ADDIS ABABA UNIVERSITY

SCHOOL OF INFORMATION SCIENCE

Face Recognition using Eigenfaces Method

By

Daniel Arega Asmamaw

A thesis submitted to the school of Information Science of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree Masters of Science in Information Science

May, 2011

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Approved by examining board:

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Abstract

This study attempted to develop a prototype face recognition system and the performance of the system is tested on a face database of Ethiopian faces. An Eigenfaces approach, which was one of first successful demonstrations of machine recognition of faces, is adopted. Towards this end, literature is reviewed on face recognition, Eigenface method and Principal Component Analysis (PCA).

In the progression, a database of 76 face images, of 14 different individuals, was constructed. The database constitutes 14 normal frontal faces (Category_A), 14 face with a smiley expression (Category_B), 7 face images from Category_A and 7 from Category_B with head orientations rotated by 45^0, and 14 face images where the background in Category_A were removed by appropriate mask, 14 face images by decreasing the illumination level in Category_A by 10% and 6 more face images from Category_A after facial details are added manually.

Appropriate tools, like Matlab development environment, were used to realize the system. The proposed system has four major components; the preprocessing module, feature extraction and dimension reduction via PCA module, database construction and updating module and face recognition module.

The experimentation process involves determining critical threshold values' the system uses in times of recognition. The system was tested to explore the impact of changes in head orientation, illumination level, and face background. Finally the performance of the system was tested and the preprocessing module was used to improve the accuracy. The result shows that the system performs very well for probes in the face library but the general performance is found to be 85.71%. Moreover when top five ranks are considered 92.86% accuracy was achieved. In conclusion, its observed that the eigenface algorithm performs well on a database of Ethiopian faces.

The results are encouraging and with more optimization works, such as using face detection algorithms and construction of larger face databases, as per the recommendations made in the research work, better results can be achieved in the future.

Keywords: Face Recognition, Eigenfaces Method, Principal Component Analysis (PCA)

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List of Acronyms

AFIS Automated Finger Imaging Systems

AI	Artificial Intelligence
BMP	Windows Bitmap
CCA	Canonical correlation analysis
DARPA	Defense Advanced Research Projects Agency
DCT	Discrete Cosine Transform
DLA	Dynamic Link Architecture
EBGM	Elastic Bunch Graph Matching
FERET	Face Recognition Technology
FLD	Fisher Linear Discriminant Analysis
FR	Face Recognition
DFT	Discrete Fourier Transform
FFT	Fast Fourier Transform
GWT	Gabor Wavelet Transform
HMM	Hidden Markov Model
ICA	Independent Component Analysis
JPEG	Joint Photographic Experts Group
LDA	Linear Discriminant Analysis
NN	Neural Network
PCA	Principal Component Analysis
PLS	Partial Least Squares
RBF	Radial Basis Function
SVM	Support Vector Machine

Chapter 1 Introduction

1.1 Biometrics and Face Recognition Backgrounds

Globalization-the very idea of our world's trend since the invention of computers and empowerment of mankind to communicate and interact, via the internet, in unprecedented manner is said to be making the world a small village. The world is getting 'smaller' virtually but complex; companies are no longer bounded in one country. Organizations are coming to be international as they have customers from all over the world. Despite the fact that this is making life easier and more prosperous, it has its own curse. Organizations are becoming more vulnerable to fraudulent activities of many people around the world including their own employees and "esteemed" customers. Security is and has been growing to be an indispensable aspect of their very survival. They all need to optimize security without compromising individual freedoms. This is where the concept of biometrics came to the picture.

The term biometrics comes from the Greek words bio (life) and metrikos (measure). According to Jane et.al [4] biometrics can be defined as an automatic recognition of a person based on physiological or behavioral characteristics. Woodward et al. [33] states that any automatically measurable, robust and distinctive physical characteristic or personal trait that can be used to identify an individual or verify the claimed identity of an individual. From these two definitions we can say that biometrics is an automatic recognition of a person using distinguishing traits which could either be physical or behavioral or both [4].

1.2 Biometric Systems

A biometric system is essentially a pattern-recognition system that recognizes a person based on a feature vector derived from a specific physiological or behavioral characteristic that the person possesses.
The specific physical or behavioral characteristics should be universal, measurable, robust, distinctive, collectable and permanent [4].

- **Universal**- Each person should have the biometric characteristic.
- **Measurable**- the characteristic or trait can be easily presented to a sensor, located by it, and converted into a quantifiable, digital format. This measurability allows for matching to occur in a matter of seconds and makes it an automated process. The fact that the characteristic should be quantitatively measurable is sometimes referred as collectability.

- **Robust**-refers to the extent to which the characteristic or trait is subject to significant changes, that could occur as a result of age, injury, illness, occupational use, or chemical exposure, over time. A highly robust system is sufficiently invariant (with respect to the matching criterion), which sometimes referred as permanence, to those and other similar changes. For example an iris biometric is more robust or has a better permanence than voice biometric.

- **Distinctive**- is a measure of the variations or differences in the biometric pattern among the general population. Iris and retina have higher degree of distinctiveness than hand or finger geometry.

Depending on the application context, a biometric system typically operates in one of two modes: verification or identification [5, 6].
Identification- system attempts to answer the question 'who is x?'. The biometric device reads the sample and compares it against every record in the template database. i.e The system conducts a one-to-many (1:N) comparison, between the sample and every record in the database, to establish an individual's identity (to find out if the subject is not already in the system database). Depending on how the system is designed it can make the 'best' match or it can score possible matches. Identification applications are critical components of negative recognition in which the system establish whether the person is who he/she (implicitly or explicitly) denies being. It is commonly used to identify criminals or terrorists particularly through surveillance. In general the aim of identification applications is to prevent a single person from using multiple identities.

Verification-occurs when the biometric system asks and attempts to answer the question 'is this x?'. This application requires input from the user (from the one who claimed to be someone) via a password token name or a biometric sample (or any combination of these). The input points the system to a template in the database and compares the sample to or against the pointed template. i.e verification applications conduct a 'one-to-one' search (1:1) between the input and a template in the database. The system will either find or fail to find a match between the two. Verification is commonly used for physical or computer access. Figure 1-1 shows that enrollment creates an association between an identity and its biometric characteristics. In a verification task, an enrolled user claims an identity and the system verifies the authenticity of the claim based on his/her biometric feature. An identification system identifies an enrolled user based on his/her biometric characteristics without the user having to claim an identity.

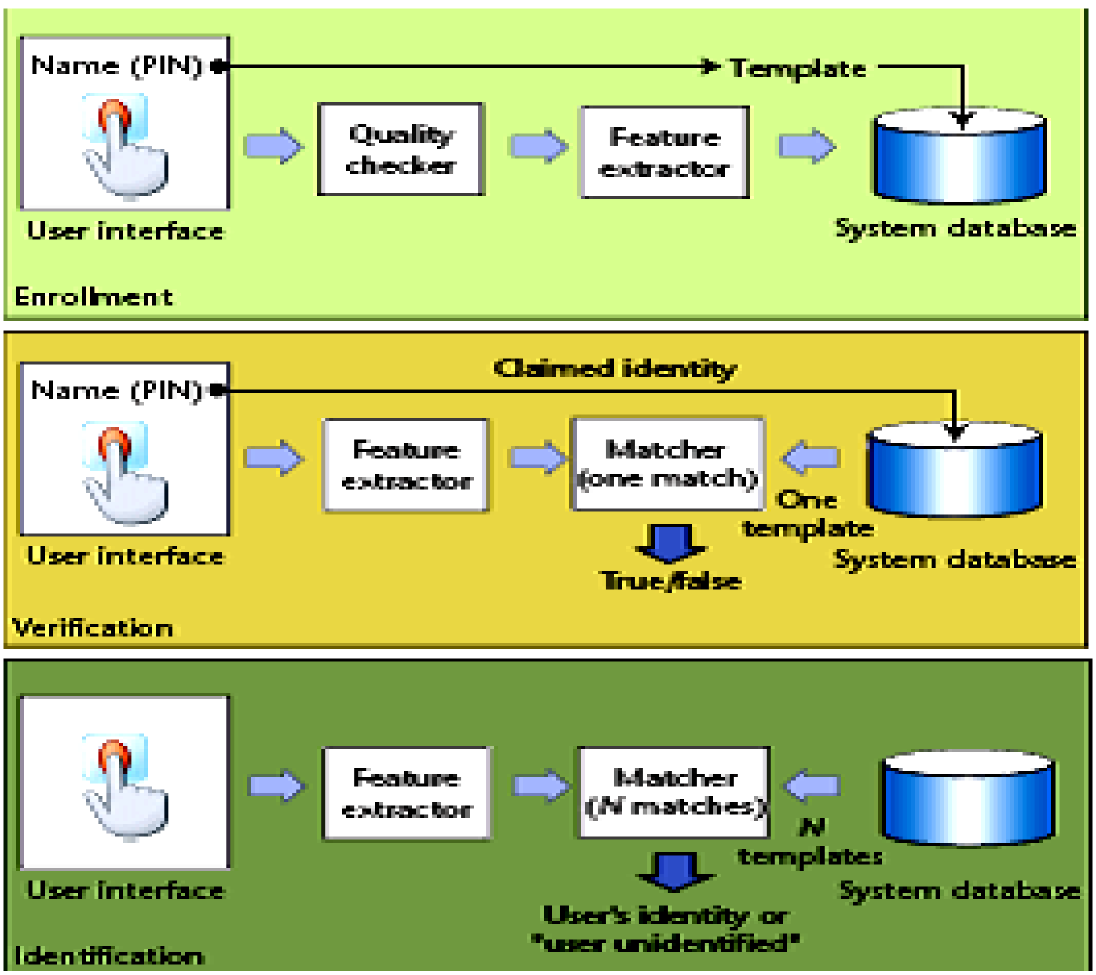

Figure 1-1: Block diagrams of enrollment, verification, and identification tasks [3].

1.3 An Overview of Face Recognition Systems

In general face recognition algorithms try to solve the problem of both verification and identification. Systems developed to deal with the problem of identification, which is the focus of this research, is trained by some images of known individuals and given test images, it decides to which individual it belongs to.

The first step of human face identification is to extract the relevant features from facial images. Research in the field primarily intends to generate sufficiently reasonable familiarities of human faces so that another human can correctly identify the face. The question naturally arises as to how well facial features can be quantized. If such a quantization is possible then a computer should be capable of recognizing a face given a set of features. Investigations by numerous researchers [4, 5, 6] over the past several years have indicated that certain facial characteristics are used by human beings to identify faces.

There are three major research groups which propose three different approaches to the face recognition problem. The first (largest) group [33, 49, 63] have dealt with facial characteristics which are used by human beings in recognizing individual faces. The second group [62, 31, 51, 30] performs human face identification based on feature vectors extracted from profile silhouettes. The third group [15, 44] uses feature vectors extracted from a frontal view of the face.

Although there are three different approaches to the face recognition problem, there are two basic methods from which these three different approaches arise. The first method is based on the information theory concept which is based on the principal component analysis (PCA) method. In this approach, the most relevant information that best describes a face is derived from the entire face image. Based on the Karhunen-Loeve expansion (PCA) in pattern recognition, Kirby and Sirovich [40] have shown that any particular face could be economically represented in terms of a best coordinate system known as "eigenfaces"; i.e, PCA can be used as dimensionality-reducing preprocessing transform and its known to provide an optimally compact linear basis (with respect to the RMS error) for a given class of signal.

These are the eigen functions of the averaged covariance of the ensemble of faces. Later, Turk and Pentland [38] have proposed a face recognition method based on the eigenfaces approach.

The second method, so called feature based, extracts feature vectors from the basic parts of a face such as eyes, nose, mouth, and chin. In this method, with the help of deformable templates and extensive mathematics, key information from the basic parts of a face is gathered and then converted into a feature vector. Yullie and Cohen [66] played a great role in adapting deformable templates to contour extraction of face images.

1.4 Examples of Biometric systems

In the next few sections some examples of biometric systems are discussed [33].

Iris Scan

Iris scanning measures the iris pattern in the colored part of the eye, although the iris color has nothing to do with the biometric. Iris patterns are formed randomly. As a result, the iris pattern is a unique feature of a person. This iris patterns even in a person's left and right eyes are different, and so are the iris patterns of identical twins. Iris scanning can be used quickly for both identification and verification applications because the iris is highly distinctive and robust.

Retinal Scan

Retinal scans measure the blood vessel patterns in the back of retina inside the eye. The device involves a light source shined into the eye of a subject who must be standing very still within inches of the device. Because users perceive the technology to be somewhat intrusive, retinal scanning has not gained popularity; currently retinal scanning devices are not commercially available.

Facial Recognition

Facial recognition records the spatial geometry of distinguishing features of the face. Different vendors use different methods of facial recognition, however, all focus on measuring key features of the face. Because a person's face can be captured by a camera from some distance away, facial recognition has a clandestine or covert capability (i.e. the subject does not necessarily know he/she has been observed). For this reason, facial recognition has been used in projects to identify card counters or other undesirables in casinos, shoplifters in stores, criminals and terrorists in urban areas.

Speech Recognition

Automatic Speech recognition is the process of converting an acoustic signal, captured by a microphone or a telephone, to a set of words [59]. The recognized words can be the final results, for applications such as commands & control, data entry, and document preparation. They can also serve as the input to further linguistic processing in order to achieve speech understanding.

However, speech recognition can be affected by environmental factors such as background noise. This technology has been the focus of considerable efforts on the part of the telecommunications industry and scholar researches in Ethiopia specially in developing such system for different languages.

Fingerprint

Fingerprint biometric system is an automated digital version of the old ink-and-paper method used for more than a century for identification, primarily by law enforcement agencies. The biometric device involves users placing their finger on a platen for the print to be electronically read. The minutiae are then extracted by the vendor's algorithm, which also makes a fingerprint pattern analysis. Fingerprint currently has three main application arenas: large-scale Automated Finger Imaging Systems (AFIS) generally used for law enforcement purposes, fraud prevention in entitlement programs, and physical and computer access.

Hand/Finger Geometry

Hand or finger geometry is an automated measurement of many dimensions of the hand and fingers. Neither of these methods takes actual prints of the palm or fingers. Spatial geometry is examined as the user puts his/her hand on the sensor's surface and uses guiding poles between the fingers to properly place the hand and initiate the reading. Finger geometry usually measures two or three fingers. Hand geometry is a well-developed technology that has been thoroughly field-tested and is easily accepted by users. Because hand and finger geometry have a low degree of distinctiveness, the technology is not well-suited for identification applications.

Dynamic Signature Verification

Humans have long used a written signature as a means to acknowledge our identity. Dynamic signature verification is an automated method of measuring an individual's signature. This technology examines such dynamics as speed, direction, and pressure of writing; the time that the stylus is in and out of contact with the "paper," the total time taken to make the signature; and where the stylus is raised from and lowered onto the "paper."

Keystroke Dynamics

Keystroke dynamics is an automated method of examining an individual's keystrokes on a keyboard. This technology examines such dynamics as speed and pressure, the total time taken to type particular words, and the time elapsed between hitting certain keys. This technology's algorithms are still being developed to improve robustness and distinctiveness. One potentially useful application that may emerge is computer access, where this biometric could be used to verify the computer user's identity continuously.

1.5 Statement of the Problem and Justification

The problem of face recognition can be stated as follows: Given still images or video of a scene, identifying one or more persons in the scene by using a stored database of faces. The problem is mainly a classification problem. Training the face recognition system with images from the known individuals and classifying the newly coming test images into one of the classes is the main aspect of the face recognition systems [51].

The topic seems to be easy for a human, whereas the problem for machine is manifold. Some of possible problems for a machine face recognition system include;

- Facial expression change: A smiling face, a crying face, a face with closed eyes, even a small nuance in the facial expression can affect facial recognition system significantly.
- Illumination change: The direction where the individual in the image has been illuminated greatly affects the success rate of face recognition systems. A study on illumination effects on face recognition showed that lighting the face bottom up makes face recognition a hard task [63].
- Aging: Images taken some time apart varying from 5 minutes to 5 years seriously affects the accuracy of a system.
- Rotation: Rotation of the individual's head clockwise or counter clockwise (even if the image stays frontal with respect to the camera) affects the performance of the system.
- Size of the image: A test image of size 20x20 may be hard to classify if original class of the image was 100x100.
- Frontal vs. Profile: The angle in which the photo of the individual was taken with respect to the camera affects the system accuracy.

This research is focused toward developing unsupervised face recognition system. Eigenfaces approach seemed to be an adequate method to be used in face recognition due to its simplicity, speed and learning capability. Even if such systems have been developed for different databases, it has never been tested on face databases constructed from Ethiopian faces. Developing such system and a face database will pave a way for farther local researches in the field.

The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called eigenfaces, which may be thought of as the principal components of the initial training set of face images. Recognition is performed by projecting a new image onto the subspace spanned by the eigenfaces and then classifying the face by measuring the Euclidean distance of its position in the face space and from the positions of known individuals.

1.6 Objectives of the Research

1.6.1 General Objective

The general objective of this research is to develop a prototype computer based face recognition system using an Eigenface approach and to construct a face database of Ethiopian face images on which the system will be evaluated.

1.6.2 Specific Objectives

In order to achieve the general objective, a set of specific objectives are set out. These specific objectives include:

- Perform a comprehensive literature review on automatic face recognition systems specially the eigenface approach, related to their type, approach and trend;
- Explore the available Face Recognition tools and techniques (algorithms) that are more convenient to carry out the research.
- Acquire face images of individuals, using the appropriate tool, and construct a face database that would be used to train and test the system to be developed.
- Design a face recognition system prototype with modules to perform:
    - Image preprocessing
    - Feature extraction using PCA
    - Constructing and updating image database.
    - Face recognition
- Evaluate the performance of the face recognition prototype and report the findings of this research work.
- Draw concluding remarks and suggest recommendations for further research in the area.

1.7 Methodology

The research methodology describes the procedures used to conduct the research along with description of the necessary tools. For the achievement of the objectives of this research, the following approaches are followed:

1.7.1 Literature Review

Identification and understanding of theoretical concepts and other related researches is considered to be one of the critical phases in this research. A comprehensive literature review is performed pertaining to the Eigenface approach and PCA. Inevitably, understanding the tools involved in experimentation of the research project contributed significantly to the successful completion of the research.

Hence, in this research the literature review performed is mainly targeted in addressing the following important aspects.

- Understand the theoretical foundations of human and machine face recognition systems in general and statistical approaches to face recognition in particular.
- Understanding what has been done before in the area of face recognition
- Identify the various face recognition algorithms, techniques and tools that are used to assist the experimentation

1.7.2 Data Acquisition, Selection and Preprocessing

The machine based face recognition system that is studied in this research demands face images of individuals as an inputs. Acquisition of these images is conducted using a 2 mega pixel resolution digital Sony camera. The images taken are made to be representative of Ethiopian faces. The researcher believes that the resulting system could be modified for use in any organization where face recognition is required. Besides being representative images are captured in relatively similar environment. This is to control the impact of environmental factors (illumination and angle of the camera during capturing the images etc…) on recognition rate.

Therefore Face images of individuals were captured and each face images was manually processed. Accordingly facial details were added to some of the images manually, and all were resized to 256x256x24. Finally a face database of 76 face images and 4 non-faces images was constructed.

1.7.3 Tools

Selection of appropriate tool has a significant role to play for the success of the research.

True color images in computers are represented as 3-dimensional matrix. Matlab (Matrix Laboratory) development environment is a powerful high level programming tool to deal with mathematical computations such as matrix and linear algebra. Therefore Matlab version 7.0.0.19920 (R14), which was released on May 6, 2004, was used to realize the proposed face recognition system. Additionally Nero photoSnap -version 2.0.1.0 of Nero 9, which was released in 2008, were used to perform pre-processing.

