An Intelligent Face Authentication System for ATM Access

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Master Thesis

Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Computer Science

at

Middle East University for Graduate Studies

May, 2008

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Declaration

I do hereby declare the present research work has been cared out by me under the supervisor Dr Shilbaeh N.

And this work has not been submitted else were for any other degree, fellowship or any other similar title.

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Acknowledgments

I am grateful to my supervisor Dr. Shilbayeh N, who spares his valuable time in guiding me for my research work. He encourages me always. I am short in word to express his contribution to this thesis through criticism, suggestions and discussions.

I would also like to thank Dr. Musbah Aqel from Middle East University for graduated studies for his guidance and valuable discussions.

Last but not least, I would like to thank my family for all their support, specially my Father, Mother and my wife whom gave me the courage and support to pursue my dreams, and I hope I make them proud.

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Terminologies

- **Pose**. The images of a face vary due to the relative camera-face pose (frontal, 45 degree, profile, upside down), and some facial features such as an eye or the nose may become partially or wholly occluded. [10]
- **Facial expression.** The appearance of faces is directly affected by a person's facial expression.[10]
- **Image orientation**. Face images directly vary for different rotations about the camera's optical axis.[10]
- **Imaging conditions**. When the image is formed, factors such as lighting (spectra, source distribution and intensity) and camera characteristics (sensor response, lenses) affect the appearance of a face.[10]
- **Face localization** aims to determine the image position of a single face; this is a simplified detection problem with the assumption that an input image contains only one face.[10]
- **Face Detection** Face detection is a computer technology that identifies human faces in arbitrary images. It detects facial features and ignores anything else, such as buildings, trees and bodies.[7]
- **Face Recognition** Given a test face and a set of reference faces in a database; find the N most similar reference faces to the test face**.**
- **Face Authentication** Given a test face and a reference one; decide if the test face is identical to the reference face. [10]

Abstract

Biometrics represent a promising approach for reliable and secure user authentication, typical authentication by using biometrics such as face, voice, finger print, Iris and hand geometry are more securely than using the regular authentication methods like PIN code or password. Our objectives are to introduce a new face authentication system for ATM access using the face, we consider robust face detection based on maximal rejection classifier and color segmentation algorithms, also we consider robust face verifies based on principal component analysis algorithms, the other contribution is to present two methods the pose orientation method which improves the face recognition system, and the face regeneration method which improves corrupted face.

Keyword:

Face Authentication, color segmentation, maximal rejection classifier, principle component analysis, pose orientation and face regeneration.

الملخص

نظام خاص بجهاز الصراف الآلي (ATM) والذي يعنى بالاخص بنظام الحماية للصراف فيتم التحقق من هوية الزبون باستخدام الوجه, بحيث يتم اخذ صورة للوجه عند ادخال البطاقة وتمر هذه الصور بعدة عمليات يتم من خلالها التاكد من هوية المستخدم.وايضا تم اضافة طريقتين جديدتين لمساعدة نظام تحديد الوجه وهما:1 – تعديل الميلان بالوجة.2– نظام استعادة الجزء المفقود من الوجه.

Chapter 1

Introduction

In recent years, there are an increasing trend of using biometrics information, which refers the human biological features used for person authentication, such as fingerprint, iris, voice, hand geometry and face, to strengthen the security measure of different electronic/embedded systems, including smart card systems. Compared to the digit Personal Identification Number (PIN), the critical data stored in the card can be protected more securely by using the biometric information. Currently, we need a PIN to get cash from ATM; a password to access a computer or internet services and a key to unlock our door. However, these measures are not secure. For example, password can be guessed easily as people probably pick ones that are easy to remember like child's name or favorite sport; card key can also be lost or snooped easily. Only biometric characteristics cannot be borrowed, stolen or forgotten. Users can not pass their characteristics to other. All these prove that biometric is the most secure authentication approach among the three security measures. Among biological features, the face is one of the most acceptable biometrics, because humans use it in their visual interactions and acquiring face images is non-intrusive. However, it is known that recognizing human faces is very difficult due to similarity in the global face structure with only minor differences from person to person. Face recognition, seen as an object classification problem, deals with objects, which can be thought of as belonging to the same class, namely that of the human face [23] [40].

1.1 Motivations for the research

Biometrics is the study of methods for measuring physical or behavioral traits of an individual that can be used for uniquely recognizing or verifying that individual's identity. Physical biometrics based on fingerprints, eye retinas and irises, facial patterns, and hand shapes are more common since they are easier to measure than behavioral biometrics such as handwriting, gait, and typing patterns. Biometric methods are divided to physical and behavioral methods, which in turn can be divided into invasive and noninvasive methods. Invasive methods are those that require the cooperation of the individual in order to acquire data needed to compare his biometric features to the ones stored in a database. Noninvasive biometrics does not require the cooperation of the individuals; in fact data capture may be done without their knowledge. Applications for biometrics are most common in security, medical, and robotics areas related to fingerprint, face, iris, and gait. These biometric areas have gained the most attention among the research community [19].

Face is one of the most common used biometric methods for many application like face authentication can be used to allow access to an ATM machine as a computer, to control the entity of people into restricted areas, to recognize people in a specific areas (bank, store), or in a specific database such as police database.

1.2 The need for biometric authentication

Access control applications include door access, time & attendance, keep-out during off-hours, and the control of sensitive and restricted access points. Recognition in one-to-many searches seeks to identify an unknown individual based on comparison to a database of known individuals (e.g., law enforcement, surveillance, and recently driver licenses). Authentication involves performing verification based on a one-to-one search to validate the identity claim of the individual (i.e., access control for a building, room, or for making a transaction at an ATM terminal) and is the focus of this thesis. Authentication is in one sense a simpler process: comparisons are made only to the claimed identity, and a threshold of similarity is used to accept or reject the claim. Several approaches have been promoted to recognize and authenticate an individual or a group of people. Access control applications authenticate by physical appearance (by guard personnel, receptionist); by something the individual knows (pins, passwords); by something the individual has (lock/key, card, badge, token); by biometric evidence (a unique physiological or behavioral characteristic of the individual); or by a combination of both "what one has" (i.e., a card) and "what one knows" (i.e., their pass code). Most workplace entry points are typically controlled by a badge/card or by physical appearance. All of these methods, except biometrics, are fallible and can be circumvented, lost, or stolen. For that reason, biometrics has been explicitly cited in several pieces [29].

Overview of work

Automated human identification systems have become increasingly important in society. Human identification is involved in many applications such as gaining access to secure locations, or for surveillance. Our goal is to develop a face authentication system that can be used in real time face identification system as shown in figure 1.1 Our face identification system must operate under a variety of conditions, such as varying illuminations and backgrounds, it must handle non frontal facial images of both males and females of different ages and faces.

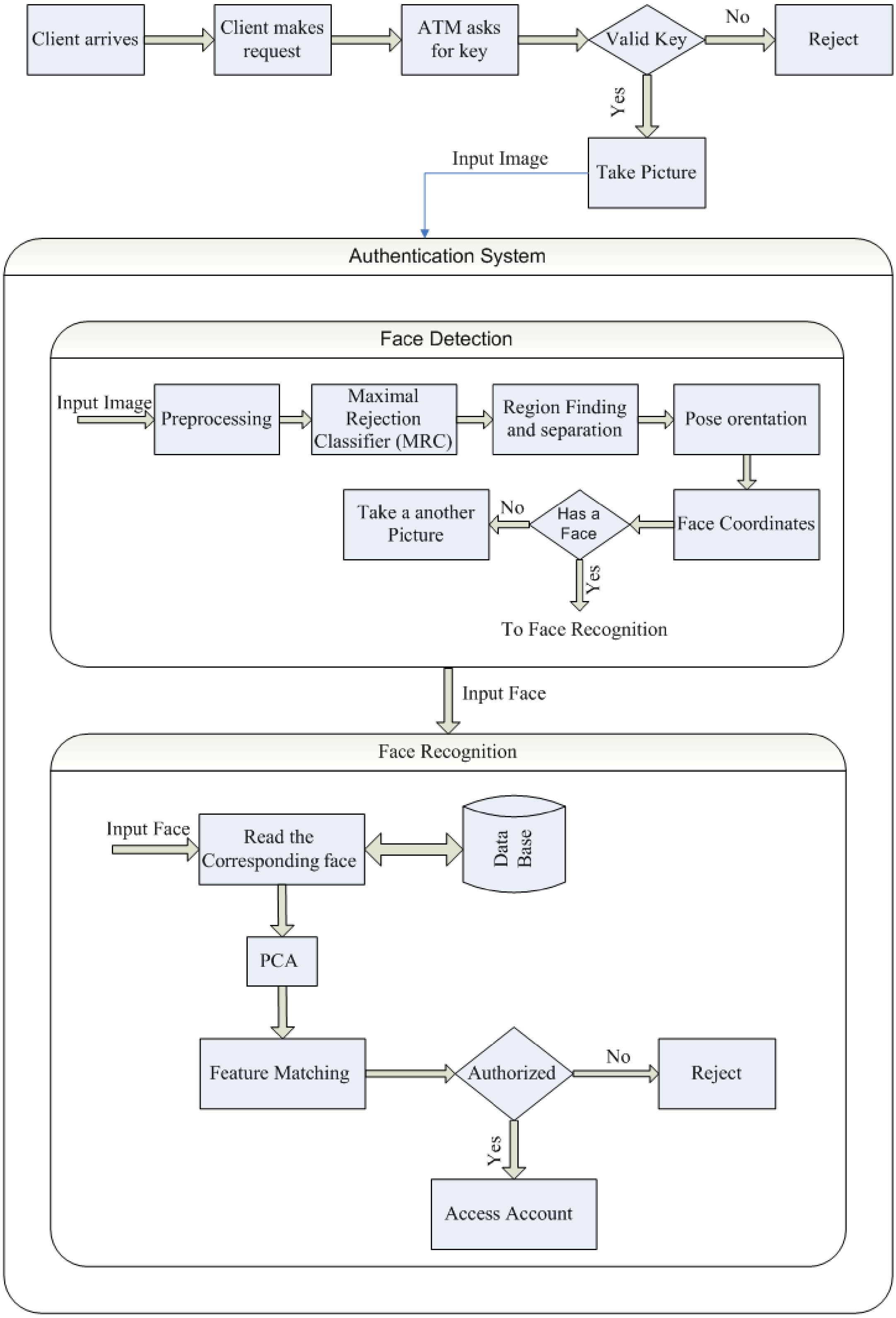


Figure 1.1 the overall face authentication system

Anew face authentication system specially designed for the automated teller machine (ATM) which will use the face for the authentication and a key for the ATM request, this key is added to give more security to the authentication process because there are some cases like twins who some time are look like each other and because the face are not a unique identification for the people there are some people that are in some how similar to each other, the key is added to add more uniqueness to the system, and to simplify the over all process.

Because when the person come to the ATM machine and enter his key then the system respond if it's a valid key or not, this key is the first authentication the person should move on. After that the face authentication system will begin by take a picture for the person and move it on the system process walking throw the detection system which should find the face coordinates and extract it from the picture to next process. Then the system will move to the recognition process which should take the picture and fetch the corresponding face from the database (according to the entered key) and make some operation on both faces to see if they belong to the same person or not. This proposed system include two main subsystem the first one is the face detection and the second is the face recognition, the face detection subsystem should fine the face and respond within short time (less than two second maximum) because of that we use two main algorithms for the detection system the first is the color segmentation and the second is the maximal rejection classifier MRC, these two algorithms have a very good result and they are simple and the most important they do not take too much time. The second subsystem used is the face recognition which also needs to recognize the face and authenticate them in a few second, we use the principle component analysis PCA (eigenface) algorithm for the recognition system because its simplicity and the fast result it gives.

