Faceprint

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Abstract

This thesis presents a comprehensive overview of the problem of facial recognition. A survey of available facial recognition algorithms as well as implementation and tests of a computationally efficient and near real time well established approach to face recognition is presented.

One of the oldest and robust face recognition algorithms, Eigenface, along with enhancement to that algorithm Histogram Equalization, Circular Tracing, Principal Component Analysis and Averaging techniques are added to get better results to identify individual from face dataset.

A proof of concept implementation is provided, that is written in Visual Basic 6 on Visual Studio 6 platform.

Extensive testing of the project along with performance measures are presented in easy to understand graphical images. These test evaluations showed that the proposed implementation of eigenface technique can be increased by better preprocessing and normalization of the input face space before raw eigenface approach takes over. Tests also suggested that the core eigenface technique hits a plateau once it hits the threshold of optimal number of eigenvectors.

Finally, this thesis presents a discussion of the test results and a section on future direction this project may be led on.

Keywords: Face Recognition, Face Detection, Eigenfaces, Reconstruction, Principal Component Analysis, Histogram Analysis, Averaging Technique.

Preface

This thesis was prepared as a partial fulfillment of the requirements for acquiring the degree Bachelor of Science in Computer Science, in the Department of Mathematics and Computer Science, located at the Algoma University College of Sault Ste Marie, Ontario, Canada,

The thesis deals with different aspects of face recognition using both the geometrical and photometrical information of facial images. The main focus will be on face recognition from 2D grayscale images.

The thesis consists of this report, two presentations and a demonstration of a proof of concept implementation of the algorithms and techniques discussed in this paper.

It is assumed that the reader has a basic knowledge in the areas of statistics and image analysis.

Sault Ste. Marie, March 2007
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Chapter 1

Introduction

The task of face recognition performed by human happens so effortlessly and such an extensive number of times everyday, that in order to formulate a structured method to make a computer perform the same task using similar fashion, one first needs to understand how his or her perception works. This is where the dilemma comes in. Human perception is so convoluted and nebulous that it is easy to get lost. Moreover human uses more than one sensory organ to recognize another human, sight, sound, touch, smell, intuition just to name a few while a machine can not have all this information with current technologies available nor would it be computationally judicious to devise such system.

Research in automated face recognition has been conducted since the 1960's, it has gained wide popularity only recently in the scientific community. Perhaps the need for better security and the advent of more advanced tools facilitated devising more robust face recognition systems. Many face analysis and face modeling techniques have progressed significantly in the last decade [12]. However, the reliability of face recognition schemes still poses a great challenge to the scientific community.

Falsification of identity cards or intrusion of physical and virtual areas by cracking alphanumerical passwords appears frequently in the media. These problems of modern society have triggered a real necessity for reliable, user-friendly and widely acceptable control mechanisms for the identification and verification of the individual.

Biometrics, which is based on authentication on the intrinsic aspects of a specific human being, appears as a viable alternative to more traditional approaches (such as PIN codes or passwords). Among the oldest biometric techniques is fingerprint recognition [3]. This technique was used in China as early as 700 AD for official certification of contracts. Later on, in the middle of the 19th century, it was used for identification of persons in Europe [13]. A currently developed biometric technique is iris recognition [17]. This technique is now used instead of passport identification for frequent flyers in some airports in United Kingdom, Canada and the Netherlands. As well as for access control of employees to restricted areas in Canadian airports and in New York's JFK airport. These techniques are inconvenient due to the necessity of interaction with the individual who is to be identified or authenticated. Face recognition on the other hand can be a non-intrusive technique. This is one of the reasons why this technique has caught an increased interest from the scientific community in the recent decade.

In a study considering the compatibility of six biometric techniques (face, finger, hand, voice, eye, signature) with machine readable travel documents (MRTD), [10] facial features scored the highest percentage of compatibility, see Figure 1.1. In this study parameters like the enrollment, renewal, machine requirements and public perception were considered. However, facial features should not be considered the most reliable biometric.

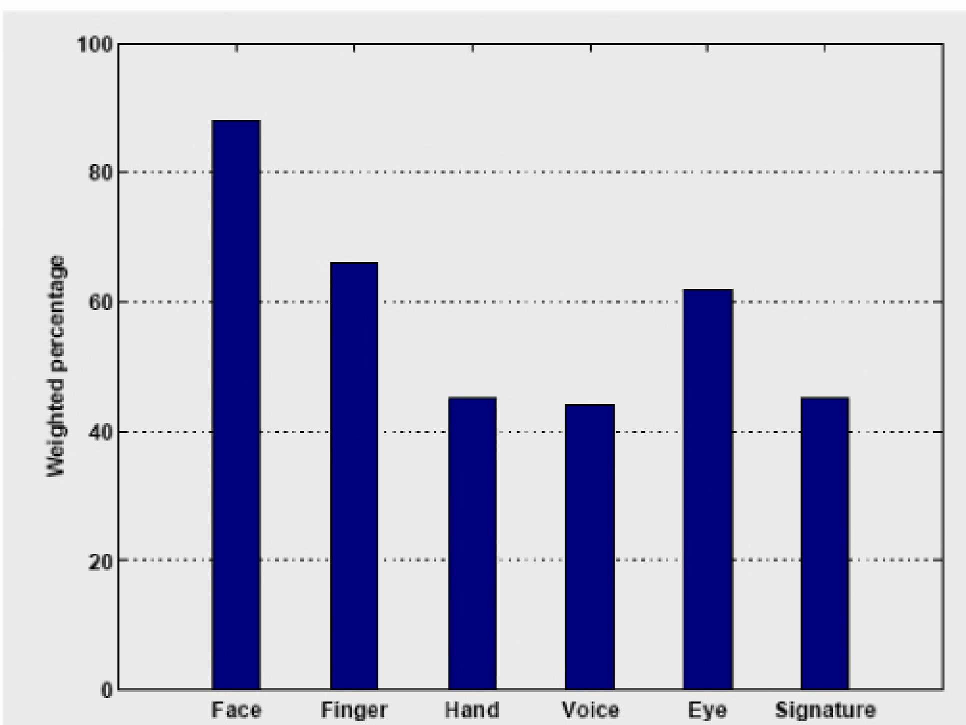


Figure 1.1: Comparison of machine readable travel documents (MRTD) compatibility with six biometric techniques; face, finger, hand, voice, eye, signature. Courtesy of Hietmeyer [10].

Besides applications related to identification and verification such as access control, law enforcement, ID and licensing, surveillance, etc., face recognition is also useful in human-computer interaction, virtual reality, database retrieval, multimedia, computer entertainment, etc.

1.1 Motivation and Objectives

Face recognition has recently received a blooming attention and interest from the scientific community as well as from the general public. The interest from the general public is mostly due to the demand for useful security systems. Facial recognition applications are far from limited to security systems as described above. To construct these different applications, precise and robust automated facial recognition methods and techniques are needed. However, these techniques and methods are currently not available or only available in highly complex, expensive setups.

The topic of this thesis is to help solve the difficult task of robust face recognition in a simple setup. Such a solution would be of great scientific importance and would be useful to the public in general.

The objectives of this thesis will be:

- To discuss and summarize the process of facial recognition.
- To look at currently available facial recognition techniques.
- To design develop and test a robust facial recognition system. The system will be fed grayscale facial images from publicly available databases (Rice, AT&T, Yale) and no specialized equipment will be used.

Besides these theoretical objectives, a proof-of-concept implementation of the developed method will be carried out.

1.2 Thesis Overview

In the fulfillment of the objectives, this thesis is naturally divided into five parts, where each part requires knowledge from the preceding parts.

Part I Face Recognition in General. This section presents a summary of the history of face recognition. Discusses the different commercial face recognition systems, the general face recognition process and the different considerations regarding facial recognition.

Part II Assessment. Presents an assessment of the central tasks of face recognition identified in Part I, which includes face detection, preprocessing of facial images and feature extracting.

Part III Development. Documents the design, development and testing of the Eigenfaces method of face recognition algorithm. Furthermore, enhancement modules are also developed and discussed in detail.

Part IV Test Results. Documents a discussion on the results obtained and the other works done in this thesis

Part V Conclusion/Discussion. Documents a discussion and concluding remarks and epiphanies encountered while carrying out the project also a discussion included on the possible future direction

1.3 Mathematical Notation

Throughout this thesis the following mathematical notations are used:

Scalar values are denoted with lower-case italic Latin or Greek letters:

$$x$$

Vectors, are denoted with lower-case, non-italic bold Latin or Greek letters. In this thesis only column vectors are used:

$$x = \left[x_1, x_2 \ldots x_n \right]^T$$

Matrices are denoted with capital, non-italic bold Latin or Greek letters:

$$X = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

Sets of objects such as scalars, vectors, images etc. are shown in vectors with curly braces:

$$\left\{ a, b, c, d \right\}$$

Indexing into a matrix is displayed, as row-column subscript of either scalars or vectors:

$$M_{xy} = M_x, x = \left[x, y \right]$$

The mean vector of a specific dataset is denoted with lower-case, non-italic bold Latin or Greek letters with a bar:

$$\overline{x}$$

1.4 Nomenclature

Landmarks set is a set of x and y coordinates that describes features (here facial features) like eyes, ears, noses, and mouth corners.

Geometric information is the distinct information of an object's shape, usually extracted by annotating the object with landmarks.

Photometric information is the distinct information of the image, i.e. the pixel intensities of the image.

Shape is according to Kendall [11] all the geometrical information that remains when location, scale and rotational effects are filtered out from an object.

Variables used throughout this thesis are listed below:

x_i A sample vector in the input space.

y_i A sample vector in the output space.

Φ An eigenvector matrix.

ϕ_i The ith eigenvector.

Λ A diagonal matrix of Eigenvalues.

λ_i The Eigenvalue corresponding to the ith eigenvector.

Σ A covariance matrix.

I The identity matrix.

1.5 Abbreviations

A list of the abbreviations used in thesis can be found below:

PCA Principal Component Analysis.

FLDA Fisher Linear Discriminant Analysis.

LPP Locality Preserving Projections.

KFDA Kernel Fisher Discriminant Analysis.

HE Histogram Equalization.

FAR False Acceptance Rate.

FRR False Rejection Rate.

EER Equal Error Rate.

TER Total Error Rate.

CIR Correct Identification Rate.

FIR False Identification Rate.

ROC Receiver Operating Characteristic (curve).

PDM Point Distribution Model.

Part I

Face Recognition in General

Chapter 2

History of Face Recognition

The most intuitive way to carry out face recognition is to look at the major features of the face and compare these to the same features on other faces. Some of the earliest studies on face recognition were done by Darwin [8] and Galton. The first real attempts to develop semi-automated facial recognition systems began in the late 1960's and early 1970's, and were based on geometrical information. Here, landmarks were placed on photographs locating the major facial features, such as eyes, ears, noses, and mouth corners. Relative distances and angles were computed from these landmarks to a common reference point and compared to reference data. These markers proved very hard to automate due to the subjective nature of many of the measurements still made completely by hand.