1.7.4 Testing Mechanisms

The general evaluation procedures of the algorithm include three general principles. The first one enforces every image to have a unique identifier. The second design principle imposes the training phase to be concluded before the start of the evaluation in order to perform a controlled evaluation test. The third one deal with the similarity or distance should be measured between all combination of the images from the gallery and probe sets.

Once the eigenface based face recognition system is realized in the Matlab development environment, the system was trained using a set image from the face database and a face library was constructed for each test. The most important and common testing parameter used to evaluate face recognition system is rate of correct recognition by measuring the Euclidean distance between face classes in the library, after being projected to the face space spanned by the training (i.e using the major eigenfaces extracted from the training set), and the input faces.

1.8 Scope and Limitation of the Study

The scope of this research is only to develop a prototype for face recognition system using frontal face images. There are studies on face recognition from profile images, but this problem is out of the scope of this research. All the images are assumed to be frontal with a maximum rotation of 10-15 degrees to the right or left.

Face recognition system is the next step of a face detection system. In this study, it is assumed that all the images used to train or test the system are all face images. Some non-face images are also used, to determine threshold values, to critically reject non-face images in case they are presented to the system by mistake or otherwise. Face detection is out of the scope of this thesis, but some preprocessing techniques are applied to ensure that all the faces were oriented in relatively the same location in all the images.

The major limitation of this study is that it was tested on small database. This is mainly because of unavailability of face image databases, which was designed for such purpose, in Ethiopia. Due to the restriction of time in completion of this research, it was difficult to construct a larger face database. The other limitation of the propose system is it assumes the inputs are all face images.

1.9 Applications of the Study

Conducting a research on machine based face recognition system is worth undertaking for various reasons apart from the academic challenges that it poses to qualify as thesis.

This work will pave the way in developing a full fledged face recognition system that would make the daily routine of many organizations fast, efficient and modern. In general face recognition system has a wide range of commercial and law enforcement application. Law enforcement agencies can use the system to store face images of criminals and make a database search using face images as an input. These images can be collected in different ways including from the security cameras installed in some specific areas. Very recently, Ethiopian government has installed CCTV cameras in some areas of the metropolis. In such cases the availability of face recognition systems would optimize data processing. Organizations can use such systems to provide specific permits to targeted customers only. The traffic office can use such system to verify driving licenses for the claimed identity by drivers.

According to Jain (2004), offers greater security and convenience than traditional methods of personal recognition. In many private and governmental organizations face recognition system, being a part of systems, can replace or supplement the existing technology. In others, it is the only viable approach. In general applications of biometric systems fall in to three major categories:

- **Commercial applications:** such as computer network logins, electronic data security, e-commerce, Internet access, ATMs, credit cards, physical access control, medical records management, and distance learning;

- **Government applications:** such as national ID cards, correctional facilities, driver's licenses, social security(though we have no social security numbers so far, some day we will), border control and passport control; and

• **Forensic applications:** such as corpse identification, criminal investigation, terrorist identification, parenthood determination, and missing children.

In general researches on face recognition systems feature the following important advantages in the particular application areas mentioned.

- Face recognition systems are non-intrusive; it does not require the involvement of the person we are searching for. The characteristic, face, is not a secret. It is often possible to obtain a person's face, without that person's knowledge. This permits covert recognition of previously enrolled people. We can easily collect some ones face from the security cameras we mentioned earlier.
- It does not require specialized skill to use the system.
- It is almost impossible to forge some ones face.

1.10 Organization of the Research Report

This research report is organized in to six chapters that clearly present what essential tasks have been done in the research

The first chapter presents an introduction to the subject matter under investigation. It provides an overview of face recognition and a description of the statement of the problem along with the justifications, objectives, methodologies, scope and limitation and applications of the study.

The second chapter relates to review of literatures on the concept of human and machine based face recognition and their relationships. Additionally the different approaches to the problem of face recognition and corresponding previous works are discussed.

The third chapter of this research constitutes pattern classification basics. In this chapter the major dimension reduction techniques including Principal Component Analysis (PCA) are rigorously discussed.

The fourth chapter was dedicated for the discussion of the procedural and mathematical aspects of Eigenface method.

The fifth chapter, the backbone of this research, constitutes results of experiments conducted and discussion of the outcomes of each experiment.

The last chapter presents concluding remarks as well as the recommendations to show future research directions and insights based on the findings of the study.

Chapter 2 Face Recognition Methods

Face Recognition has been an interesting issue for both neuroscientists and computer engineers dealing with artificial intelligence (AI). A healthy human can detect a face easily and identify that face, whereas for a computer to recognize faces, the face area should be detected and recognition comes next. Hence, for a computer to recognize faces the photographs should be taken in a controlled environment; a uniform background and identical poses makes the problem easy to solve. These face images are called mug shots [31]. From these mug shots, canonical face images can be manually (see Figure 2-1) or automatically produced by some preprocessing techniques like cropping, rotating, histogram equalization and masking. In a canonical face image, the size and position of the face are normalized approximately to the predefined values and the background region is minimized.

Figure 2-1: Examples of manually cropped (using Nero PhotoSnap) canonical face image

The history of studies on human face perception and machine recognition of faces are given in the next sections.

2.1 Human Face Recognition

Like almost everything associated with the Human body - The Brain, perceptive abilities, cognition and consciousness, face recognition in humans is a wonder. We are not yet even close to an understanding of how we manage to do it. What is known is that the Temporal Lobe in the brain is partly responsible for this ability. Damage to the temporal lobe can result in the condition in which the patient can lose the ability to recognize faces. This specific condition where an otherwise normal person who suffered some damage to a specific region in the temporal lobe loses the ability to recognize faces is called prosopagnosia. It is a very interesting condition when it occurs as the perception of faces remains normal (vision pathways and perception is fine) and the person can recognize people by their voice but not by faces [63, 53].

When building artificial face recognition systems, scientists try to understand the architecture of human face recognition system. Focusing on the methodology of human face recognition system may be useful to understand the basic system. However, the human face recognition system utilizes more than that of the machine recognition system which is just 2-D data. The human face recognition system uses some data obtained from some or all of the senses; visual, auditory, tactile, etc. All these data is used either individually or collectively for storage and remembering of faces. In many cases, the surroundings also play an important role in human face recognition system. It is hard for a machine recognition system to handle so much data and their combinations.

However, it is also hard for a human to remember many faces due to storage limitations. A key potential advantage of a machine system is its memory capacity [63], whereas for a human face recognition system the important feature is its parallel processing capacity.

The issue "which features humans use for face recognition" has been studied and it has been argued that both global and local features are used for face recognition. It is harder for humans to recognize faces which they consider as neither "attractive" nor "unattractive" [63].

The low spatial frequency components are used to clarify the sex information of the individual whereas high frequency components are used to identify the individual. The low frequency components are used for the global description of the individual while the high frequency components are required for finer details needed in the identification process [63].

Both holistic and feature information are important for the human face recognition system. Studies suggest the possibility of global descriptions serving as a front end for better feature-based perception [63]. If there are dominant features present such as big ears, a small nose, etc. holistic descriptions may not be used. Also, recent studies show that an inverted face (i.e. all the intensity values are subtracted from 255 to obtain the inverse image in the grey scale) is much harder to recognize than a normal face. Hair, eyes, mouth, face outline have been determined to be more important than nose for perceiving and remembering faces. It has also been found that the upper part of the face is more useful than the lower part of the face for recognition. Also, aesthetic attributes (e.g. beauty, attractiveness, pleasantness, etc.) play an important role in face recognition; the more attractive the faces are easily remembered [63].

For humans, photographic negatives of faces are difficult to recognize. But, there is not much study on why it is difficult to recognize negative images of human faces. Also, a study on the direction of illumination [63, 62] showed the importance of top lighting; it is easier for humans to recognize faces illuminated from top to down than the faces illuminated from bottom to up.
According to the neurophysicists [28], the analysis of facial expressions is done in parallel to face recognition in human face recognition system. Some prosopagnosic patients seem to recognize facial expressions due to emotions. Patients who suffer from organic brain syndrome do poorly at expression analysis but perform face recognition quite well [53].

2.2 Machine Recognition of Faces

Face recognition from images is a sub-area of the general object recognition problem. It is of particular interest in a wide variety of applications. Applications in law enforcement for mugshot identification, verification for personal identification such as driver's licenses and credit cards, gateways to limited access areas, surveillance of crowd behavior are all potential applications of a successful face recognition system [33, 31].

Recently Face recognition, a task which is done by humans in daily activities, comes from a virtually uncontrolled environment and has received significant attention [6, 63]. It plays an important role in many application areas, such as human-machine interaction, authentication and surveillance. However, the wide-range variations in this uncontrolled environment present complex problems which results in a highly complex distribution and deteriorate the recognition performance. The problems include [6, 63]:

- more than one face may appear in an image;
- lighting condition (illumination) may vary tremendously;
- facial expressions also vary from time to time;
- faces may appear at different scales, positions and orientations and
- facial hair, make-up and masks all obscure facial features.

But locating individual face is the work of face detection systems which is beyond the scope of this paper. Since face recognition in a general setting is very difficult, an application system typically restricts one of many aspects, including the environment in which the recognition system will take place (fixed location, fixed illumination, uniform background, single face, etc.), the allowable face change (neutral expression, negligible aging, etc.), the number of individuals to be matched against, and the viewing condition (front view, profile view etc.).

A general statement of the problem of machine recognition of faces can be formulated as follows:

Given still or video images of a scene, extract individuals' face(s) manually or using face detection algorithms, identify or verify one or more persons in the scene using a stored database of faces.

Although studies on human face recognition were expected to be a reference on machine recognition of faces, research on machine recognition of faces has developed independent of studies on human face recognition. During 1970's, typical pattern classification techniques, which use measurements between features in faces or face profiles, were used [51]. During the 1980's, work on face recognition remained nearly stable. Since the early 1990's, research interest on machine recognition of faces has grown tremendously. The interest is not bounded to those in the field of face recognition. Researches indicate that due to the diversity of variables considered, the problem of machine recognition of human faces has attracted researchers from varies disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology[6]. But for those in the field of computer recognition of faces, the reasons may be;

- An increase in emphasis on civilian/commercial research projects,
- The studies on neural network classifiers with emphasis on real-time computation and adaptation,
- The availability of real time hardware,
- The growing need for surveillance applications.

The basic question relevant for face classification is that; what form the structural code (for encoding the face) should take to achieve face recognition. Two major approaches are used for machine identification of human faces; geometrical local feature based methods, and holistic template matching based systems. Also, combinations of these two methods, namely hybrid methods, are used. The first approach, the geometrical local feature based one, extracts and measures discrete local features (such as eye, nose, mouth, hair, etc.) for retrieving and identifying faces. Then, standard statistical pattern recognition techniques and/or neural network approaches are employed for matching faces using these measurements [**Error! Reference source not found.**]. One of the well known geometrical-local feature based methods is the Elastic Bunch Graph Matching (EBGM) technique.

The other approach, the holistic one, conceptually related to template matching, attempts to identify faces using global representations [30].

Holistic methods approach the face image as a whole and try to extract features from the whole face region. In this approach, as in the previous approach, the pattern classifiers are applied to classify the image after extracting the features. One of the methods to extract features in a holistic system is applying statistical methods such as Principal Component Analysis (PCA) to the whole image. Note that, PCA can also be applied to a face image locally; in that case the approach is not holistic.

Whichever method is used, the most important problem in face recognition is the curse of dimensionality problem. Appropriate methods should be applied to reduce the dimension of the studied space. Working on higher dimension causes **overfitting** where the system starts to memorize [54]. Also, computational complexity would be an important problem when working on large databases.

2.3 Face Recognition Approaches

A wide variety of approaches to machine recognition of faces has been published in the literature. Categorization of the approaches may depend on different criteria. In terms of the sensing modality, a system can take 2-D intensity images, color images, infra-red images, 3-D range images, or a combination of them. In terms of viewing angle, a system may be designed for frontal views, profile views, general views, or a combination of them. In terms of temporal component, a system can be designed for a static image or for time-varying image sequences (which may facilitate face segmentation, face tracking, expression identification, and other use

of temporal context). In terms of computational tools used, a system can use programmed knowledge rules, statistical decision rules, neural networks, genetic algorithms, etc.
In general, many literatures argue, that there are two basic approaches to face recognition problem. Holistic and part-based approaches which employ either statistical or neural or a combination of both techniques to extract facial features.

Part-based approach to face recognition: Bobis et al. [20] suggested the use of geometric information to face. In this approach face recognition extracts and measures the overall geometrical configuration of face features by a vector of numeric data representing the size, shape and position of facial features such as eyes, nose, and mouth.

Holistic approach to face recognition: this approach emphasizes with the global features rather than specific part of the face. Turk and Pentland [38] were among the first to introduce this approach; But in dealing with the global features researchers realized that direct template matching suffers from computational complexity because of the extreme dimensionality. Then statistical data-reductionist techniques, like PCA and LDA, were employed to deal with this curse of dimensionality.

The last few years have seen very active research on face recognition. Accompanying the increase in research activities is a wave of commercialization for face recognition technology. In a survey by Technology Today [15], a total of 25 commercially available facial systems from 13 companies were listed. The FERET program, a face recognition program administered by US Army Research Laboratory, provided, for the first time, a large face database and conducted a series of blind tests for many face recognition algorithms [44].
Many factors have contributed to the recent increase in these face recognition activities and the successes. One of the major reasons is attributed to a basic, but fundamental change in methodology. That is, manually defining features versus automatically deriving features using statistical methods [31].

- Manually Defining Features

Traditionally, face recognition methods have relied on humans to define geometry-dependent features to be used for recognition. These feature values depend on the detection of geometric facial features, including items such as the distance and angles between geometric points such as eye corners, mouth extremities, nostrils and chin top. The features defined for face profiles (side views) typically include a set of characteristic points on the profile (such as the notch between the brow and the nose or the tip of the nose) and the angles between these points.

- Automatically Deriving Features

Manually defined features are intuitively understandable. However, methods based on this approach have run into basic problems. First, automatic detection of these features is not reliable due to various variations. Second, the number of features measurable is small. Third, the reliability of each feature measurement is difficult to estimate accurately. Thus, the subsequent classification method, even if it is optimal, does not result in a reliable overall system. An important advance is brought about by neural networks which implicitly but automatically derive features.

In any of the possible approaches to face recognition the selection or use of computational tools is vital to the success of the resulting face recognition system. In the following sections researches are reviewed in light of the recognition techniques applied as statistical, neural or others.

2.3.1 Statistical Approaches

This type of approach originated from an image representation task. Kirby and Sirovich [36, 40] treated a face image as a high dimensional vector, each pixel being mapped to a component in that vector. Their idea of representing the intensity image of a face by a linear combination of the principle component vectors has been used for recognition as well.

Statistical methods include template matching based systems where the training and test images are matched by measuring the correlation between them. Moreover, statistical methods include the projection based methods, such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), to the corresponding vector space for face image characterization. In fact, as explained earlier projection based systems came out due to the shortcomings of the straightforward template matching based approaches; that is, trying to carry out the required classification task in a space of extremely high dimensionality. As suggested by Brunelli and Poggio [50] the optimal strategy for face recognition is holistic and corresponds to template matching. In their study, a comparison was made between a geometric feature based technique and a template matching based system. In the simplest form of template matching, the image (as 2-D intensity values) is compared with a single template representing the whole face using a distance metric.

Although recognition by matching raw images has been successful under limited circumstances, it suffers from the usual shortcomings of straightforward correlation-based approaches, such as sensitivity to face orientation, size, variable lighting conditions, and noise. The reason for this vulnerability of direct matching methods lies in their attempt to carry out the required classification in a space of extremely high dimensionality. In order to overcome the curse of dimensionality, the connectionist equivalent of data compression methods is employed first. However, it has been successfully argued that the resulting feature dimensions do not necessarily retain the structure and that more general and powerful methods for feature extraction such as projection based systems are required. The basic idea behind projection based systems is to construct low dimensional projections of a high dimensional point cloud, by maximizing an objective function such as the deviation from normality. It has been proposed that this type of approaches be called appearance-based approach, in order to distinguish it from other view-based approaches (e.g., aspect graph based). For distinguishing it from neural-network based approaches that use intensities directly, we call them appearance-based statistical approaches.

Appearance-based statistical methods derive features directly from intensity images, using statistical techniques. They do not require humans to write explicit procedures to detect facial features, such as eyes, nose, and mouth. Here are some of researches conducted via statistical approach;

2.3.1.1 Face Detection and Recognition by PCA

The Eigenface Method, which is also the focus of this research, of Turk and Pentland [38] is one of the main methods applied in the literature which is based on the Karhunen-Loeve expansion. Their study is motivated by the earlier work of Sirovich and Kirby [36, 40] which is based on the application of Principal Component Analysis to the human faces. It treats the face images as 2-D data, and classifies the face images by projecting them to the eigenface space which is composed of eigenvectors obtained by the variance (covariance to be precise) of the face images. Eigenface recognition derives its name from the German prefix eigen, meaning own or individual. The Eigenface method of facial recognition is considered the first working facial recognition technology [8].

Turk and Pentland [38] were the first to propose this method and have followed a holistic approach to face recognition as they worked on the image as a whole. The Nearest Mean classifier was used to classify the face images. By using the observation that the projection of a face image and non-face image are quite different, a method of detecting the face in an image is obtained. They applied the method on a database of 2500 face images of 16 subjects, digitized at all combinations of 3 head orientations, 3 head sizes and 3 lighting conditions. They conducted several experiments to test the robustness of their approach to illumination changes, variations in size, head orientation, and the differences between training and test conditions. They reported that the system was fairly robust to illumination changes, but degrades quickly as the scale changes. This can be explained by the correlation between images obtained under different illumination conditions; the correlation between face images at different scales is rather low. The eigenface approach works well as long as the test image is similar to the training images used for obtaining the eigenfaces.

Later, derivations of the original PCA approach are proposed for different applications.

- PCA and Image Compression: In their study Moghaddam and Pentland [12] used the Eigenface Method for image coding of human faces for potential applications such as video telephony, database image compression and face recognition.

- Face Detection and Recognition Using PCA: Lee et al. [57] Another method, which is also studied throughout this thesis for face recognition only, using PCA which detects the head of an individual in a complex background and then recognize the person by comparing the characteristics of the face to those of known individuals.

- PCA Performance on Large Databases: Lee et al. [58] proposed a method for generalizing the representational capacity of available face database.

- PCA & Video: In a study by Crowley and Schwerdt [32], PCA is used for coding and compression for video streams of talking heads. They suggest that a typical video sequence of a talking head can often be coded in less than 16 dimensions.

- Bayesian PCA: A method suggested by Moghaddam et al. [9, 13]. By this system, the Eigenface Method based on simple subspace-restricted norms is extended to use a probabilistic measure of similarity. Also, another difference from the standard Eigenface approach is that this method uses the image differences in the training and test stages. The difference of each image belonging to the same individual with each other is fed into the system as intrapersonal difference, and the difference of one image with an image from different class is fed into the system as extrapersonal difference. Finally, when a test image comes, it is subtracted from each image in the database and each difference is fed into the system. For the biggest similarity (i.e. smallest difference) with one of the training images, the test image is decided to be in that class. The mathematical theory is mainly studied in [14]

Also, Moghaddam [10] introduced his study on several techniques; Principal Component Analysis (PCA), Independent Component Analysis (ICA), and nonlinear Kernel PCA (KPCA). He examined and tested these systems using the FERET database. He argued that the experimental results demonstrate the simplicity, computational economy and performance superiority of the Bayesian PCA method over other methods.