Problem Statement

- ❖ Given an image, to identify it as a face and/or extract face image from it.
- ❖ Given a training database of pre-processed face images, train an automated system to recognize the identity of a person from a new image of the person, using the Principle component analysis algorithm. Examine sensitivity to pose, lighting condition and illumination.

1.3 Existing biometric Authentication Systems

As of February of this year 20,000 of Japan's 110,000 bank machines have been outfitted with scanners that takes a snapshot of the customers palm or index finger and compare the vein patterns in the palm or finger to a digital stored image on the customers bank card. This new way of authentication have cut down on fraud and id theft and has allowed banks to allow their customer to withdrawal more money from ATMs. The daily cash withdrawal limit has been increased dramatically sometimes up to $10,000 or more. Some security experts think however that the higher withdrawal limit would make ATM robberies a lot more attractive to criminals**.**

1.4 Contributions

- ❖ Develop and implement an integrated Face Authentication system for ATM access.
- ❖ Presenting new method for pose orientation based on eye extraction.
- ❖ Presenting new method called face regeneration that recover corrupted or missed part of the face.

1.5 Organization of this thesis

The thesis is organized into five chapters. Chapter 1 Introduction of the thesis gives a motivation, the need for biometric authentication, work overview, and the proposed system. Chapter 2 gives an overview for face detection and recognition algorithms and there characteristics and the advantages, disadvantage for each one. Chapter 3 introduces the face detection system, and presenting the new methods to improve the detection system. Chapter 4 Introduces the face recognition system using the PCA algorithms, and the proposed authentication system. Chapter 5 conclusions and future work: this chapter lists the goal achieved by this thesis and the new methods we present and the future work.

Chapter 2

Literature review

This chapter gives an overview on the major human face detection and face recognition techniques, the advantages and disadvantages for each method and the differences between them.

2.1 Face Detection algorithms overview

The face is distinctive and widely used key to a person's identity. The area of face detection has attracted considerable attention in the advancement of human-machine interaction as it provides a natural and efficient way to communicate between humans and machines. The problem of detecting the faces and facial parts in image sequences has become a popular area of research due to emerging applications in intelligent human-computer interface, surveillance systems, content based image retrieval, video conferencing, financial transaction, forensic applications, pedestrian detection, and image database management system and so on. Face detection is essentially localizing and extracting a face region from the background. This may seem like an easy task but the human face is a dynamic object and has a high degree of variability in its appearance, which makes face detection a difficult problem in computer vision [26] the following figure 2.1 shows the categorization of face detection techniques.

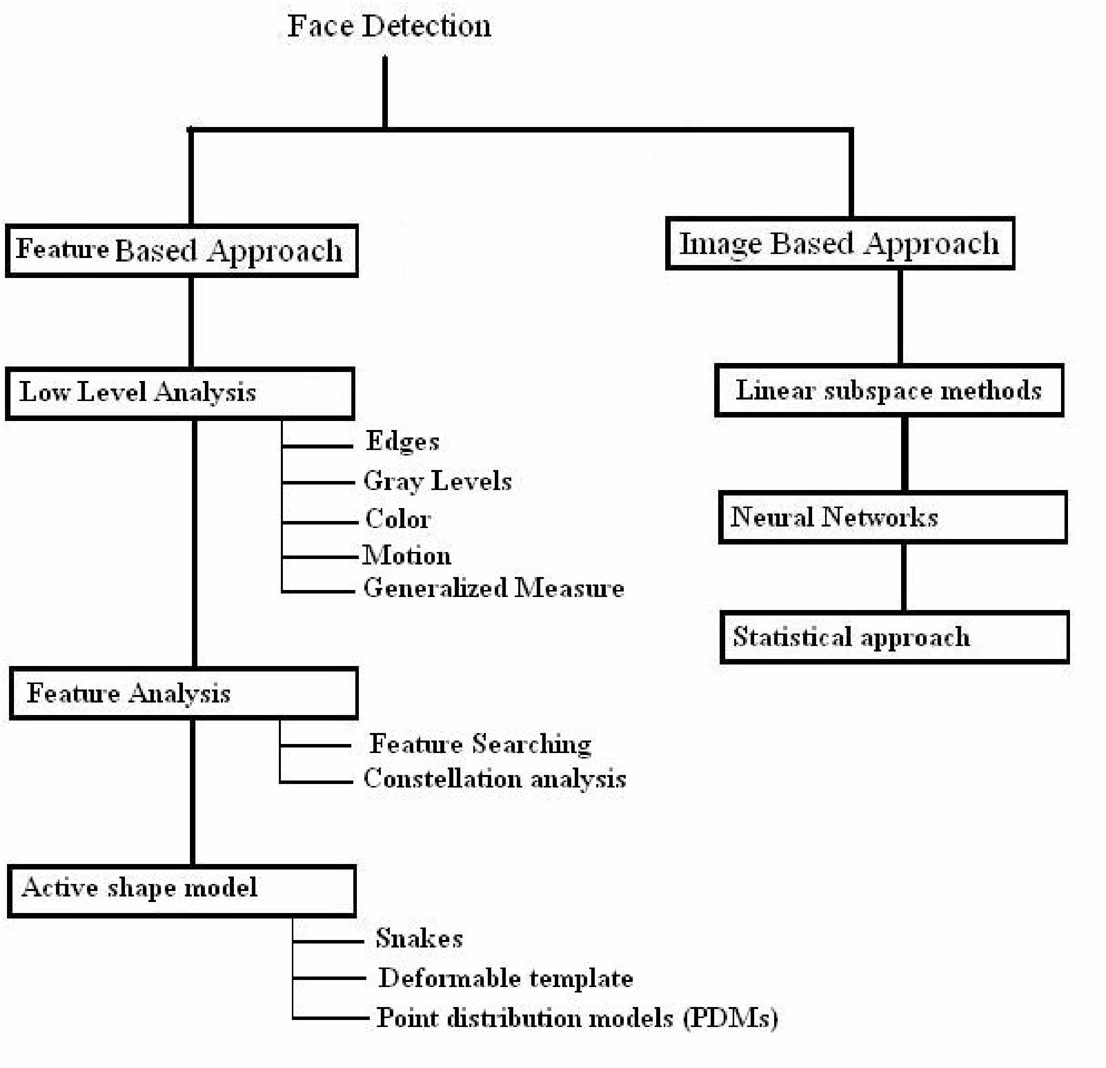


Figure 2.1 Categorization of face detection techniques [32]

Evolution of face detection research

Early efforts in face detection have dated back as early as the beginning of the 1970s, where simple heuristic and anthropometric techniques were used. These techniques are largely rigid due to various assumptions such as plain background, frontal face a typical passport photograph scenario. To these systems, any change of image conditions would mean fine-tuning, if not a complete redesign. Despite these problems the growth of research interest remained stood until the 1990s, when practical face recognition and video coding systems started to become a reality. Over the past decade there has been a great deal of research interest spanning several important aspects of face detection. More robust segmentation schemes have been presented, particularly those using motion, color, and generalized information. The use of statistics and neural networks has also enabled faces to be detected from cluttered scenes at different distances from the camera. Additionally, there are numerous advances in the design of feature extractors such as the deformable templates and the active contours which can locate and track facial features accurately. Because face detection techniques requires a priori information of the face, they can be effectively organized into two broad categories distinguished by their different approach to utilizing face knowledge. The techniques in the first category make explicit use of face knowledge and follow the classical detection methodology in which low level features are derived prior to knowledge-based analysis. The apparent properties of the face such as skin color and face geometry are exploited at different system levels. Typically, in these techniques face detection tasks are accomplished by manipulating distance, angles, and area measurements of the visual features derived from the scene. Since features are the main ingredients, these techniques are termed the feature-based approach [33].

2.1.1 Feature Based Method

This area contains techniques that are classified as low-level analysis. These are methods that deal with the segmentation of visual features using pixel properties such as gray-scale and color. The features that these low-level methods detect can be ambiguous, but these methods are easy to implement and fast. Another area of techniques called feature analysis, where face detection is based upon facial features using information of face geometry. Through feature analysis, feature ambiguities are reduced and locations of the face and facial features are determined. The last group involves the use of active shape models. These have been developed for the purpose of complex and non-rigid feature extraction such as eyes and lip tracking. [4].

2.1.1.1 Low-level Analysis:

This is the most primitive feature in face detection applications. Most of the work was based on basic line drawings of faces from photographs, aiming to locate facial features. This was the basis of the detection program, where the next step was feature analysis to determine if the shape detected was indeed a human face shape. Edge detection essentially locates major outlines in the image (the threshold can be set to detect predominant lines or indeed all lines). It then assigns each pixel on the line with a binary digit to set it out from the back ground. Many types of edge operators exist. They all operate on the same premise and give similar results. In an edge-detection based approach to face-detection, the edges (after identification) need to be labeled and matched to a face model in order to verify correct detections. Features have to be located and identified such as eyes, hairline or jaw line. If these all seem to be in ratio and in place a face is detected. This method is accurate in images with no complex backgrounds and the face needs to be in clear view facing front. These limitations sometimes restrict edge detection implemented as a pre-processing tool to identify face shapes and then these figures are handed over to a pattern based system for more accurate detection process [26].

2.1.1.2 Feature Analysis Searching:

Feature searching works on the premise that it exclusively looks for prominent facial features in the image. After this main detection less prominent features are searched for using standard measurements of facial geometry. A pair of eyes is the most commonly applied reference feature, other features include the top of the head and the main face axis. This method is often combined with edge detection where the edge densities are detected from a top-down approach starting from the top of the head. These are measured and after distinguishing a reference measurement. These measurements are plotted against the average lengths of facial measurements (which are found by measuring a set of varying face images held on a database).This method does not rely on skin color and so manages to detect various races. This method is also restricted to frontal face images with a plain background and it need a clear forehead not hidden by hair to ensure detection. If facial hair, earrings and eyewear are worn on the face it fails to detect the face. [32]

2.1.1.3 Active Shape Models:

Snakes (or Active Contours). They are commonly used to locate a head boundary. This is done by firstly initializing the snake at the proximity around the head boundary. The snake locks onto the nearby edges and subsequently assumes the shape of the head. The snake's path is determined by minimizing an energy function. The internal energy defines the snake's natural evolution and external counteracts the internal energy to enable the contours to deviate from the natural evolution and assume the shape of nearby features--ideally the head boundary. The appropriate energy terms have to be considered. Elastic energy is used commonly as internal energy--this can give the snake the elastic-band characteristic that causes the snake's evolution (by shrinking and expanding). The external energy requirement can include a skin color function which attracts the skin color function to the face region. Snakes are well equipped to detect feature boundaries but it still has its problems. The contours often get trapped on false image features causing the program to crash. Snakes also try to keep to the minimum curvature and this can lead to problems as some face shapes may not be completely convex and thus will return false results [26].

