the camera and this may cause a problem. This is in addition to changes in the environment surrounding the person , such as lighting will produce images cannot for the computer to find them similar in his memory , and the change in the same person , such as that he had not styling his hair or his palace , change the make-up, shaved chin or exemption or wearing or removing glasses are considered one of the behaviors that affect the ability of the system hardware footprint flip to determine the peculiarities of the person , leading to rejection of conformity and this has caused the failure of the face recognition system . To resolve this problem has been the use of modern devices that rely on the three- dimension [15, 18, and 19].

3.5 Steps of Modern Systems Work Programs Distinguish Faces

Triple dimension claims he can solve that problem by using the winding through areas and curves in the face and use features that do not change with time. This process is concerned with the achievement:

- Registration for users and stored in databases in the system.

- Verification, any comparison between the people posed in front of the camera and the images in the database. This is done in a series of steps to be able at the end of the facial recognition.

The steps are:

(1) Detection:

Take a picture and it either through bilateral dimension images using electronic scanners or triple dimension using video cameras.
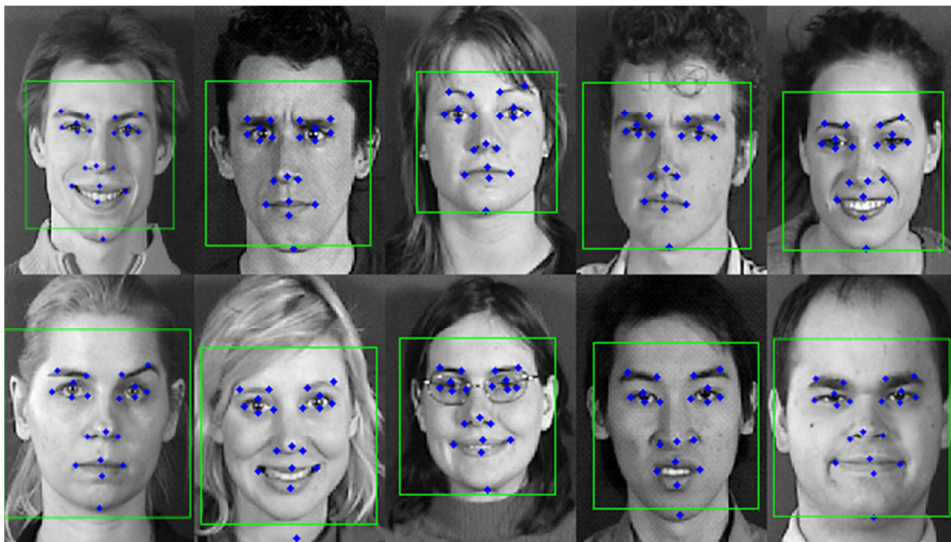
Figure 3.2: Image detection [20].

(2) Alignment:

After image capture system selects the position of the head and the size and direction. If the disclosure has been using a video camera, "three - dimensional" it is unable to determine that even if the image side of any 90 degrees. While if the two-dimensional image should not exceed arcing between the face and the camera 35 degrees.
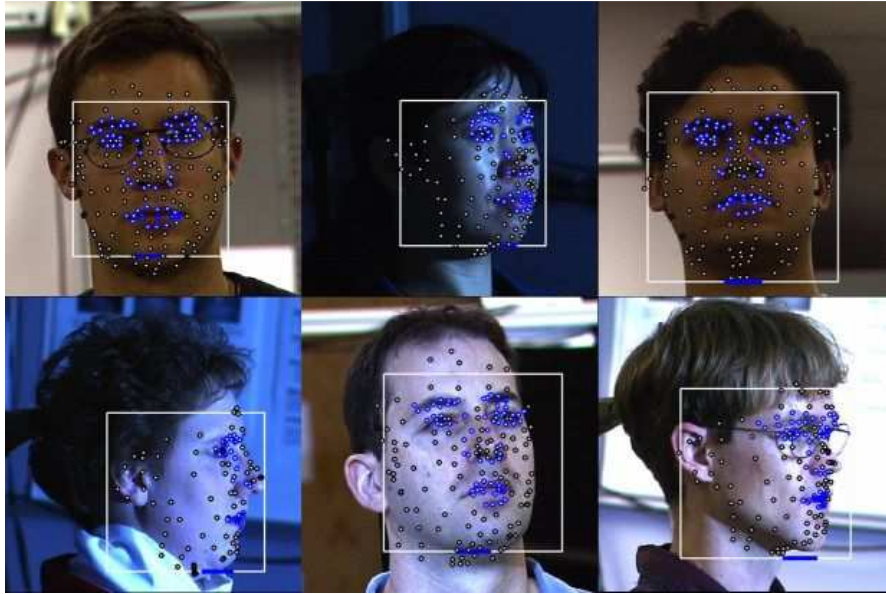
Figure 3.3: Image detection, alignment [21].

(3) Measurement:

The system software to calculate the meandering curves and on the face accurately up to portions of mm and converts that information into a template for the face and is intended to draw the hallmarks of the physiological and behavioral characteristics so as to put the template in the database "information."
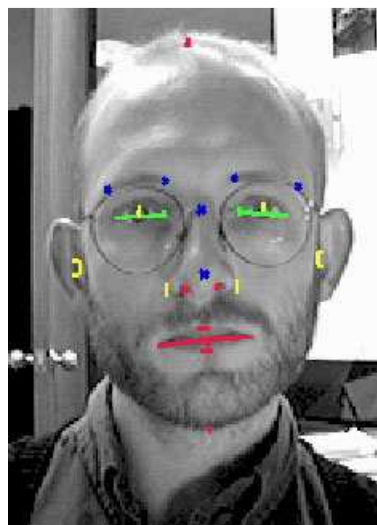
Figure 3.4: Face measurement [22].

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(4) Representation:

The system in this step to translate the mold and turn it into a code made up of a set of numbers representing the features of this template where these codes are unique to each template.

Figure 3.5: Face representation [23].

(5) Matching:

Where manufacturer's method used to compare the properties of the corresponding templates, any supported setting the standard for determining the strength of any matching if exceeded the corresponding level previously specified level matching process is considered complete. If the images in the database is three-dimensional images of the matching process does not require any conversion of the image If the two-dimensional This causes a bit of a challenge where you must template is converted to a two-dimensional image through use Algorithm and then matching.
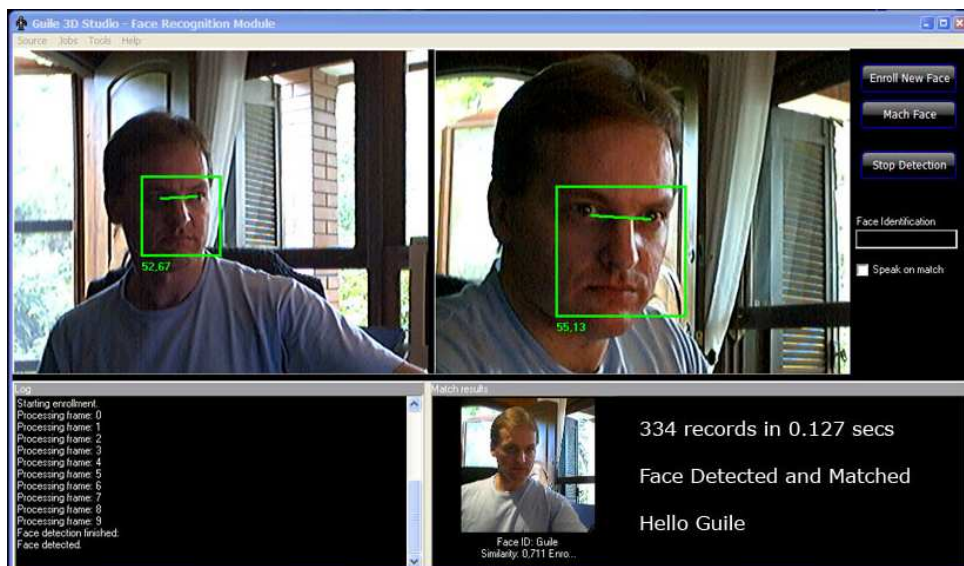
Figure 3.6: Face matching [24].

(6) Identification or verification

At this stage, there are two steps: Check if the purpose is to verify it must be a 1:1 relationship that is, it must be the result of Conformity is a single image. While if the goal is to identify matching result may give many images are likely to be matched.

Figure 3.7: Face identification [25].

It might not be sufficient previous steps to identify or verify the identity of the person completely and to increase the accuracy Identic Company has developed a new product called Facet Argus a program for a computer and relies on distinctive imprint the skin and the topography of the surface of the face.

The idea of fingerprint skin likened much in its stride imprint face the above-mentioned but he is utilized here from the image to get a sample of the skin is then fractionation this sample into small parts and algorithm is used to convert them to the viewable area measured so that the system measuring the skin of this area in terms of lines and pores, etc. and then use can even distinguish between the twins and according to statistics, the company said that the process of identifying or discrimination and matching ratio increased by 20 or 25% [16, 19].

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3.6 Face Recognition Systems Applications

3.6.1 Face Identification

Recognize these systems to people based on their pictures , unlike identification systems old , these systems give an alert presence of persons non grata and not just the verification of identity and this supports significantly security where they can be used in the publication of photographs of criminals in public places in order to identify them, in airports and seaports to search for personal counterfeit , by the Immigration Department to search for the retarded and outlaws , pitch to search for rioters (use in the United States) , in the voting process (used by the Mexican government in 2000), recording observations on the street (in England), the system BIOS licenses (in the state of Illinois in the United States) [16].

3.6.2 Permittivity and Verification Access Control

In many applications, such as offices or permittivity login on computer systems, the number of people required to allow them to carry out the process is usually small, and that the system works in pre-defined constraints such as: specific lighting, hand specific vision and other restrictions.

And both permittivity and learn is one of the security concerns that we need in our lives in airport security and travelers at the present time is a matter of discrimination faces major importance, as a result of terrorist threats ; therefore has many airports application systems known faces, in order to identify persons suspected really care about .

We can in some security applications impose lighting specific point of view as well as specific, but the biggest challenge faced by systems known faces is applied in public places, where there are no restrictions on the viewpoint or lighting There is also a large number of people who need to get to know them, in such these places have less what systems performance ratio can be identify elevated wrong. Mention of airports which apply systems known faces: Fresno Yosemite International airport in the U.S. state of California, Sydney airport in Australia and Malaysia Airports [18].

3.7 Traditional Techniques

The methods can be divided into traditional facial recognition into two groups [26]. Recognize the image of the whole face. These methods are based on the link. Simpler classification scheme, which uses a comparison of the models confession, is matching template. Template matching problem is that you have to compare many of the features (for him, the pixel is a feature), and if we consider that in the database, M people, with n photo of each person, and we note that this method cannot be implemented in real time. So, working with other means de correlational the features together to get a reduction of the area of the face to a smaller number of transactions, which have a high discriminatory power among the people? This is what is called subspace in the face. Examples of methods that work spaces and partial principal component analysis (PCA - analysis of the major components) of Eigen faces, and linear differentiation analysis (LDA - linear differentiation analysis) or linear differentiation Fisher (FLD - Fisher linear differentiation) of Fisher faces.

PCA technology is the one that provides the highest performance. It works by dropping the images on the face of the area that features include large differences between images of known faces. Senior faction called Eigen faces, because they are self - vectors, or key components, and a set of faces. Drop distinguishes the facial image of the individual as the sum of the weights of all the different factions and, in the same way, and to identify a certain image of the face will only need to compare these weights with the interests of the individuals previously known. No information you need to consider what images belong to the same person. It is very sensitive to changes in lighting conditions in the different images of the same person [27].

LDA method allows information between members of the same category (images of the same person) to develop a set of feature vectors where he stressed the differences between the different faces , while the changes due to lighting , facial expressions and head and face .which increases the contrast between the layers of samples, and reduces between samples of the same category? [28].

FLD technology equivalent of LDA results obtained with FLD is much better than we can get with PCA, especially when different lighting conditions across a range of images training and testing, as well as changes in facial expressions, and give more weight to areas such as the eyes, nose, cheeks, mouth because it is not subject to change in different areas of expression that a person can be [29].