- PCA and Gabor Filters: Chung et al. [34] suggested the use of PCA and Gabor Filters together. Their method consists of two parts: In the first part, Gabor Filters are used to extract facial features from the original image on predefined fiducial points (characteristic points). In the second part, PCA is used to classify the facial features optimally. They suggest the use of combining these two methods in order to overcome the shortcomings of PCA. They argue that, when raw images are used as a matrix of PCA, the eigen space cannot reflect the correlation of facial feature well, as original face images have deformation due to in-plane, in-depth rotation and illumination and contrast variation. Also they argue that, they have overcome these problems using Gabor Filters in extracting facial features.

2.3.1.2 Face Recognition by LDA

Etemad and Chellappa [35] proposed a method on appliance of Linear/Fisher Discriminant Analysis for the face recognition process. LDA is carried out via scatter matrix analysis. The aim is to find the optimal projection which maximizes between class scatter of the face data and minimizes within class scatter of the face data. As in the case of PCA, where the eigenfaces are calculated by the eigenvalue analysis, the projections of LDA are calculated by the generalized eigenvalue equation.

An alternative method which combines PCA and LDA is Subspace LDA which is studied in [45, 11]. This method consists of two steps; the face image is projected into the eigenface space which is constructed by PCA, and then the eigenface space projected vectors are projected into the LDA classification space to construct a linear classifier. In this method, the choice of the number of eigenfaces used for the first step is critical; the choice enables the system to generate class-separable features via LDA from the eigenface space representation. The generalization/overfitting problem can be solved in this manner. In these studies, a weighted distance metric guided by the LDA eigenvalues was also employed to improve the performance of the method.

2.3.1.3 Transformation Based Systems

- Discrete Cosine Transform (DCT): Podilchuk and Zang [19] proposed a method which finds the feature vectors using DCT and tries to detect the critical areas of the face. The system is based on matching the image to a map of invariant facial attributes associated with specific areas of the face. They claim that this technique is quite robust, since it relies on global operations over a whole region of the face. A codebook of feature vectors or code-words is determined for each person from the training set. They examine recognition performance based on feature selection, number of features or codebook size, and feature dimensionality. For feature selection, they tried several block-based transformations and the K-means clustering algorithm [54] to generate the code-words for each codebook. They argue that the block-based DCT coefficients produce good low-dimensional feature vectors with high recognition performance. This brings the possibility of performing face recognition directly on a DCT-based compressed bitstream without having to decode the image.
- DCT & Hidden Markow Models (HMMs): Eickeler et al. [56] suggested a system based on Pseudo 2-D HMMs and coefficient of the 2-D DCT as the features. A major advantage of their approach is that the system works directly on JPEG-compressed face images, i.e. it uses the DCT-coefficients provided by the JPEG standard. Thus, it does not need any

further decompressing of the image. Also Nefian and Hayes [2] studied on first using DCT as the feature vectors and using HMMs.

- Fourier Transform (FT): Spies and Ricketts [25] proposed a face recognition system based on an analysis of faces via their Fourier spectra. Recognition is achieved by finding the closest match between feature vectors containing the Fourier coefficients at selected frequencies. This technique is based on the Fourier spectra of facial images, thus it relies on a global transformation, i.e. every pixel in the image contributes to each value of its spectrum. The Fourier spectrum is a plot of the energy against spatial frequencies, where spatial frequencies relate to the spatial relations of intensities in the image. In the case of face recognition, this translates to distances between areas of particular brightness, such as the overall size of the head, or the distance of the eyes. Higher frequencies describe finer details and they claim that these are less useful for identification of a person. They also suggest that, humans can recognize a face from a brief look without focusing on small details. They perform the recognition of faces by finding the Euclidian distance between a newly presented face and all the training faces. The distances are calculated between feature vectors with entries that are the Fourier Transform values at specially chosen frequencies. They argue that, as few as 27 frequencies yield good results (98 %). Moreover, this small feature vector combined with the efficient Fast Fourier Transform (FFT) makes this system extremely fast.

2.3.1.4 Face Recognition by SVM

Phillips [43] applied Support Vector Machine (SVM) to face recognition. In this method face recognition is a K-class problem, where K is the number of known individuals; and SVM is a binary classification method. By reformulating the face recognition problem and reinterpreting the output of the SVM classifier, they developed a SVM-based face recognition algorithm. They formulated the face recognition problem in difference space, which models dissimilarities between two facial images. In difference space, they formulated the face recognition as a two class problem. The classes are; dissimilarities between faces of the same person and dissimilarities between faces of different people. By modifying the interpretation of the decision surface generated by SVM, they generated a similarity metric between faces, learned from examples of differences between faces [43].

2.3.1.5 Feature-based Approaches

Bobis et al. [20] studied on a feature based face recognition system. They suggested that a face can be recognized by extracting the relative position and other parameters of distinctive features such as eyes, mouth, nose and chin. The system described the overall geometrical configuration of face features by a vector of numerical data representing position and size of main facial features. First, they extracted eyes coordinates. The interocular distance and eyes position is used to determine size and position of the areas of search for face features. In these areas binary thresholding is performed, system modifies threshold automatically to detect features. In order to find their coordinates, discontinuities are searched for in the binary image. They claim that, their experimental results showed that their method is robust, valid for numerous kind of facial image in real scene, works in real time with low hardware requirements and the whole process is conducted automatically.

- Feature Based PCA: Cagnoni and Poggi [55] suggested a feature-based approach instead of a holistic approach to face recognition. They applied the eigenface method to sub-images (eye, nose, and mouth). They also applied a rotation correction to the faces in order to obtain better results.
- A feature based approach using PCA vs. Independent Component Analysis (ICA): Guan and Szu [3] compared the performance of PCA and ICA on face images. They argue that, ICA encodes face images with statistically independent variables, which are not necessarily associated with the orthogonal axes, while PCA is always associated with orthogonal eigenvectors. While PCA seeks directions in feature space that best represent the data in a sum-squared error sense, ICA seeks directions that are most independent from each other [54]. They also argue that, both these pixel-based algorithms have the major drawback that they weight the whole face equally and therefore lack the local geometry information. Hence, Guan and Szu suggest approaching the face recognition problem with ICA or PCA applied on local features.

- A feature based approach using PCA, Bayesian Classifier, and HMMs: Martinez [1] proposed a different approach based on identifying frontal faces. Their approach divides a face image into n different regions, analyzes each region with PCA, and then uses a Bayesian approach to find the best possible global match between a probe and database image. The relationship between the n parts is modeled by using Hidden Markov Models (HMMs).

2.3.2 Neural Network Approaches

The Neural Networks are among the most successful decision making systems that can be trained to perform complex functions in various fields of applications including pattern recognition, optimization, identification, classification, speech, vision, and control systems. Using a neural network, humans do not need to define facial features for face recognition. Kohonen [60] demonstrated the use of a self-organizing map for face recollection applications. Even when the input images were very noisy or had portions missing, an accurate recall capability was achieved on a small set of face images. Neural Network approaches have been used in face recognition generally in a geometrical local feature based manner, but there are also some methods where neural networks are applied holistically.

- Feature based Backpropagation NN: Temdee et al. [47] presented a frontal view face recognition method by using fractal codes which are determined by a fractal encoding method from the edge pattern of the face region (covering eyebrows, eyes and nose). In their recognition system, the obtained fractal codes are fed as inputs to Backpropagation Neural Network for identifying an individual. They tested their system performance on the ORL face database. They report their performance as 85 % correct recognition rate in the ORL face database.

- Dynamic Link Architectures (DLA): Lades et al. [41] presented an object recognition system based on Dynamic Link Architectures, which is an extension of the Artificial Neural Networks. The DLA uses correlations in the fine-scale cellular signals to group neurons dynamically into higher order entities. These entities can be used to code high-level objects, such as a 2-D face image. The face images are represented by sparse graphs, whose vertices are labeled by a multiresolution description in terms of local power spectrum, and whose edges are labeled by geometrical distance vectors. Face recognition can be formulated as elastic graph matching, which is performed in this study by stochastic optimization of a matching cost function.

- Elastic Bunch Graph Matching (EBGM): Wiskott et al. [37] presented a geometrical local feature based system for face recognition from single images out of a large database containing one image per person, which is known as Elastic Bunch Graph Matching (EBGM). In this system, faces are represented by labeled graphs, based on a Gabor Wavelet Transform (GWT). Image graphs of new faces are extracted by an Elastic Graph Matching process and can be compared by a simple similarity function. In this system, phase information is used for accurate node positioning and object-adapted graphs are used to handle large rotations in depth. The image graph extraction is based on the bunch graph, which is constructed from a small set of sample image graphs. In contrast to many neural-network systems, no extensive training for new faces or new object classes is required. Only a small number of typical examples have to be inspected to build up a bunch graph, and individuals can then be recognized after storing a single image. The system inhibits most of the variance caused by position, size, expression and pose changes by extracting concise face descriptors in the form of image graphs. In these image graphs, some predetermined points on the face (eyes, nose, mouth, etc.) are described by sets of wavelet components (jets). The image graph extraction is based on the bunch graph, which is constructed from a small set of image graphs.

2.3.3 Hybrid Approaches

It should be noted that neural network and statistical methods are not incompatible. In fact, a significant amount of recent research on neural networks uses statistical methods in combination with a network computational structure.

- PCA and RBF: The method by Er et al. [39] suggests the use of Radial Basis Function (RBF) Neural Networks on the data extracted by discriminant eigen features. They used a hybrid learning algorithm to decrease the dimension of the search space in the gradient method, which is crucial on optimization of high dimension problem. First, they tried to extract the face features by both the PCA and LDA methods. Next, they presented a hybrid learning algorithm to train the RBF Neural Networks, so the dimension of the search space is significantly decreased in the gradient method.

Thomaz et al. [16] also studied on combining PCA and RBF neural network. Their system is a face recognition system consisting of a PCA stage which inputs the projections of a face image over the principal components into a RBF network acting as a classifier. Their main concern is to analyze how different network designs perform in a PCA+RBF face recognition system. They used a forward selection algorithm, and a Gaussian mixture model. According to the results of their experiments, the Gaussian mixture model optimization achieves the best performance even using less neurons than the forward selection algorithm. Their results also show that the Gaussian mixture model design is less sensitive to the choice of the training set.

2.3.4 Other Approaches

A. Range Data

One of the different methods used in face recognition task is using the range images. In this method data is obtained by scanning the individual with a laser scanner system. This system also has the depth information; so the system processes 3-dimensonal data to classify face images [51].

B. Infrared Scanning

Another method used for face recognition is scanning the face image by an infrared light source.

Yoshitomi et al. [64] used thermal sensors to detect temperature distribution of a face. In this method, the front-view face in input image is normalized in terms of location and size, followed by measuring the temperature distribution, the locally averaged temperature and the shape factors of face. The measured temperature distribution and the locally averaged temperature are separately used as input data to feed a Neural Network, while the values of shape factors are used for supervised classification. By integrating information from the Neural Network and supervised classification, the face is identified. The disadvantage of visible ray image analysis that the accuracy of face identification is strongly influenced by lighting condition including variation of shadow, reflection and darkness is overcome by this method which uses infrared rays.

C. Profile Images

Liposcak and Loncaric [67] worked on profile images instead of frontal images. Their method is based on the representation of the original and morphological derived profile shapes. Their aim is to use the profile outline that bounds the face and the hair. They take a grey-level profile image, threshold it to produce a binary image, representing the face region. They normalize the area and orientation of this shape using dilation and erosion. Then, they simulate hair growth and haircut and produce two new profile silhouettes. From these three profile shapes they obtain the feature vectors. After normalizing the vector components, they use the Euclidean distance measure for measuring the similarity of the feature vectors derived from different profiles.

2.4 Face Databases

Face images are at the heart of automatic face recognition technology. Because of the fact that faces are highly deformable and complex structures that differ in slightly ways, appearance is affected by a large number of factors including pose, expression illumination and aging. The development of algorithms that is robust to these variations requires sufficient and reasonable datasets of face images that consider the controlled variations of these factors. Along with the development of FR algorithms, various databases have been collected for evaluating the performance and capability of the algorithms under investigation. Besides FERET and FRVT, there are many face databases available for researches in the face recognition community; Yale [65], PIE [48], AR [7] and HLR [27] are some examples of face databases that are publicly available for researchers. FERET has been used, as a standard evaluation methodology for face recognition research and application for many years and is still a de facto standard for measuring the performance of FR algorithms; however, none of the tests include Ethiopian faces either for training or testing purposes.

In general, the performance of FR algorithms largely depends on the on the dataset being used for training and testing. Though it is difficult to construct a face database where every factor that affect face appearance is fully controlled [46, 42] it is the aim of this research to construct a face database of Ethiopian faces and evaluate the performance of eigenface algorithm on this dataset.

Chapter 3 Pattern Classification

The problem of face recognition is fundamentally a classification problem. In this section, the idea behind the algorithm applied throughout this research had been summarized. The pattern classification basics, the discipline behind the statistical pattern classifiers; Bayesian Classifier, Nearest Mean Classifier, and the main projection techniques; Principal Component Analysis (PCA) and a Linear Discriminant Analysis (LDA) will be discussed.

3.1 Pattern Recognition Basics

Pattern recognition can be defined as the categorization of input data into identifiable classes via the extraction of significant features or attributes of the data from a background of irrelevant detail. It is a science concerned about the description or classification of measurements. A typical pattern recognition system takes the input data, extracts the features, trains the classifier and evaluates the test pattern. The features are the representatives of the input data in the classification system used and they are obtained by directly using the input data or by applying different kinds of dimension reduction techniques on the input data. An ideal feature extractor would yield a representation that makes the job of the classifier trivial.
In general a pattern recognition system design requires [29]:-

- to deal with the representation of input data
- The extraction of characteristic features or attributes from the received input data and the reduction of the dimensionality of pattern vectors. This is often referred to as the pre-processing and the feature extraction problem. and
- The determination of the optimum decision procedures, which are needed in the identification and classification process.

The block diagram of an adaptive pattern recognition system is depicted in Figure 3-1.

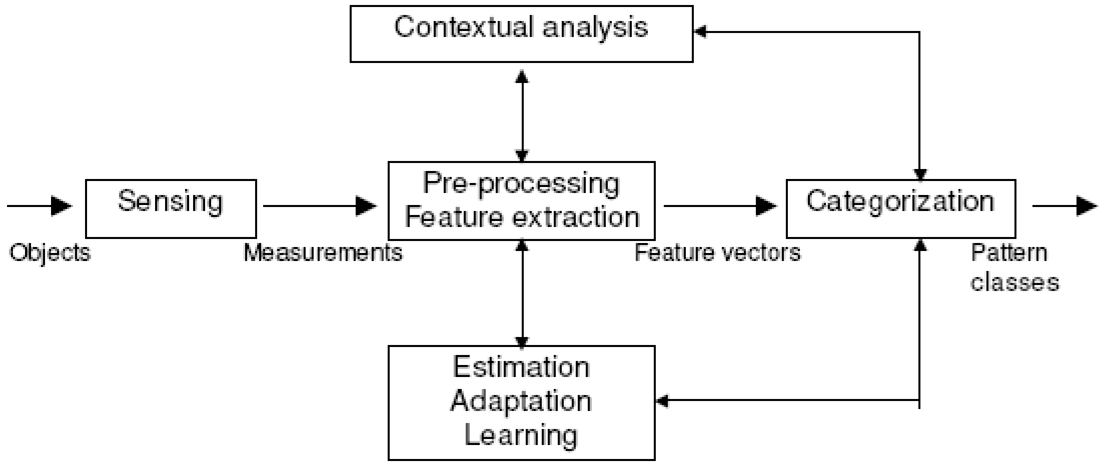

Figure 3-1: Functional block diagram of an adaptive pattern recognition system [29].

- Sensing:-

A pattern class is a category determined by some given common attributes or features. The features of a pattern class are the characterizing attributes common to all patterns belonging to that class. Such features are often referred to as intraset features. The features which represent the differences between pattern classes may be referred to as the interset features [52].

A pattern is the description of any member of a category representing a pattern class. For convenience, patterns are usually represented by a vector such as:

$$X = \begin{Bmatrix} x_1 \\ x_2 \\ \cdots \\ \cdots \\ x_n \end{Bmatrix} \qquad (3\text{-}1)$$

Where each elementx_j, represents a feature of that pattern; it is often useful to think of a pattern vector as a point in an n-dimensional Euclidean space.

3.2 Pattern Recognition Approaches

There are three main pattern recognition approaches [52];

- Statistical Pattern Recognition; assumes the underlying model as a set of probabilities, but ignores the structure,
- Syntactic Pattern Recognition; concentrates on the interrelations between primitives that build the whole pattern (which are not easy to find),
- Neural Pattern Recognition; imitates human neural system.

Representation of input data, a face image in our case, is a critical component in the processes of designing a robust automatic pattern recognition system. As discussed in section 2.3.1 the task of image representation as vector is typically a statistical approach towards the problem of face recognition which is part of the general pattern classification problem. Throughout this thesis study, statistical pattern classification is used. Hence, it will be the main concern to discuss in this section.

3.2.1 Statistical Pattern Recognition

It is an approach of the pattern classification problem, which concentrates on developing decision or classification strategies that form classifiers [29]. In statistical pattern recognition, each pattern is represented in terms of d-features or measurements and can be viewed as a point in a d-dimensional space. The objective of a statistical pattern recognition system is to choose features that allow the patterns belonging to different classes to occupy different regions in a d-dimensional feature space. The representation space or feature space is assumed to be effective, if the patterns from different classes are well separated and if the feature space greatly represents the general properties of the input data. Decision boundaries separate patterns belonging to different classes and they are determined by the specified probability distributions of the patterns belonging to each class.

While a heavily complex system may allow perfect classification of the training samples, it may not perform well on new patterns. This situation is known as overfitting (or memorization) [54]. One of the most important areas of research in statistical pattern classification is determining how to adjust the complexity of the model.

For the case, where the training samples used to design, a classifier are labeled by their category membership, the procedure is accepted as supervised. The opposite case is called unsupervised system where the training data is unlabeled.

3.2.2 Supervised and Unsupervised Pattern Recognition

In most cases, representative patterns from each class under consideration are available. In these situations, supervised pattern recognition techniques are applicable. In a supervised learning environment, the system is taught to recognize patterns by means of various adaptive schemes. The essentials of this approach are a set of training patterns of known classification and the implementation of an appropriate learning procedure. In some applications, only a set of training patterns of unknown classification may be available. In these situations, unsupervised pattern recognition techniques are applicable. As mentioned above, supervised pattern recognition is characterized by the fact that the correct classification of every training pattern is known. In the unsupervised case however, one is faced with the problem of actually learning the pattern classes present in the given data. This problem is also known as "learning without a teacher" [54].

3.3 Classifiers

3.3.1 Bayesian Classifier

Bayesian classifier is one of the most widely applied statistical approaches in the standard pattern classification. It assumes that the classification problem is posed in probabilistic terms, and that all the relevant probability values are known.

The decision process in statistical pattern recognition can be explained as follows: Given an input pattern, represented as a vector of d feature values $x = (x_{1,} x_2 ..., x_d)$, assign it to one of c categories $w_1, w_2, ..., w_c$ by taking one of the a possible actions $\alpha_1, \alpha_2, ..., \alpha_a$. Assuming that each feature has a probability density (represented as p(.)) or mass function (represented as P(.)) conditioned on the pattern class, a pattern vector x belonging to class w_j can be viewed as an observation drawn randomly from the class-conditional probability function, $p(x|w_i)$ [21].