A more consistent approach to do facial recognition was done by Fischer et al. [1] (1973). This approach measured the facial features using templates of single facial features and mapped these onto a global template.

In summary, most of the developed techniques during the first stages of facial recognition focused on the automatic detection of individual facial features. The greatest advantages of these geometrical feature-based methods are the insensitivity to illumination and the intuitive understanding of the extracted features. However, even today facial feature detection and measurement techniques are not reliable enough for the geometric feature-based recognition of a face and geometric properties alone are inadequate for face recognition [12].

Due to this drawback of geometric feature-based recognition, the technique has gradually been abandoned and an effort has been made in researching holistic color-based techniques, which has provided better results. Holistic color-based techniques align a set of different faces to obtain a correspondence between pixels intensities, a nearest neighbor classifier [16] can be used to classify new faces when the new image is first aligned to the set of already aligned images. By the appearance of the Eigenfaces technique [22], a statistical learning approach, this coarse method was notably enhanced. Instead of directly comparing the pixel intensities of the different facial images, the dimension of the input intensities were first reduced by a Principal Component Analysis (PCA) in the

Eigenface technique. Eigenfaces is a basis component of many of the image based facial recognition schemes used today. One of the current techniques is Fisherfaces. This technique is widely used and referenced [1].

After development of the Fisherface technique, many related techniques have been proposed. These new techniques aim at providing an even better projection for separation of the faces from different persons. Techniques like Kernel Fisherfaces [1], Laplacianfaces [27] or discriminative common vectors [7] can be found among these approaches.

Chapter **3**

Face Recognition Systems

This chapter deals with the tasks of face recognition and how to report performance. The performance of some of the best commercial face recognition systems is included as well.

3.1 Experimental perspective

- Verification (authentication) - Am I who I say I am? (one to one search)
- Identification (recognition) - Who am I? (one to many search)
- Watch list - Are you looking for me? (one to few search)

Different schemes are to be applied to test the three tasks described above.

Which scheme should be used depends on the nature of the application.

3.1.1 Verification

The verification task is aimed at applications requiring user interaction in the form of an identity claim, i.e. access applications.

The verification test is conducted by dividing persons into two groups:

- Clients, people trying to gain access using their own identity.
- Imposters, people trying to gain access using a false identity, i.e. an identity known to the system but not belonging to them.

The percentage of imposters gaining access is reported as the False Acceptance Rate (FAR) and an the percentage of client rejected access is reported as the False Rejection Rate (FRR) for a given threshold. An illustration of this is displayed in Figure 2.1.

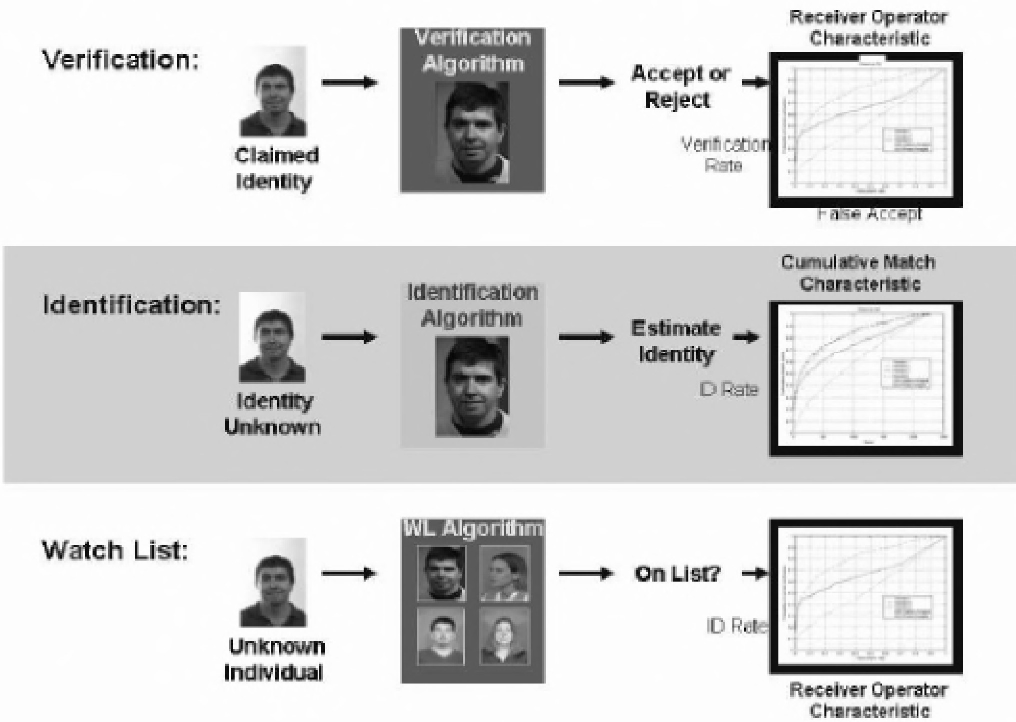


Figure 3.1: Three face recognition tasks: verification, identification, watch list (courtesy of P.J.Phillips [14]).

3.1.2 Identification

The identification task is mostly aimed at applications not requiring user interaction, i.e. surveillance applications.

The identification test works from the assumption that all faces in the test are of known persons. The percentage of correct identifications is then reported as the Correct Identification Rate (CIR) or the percentage of false identifications is reported as the False Identification Rate (FIR).

3.1.3 Watch List

The watch list task is a generalization of the identification task which includes unknown people.

The watch list test is like the identification test reported in CIR or FIR, but can have FAR and FRR associated with it to describe the sensitivity of the watch list, meaning how often is an unknown classified as a person in the watch list (FAR).

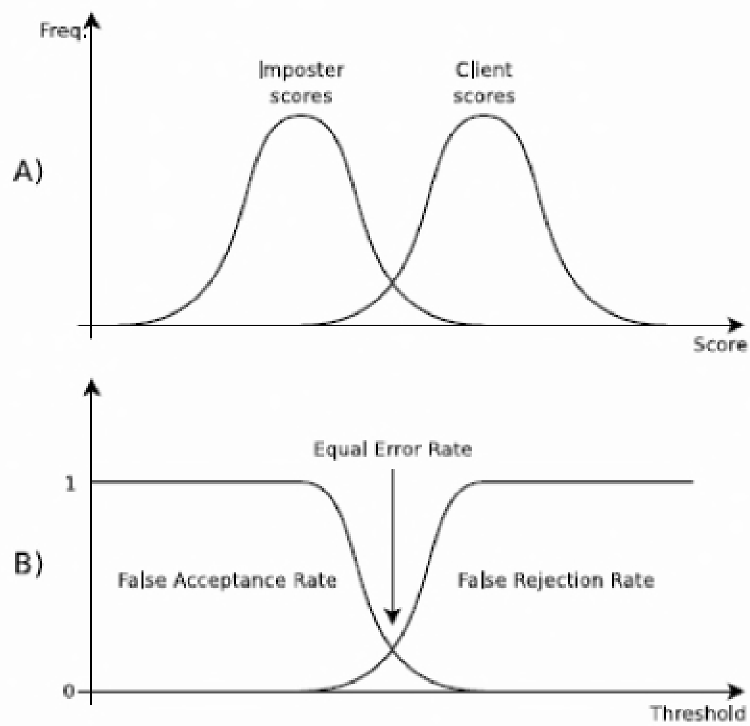


Figure 3.2: Relation of False Acceptance Rate (FAR), False Rejection Rate (FRR) with the distribution of clients, imposters in a verification scheme. A) Shows the imposters and client populations in terms of the score (high score meaning high likelihood of belonging to the client population). B) The associated FAR and FRR, the Equal Error Rate (EER) is where the FAR and FRR curve meets and gives the threshold value for the best separability of the imposter and client classes.

3.2 Face Recognition Vendor Test 2002

In 2002 the Face Recognition Vendor Test 2002 [15] tested some of the best commercial face recognition systems for their performance in the three primary face recognition tasks described in Section 3.1. This test used 121589 facial images of a group of 37437 different people. The different systems participating in the test are listed in Table 3.1. The evaluation was performed in reasonable controlled indoor lighting conditions[1].

Company	**Web site**
AcSys Biometrics Corp	http://www.acsysbiometricscorp.com
C-VIS GmbH	http://www.c-vis.com
Cognitec Systems GmbH	http://www.cognitec-systems.com
Dream Mirh Co., Ltd	http://www.dreammirh.com
Eyematic Interfaces Inc.	http://www.eyematic.com
Iconquest	http://www.iconquesttech.com
Identix	http://www.identix.com
Imagis Technologies Inc.	http://www.imagistechnologies.com
Viisage Technology	http://www.viisage.com
VisionSphere Technologies Inc.	http://www.visionspheretech.com

Table 3.1: Participants in the Face Recognition Vendor Test 2002.

The systems providing the best results in the vendor test show the characteristics listed in Table 3.2.

[1] Face recognition tests performed outside with unpredictable lighting conditions show a drastic drop in performance compared with indoor experiments [17].

Tasks	CIR	FRR	FAR
Identification	73%		
Verification		10%	1%
Watch List	56% to 77%[2]		1%

Table 3.2: The characteristics of the highest performing systems in the Face Recognition Vendor Test 2002. The highest performing system for the identification task and the watch list task was Cognitec. Cognitec and Identix was both the highest performing system for the verification task.

Selected conclusions from the Face Recognition Vendor Test 2002 are:

• The identification task yields better results for smaller databases, than larger ones. The identification task gave a higher score the smaller database used. Identification performance showed a linear decrease with respect to the logarithm of the size of the database. For every doubling of the size of the database, performance decreased by 2% to 3%. See Figure 3.2.

• The face recognition systems showed a tendency to more easily identify older than younger people. The three best performing systems showed an average increase of performance by approximately 5% for every ten years increase of age of the test population. See Figure 3.4.

• The more time that elapses from the training of the system to the presentation of a new "up-to-date" image of a person the more recognition performance is

[2] 56% and 77% corresponds to the use of watch lists of 3000 and 25 persons, respectively.

decreased. For the three best performing systems there was an average decrease of approximately 5% per year. See Figure 3.5.