Other ways instead of using partial facial spaces follow neural network classification and templates deformation and unusual - Elastic graph matching.
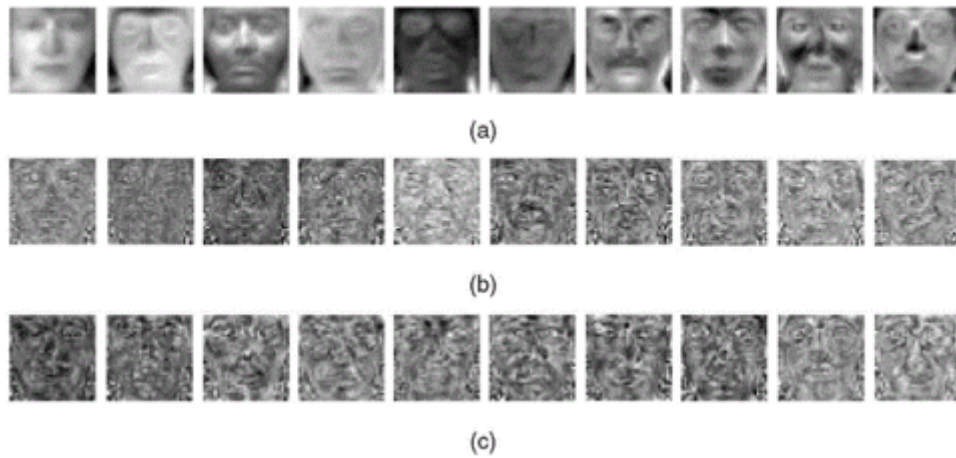
Figure 3.8: a) Eigenfaces, the b) Fisherfaces, the c) Laplacianfaces calculated from the images in the database object [30].

3.8 Cons Face Discrimination Technology

Despite the success of these systems and their evolution, but it does not reach a perfect score after because there are some factors that may hinder the process of facial recognition, and these constraints as follows [31]:

1. Glare caused by wearing sun glasses.

2. Long hair obscures the central part of the face.

3. Dim lighting that the resulting images are not clear.

4. Double precision and clarity of images that are taken from a distance.

5. Changes in physiological characteristics in the face, either because of old age or other.

6. Changes in the work environment reduce the accuracy of matching.

7. The possibility of misuse of the privacy of persons when the registration process in the case of uncooperative users and potential tariff.

4. FEATURE EXTRACTION

4.1 Overview

The algorithm Principal component analysis PCA is one of the most successful techniques that have been used in the field of image recognition in the field of image compression. PCA is classified as one of the statistical methods in this field.

The main objective of the PCA algorithm lies in reducing the large dimensions of the data to another smaller dimension. Containing basic and important features of the original data, and therefore, by reducing the dimensions of this we have been described more economic data.

Fisher linear discriminant analysis FLD is used to reduce the dimension of feature space to *N-1* (*N* denotes the number of training samples). Then, the transformed space is divided into two subspaces: the null space of within- class scatter matrix and its orthogonal complement, from which two cases of optimal discriminant vectors are selected respectively.

4.2 Recognition System and Problems of Large Dimensions

Problems usually appear in face recognition systems when dealing with systems large-dimensional images can make many improvements and cross-matching and data transfer existing data to lower dimensions. Thus we may have dimensionality reduction of the original image with large dimensions of the new image with smaller dimensions.

For example, we have the following [32]:

$$X = [X_1, X_2 ..., X_N]^T \tag{4.1}$$

And that within the space of *N* after the author, by reducing the dimensions we move to the last beam to any space consisting of *K* so that after *K* <*N* [33].

$$y = [y_1, y_2 ..., y_k]^T \tag{4.2}$$

The decrease Dimensions in turn leads to the loss and the loss of information, but the goal of the algorithm is to reduce the dimensions of the PCA data while retaining as much as possible and important part of the information in the original data. This process is equivalent to retain as much as possible of the variations and changes contained within the original data.

The PCA calculates linear transformation **T**, which compares the data contained within the space dimensions to the information to approve it within a partial-dimensional space, at least, as the subject below:

$$\begin{cases} y_1 = t_{11}x_1 + t_{12}x_2 + \dots + t_{1N}x_N \\ y_2 = t_{21}x_1 + t_{22}x_2 + \dots + t_{2N}x_N \\ \dots \\ y_k = t_{k1}x_1 + t_{k2}x_2 + \dots + t_{kN}x_N \end{cases} \qquad (4.3)$$

Or in other words

$$y = T_X \qquad (4.4)$$

Whereas

$$T = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1N} \\ t_{21} & t_{22} & \cdots & t_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ t_{k1} & t_{k2} & \cdots & t_{kN} \end{bmatrix} \qquad (4.5)$$

The optimum conversion **T** is a conversion that where the value $/X - y/$ minimal. Depending on the theory of PCA [35], it can define a space with dimensions of at least optimized through the use of the best X-self eigenvectors own matrix variation of the data covariance matrix of the data. We mean: the rays of self-approval of the values of self-largest largest eigenvalues of the matrix, contrast, and also referred to as the basic components "principal components".

Suppose that $\mathbf{I_1, I_2, \dots, I_M}$ a set of M beam, each beam has the following dimensions $N \times 1$ [34].

4.3 The Basic Steps of PCA Algorithm

First step: we calculate the average beam for a given radiation

$$\bar{\mathbf{I}} = \frac{1}{M} \sum_{i=1}^{M} \mathbf{I}_i \qquad (4.6)$$

Second step: We are Normalize each scan, and put it through the center of the beam, which was calculated in the first step

$$\Phi_i = \mathbf{I}_i - \bar{\mathbf{I}} \qquad (4.7)$$

Third step: the formation of the matrix $A = \left[\Phi_1, \Phi_2, \cdots, \Phi_M\right]$ Dimensions $N \times M$.

Fourth Step: we calculate the variance matrix (covariance matrix)

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = A A^T \tag{4.8}$$

it is a matrix dimensions $N \times N$ [35].

Fifth step: Calculate the eigenvalues $\lambda_1, \lambda_{2,...}, \lambda_N$ and self-rays $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N$ matrix C (Assuming that $\lambda_1, \lambda_{2,...}, \lambda_N$) [35].

Since the matrix C Symmetrical, the $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N$ form the a set of X-basis vectors, and therefore, any beam **I** within the same space can be written in the form of a linear fitting of radiology self-linear combination of the eigenvectors, using the radiation that has been holding normalize them, and therefore we have the following:

$$\mathbf{I} - \bar{\mathbf{I}} = y_1 u_1 + y_2 u_2 + \cdots + y_N u_N = \sum_{i=1}^{N} y_i u_i \tag{4.9}$$

Sixth step (Dimensions loss): It is here in this step represent each beam **I** by retaining only approved for the largest values K intrinsic value:

$$\hat{\mathbf{I}} - \bar{\mathbf{I}} = y_1 u_1 + y_2 u_2 + \cdots + y_k u_k = \sum_{i=1}^{k} y_i u_i \tag{4.10}$$

Where $K < N$, in this case, the $\hat{\mathbf{I}}$ convergence **I** so that it is $|\mathbf{I} - \hat{\mathbf{I}}|$ smaller.

Therefore, the linear transfer **T** included within the PCA defined by the basic components of variance matrix covariance matrix.

$$T = \begin{bmatrix} u_{11} & u_{21} & \cdots & u_{k1} \\ u_{12} & u_{22} & \cdots & u_{k2} \\ \vdots & \vdots & \ddots & \vdots \\ u_{1N} & u_{2N} & \cdots & u_{kN} \end{bmatrix} \tag{4.11}$$

The PCA drop data along the trends that differ by more data than others (Figure 4.1). These trends are identified through self-ray contrast matrix (eigenvectors of the covariance matrix) of the values of self-approval largest (largest eigenvalues).

The magnitude of the size and amplitude values compatible with the self-variation data along trends self-rays.
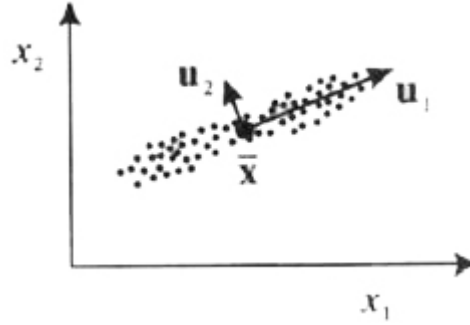
Figure 4.1: Geometric interpretation algorithm PCA [36].

To decide what the number of principal components is core components that we need to keep (mean value of **K**), it can be used the following criteria:

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{N} \lambda_i} > t \tag{4.12}$$

Where **t** is the threshold (for example: take the following values of 0.8 or 0.9) and **t** value that specifies the amount of information that will be kept within the data. What determines the value of **t**; it can then determine the value of **K**. We cannot say that the error due to dimensional reduction step given the following words:

$$error = \frac{1}{2} \sum_{i=k+1}^{N} \lambda_i \tag{4.13}$$

It should be noted that the principal components based on units used to measure the original variables as well as on the field values that are assumed. Therefore, it should always unite us (to make it a standard) data before using the algorithm PCA.

4.4 Self-Face Eeigenface PCA Algorithm Applied to Face Images

The approach to facial self (eigenface approach) algorithm uses PCA to represent the faces within the subspace low-dimensional, and is extracted this space by taking advantage of the X-self (eigenvectors) best any faces self (eigenfaces) matrix contrast portraits (covariance matrix of the face images) [37].

Assume that we have a group of M-face training $\mathbf{I_1, I_2, \ldots, I_M}$ each face image has the following dimensions $N \times N$. The basic steps necessary to implement the PCA algorithm on a set of pictures faces [37]:

First step: are converted to represent each face image $\mathbf{I}_i$ Dimensions of the following $N \times N$ to single beam $\mathbf{\Gamma}_i$ the following dimensions $N^2 \times 1$. This process can be accomplished simply by row lines and one of them after the other, to turn from the matrix to the single beam (as in Figure 4.2).
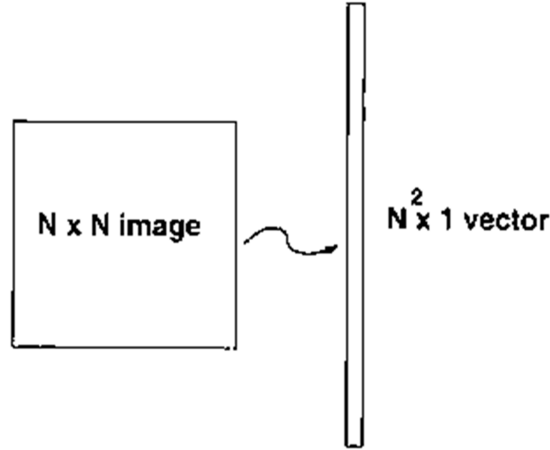
Figure 4.2: Beam represents a facial image [38].

Second step: Central face is calculated through the following relationship:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \qquad (4.14)$$

Third step: Normalize is done for each beam images Γ_i and put forward through the middle of the face are as follows:

$$\Phi_i = \Gamma_i - \Psi \qquad (4.15)$$

Fourth step: The formation of the matrix $A = \begin{bmatrix} \Phi_1, \Phi_2, \cdots, \Phi_M \end{bmatrix}$ consisting of $N^2 \times M$.

Fifth step: is calculated contrast dimensional matrix containing variations faces. According to the method of PCA, we need to calculate the self-ray u_i matrix $\mathbf{AA^T}$. But a very large matrix (i.e. equal to expel $N^2 \times N^2$), and therefore, it is not feasible that we calculate her self-rays. Instead, we will take into account Self-rays V_i matrix $\mathbf{A^T A}$ .Which in turn is much smaller than the matrix (i.e., that the dimensions $M \times M$).And then we calculate self-rays of the matrix $\mathbf{AA^T}$ from self-rays of the matrix.

Sixth step: Calculations of the self-ray V_i of the matrix $\mathbf{AA^T}$. It can simply show the relationship between u_i and V_i . As the V_i X is a self-matrix $\mathbf{A^T A}$, they bring the following relationship: $A^T A V_i = \mu_i V_i$ That's where μ_i represents the values of self-approval. If we beat both parties within the following matrix equation $\mathbf{A}$ Then we will get

$$AA^T A V_i = A \mu_i V_i \tag{4.16}$$

Or

$$C A V_i = A \mu_i V_i \text{ or } C u_i = \mu_i u_i \tag{4.17}$$

Each of the $\mathbf{AA^T}$ and $\mathbf{A^T A}$ has the same values as self-linked self-rays through the following relationship:

$$u_i = A V_i \tag{4.18}$$

It is worth to note that the matrix $\mathbf{AA^T}$ can have up to N^2 self-beam, while the matrix $\mathbf{A^T A}$ Can have up to M self- ray.

Rays can show that the self-matrix $\mathbf{A^T A}$ Better compatibility M ray self-matrix $\mathbf{AA^T}$ (In other words, self-rays agree eigenvalues larger).

Seventh step: Self-rays are calculated u_i the matrix $\mathbf{AA^T}$ Using the relationship

$$u_i = A V_i \tag{4.19}$$

Note: You must do to normalize u_i So that it is $|u_i| = 1$.