A loss function $\lambda(\alpha_i \mid w_j)$ is simply defined as the loss for deciding the class w_j where the true class is class w_j [22], that is;

$$\text{Loss Function} \quad \lambda(\alpha_i \mid w_j) = \begin{cases} 0 & i = j \\ 1 & i \neq j \end{cases} \quad \text{.......... (3-2)}$$

The Bayes decision rule for minimizing the risk, which is the expected value of the loss function, can be stated as follows [44]: Assign input pattern x to class w_j where the conditional l risk $R(\alpha_i \mid x)$ is minimum. In mathematical terms;

$$R(\alpha_i \mid x) = \sum_{j=1}^{c} \lambda(\alpha_i \mid w_j) P(w_j \mid x) \quad \text{.......... (3-3)}$$

Conditional Risk should be minimized for any i = 1, 2… c to classify the input pattern to the i^{th} class.

Under these assumptions, the Bayes classifier assigns the input pattern x to class w_i for which the posterior probability $P(w_i \mid x)$ is the maximum; that is,

Bayes Classifier decides on w_i if $P(w_i \mid x) > P(w_j \mid x) \;\; for \;\; i \neq j$

The idea underlying Bayes classifier is very simple. In order to minimize the overall risk, the action that minimizes the conditional risk $R(\alpha \mid x)$ should be taken. In particular, in order to minimize the probability of error in a classification problem, the maximum posterior probability $P(w_i \mid x)$ should be chosen. Bayes formula is a way to calculate such probabilities from the prior probabilities $P(w_j)$ and the class conditional densities $P(x \mid w_j)$ [22].

Bayes Formula:

$$P(w_j \mid x) = \frac{P(x \mid w_j)p(w_j)}{p(x)} = \frac{P(x \mid w_j)p(w_j)}{\sum_{j=1}^{c} P(x \mid w_j)p(w_j)} \quad \text{(3-4)}$$

For most of the pattern classification applications, the main problem in applying the Bayes classifier is that the class-conditional densities $P(x \mid w_j)$ are not known. However, in some cases, the form of these densities can be known without exact knowledge on parameter values. In a classic case, the densities are known to be (or assumed to be) multivariate normal, but the values of the mean vector and the covariance matrix are not known [54]. In this case, the multivariate normal density in d dimensions can be written as [17];

Multivariate Normal Density $$P(x \mid w_j) = \frac{e^{\left(-\frac{1}{2}(x-\mu_j)^{\tau} \sum^{-1} (x-\mu_j)\right)}}{(2\pi)^{d/2} \left|\sum\right|^{1/2}} \quad \text{(3-5)}$$

where Σ is the covariance matrix of size (d x d).

3.3.2 Nearest Mean Classifier

Nearest Mean Classifier is an analogous approach to the Nearest Neighbor Rule (NN-Rule). In the NN-Rule, after the classification system is trained by the samples, a test data is fed into the system and it is classified in the class of the nearest training sample in the data space with respect to Euclidean Distance. In the Nearest Mean Classifier, again the Euclidean distance from each class mean (in this case) is computed for the decision of the class of the test data [21].

In mathematical terms, the Euclidean distance between the test sample x, and each face class mean μ_i is;

Euclidean Distance

$$d_i = \|x - \mu_i\| = \sqrt{\sum_{k=1}^{d} (x_k - \mu_{ik})^2} \quad \text{(3-6)}$$

where x is a d dimensional input data.

After computing the distance to each class mean, the test data is classified into the class with minimum Euclidean Distance. It is this classifier, which I have used to develop a Face Recognition system that classify a probe image, after a proper learning procedure, as known, unknown or not even a face.

3.4 Feature Dimension Reduction

Feature selection in pattern recognition involves the derivation of certain features from the input data in order to reduce the amount of data used for classification and provide discrimination power. Due to the measurement cost and classification accuracy, the number of features should be kept as small as possible. A small and functional feature set makes the system work faster and use less memory. On the other hand, using a wide feature set may cause “curse of dimensionality” which is the need for exponentially growing number of samples [54].

Feature extraction methods try to reduce the feature dimensions used in the classification step. There are especially two methods used in pattern recognition to reduce the feature dimensions; Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [54].

The general philosophy that motivates dimensionality reduction techniques is the fact that real-life data contain redundancies and noise. Dimensionality reduction is often a good way to deal with this: by using a low-dimensional approximate representation, noise can be suppressed and redundancies removed. The data are replaced by a summary that still captures as much information as possible.

The relative places of the data between each other are never changed according to the utilized feature dimension reduction technique, PCA or LDA. Only the axes are changed to handle the data from a “better” point of view. Better point of view is simply generalization for PCA and discrimination for LDA. Figure 3-2 shows how the axis the second case provides a better relative comparison between features in the two classes than the first axis which doesn’t help to identify which features are principal components or /and which features are not.

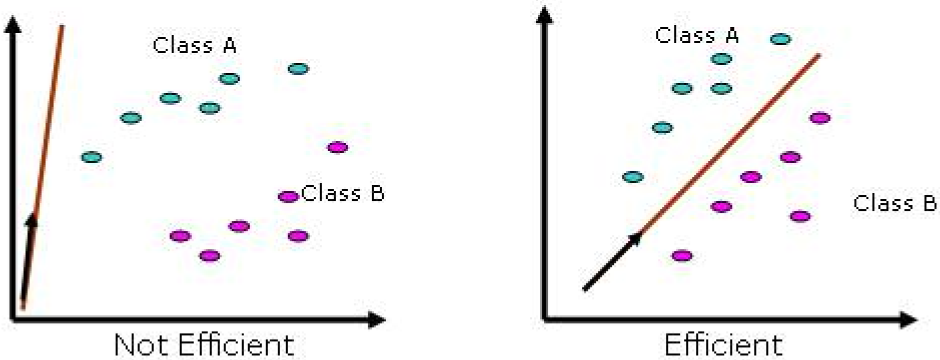

Figure 3-2: Only the axes are changed to handle the data from a "better" point of view [54]

3.4.1 Principal Component Analysis (PCA)

The advantage of PCA comes from its generalization ability. It reduces the feature space dimension by considering the variance of the input data. The method determines which projections are preferable for representing the structure of the input data. Those projections are selected in such a way that the maximum amount of information (i.e. maximum variance) is obtained in the smallest number of dimensions of feature space.

In order to obtain the best variance in the data, the data is projected to a subspace (of the image space) which is built by the eigenvectors from the data. In that sense, the eigen value corresponding to an eigenvector represents the amount of variance that eigenvector handles. The mathematical formulation (the algorithm) of PCA is discussed in the upcoming section.

3.4.2 Canonical Correlation Analysis (CCA)

While PCA deals with only one data space X where it identifies directions of high variance, canonical correlation analysis (CCA, first introduced in [24]) proposes a way for dimensionality reduction by taking into account relations between samples coming from two spaces X and Y. The assumption is that the data points coming from these two spaces contain some joint information that is reflected in correlations between them. Directions along which this correlation is high are thus assumed to be relevant directions when these relations are to be captured.

3.4.3 Partial Least Squares (PLS)

Partial least squares (PLS, introduced in [11, 19]) can be interpreted in two ways. The first PLS component is the maximally regularized version of the first CCA component (the case where $\gamma \to \infty$, after rescaling the eigenvalues by multiplying them with γ). Another view is as a covariance maximizer instead of a correlation maximizer, this again for the first PLS component. Whereas all PLS formulations compute the first component in the same way, there is no one way to compute the other components. There are two variants: so-called EZ-PLS, which consists of only one eigen value decomposition (or a singular value decomposition) and which is used mainly for exploratory purposes (similar to CCA), and regression-PLS which is a more involved version that is most widely used in (multivariate) regression applications.

3.4.4 Linear Discriminant Analysis (LDA)

While PCA tries to generalize the input data to extract the features, LDA tries to discriminate the input data by dimension reduction (See Figure 3-3). Three 3-dimensional distributions are projected onto 2-dimensional subspaces as described by normal vectors W1 and W2. Since LDA tries to find the greatest separation among the classes, Figure 3-3 shows that W1 is optimal for LDA, as the separation between the two classes is more clearer than W2 [22].

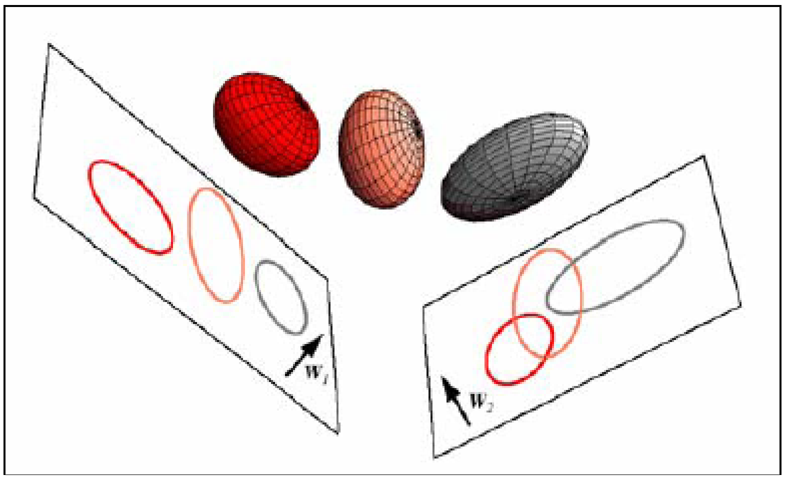

Figure 3-3: Three dimensional distributions are projected onto two dimensional subspaces [22].

LDA searches for the best projection to project the input data on a lower dimensional space in which the patterns are discriminated as much as possible. For this purpose, LDA tries to maximize the scatter between different classes and minimize the scatter between the input datas in the same class. In Figure 3-3, the selection criteria for LDA can be observed. LDA uses generalized eigen value equation to obtain this discrimination [22].

Chapter 4 Face Recognition via Dimensionality Reduction

In this section, the theoretical background of the implemented method, namely the eigenface method, is discussed.

4.1 Face Recognition via Eigenface Method

Face recognition is a pattern recognition task performed specifically on faces. ‘Eigenfaces for Recognition’ seeks to implement a system capable of efficient, simple, and accurate face recognition in a constrained environment (such as a household or an office). The system does not depend on 3-D models or intuitive knowledge of the structure of the face (eyes, nose, or mouth). Classification is instead performed using a linear combination of characteristic features (eigenfaces). Eigenfaces are fundamentally nothing more than basis vectors for real faces. This can be related directly to one of the most fundamental concepts in electrical engineering: Fourier analysis. Fourier analysis reveals that a sum of weighted sinusoids at deferring frequencies can recompose a signal perfectly! In the same way, a sum of weighted eigenfaces can seamlessly reconstruct a specific person's face; which means a face can be expressed as a linear combination of face-like features so called eigenfaces. Eigenfaces has an interesting parallel in one of the most fundamental ideas in mathematics and signal processing-so called Fourier series.

Fourier series are named so in the honor of Jean Baptiste Joseph Fourier who made important contributions to their development. Representation of a signal in the form of a linear combination of complex sinusoids is called the Fourier Series. What this means is that you can’t just split a periodic signal into simple sines’ and cosines’, but you can also approximately reconstruct that signal given you have information how the sines’ and cosines’ that make it up are stacked [25].

Suppose $f(x)$ is a periodic function with period 2π defined in the interval $c \le x \le c + 2\pi$ and satisfies a set of conditions called the Dirichlet’s conditions:

1. $f(x)$ is finite, single valued and its integral exists in the interval.
2. $f(x)$ has a finite number of discontinuities in the interval.
3. $f(x)$ has a finite number of extrema in that interval.

Then $f(x)$ can be represented by the trigonometric series

$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} \left[a_n \cos(nx) + b_n \sin(nx) \right] \quad \text{(4-1)}$$

The above representation of $f(x)$ is called the Fourier series and the coefficients a_0, a_n and b_n are called the fourier coefficients and are determined from $f(x)$ by Euler's formulae. The coefficients are given as :

- $a_0 = \frac{1}{\pi}\int_{c}^{c+2\pi} f(x)dx$ .... (4-2)
- $a_n = \frac{1}{\pi}\int_{c}^{c+2\pi} f(x)\cos(nx)dx$ .... (4-3)
- $b_n = \frac{1}{\pi}\int_{c}^{c+2\pi} f(x)\sin(nx)dx$ .... (4-4)

Though not exactly the same, the idea behind Eigenfaces is similar. The aim is to represent a face as a linear combination of a set of basis images (See Equation 4-5).

$$\Phi_i = \sum_{j=1}^{K} w_j u_j \qquad \text{(4-5)}$$

Where Φ_i represents the i^{th} face with the mean subtracted from it, w_j represent weights and u_j the eigenvectors.

This can be represented aptly in Figure 4-1:

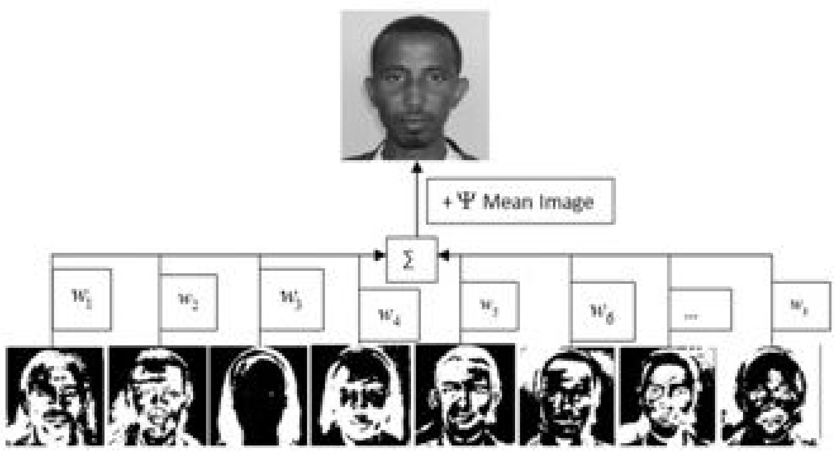

Figure 4-1: A face in the training database and the way it was reconstructed by taking a weighted summation of all the basis faces and then adding to them the mean face.

The eigenface technique is a powerful yet simple solution to the face recognition dilemma. In fact, it is really the most intuitive way to classify a face. Before the eigenfaces method was introduced, most of the literature in the field of face recognition dealt with local and intuitive features, such as distance between eyes, ears and similar other features. This wasn't very effective. Eigenfaces was a significant departure from the idea of using only intuitive features. It uses an Information Theory approach wherein the most relevant face information is encoded in a group of faces (patterns) that will best distinguish the faces. These patterns include, but are not limited to, the specific features of the face. By using more information, eigenface analysis is naturally more effective than feature-based face recognition. It transforms the face images in to a set of basis faces, which essentially are the principal components of the face images. Determining what these eigenfaces is the crux of this technique [40 38].

4.2 Procedures of the Eigenface Approach to Face Recognition

As proposed by Turk and Pentland [38], the recognition system is initialized or trained with the following operations:

1. An initial set of face images is acquired to form the training set.

2. The Eigenfaces are calculated from the training set. Only M Eigenfaces corresponding to the M largest eigenvalues are retained. These Eigenfaces span a face space constituted of the training set.

3. M Eigenface-weights are calculated for each training image by projecting the image onto the face space spanned by the Eigenfaces. Each face image then will be represented by M weights- an extremely compact representation.

After initialization, the following steps are followed to recognize test images:

4. The set of M weights corresponding to the test image are found by projecting the test image onto each of the Eigenfaces.

5. The test image and images in the face library will be reconstructed and the test image is checked if it is a face at all by considering whether it is sufficiently close to the face space. This is done by comparing the distance between the test image and the face space (i.e the distance between the reconstructed test and face library face images) to an arbitrary distance threshold.
6. If it is sufficiently close to the face space, compute the distance of the M weights of the test image to the M weights of each face image in the training set. A second arbitrary threshold is put in place to check whether the test image corresponded at all to any known identity in the training set.

7. If the second threshold is overcome, the test image was assigned with the identity of the face image with which it has the smallest distance.

8. (Optional) For a test image with a previously unknown identity, the system can be re-trained by adding this image to the training set.

4.2.1 The Training Procedure of Eigenface Approach

A face image, $T(x, y)$, is a two-dimensional N by N matrix of intensity values, which are usually quantized to 8-bit values. Each x and y pair denotes a position in the image. For the purpose of exposition, it is convenient to represent the matrix of intensity values as a vector, where each row is concatenated (see Equation 4-6). Now, instead of having a matrix of dimension N by N, we have a vector of dimension N2. As an example, a typical image with size 256 by 256 pixels becomes a point in a 65536(256*256)-dimensional space. Equation 4-6 shows how the N by N matrix is changed to vector of size N2.

$$T_i = \begin{bmatrix} a_{11} & a_{12} \dots a_{1N} \\ a_{21} & a_{22} \dots a_{2N} \\ \vdots & \vdots \quad \ddots \vdots \\ a_{N1} & a_{N2} \dots a_{NN} \end{bmatrix}_{NxN} \xrightarrow{[\text{Concatination}]} \begin{bmatrix} a_{11} \\ \vdots \\ a_{1N} \\ \vdots \\ a_{2N} \\ \vdots \\ a_{NN} \end{bmatrix}_{N^2 x1} = \Gamma_i \quad \text{.....................(4-6)}$$

To obtain the Eigenfaces for a training set, it is crucial to first determine the mean vector, deviation-from-mean vectors and the covariance matrix for the particular training set. Let the images in the training set be represented by {T_1, T_2, T_3...T_M}, where each T_n is a vector of N^2-dimension. The value M is the number of images in the training set. With this representation, the mean vector is:

$$\psi = \frac{1}{M}\sum_{n=1}^{M} T_n \quad \text{..(4-7)}$$

The set of deviation-from-mean vectors $\{\phi_1, \ \phi_2, \ \phi_3, \dots, \phi_M\}$ contains the individual difference of each training image from the mean vector. Kirby and Sirovich [40] refer to these vectors as caricatures. They are simply defined as:

$$\phi_i = T_i - \psi \quad \text{.. (4-8)}$$

As a concrete illustration, the training set in Figure 4-2, which is a subset of the face Database, yields the average face in Figure 4-3. The caricatures corresponding to the training set are displayed in Figure 4-5.