2.1.1.4 Point Distributed Models:

This method takes the statistical information of the shape given in an image and compares it to a pre-defined training set to determine whether the shape is a head (or indeed a head shape). The point distributed model created by the program is put into a set of points which are labeled. Variations of these points are first determined by using the training set that includes objects of different sizes and poses. Using principal component analysis, variations of the features in a training set are constructed as a linear flexible model. The model comprises the mean of all the features in the sets and the principle modes of variation for each point where x represents a point on the point distributed model, x is the mean feature in the training set for that point, P = [p1 p2 ... pt] is the matrix of the t most significant variation vectors of the covariance of deviations, and v is the weight vector for each mode. Face point distribution models were first developed by Lanitis et al. as a flexible model. This model defines a global model for a face which includes facial features such as eye-brows, the nose and eyes. Using 152 manually planted control points (x) and 160 (WHY) training face images, the face point distribution model are obtained. For comparison the mean shape model x is placed on top (or near) the area being tested. The labels of each image are then compared. During the comparison the corresponding points are only allowed to differ in a way that is consistent with the training set data. The global characteristic of the model means that all features can be detected simultaneously so this means that the need for feature searching is removed, cutting down pre-processing time. Another advantage of this technique is that it can detect a face even if a feature is missing--hidden or removed. This is because other feature comparisons can still detect the face. This technique needs to be further developed to detect multiple faces in images. [32]

2.1.1.5 Face Detection Using Color Segmentation:

The purpose of the color segmentation is to reduce the search space of the subsequent techniques, so it is important to determine as tight a box as possible without cutting off the face. After the color image has been mapped into a binary image of ones and zeros representing skin and non-skin regions. It is common during the color segmentation to return values that are closely skin but non-skin, or other skin-like colored regions that is not part of the face or the body. These erroneous values are generally isolated pixels or group of pixels that are dramatically smaller than the total face regions. Inclusion of these noisy pixels would result in a box that is much larger than intended and defeat the purpose of the segmentation. Further morphological refinements are applied to the binary output in order to reduce some of the effects of these noisy pixels. Since these spurious errors are generally much smaller than the face region itself, morphological techniques such as erosion, filtering and closing are good tools to use to eliminate these pixels [12] [20] [21].

2.1.2 Image Based Approach to Face Detection:

The image based approach to face detection is plagued by the unpredictability of image environmental conditions and unpredictable face appearances. The image based approach is usually limited to detecting one face in a non complex background with ideal conditions. There is a need for techniques that can detect multiple faces with complex backgrounds. The pattern recognition area of face detection was developed for these reasons. This technique works on the idea that the face is recognized by comparing an image to examples of face patterns. This eliminates the use of face knowledge as the detection technique. This means inaccurate or uncompleted data from facial images can still be detected as a face. The approach here is to classify an area as either face or non-face, so a set of face and non face prototypes must be trained to fit these patterns. These form a 2D intensity array (thus the name image based) to be compared with a 2D array taken from the input image test area. This then decides whether the face falls into a face or non-face type. [44]

2.1.2.1 Eigen Faces:

In the late 1980s developed a technique using principal component analysis to efficiently represent human faces. Given an ensemble of different face images, the technique first finds the principal components of the distribution of faces, expressed in terms of eigenvectors (taken from a 2D image matrix). Each individual face in the face set can then be approximated by a linear combination of the largest eigenvectors, more commonly referred to as Eigen faces, using appropriate weights. The Eigen faces are determined by performing a principal component analysis on a set of example images with central faces of the same size. In addition the existence of a face in a given image can be determined. By moving a window covering a sub image over the entire image faces can be located within the entire image. A pre compiled set of photographs comprise the training set, and it is this training set that the Eigen faces are extracted from. The photographs in the training set are mapped to another set which are the Eigen faces. As with any other mapping in mathematics, we can now think of the data (the photographs and the Eigen faces) as existing in two domains. The photographs in the training set are one of these domains, and the Eigen faces comprise the second domain that is often referred to as the face space. The Eigen faces that comprise the face space are added together with appropriate weights to re-compose one of the photographs in the training set. It is through the analysis of these weights that face detection can be realized. A training set of 100 to 150 images is enough to generate appropriate Eigen faces [13] [44].

2.1.2.2 Neural Networks

Neural Networks have become a popular technique for pattern recognition face detection. They contain a stage made up of multilayer perceptrons. Other techniques are also applied to add to the complexity of its process. The first neural approaches were based on Multi-layer perceptrons which gave promising results with fairly simple datasets. The first advanced neural approach which reported results on a large, difficult dataset was by [3]. Rowley's system incorporates face knowledge in a retinally connected neural network; the neural network is designed to look at windows of 20 x 20 pixels (thus 400 input units). There is one hidden layer with 26 units, where 4 units look at 10 x 10 pixel sub regions, 16 look at 5 x 5 sub regions, and 6 look at 20 x 5 pixels overlapping horizontal stripes. The input window is pre-processed through lighting correction (a best fit linear function is subtracted) and histogram equalization. A problem that arises with window scanning techniques is overlapping detections. [14] Deals with this problem through two heuristics:

1. Thresholding: the number of detections in a small region surrounding the current location is counted, and if it is above a certain threshold, a face is present at this location.
2. Overlap elimination: when a region is classified as a face according to thresholding, then overlapping detections are likely to be false positives and thus are rejected.

During training, the target for a face-image is the reconstruction of the image itself, while for nonface examples; the target is set to the mean of the n nearest neighbours of face images. A training algorithm based on the bootstrap algorithm of Sung and Poggio [43] was employed (and also a similar pre-processing method consisting of histogram equalization and smoothing). The system is trained with a simple learning rule which promotes and demotes weights in cases of misclassification. Similar to the Eigen face method, [35] use the bootstrap method of Sung and Poggio for generating training samples and pre-process all images with histogram equalization. The training set outlined in Error! Reference source not found. Can also be used in this training circumstance. [14]

2.1.2.3 Support Vector Machines:

Support vector machine is a patter classification algorithm developed by V. Vapnik and his team at AT &T Bell Labs [5, 20]. While most machine learning based classification techniques are based on the idea of minimizing the error in training data (empirical risk) SVM's operate on another induction principle , called structural risk minimization, which minimizes an upper bound on the generalization error. Training is performed with a boot-strap learning algorithm [14]. Generating a training set for the SVM is a challenging task because of the difficulty in placing "characteristic" non-face images in the training set. To get a representative sample of face images is not much of a problem; however, to choose the right combination of non-face images from the immensely large set of such images is a complicated task. For this purpose, after each training session, non-faces incorrectly detected as faces are placed in the training set for the next session. This "bootstrap" method overcomes the problem of using a huge set of non-face images in the training set, many of which may not influence the training [43]. To test the image for faces, possible face regions detected by another technique (say, colour segmentation) will only be tested to avoid exhaustive scanning. We wish to determine among the infinite such points in an N-dimensional space which of two classes of such points a given point belongs to. If the two classes are linearly separable, we need to determine a hyper-plane that separates these two classes in space. However, if the classes are not clearly separable, then our objective would be to minimize the smallest generalization error. Intuitively, a good choice is the hyper-plane that leaves the maximum margin between the two classes (margin being defined as the sum of the distances of the hyper-plane from the closest points of the two classes), and minimizes the misclassification errors. The same data used to train a neural network can be trained here. The learning time for SVM algorithms are significantly smaller than that for the neural network. Back propagation of a neural network takes more time than the required training time of a SVM training period. [7]

2.2 Face Recognition algorithms overview

As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years. At least two reasons account for this trend: the first is the wide range of commercial and law enforcement applications, and the second is the availability of feasible technologies after 30 years of research. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system. The problem is so complicated that the achievement in the field of automatic face recognition by computer is not as satisfied as the finger prints. Facial feature extraction has become an important issue in automatic recognition of human faces [51].

Evolution of face recognition research

The subject of face recognition is as old as computer vision, both because of the practical importance of the topic and theoretical interest from cognitive scientists. Despite the fact that other methods of identification (such as fingerprints, or iris scans) can be more accurate, face recognition has always remains a major focus of research because of its non-invasive nature and because it is people's primary method of person identification. Perhaps the most famous early example of a face recognition system is due to Kohonen who demonstrated that a simple neural net could perform face recognition for aligned and normalized face images. The type of network he employed computed a face description by approximating the eigenvectors of the face image's autocorrelation matrix; these eigenvectors are now known as `eigenfaces.' Kohonen's system was not a practical success, however, because of the need for precise alignment and normalization. In following years many researchers tried face recognition schemes based on edges, inter-feature distances, and other neural net approaches. While several were successful on small databases of aligned images, none successfully addressed the more realistic problem of large databases where the location and scale of the face is unknown [27].

Kirby and Sirovich (1989) later introduced an algebraic manipulation which made it easy to directly calculate the eigenfaces, and showed that fewer than 100 were required to accurately code carefully aligned and normalized face images. Turk and Pentland (1991) then demonstrated that the residual error when coding using the eigenfaces could be used both to detect faces in cluttered natural imagery, and to determine the precise location and scale of faces in an image. They then demonstrated that by coupling this method for detecting and localizing faces with the eigenface recognition method, one could achieve reliable, real-time recognition of faces in a minimally constrained environment. This demonstration that simple, real-time pattern recognition techniques could be combined to create a useful system sparked an explosion of interest in the topic of face recognition [45] [25].

Categorization of Face Recognition Techniques [50]

1. Holistic methods which can be divided into
    1.1 Principal-component analysis (PCA)
        a. Eigenfaces

b. Probabilistic eigenfaces

c. Fisherfaces/subspace LDA

d. Support vector machine SVM

e. Evolution pursuit

f. Feature lines

g. Independent Component Analysis ICA

1.2 Other representations

a. Linera Discreminant Analysis LDA/FLD

b. PDBNN

2. Feature-based methods

2.1 Pure geometry methods

2.2 Dynamic link architecture

2.3 Hidden Markov model

2.4 Convolution Neural Network

3 Hybrid methods

3.1 Modular eigenfaces

3.2 Hybrid LFA

3.3 Shape-normalized

3.4 Component-based

2.2.1 Holistic methods

2.2.1.1 Principal Component Analysis.

Starting from the successful low dimensional reconstruction of faces using KL or PCA projections, eigen pictures have been one of the major driving forces behind face representation, detection, and recognition. It is well known that there exist significant statistical redundancies in natural images. For a limited class of objects such as face images that are normalized with respect to scale, translation, and rotation, the redundancy is even greater. One of the best global compact representations is

KL/PCA, which decorrelates the outputs. More specifically, sample vectors x can be expressed as linear combinations of the orthogonal basis an advantage of using such representations is their reduced sensitivity to noise. Some of this noise may be due to small occlusions, as long as the topological structure does not change. For example, good performance under blurring, partial occlusion and changes in background has been demonstrated in many Eigen picture based systems, This should not come as a surprise, since the PCA reconstructed images are much better than the original distorted images in terms of their global appearance. For better approximation of face images outside the training set, using an extended training set that adds mirror-imaged faces was shown to achieve lower approximation error. Using such an extended training set, the eigenpictures are either symmetric or antisymmetric, with the most leading eigenpictures typically being symmetric. [32]

2.2.2 Feature-based methods

Many methods in the structural matching category have been proposed, including many early methods based on geometry of local features as well as 1D and pseudo-2D HMM methods. One of the most successful of these systems is the Elastic Bunch Graph Matching (EBGM) system, which is based on DLA. Wavelets, especially Gabor wavelets, play a building block role for facial representation in these graph matching methods. A typical local feature representation consists of wavelet coefficients for different scales and rotations based on fixed wavelet bases. These locally estimated wavelet coefficients are robust to illumination change, translation, distortion, rotation, and scaling. DLAs attempt to solve some of the conceptual problems of conventional artificial neural networks, the most prominent of these being the representation of syntactical relationships in neural networks. DLAs use synaptic plasticity and are able to form sets of neurons grouped into structured graphs while maintaining the advantages of neural systems. Both Buhmann et al. and Lades et al. used Gabor-based wavelets as the features. Recognition of a new image takes place by transforming the image into the grid of jets, and matching all stored model graphs to the image. Conformation of the DLA is done by establishing and dynamically modifying links between vertices in the model domain. Of jets (called the bunch graph representation), each derived from a different face image. To handle the pose variation problem, the pose of the face is first determined using prior class information, and the “jet” transformations under pose variation are learned [Maurer and Malsburg 1996a]. Systems based on the EBGM approach have been applied to face detection and extraction, pose estimation, gender classification, sketch-image-based recognition, and general object recognition. The success of the EBGM system may be due to its resemblance to the human visual system [32].