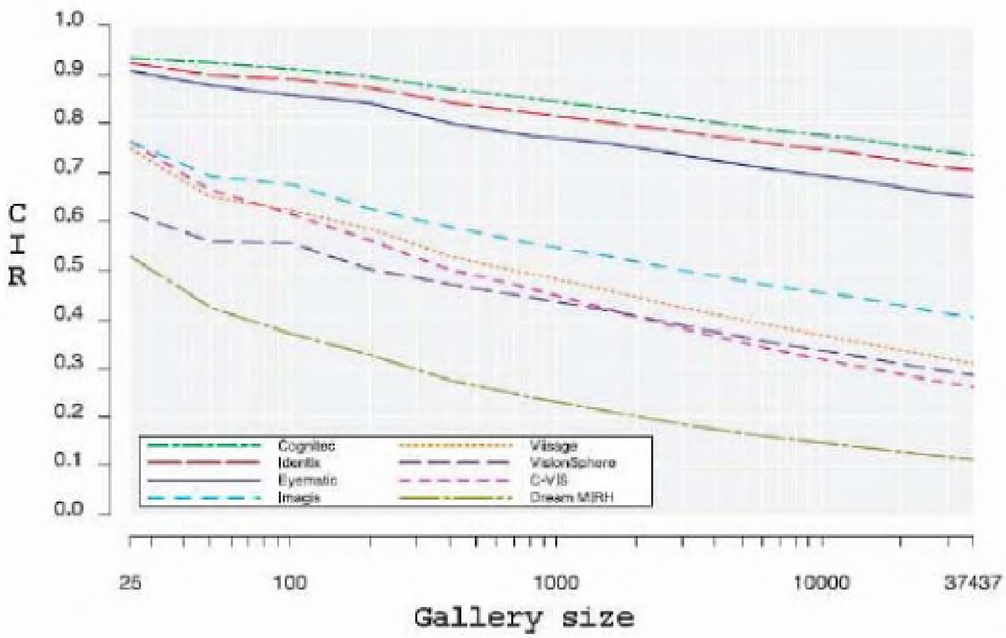


Figure 3.3: The Correct Identification Rates (CIR) plotted as a function of gallery size. Color of curves indicate the different vendors used in the test. Courtesy of Phillips et al. [15].

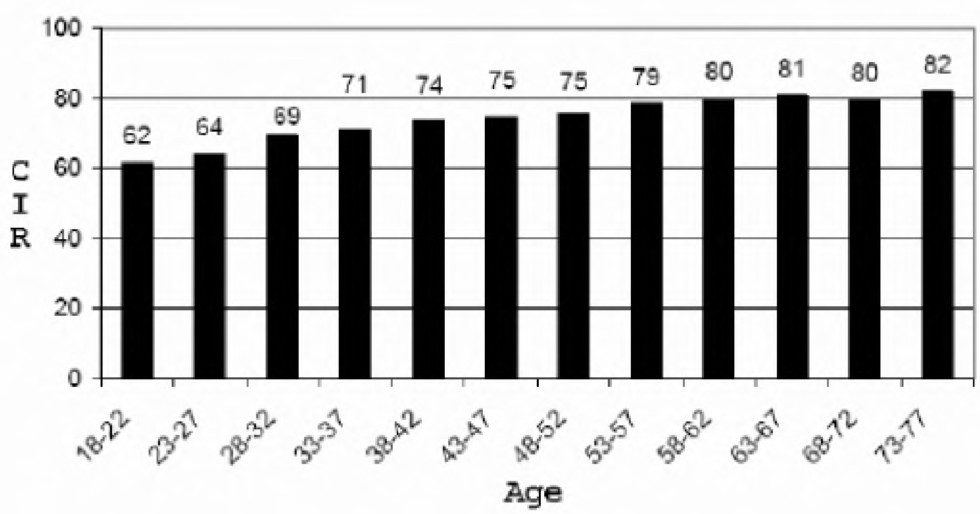


Figure 3.4: The average Correct Identification Rates (CIR) of the three highest performing systems (Cognitec, Identix and Eyematic), broken into age intervals. Courtesy of Phillips et al. [15].

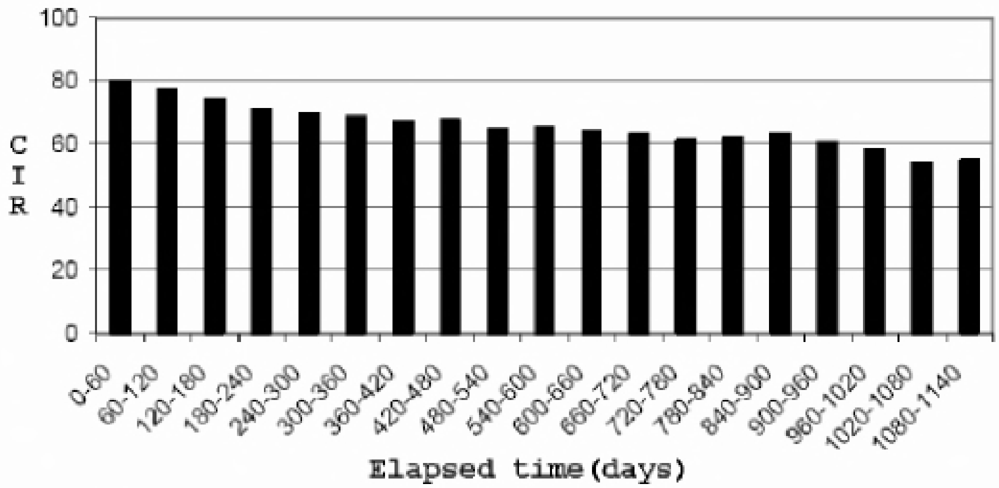


Figure 3.5: The average Correct Identification Rates (CIR) of the threehighest performing systems (Cognitec, Identix and Eyematic), divided into intervals of elapsed time from the time of the systems construction to the time a new image is introduced to the systems. Courtesy of Phillips et al.[15].

3.3 Discussion

Interestingly, the results from the Face Recognition Vendor Test 2002 indicate a higher identification performance of older people compared to younger. In addition, the results indicate that it gets harder to identify people as time elapses, which is not surprising since the human face continually changes over time. The results of the Face Recognition Vendor Test 2002, reported in Table 3.2, are hard to interpret and compare to other tests, since change in the test protocol or test data will yield different results. However, these results provide an indication of the performance of commercial face recognition systems.

Chapter 4

The Process of Face Recognition

Facial recognition is a visual pattern recognition task. The three-dimensional human face, which is subject to varying illumination, pose, expression etc. has to be recognized. This recognition can be performed on a variety of input data sources such as:

- A single 2D image.
- Stereo 2D images (two or more 2D images).
- 3D laser scans.

The dimensionality of these sources can be increased by one by the inclusion of a time dimension (video sequence). The advantage is that the identification of a person can be determined more precisely from a video sequence than from a picture since the identity of a person can not change from two frames taken in sequence from a video sequence.

This thesis is constrained to face recognition from single 2D images. However, there are ways of reconstruction of faces from one or more 2D images using statistical models of 3D laser scans which will not be discussed here.

Facial recognition systems usually consist of four steps, as shown in Figure 4.1; face detection (localization), face preprocessing (face alignment/normalization, light correction and etc.), feature extraction and feature matching. These steps are described in the following sections.

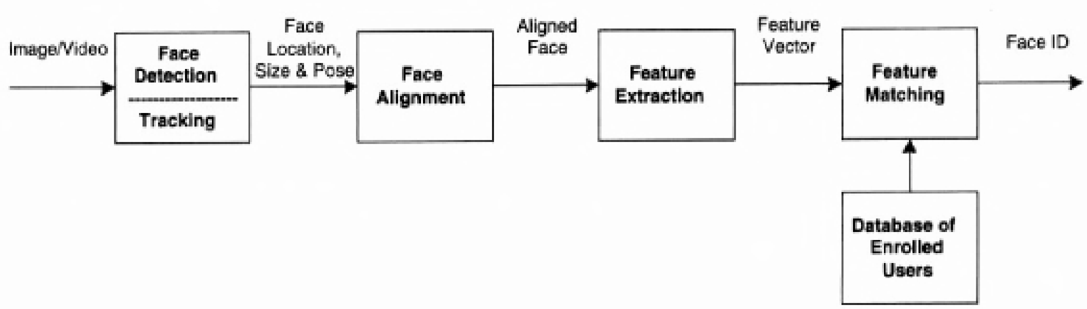


Figure 4.1: The four general steps in facial recognition.

4.1 Face Detection

The aim of face detection is localization of the face in an image. In the case of video input, it can be an advantage to track the face in between multiple frames, to reduce computational time and preserve the identity of a face (person) between frames. Methods used for face detection includes: Shape templates, Neural networks and Active Appearance Models (AAM).

4.2 Preprocessing

The aim of the face preprocessing step is to normalize the coarse face detection, so that robust feature extraction can be achieved. Depending of the application, face preprocessing includes: Alignment (translation, rotation, scaling) and light normalization/correlation.

4.3 Feature Extraction

The aim of feature extraction is to extract a compact set of interpersonal discriminating geometrical or/and photometrical features of the face. Methods for feature extraction include: PCA, FLDA and Locality Preserving Projections (LPP).

4.4 Feature Matching

Feature matching is the actual recognition process. The feature vector obtained from the feature extraction is matched to classes (persons) of facial images already enrolled in a database. The matching algorithms vary from the fairly obvious Nearest Neighbor to advanced schemes like Neural Networks.

4.5 Thesis Perspective

This thesis will cover all four general areas in face recognition, though the primary focus is on feature extraction and feature matching.

A survey of face detection algorithms is presented in Chapter 7. Preprocessing of facial images is discussed in Chapter 8. A more in-depth description of feature extraction methods is presented in Chapter 9. The development of face recognition algorithm is described in Chapter 11. The performance of these feature extraction methods is presented in Chapter 13.

Chapter 5

Face Recognition Considerations

In this chapter general considerations of the process of face recognition are discussed. These are:

- The variation of facial appearance of different individuals, which can be very small.
- The non-linear manifold on which face images reside.
- The problem of having a high-dimensional input space and only a small number of samples.

The scope of this thesis is further defined with the respect to these considerations.

5.1 Variation in Facial Appearance

A facial image is subject to various factors like facial pose, illumination and facial expression as well as lens aperture, exposure time and lens aberrations of the camera. Due to these factors large variations of facial images of the same person can occur. On the other hand, sometimes small interpersonal variations occur. Here the extreme is identical twins, as can be seen in Figure 5.1.

In a situation where the variation among images obtained from the same person is larger than the variation among images of two individuals more comprehensive data than 2D images must be acquired to do computer based facial recognition. Here, accurate laser scans or infrared images (showing the blood vessel distribution in the face) can be used. These methods are out of the scope of this thesis and will not be discussed further. This thesis is mainly concerned with 2D frontal face images.

Figure 5.1: Small interpersonal variations illustrated by identical twins. Courtesy of www.digitalwilly.com.

5.2 Face Analysis in an Image Space

When looking at the photometric information of a face, face recognition mostly relies on an analysis of a subspace, since faces in images reside in a submanifolds of the image space. This can be illustrated by an image consisting of 32 x 32 pixels. This image contains a total of 1024 pixels, with the ability to display a long range of different sceneries. Using only an 8-bit gray scale per pixel this image can show a huge number of different configurations, exactly $256^{1024} = 2^{8192}$. It is clear that only a small fraction of these image configurations will display faces. As a result most of the original image space representation is very redundant from a facial recognition point of view. It must therefore be possible to reduce the input image space to obtain a much smaller subspace, where the objective of the subspace is to remove noise and redundancy while preserving the discriminative information of the face.

However, the manifolds where faces reside seem to be highly non-linear and non-convex [5, 14].