Eighth step: (D-loss) are represented by each face "**T**" Transient retain only the values that greater consensus *K* intrinsic value:

$$\hat{\Gamma} - \Psi = y_1 u_1 + y_2 u_2 + \cdots + y_k u_k = \sum_{i=1}^{k} y_1 u_i \qquad (4.20)$$

Figure 4.3 below provides us emulates to self-face approach eigenface approach. In the first row, is showing a group of self-faces eigenfaces (no self-compatibility faces great eigenvalues) comes the phrase "self-face" by the fact that self-rays look like ghost images). The second row, it shows us a new face, was expressed in the written form of the installation of self-faces.
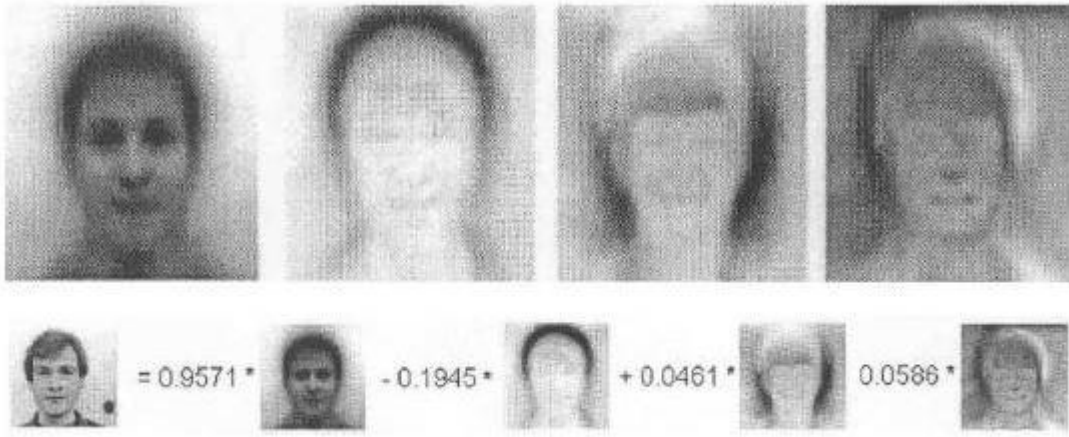
Figure 4.3: Simulation and representation of self-face approach eigenface approach, each face can be represented in the form of a linear fitting of self-faces [39].

Using PCA, each face image **T** can be represented within the space with dimensions smaller than the dimensions of the original image, using the linear expansion coefficients:

$$\Omega = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} \qquad (4.21)$$

4.5 Fisher Linear Discriminant Analysis

The fisher linear discriminant analysis FLD is one of the predictive discriminant analysis techniques. It is to explain and predict an individual's membership in a class (group) preset from its measured characteristics using predictive variables. In the example of Article discriminant analysis, the Flea Beetles file, the objective is to determine the membership of chips to a particular species from the width and angle of the aedeagus (genitalia males of the insect.)

The variable is bound to predict categorical (discrete), it has three terms in our example. Predictors are a priori all continuous. However, it is possible to treat the discrete predictors for adequate data preparation. The fisher linear discriminant analysis can be compared to supervised methods developed in machine learning and logistic regression developed in statistics [40].

4.5.1 Assumptions and Formulas

We have a sample of n , observations distributed in K, staff groups n_k . Note Y, the variable to predict, it takes its values in $\{y_1, \cdots, y_k\}$, We have J predictor variables $x = (x_1, \cdots, x_J)$. We note μ_k , the centers of gravity of clouds conditional points W_k their variance-covariance matrix.

4.5.2 Bayesian Rule

The objective is to produce an allocation rule $F : X \Rightarrow \{y_1, \cdots, y_k\}$ that predicts, for an observation ω given its associated value of Y from the values taken by X. Bayesian rule is to produce an estimate of the posterior probability of assignment [41].

$$P\left(Y = y_k / X\right) = \frac{P\left(Y = y_k\right) \times P\left(X / Y = y_k\right)}{\sum_{i=1}^{k} P\left(Y = y_i\right) \times P\left(X / Y = y_i\right)} \qquad (4.22)$$

$P\left(Y = y_k\right)$ is the prior probability of belonging to a class. $P\left(Y = y_k\right)$, is the density function of X conditional on the class y_k .

The allocation rule for an individual ω rating becomes

$$Y\left(\omega\right)=y\;*_{k}\;\text{ if and only if}$$

$$y\;*_{k}\;=\arg\max_{k}\;P\left[Y\left(\omega\right)=y_{k}\Big/X\left(\omega\right)\right] \tag{4.23}$$

The whole issue of discriminant analysis is then up to offer an estimate of the quantity

$$P\left(X\Big/Y\;=y_{k}\right). \tag{4.24}$$

4.5.3 The Parametric Discriminant Analysis - Hypothesis Multi Normality

There are two main approaches to correctly estimate the distribution $P\left(X\Big/Y\;=y_{k}\right)$

- The nonparametric approach makes no assumption about the distribution of local but has a probability estimation procedure, adjacent the observation ω, rating. The best-known procedures are Parzen kernels and method of nearest neighbors. The main difficulty is to define adequately the neighborhood [42].

- The second approach makes an assumption about the distribution of clouds conditional points; we speak in this case of parametric discriminant analysis. The hypothesis most commonly used is undoubtedly the hypothesis multi normality.

In the case of multidimensional normal distribution, the distribution of clouds conditional points written

$$fk\left(x\right)=\frac{1}{\left(2\pi\right)^{j/2}\times|Wk\;|^{1/2}}\times e^{-\frac{1}{2}(X-\mu k\,)'Wk^{-1}(X-\mu k\,)} \tag{4.25}$$

Where $|\mathbf{W_{k}}|$ is the determinant of the variance-covariance matrix conditional on y_{k}

The objective is to determine the maximum a posteriori probability assignment, we can neglect all that does not depend on k. Passing the logarithm, we obtain the discriminant score which is proportional to $P\left(Y\;=y_{k}\Big/X\right)$.

$$D\left[Y\;=y_{k}\,,X\;\right]=2\times L_{n}\left[P\left(Y\;=y_{k}\,\right)\right]-L_{n}\;|\mathbf{W_{k}}|-\left(X-\mu_{k}\,\right)'W_{k}^{-1}\left(X-\mu_{k}\,\right) \tag{4.26}$$

The allocation rule is therefore

$$y\;*_{k}\;=\arg\max_{k}\;D\left[Y\left(\omega\right)=y_{k}\,,X\left(\omega\right)\right] \tag{4.27}$$

If we fully develop the discriminant score, we find that it is expressed in terms of square and cross product between the predictor variables. This is called quadratic discriminant analysis. Widely used in research because it behaves very well in terms of performance compared to other methods, it is less common among practitioners. Indeed, the expression of the discriminant score is rather complex, it is difficult to clearly discern the direction of causality between predictor variables and class membership. It is particularly easy to distinguish evil really critical variables in the classification; interpretation of results is quite dangerous.

4.6 The Homoscedasticity Assumption

A second hypothesis can further simplify the calculations, it is homoscedasticity: variance covariance matrices are identical from one group to another. Geometrically, this means that the point clouds have the same shape (and volume) in the space of representation.

The variance-covariance matrix is estimated in this case the variance-covariance matrix calculated within-class with the following expression.

$$W = \frac{1}{n-K} \sum_k n_k \times W_k \tag{4.28}$$

Again, we can evaluate the discriminant score all that no longer depends on k, it becomes

$$D\left[Y = y_k, X\right] = 2 \times L_n\left[P\left(Y = y_k\right)\right] - \left(X - \mu_k\right)' W^{-1}\left(X - \mu_k\right) \tag{4.29}$$

4.7 Linear Ranking Function

By developing the expression of the discriminant score after introduction of homoscedasticity, we see that it is expressed linearly with respect to the predictor variables.

There are many ranking functions as categories of the variable to predict, they are linear combinations of the following form:

$$D\left(y_1, X\right) = a_0 + a_1 \times X_1 + \cdots + a_J \times X_J \tag{4.30}$$

$$D\left(y_2, X\right) = b_0 + b_1 \times X_1 + \cdots + b_J \times X_J \tag{4.31}$$

This presentation is attractive in more ways than one. It is possible, by studying the value and sign of the coefficients to determine the direction of causality in the rankings. Similarly, it is possible, as we shall see later, to assess the significant role of variables in the prediction.

4.8 Euclidean Distance

In mathematics, the Euclidean distance is the distance between two points that is the extent of the segment joining the two extreme points. By using this formula as distance, Euclidean space becomes a metric space (in particular). The traditional literature refers to this metric as Pythagorean metric.

4.8.1 Fundamentals of Euclidean Distance

Tools Euclidean distance describes the relationship of each cell to the source or group of sources on the basis of the distance along a straight line. There are three Euclidean tools [43].

Euclidean distance of the instrument shows the distance from each cell of the raster to the nearest source. Tool Euclidean direction indicates the direction from each cell to the nearest source. Symbol distribution Euclidean distance (Euclidean Allocation) is used to determine the cells which should be assigned to the source based on the maximum proximity.

4.8.2 The Euclidean Distance Algorithm

Euclidean distance is calculated from the sources to the center of a cell from the center of each surrounding cell. In the tools to determine the distance the true Euclidean distance is calculated to each cell. From a conceptual point of view, the Euclidean algorithm works as follows. For each cell, the distance to the source of each cell is calculated by computing the hypotenuse, and the values are the legs of x_max and y_max. This calculation gives a true Euclidean distance, and not the distance between cells. Measure the shortest distance to the source, and if it is less than a predetermined maximum distance, location on the output raster is assigned a value [44].
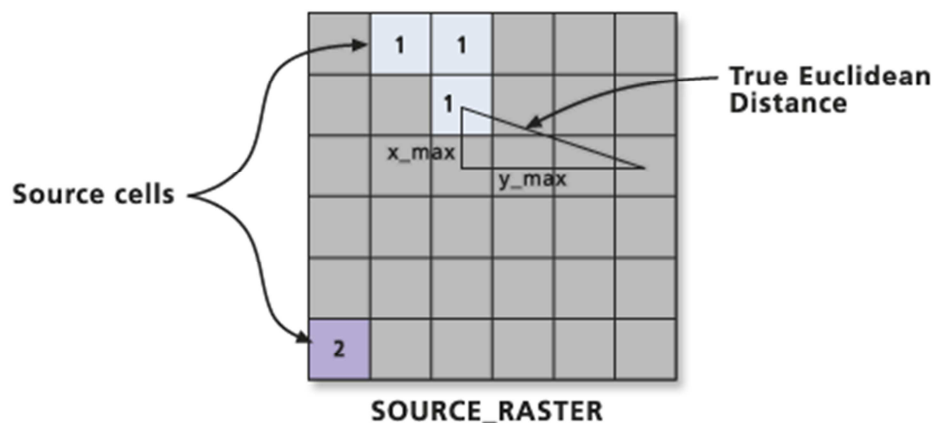
Figure 4.4: Determining the true Euclidean distance [45].

The output values for the raster Euclidean distance - distance values denominated floating-point numbers. If the cell is located at the same distance from two or more sources, it will be attributed to the source, which was first found in the scanning process. The scanning process cannot control you.

Description above - this is a conceptual description of how the values were obtained. The actual algorithm computes the information using a twice- scanning. This process sets the speed of the tool, which does not depend on the number of cell sources, the distribution of cell sources and a given maximum distance. The computation time is linearly proportional to the number of cells in the analysis.

4.8.3 Distance One-Dimensional

For two-dimensional points, $P = (p_x) e Q = (q_x)$, the distance is calculated as:

$$\sqrt{(p_x - q_x)^2} = |p_x - q_x|$$ (4.32)

It uses the absolute value since the distance is usually a positive integer.

4.8.4 Distance Bi Dimensional

For two points in two dimensions, $P = (p_x, p_y) e Q = (q_x, q_y)$, the distance is calculated as [46]:

$$\sqrt{(p_x - q_x)^2 + (p_y - q_y)^2}$$ (4.33)

4.8.5 Approximation for 2D Applications

A quick approximation of the distance in 2D based on an octagonal around can be calculated as follows. Both $d_x = |\mathbf{p_x} - q_x|$ (absolute value) $e d_y = |\mathbf{p_y} - q_y|$.

There are other types of approximation. All generally try to avoid the square roots, since they are expensive in computational terms, and are the source of several errors: speed ratio. Using the above notation, the approximation $dx + dy - (1/2) \times min(dx, dy)$, an error between 0% and 12%. Best approximated in terms of RMS error is $dx + dy - (5/8) \times min(dx, dy)$, for which an error is estimated between -3% and 7% [47].

Note that if you need to compare distances (for which you just want to know for example what the greater, not is the actual difference) is not necessary to calculate the square root of all if you take into account the following properties:

- If A^2 is greater than B^2, then also the distance **A** will be greater than the distance **B**;

- Check if the distance **A** is greater than the distance **2B** is as compare with $A^2(2B^2, 4B^2)$, and so on.