2.2.3 Hybrid methods

Use both holistic and local features. For example, the modular eigenfaces approach uses both global eigenfaces and local eigenfeatures. In Pentland et al. [1994], the capabilities of the earlier system were extended in several directions. In mugshot applications, usually a frontal and a side view of a person are available; in some other applications, more than two views may be appropriate. One can take two approaches to handling images from multiple views. The first approach pools all the images and constructs a set of eigenfaces that represent all the images from all the views. The other approach uses separate eigenspaces for different views, so that the collection of images taken from each view has its own eigenspace. The second approach, known as view-based eigenspaces, performs better. The concept of eigenfaces can be extended to eigenfeatures, such as eigeneyes, eigenmouth, etc. Using a limited set of images (45 persons, two views per person, with different facial expressions such as neutral vs. smiling), recognition performance as a function of the number of eigenvectors was measured for eigenfaces only and for the combined representation. For lower-order spaces, the eigenfeatures performed better than the eigenfaces; when the combined set was used, only marginal improvement was obtained. These experiments support the claim that feature-based mechanisms may be useful when gross variations are present in the input images. It has been argued that practical systems should use a hybrid of PCA and LFA [45].

2.3 Face recognition and face authentication

Recognition in one-to-many searches seeks to identify an unknown individual based on comparison to a database of known individuals (e.g., law enforcement, surveillance, and recently driver licenses). Authentication involves performing verification based on a one-to-one search to validate the identity claim of the individual as in ATM terminal. Authentication is in one sense a simpler process: comparisons are made only to the claimed identity, and a threshold of similarity is used to accept or reject the claim. In another sense, authentication is more difficult, because of the need to determine this threshold rather than using a "best match" criterion as in many face recognition applications. [7]

Interest in authentication using biometrics is therefore growing dramatically. Biometric access control uses measurable physiological or behavioral traits to automatically authenticate a person's identity. Biometric characteristics must be distinctive of an individual, easily acquired and measured, and comparable for purposes of security validation. The characteristic should change little over time (i.e., with age or voluntary change in appearance) and be difficult to change, circumvent, manipulate, or reproduce by other means. Typically, high-level computer based algorithms and database systems analyze the acquired biometric features and compare them to features known or enrolled in the database [22].

Chapter 3

Face Detection Based in Maximal Rejection Classifier

In recent years, there is an increasing trend of using biometrics information, which refers the human biological features used for user authentication, such as fingerprint, iris, and face, to strengthen the security measure of different electronic systems, including smart card systems. Compared to the digit Personal Identification Number (PIN), the critical data stored in the card can be protected more securely by using the biometric information. Furthermore, cardholder's fingerprint or iris pattern cannot be stolen or forgotten. Smart cards can play an important role in biometrics, too. For instance, in an identification system, the biometrics templates are often stored in a central database. With the central storage of a biometrics, there is an open issue of misuse of the same for purposes that the owner of the biometrics may not be aware of. We can decentralize the database storage part into millions of smart cards and give it to the owners [23].

The Detection Algorithm steps

The Following figure 3.1 shows the algorithm step for face detection.

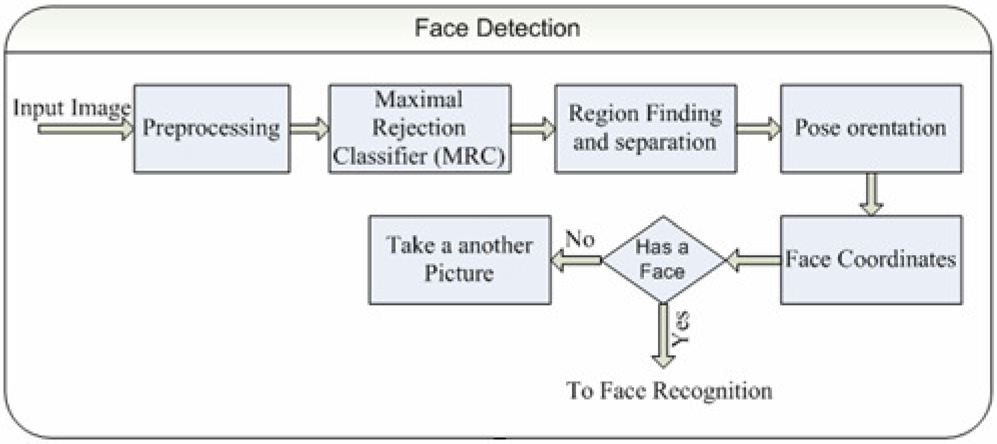


Figure 3.1 Face Detection algorithms

3.1 Preprocessing

3.1.1 Noise Removal

Some noises make the Image take a lot of time because every pixels in the image should be scanned and the noise in some pixels take time to scanned by the system (it might be a possible place for a face).Median filtering is a nonlinear operation often used in image processing to reduce noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges because of that we applying the median filter for the input image to remove these noises from the Image.

After that we need to handle the lighting condition for the Image it might be taken in the night and the light for the ATM machine is low than the expected so the image become darker. We need some enhances for the contrast of images and this is well be solved if we apply the histogram equalization to the Image.

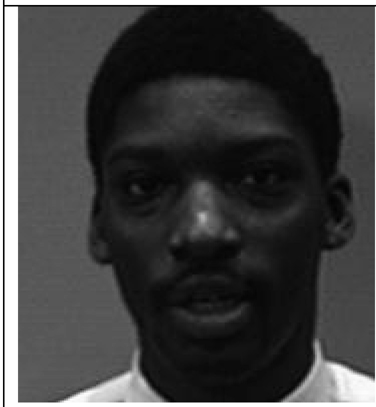
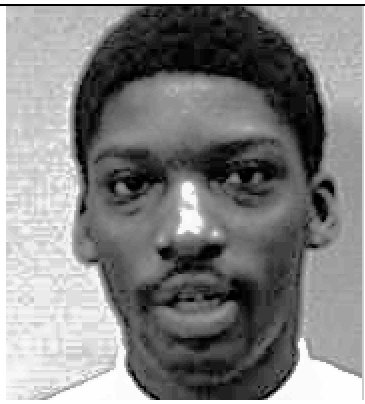
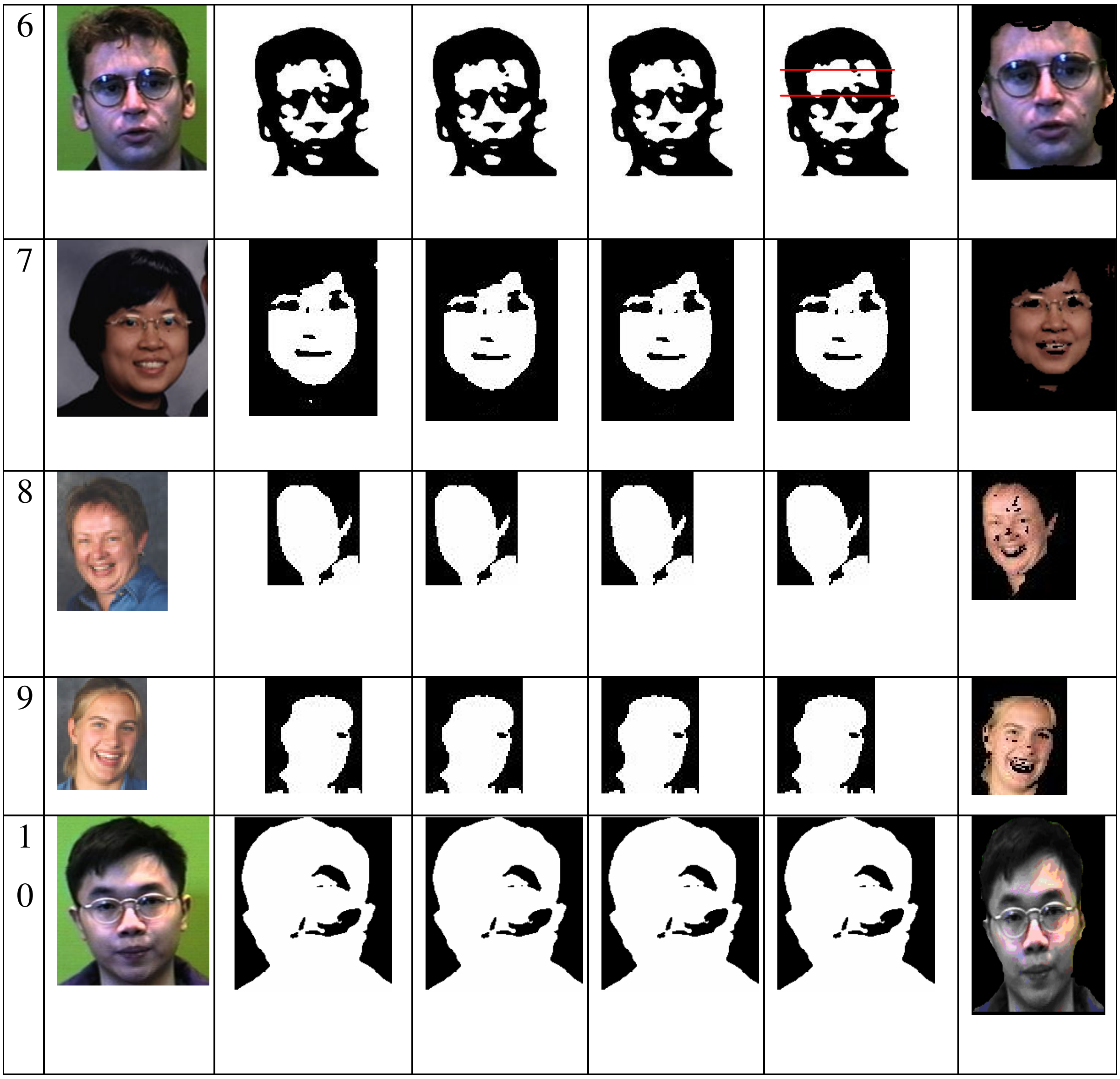
Image Before Histogram Equalization	Image After Histogram Equalization
	

Figure 3.2 Histogram Equalization

As we can see in the above figure 3.2 the input image is too dark, features like the eyes and skin are not clear after applying the Histogram Equalization the image and feature in it are clearer.

The Following Figure 3.3 shows some example of tested Images.



Figures 3.3 test images used in detection system.

3.1.2 Color Based mask Generation

Detection of skin color in color images is a very popular and useful technique for face detection. Many techniques have reported for locating skin color regions in the input image. While the input color image is typically in the RGB format, these techniques usually use color components in the color space, such as the HSV or YIQ formats. That is because RGB components are subject to the lighting conditions thus the face detection may fail if the lighting condition changes.

3.1.2.1 Skin-color models

In order to segment human skin regions from non-skin regions based on color, we need a reliable skin color model that is adaptable to people of different skin colors and to different lighting conditions [20]. To determine the color distribution of human skin in chromatic color space we need a large image samples that are taken from persons of different ethnicities: Asian, Caucasian and African. As the skin samples were extracted from color images, as much we add more images to skin model we will get the exact threshold for skin segmentation. The previous Figures 3.3 are from sample of 10 person Images are taken from different kind of people just to test the system on them (to get the a sample threshod). Figure 3.4 shows the color distribution of these skin samples in the chromatic color space.