5.3 Dealing with Non-linear Manifolds

As described above is the face manifold highly non-linear and non-convex. The linear methods discussed later in Chapter 9 such as Principal Component

Analysis (PCA) and Fisher Linear Discriminant Analysis (FLDA) is as a result only partly capable of preserving these non-linear variations.

5.3.1 Technical Solutions

To overcome the challenges of non-linear and non-convex face manifolds there are two general approaches:

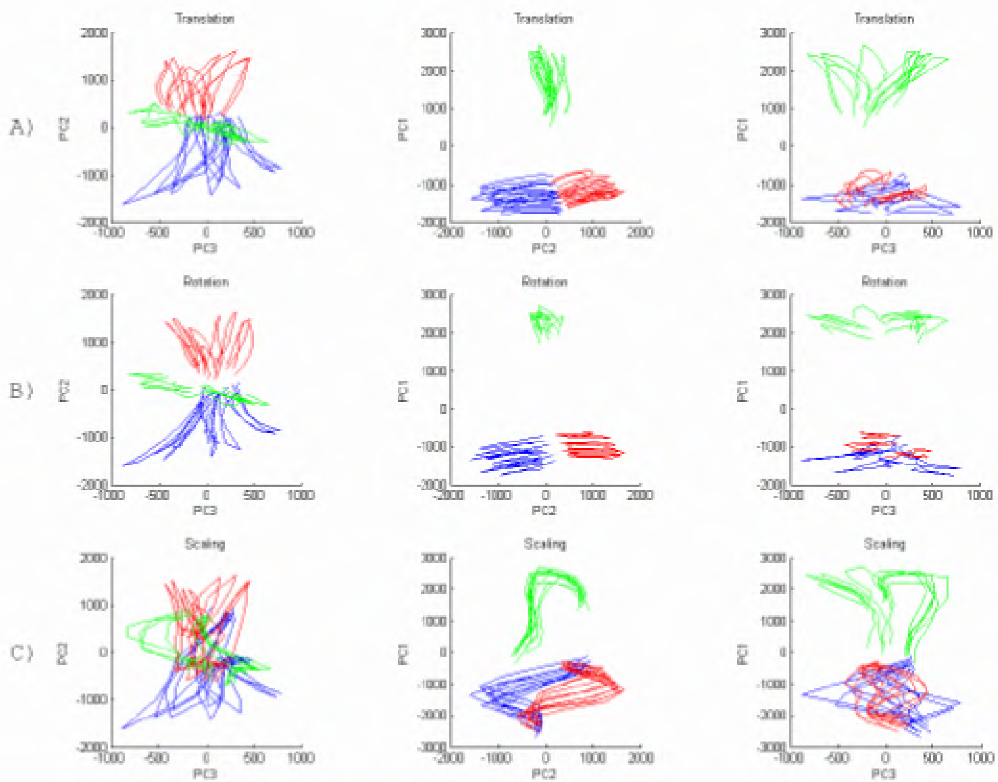


Figure 5.3: Results of the exploration of facial submanifolds. The 990 images derived from 30 original facial images are mapped into a three-dimensional space spanned by the three largest eigenvectors of the original images. The images derived form the original images are connected. The images of the three persons are plotted in different colors. The three sets of 30 × 11 images derived by translation, rotation and scaling are displayed in row A, B and C, respectively

The first approach is to construct a feature subspace where the face manifolds become simpler, i.e. less non-linear and non-convex than the input space. This can be obtained by normalization of the face image both geometrically and photometrically to reduce variation. Followed by extraction of features in normalized image. For this purpose linear methods like PCA, FLDA or even non-linear methods as Kernel Fisher Discriminant Analysis (KFDA) can be used [1]. Only PCA will be described in this thesis.

- The second approach is to construct classification engines capable of solving the difficult non-linear classification problems of the image space. Methods like Neural Networks, Support Vector Machines etc. can be used for this purpose.

In addition the two approaches can be combined.

Work done using only the first approach to statistically understand and simplify the complex problem of facial recognition is pursued in this thesis.

5.4 High Input Space and Small Sample Size

Another problem associated with face recognition is the high input space of an image and the usually small sample size of an individual. An image consisting of 32 x 32 pixels resides in a 1024-dimensional space; where as the number of images of a specific person typically is much smaller. A small number of images of a specific person may not be sufficient to make an appropriate approximation of the manifold, which can cause a problem. An illustration of this problem is displayed in Figure 5.4. Currently, no known solution comes to mind for solving this problem, other than capturing a sufficient number of samples to approximate the manifold in a satisfying way.

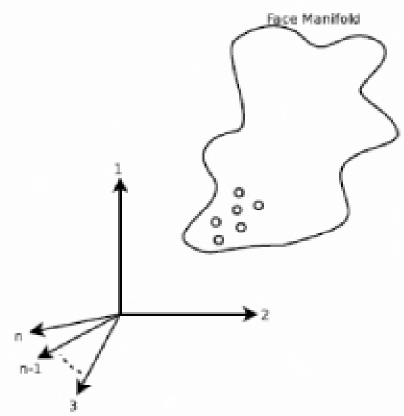


Figure 5.4: An illustration of the problem of not being capable of satisfactory approximating the manifold when only having a small number of samples. The samples are denoted by circles.

Chapter 6

Available Data

This chapter presents a small survey of databases used for facial detection and recognition.

These databases include the IMM Face Database [12], which have been recorded and annotated with landmarks as a part of this thesis. CMU Pose, Illumination and Expression (PIE) Database and Yale Face Database. The three databases used are:

6.1 Data Set I

Data set I consists of the entire IMM Frontal Face Database [12]. In summary, this database contains 120 images of 12 persons (10 images a person). The 10 images of a person display varying facial expressions. The images have been annotated in a 73-landmark scheme, see Figure 6.1.

6.2 Data Set II

Data set II consists of a subset of images from the AT&T, Rice, Yale and PIE database, where 50 (25 male and 25 female) were randomly selected. Fourteen images per person are included in data set II, which are obtained from the two recording sessions (seven images per person per session).

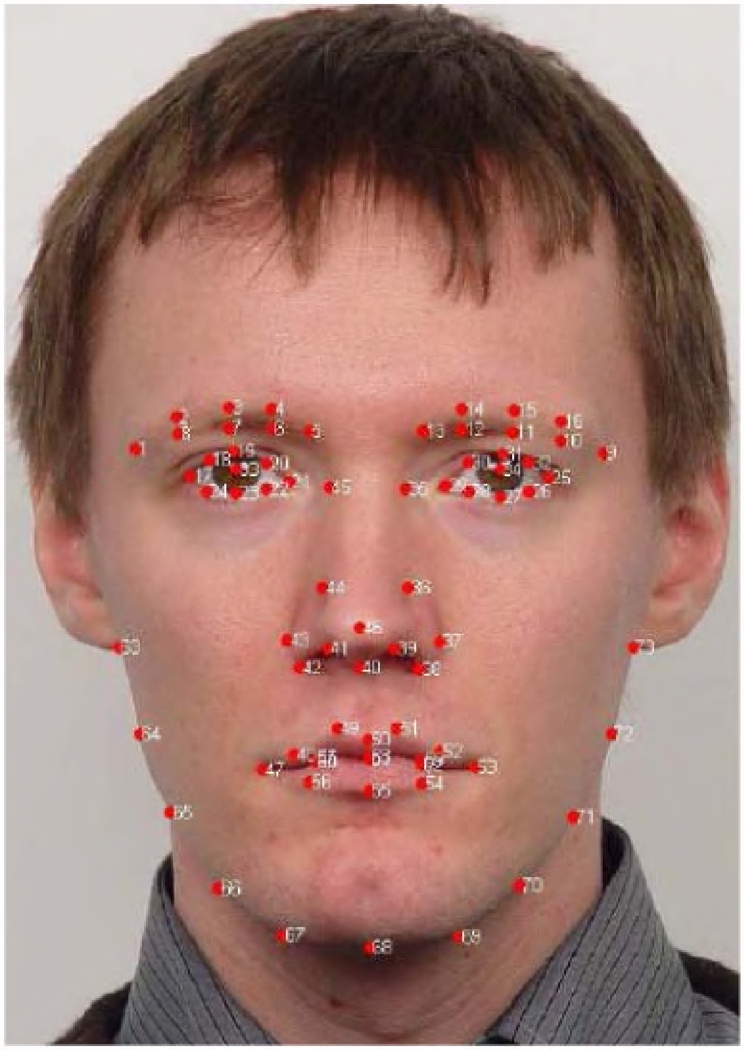


Figure 6.1: The 73-landmark annotation scheme used on the IMM Frontal Face Database.

Part II

Assessment

Chapter 7

Face Detection: A Survey

This chapter deals with the problem of face detection. Since the scope of this thesis is face recognition, this chapter will serve as an introduction to already developed algorithms for face detection.

As described earlier in Chapter 4, face detection is the necessary first step in a face recognition system. The purpose of face detection is to localize and extract the face region from the image background. However, since the human face is a highly dynamic object displaying large degree of variability in appearance, automatic face detection remains a difficult task.

The problem is complicated further by the continually changes over time of the following parameters:

- The three-dimensional position of the face.
- Removable features, such as spectacles and beards.
- Facial expression.
- Partial occlusion of the face, e.g. by hair, scarves and sunglasses.
- Orientation of the face.
- Lighting conditions.

The following will distinguish between the two terms face detection and face localization.

Definition 7.1 ***Face detection,*** the process of detecting all faces (if any) in a given image.

Definition 7.2 ***Face localization,*** the process of localizing one face in a given image, i.e. the image is assumed to contain one, and only one face.

More than 150 methods for face detection have been developed, though only a small subset is addressed here. In Yang et al. [25] face detection methods are divided into four categories:

- **Knowledge-based methods:** The knowledge-based methods use a set of rules that describe what to capture. The rules are constructed from the intuitive human knowledge of facial.

- **Feature invariant approaches:** The aim of feature invariant approaches is to search for structural features, which are invariant to changes in pose and lighting conditions.

- **Template matching methods:** Template matching methods constructs one or several templates (models) for describing facial features. The correlation between an input image and the constructed model(s) enables the method to discriminate over the case of face or non-face. The Faceprint implementation includes an established template matching technique that makes use of Mask and known as Circular Tracing

- **Appearance-based methods:** Appearance-based methods use statistical analysis and machine learning, containing both geometrical information and the photometric information to extract the relevant features of a face to be able to discriminate between face and non-face images.

The knowledge-based methods and the feature invariant approaches are mainly used only for *face localization,* where as template matching methods and appearance-based methods can be used for *face detection* as well as *face localization.*

Approach	Representative Work
Knowledge-Based	Multiresolution rule-based method
Feature invariant	
-Facial Features	Grouping of edges
-Textures	Space Gray-Level Dependence matrix of face pattern
-Skin Color	Mixture of Gaussian
-Multiple Features	Integration of Skin color, size and shape
Template Matching	
-Predefined face templates	Shape templates
-Deformable templates	Active shape templates
Appearance-based method	
-Eigenfaces & fisher faces	Eigenvector decomposition and clustering [23]
-Neural Network	Ensemble of neural networks and arbitration schemes [14]
-Deformable models	Active Appearance Models [10]

Table 7.1: Categorization of methods for face detection within a single image.