4.8.6 Distance Tri Dimensional

For two points in three dimensions, $P = (p_x, p_y, p_z) e Q = (q_x, q_y, q_z)$, the distance is calculated as [48]:

$$\sqrt{(p_x - q_x)^2 + (p_y - q_y)^2 + (p_z - q_z)^2}$$

(4.34)

5. DESIGN OF FACE RECOGNITION SYSTEM

5.1. Overview

In this chapter the design of face recognition system has been performed. For feature extraction of face images Principal Component Analysis PCA and Fisher Linear Discriminant are used. For comparative analysis the Fast Pixel Based Matching FPBM were used. The basic structure of face recognition system is given. The flowcharts of the designed program have been described. The Euclidean distance has been applied for classification of the faces.

5.2 General Structure of Face Recognition

The general structure of the face recognition program is shown in Figure 5.1. The inputs of the system are face images. These images are accumulated in image database. After database creation, the used image is sent to the feature extraction block. In these thesis two methods- PCA and FLD are used for feature extraction. These methods are applied to obtain the principal components and linear components of face images. Using these features the classification of the images are carried out. The decision is made if there is matching in the classification block.
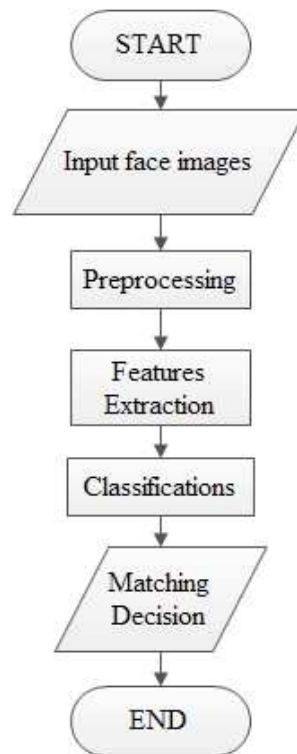
Figure 5.1: General Structure of Face recognition program.

5.3 Flowcharts of Feature Extraction Methods

The two methods PCA, FLD were used for feature extraction during simulation. Each of them was explained in chapter 4, and the flowcharts of these methods were given in this section.

All image data are represented by greyscale values. Principles Component Analysis PCA are used for feature extraction. Some operations should be done for pre-processing of the images. Figure 5.2 show converting all images from 2D to 1D. Store 1D images in vector called **T**. Converting from 2D vector to 1D vector is done using reshape function.

```
          ( START )
             │
             ▼
     / Read images from /
     /    database      /
             │
             ▼
   ┌──────────────────────┐
   │ reshape all images   │
   │ from 2D to 1D        │
   │ vector (T)           │
   └──────────────────────┘
             │
             ▼
       / outputs T /
             │
             ▼
          ( END )
```
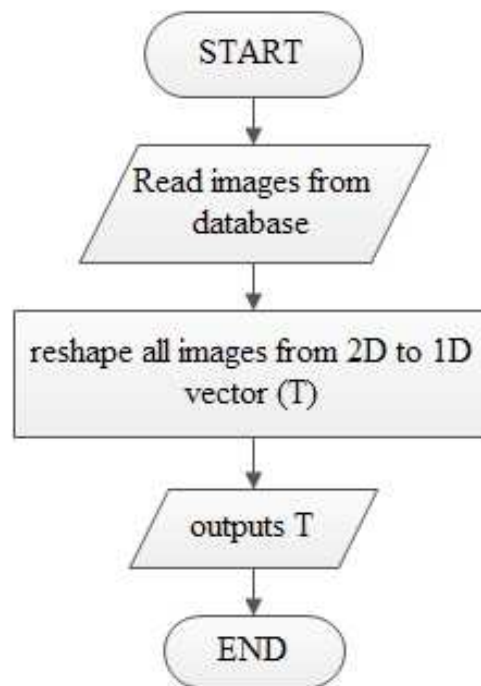
Figure 5.2: Flowchart of converting 2D images to 1D.

Figure 5.3 shows the computing for mean, deviation and eigenvector. After reading T vectors from previous function, compute the mean image. The mean image means the average for all images. After that, compute the deviation for all images (each one alone) from the mean image. The deviation means the subtracting between an image and the mean image. Then, compute the surrogate for covariance matrix.

Finally, compute the eigenvectors by multiplication of the deviation of an image and surrogate matrix.
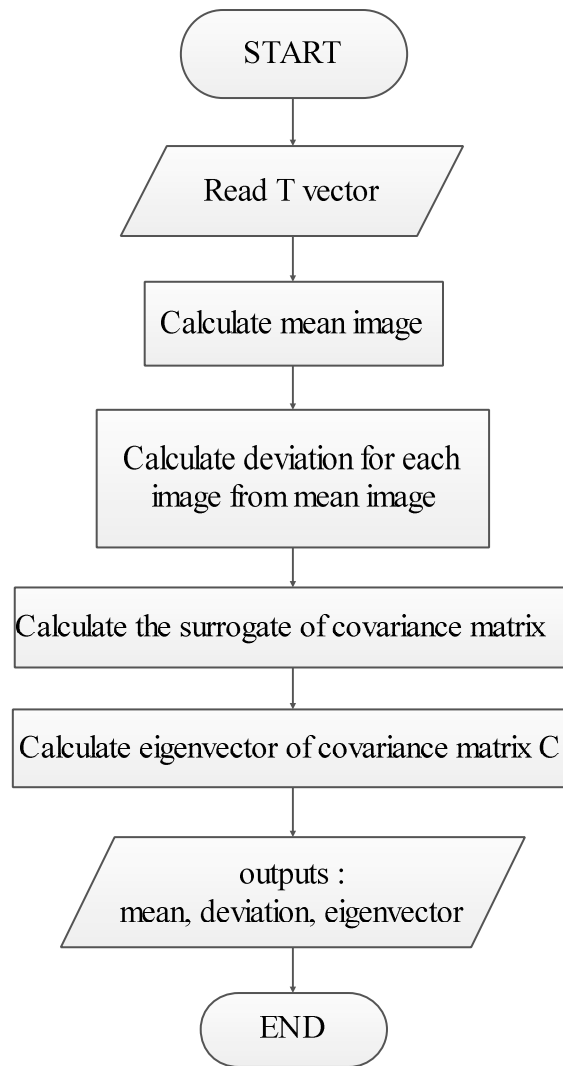
Figure 5.3: Flowchart for computing eigenvectors.

To make recognition, compute the minimum distance from Euclidean distances. Next compute Euclidean distances, compute the database images feature vectors into face space.

Figure 5.4 shows the steps for extracting the PCA features from test image to make recognition. PCA features are:

- Reshape tested image to 1D image vector.

- Compute the deviation for tested image and the mean image.

- Compute the test image feature vector into face space.
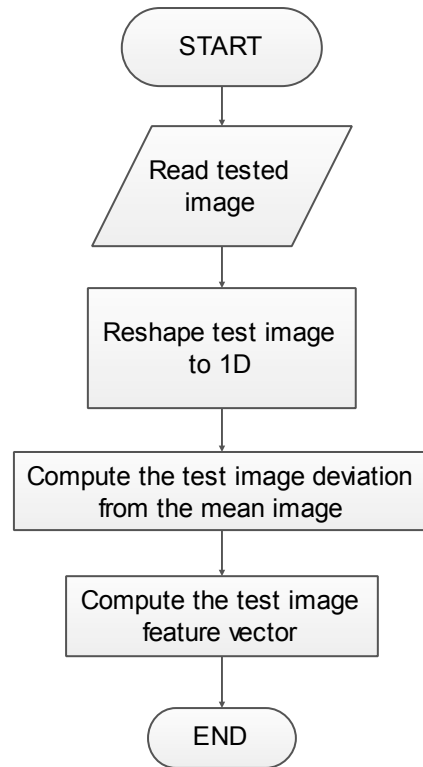
Figure 5.4: Flowchart for extracting of PCA features for tested image.

Finally computed and store Euclidean distances in a vector by Subtraction of database images features vectors from the test image features vector then:

1. Applying norm function for the result.

2. Square the result, the store it in that vector. See Figure 5.5.

Euclidean distance measure is applied to make recognition and compute the minimum distance. To compute Euclidean distances, image vector is projected into face space. The deviations between test projected image and all the images in database are determined. These deviations are normalized and formed as Euclidean distance and recognized index. Using Euclidian distance the recognized index is determined. If the recognized index belong to the same person, that means success fully recognition, otherwise recognition failed.
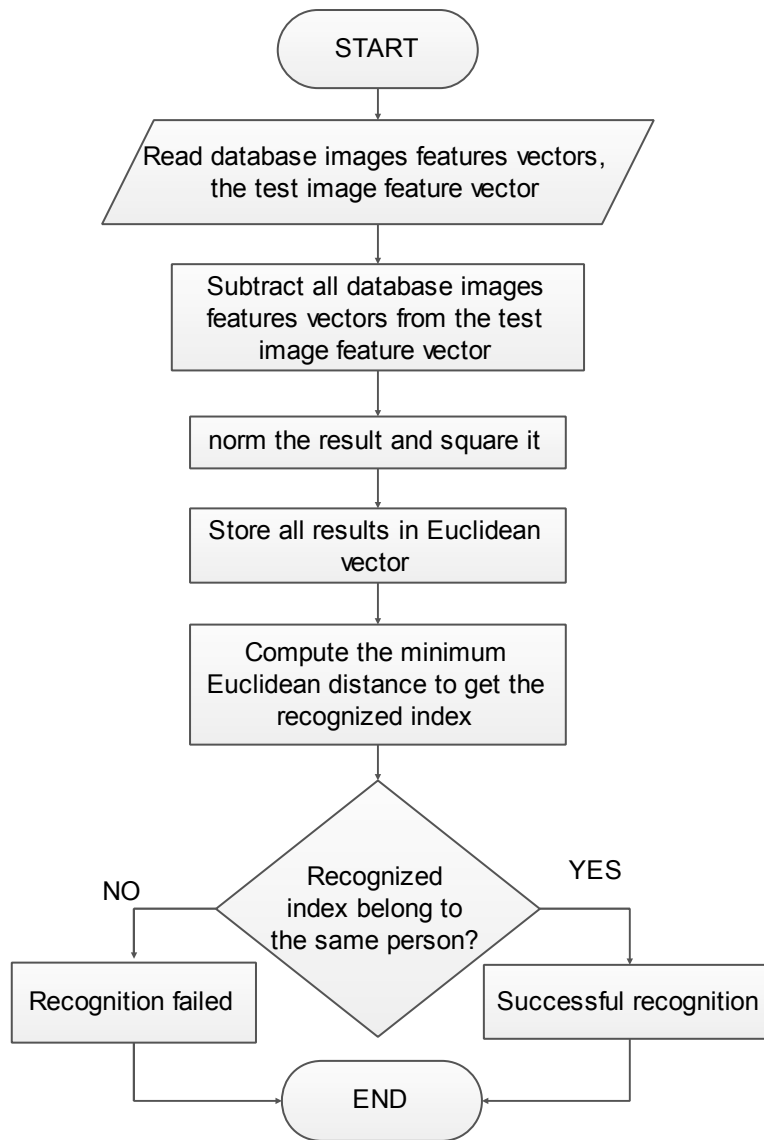
Figure 5.5: Flowchart of recognition process from Euclidean distance.

Feature extractions in Fisher Linear Discriminant analysis FLD use Euclidean distance. So, it must be calculate some elements. PCA and FLD share a lot of characteristics and differ in some of characteristics. In this section, the common and the different characteristics were explained.

Figure 5.2 shows converting all images from 2D to 1D. Store 1D images in vector called **T** using reshape function. This converting process is same as process in PCA.

Figure 5.6 shows the computation of the mean images, the deviation, and eigenvector for PCA algorithm; database features vectors Fisher and Fisher discriminant. Calculations of the mean image and the deviation in FLD and PCA have the same equations. The mean image is the average of all database images. The deviation for all images from the mean image is the subtraction between an image and the mean image. After that, compute the surrogate of covariance matrix. Then, calculate the database features vectors on eigenspace as in PCA algorithm. All of previous calculations are same as PCA calculations. So, FLD is called sometimes Fisher PCA.