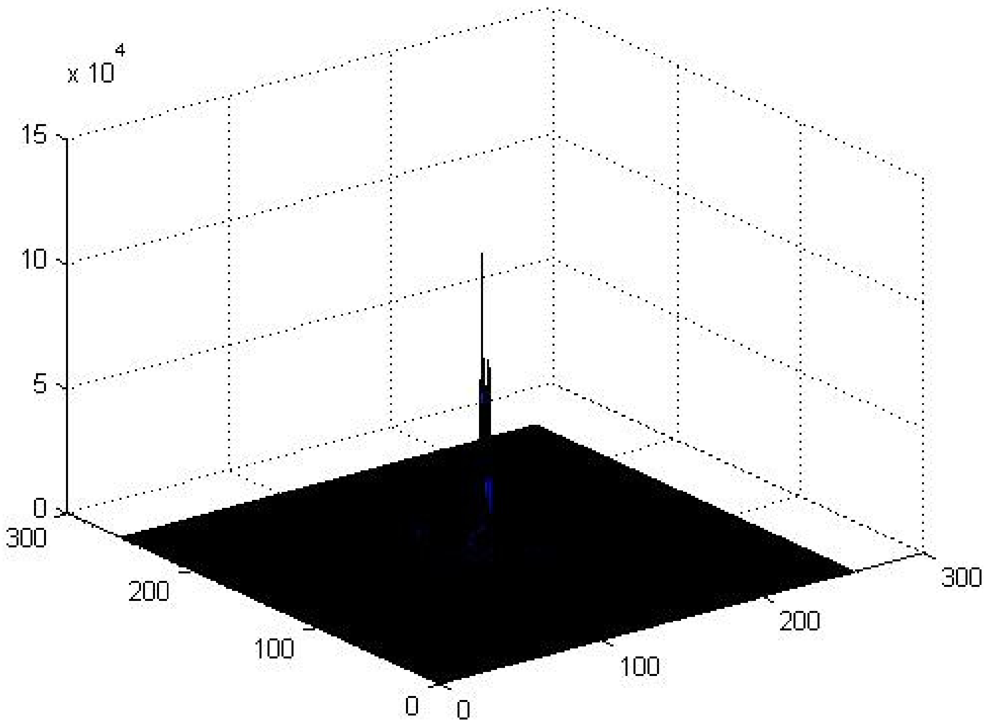


Figure 3.4 Color distribution for skin-color of different people

The color histogram revealed that the distributions of skin-color of different people are clustered in the chromatic color space and a skin color distribution can be represented by a Gaussian model Figure 3.5 shows the Gaussian Distribution N (m, C) fitted by our data.

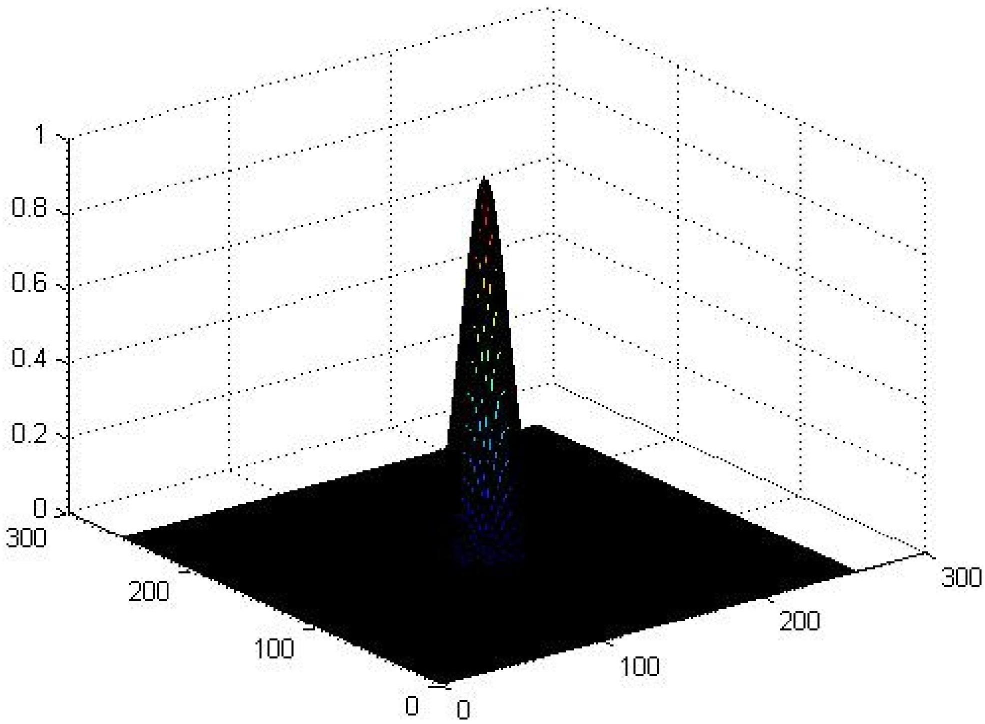


Figure 3.5 Fitting skin color into a Gaussian Distribution

With this Gaussian fitted skin color model, we can now obtain the likelihood of skin for any pixel of an image. Therefore, if a pixel, having transform from RGB color space to chromatic color space, has a chromatic pair value of (r,b) , this skin color model can transform a color image into a gray scale image such that the gray value at each pixel shows the likelihood of the pixel belonging to the skin. With appropriate thresholding, the gray scale images can then be further transformed to a binary image showing skin regions and non-skin regions. This process of transforming a color image to a skin-likelihood image and then to a skin-segmented image is detailed in the next section. [21]

3.1.2.2 Skin Segmentation

Beginning with a color image, the first stage is to transform it to a skin-likelihood image. This involves transforming every pixel from RGB representation to chroma representation and determining the likelihood value. The skin-likelihood image will be a gray-scale image whose gray values represent the likelihood of the pixel belonging to skin. A sample color image and its resulting skin-likelihood image are shown in Figure 3.7 All skin regions (like the face, the hands and the arms) were shown brighter than the non-skin region.

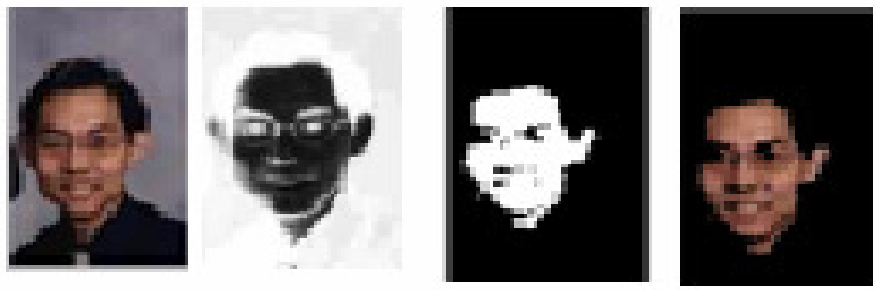


Figure 3.6 Input, skin-likehood, binary and final images.

However, it is important to note that the detected regions may not necessarily correspond to skin. It is only reliable to conclude that the detected region has the same color as that of the skin. The important point here is that this process can reliably point out regions that do not have the color of the skin and such regions would not need to be considered anymore in the face finding process. Since the skin regions are darker than the other parts of the images, the skin regions can be segmented from the rest of the image through a thresholding process. To process different images of different people with different skin, a fixed threshold value is not possible to be found. Since people with different skins have different likelihood, an adaptive thresholding process is required to achieve the optimal threshold value for each run. [21]

The adaptive thresholding is based on the observation that stepping the threshold value down may intuitively increase the segmented region.

However, the increase in segmented region will gradually decrease (as percentage of skin regions detected approaches 100%), but will increase sharply when the threshold value is considerably too small that other non-skin regions get included. The threshold value at which the minimum increase in region size is observed while stepping down the threshold value will be the optimal threshold. In our thesis, the threshold value is decremented from 0.65 to 0.05 in steps of 0.1. If the minimum increase occurs when the threshold value was changed from 0.45 to 0.35, then the optimal threshold will be taken as 0.4. Using this technique of adaptive thresholding, many images yield good results; the skin-colored regions are effectively segmented from the non-skin colored regions. The skin segmented image of previous color image resulting from this technique shown in Figure 3.7 We present some more results using this skin detection technique in figure 3.3.

Figure 3.7 skin segment

It is clear from the results from figure 3.3 that not all detected skin regions contain faces. Some correspond to the hands and arms and other exposed part of the body, while some corresponds to objects with colors similar to those of the skin see example number 5 from figure 3.3. Note: To reduce the effect of noise in an image is useful to use a filter that can remove small noises; we use median filter again to remove small noises. See figure 3.3 example number 3.

3.1.2.3 Skin-Segmented Image

The second step is creating a skin-segmented image by using a threshold value of probability. If the probability of a pixel in skin-likehood image is more or equal to estimated threshold value, we suppose that this pixel represents skin color. If not, we suppose that this pixel does not represent skin color. The skin color pixels are white and the other ones are black in skin-segmented image. Estimating a threshold value is very important for next steps of image processing. We can use fixed threshold value for every image or adaptive thresholding. The adaptive thresholding is based on the observation that decreasing the threshold value may intuitively increase the segmented region. However, the increase in segmented region will gradually decrease, but will increase sharply when the threshold value is too small that other non-skin regions get included. The threshold value at which the minimum increase in region size is observed while decreasing the threshold value will be the optimal threshold. [12]

Applying Median Filter

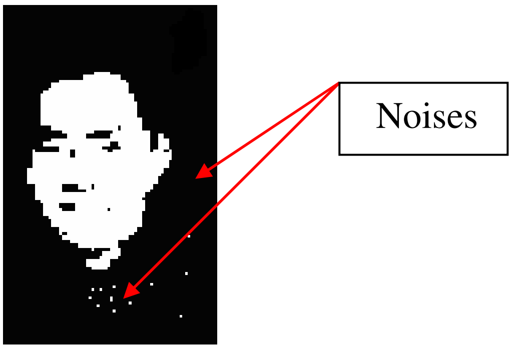


Figure 3.8 image with noises

As we can see in figure 3.8 there are some noises in the Image which could effect the detection of the face. After Applying the Median Filter the noises will be removed see figure 3.9

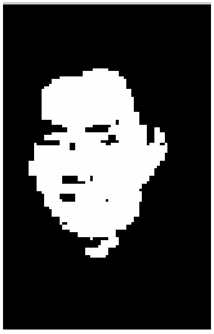


Figure 3.9 noise free

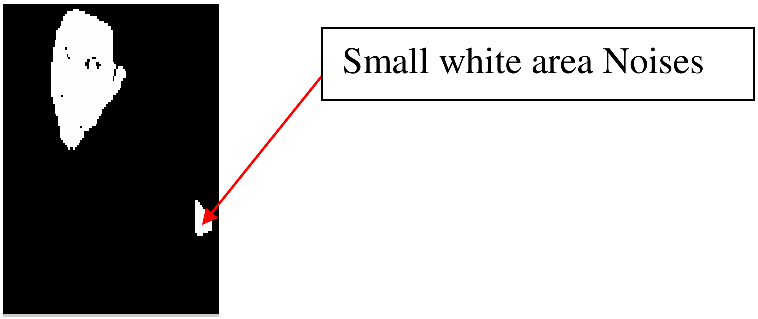


Figure 3.10 image with two areas

If we take the Example Number 4 in figure 3.3 after applying the median Filter the Image will be as showing in figure 3.10 there is still a small white area not removed by the Median filter; This white area could effect the detection system by give false detection; So By Using the MRC We will reject these white areas and make the detection system work better and give more accurate result.

3.2 Maximal Rejection Classifier (MRC)

3.2.1 Theory-Training:

We are given two sets; the non-face image set {Yk} and the face image set {Xk}. The non-face image set is assumed to be much larger than the face set. The images are assumed to be gray-value images. The images can be projected onto a one-dimensional line by a kernel θ, which is easily found from the image set statistics The projection of the face set will occupy a certain range d1 and d2 on the line, while the projection of the non-face set will occupy another range (hopefully much larger). The goal of this projection is to minimize the number of non-face images projected onto the [d1, d2] range. This eliminates as many non-face images as possible while keeping all the face images. The remaining images (complete face set and non-face images that weren't rejected) are then used to find another θ to project onto, where a new [d1, d2] is found to reject as many non-faces as possible. The iterations are repeated and more θ's are found until practically all of the non-face images have been eliminated.