7.1 General Aspects of Face Detections Algorithms

Most face detection algorithms work by systemically analyzing subregions of an image. An example of how to extract these subregions could be, to capture a subimage of 20 x 20 pixels in the top left corner of the original image and continuing to capture subimages in a predefined grid. All these subimages are hen evaluated using a face detection algorithm. Subsampling of the image in pyramid fashion enables capture of different sizes face. This is illustrated in Figure 7.1.

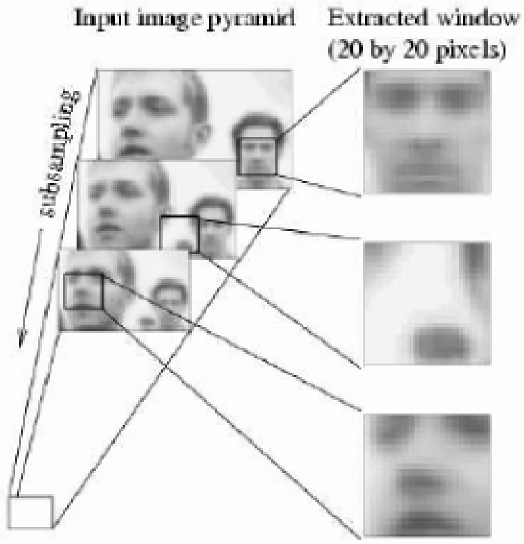


Figure 7.1: Illustration of the subsampling of an image in a pyramid fashion. Which enables the capture of different size of faces. Besides, rotated faces can be captured by rotating the subwindow. Courtesy of owley et al. [26].

7.2 Eigenfaces

The Eigenface method uses PCA to construct a set of Eigenface images. Examples of Eigenface images are displayed in Figure 7.2. These Eigenfaces can be linearly combined to reconstruct the images of the original training set. When introducing a new image an error (ξ) can be calculated from the best image reconstruction using the Eigenfaces to the new image. If the Eigenfaces are constructed from a large face database, the size of the error ξ can be used to determine whether or not a newly introduced image contains a face.

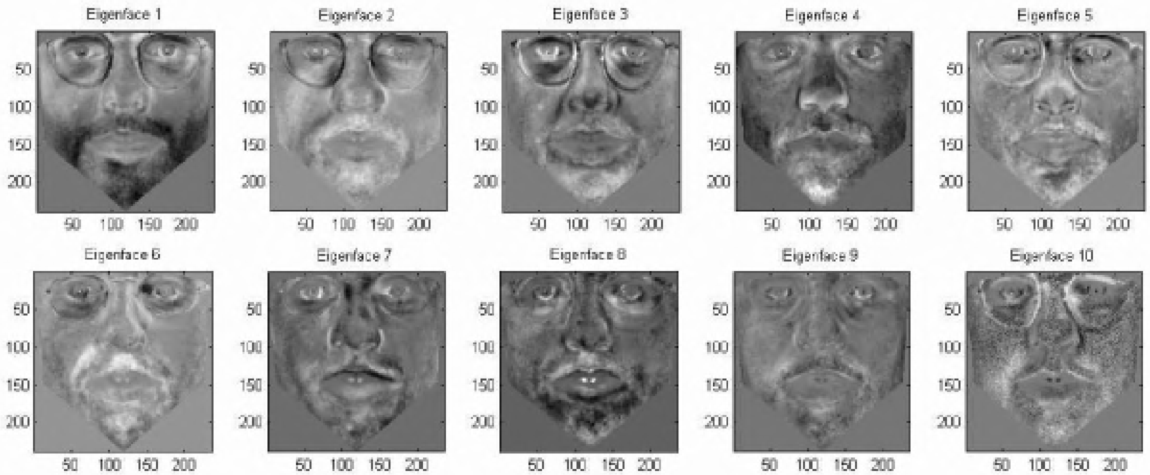


Figure 7.2: Example of 10 Eigenfaces. Notice that Eigenface no. 10 contains much noise and that the Eigenfaces are constructed from the shape free images described in Section 7.2.5.

Another more robust way is to look upon the subspace provided by the Eigenfaces, and cluster face images and non-face images in this subspace [22].

Chapter 8

Preprocessing of a Face Image

The face preprocessing step aims at normalizing, i.e. reducing the variation of images obtained during the face detection step. Since this already has been described previously in this thesis only the subject of light correction will be described within this chapter.

8.1 Light Correction

As described in Section 3.2, unpredictable changes in lighting conditions are a problem in facial recognition. Therefore, it is desirable to normalize the photometric information in terms of light correction to optimize the facial recognition. Here, two light correction methods are described.

8.1.1 Histogram Equalization

Histogram equalization (HE) can be used as a simple but very robust way to obtain light correction when applied to small regions such as faces. The aim of HE is to maximize the contrast of an input image, resulting in a histogram of the output image which is as close to a uniform histogram as possible. However, this does not remove the effect of a strong light source but maximizes the entropy of an image, thus reducing the effect of differences in illumination within the same "setup" of light sources. By doing so, HE makes facial recognition a somehow simpler task. Two examples of HE of images can be seen in Figure 8.1. The algorithm of HE is straight forward and will not be explained here, an interested reader can obtain the algorithm in Finlayson et al. [22].

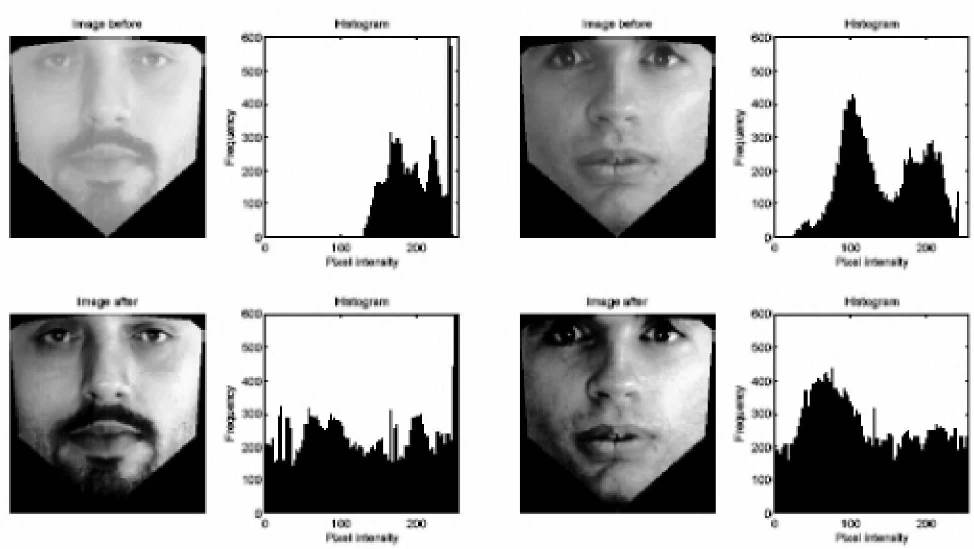


Figure 8.1: Examples of histogram equalization used upon two images to obtain standardized images with maximum entropy. Notice, only the facial region of an image is used in the histogram equalization.

8.1.2 Removal of Specific Light Sources based on 2D Face Models

The removal of specific light sources based on 2D face models [14] is another method to obtain light correlation of images. The method creates a pixel-wise correspondence of images. By doing so, the effect of illumination upon each pixel $\mathrm{x} = \{x, y\}$ of an image can be expressed by the equation

$$\tilde{F}_x = a_{i,x} \cdot F_x + b_{i,x}$$

Where, F and $\tilde{F}$ are the images of the same scene recoded at normal lighting condition (diffuse lighting) and upon the influence of a specific light source (illumination mode i), respectively. $a_{i,x}$ is the multiplication compensation, and $b_{i,x}$ is the additive compensation of the illumination mode i of pixel x in the image $\tilde{F}$.

8.2 Discussion

It is clear that HE is a good and robust way of normalizing images. The more complex method of removing specific illumination conditions seems to yield impressive results, but has the drawback of sometimes imposing artifacts onto the images, as can be seen in Figure 8.3, where “shadows of spectacles” can be seen on persons not wearing spectacles. It was decided to only preprocess

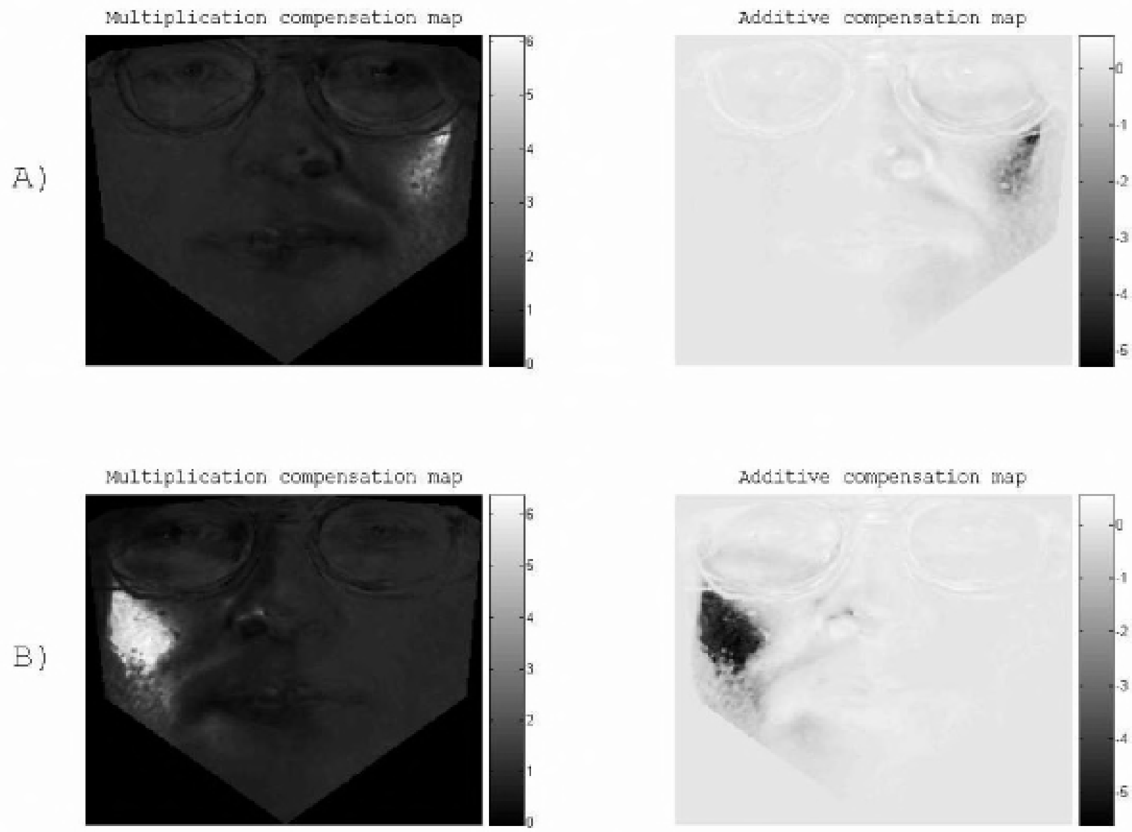


Figure 8.4: Illumination compensation maps used for removal of specific illumination conditions. Rows A) and B) display the illumination compensation maps for facial images captured under left and right illumination, respectively.

facial images with HE to ensure that the images are independent. No tests were performed to see how facial recognition performs under the influence of the artifacts introduced by the removal of specific light sources based on 2D face models. This will be saved for future work.