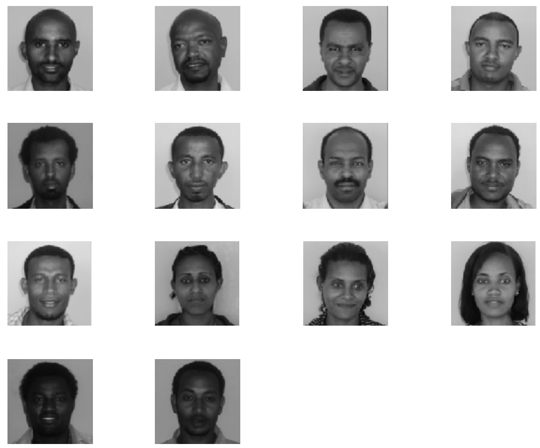

Figure 4-2: Training images-14

Figure 4-3: Mean image of the 14 training images

Figure 4-4: Top 13 eigenfaces

Figure 4-5: The caricatures (i.e the difference of each image from the mean image in Figure 4-3)

As described previously, the eigenfaces are the set of principal components of the training set. To obtain the eigenface description of the training set, the training images are subjected to Principal Component Analysis (PCA), which seeks a set of vectors (the principal components) which significantly describes the variations of the data. Mathematically, the principal components of the training set are the eigenvectors of the covariance matrix of the training set [40]. The covariance matrix is given by:

$$C = \frac{1}{M}\sum_{n=1}^{M} \phi_n \phi_n^T \qquad \text{(4-9)}$$

It is from this matrix that we are interested in finding the set of vectors u_k and scalars λ_k that satisfy the relations

$$Cu_k = \lambda_k u_k$$

$$u_l^T u_k = \begin{cases} 1, & if\ l = k \\ 0, & if\ l \neq k \end{cases} \qquad \text{(4-10)}$$

It is clear from Equation 4-10 that the vectors u_k are orthonormal. Another way of representing the covariance matrix is by writing

$$A = [\phi_1\ \ \phi_2\ \ \phi_3 \ldots \phi_M] \qquad \text{(4-11)}$$

$$C = \frac{1}{M} AA^T \qquad \text{(4-12)}$$

A closer look at Equation (4-12) reveals that matrix C has a dimension of N^2 by N^2, and determining N^2 eigenvectors and eigenvalues from a matrix this large (65536 by 65536 for our example) is unwieldy. Furthermore, the purpose of employing PCA in the first place is to obtain a low-dimensional representation that can succinctly describe the training set, and using N^2 eigenvectors for that will defeat the purpose. In fact, if the number of data points in the image space for which we wish to find a compact representation is less than the dimension of the image space (i.e. M << N2), only M-1 eigenvectors will be meaningful.

To circumnavigate the problem, Turk and Pentland proposed the following solution.

Consider the eigenvectors v_i of $A^T A$ such that

$$A^T A v_i = u_i v_i \qquad \text{(4-13)}$$

The scalars u_i are the corresponding eigenvalues of v_i. Multiplying $\frac{1}{M} A$ from the left for both sides of the equation yields;

$$\frac{1}{M} AA^T Av_i = \frac{1}{M} u_i Av_i$$

$$CAv_i = \frac{1}{M} u_i Av_i \qquad \text{(4-14)}$$

which implies that Av_i are the eigenvectors of the covariance matrix. With this treatment, we have effectively reduced the dimension of the matrix on which we have to work on from N^2 by N^2 to M by M (M<<N2).

Following this method, we should first construct the matrix L = $A^T A$ of M by M dimensions and find the M eigenvectors, v_i, of L. The first M eigenvectors of the covariance matrix can be obtained by finding Av_i, and the corresponding eigenvalues allow us to rank the eigenvectors according to their significance. As described in detail previously, these eigenvectors are termed eigenfaces for our purpose, and the top thirteen eigenfaces for our training set are displayed in Figure 4-4. Extracting the eigenfaces leads to the question of how many of these eigenfaces should be used? We obviously want to capture as much variations as possible of the training set with as fewer numbers of eigenfaces (M’) as possible. For the small sized training set of individuals used in this research, it was found that less than 9 Eigenfaces were enough to account for more than 93% of the variations among the training set, i.e.

$$\frac{\sum_{i=1}^{M'} u_i}{\sum_{j=1}^{M} u_j} > 0.93$$

$$where \;\; M' < M << N^2 \quad \text{.......... (4-15)}$$

For our particular training set, it was found that the first 9 Eigenfaces were sufficient. It was reported in [6] that for an ensemble of 115 images, 40 Eigenfaces were sufficient for a "very good description" of the training set.

Each element of the training set {T_1, T_2, T_3...T_M} is projected onto "face space" by the following operation

$$\omega_k = (Av_k)^T (T_i - \psi)$$
$$1 \le k \le M', 1 \le i \le M \quad \text{.......... (4-16)}$$

Therefore, for each face image in the training set, we would have a set of M' weights. $\Omega_i = \{\omega_1 \; \omega_2 \; ... \omega_{M'}\}, 1 \le i \le M$, which describes the contribution of each Eigenface to the face image, treating the eigenfaces as a basis set for face images. The feature vector is then used in a standard pattern recognition algorithm to find which of the predefined face classes, if any, best describes the face. The face classes Ω_i can be calculated by averaging the results of the eigenface representation over a small number of face images (as few as one) of each individual. In the proposed face recognition system, face classes contain only one representation of each individual in the training set but up to 5 classes in the face library.

4.2.2 Rebuilding a Face Image with Eigenfaces

A face image can be approximately reconstructed (rebuilt) by using its feature vector and the eigenfaces as:

$$T' = \Psi + \Phi_k \quad \text{.......... (4-16)}$$

$$\Phi_k = \sum_{i=1}^{M'} \omega_i u_i \quad \text{.......... (4-17)}$$

Where ϕ_k is the projected image; moreover Equation (4-17) tells that the face image under consideration is rebuilt just by dot product of each eigenface u_i with its contribution w_i; and adding to the average of the training set images (Equation (4-16)). The degree of the fit or the "rebuild error ratio" can be expressed by means of the Euclidean distance between the original and the reconstructed face image as given in Equation (4-18).

$$\text{Rebuild Error Ratio} = \frac{\|T' - T\|}{\|T\|} \qquad \text{(4-18)}$$

4.2.3 Classifying a Face Image

With each training image represented by the set of weights, standard pattern classification methods can be used to classify input images into known identity classes. For this case, the Euclidean distance was used as the measure for classification. Before the value can be calculated, the test image, T_p, has to be projected onto the face space as well, using equation (4-17), yielding the set Ω_p. The test image is assigned to the class k which minimizes

$$\varepsilon_{C,k}^2 = \left\|\Omega_p - \Omega_k\right\|^2 \quad where\ 1 \le k \le M \qquad \text{(4-19)}$$

Since recognition is performed by projection first, any image similar-sized (or will be resized automatically) can be fed into the system. Images of individuals not previously seen in the training set, as well as non-face images, can be projected onto face space, yielding the set of weights Ω_p. Hence, a competent face recognition must be able differentiate between a face image and non-face image, and if a face image is received, whether it corresponds to one or none of the individuals in the training set. For this purpose, the distance between the input image and face space, is proposed by Turk and Pentland [38] to countercheck whether an input image is indeed a face image.

$$\varepsilon_F^2 = \left\|\phi_p - \phi_I\right\|^2 \quad with \quad \phi_p = \Gamma_i - \psi \ \ and \ \ \phi_i = \sum_{i=1}^{m'} \omega_i (Av_i) \qquad \text{(4-20)}$$

The value of ϕ_i is simply the reconstructed image (less the mean vector) of the projection of the input image onto the face space spanned by the eigenvectors.

For the evaluations whether the distances ε_C^2 and ε_F^2 are sufficiently close, two arbitrarily chosen thresholds, θ_C and θ_F , were used to define the maximum allowable distance to any face class, and the maximum allowable distance to face space.
With the treatment presented, for every input image to a trained system, we would have four possible scenarios:

1. $\varepsilon_F^2 < \theta_F$ *and* $\min[\varepsilon_{C,k}^2 : 1 \le k \le M] < \theta_C$
2. $\varepsilon_F^2 < \theta_F$ *and* $\min[\varepsilon_{C,k}^2 : 1 \le k \le M] > \theta_C$
3. $\varepsilon_F^2 > \theta_F$ *and* $\min[\varepsilon_{C,k}^2 : 1 \le k \le M] < \theta_C$
4. $\varepsilon_F^2 > \theta_F$ *and* $\min[\varepsilon_{C,k}^2 : 1 \le k \le M] > \theta_C$

For the first two cases, the input image is found to be a face image. For scenario (1), the input image should be assigned the class k for which is $\varepsilon_{C,K}^2$ the minimum, whereas for case (2), it should be concluded that the input image is a face which is unknown. For the last 2 cases, the results indicate that the input image is not a face image at all. Scenario (3) is a false recognition which might have been undetected if not for the ε_F^2 measure.

Chapter 5 Experimental Results

In this section, experimental results that were obtained from the proposed face recognition system are discussed.

5.1 Database of Face Images

In order to test the viability of the proposed system, a sample set of face images were created under relatively similar illumination and controlled variation of head orientations. Some of These images were manually decorated resized and cropped to fit some standard. In some of the images facial details such as masks and mustache were added.

All the images in the database, which are collected by the researcher, were in format of 256x256x24 JPEG. They contain different appearances of 14 individuals' digitized under three head orientations. And after adding some facial features a face Category of 6 members were created. For convenience these images were classified with the name individuals followed by a suffix indicating the category of property of the current appearance of that individual. The face classes are included for each subject is depicted in Table 5-1.

a. "Category_A" contains original appearances. There are 14 face classes in this category.
b. "Category_B" contains faces with 'smile' facial expression of individuals in category_A.
c. "Category_C" contains faces 7 in category_A and 7 in category_B, with head orientations were rotated 450 to the left. There are 14 face images in this category.
d. "Category_D"-Back ground removal. In order to test the effect of face images background on recognition performance, the background of the face images in category_A were replaced with a constant color. There are 14 individuals in this category.
e. "Category_E" –Illumination change. Faces in Category_A were darkened by 10% in order to test the effect of illumination level. There are 14 images in this category.
f. "Category_F" contains FACE and NonFace images. The face images were all taken from Category_E.

Additionally 6 face images in category_A were manually decorated with facial details, like masks eyeglasses and mustache.

Table 5-1: Different Face Classes used during experiments

Classes	Different Apperances
Alex'	_A, _B, _C, _D
Amberber'	_A, _B, _C, _D
Belete'	_A, _B, _C, _D+G (with Mask)
Dereje'	_A, _B, _C, _D+G (with moustache)
Ermiyas'	_A, _B, _C, _D
Gashaw'	_A, _B, _C, _D+G (with Light glass)
John'	_A, _B, _C, _D+G (with dark glasses)
Kefyalew'	_A, _B, _C, _D+G (with dark glasses)
Kelemu'	_A, _B, _C, _D
Makida'	_A, _B, _C, _D+G (with dark glasses)
Meklit'	_A, _B, _C, _D
Meron'	_A, _B, _C, _D
Solomon'	_A, _B, _C, _D
Yadeta'	_A, _B, _C, _D

5.2 Rebuild Error Ratio (RER)

Rebuilding an input image will help us to measure the difference between an input, before being projected to the face space, and its representation in the face space; i.e. RER indicate how well an input image is represented in the face space generated by the eigenfaces used. A training image of 14 individuals from category_A was chosen and each was rebuilt using 5, 7, 9, 11 and 13 eigenfaces. The rebuild error ratios are collected using Equation (4-18). The results are given in Table 5-2.

Table 5-2: Eigenface count and rebuild error ratio relation.

		Rebuild error ratio (%) for different number of eigenfaces.				
NO	Members rebuilt	5	7	9	11	13
1	Dereje_A	30.57	30.34	30.24	30.28	29.95
2	Kelemu_A	39.92	39.42	39.98	39.92	39.82
3	Makida_A	58.91	61.02	61.52	60.66	60.83
4	John_A	36.75	37.88	38.53	38.14	38.16
5	Yadeta_A	70.65	70.39	70.46	70.82	70.94
6	Kefyalew_A	37.56	35.59	35.1	34.95	34.96
7	Ermiyas_A	71.12	70.26	72.12	72.02	71.56
8	Meron_A	56.7	56.56	56.63	56.57	56.59
9	Slomon_A	83.15	84.31	83.78	83.73	84.05
10	Belete_A	37.12	35.73	36.25	36.01	36.04
11	Meklit_A	65.69	66.82	65.66	65.85	65.8
12	Alex_A	45.73	45.02	45.01	43.67	43.52
13	Gashaw_A	41.23	39.02	37.69	37.36	37.29
14	Amberber_A	43.69	43.58	43.07	42.89	42.55
Average error ratio		51.34	51.14	51.15	50.92	50.86

From this experiment it is observed that, generally the Rebuild Error Ratio (RER) decreases as the number of eigenfaces increase. This implies that an image is better represented in the face space if more number of eigenfaces is used. It is also seen that the major variations is gathered by the eigenfaces in the order given in the Table 5-3. The weight of each of the Eigenfaces, which is calculated using Equation (4-16), to describe a face class is also explored (See Table 5-4).

Table 5-3: Contribution of the first (1-n) n-eigenfaces; It shows the first 11 eigenfaces hold more than 95% of the variations in the training face classes.

	EigenFaces													
	1-2	1-3	1-4	1-5	1-6	1-7	1-8	1-9	1-10	1-11	1-12	1-13	1-14	1-15
Contributions of EigenFaces(%)	41.53	61.79	70.96	77.17	81.79	85.7	88.82	91.39	93.73	95.95	97.81	98.97	100	100

Table 5-4: weight of each eigenfaces to hold variations in each face class

	Dereje_A'	Kelemu_A'	Makida_A'	John_A'	Yadeta_A'	Kefyalew_A'	Ermiyas_A'	Meron_A'	Solomon_A'	Belete_A'	Meklit_A'	Alex_A'	Gashaw_A'	Amberber_A'
eigenface 1	-9.16E-08	2.94E-08	-3.46E-09	3.57E-09	-1.76E-08	5.57E-08	-6.94E-09	3.67E-08	3.37E-09	-2.33E-08	5.14E-10	-1.30E-09	2.78E-08	-1.29E-08
eigenface 2	-3.08E+05	-2.56E+04	2.72E+05	-6.90E+05	1.17E+06	4.21E+05	8.64E+05	-3.16E+04	-1.89E+06	-3.69E+05	-9.52E+04	9.96E+04	-2.30E+05	8.10E+05
eigenface 3	5.04E+05	4.39E+05	-4.36E+05	4.07E+04	1.96E+06	-5.90E+05	-1.35E+06	1.61E+05	3.02E+05	-1.29E+05	-3.70E+05	-1.45E+06	6.55E+05	2.59E+05
eigenface 4	9.97E+05	-2.97E+05	-1.59E+06	-1.88E+06	8.87E+05	-1.43E+06	-5.79E+05	4.47E+04	-3.68E+05	2.09E+06	-5.19E+05	2.95E+06	4.95E+05	-8.04E+05
eigenface 5	2.15E+06	-2.58E+06	-3.08E+06	4.19E+05	-3.45E+05	8.50E+05	2.57E+06	-1.11E+05	-2.07E+05	1.48E+04	4.45E+05	-1.68E+06	1.81E+06	-2.58E+05
eigenface 6	-5.63E+05	-3.87E+06	1.97E+06	-9.61E+05	-3.02E+05	1.48E+06	-2.56E+06	1.76E+05	1.55E+05	-5.50E+05	1.00E+05	9.03E+05	2.66E+06	1.36E+06
eigenface 7	-2.90E+05	-2.38E+06	1.61E+06	4.38E+06	9.73E+05	-1.56E+06	4.12E+05	5.13E+05	-1.57E+06	2.17E+06	-2.59E+06	1.13E+05	-5.85E+05	-1.18E+06
eigenface 8	-2.62E+06	3.10E+05	-1.46E+06	-1.36E+06	-1.64E+06	1.00E+06	3.07E+05	9.63E+05	1.00E+06	4.67E+06	-2.78E+06	-2.16E+06	-4.24E+05	4.19E+06
eigenface 9	1.11E+06	-2.06E+06	-2.88E+06	1.67E+06	2.25E+06	5.63E+06	-3.18E+06	-3.34E+05	6.96E+05	7.50E+05	1.33E+06	1.25E+06	-6.34E+06	1.07E+05
eigenface 10	2.80E+06	-1.99E+06	5.76E+05	1.12E+06	-1.78E+06	-6.17E+06	-1.41E+06	-1.71E+06	-1.67E+06	1.61E+06	6.52E+06	-9.48E+05	-2.85E+06	5.89E+06
eigenface 11	-1.09E+07	7.93E+05	-4.98E+06	3.86E+06	1.96E+06	1.89E+05	-1.28E+06	-5.46E+05	-2.35E+06	2.78E+06	8.24E+06	4.66E+05	4.51E+06	-2.77E+06
eigenface 12	-3.15E+06	4.01E+05	-9.68E+06	7.24E+06	-1.01E+06	-4.52E+06	-4.99E+05	7.71E+06	1.78E+06	-1.21E+07	-5.54E+06	8.83E+06	6.05E+05	9.95E+06
eigenface 13	-6.91E+06	-2.29E+06	-2.26E+05	5.19E+06	1.21E+07	-1.64E+06	1.03E+07	-4.47E+07	1.74E+07	-2.90E+06	-8.21E+06	8.71E+06	2.77E+06	1.05E+07
eigenface 14	3.07E+07	4.12E+07	-1.21E+07	2.97E+07	-3.61E+07	2.75E+07	-3.70E+07	-3.42E+07	-5.04E+07	8.11E+06	-1.55E+07	6.59E+06	3.09E+07	1.07E+07

From the results given in Table 5-4, it is observed that some of the Eigenfaces represent a significant weight for some of the images (for example eigenface 11 has a higher weight than eigenface 6 to describe Dereje_A but eigenface 6 has a higher weight than eigenface 11 to describe Kelemu_A). Table 5-5 also shows the order in which these eigenfaces contribute to describe a face class. The weight of each eigenfaces in describing a face class is given in Table 5-4.

Table 5-5: Eigenfaces In their decreasing contribution to describe the corresponding faces classes

	Dereje_A'	Kelemu_A'	Makida_A'	John_A'	Yadeta_A'	Kefyalew_A'	Ermiyas_A'	Meron_A'	Solomon_A'	Belete_A'	Meklit_A'	Alex_A'	Gashaw_A'	Amberber_A'
Eigen Faces In their decreasing contribution to describe the corresponding faces classes	eigenface 14	eigenface 14	eigenface 14	eigenface 14	eigenface 14	eigenface 14	eigenface 14	eigenface 13	eigenface 14	eigenface 12	eigenface 14	eigenface 12	eigenface 14	eigenface 14
	eigenface 11	eigenface 6	eigenface 12	eigenface 12	eigenface 13	eigenface 10	eigenface 13	eigenface 14	eigenface 13	eigenface 14	eigenface 11	eigenface 13	eigenface 9	eigenface 13
	eigenface 13	eigenface 5	eigenface 11	eigenface 13	eigenface 9	eigenface 9	eigenface 9	eigenface 12	eigenface 11	eigenface 8	eigenface 13	eigenface 14	eigenface 11	eigenface 12
	eigenface 12	eigenface 7	eigenface 5	eigenface 7	eigenface 3	eigenface 12	eigenface 5	eigenface 10	eigenface 2	eigenface 13	eigenface 10	eigenface 4	eigenface 10	eigenface 10
	eigenface 10	eigenface 13	eigenface 9	eigenface 11	eigenface 11	eigenface 13	eigenface 6	eigenface 8	eigenface 12	eigenface 11	eigenface 12	eigenface 8	eigenface 13	eigenface 8
	eigenface 8	eigenface 9	eigenface 6	eigenface 4	eigenface 10	eigenface 7	eigenface 10	eigenface 11	eigenface 10	eigenface 7	eigenface 8	eigenface 5	eigenface 6	eigenface 11
	eigenface 5	eigenface 10	eigenface 7	eigenface 9	eigenface 8	eigenface 6	eigenface 3	eigenface 7	eigenface 7	eigenface 4	eigenface 7	eigenface 3	eigenface 5	eigenface 6
	eigenface 9	eigenface 11	eigenface 4	eigenface 8	eigenface 2	eigenface 4	eigenface 11	eigenface 9	eigenface 8	eigenface 10	eigenface 9	eigenface 9	eigenface 3	eigenface 7
	eigenface 4	eigenface 3	eigenface 8	eigenface 10	eigenface 12	eigenface 8	eigenface 2	eigenface 6	eigenface 9	eigenface 9	eigenface 4	eigenface 10	eigenface 12	eigenface 2
	eigenface 6	eigenface 12	eigenface 10	eigenface 6	eigenface 7	eigenface 5	eigenface 4	eigenface 3	eigenface 4	eigenface 6	eigenface 5	eigenface 6	eigenface 7	eigenface 4
	eigenface 3	eigenface 8	eigenface 3	eigenface 2	eigenface 4	eigenface 3	eigenface 12	eigenface 5	eigenface 3	eigenface 2	eigenface 3	eigenface 11	eigenface 4	eigenface 3
	eigenface 2	eigenface 4	eigenface 2	eigenface 5	eigenface 5	eigenface 2	eigenface 7	eigenface 4	eigenface 5	eigenface 3	eigenface 6	eigenface 7	eigenface 8	eigenface 5
	eigenface 7	eigenface 2	eigenface 13	eigenface 3	eigenface 6	eigenface 11	eigenface 8	eigenface 2	eigenface 6	eigenface 5	eigenface 2	eigenface 2	eigenface 2	eigenface 9
	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1	eigenface 1

5.3 Face Background and Rebuild Error Ratio (RER)

Face background plays an important role in holistic eigenface approach as the entire information in the face image is considered during the process of digitization and consequent processing in the Matlab development environment. The aim of this experiment is to assess the impact of background information on the rebuilding performance. Without this background, the recognition performance is expected to increase because now, the system only deals with facial information. 14 images in category_D were chosen to form the training set and a face library with members of Category_A and Category_B was formed. (Note that category_D is formed after the background of each images in category_A was removed). Category_D images are chosen as a training set because the eigenfaces extracted represent only features of a face not the unwanted background. Here again the performance to rebuild these probe images is tested for varying number of eigenfaces. The result is given in Table 5-6. When removing the background of an image an appropriate mask was used for each image. During the processes of removing the background, sometimes it was difficult to set a threshold pixel value to differentiate the background and some parts of the face images. This is mainly because, in some cases, the two have same RGB (Read, Green and Blue) values. To deal with this problem an attempt was made with the aim of keeping the values on the face as it was and yet removing the background. This was done by using different Read, Green and Blue threshold values or a combination of two or three distinct values for each face class. The contribution of each Eigenfaces in describing a face class is also given in Table 5-6.