The calculation of θ is very simple and only requires finding the mean (Mx and My) and covariance matrices (Rx and Ry) of each image set:

$$M_x = \frac{1}{Nx} \sum_{i=1}^{Nx} Xk$$

$$My = \frac{1}{Ny} \sum_{t=1}^{Ny} yk$$

$$Rx = \frac{1}{Nx} \sum_{t=1}^{Nx} (Xk - Mx)(Xk - Mx)t$$

$$Ry = \frac{1}{Ny} \sum_{t=1}^{Ny} (Yk - Mx)(Yk - Mx)t$$

The Objective Function can be written as:

$$F\{\theta\} = \frac{\theta t\{[Mx - My][Mx - My]t + Rx + Ry\}\theta}{\theta t\ Rx\theta}$$

The goal is to maximize the above function, which has the effect of maximizing the distance between the PDFs of the face set and non-face set. Taking the derivative of the objective function and setting to zero we find:

$$[M_x - M_y][M_x - M_y]^T + Rx + Ry\}\theta = \lambda Rx\theta$$

This equation is of the form $R\theta = \lambda Q\theta$, which is a generalized eigenvalue problem. Θ is then the eigenvector that corresponds to the largest eigenvalue.

3.2.2 Theory-Detecting Faces:

Once an adequate number of θ's and their corresponding [d1, d2] ranges have been found (for our algorithm we acquired 10 θ's), we apply the kernels to a test image to find faces. The basic idea is to go through the image taking consecutive blocks of a certain size (same as all the data set images). The first θ is applied to he block, and we check if the projection falls within the specified [d1, d2] range. If it does, then we apply the second θ and check if the projection falls within the corresponding [d1, d2]. As long as the block keeps satisfying the [d1, d2] range for each kernel, we apply the next θ. If we run through all the kernels and the 9 block satisfies every one, the block is classified as a face. If for any θ the block falls outside the "face" range, the block is discarded and classified as non-face. This is done for every block in the image. The key here is that we must work with multiple resolutions of the image. Since the training data is of a certain size 15x15, it is geared to find faces that are of the same size. In a given image, the faces could be of all different sizes, so faces will be found on different resolutions of the input image. [35]

3.2.3 Integration of MRC and Color Segmentation/Region Finding:

We use color segmentation/region finding (from now on referred to as just color segmentation) to segment the input image into different blocks; the color segmentation algorithm "claims" each selected block as having one face. We then take each of these selected blocks and perform MRC to determine if there really is a face in the block or maybe it's just a flesh-colored orange. The MRC works with the block in five different resolutions to find a face; once it finds a face in the block at a certain resolution, it stops and labels the block as a face. The benefits of integrating MRC and color segmentation are numerous. Doing color segmentation then MRC saves time because the MRC algorithm no longer has to go through every successive block in the input image. Instead it only has to go through the 2 or so blocks (as there is only one face in the entire Image) identified by the color segmentation. Another advantage is that MRC can get rid of false detections from the color segmenting. A flesh colored shirt that is segmented looks nothing like a face to MRC and is eliminated. We don't have to worry about MRC false detections since the color segmenting gets rid of so much of the input image, decreasing the chances of a false detection (that would have occurred if MRC had to traverse the entire image). Yet another benefit is that now we don't have to worry about finding the same face at multiple resolutions. We know that there's either one face or no faces in the selected block. So once we find a face, there's no need to continue processing at lower resolutions, so we fined the Face. The input blocks into the MRC algorithm never contained more than one [35].

The only real problem with this integration is that sometimes there really is a face in the block that color segmentation identifies, but MRC fails to find it. This often occurs if the face is partially obstructed or severely rotated.

3.3 Region Finding and separation:

3.3.1 Selection of face regions

As my detection system need to detect only one face in the image, the face we are looking for is a closed white (skin) region that has one or more black (not-skin) regions inside it see figure 3.11.

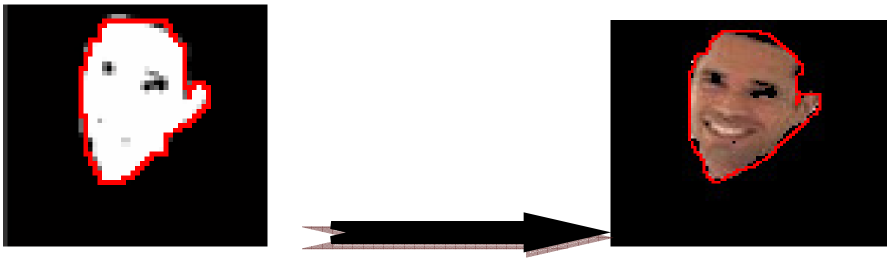


Figure 3.11 select of face region

3.3.2 Region Separation

Make a copy of the selected region and move it to the next process but as we see in figure 3.12 the face is not in front its has the Pose problem which the next section will fixit.

3.4 Pose Orientation

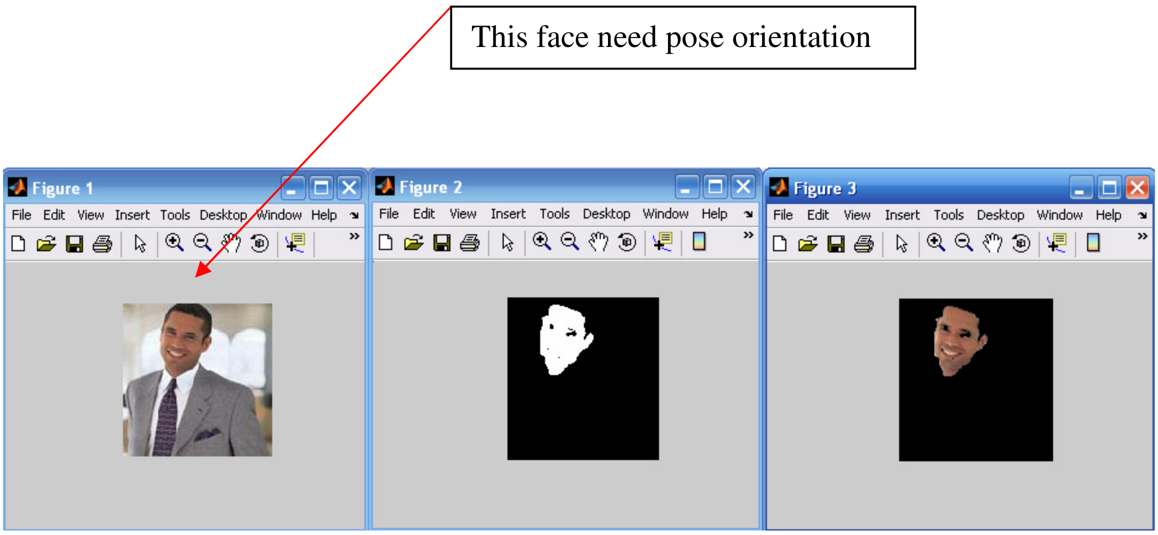
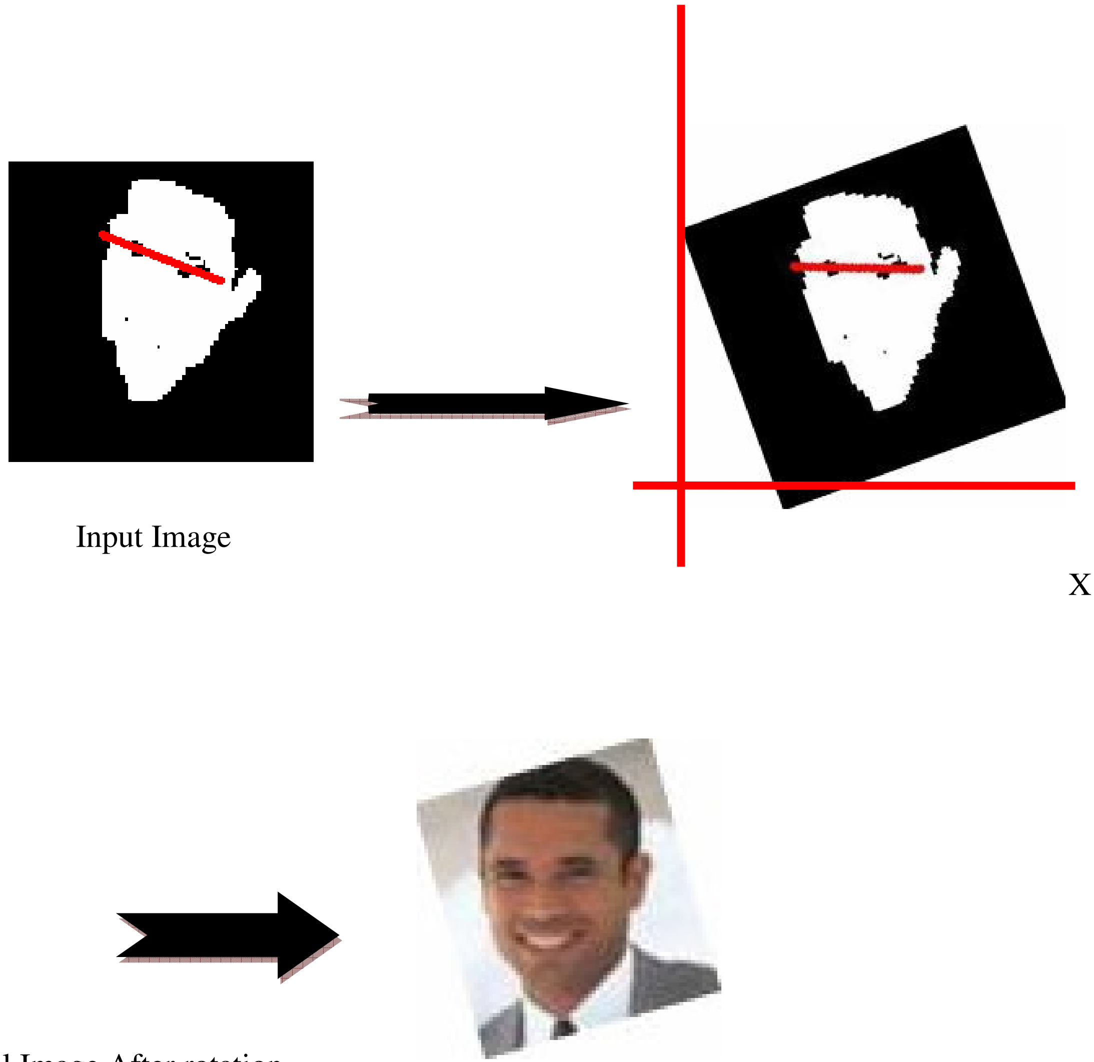


Figure 3.12 face with pose Problem

We present new method to solve pose problem based on eye extraction. The main Idea of the proposed method is to extract the eyes from the face image this can be done in too many ways like the color segmentation method proposed in this thesis or the eigenvector based method as it might give more accurate result. After we know the place of the eyes see figure 3.13 they appears like a black hole we connect these two holes with a red line and rotate the entire image until the red line become Parallel with x axis's (left rotation) as shown in figure 3.13 which shows the steps for the proposed method



Input Image

X axes

Final Image After rotation

Figure 3.13 Pose orientation steps

3.5 Face Coordinates

After Finishing the Entire Detection Procedure we will take the face coordinate to next system to make the Authentication for that face if the detection procedure could not find any face it will force the system to take another picture for the person.

Face Regeneration

Face regeneration is new presented method used to recover a face if some part of it is missing, this new method will generate the missing part from the existing one depend on the other half of the face as if we look at the following figure image 3.14.