Next, calculate the mean image for each person (each class in database) in eigenspace. From those mean images, generate two matrices. The first matrix called the Within Scatter matrix **Sw** and the second called the Between Scatter matrix **Sb**. The calculations of those matrices depend on the mean images for each person alone (see FLD implementation). From those matrices, the getting of Fisher discriminant is very easy by applying the eig (A, B) function. To finish this algorithm, compute the projection of all database images onto Fisher Linear space to use them in recognition process.

```
                    ┌─────────────┐
                    │    START    │
                    └──────┬──────┘
                           │
                    ╱──────┴──────╲
                   ╱ Read T vector ╲
                  ╱─────────┬───────╲
                           │
        ┌──────────────────┴──────────────────┐
        │ Calculate the mean image, the        │
        │ deviation, the surrogate and         │
        │ eigenvectors of covariance matrix.   │
        └──────────────────┬──────────────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Compute database  │
                 │ images features   │
                 │ vectors           │
                 └─────────┬─────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Calculate the mean│
                 │ of each person in │
                 │ Eigenspace        │
                 └─────────┬─────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Calculate the     │
                 │ Within scatter    │
                 │ matrix (Sw) and   │
                 │ the Between       │
                 │ scatter matrix(Sb)│
                 └─────────┬─────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Projecting image  │
                 │ onto Fisher Linear│
                 │ space             │
                 └─────────┬─────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Calculate the     │
                 │ Fisher discriminate│
                 │ basis's           │
                 └─────────┬─────────┘
                           │
                 ┌─────────┴─────────┐
                 │ Eliminating small │
                 │ Eigen and sorting │
                 │ in descend order  │
                 └─────────┬─────────┘
                           │
              ╱────────────┴────────────╲
             ╱ Outputs:-                  ╲
            ╱ the mean image,              ╲
           ╱ Eigenvector for PCA,           ╲
          ╱ database features vectors for    ╲
         ╱ Fisher images,                     ╲
        ╱ Fisher discriminant                  ╲
       ╱────────────────┬──────────────────────╲
                        │
                 ┌──────┴──────┐
                 │     END     │
                 └─────────────┘
```
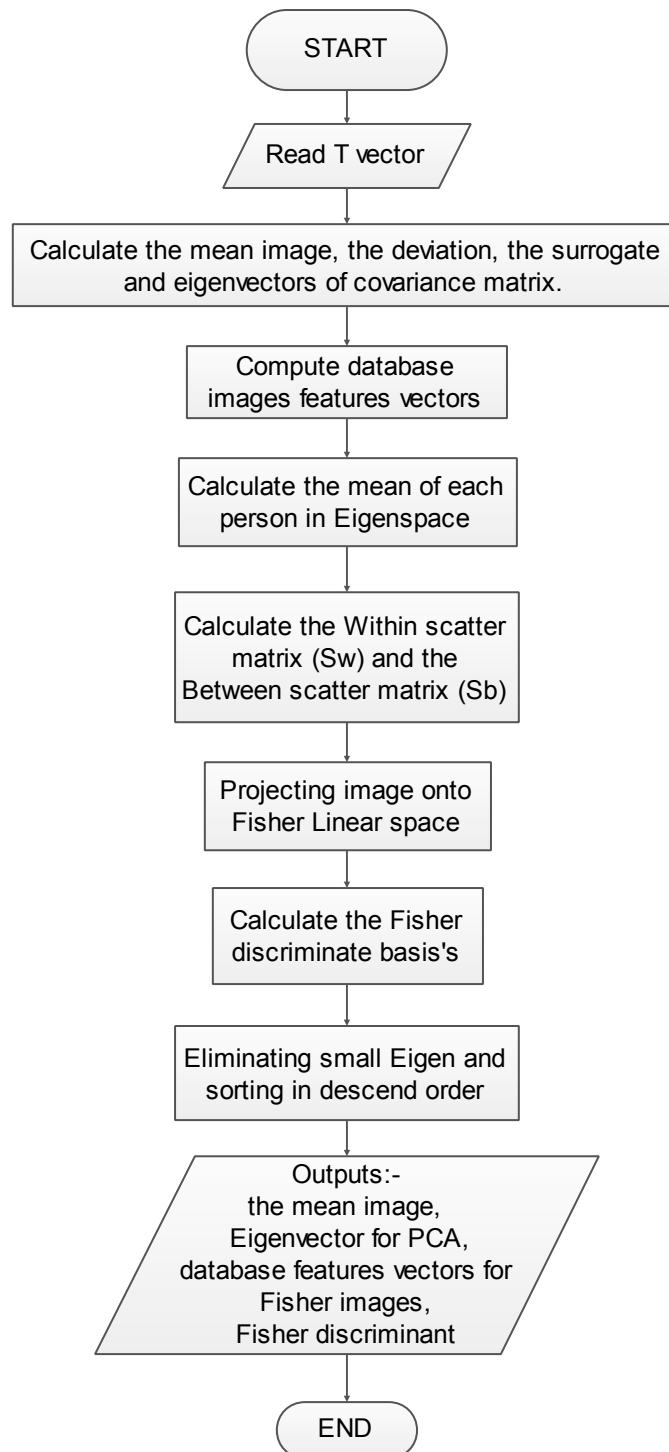
Figure 5.6: Flowchart of FLD algorithm.

To make recognition, compute the minimum distance from Euclidean distances. Figure 5.4 shows the steps for extracting the FLD features from test image to make recognition. FLD features are:

- Reshape tested image to 1D image vector.

- Compute the deviation for tested image and the mean image.

- Compute the test image features vector.

Finally computed and store Euclidean distances in a vector by Subtraction of the database feature vectors from test image feature vector then:

1. Applying norm function for the result.

2. Square the result, and store it in that vector. See Figure 5.5.

Euclidean distance measure is applied to make recognition and compute the minimum distance. To compute Euclidean distances, image vector is projected into face space. The deviations between test projected image and all the images in database are determined. These deviations are normalized and formed as Euclidean distance and recognized index. Using Euclidian distance the recognized index is determined. If the recognized index belong to the same person, that means success fully recognition, otherwise recognition failed.

5.4 Implementation of Principal Component Analysis

The colored images are converted in greyscale mode using rgb2gray(x) function in Matlab. Obtained images in database are converted from 2D matrix to 1D image vectors. Those become a train folder. We get

$$T_i = \begin{bmatrix} P_1 ... P_m \end{bmatrix}^T , i = 1, \ ... \ , M \tag{5.1}$$

Before computing **T** vector we need to check if all images are in greyscale or not. If not, convert to greyscale Figure 5.10. **T** is a vector that contains the reshaping matrix from 2D to 1D for all images. Number of rows in 1D matrix is multiplication of the original rows and columns. Assume there are 120 images in database folder, Figure 5.7. All images have the same dimensions 92×112, for that the size of **T** vector will be 10304×120.

Figure 5.7: Original database images samples.

Figure 5.8: Tested images set (1).

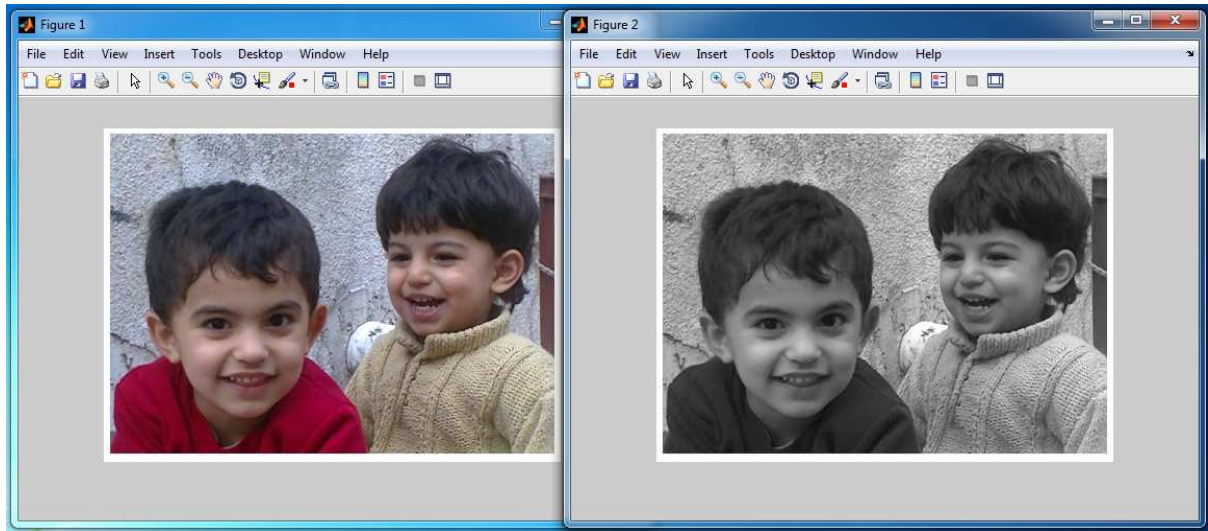Figure 5.9: Tested images set (2).

Figure 5.10: Convert from RGB to grayscale.

Now calculate the mean image for database images, by summation of all **Ti** according to equation:

$$m = \frac{1}{M} \sum_{i=1}^{M} T_i \quad , i = 1, 2, ..., M$$

(5.2)

Size of the mean image matrix for the same number of images in database is 10304×1 because of division by the number of images in database. After that compute the deviation of each image from the mean image according to this formula:

$$A_i = T_i - m$$

(5.3)

The size of the deviation vector equals the size of **T** vector 10304×120. It is necessary to get the surrogate of covariance matrix **C** which is equal to **C** = A × A'. The surrogate (**L**) is equal to **L** = A × A'. The size of surrogate is 120 × 120 because the size of A' = 120×10304 and the size of A equals to 10304×120. Use eig(**L**) function, to get [**V D**] variables. Diagonal elements vector of D are eigenvalues for both of covariance and surrogate matrices. Sort and eliminate all small eigenvalues. Those eigenvalues must be greater than 1. If (D (i, i) > 1) then add V to Diagonal elements vector. In this case the size of Diagonal elements vector 120×116 because of D (1, 1), D (2, 2), D (3, 3) and D (4, 4) are less than 1.

Next, calculations for Eigen vectors of covariance matrix are ready. Eigenvectors are the multiplication between the deviation vectors and diagonal elements vectors. The sizes of them are 10304×120 and 120×116 respectively. So the size of Eigenvectors is 10304×116. To classify the recognition results, it is necessary to compute Euclidean distances between projected test image and projected database image.

For database image, compute images features vectors into face space by multiplication of the transpose of Eigenvectors and the deviation vectors of all images. Its size equals to 116×116 because of transpose of Eigenvectors size is equal to 116×10304. The size of the deviation vector is 10304×120. There are 116 rows only; they will be multiply with 116 columns of deviation vector. So the size will be 116×116.

Next compute calculations with projected test images Figure 5.8, 5.9. It must calculate all PCA features:

1. Convert test image to 1D vector.

2. Compute the deviation of tested image from the mean image.

3. Compute the features vector for tested image by multiplication of transpose of Eigenvectors with the deviation of tested image.

To generate Euclidean distance vector, compute the difference of projected tested image from all projected database images. Then compute the norm and the square for these computed differences. Next compute the minimum Euclidean distance and its index. If this index belong to the same person then the tested image belong to the same image. Then the image is recognized successfully otherwise, no recognition.

5.5 Implementation of Fisher Linear Discriminant

FLD is a method used to extract features for face images. Firstly, it must construct 2D matrix from 1D image vectors, using reshape(image) function in Matlab, those are in database folder. By reshaping all image according to Equation (5.1). But, before computing **T** vectors, check if all images is grayscale or not. If not, convert to grayscale Figure 5.10. T is a vector contains the reshaping matrices from 2D to 1D for all images. Number of rows in 1D matrix is multiplication of the original rows and columns. Assume there are 120 images in database folder, Figure 5.7. All images have the same dimensions 92×112. The size of **T** vector will be 10304×120.

Next calculate the mean image for database images, by summation of all Ti according to Equation (5.2). The size of the mean image matrix for the same number of images in database is 10304×1 because of division by the number of images in database. After that, compute the deviation of each image from the mean image according to Equation (5.3).

The size of the deviation vector equals the size of **T** vector 10304×120. It is necessary to get the surrogate of covariance matrix C which is equal to $C = A \times A'$. The surrogate (L) is equal to $L = A \times A'$. The size of surrogate is 120 × 120 because the size of A' = 120×10304 and the size of A equals to 10304×120. Use eig (L) function, to get Diagonal elements [**V D**]. Diagonal elements vector of D are eigenvalues for both of covariance and surrogate matrices. Sort and eliminate all small eigenvalues. Those eigenvalues must be greater than 1. If (D (i, i) > 1) then add V to Diagonal elements vector.

In this case, the size of Diagonal elements vector 120×108 because of eliminating the small eigenvalues. Next, calculations for Eigen vectors of covariance matrix are ready. Eigenvectors are the multiplication between the deviation vectors and diagonal elements vectors. The sizes of them are 10304×120 and 120×108 respectively. So the size of Eigenvectors is 10304×108. To classify the recognition results, it is necessary to compute Euclidean distances between the features vector of tested image and database images features vectors.