Table 5-6: Rebuilt Error Ratio after back ground removal of Training Images

		Rebuild error ratio (%) for different number of eigenfaces.				
NO	Members rebuilt	5	7	9	11	13
1	'Alex_D.JPG'	58.44	57.65	54.69	55.51	55.15
2	'Amberber_D.JPG'	60.75	53.32	56.24	55.75	56.03
3	'Belete_D.JPG'	48.83	48.37	48.05	48.19	48.09
4	'Dereje_D.JPG'	50.92	50.83	50.94	50.38	50.22
5	'Ermiyas_D.JPG'	50.99	48.13	48.13	48.03	47.70
6	'Gashaw_D.JPG'	55.30	56.15	54.18	53.52	52.29
7	'John_D.JPG'	57.14	57.02	57.32	56.42	55.34
8	'Kefyalew_D.JPG'	51.96	51.99	51.90	52.28	52.11
9	'Kelemu_D.JPG'	56.07	55.31	56.16	55.27	56.07
10	'Makida_D.JPG'	48.40	48.37	48.09	47.81	47.80
11	'Meklit_D.JPG'	54.66	51.93	51.73	51.60	51.55
12	'Mihiret_D.JPG'	50.18	49.95	49.97	49.96	49.97
13	'Solomon_D.JPG'	52.01	52.16	52.28	52.25	51.70
14	'Yadeta_D.JPG'	51.12	50.61	50.80	50.33	50.14
Average error ratio		53.34	52.27	52.18	51.95	51.72

Table 5-7: Contribution of the first (1-n) n eigenfaces to training set

	EigenFaces													
	1-2	1-3	1-4	1-5	1-6	1-7	1-8	1-9	1-10	1-11	1-12	1-13	1-14	1-15
Contributions of eigenfaces (%)	28.36	46.56	60.15	66.98	73.39	79.2	83.95	87.9	90.8	93.45	95.99	98.1	100	100

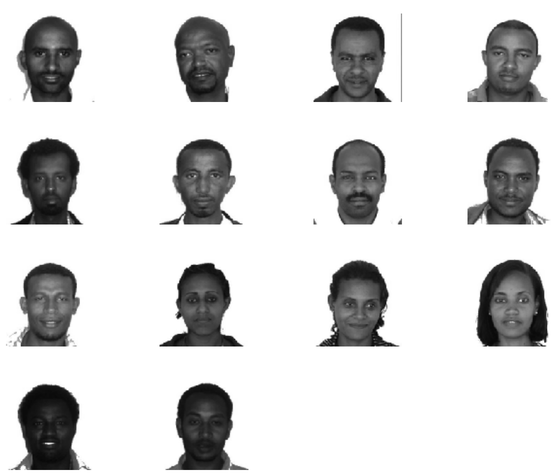

Figure 5-1: Training image after the background removal

Figure 5-2: Reconstructed images after the background is removed

The reconstructed images (see Figure 5-2) are of poor quality. This is mainly because of the information loss during the processing steps and the original images were taken with 2megapixle resolution digital camera, which results in too much information but unfortunately cannot be kept unchanged. The result shows that the RBE is high for there is a considerable information difference between training faces and the rebuilt ones. But generally the RER decreases as the number of eigenfaces used increases. Moreover Table 5-7, shows that the top 11 eigenfaces holds more than 93% of the variation between training faces.

5.4 Training Sets and Rebuild Relation

Eigenfaces are obtained from a training set and they span M'-dimensional (14-in this case) face space. These eigenfaces are later used to represent the face space as a linear combination of the eigenfaces. As a result, rebuilding face images, approximately maps a probe to a training set member.

In this experiment a training set of 10-faces from category_A, depicted in Figure 5-3, were chosen and 4-members of category_A, which were not in the training set, were rebuilt. This is done with ratio of 71% and 29% for training and testing respectively. The result, as shown in Figure 5-4, shows that these 4-members were mapped to one of the 10-members in the training set.

Figure 5-3: Training faces

Figure 5-4: Images rebuilt using eigenfaces obtained from the training set in Figure 5-3

5.5 Recognition Performance and Threshold Values

In this section, the trade-off between threshold values and correct recognition performance rate, for different number of eigenfaces, was tested. The result is used to determine the critical threshold values for a better performance. In order to achieve this, a face library that contains all members of category _A, _B, _C and _D with six more face images that contain more facial details like masks, mustache and eyeglasses (see Figure 5-6) were constructed. But rather than searching the whole library, Category_F members were searched for, 5, 7, 9, 11 and 13 eigenfaces, of the training set members only. All members of category_A were in the training set. The different threshold values, which are obtained using Equation (4-19) and (4-20), are used to classify probe images as 'known' or 'unknown' depending on the Euclidean distance of the probe image and the face space spanned by members of the training set. The detail mathematical procedures are given in the previous section. As discussed in the previous chapter the system calculate two kinds of Euclidean distances. The first being the distance between the caricatures of probe image and face space (ε_F^2) (i.e reconstruction of input and the library), which is used to classify the input as face or non-face; and the second one being the distance between the projected images of the face library members and the probe image ($\varepsilon_{C,F}^{2}$), which helps to classify the input to a face class k.

5.5.1 Threshold Values to Classify an Input to a Face Class

In this experiment the threshold values to classify an input to a face class is explored. Here, members of category_A and Category_B were searched in the face library where the training set is still Category_A. The result is given in Table 5-8 and Table 5-9.

Table 5-8: Distance of probe images in Category_A (13-Eigenfaces used)

Input Face Classes	Dereje_A.JPG	Kelemu_A.JPG	Makida_A.JPG	John_A.JPG	Yadeta_A.JPG	Kefyalew_A.JPG	Ermiyas_A.JPG	Meron_A.JPG	Solomon_A.JPG	Belete_A.JPG	Meklit_A.JPG	Alex_A.JPG	Gashaw_A.JPG	Amberber_A.JPG
Distance of Input from the Training Face Classes(Decreasing Order)	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	1.34E+07	1.68E+07	2.37E+07	8.67E+06	1.19E+07	4.51E+07	8.67E+06	1.19E+07	1.34E+07	1.89E+07	1.89E+07	1.90E+07	1.55E+07	1.52E+07
	1.79E+07	1.70E+07	2.39E+07	1.68E+07	2.32E+07	5.32E+07	1.70E+07	2.49E+07	1.52E+07	2.37E+07	2.77E+07	4.49E+07	1.71E+07	1.83E+07
	1.83E+07	4.44E+07	2.54E+07	2.98E+07	2.73E+07	5.60E+07	3.02E+07	2.54E+07	1.55E+07	2.91E+07	3.15E+07	2.26E+07	1.79E+07	1.83E+07
	2.26E+07	4.61E+07	2.73E+07	3.22E+07	2.75E+07	5.77E+07	3.15E+07	2.83E+07	2.11E+07	2.98E+07	3.22E+07	7.09E+07	1.83E+07	1.90E+07
	2.32E+07	5.84E+07	2.77E+07	4.54E+07	2.89E+07	6.31E+07	4.43E+07	2.84E+07	2.75E+07	3.02E+07	3.35E+07	1.71E+07	2.39E+07	3.63E+07
	2.49E+07	6.26E+07	2.89E+07	4.92E+07	3.18E+07	6.46E+07	4.87E+07	2.91E+07	2.83E+07	3.33E+07	3.81E+07	7.09E+07	2.84E+07	3.66E+07
	3.11E+07	6.41E+07	2.93E+07	4.99E+07	3.33E+07	6.74E+07	4.95E+07	3.35E+07	2.89E+07	4.21E+07	4.51E+07	7.69E+07	2.89E+07	3.81E+07
	4.68E+07	6.46E+07	3.11E+07	5.60E+07	3.63E+07	7.17E+07	5.77E+07	3.37E+07	4.59E+07	4.44E+07	4.61E+07	8.55E+07	4.21E+07	5.52E+07
	4.99E+07	8.08E+07	3.66E+07	6.66E+07	3.81E+07	7.66E+07	6.56E+07	3.81E+07	4.99E+07	4.49E+07	4.64E+07	2.93E+07	4.64E+07	5.88E+07
	6.70E+07	8.18E+07	4.87E+07	6.80E+07	4.95E+07	7.69E+07	6.70E+07	4.43E+07	6.84E+07	4.59E+07	4.99E+07	5.03E+07	6.56E+07	7.90E+07
	6.80E+07	8.33E+07	4.92E+07	6.88E+07	4.99E+07	8.13E+07	6.84E+07	4.54E+07	6.88E+07	4.68E+07	4.99E+07	3.37E+07	6.66E+07	7.95E+07
	8.15E+07	8.55E+07	6.31E+07	7.09E+07	6.26E+07	8.15E+07	7.09E+07	5.84E+07	8.13E+07	5.32E+07	5.03E+07	2.11E+07	7.66E+07	8.70E+07
	8.18E+07	9.39E+07	6.41E+07	7.95E+07	7.17E+07	8.70E+07	7.90E+07	6.74E+07	8.33E+07	5.52E+07	5.88E+07	3.18E+07	8.08E+07	9.39E+07
Average	3.90E+07	5.71E+07	3.42E+07	4.58E+07	3.51E+07	6.30E+07	4.56E+07	3.35E+07	3.91E+07	3.55E+07	3.77E+07	4.10E+07	3.77E+07	4.54E+07
Maximum distance	8.18E+07	9.39E+07	6.41E+07	7.95E+07	7.17E+07	8.70E+07	7.90E+07	6.74E+07	8.33E+07	5.52E+07	5.88E+07	8.55E+07	8.08E+07	9.39E+07
minimum distance	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
standard deviation	2.67E+07	2.90E+07	1.71E+07	2.50E+07	1.88E+07	2.18E+07	2.48E+07	1.72E+07	2.72E+07	1.50E+07	1.54E+07	2.62E+07	2.56E+07	3.04E+07
Recognition	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct	Correct

Every probe image in category_A is correctly recognized as the closest distance of an input face is found to be zero for all faces and a 100% recognition rate was attained. But this is not a surprise for the probe images are all in the training set and in fact it was helpful to pick the values we needed. As a result, a second test was required to see recognition performance for category_B members and consequently enable us to collect the possible threshold values (see Table 5-9). Remember that category_B contains face images of individuals in the training set but with a different facial expression of individuals in category_A.

Table 5-9: Distance between probe images in Category_B and training images (13-Eigenfaces used)

Input Face Classes	Alex_B.JPG'	'Amberber_B.JPG'	'Belete_B.JPG'	'Dereje_B.JPG'	'Ermiyas_B.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Kefyalew_B.JPG'	'Kelemu_B.JPG'	'Makida_B.JPG'	'Meklit_B.JPG'	'Meron_B.JPG'	'Solomon_B.JPG'	'Yadeta_B.JPG'
Distance of Input from the Training Face Classes(Decreasing Order)	1.73E+07	9.38E+06	1.35E+07	7.47E+06	4.65E+06	1.61E+07	7.32E+06	6.88E+06	3.38E+07	1.56E+07	2.18E+07	1.96E+07	4.92E+06	3.99E+06
	2.05E+07	1.27E+07	1.68E+07	1.39E+07	8.63E+06	1.87E+07	1.22E+07	1.40E+07	4.54E+07	2.23E+07	2.40E+07	4.92E+07	1.27E+07	8.24E+06
	2.67E+07	1.47E+07	2.35E+07	1.72E+07	1.94E+07	2.15E+07	1.32E+07	1.53E+07	4.61E+07	2.27E+07	2.51E+07	5.16E+07	1.32E+07	1.83E+07
	2.69E+07	1.50E+07	2.53E+07	1.99E+07	2.75E+07	2.19E+07	1.90E+07	1.58E+07	4.71E+07	2.36E+07	2.60E+07	5.40E+07	4.02E+07	2.89E+07
	3.06E+07	1.66E+07	2.63E+07	2.21E+07	3.64E+07	2.27E+07	1.97E+07	1.84E+07	4.85E+07	3.32E+07	2.75E+07	5.61E+07	4.93E+07	3.73E+07
	4.23E+07	2.37E+07	2.68E+07	3.26E+07	4.40E+07	3.36E+07	2.04E+07	2.49E+07	6.72E+07	3.67E+07	2.96E+07	5.61E+07	5.38E+07	4.14E+07
	4.75E+07	2.57E+07	2.72E+07	3.57E+07	4.67E+07	3.40E+07	2.07E+07	3.07E+07	6.75E+07	3.78E+07	3.40E+07	7.10E+07	5.80E+07	4.63E+07
	4.95E+07	3.09E+07	3.17E+07	3.78E+07	4.86E+07	3.44E+07	2.55E+07	3.07E+07	7.03E+07	4.22E+07	3.73E+07	7.28E+07	5.97E+07	4.71E+07
	5.54E+07	4.22E+07	3.21E+07	4.48E+07	5.30E+07	3.52E+07	3.65E+07	3.70E+07	8.02E+07	4.31E+07	3.87E+07	7.71E+07	6.21E+07	5.62E+07
	6.13E+07	4.59E+07	3.82E+07	5.03E+07	6.43E+07	3.52E+07	4.07E+07	4.38E+07	8.74E+07	5.18E+07	4.58E+07	8.67E+07	7.60E+07	6.33E+07
	8.79E+07	6.74E+07	4.84E+07	7.60E+07	6.63E+07	4.06E+07	6.16E+07	6.81E+07	1.12E+08	5.53E+07	6.88E+07	8.75E+07	7.72E+07	6.45E+07
	8.82E+07	6.82E+07	4.84E+07	7.63E+07	6.69E+07	4.60E+07	6.26E+07	6.89E+07	1.12E+08	5.66E+07	7.13E+07	9.05E+07	7.86E+07	6.59E+07
	9.00E+07	8.03E+07	5.39E+07	8.03E+07	6.87E+07	4.91E+07	7.59E+07	7.45E+07	1.14E+08	5.70E+07	7.14E+07	9.10E+07	8.08E+07	6.85E+07
	1.03E+08	8.22E+07	6.35E+07	9.10E+07	7.73E+07	6.30E+07	7.67E+07	8.34E+07	1.27E+08	6.57E+07	8.63E+07	9.81E+07	8.91E+07	7.64E+07
Average	**5.34E+07**	**3.82E+07**	**3.40E+07**	**4.33E+07**	**4.52E+07**	**3.37E+07**	**3.52E+07**	**3.80E+07**	**7.56E+07**	**4.03E+07**	**4.34E+07**	**6.87E+07**	**5.40E+07**	**4.47E+07**
Maximum distance	**1.03E+08**	**8.22E+07**	**6.35E+07**	**9.10E+07**	**7.73E+07**	**6.30E+07**	**7.67E+07**	**8.34E+07**	**1.27E+08**	**6.57E+07**	**8.63E+07**	**9.81E+07**	**8.91E+07**	**7.64E+07**
minimum distance	**1.73E+07**	**9.38E+06**	**1.35E+07**	**7.47E+06**	**4.65E+06**	**1.61E+07**	**7.32E+06**	**6.88E+06**	**3.38E+07**	**1.56E+07**	**2.18E+07**	**1.96E+07**	**4.92E+06**	**3.99E+06**
standard deviation	**2.88E+07**	**2.63E+07**	**1.46E+07**	**2.76E+07**	**2.32E+07**	**1.31E+07**	**2.43E+07**	**2.56E+07**	**3.06E+07**	**1.56E+07**	**2.17E+07**	**2.19E+07**	**2.73E+07**	**2.30E+07**
Recognition	**Incorrect**	**Incorrect**	**Correct**	**Correct**	**Correct**	**Incorrect**	**Correct**	**Correct**	**Correct**	**Correct**	**Incorrect**	**Correct**	**Correct**	**Correct**
Distance From The correct face	**4.95E+07**	**2.37E+07**	**1.35E+07**	**7.47E+06**	**4.65E+06**	**3.44E+07**	**7.32E+06**	**6.88E+06**	**3.38E+07**	**1.56E+07**	**3.40E+07**	**1.96E+07**	**4.92E+06**	**3.99E+06**

Table 5-10: Recognition performance (with 13-eigenfaces)

Recognition Performance (%)	correctly classified	10	**71.43%**
	Wrongly classified	4	

	Maximum	Minimum	Average
Average Distance	7.65E+07	3.40E+07	4.78E+07
Minimum Distance	1.27E+08	6.32E+07	8.51E+07
Maximum Distance	3.38E+07	3.94E+06	1.38E+07

This result shows that, for a slight change in facial expression, 4 of the probe images were wrongly classified. The Euclidean distance of these images from the correct face classes ranges from 2.37+07 to 4.95+07. Then in order to test the performance of recognition for different threshold values, with varying number of eigenfaces, the following values were selected:

Reason for selection	Threshold Values
Minimum of the minimum distances	3.94E+06
Maximum of the minimum distances	3.38E+07
Average of the average distance	4.78E+07
Minimum of the maximum distances	6.32E+07
Maximum of the average distances	7.65E+07
Average of the maximum distance	8.51E+07
Maximum of the maximum distances	1.27E+08

The result shows (see Table 5-11) that the threshold value of 4.78E+07 provides a recognition rate of 92% and 6.32E+07 provides a 100% rate. Therefore 6.32E+07 is considered as an optimal threshold value for our training set. Remember that this experiment was conducted to find an optimal threshold value to classify an input to a face class in the library. (Here Category_A members are used both as training set and face library) .But this threshold does not answer the question whether an input image is face or not; so we need a second threshold value to do this.