Chapter 9

Face Feature Extraction: Dimensionality Reduction Methods

Table 9.1 lists the most promising dimensionality reduction methods (feature extraction methods) used for face recognition. Out of these Principal Component Analysis will be described in the following.

Preserving	**Technique**	**Method**
Global Structure	Linear	Fisher Linear Discriminant Analysis
		Principal Component Analysis
	Non-Linear	Kernel Fisher Linear Discriminant Analysis
		Kernel Principal Component Analysis
Local Structure	Linear	Locality Preserving Projections
	Non-Linear	Isomap
		Laplacian Eigenmap

Table 9.1: Dimensionality reduction methods.

9.1 Principal Component Analysis

Principal Component Analysis (PCA), also known as Karhunen-Lo`eve transformation, is a linear transformation which captures the variance of the input data. The coordinate system in which the data resides is rotated by PCA, so that the first-axis is parallel to the highest variance in the data (in a one-dimension projection). The remaining axes can be explained one at the time as being parallel to the highest variance of the data, while all axes are constrained to be orthogonal to all previous found axes. To summarize, the first-axis will contain highest variance, the second-axis contain the second highest variance, etc. An example in two dimensions is shown in Figure 9.1. PCA, which is an unsupervised method, is a powerful tool for data analysis, especially if data resides in a space higher than three dimensions, where graphical representations are hard. One of the main applications of PCA is dimension reduction, with little or no loss of data variation. This is used to remove redundancy and compress data.

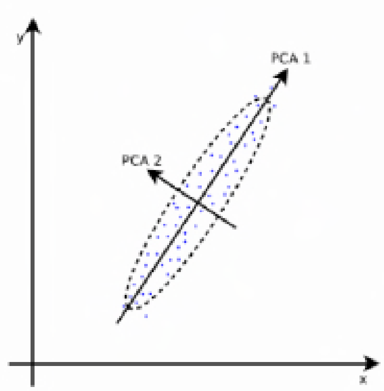


Figure 9.1: An example of PCA in two dimensions, showing the PCA axis that maximizes the variation in the first principal component: PCA 1.

9.1.1 PCA Algorithm

Different methods can be used to calculate the PCA basis vectors. Here eigenvalues and eigenvectors of the covariance matrix of the data are used. Considering the data

$$X=\left[x_1,x_2,\cdots,x_n\right] \tag{9.1}$$

where n is the amount of data samples, xi is the ith data sample of dimension d. First is the mean of X subtracted from the data

$$\hat{X}=\left[x_1-\bar{x},x_2-\bar{x},\cdots,x_n-\bar{x}\right] \tag{9.2}$$

The covariance matrix $\sum_{\hat{X}}$ is calculated by

$$\sum_{\hat{X}}=\frac{1}{n}\hat{X}\hat{X}^T \tag{9.3}$$

The principal axes are now given by the eigenvectors $\Phi_{\hat{X}}$ of the covariance matrix

$$\sum_{\hat{X}}\Phi_{\hat{X}}=\Phi_{\hat{X}}\Lambda_{\hat{X}} \tag{9.4}$$

Where,

$$\Lambda_{\hat{X}}=\begin{bmatrix}\lambda_1 & 0 & \cdots & 0\\ 0 & \lambda_2 & \ddots & \vdots\\ \vdots & \ddots & \ddots & 0\\ 0 & \cdots & 0 & \lambda_d\end{bmatrix} \tag{9.5}$$

is the diagonal matrix of eigenvalues corresponding to the eigenvectors of

$$\Phi_{\hat{X}} = \left[\phi_1, \phi_2, \cdots, \phi_d\right] \tag{9.6}$$

The eigenvector corresponding to the highest eigenvalue represents the basis vector containing the most data variance, i.e. the first principal component.

The *i*th data sample, x_i, can be transformed into the PCA space by

$$y_i = \Phi_{\hat{X}}^{-1}\left(x_i - \overline{x}\right) = \Phi_{\hat{X}}^{T}\left(x_i - \overline{x}\right) \tag{9.7}$$

Notice that an orthogonal matrix as $\Phi_{\hat{X}}$ has the property $\Phi_{\hat{X}}^{-1} = \Phi_{\hat{X}}^{T}$. Data in the PCA space can be transformed back into the original space by

$$x_i = \Phi_{\hat{X}} y_i + \overline{x} \tag{9.8}$$

If only a subset of the eigenvectors in $\Phi_{\hat{X}}$ is selected, then this will result in data being projected into a PCA subspace. This can be very useful to reduce redundancy in the data, i.e. remove all eigenvectors equal to zero. The above method is described in greater detail in Ersbøll et al. [19].

9.1.2 Computational Issues of PCA

If one has *n* data samples in a d high-dimensional space where n ≪ d. Then the computational time is quite large for retrieving eigenvectors and eigenvalues from the *d* x *d* covariance matrix. The time needed for eigenvector decomposition increases by the cube of the covariance matrix size [1]. However, it is possible to calculate the eigenvectors of the non-zero eigenvalues from a much smaller matrix with size n x n, by use of

$$\sum_{n} = \frac{1}{n}\hat{X}^{T}\hat{X} \tag{9.9}$$

where $\hat{X}$ is calculated by Eq. 9.2. The non-zero eigenvalues of the matrices in Eq. 9.4 and Eq. 9.9 are equal

$$\Lambda_{n} = \Lambda_{\hat{X}} \tag{9.10}$$

The eigenvectors corresponding to non-zero eigenvalues can be expressed as

$$\hat{\Phi}_{\hat{X}} = \hat{X}\Phi_{n} \tag{9.11}$$

Notice that these eigenvectors are not normalized. This can be proved by the Eckhart-Young Theorem [50].

Chapter 10

Evaluation: Feature Extraction Methods

The purpose of this chapter is to evaluate the four feature extraction methods described in Chapter 9. To summarize, the four extraction methods are:

- Principal Component Analysis
- Locality Preserving Projections
- Fisher Linear Discriminant Analysis
- Kernel Fisher Discriminant Analysis

10.1 Illustration of the Feature Spaces

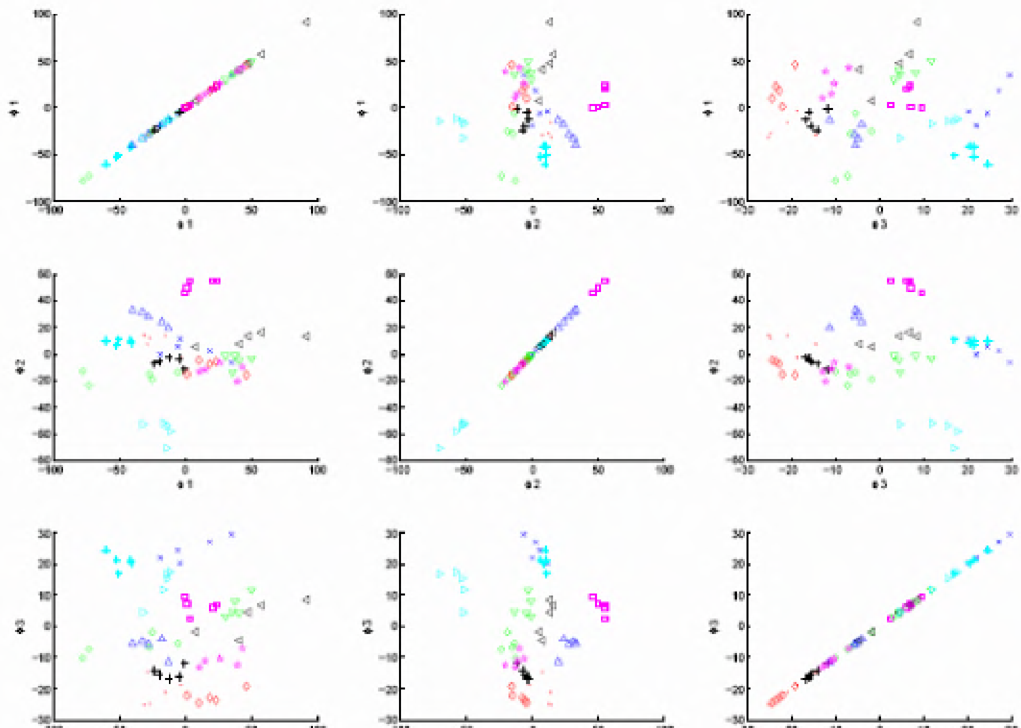


Figure 10.1: The PCA scatter plot matrix of the combined features from data set I. The 12 persons of data set I are displayed by different colors and symbols.

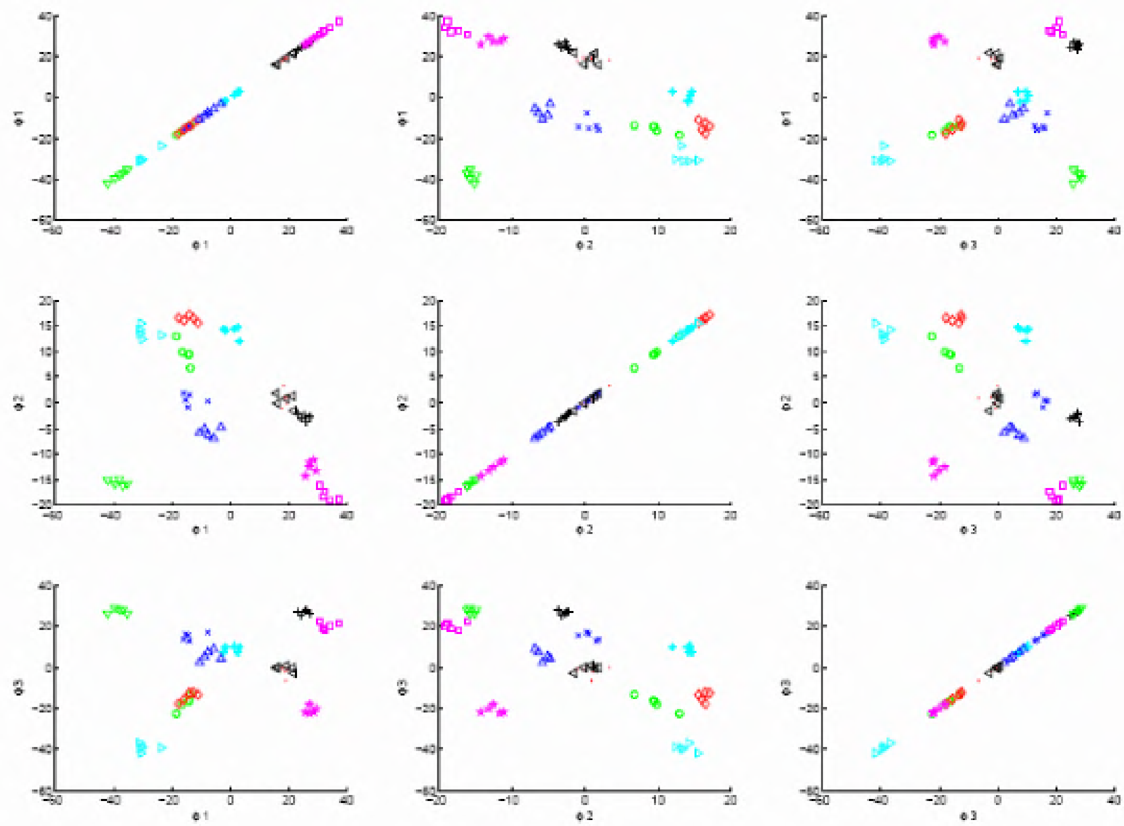


Figure 10.2: The LPP scatter plot matrix of the combined features from data set I. The 12 persons of data set I are displayed by different colors and symbols.