Compute the eigenvectors in PCA by multiplying of the deviation vectors of all images and Diagonal elements vectors. Its size equals to 10304×108 because the size of the deviation vectors is 10304×120 and the size of diagonal elements vectors equals to 120×108. There are 108 columns in diagonal elements vectors; they will be multiply with 120 rows of deviation vector. So the size will be 10304×108.

To compute the Fisher LDA vector values, compute the two matrices. First matrix is the Within Scatter matrix and the second is the Between Scatter matrix.

Now compute calculations with the features vector of tested image Figure 5.8, 5.9. It must calculate all FLD features:

1. Convert test image to 1D vector.

2. Compute the deviation of tested image from the mean image.

3. Compute the features vector for tested image by multiplication of transpose of Fisher values vectors, transpose of PCA eigenvectors and the deviation of tested image.

To generate Euclidean distance vector, compute the difference between the FLD tested image features vector and all FLD features vectors of database images. Then, compute the norm and square for differences results respectively. Next compute the minimum distance of Euclidean distances and its index. If this index belong to the same person that the tested image belong to him, this image is recognized successfully otherwise, no recognition.

5.6 The Design Face Recognition Program

The system was developed for face recognition using to method for feature extraction PCA, FLD. This system can accept BMP images. BMP images stored in a special folder called database. TOSHIBA (Satellite-C850, A965, Intel® Core™, i3-2310 M, CPU @ 2.10 GHz, Windows 7- 32 bit) was used as a device to run the system using Matlab R2012a.

This section shows the general design of the program and the function of each control unit. Figure 5.11 shows the main window for the program.
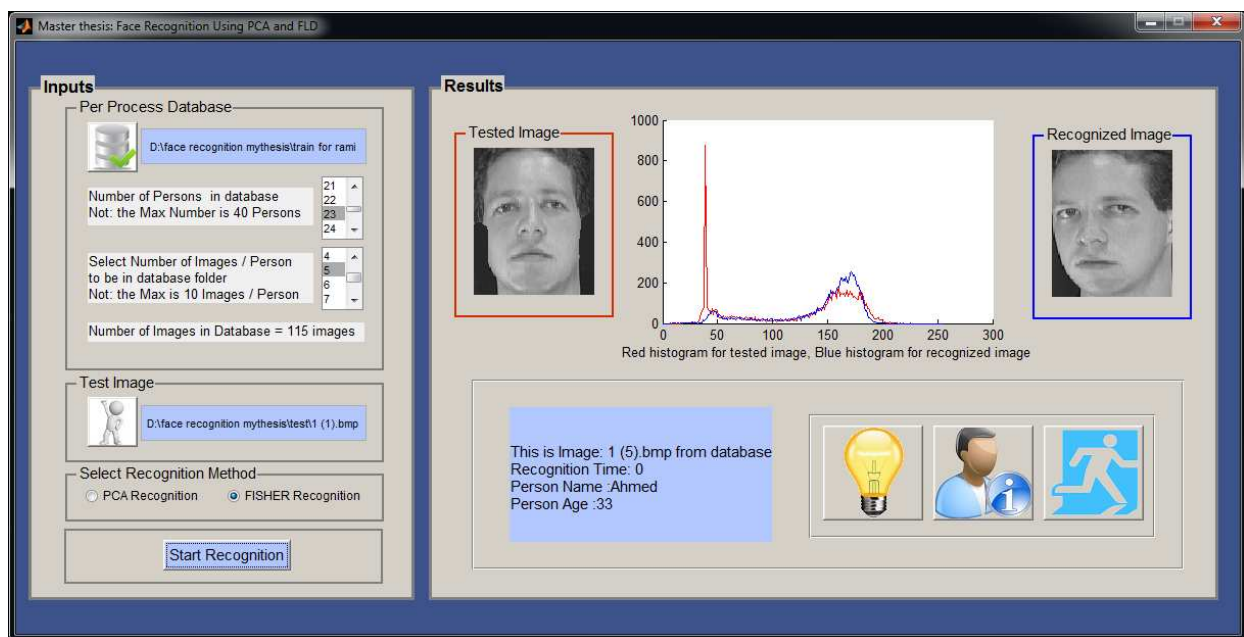

Figure 5.11: Start Program with default number of persons and images per person.

To select a tested face image from test folder, click the open test image button Figure 5.12, 5.13.
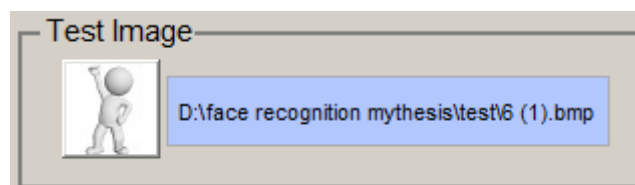

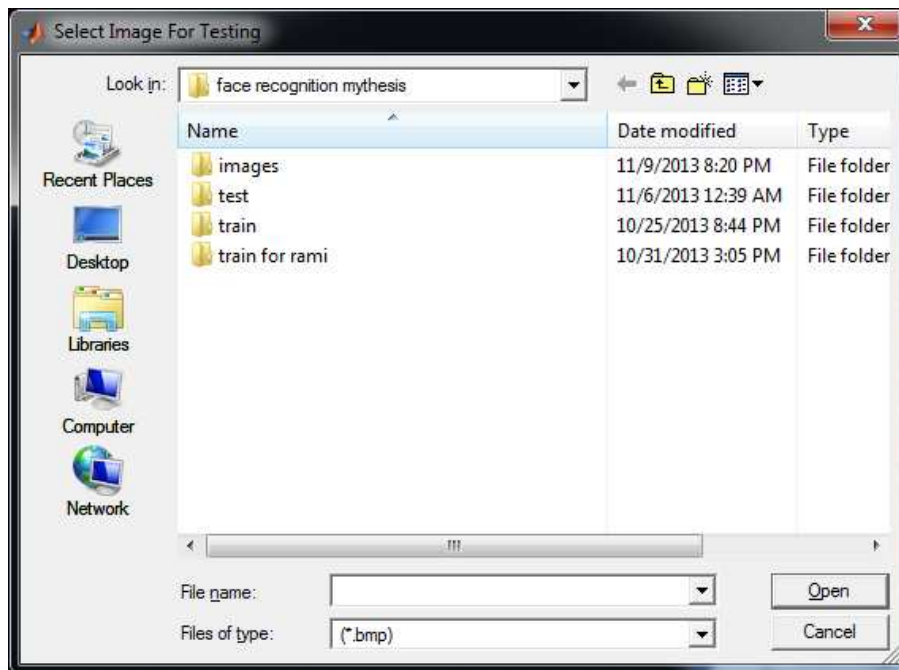Figure 5.12: Input test image by clicking the open button.

Figure 5.13: Window for input test image.

Select the database path by click the database button Figure 5.14. Then select the number of persons in database (number of classes) and number of images per person from list boxes Figure 5.15. The program designed to prevent all bugs. So, you cannot enter the path of database and the path of tested image. Figure 5.16 shows messages to prevent bugs.

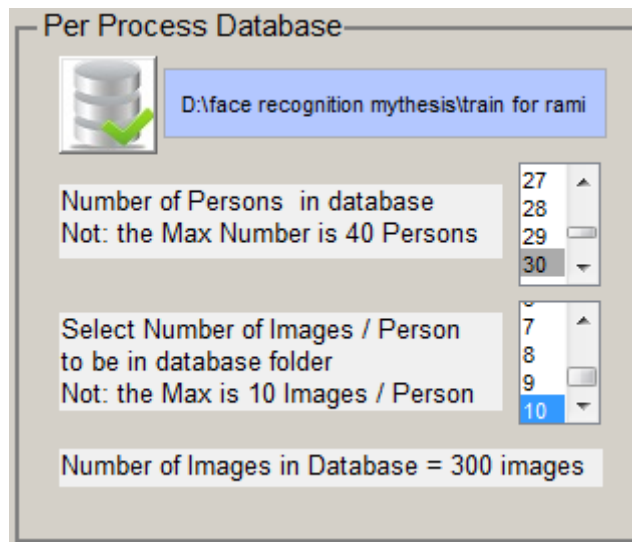Figure 5.14: Selection of database folder path.

Figure 5.15: Determination of database images.

Figure 5.16: Messages to prevent bugs.

There are two methods used in this program PCA and Fisher LDA. Each method has a special radio button Figure 5.17. The default selection is PCA recognition to prevent bug.
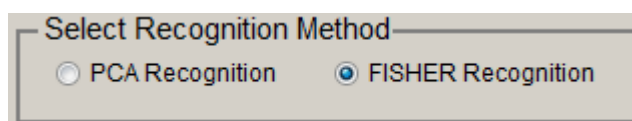

Figure 5.17: Selection of recognition methods (PCA, FLD).

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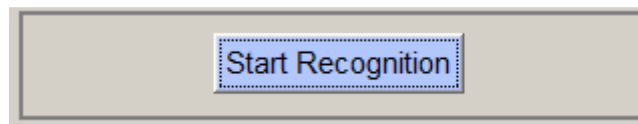After doing of all previous tasks, press start recognition button to get the results Figure 5.18.

Figure 5.18: Start recognition button.

Figure 5.19 show the results part in general. Figure 5.20 shows the selected tested image and rounded with red color for histogram drawing Figure 5.22.
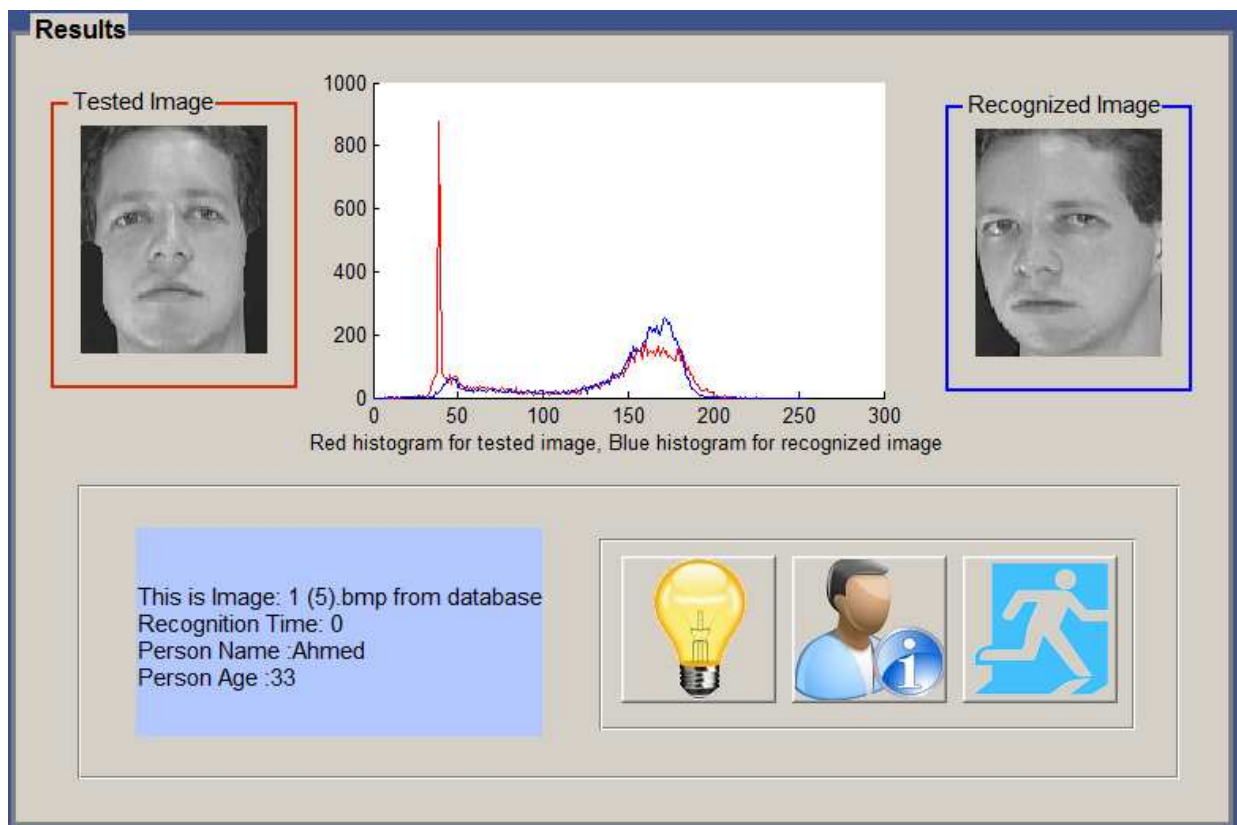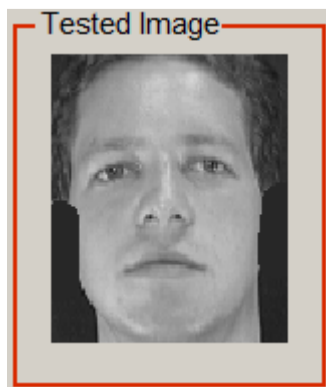

Figure 5.19: Results in the program.