Table 5-11: Recognition performance (an input face class is considered as correctly classified if it is found under the specified threshold)

Threshold Values (Using 13,11,9,7and 5 EigenFaces)	Inputs Classified as known		Performance(No of Correctly classified by total input)
	Correctly classified	Wrongly classified	
3.94E+06	0	14	0.00%
3.38E+07	11	3	78.57%
4.78E+07	13	1	92.86%
6.32E+07	14	0	100.00%
7.65E+07	14	0	100.00%
8.51E+07	14	0	100.00%
1.27E+08	14	0	100.00%

5.5.2 Threshold values to classify an input as 'Face' or 'Non-Face'

To conduct this experiment, a Training set and a Face library form all members of Category_A was formed; there are 14 images in this category. Category_F, which was formed from 5 face and 4 Nonface images was used, as test set, to compare the distance between inputs and training set.

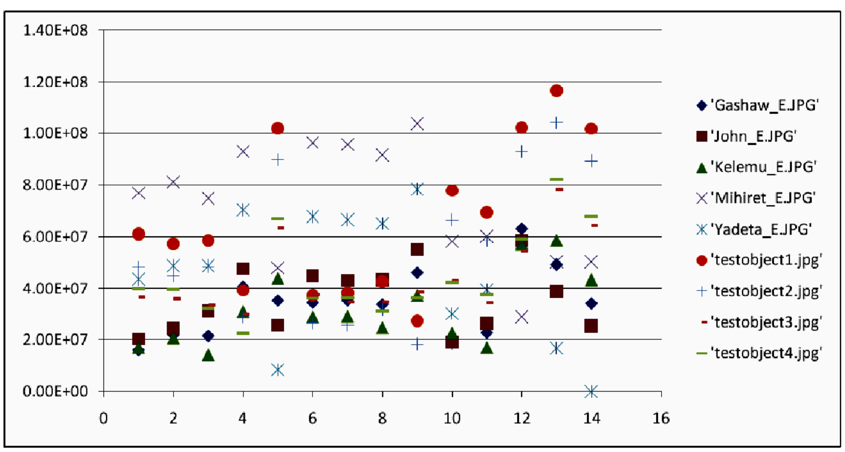

Figure 5-5: The distribution of face and non-face images in category_F against the training set

Figure 5-5 shows that using the previous distance measure which was used to classify an input to a face class, some of the Non-face images are found closer to a face class in the training set than the face images. This approves the need for a second threshold which enable the system to differentiate face and non-face images, which can be calculated using equation (4-20). The threshold values were chosen from Table 5-12 and the discriminating power of each value was tested for varying number of eigenfaces.

Table 5-12: Distance between input images and members of the face library

	'Gashaw_E.JPG'	'John_E.JPG'	'Kelemu_E.JPG'	'Mihiret_E.JPG'	'Yadeta_E.JPG'	'testobject1.jpg'	'testobject2.jpg'	'testobject3.jpg'	'testobject4.jpg'
Distance of inputs(in Category_E) from the Face Library(_A)	1.12E+11	1.07E+11	7.59E+10	2.77E+11	0.00E+00	2.34E+11	1.16E+11	2.01E+11	1.74E+11
	1.30E+11	1.74E+11	1.03E+11	3.69E+11	3.00E+10	3.43E+11	2.22E+11	2.20E+11	1.98E+11
	1.45E+11	1.98E+11	1.20E+11	3.81E+11	1.58E+11	3.45E+11	2.24E+11	2.28E+11	2.10E+11
	1.55E+11	2.39E+11	1.32E+11	4.00E+11	2.72E+11	3.61E+11	2.35E+11	2.52E+11	2.44E+11
	1.58E+11	2.48E+11	1.82E+11	5.39E+11	3.59E+11	3.78E+11	2.57E+11	2.54E+11	2.54E+11
	3.26E+11	2.54E+11	2.42E+11	5.79E+11	4.23E+11	5.63E+11	4.36E+11	2.55E+11	2.76E+11
	3.43E+11	2.57E+11	2.75E+11	7.31E+11	4.43E+11	5.70E+11	4.50E+11	2.68E+11	2.83E+11
	3.46E+11	4.01E+11	2.81E+11	7.35E+11	4.79E+11	6.00E+11	4.73E+11	2.68E+11	2.86E+11
	3.53E+11	4.26E+11	2.81E+11	7.78E+11	4.86E+11	7.06E+11	5.86E+11	3.24E+11	2.90E+11
	3.57E+11	4.40E+11	3.82E+11	9.19E+11	6.67E+11	7.81E+11	6.58E+11	3.41E+11	3.72E+11
	3.72E+11	4.55E+11	4.34E+11	9.42E+11	6.86E+11	1.03E+12	9.11E+11	5.25E+11	5.71E+11
	4.65E+11	4.58E+11	4.42E+11	9.55E+11	6.98E+11	1.04E+12	9.18E+11	5.91E+11	6.34E+11
	5.02E+11	4.67E+11	5.00E+11	9.62E+11	7.07E+11	1.04E+12	9.19E+11	5.94E+11	6.37E+11
	5.11E+11	5.64E+11	5.91E+11	1.06E+12	8.08E+11	1.19E+12	1.07E+12	7.42E+11	7.87E+11
Average	**3.05E+11**	**3.35E+11**	**2.89E+11**	**6.87E+11**	**4.44E+11**	**6.56E+11**	**5.34E+11**	**3.62E+11**	**3.73E+11**
Minimum distance	**1.12E+11**	**1.07E+11**	**7.59E+10**	**2.77E+11**	**0.00E+00**	**2.34E+11**	**1.16E+11**	**2.01E+11**	**1.74E+11**
Maximum distance	**5.11E+11**	**5.64E+11**	**5.91E+11**	**1.06E+12**	**8.08E+11**	**1.19E+12**	**1.07E+12**	**7.42E+11**	**7.87E+11**

Table 5-13: Classification of input images as 'FACE' or 'NON_FACE' for the given threshold values

13-EigenFaces	7.59E+10	1.07E+11	1.12E+11	1.16E+11	1.74E+11	2.01E+11	2.34E+11	2.77E+11	2.89E+11
face 1	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'
face 2	'NON_FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'
face 3	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'
face 4	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'
face 5	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'
NonFace 1	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'
NonFace 2	'NON_FACE'	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'	'FACE'
NonFace 3	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'	'FACE'
NonFace 4	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'NON_FACE'	'FACE'	'FACE'	'FACE'	'FACE'

Table 5-14: Discriminating powers of each threshold Value (using 13-eigenfaces)

Threshold Values		OutPut Classification		Threshold Power		Overall
		Face	NonFace	To Face	To NonFace	Performance
7.59E+10	Face	2	3			
	NonFace	0	4	40.00%	100.00%	66.67%
1.07E+11	Face	3	2			
	NonFace	0	4	60.00%	100.00%	77.78%
1.12E+11	Face	4	1			
	NonFace	0	4	80.00%	100.00%	88.89%
1.16E+11	Face	4	1			
	NonFace	1	3	80.00%	75.00%	77.78%
1.74E+11	Face	4	1			
	NonFace	1	3	80.00%	75.00%	77.78%
2.01E+11	Face	4	1			
	NonFace	2	2	80.00%	50.00%	66.67%
2.34E+11	Face	4	1			
	NonFace	3	1	80.00%	25.00%	55.56%
2.77E+11	Face	5	0			
	NonFace	4	0	100.00%	0.00%	55.56%
2.89E+11	Face	5	0			
	NonFace	4	0	100.00%	0.00%	55.56%

From the results in Table 5-13 and Table 5-14 we can conclude that 1.12E+11 provides an optimal value. The result for all (13, 11, 9, 7 and 5) eigenfaces is found to be similar. Therefore the threshold values 1.12E+11, 1.16E+11 and 1.74E+11, are chosen to classify an input as face or non-face.

Note that all threshold values are selected without the consideration of level or change illumination of the probe image(s). Experimental results that consider of this factor are given in the upcoming section.

5.6 Recognition Performance and Head Orientations

In this experiment the recognition rate of the system is tested to see the impact of change in head orientation. Members of category_A were used to form the training set and a face library of 42 face classes from category _A, _B, _D was formed. Finally the performance of the system was tested using category_C members as probe and using 5, 7, 9, 11 and 13-EigenFaces. The result shows (see Table 5-15) that the recognition rate is very low despite the change in number of eigenfaces.

Table 5-15: Recognition Performance of the system when head orientation is changed

	Recognition Performance for different eigenfaces					Average
	13-EigenFaces	11-EigenFaces	9-EigenFaces	7-EigenFaces	5-EigenFaces	Performance
Top 1	7.14%	7.14%	7.14%	7.14%	7.14%	7.14%
Top 2	14.29%	14.29%	7.14%	7.14%	14.29%	11.43%
Top 3	14.29%	14.29%	7.14%	7.14%	14.29%	11.43%
Top 4	21.43%	21.43%	14.29%	14.29%	21.43%	18.57%
Top 5	21.43%	28.57%	21.43%	21.43%	28.57%	24.29%

5.7 Recognition Performance and Illumination Change

In this experiment, the effect of illumination level on recognition performance was tested. A training set from all members of category_A (using 5, 7, 9, 11 and13-EigenFaces) and a library of 42 face classes (_A, _B, _D) was chosen. Later, a library search for all members of Category _E was performed. As you recall, members of Category_E, were obtained synthetically from the members of Category_A, by subtracting 10% of the original pixel values.

The result shows (see Table 5-16: Inputs (all members of Category_E) tested for Face, Non-Face threshold) that 6 and 5 of the original images were not even considered as a face after the illumination is decreased by 10%. But for threshold value of 1.74E+11 all were considered as FACE. The result shows that the recognition rate was improved as the threshold values increases. Threshold values 4.78E+07 and 6.32E+07 provide good results and as the value increases, the result is similar. For higher threshold values a given face class looks to be closer to the face space. Now the threshold value 1.74E+11 is used to classify an input as “FACE” or

"NON_FACE". Results are depicted in Table 5-16: Inputs (all members of Category_E) tested for Face, Non-Face threshold

Table 5-16: Inputs (all members of Category_E) tested for Face, Non-Face threshold

	Threshold Values		
	1.12E+11	1.16E+11	1.74E+11
'darkened_Alex_A.JPG'	'NON_FACE'	'NON_FACE'	'FACE'
'darkened_Amberber_A.JPG'	'NON_FACE'	'NON_FACE'	'FACE'
'darkened_Belete_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Dereje_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Ermiyas_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Gashaw_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_John_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Kefyalew_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Kelemu_A.JPG'	'FACE'	'FACE'	'FACE'
'darkened_Makida_A.JPG'	'NON_FACE'	'NON_FACE'	'FACE'
'darkened_Meklit_A.JPG'	'NON_FACE'	'NON_FACE'	'FACE'
'darkened_Meron_A.JPG'	'NON_FACE'	'NON_FACE'	'FACE'
'darkened_Solomon_A.JPG'	'NON_FACE'	'FACE'	'FACE'
'darkened_Yadeta_A.JPG'	'FACE'	'FACE'	'FACE'
Performance	57.14%	64.29%	100.00%

Table 5-17: The performance of the system for illumination change (using 9-eigenfaces)

	Recognition Performance(9-EigenFaces)		
	Correctly classified	Misclassified	Recognition rate
Top 1	3	11	21.43%
Top 2	5	9	35.71%
Top 3	12	2	85.71%
Top 4	13	1	92.86%
Top 5	13	1	92.86%

Table 5-17 shows the performance of the system is 92.86% when the 4 of the closest face classes from the face library are retrieved. The result is the same for every threshold values other than 3.38+09, when this threshold is used every input were classified as 'Unknown'. As the threshold value increases the performance is very much improved though one person still is misclassified.

Table 5-18: The top five face classes in decreasing order of closeness to the input Face class in the first row (using 13-EigenFaces)

	'darkened_Alex_A.JPG'	'darkened_Amberber_A.JPG'	'darkened_Belete_A.JPG'	'darkened_Dereje_A.JPG'	'darkened_Ermiyas_A.JPG'	'darkened_Gashaw_A.JPG'	'darkened_John_A.JPG'	'darkened_Kefyalew_A.JPG'	'darkened_Kelemu_A.JPG'	'darkened_Makida_A.JPG'	'darkened_Meklit_A.JPG'	'darkened_Meron_A.JPG'	'darkened_Solomon_A.JPG'	'darkened_Yadeta_A.JPG'
1st	'Gashaw_B.JPG'	'Alex_A.JPG'	'Makida_A.JPG'	'Belete_B.JPG'	'Solomon_B.JPG'	'Alex_A.JPG'	'Alex_A.JPG'	'Belete_A.JPG'	'John_B.JPG'	'Makida_B.JPG'	'Makida_B.JPG'	'Meron_B.JPG'	'Solomon_A.JPG'	'Solomon_B.JPG'
2nd	'Alex_A.JPG'	'Gashaw_B.JPG'	'Meklit_A.JPG'	'Belete_A.JPG'	'Solomon_A.JPG'	'John_B.JPG'	'Amberber_A.JPG	'Belete_B.JPG'	'Kefyalew_B.JPG'	'Makida_A.JPG'	'Meklit_A.JPG'	'Meron_A.JPG'	'Solomon_B.JPG'	'Solomon_A.JPG'
3rd	'Makida_A.JPG'	'Amberber_A.JPG	'Belete_A.JPG'	'Dereje_A.JPG'	'Ermiyas_A.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Alex_A.JPG'	'Kefyalew_A.JPG'	'Ermiyas_B.JPG'	'Makida_A.JPG'	'Makida_B.JPG'	'Ermiyas_A.JPG'	'Yadeta_A.JPG'
4th	'Meklit_A.JPG'	'Makida_A.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Ermiyas_B.JPG'	'Amberber_A.JPG	'John_A.JPG'	'Gashaw_B.JPG'	'Amberber_B.JPG	'Ermiyas_A.JPG'	'Ermiyas_B.JPG'	'Mihiret_D.JPG'	'Yadeta_A.JPG'	'Ermiyas_A.JPG'
5th	'Amberber_A.JPG	'Meklit_A.JPG'	'Makida_B.JPG'	'Kefyalew_A.JPG'	'Yadeta_A.JPG'	'Belete_A.JPG'	'Gashaw_B.JPG'	'Kefyalew_A.JPG'	'Gashaw_A.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'	'Ermiyas_B.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'

The performance is given in table 5-19

Table 5-19: Recognition performance using 13-eigenFaces (for threshold values greater than 3.38+06)

	Recognition Performance(13-EigenFaces)		
	Correctly classified	Misclassified	Recognition rate
Top 1	3	11	21.43%
Top 2	5	9	35.71%
Top 3	12	2	85.71%
Top 4	12	2	85.71%
Top 5	13	1	92.86%

Table 5-20: The top five face classes in decreasing order of closeness to the input Face class in the first row (using 11-EigenFaces)

10%	'darkened_Alex_A.JPG'	'darkened_Amberber_A.JPG'	'darkened_Belete_A.JPG'	'darkened_Dereje_A.JPG'	'darkened_Ermiyas_A.JPG'	'darkened_Gashaw_A.JPG'	'darkened_John_A.JPG'	'darkened_Kefyalew_A.JPG'	'darkened_Kelemu_A.JPG'	'darkened_Makida_A.JPG'	'darkened_Meklit_A.JPG'	'darkened_Meron_A.JPG'	'darkened_Solomon_A.JPG'	'darkened_Yadeta_A.JPG'
Top 5 closest face classes from the face library	'Gashaw_B.JPG'	'Alex_A.JPG'	'Makida_A.JPG'	'Belete_B.JPG'	'Solomon_B.JPG'	'Alex_A.JPG'	'Alex_A.JPG'	'Belete_A.JPG'	'John_B.JPG'	'Makida_B.JPG'	'Makida_B.JPG'	'Meron_B.JPG'	'Solomon_A.JPG'	'Solomon_B.JPG'
	'Alex_A.JPG'	'Gashaw_B.JPG'	'Meklit_A.JPG'	'Belete_A.JPG'	'Solomon_A.JPG'	'Gashaw_B.JPG'	'Amberber_A.JPG'	'Belete_B.JPG'	'Kefyalew_A.JPG'	'Makida_A.JPG'	'Meklit_A.JPG'	'Meron_A.JPG'	'Solomon_B.JPG'	'Solomon_A.JPG'
	'Makida_A.JPG'	'Amberber_A.JPG'	'Belete_A.JPG'	'Dereje_A.JPG'	'Ermiyas_A.JPG'	'John_B.JPG'	'John_B.JPG'	'Alex_A.JPG'	'Amberber_B.JPG'	'Ermiyas_B.JPG'	'Makida_A.JPG'	'Makida_B.JPG'	'Ermiyas_A.JPG'	'Yadeta_A.JPG'
	'Amberber_A.JPG'	'Makida_A.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Ermiyas_B.JPG'	'Amberber_A.JPG'	'John_A.JPG'	'Gashaw_B.JPG'	'Kefyalew_B.JPG'	'Ermiyas_A.JPG'	'Ermiyas_B.JPG'	'Mihiret_D.JPG'	'Yadeta_A.JPG'	'Ermiyas_A.JPG'
	'Yadeta_B.JPG'	'Meklit_A.JPG'	'Makida_B.JPG'	'Kefyalew_A.JPG'	'Yadeta_A.JPG'	'Belete_A.JPG'	'Gashaw_B.JPG'	'Kefyalew_A.JPG'	'Gashaw_A.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'	'Ermiyas_B.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'

The performance using 11 Eigenfaces is given in Table 5-21.

Table 5-21: Recognition performance using 11-eigenFaces

	Recognition Performance(using 11-Eigenfaces)		
11	Correctly classified	Misclassified	Recognition rate
Top 1	3	11	**21.43%**
Top 2	6	8	**42.86%**
Top 3	12	2	**85.71%**
Top 4	13	1	**92.86%**
Top 5	13	1	**92.86%**

Table 5-22: The top five face classes in decreasing order of closeness to the input Face class in the first row (using 7-EigenFaces)

	'darkened_Alex_A.JPG'	'darkened_Amberber_A.JPG'	'darkened_Belete_A.JPG'	'darkened_Dereje_A.JPG'	'darkened_Ermiyas_A.JPG'	'darkened_Gashaw_A.JPG'	'darkened_John_A.JPG'	'darkened_Kefyalew_A.JPG'	'darkened_Kelemu_A.JPG'	'darkened_Makida_A.JPG'	'darkened_Meklit_A.JPG'	'darkened_Meron_A.JPG'	'darkened_Solomon_A.JPG'	'darkened_Yadeta_A.JPG'
1st	'Gashaw_B.JPG'	'Alex_A.JPG'	'Makida_A.JPG'	'Belete_B.JPG'	'Solomon_B.JPG'	'Alex_A.JPG'	'Alex_A.JPG'	'Belete_A.JPG'	'John_B.JPG'	'Makida_B.JPG'	'Makida_B.JPG'	'Meron_B.JPG'	'Solomon_A.JPG'	'Solomon_B.JPG'
2nd	'Alex_A.JPG'	'Gashaw_B.JPG'	'Meklit_A.JPG'	'Belete_A.JPG'	'Solomon_A.JPG'	'John_B.JPG'	'Amberber_A.JPG'	'Belete_B.JPG'	'Kefyalew_A.JPG'	'Ermiyas_B.JPG'	'Makida_A.JPG'	'Meron_A.JPG'	'Solomon_B.JPG'	'Solomon_A.JPG'
3rd	'Makida_A.JPG'	'Amberber_A.JPG'	'Gashaw_B.JPG'	'Dereje_A.JPG'	'Ermiyas_A.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Alex_A.JPG'	'Kefyalew_B.JPG'	'Makida_A.JPG'	'Meklit_A.JPG'	'Makida_B.JPG'	'Ermiyas_A.JPG'	'Yadeta_A.JPG'
4th	'Meklit_A.JPG'	'Makida_A.JPG'	'Belete_A.JPG'	'John_B.JPG'	'Ermiyas_B.JPG'	'Amberber_A.JPG'	'Gashaw_B.JPG'	'Gashaw_B.JPG'	'Gashaw_A.JPG'	'Ermiyas_A.JPG'	'Ermiyas_B.JPG'	'Mihiret_D.JPG'	'Yadeta_A.JPG'	'Ermiyas_A.JPG'
5th	'Amberber_A.JPG'	'Meklit_A.JPG'	'Makida_B.JPG'	'Kefyalew_A.JPG'	'Yadeta_A.JPG'	'Belete_A.JPG'	'John_A.JPG'	'Kefyalew_A.JPG'	'Amberber_B.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'	'Ermiyas_B.JPG'	'Ermiyas_B.JPG'	'Yadeta_B.JPG'

The performance is given in table 5-22.