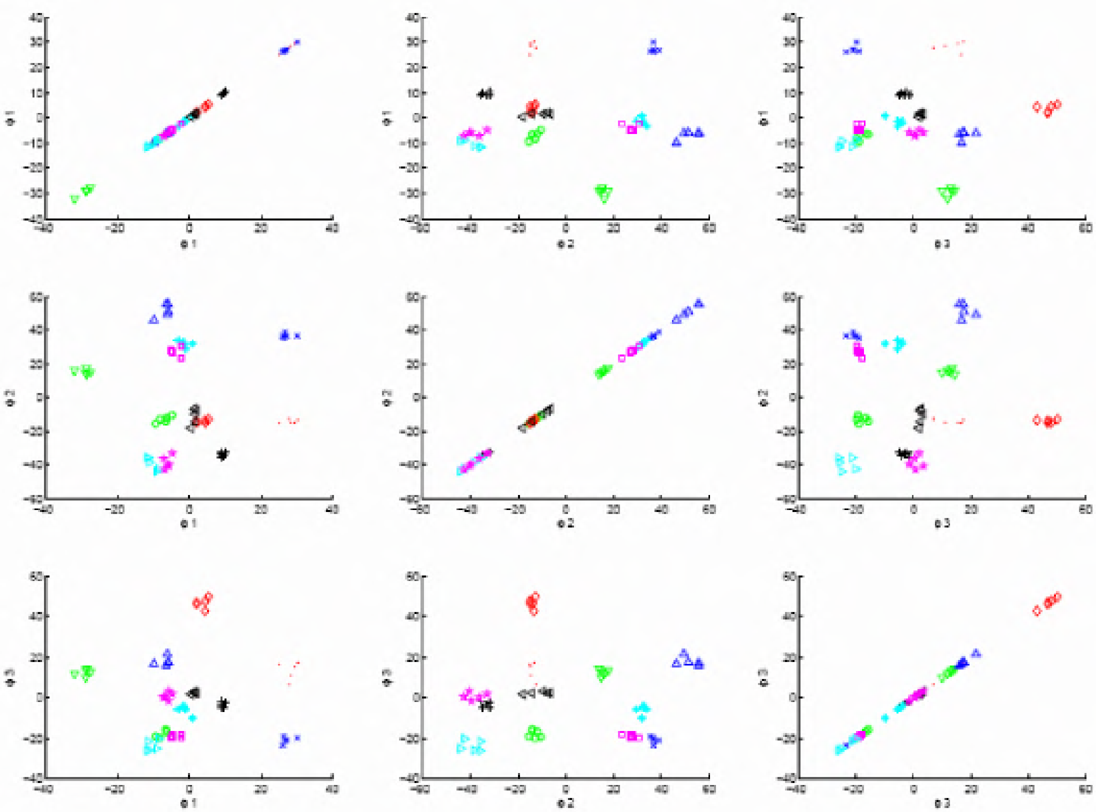


Figure 10.3: The FLDA scatter plot matrix of the combined features from data set I. The 12 persons of data set I are displayed by different colors and symbols.

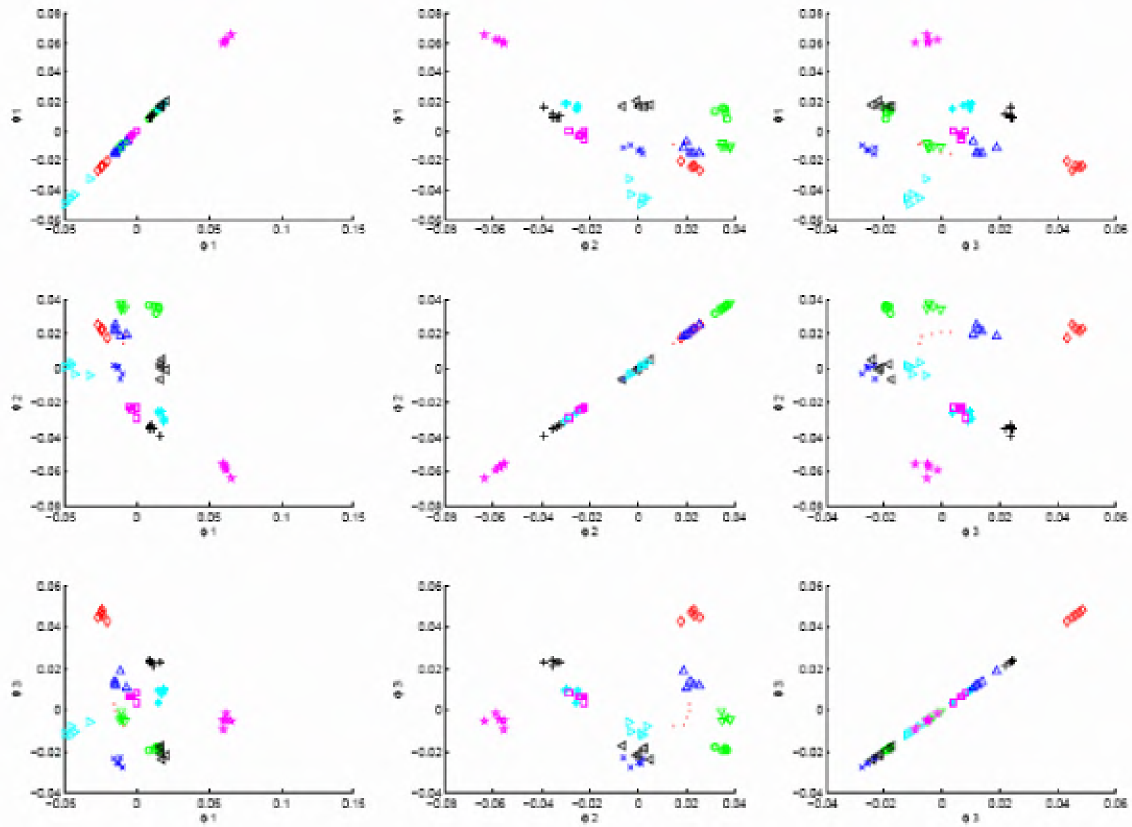


Figure 10.4: The KFDA scatter plot matrix of the combined features from data set I. The 12 persons of data set I are displayed by different colors and symbols.

10.2 Discussion

Analysis of the scatter plot matrices, displayed in Figure 10.1, Figure 10.2, Figure 10.3 and Figure 10.4 indicate that the methods LPP, FLDA and KFDA improve the separability of the classes (persons) compared to PCA. Though, LPP seems to have a problem separating two of the classes. For easier implementation PCA is used in this thesis.

Part III

Development

Chapter 11

Eigenface Approach

The eigenface method for face recognition is computationally very cheap and easy to implement which is why it has been chosen among several other algorithms discussed previously. This project uses naïve eigenface method and adds histogram equalization for illumination correction and masking technique on several image sets in order to determine improvement of recognition performance.

This project is able to recognize an individual's face by comparing the shape and features to that of a known person. This is achieved by using frontal facial photographs of individuals to represent a 2D representation of a human head. The system then projects the representation onto a face-space of basis Eigenfaces. Due to the similarity of an individuals face structure and features within, from person to person, face images coincide within a relatively small region of the sub-space and can be reproduced with less than complete knowledge of the image space. The eigenface approach uses a combination of linear algebra and statistical analysis to generate a set of basis vector spaces--the Eigenfaces--against which inputs are tested.

The added Histogram Equalization (HE) module is used to in the image prepossessing part in order to smooth-out the lighting condition. HE maximizes the contrast of an input image, resulting in a histogram of the output image which is as close to a uniform histogram as possible However, this does not remove the effect of a strong light source but maximizes the entropy of an image, thus reducing the effect of differences in illumination within the same "setup" of light sources.

11.1 Algorithm Description

The system can be broken down into two major segments: derivation of the eigenface basis and recognition of a new face

11.1.1 Deriving the Eigenface-Basis

Eigenface method is inherently a very intuitive way of classifying a face. Even though most other face recognition techniques focus on particular features of the face. The eigenface approach used much more information by classifying faces based on general facial patterns including the specific features of the face. So naturally eigenface approach is much more robust than feature-based methods

Eigenfaces are basically nothing more than vectorization of real faces. One of the fundamental concepts in electrical engineering, Fourier analysis says that's a sum of weighted sinusoids at different frequencies can recompose a signal perfectly. By the same token a sum of weighted Eigenfaces can perfectly recompose a specific person's face

First, a set of face image is collected from publicly available face databases. Later it will be determined if an unknown face matches any of these known faces. All the faces must be of same size (in pixels) for this project and they must be grayscale images with values ranging from 0-255. Each face is then converted into a vector Γ_n of length N (N=image width x image height) One of the most useful features of a known face database is for it to have multiple samples of a person which will increase the accuracy tremendously, due to the increased number of facial information available for each known person. This known database is otherwise known as the "face space" of dimension N