Figure 5.20: Tested image rounded with red color.
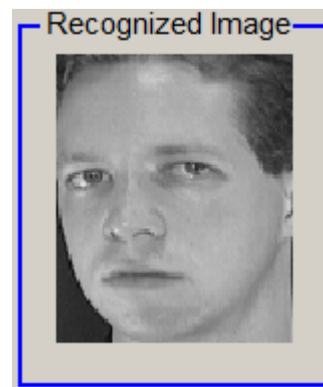
Figure 5.21: Recognized image rounded with blue. Color

Figure 5.21 shows the recognized image from database folder rounded with blue color for histogram drawing Figure 5.22.
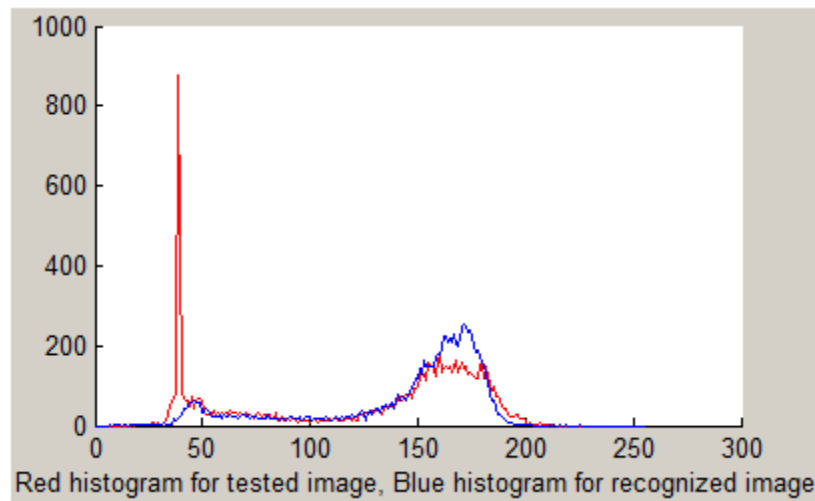
Figure 5.22: Comparing histogram of input and output images.

Each output recognized image or not recognized image is associated with texts to explain the results Figure 5.23, 5.24. The texts consist of:

1. Name of recognized image from database folder.
2. The time of recognition.
3. Person name and age.

Figure 5.23: Text results for the recognized image.

Figure 5.24: Text results for the recognized image.

The last part of the program shows some helpful buttons. To make the program integrated.

The HELP button shows all steps to do the recognition using PCA and FLD.

Figure 5.25: HELP button.

The ABOUT button shows information about the student and the department.

Figure 5.26: ABOUT button.

The EXIT button show a question dialog options Figure 5.28

Figure 5.27: EXIT button.

Figure 5.28: Question dialog options.

5.7 Tested Samples

The original Database of Faces that used as database, (formerly 'The ORL Database of Faces'), contains a set of face images taken between April 1992 and April 1994 at the lab [49]. The database was used in the context of a face recognition project carried out in collaboration with the Speech, Vision and Robotics Group of the Cambridge University Engineering Department. For some subjects (persons), the images were taken at different times, varying the lighting, facial expressions: open, closed eyes, smiling, not smiling and facial details: glasses and no glasses.

- **First Test Sample**: This sample test consists of 23 persons in database and 5 different images per person. The tested image is "1 (1).bmp" from test folder. Images extension in database and test folders is BMP.
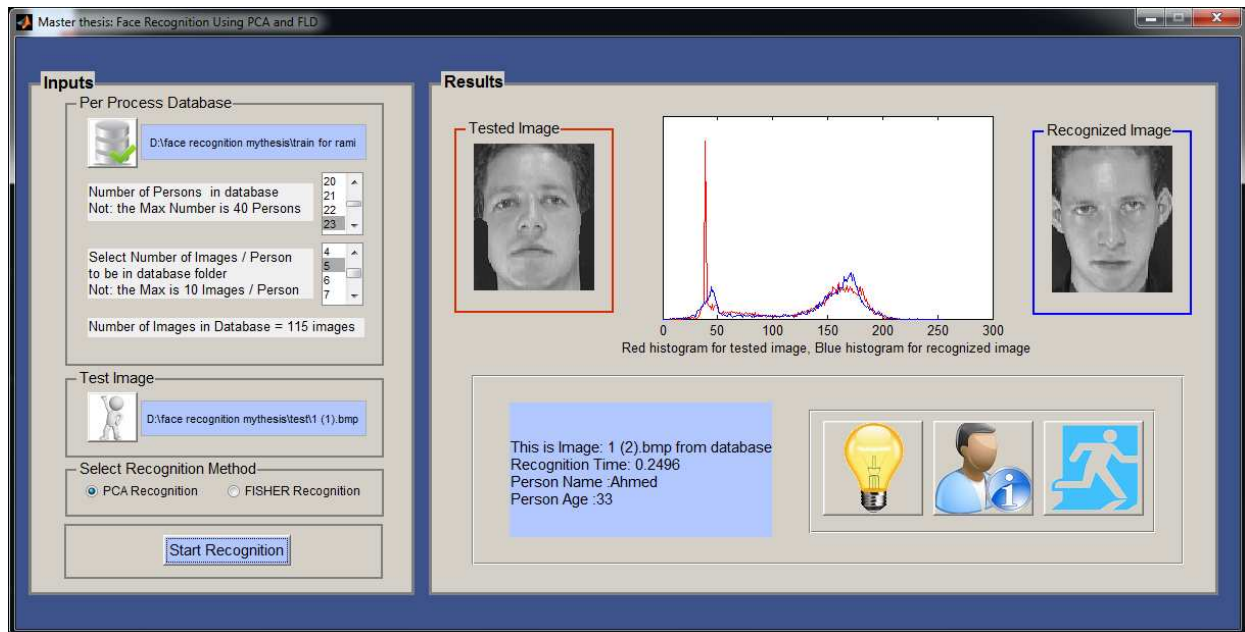

Figure 5.29: Snapshot for tested sample.

Information tables about images in database and tested image using PCA algorithm.

Table 5.1: Information about images and matrices in database folder for PCA.

Information about images in database folder PCA	
Extension of images	BMP
Size of images	92×112
Color of images	Grayscale
Number of persons in database	23
Number of images per person	5
Number of images in database	115
Size of $\mathbf{T}$ vector	10304×115
Size of The mean $\mathbf{m}$	10304×1
Size of The deviation $\mathbf{A}$	10304×115
Size of features vectors of database images – PCA	114×114
Size of Euclidean distances	1×114
Minimum Euclidean distance	3.1732e+14

Table 5.2: Information about test image and matrices in test folder PCA.

Information tested image PCA	
Extension of image	BMP
Size of image	92×112
Color of image	Grayscale
Size of $\mathbf{T}$ vector	10304×1
Size of The deviation $\mathbf{A}$	10304×1
Size of features vector of test image	114×1

Information tables about images in database and tested image using FLD algorithm.

Table 5.3: Information about images and matrices in database folder FLD.

Information about images in database folder FLD	
Extension of images	BMP
Size of images	92×112
Color of images	Grayscale
Number of persons in database	23
Number of images per person	5
Number of images in database	115
Size of $\mathbf{T}$ vector	10304×115
Size of The mean $\mathbf{m}$	10304×1
Size of The deviation $\mathbf{A}$	10304×25
Size of features vectors of database images – PCA	10304×20
Size of features vectors of database images – FLD	4×25
Size of $\mathbf{Sw}$ and $\mathbf{Sb}$ matrices	20×20
Size of Euclidean distances	1×25
Minimum Euclidean distance	0.9165

Table 5.4: Information test image and matrices in test folder FLD.

Information tested image FLD	
Extension of image	BMP
Size of image	92×112
Color of image	Grayscale
Size of $\mathbf{T}$ vector	10304×1
Size of The deviation $\mathbf{A}$	10304×1
Size of features vector of test image	4×1

Table 5.5: Results for "1 (1).bmp" face image using PCA.
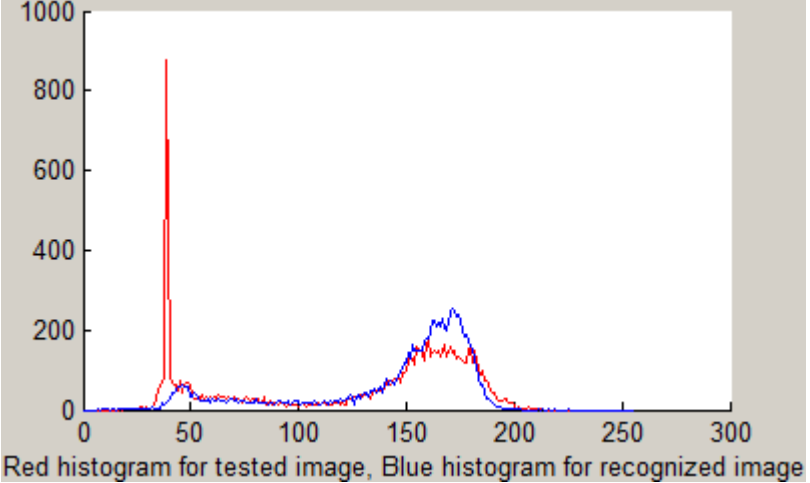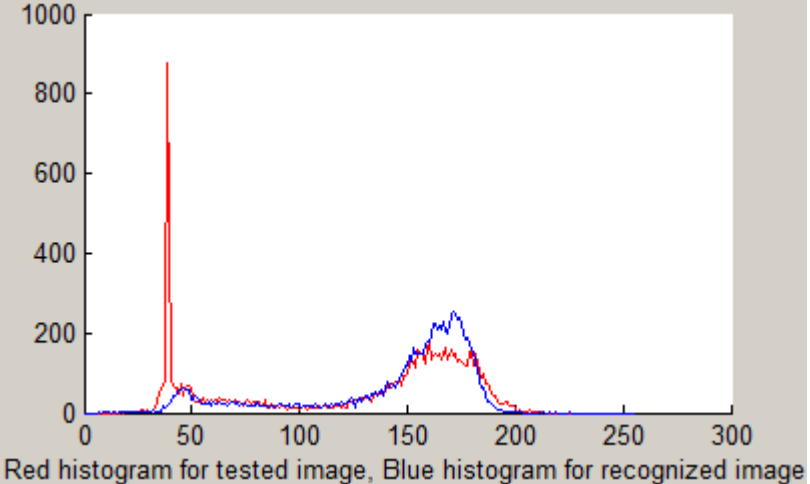
Results for "1 (1).bmp" recognition PCA	
Tested image	Figure 5.30: Tested image "1 (1).bmp".
Results using PCA	This is Image: 1 (2).bmp from database Recognition Time: 0.2652 Person Name :Ahmed Person Age :33 Figure 5.31: Recognized image using PCA algorithm.
Tested image histogram vs. Recognized image histogram	Figure 5.32: Input and output histograms.

Table 5.6: Results for "1 (1).bmp" face image using FLD.

Results for "1 (1).bmp" recognition FLD	
Tested image	 Figure 5.33: Tested image "1 (1).bmp".
Results using FLD	 This is Image: 1 (5).bmp from database Recognition Time: 0.0468 Person Name :Ahmed Person Age :33 Figure 5.34: Recognized image using FLD algorithm.
Tested image histogram vs. Recognized image histogram	 Figure 5.35: Input and output histograms.