Table 5-23: Recognition performance using 7-eigenFaces (for the Threshold values greater than 3.38+06)

	Recognition Performance(7-EigenFaces)		
	Correctly classified	Misclassified	Recognition rate
Top 1	3	11	21.43%
Top 2	4	10	28.57%
Top 3	11	3	78.57%
Top 4	12	2	85.71%
Top 5	13	1	92.86%

Table 5-24 The top five face classes in decreasing order of closeness to the input Face class in the first row (using 5-eigenfaces)

	'darkened_Alex_A.JPG'	'darkened_Amberber_A.JPG'	'darkened_Belete_A.JPG'	'darkened_Dereje_A.JPG'	'darkened_Ermiyas_A.JPG'	'darkened_Gashaw_A.JPG'	'darkened_John_A.JPG'	'darkened_Kefyalew_A.JPG'	'darkened_Kelemu_A.JPG'	'darkened_Makida_A.JPG'	'darkened_Meklit_A.JPG'	'darkened_Meron_A.JPG'	'darkened_Solomon_A.JPG'	'darkened_Yadeta_A.JPG'
1st	'Gashaw_B.JPG'	'Alex_A.JPG'	'Makida_A.JPG'	'Belete_B.JPG'	'Solomon_B.JPG'	'Alex_A.JPG'	'Alex_A.JPG'	'Belete_A.JPG'	'John_B.JPG'	'Makida_B.JPG'	'Makida_B.JPG'	'Meron_B.JPG'	'Solomon_A.JPG'	'Solomon_B.JPG'
2nd	'Alex_A.JPG'	'Gashaw_B.JPG'	'Meklit_A.JPG'	'Belete_A.JPG'	'Solomon_A.JPG'	'John_B.JPG'	'Amberber_A.JPG'	'Belete_B.JPG'	'Kefyalew_A.JPG'	'Ermiyas_B.JPG'	'Makida_A.JPG'	'Meron_A.JPG'	'Solomon_B.JPG'	'Solomon_A.JPG'
3rd	'Makida_A.JPG'	'Amberber_A.JPG'	'Gashaw_B.JPG'	'Dereje_A.JPG'	'Ermiyas_A.JPG'	'Amberber_A.JPG'	'John_B.JPG'	'Gashaw_B.JPG'	'Kefyalew_B.JPG'	'Makida_A.JPG'	'Meklit_A.JPG'	'Makida_B.JPG'	'Ermiyas_A.JPG'	'Ermiyas_A.JPG'
4th	'Amberber_A.JPG'	'Makida_A.JPG'	'Belete_A.JPG'	'Kefyalew_A.JPG'	'Yadeta_A.JPG'	'Belete_A.JPG'	'Gashaw_B.JPG'	'Alex_A.JPG'	'Gashaw_A.JPG'	'Ermiyas_A.JPG'	'Ermiyas_B.JPG'	'Mihiret_D.JPG'	'Yadeta_A.JPG'	'Yadeta_A.JPG'
5th	'Meklit_A.JPG'	'Meklit_A.JPG'	'Makida_B.JPG'	'John_B.JPG'	'Ermiyas_B.JPG'	'Gashaw_B.JPG'	'John_A.JPG'	'Kefyalew_A.JPG'	'Amberber_B.JPG'	'Yadeta_B.JPG'	'Yadeta_B.JPG'	'Ermiyas_B.JPG'	'Ermiyas_B.JPG'	'Ermiyas_B.JPG'

Table 5-25: The resulting performance using 5-EigenFaces (for the threshold values greater than 3.38+06)

	Recognition Performance(5-EigenFaces)		
	Correctly classified	Misclassified	Recognition rate
Top 1	3	11	21.43%
Top 2	4	10	28.57%
Top 3	9	5	64.29%
Top 4	11	3	78.57%
Top 5	13	1	92.86%

In every case, one person is always found to be misclassified, but the best result was achieved when using 11-EigenFaces.The overall performance of the system is dropped to 21.43% for top 1 because of the illumination change. But for top 5 is was found to be 92%. In order to see the impact of illumination change, every member of Category_A was searched using the same Face library containing Category_A, _C and _D using 11-EigenFaces. The result is given in Table 5-26.

Table 5-26: The top five face classes in decreasing order of closeness to the input Face class in the first row (using 9-EigenFaces)

	Dereje_A'	Kelemu_A'	Makida_A'	John_A'	Yadeta_A'	Kefyalew_A'	Ermiyas_A'	Meron_A'	Solomon_A'	Belete_A'	Meklit_A'	Alex_A'	Gashaw_A'	Amberber_A'
1st	'Dereje_A.JPG'	'Kelemu_A.JPG'	'Makida_A.JPG'	'John_A.JPG'	'Yadeta_A.JPG'	'Kefyalew_A.JPG'	'Ermiyas_A.JPG'	'Meron_A.JPG'	'Solomon_A.JPG'	'Belete_A.JPG'	'Meklit_A.JPG'	'Alex_A.JPG'	'Gashaw_A.JPG'	'Amberber_A.JPG'
2nd	'Dereje_B.JPG'	'Dereje_B.JPG'	'Makida_B.JPG'	'John_B.JPG'	'Yadeta_B.JPG'	'Kefyalew_B.JPG'	'Ermiyas_B.JPG'	'Meron_B.JPG'	'Solomon_B.JPG'	'Belete_B.JPG'	'Makida_B.JPG'	'Amberber_A.JPG'	'John_B.JPG'	'Alex_A.JPG'
3rd	'Kefyalew_B.JPG'	'Amberber_B.JPG'	'Meklit_A.JPG'	'Amberber_B.JPG'	'Ermiyas_A.JPG'	'John_B.JPG'	'Yadeta_B.JPG'	'Mihiret_D.JPG'	'Ermiyas_A.JPG'	'Meklit_A.JPG'	'Makida_A.JPG'	'Gashaw_B.JPG'	'Amberber_B.JPG'	'John_B.JPG'
4th	'Amberber_B.JPG'	'Gashaw_A.JPG'	'Gashaw_B.JPG'	'Gashaw_A.JPG'	'Ermiyas_B.JPG'	'Amberber_B.JPG'	'Yadeta_A.JPG'	'Makida_B.JPG'	'Yadeta_A.JPG'	'Gashaw_B.JPG'	'Belete_B.JPG'	'John_B.JPG'	'John_A.JPG'	'Gashaw_B.JPG'
5th	'Kefyalew_A.JPG'	'Kefyalew_B.JPG'	'Belete_B.JPG'	'Kefyalew_B.JPG'	'Solomon_B.JPG'	'Gashaw_A.JPG'	'Solomon_B.JPG'	'Meklit_A.JPG'	'Yadeta_B.JPG'	'Makida_A.JPG'	'Gashaw_B.JPG'	'John_A.JPG'	'Kelemu_A.JPG'	'Solomon_D.JPG'

It is obvious that the recognition rate this time, is 100%. In contrast to the performance rate of 21.43% when the illumination level of probes is changed (darkened by 10% in our case) the impact was significant. As can be seen in Table 5-27 the average performance of the system is 92% if top five closest face classes are retrieved. And using 11-EigenFaces provides the leverage of storing smaller data (in size) and still an optimum result.

In general the change in the illumination levels of images under consideration has a significant impact on the recognition performance of the proposed system.

Table 5-27: Average Performance of the system; if top-N closest classes are retrieved

	Recognition Performance for Different Number of Eigenfaces					Average Performance
	13-EigenFaces	11-EigenFaces	9-EigenFaces	7-EigenFaces	5-EigenFaces	
Top 1	21.43%	21.43%	21.43%	21.43%	21.43%	21.43%
Top 2	35.71%	42.86%	35.71%	28.57%	28.57%	34.28%
Top 3	85.71%	85.71%	85.71%	78.57%	64.29%	80.00%
Top 4	85.71%	92.86%	92.86%	85.71%	78.57%	87.14%
Top 5	92.86%	92.86%	92.86%	92.86%	92.86%	92.86%

5.8 Recognition Performance and Presence of Details

In this experiment, the effect of the presence of facial details such as dark glasses, masks and moustaches on recognition performance was tested. To achieve this, a face library that contained all members of categories "_A, _B, _D" was formed. Then, a training set from all members of category "_A" (11-eigenfaces) was chosen. Then every member of Category_G was searched and the result is given in Table 5-28 and Table 5-29. It is observed that the system performs very well despite the fact that some of the details were too much and retrieving two of the closest images results in a 100% recognition rate.

Figure 5-6: Faces after manually adding facial details and the corresponding reconstructed faces (using 9-EigenFaces)

Table 5-28: The top five face classes in decreasing order of closeness to the input Face class in the first row (using 9-EigenFaces)

	'Belete_G.jpg'	'Dereje_G.jpg'	'Gashaw_G.jpg'	'John_G.jpg'	'Kefyalew_G.jpg'	'Makida_G.jpg'
Top 1	'Gashaw_B.JPG'	'Dereje_A.JPG'	'Gashaw_A.JPG'	'Amberber_B.JPG'	'Kefyalew_A.JPG'	'Makida_A.JPG'
Top 2	'Belete_A.JPG'	'Dereje_B.JPG'	'Kelemu_A.JPG'	'John_A.JPG'	'Kefyalew_B.JPG'	'Makida_B.JPG'
Top 3	'Makida_A.JPG'	'Amberber_B.JPG'	'Amberber_B.JPG'	'John_B.JPG'	'John_B.JPG'	'Meklit_A.JPG'
Top 4	'Meklit_A.JPG'	'Kefyalew_B.JPG'	'John_B.JPG'	'Gashaw_A.JPG'	'Amberber_B.JPG'	'Gashaw_B.JPG'
Top 5	'Alex_A.JPG'	'Kefyalew_A.JPG'	'John_A.JPG'	'Kefyalew_A.JPG'	'Gashaw_A.JPG'	'Ermiyas_B.JPG'

Table 5-29: The performance of the system, when facial details are added and used as probe images

	Recognition Performance		
	Correctly classified	Misclassified	Recognition rate
Top 1	4	2	**66.67%**
Top 2	6	0	**100.00%**
Top 3	6	0	**100.00%**

5.9 Recognition Performance and Pre-processing Techniques

Now the general performance of the system will be measured using 11-Eigenfaces, threshold values of 1.74E+11 and 6.32E+07 were imposed. Additionally, a face library of 62 face classes was formed. The test was conducted on Category_B members as test set and Category_A as training set. The result shows that all face classes were considered as face. And a perfect recognition rate of (100%) was achieved (see Table 5-30). This was not a surprise for the test classes are all members in the face library. But in reality a probe image may not always be found in the library, so even if there are three or more face classes for an individual a second library of face classes was formed by eliminating members of Category_B from the previous library. Table 5-30 shows that recognition rate is dropped to 71%; as 4 of the input classes are misclassified. To improve this performance, pre-processing modules called Discrete Cosine Transform (DCT) and Histogram Equalization were applied to the missed images and tested again.

Table 5-30: Recognition results using a face library (_A, _B, _C, _D and 6 more images)

	'Alex_B.JPG'	'Amberber_B.JPG'	'Belete_B.JPG'	'Dereje_B.JPG'	'Ermiyas_B.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Kefyalew_B.JPG'	'Kelemu_B.JPG'	'Makida_B.JPG'	'Meklit_B.JPG'	'Meron_B.JPG'	'Solomon_B.JPG'	'Yadeta_B.JPG'
Top 1	'Alex_B.JPG'	'Amberber_B.JPG'	'Belete_B.JPG'	'Dereje_B.JPG'	'Ermiyas_B.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Kefyalew_B.JPG'	'Kelemu_B.JPG'	'Makida_B.JPG'	'Meklit_B.JPG'	'Meron_B.JPG'	'Solomon_B.JPG'	'Yadeta_B.JPG'

Table 5-31: Recognition results using a face library with members, _A,_C,_D and 6 more images and the resulting performance of the system.

	'Alex_B.JPG'	'Amberber_B.JPG'	'Belete_B.JPG'	'Dereje_B.JPG'	'Ermiyas_B.JPG'	'Gashaw_B.JPG'	'John_B.JPG'	'Kefyalew_B.JPG'	'Kelemu_B.JPG'	'Makida_B.JPG'	'Meklit_B.JPG'	'Meron_B.JPG'	'Solomon_B.JPG'	'Yadeta_B.JPG'
Top 1	'Kelemu_A.JPG'	'John_G.jpg'	'Belete_A.JPG'	'Dereje_A.JPG'	'Ermiyas_A.JPG'	'Belete_G.jpg'	'John_A.JPG'	'Kefyalew_A.JPG'	'Kelemu_D.JPG'	'Makida_G.jpg'	'Dereje_A.JPG'	'Meron_A.JPG'	'Solomon_A.JPG'	'Yadeta_A.JPG'

	Recognition Performance		
	Correctly classified	Misclassified	Recognition rate
Top 1	10	4	**71.43%**

Table 5-32: One more image is correctly recognized after DCT was employed to the missed face classes and the performance is improved to 78.57%

	Recognition Performance		
	Correctly classified	Misclassified	Recognition rate
Top 1	11	3	**78.57%**

The result shows that Applying DCT to the missed images results in one addition to the correct recognition which increases the performance to 78.57%. And applying Histogram Equalization to the remaining 3 missed images again helped to correctly recognize one more image; which results in an improved performance; around 86 % (see Table 5-33).

Table 5-33: Results of recognition after histogram-equalization implementation on the missed face classes. The performance is improved.

	Recognition Performance		
	Correctly classified	Misclassified	Recognition rate
Top 1	12	2	**85.71%**

From this experiment we have observed that the general performance of the system, when only the closest image in the face library is retrieved, is **85.71%.** And implementation of pre-processing techniques helped to improve the performance of the system.

The performance of the system, in general is very good when the probe images are in the face library. But it is observed that for test images, which were not in the library, a 100% recognition result cannot be achieved. This is mainly because of the sensitivity of the algorithm employed to illumination head orientations etc of probe images. The performance of the system would be better if images in the database (both training and probe images) were taken in relatively similar environment, for example in a studio; but the aim of this research was to test the performance of the algorithm in a real environment and it was also difficult to bring all the subjects together to avoid the resulting variability.

Chapter 6 Conclusions and Recommendations

6.1 Conclusions

An Eigenface based face recognition system is intended for, given still images or video of a scene, identifying one or more persons in the scene by using a stored database of faces.

Fulfillment of this objective is done through appropriate design and integration of various components. In this study, major approaches to the face recognition problem in literatures have been studied and a face recognition system based on the Eigenfaces approach is proposed. Principal Component Analysis (PCA), which is a statistical approach to face recognition, was implemented to develop a prototype of Eigenfaces based face recognition system.

Faces are highly deformable and complex structures. Appearance is affected by a large number of factors including pose, expression, lighting (illumination) and aging. Development of robust face recognition algorithms requires sufficient and reasonable datasets of face images that consider the controlled variations of these factors. The researcher, have tried to minimize variation due to the aforementioned variable. To this effect some face images with exceptional illumination and pose were rejected, as they had unintended effect on the recognition performance.

The system was developed using a Matlab development environment. Series of tests were conducted to measure and improve the performance of the system. A face database was constructed; and PCA, which was reported in many literatures as one of the best performing method was used to extract features from the given face images. Finally a statistical pattern classifier, Euclidean distance measurement, was used to classify a probe image as not a face, unknown face or to one of the face class in the libraries. Experiments were also conducted to determine optimal threshold values to make these classifications.

The experimental results have shown that, the proposed face recognition method was very sensitive to face background head orientations and illumination changes. The removal of backgrounds results in higher rate of rebuilding error and changes in head orientation or illumination level significantly dropped the recognition performance of the system. On the other hand, presences of small facial details such as dark glasses or masks did not cause a major problem to the system. There exists a tradeoff between the correct recognition rate and the threshold value. As the threshold value increases, number of misses begins to decrease, possibly resulting in misclassifications (see Table 5-13). On the contrary, when the number of eigenfaces involved in the recognition process increases misclassification rate begins to decrease (see Table 5-27). Additionally a comparison was made between images and their reconstruction using varying number of eigenfaces; Results show that the Rebuild Error Ratio (RBE) is high for there is a considerable information difference between training faces and the rebuilt ones. But generally it decreases as the number of eigenfaces used increases (see Table 5-2).

Finally implementation of pre-processing techniques, like DCT and Histogram equalization, to the probe images has helped to improve the performance of the system. The proposed system provides a perfect recognition rate when probe images are already in the face library we search from. But for probes not in the face library while the subject is still represented by other images, the overall performance of the system is found to be 85.71%; moreover if the top five ranked are considered it rises to 92.86%.

6.2 Recommendations

The work in this thesis can be extended by:

- building a larger face database
- taking face images in a very controlled environment
- building a face database of multiple views for a subject and
- developing a full-fledged face recognition system for a particular organization.

This work is done only the frontal views of face images. Multiple views for an individual can be considered to narrow the chance of missing a match, for a probe image, only because of the input's view. It is also believed that, constructing a larger face database will improve the overall performance of the system. One of the limitation of the propose system is it assumes the inputs are all face images; for face detection, as was used by Turk & Pentland [38], to provide an input for recognition, is out of the scope of this research. The recognition performance of the system is believed to improve if such face databases were available and face detection algorithms were implemented before recognition test.

In general, an attempt was made to control variations, at least to make it similar, in the environment in which the images were captured. But variables like angel of illumination or light source could not be controlled in efficient manner. So if the environment can be controlled in such a manner that a researcher has the control over these variables, the performance of the system would be improved. Finally the performance of the system can be improved if the difference preprocessing techniques besides the one's used in this study, are implemented.

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Annex I

Consent form

Greetings

Hello! My name is Daniel Arega Asmamaw, I am working on thesis research report at Addis Ababa University School of Information Science, Department of information science. This study is to be conducted with the aim of developing a prototype face recognition system using eigenface method. You are one of the subjects selected to participate in this study, therefore you are kindly requested to participate in this study and allow us to use your images and first name.

We would like to inform you that your images and name are very essential, not only for the successful accomplishment of the study but also for producing credible and functional face recognition system that enlighten the possibility and relevance of having of such system in Ethiopia. We deeply appreciate your participation and the permission you will give us to do so. Thank you in advance in anticipation of your cooperation.

Declaration

This thesis is my original, has not been presented for a degree in any other university and that all sources of the material used for the thesis have been duly acknowledged.

Daniel Arega Asmamaw

May 2011

This thesis has been submitted for examination with my approval as a university advisor

Dereje Teferi (PhD)

May 2011