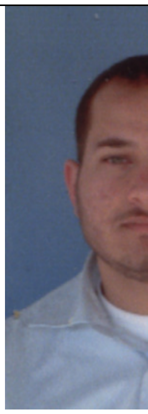
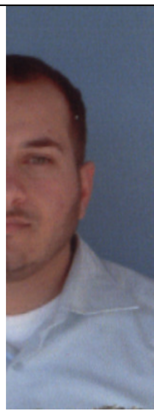
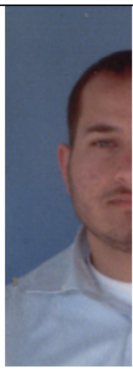
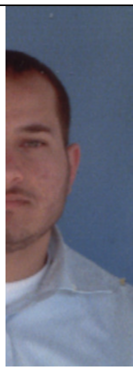
		
Original face	Left side of face	Right side of face

Figure 3.14 Face analysis

we see that the left side of the face is almost like the right side with few little differences that does not make the person look different. The main Idea of face regeneration is to recover half of the face from the other one

Original face	Original Left side	Generated Right side	Generated Face
			
			

Figures 3.15 Shows the Result of face regeneration method

If we look closely at the original and generated face they almost the same with little difference.

We wrote a small program that can generate the right side of face from the left side, look to the following figures 3.15 to see the result of it.

Finally the face regeneration method has many limitation it depends on many characteristics like the pose of the face (it's a very important issue) because the generated face will have more differences, the part that should be recovered from the Image and it need at least the half of the face to generate the other half (the partitioning should be vertical not horizontal).

3.6 Conclusions and discussion

In our face detection system we use the color segmentation algorithm and the MRC algorithms because they simplicity and they respond, it takes a second or less, The general MRC use template matching process to give more accurate result and because usually they use it when there are more than one face in the image, we remove this process because we only suppose to have one face only in the image, this will speed up the overall process, but this may make some detection of a faces goes wrong like producing two white holes, which mean that it has two faces we solve this problem by moving the two possible faces to the authentication system. If the pose process fails to do its job we ignore it and complete the remaining system process. However the face detection system gives very good result as shown in table 3.1 this table based on 10 test images

Table 3.1 Show the result of face detection system

Image #	Possible Face detected	Frontal face	Time (sec)
1	1	N	Less than 1
2	1	Y	Less than 1
3	1	Y	Less than 1
4	1	N	Less than 1
5	1	Y	Less than 1
6	1	Y	Less than 1
7	1	U	Less than 1
8	2	U	Less than 1
9	1	U	Less than 1
10	1	U	Less than 1

Y: Yes the face is frontal

N: No the face is not frontal

U: Unknown

Almost all the faces are found (9/10) and one give two possible faces for detection if so we will move both of them to the recognition system and if one of them are match the training set images we will accepted (this will help also if there is some one behind the person how make the transaction). But not all have pose orientation because we cannot extract the eyes from the images (6/10).

Chapter 4

Face Recognition using Principle Component Analysis

As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years. At least two reasons account for this trend: the first is the wide range of commercial and law enforcement applications, and the second is the availability of feasible technologies after 30 years of research. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system [23].

Though people are good at face identification, recognizing human face automatically by computer is not that easy. Face recognition has been widely applied in security system, credit-card verification, and criminal identifications, teleconference and so on. Face recognition is influenced by many complications, such as the differences of facial expression, the light Directions of imaging, and the variety of posture, size and angle. Even to the same people, the images taken in different surroundings may be unlike. Detecting the basic feature as eyes, nose and mouth exactly is necessary for most face recognition methods. Face Recognition is a high dimensional pattern recognition problem. Even low-resolution face images generate huge dimensional feature spaces (20,000 dimensions in the case of a 100x200 pixels face image). In addition to the problems of large computational complexity and memory storage, this high dimensionality makes very difficult to obtain statistical models of the input space using well-defined parametric models. Moreover, this last aspect is further stressed given the fact that only few samples for each class are normally available for the system training. However, the intrinsic dimensionality of the face space is much lower than the dimensionality of the image space, since faces are similar in appearance and contain significant statistical regularities. This fact is the starting point of the use of eigenspace-based methods for reducing the dimensionality of the input face space [11].

The recognition algorithm steps

Our face detection system is based on the standard PCA algorithm. As the system needs to compare two images with each other, and check if they belong to the same person or not this limitation makes the recognition system simpler than to compare the image with all the database images like other recognition system did. See figure 4.1 for the face system steps.

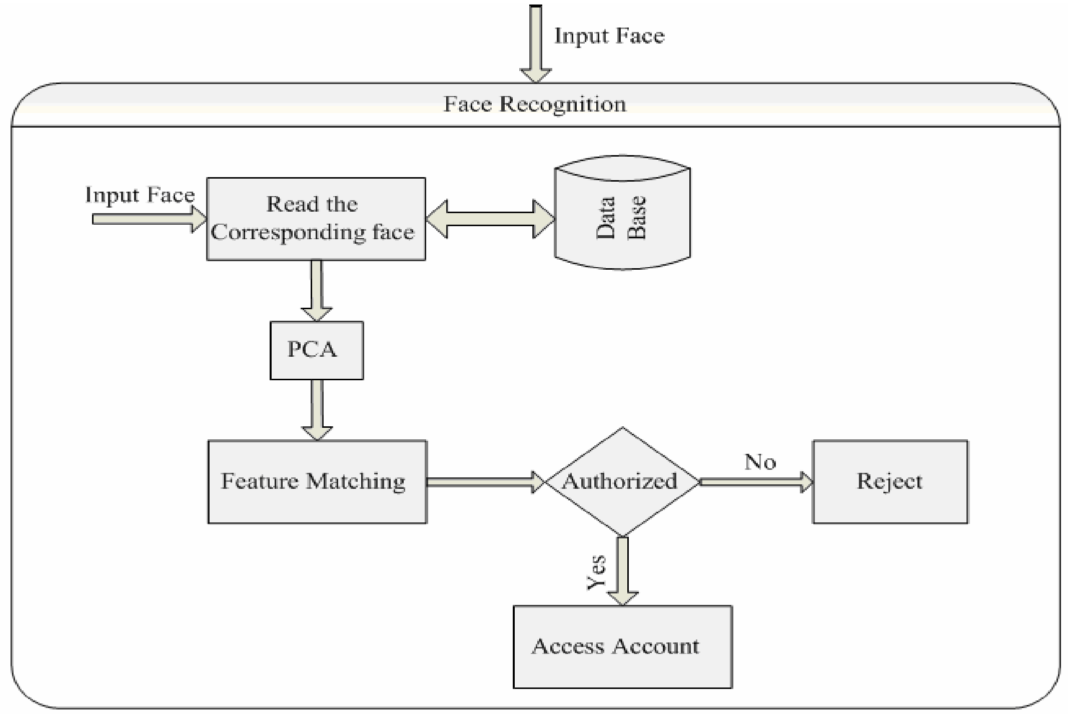


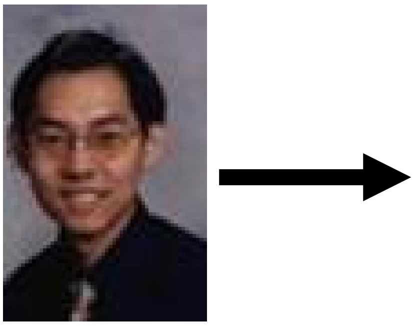
Figure 4.1 Face recognition Algorithm steps

4.1 Read from Database

In this process we should read the desired image face from the database as the customer enters his key and bring his or her picture from the database to begin the recognition system on it, to improve our system we add more than one image and compare them with the captured image to give more accurate result.

Initialization

In the initialization process we need to convert the input face and the training faces to matrixes, the first matrix for the input image (face) and the second one for the training images that ware fetch's from the database. See figure 4.2



129	129	129	130	131	131	132	132	….
130	130	130	130	130	131	131	131	
130	130	130	129	129	129	129	129	
129	129	128	128	127	126	126	126	
128	127	127	126	126	125	125	124	
127	127	127	127	127	126	126	126	
129	129	129	130	130	130	130	130	
131	131	131	132	133	133	134	134	
134	134	133	132	132	132	133	133	
134	133	133	133	132	133	133	133	
133	133	133	133	133	133	133	133	
							.	
							.	
							.	

Figure 4.2 convert the input image to a matrix

As we always covert the image to a matrix and then compute the mean and calculating the eigenvector each time for the stored images, we can make these operation and store it in to the database instead of store it as image, if we do so we do not need to make the calculation each time the customer use the ATM machine, this will reduce the time for the authentication.

4.2 Principle Component Analysis (PCA)

In the language of information theory, the objective is to extract the relevant information in a face image, encode it as efficiently as possible, and compare one face encoding with a database of models encoded in the same way. A simple approach to extract the information contained in a face image is to somehow capture the variation in a collection of face images, independent of any judgment of features, and use this information to encode and compare individual face images. In mathematical terms, the objective is to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. These eigenvectors can be thought of as a set of features which together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as a sort of ghostly face called an eigenface. Each face image in the training set can be represented exactly in terms of a linear combination of the eigenfaces. The number of possible eigenfaces is equal to the number of face images in the training set . However, the faces can also be approximated using only the "best" eigenfaces those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images. The primary reason for using fewer eigenfaces is computational efficiency. The most meaningful M eigenfaces span an M-dimensional subspace "face space" of all possible images. The eigenfaces are essentially the basis vectors of the eigenface decomposition [45].

The idea of using eigenfaces was motivated by a technique for efficiently representing pictures of faces using principal component analysis.

The eigenfaces approach for face recognition involves the following initialization operations:

1. Acquire a set of training images.
2. Calculate the eigenfaces from the training set, keeping only the best M images with the highest eigenvalues. These M images define the "face space". As new faces are experienced, the eigenfaces can be updated.
3. Calculate the corresponding distribution in M-dimensional weight space for each known individual (training image), by projecting their face images onto the face space.

Having initialized the system, the following steps are used to recognize new face images:

1. Given an image to be recognized, calculate a set of weights of the *M* eigenfaces by projecting the it onto each of the eigenfaces.
2. Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.
3. If it is a face, classify the weight pattern as either a known person or as unknown.
4. (Optional) Update the eigenfaces and/or weight patterns.
5. (Optional) Calculate the characteristic weight pattern of the new face image, and incorporate into the known faces.

Calculating Eigenfaces

Let a face image Γ(x,y) be a two-dimensional *N* by *N* array of intensity values. An image may also be considered as a vector of dimension N^2, so that a typical image of size 256 by 256 becomes a vector of dimension 65,536, or equivalently, a point in 65,536-dimensional space. An ensemble of images, then, maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principal component analysis is to find the vector that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each vector is of length N^2, describes an *N* by *N* image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, they are referred to as "eigenfaces". [11] [20] [22]

Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$. The average face of the set if defined by $\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$. Each face differs from the average by the vector $\Phi_n = \Gamma_n - \Psi$. This set of very large vectors is then subject to principal component analysis, which seeks a set of *M* orthonormal vectors, μ_n, which best describes the distribution of the data. The *k*th vector, μ_k is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(\mu_k^T \Phi_n)^2 \qquad (1)$$

is a maximum, subject to

$$\mu_l^T \mu_k = \begin{cases} 1, l = k \\ 0, otherwise \end{cases} \qquad (2)$$

The vectors μ_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi_n^T = AA^T \qquad (3)$$

where the matrix $A = [\Phi_1 \Phi_2 ... \Phi_M]$. The matrix *C*, however, is N^2 by N^2, and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. A computationally feasible method is needed to find these eigenvectors.

If the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only $M - 1$, rather than N^2, meaningful eigenvectors (the remaining eigenvectors will have associated eigenvalues of zero). Fortunately, we can solve for the N^2-dimensional eigenvectors in this case by first solving for the eigenvectors of and *M* by *M* matrix—e.g., solving a 16 x 16 matrix rather than a 16,384 x 16,384 matrix—and then taking appropriate linear combinations of the face images Φ_n. Consider the eigenvectors v_n of $A^T A$ such that

$$A^T A v_n = \lambda_n v_n \qquad (4)$$

Premultiplying both sides by *A*, we have

$$AA^T A\nu_n = \lambda_n A\nu_n \qquad (5)$$

from which we see that $A\nu_n$ are the eigenvectors of $C = AA^T$.