- **Second Test Sample:** This sample test consists of 23 persons in database and 8 different images per person. The tested image is "11 (1).bmp" from test folder. Images extension in database and test folders is BMP. The original Database of Faces is the same database that was used in the first test sample.
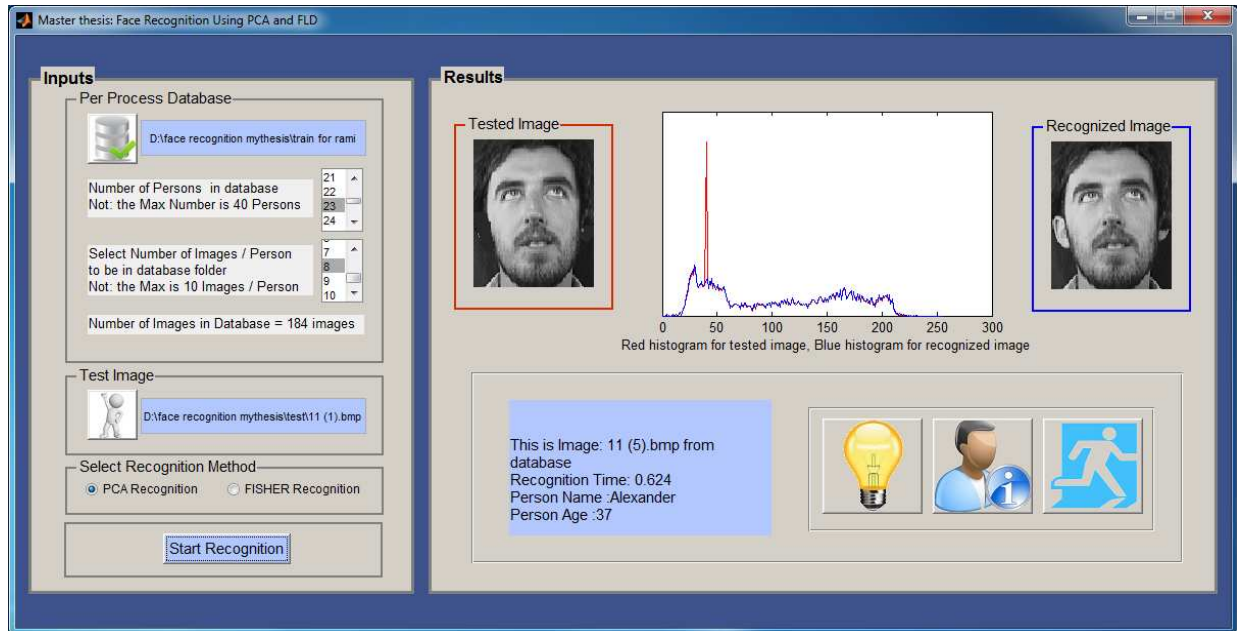
Figure 5.36: Snapshot for tested sample.

Information tables about images in database and tested image using PCA algorithm.

Table 5.7: Information about images and matrices in database folder PCA.

Information about images in database folder PCA	
Extension of images	BMP
Size of images	92×112
Color of images	Grayscale
Number of persons in database	23
Number of images per person	8
Number of images in database	184
Size of **T** vector	10304×184
Size of The mean **m**	10304×1
Size of The deviation **A**	10304×184
Size of features vectors of database images – PCA	181×181
Size of Euclidean distances	1×181
Minimum Euclidean distance	1.1226e+14

Table 5.8: Information about test image and matrices in test folder PCA.

Information tested image PCA	
Extension of image	BMP
Size of image	92×112
Color of image	Grayscale
Size of **T** vector	10304×1
Size of The deviation **A**	10304×1
Size of features vector of test image	181×1

Information tables about images in database and tested image using FLD algorithm.

Table 5.9: Information about images and matrices in database folder FLD.

Information about images in database folder FLD	
Extension of images	BMP
Size of images	92×112
Color of images	Grayscale
Number of persons in database	23
Number of images per person	8
Number of images in database	184
Size of **T** vector	10304×184
Size of The mean **m**	10304×1
Size of The deviation **A**	10304×46
Size of features vectors of database images – PCA	10304×56
Size of features vectors of database images – FLD	7×64
Size of **Sw** and **Sb** matrices	56×56
Size of Euclidean distances	1×64
Minimum Euclidean distance	5.5315e-15

Table 5.10: Information test image and matrices in test folder FLD.

Information tested image FLD	
Extension of image	BMP
Size of image	92×112
Color of image	Grayscale
Size of **T** vector	10304×1
Size of The deviation **A**	10304×1
Size of features vector of test image	7×1

Table 5.11: Results for "11 (1).bmp" face image using PCA.
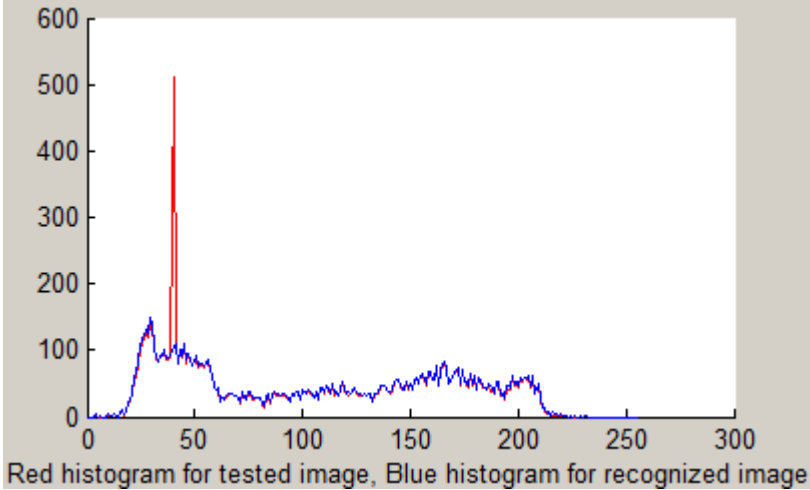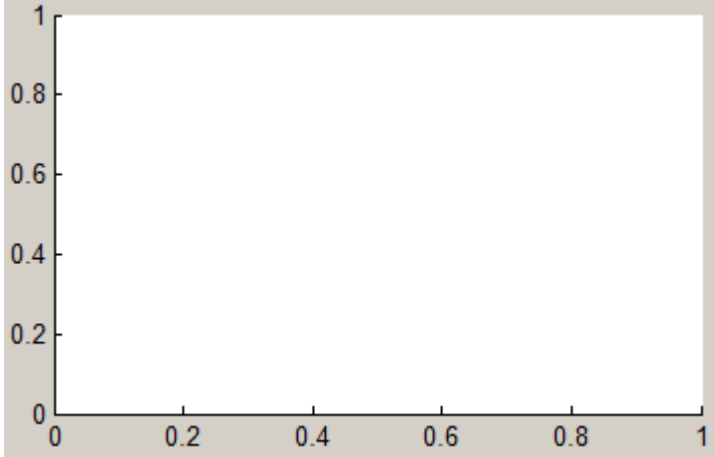
Results for "11 (1).bmp" recognition PCA	
Tested image	Figure 5.37: Tested image "11 (1).bmp".
Results using PCA	This is Image: 11 (5).bmp from database Recognition Time: 0.5772 Person Name :Alexander Person Age :37 Figure 5.38: Recognized image using PCA algorithm.
Tested image histogram vs. Recognized image histogram	Figure 5.39: Input and output histograms.

Table 5.12: Results for "11 (1).bmp" face image using FLD.

Results for "11 (1).bmp" recognition FLD	
Tested image	Figure 5.40: Tested image "11 (1).bmp".
Results using FLD	Figure 5.41: Recognized image using FLD algorithm.
Tested image histogram vs. Recognized image histogram Note: No histograms because the test image is not recognized	Figure 5.42: Input and output histograms.

5.8 Results

The simulation results of the face recognition system are obtained using PCA and FLD feature extraction techniques. The simulations are performed in two stages. In first stage the noisy tested images, in second stage tested images without noisy are considered for recognition. For each experiment the recognition rate was obtained. For the first stage, the results are given in Table 5.13. For the second stage, the results are given in Table 5.14.

In first experiment, 138 images of 23 persons are taken. In image database each person has 6 different images. The number of noisy tested images in this experiment is 46. Using PCA 40 images was recognized successfully and recognition rate was 86.9%. Using FLD 42 images was recognized successfully and recognition rate was 86.9%. Using FPBM 36 images was recognized successfully and recognition rate was 78.2%.

In the second experiment, 231 images are taken. In database these images are belonging to 33 persons. Each person has 7 different images. Number of noisy tested images that is used in this experiment was 99. Using PCA 91 images was recognized successfully with recognition accuracy 91.9%. Using FLD 92 images was recognized successfully with recognition accuracy 92.9%. Using FPBM 75 images was recognized successfully with recognition accuracy 75.6%.

In the third experiment, 320 images are taken. These images are belonging to 40 persons and each person has 8 different images. Number of noisy tested images that are used in this experiment was 80. Using PCA 71 images was recognized successfully with recognition accuracy 88.7%. Using FLD 75 images was recognized successfully with recognition accuracy 93.8%. Using FPBM 59 images was recognized successfully with recognition accuracy 73.8%.

Table 5.13: Recognition rates of the system for noisy tested face images.

Subjects	Tested faces	Faces in database	PCA		FLD		FPBM	
			R.R	E.R	R.R	E.R	R.R	E.R
23	46	138	86.9 %	13.1 %	91.3 %	8.7 %	78.2 %	21.8 %
33	99	231	91.9 %	8.1 %	92.9 %	7.1 %	75.6 %	24.4 %
40	80	320	88.7 %	11.3 %	93.8 %	6.2 %	73.8 %	26.2 %

In next stage the simulation results were obtained using non-noisy tested images from second set. Table 5.14 shows the simulation results of non-noisy faces recognition system using PCA and FLD algorithms and FPBM for comparing.

In first experiment, 65 images of 13 persons are taken. In image database each person has 5 different images. Number of tested images that used in this experiment is 65. Using PCA 59 images was recognized successfully and recognition rate was 90.8%. Using FLD 62 images was recognized successfully and recognition rate was 95.4%. Using FPBM 45 images was recognized successfully and recognition rate was 69.2%.

In the second experiment, 135 images are taken. In database these images are belonging to 27 persons. Each person has 5 different images. Number of tested images that is used in this experiment was 135. Using PCA 127 images was recognized successfully with recognition accuracy 94.1%. Using FLD 130 images was recognized successfully with recognition accuracy 96.2%. Using FPBM 90 images was recognized successfully with recognition accuracy 66.7%.

In the third experiment, 200 images are taken. These images are belonging to 40 persons and each person has 5 different images. Number of tested images that are used in this experiment was 200. Using PCA 189 images was recognized successfully with recognition accuracy 94.5%. Using FLD 191 images was recognized successfully with recognition accuracy 95.5%. Using FPBM 125 images was recognized successfully with recognition accuracy 62.5%. The simulation results demonstrate the efficiency of using of PCA and FLD methods over FPBM method in facet recognition.

Table 5.14: Recognition rates of the system for non-noisy tested face images.

Subjects	Tested faces	Faces in database	PCA		FLD		FPBM	
			R.R	E.R	R.R	E.R	R.R	E.R
13	65	65	90.8 %	9.2 %	95.4 %	4.6 %	69.2 %	30.8 %
27	135	135	94.1 %	5.9 %	96.2 %	3.8 %	66.7 %	33.3 %
40	200	200	94.5 %	5.5 %	95.5 %	4.5 %	62.5 %	37.5 %

6. CONCLUSION

In this thesis face recognition system was designed using MATLAB program. Two different feature extraction methods PCA, FLD and FPBM and Euclidean distance classification were used to develop the system. The structure of face recognition system was designed. The used feature extraction methods are described in detail. Using PCA and FLD the design of face recognition system has been performed.

The designed system was tested with two types of face image data sets. In the first data base the face images have noise and in second database face images did not have noise. The results were recorded as recognition rate.

Simulation of face recognition system has been performed for two kinds of test images: noisy and without noisy cases. The best average recognition rate of noisy face recognition system was obtained using FLD method. This recognition rate equals to 92.7%. The best average recognition rate of non-noisy face recognition system was also obtained using FLD method. This recognition rate equals to 95.7%

Simulation results for FPBM method have average recognition rate for noisy face images 75.9%. For non-noisy face images the average recognition rate was 75.1%. The best recognition rate using FPBM and with noisy face images was 78.2%. The best recognition rate using FPBM without noisy face images was 69.2%. That means, the FPBM method is not useful for noisy and non-noisy face images.

Simulation results for FLD method have average recognition rate for noisy face images 92.7%. For non-noisy face images the average recognition rate was 95.7%. The best recognition rate using FLD and with noisy face images was 93.8%. The best recognition rate using FLD without noisy face images was 95.5%. That means, the FLD method is useful for noisy face images and non-noisy face images.

Simulation results for PCA method have average recognition rate for noisy face images 89.2%. For non-noisy face images the average recognition rate was 93.1%. The best recognition rate using PCA and with noisy face images was 91.9%. The best recognition rate using PCA without noisy face images was 94.5%. That means, the PCA method is useful for noisy and non-noisy face images.

The FLD method is the best for noisy and no-noisy images. The PCA method is useful for non-noisy face images. FPBM is not useful for both noisy and on-noisy.

Face recognition system was designed using MATLAB 2012.a package. MATLAB is a good environment to develop different feature extraction methods using GUI. GUIDE (GUI development environment) provides tools for designing GUIs for custom applications. GUIDE then automatically generates the MATLAB code for constructing the UI, which you can modify to program the behavior of an application. For classification purpose the Euclidean distance algorithm is used.

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