Following this analysis, we construct the *M* by *M* matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$, and find the *M* eigenvectors ν_n of *L*. These vectors determine linear combinations of the *M* training set face images to form the eigenfaces μ_n:

$$\mu_n = \sum_{k=1}^{M} \nu_{nk}\Phi_k = A\nu_n, n = 1,......, M \qquad (6)$$

With this analysis the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (*M*). In practice, the training set of face images will be relatively small ($M < N^2$), and the calculations become quite manageable. The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizeing the variation among the images [45].

4.3 Feature matching

The eigenface images calculated from the eigenvectors of *L* span a basis set with which to describe face images. As mentioned before, the usefulness of eigenvectors varies according their associated eigenvalues. This suggests we pick up only the most meaningful eigenvectors and ignore the rest, in other words, the number of basic functions is further reduced from *M* to *M'* (*M'*<*M*) and the computation is reduced as a consequence.

In practice, a smaller *M'* is sufficient for identification, since accurate reconstruction of the image is not a requirement. In this framework, identification becomes a pattern recognition task. The eigenfaces span an

M' dimensional subspace of the original N^2 image space. The *M'* most significant eigenvectors of the *L* matrix are chosen as those with the largest associated eigenvalues.

A new face image Γ is transformed into its eigenface components (projected onto "face space") by a simple operation

$$\omega_n = \mu_n(\Gamma - \Psi) \qquad (7)$$

for *n*=1,……,*M'*. This describes a set of point-by-point image maltiplications and summations.

The weights form a vector $\Omega^T = [\omega_1, \omega_2, ..., \omega_{M'}]$ that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The vector may then be used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The simplest method for determining which face class provides the best description of an input face image is to find the face class *k* that minimizes the Euclidian distance

$$\varepsilon_k^2 = \left\| (\Omega - \Omega_k)^2 \right\| \qquad (8)$$

where Ω_k is a vector describing the *k*th face class. The face classes Ω_k are calculated by averaging the results of the eigenface representation over a small number of face images (as few as one) of each individual. A face is classified as "unknown", and optionally used to create a new face class. Because creating the vector of weights is equivalent to projecting the original face image onto to low-dimensional face space, many images (most of them looking nothing like a face) will project onto a given pattern vector. This is not a problem for the system, however, since the distance ε between the image and the face space is simply the squared distance between the mean-adjusted input image $\Phi = \Gamma - \Psi$ and $\Phi_f = \sum_{i=1}^{M'} \omega_i \mu_i$, its projection onto face space:

$$\varepsilon^2 = \left\| \Phi - \Phi_f \right\|^2 \qquad (9)$$

Thus there are four possibilities for an input image and its pattern vector: (1) near face space and near a face class; (2) near face space but not near a known face class; (3) distant from face space and near a face class; (4) distant from face space and not near a known face class.

In the first case, an individual is recognized and identified. In the second case, an unknown individual is present. The last two cases indicate that the image is not a face image. Case three typically shows up as a false positive in most recognition systems; in this framework, however, the false recognition may be detected because of the significant distance between the image and the subspace of expected face images [11] [20] [22].

Summary of Eigenface Recognition Procedure

The eigenfaces approach for face recognition is summarized as follows:

1. Collect a set of characteristic face images of the known individuals. This set should include a number of images for each person, with some variation in expression and in the lighting (say four images of ten people, so M=40).
2. Calculate the (40 x 40) matrix L, find its eigenvectors and eigenvalues, and choose the M' eigenvectors with the highest associated eigenvalues (let M'=10 in this example).
3. Combine the normalized training set of images according to Eq. (6) to produce the (M'=10) eigenfaces $\mu_k, k = 1,......, M'$.
4. For each known individual, calculate the class vector Ω_k by averaging the eigenface pattern vectors Ω [from Eq. (8)] calculated from the original (four) images of the individual. Choose a threshold θ_ε that defines the maximum allowable distance from any face class, and a threshold θ that defines the maximum allowable distance from face space [according to Eq. (9)].
5. For each new face image to be identified, calculate its pattern vector Ω, the distance ε_k to each known class, and the distance ε to face space. If the minimum distance $\varepsilon_k < \theta_\varepsilon$ and the distance $\varepsilon < \theta$, classify the input face as the individual associated with class vector Ω_k. If the minimum distance $\varepsilon_k > \theta_\varepsilon$ but $\varepsilon < \theta$, then the image may be classified as "unknown", and optionally used to begin a new face class.
6. If the new image is classified as a known individual, this image may be added to the original set of familiar face images, and the eigenfaces may be recalculated (steps 1-4). This gives the

opportunity to modify the face space as the system encounters more instances of known faces.

4.4 Result and discussion

In our face recognition system we use the principle component analysis algorithms because the simplicity and the respond time was very good for the system, we use 8 person images as a test images and 10 images for each person as training images (these images from the Olivetti Research Laboratory in Cambridge, UK).

Table 4.1 Show the result of face recognition system

Image #	Correct recognition	Situation	Time (sec)
1	Yes	Normal	1.5
2	No	Different hear style	2
3	No	Different angel	1.5
4	Yes	Different look	1.5
5	Yes	With glass	1.5
6	Yes	Smiling	1.5
7	Yes	Not smiling	1.5
8	Yes	Different look (black)	1.5

In image number one from table 4.1 we try to recognize the faces with little different as shown in figure 4.3. and the recognition was true and it takes less than 2 second

Figure 4.3 result of image number one

In image number two from table 4.1 we try to recognize the faces with different hear as shown in figure 4.4. and the recognition was false and it takes more than 2 second it gives wrong recognition.

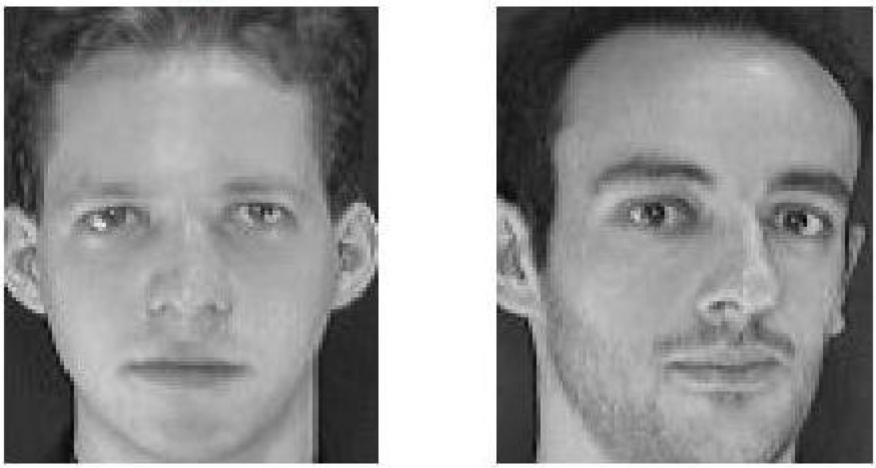


Figure 4.4 result of image number two

In image number three from table 4.1 we try to recognize the faces with different in angle as shown in figure 4.5. and the recognition was true and it takes less than 2 second

Figure 4.5 result of image number three

In image number four from table 4.1 we try to recognize the faces with different in angle as shown in figure 4.6. and the recognition was true and it takes less than 2 second

Figure 4.6 result of image number four

In image number five from table 4.1 we try to recognize the faces with Glass ware as shown in figure 4.7. and the recognition was true and it takes less than 2 second

Figure 4.7 result of image number five

In image number six from table 4.1 we try to recognize the faces with different look and smiling as shown in figure 4.8. and the recognition was true and it takes less than 2 second

Figure 4.8 result of image number six

In image number seven from table 4.1 we try to recognize the faces with different look as shown in figure 4.9. and the recognition was true and it takes less than 2 second

Figure 4.9 result of image number seven

In image number eight from table 4.1 we try to recognize the faces with different look and smiling as shown in figure 4.10. and the recognition was true and it takes less than 2 second

Figure 4.10 result of image number seven

4.5 Implementation details

The entire program consists of six stages which are:

1. Loading the database into matrix v

```
w=load_database();
```

2. Initializations

We pick an image from our database and use the rest of the images for training. Training is done on 9 pictures. We later use the picked image to test the algorithm.

```
ri=1;
```

ri=1: which mean that the index one from the tested images will be the picked picture

```
r=w (:,ri);
```

r: will have the images without the picked one.

```
v=w(:,[1:ri-1 ri+1:end]);
```

N: Number for signature for the Images

```
N=20;
```

3. Subtracting the mean from v

```
O=uint8(ones(1,size(v,2)));
```

```
m=uint8 (mean(v,2));
```

m is the mean of all images.

vzm=v-uint8(single(m)*single(O));

vzm is v with the mean removed

4. We are picking N of the 10 eigenfaces.

```
L=single(vzm)'*single(vzm);
[V,D]=eig(L);
```

Calculating eignevectors of the correlation matrix

```
V=single(vzm)*V;
V=V(:,end:-1:end-(N-1));
```

Pick the eignevectors corresponding to the 10 largest eigenvalues.

```
cv=zeros(size(v,2),N);
for i=1:size(v,2);
  cv(i,:)=single(vzm(:,i))'*V;
End
```

5. Calculating the signature for each image

Each row in cv is the signature for one image.

6. Recognition

```
p=r-m;
```

Subtract the mean

```
s=single(p)'*V;
z=[];
for i=1:size(v,2)
  z=[z,norm(cv(i,:)-s,2)];
  if (rem(i,20)==0),imshow(reshape(v(:,i),112,92)),end;
  drawnow;
```

```
end

[a,i]=min(z);
```

This code are implementation for the PCA algorithm for face recognition as we see this only about 30 line of code only, this is because the use of matlab, matlab with its toolboxes give the programmers more functions and methods that helps to easy develop an application or implement such an algorithms.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In our thesis we performed several experiments for face authentication and for human identification. The performed experiments that are presented in this thesis yielded good results that using face as a reliable biometric for human identification. In our face detection system we use the color segmentation algorithm and Maximal Rejection Classifier without any template matching to the face this make the system running faster. Also we present two new methods to improve the face detection process and face recognition which are the pose orientation methods and the face regeneration.

5.2 Future work

5.2.1 Face regeneration

In this thesis we only take one case for the face regeneration which is the half face which is one of many other cases they could happened see figure 5.1 for other case with face lost.

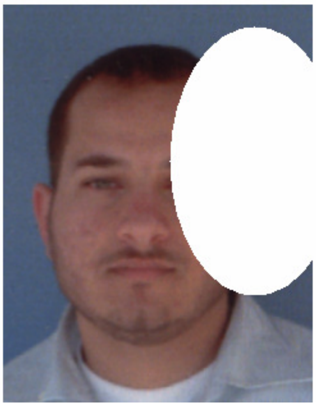


Figure 5.1 face with part missed

As we see in the previous figure that some part of the picture are missing the regeneration process will help by taking the corresponding value from the left side, this methods will help the image processing techniques to recovering the missed or corrupted pictures and get it back and improve its appearances.

5.2.2 Pose orientation

Pose orientation need more analysis to improve the presented method to make it a general solution and can be implemented.

The most difficult problem for our proposed method is the eyes extraction as if we know the place for the eyes the rest will be just a simple procedure, so what we need is the combination between two or more methods to determine the eyes place beside using the color segmentation we will use the PCA Eigen face methods which could improve the eye detection algorithm.

5.2.3 Ears recognition

One of the interesting researches is the ears recognition which make the using of ears just like the finger print to identifying the people and it's got a very good result, what we think is add a 3D view for face authentication system to make it more and more accurate and uniquely identify the person. This will make the system more secure because its use two different biometric methods.

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