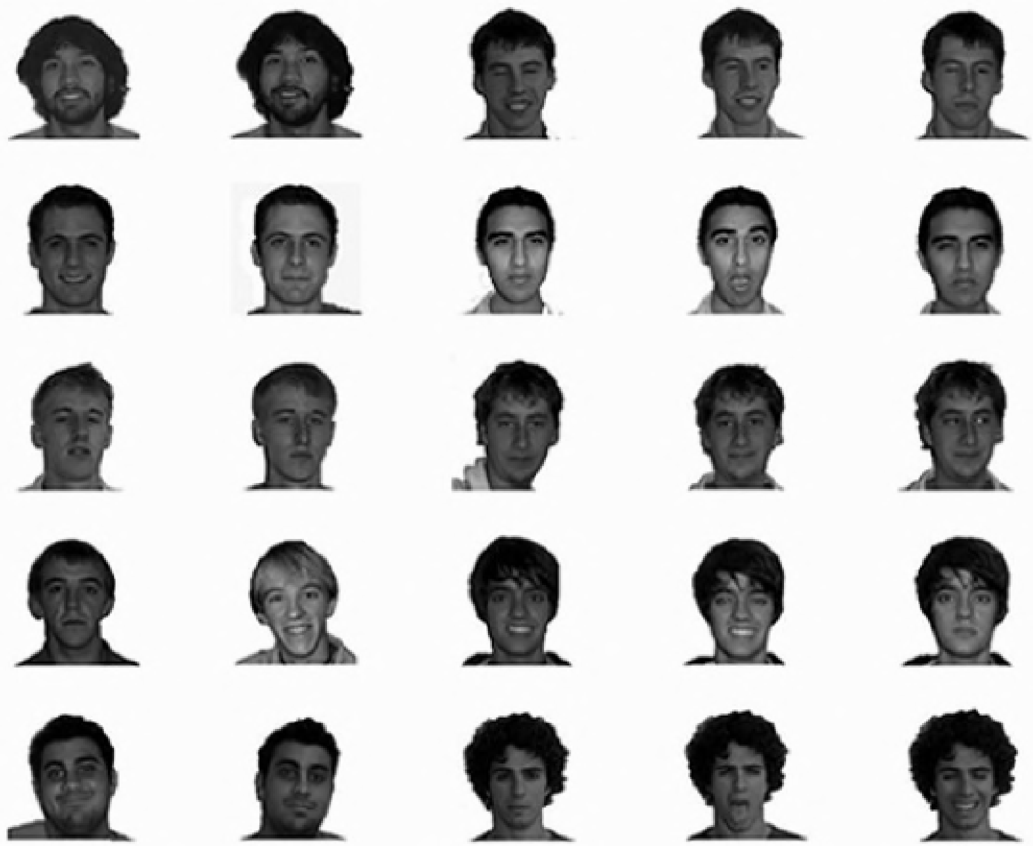


Figure11.1 Example Images from the Rice Database

Next an average face is computed in the face space. Here M is the number of faces in the training sub-space:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \qquad \textbf{\textit{(11.1)}}$$

Figure11.2: After computing average face

The difference of each faces from the average is then computed:

$$\Phi = \Gamma_i - \Psi \qquad \textit{(11.2)}$$

These differences are then used to compute the covariance matrix (C) for our sub-space. The covariance between two sets projects the correlation of two sub-spaces

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = \frac{1}{M}\sum_{n=1}^{M}\begin{pmatrix} \mathrm{var}(p_1) & \cdots & \mathrm{cov}(p_1, p_N) \\ \vdots & \ddots & \vdots \\ \mathrm{cov}(p_N, p_1) & \dots & \mathrm{var}(p_N) \end{pmatrix} = AA^T \qquad \textit{(11.3)}$$

Where $A = [\Phi_1\Phi_2\ldots\Phi_M]$ and p_i = pixel i of face n

11.1.2 Simplifying the Initial Eigenface Basis

A method known as Principal Component Analysis (PCA) is used to reduce the number of eigenvector of the above computed covariance matrix from N to M, in other statements the number of pixel in the image to the number of images in the dataset. PCA is a very effective method for finding patters in data of high dimension and is commonly used also in image compression. PCA is applicable to face recognition faces are very similar to each other as opposed to non-faces and share similar pattern and characteristics

By PCA, M images give M non-trivial eigenvectors. These eigenvectors can be solved for by taking the eigenvectors of the new M x M matrix:

$$L = A^T A \tag{11.4}$$

Doing the following manipulation

$$A^T A v_i = \mu_i v_i$$

$$A A^T A v_i = \mu_i A v_i \tag{11.5}$$

Where v_i is an eigenvector of L. This simple proof reveals that Av_i is an eigenvector of C

The M eigenvectors of L are then used to form the M eigenvectors u_l of C that form the eigenface basis

$$u_l = \sum_{n=1}^{M} v_{lk} \Phi_k \tag{11.5}$$

It turns out that only M-k would suffice to construct a complete basis for the face space, where k is the number of unique persons in known dataset

It is possible to get a decent recomposition of the image using only a few eigenfaces (M'), where M' ranges anywhere from .1M to .2M. These correspond to the vectors with the highest eigenvalues and represent the most variance within face space

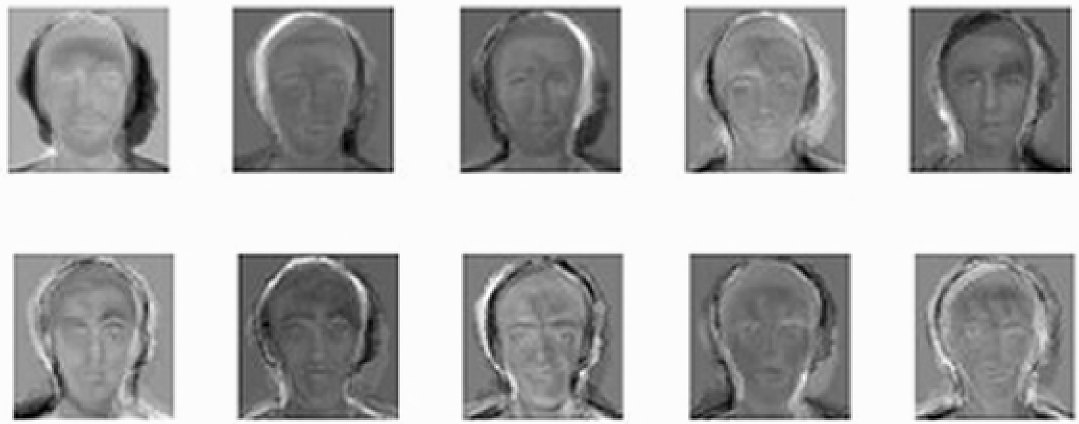


Figure 11.3: top ten Eigenfaces from Rice database

As previously mentioned using only a weighted sum of these Eigenfaces it is possible to recompose every face in the database. The project although goes one step further. With the basis known, individuals can be processed to prepare the system for recognition by setting thresholds and computing matrices of weights.

11.1.3 Threshold For Eigenface recognition

When a new image comes into the system, there are three special cases for recognition.

- Image is a known face in the database
- Image is a face, but of an unknown person
- Image is not a face at all. May be a dog, a house, or a lamp.

For real systems, where the photograph follows standards like driver's license photo, first two cases are useful. In general when one tries to identify a random picture, such as a shoe with a set of image is unrealistic at the very least. Nevertheless, threshold values still need to be defined to characterize the images

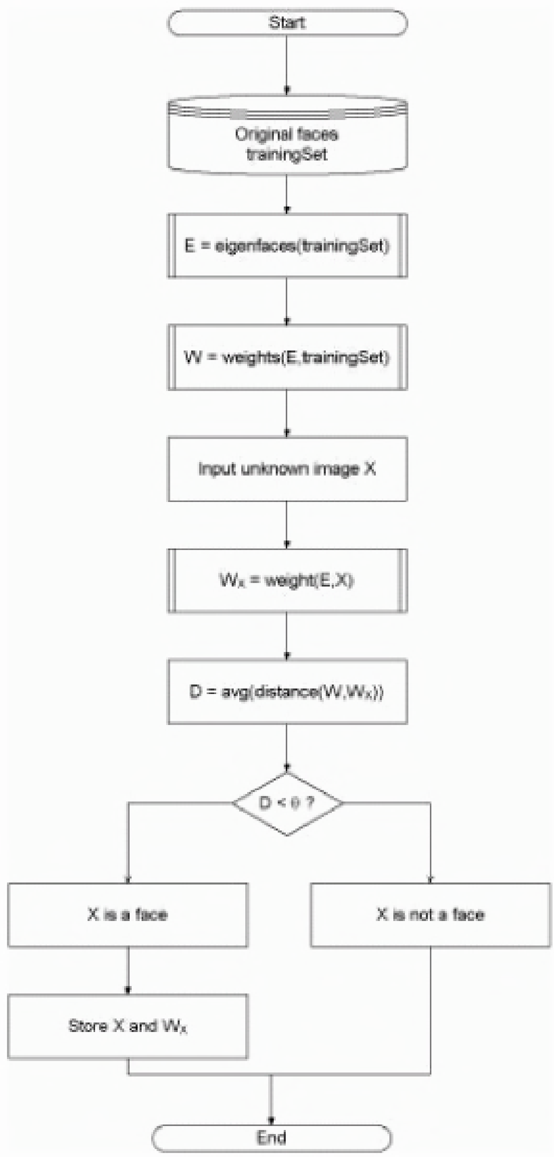
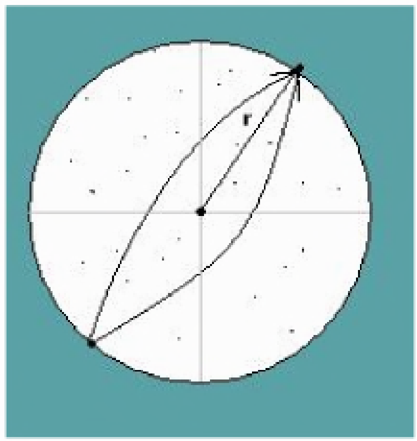


Figure 11.4: High-level functioning principle of the eigenface-based facial recognition algorithm

Using the weight matrix of values of M Eigenfaces, an M dimensional spherical face space can be defined that encloses all weight vectors in the complete database. Then, a radius can be obtained from the fair approximation of the half of the diameter of this sphere.



$$\theta_{threshold} = \frac{1}{2}\max\left(\sqrt{\|\Omega - \Omega_k\|^2}\right) \tag{11.6}$$

In order to tell whether a new input image falls within the radius, the reconstruction error between the image and its reconstruct is computed using M Eigenfaces. If the image projects onto the space relatively well, then the error will be small. However a non-face will always fall outside the radius of the face space

$$\Phi_{recon} = \sum_{n=1}^{M} \omega_i \mu_i \tag{11.7}$$

$$\varepsilon^2 = \|\Phi_{image} - \Phi_{recon}\|^2 \tag{11.8}$$

$$\varepsilon > \theta_{theshold} \tag{11.9}$$

If the resulting construction error is greater than the threshold, then the input image is not a face to begin with and therefore discarded

11.2 Face Recognition Using Eigenfaces

The next step is the recognition process, once the eigenface vectors are collected. Eigenface is a very easy, computationally economical technique to determine if a given input face is a known person, a new entry into the database or a non-face. Eigenfaces are linearly independent basis for face space and the vectors are autonomous. It should also be noted that Eigenfaces represent the principal component of the face set.

First, all the mean subtracted images in the database are taken and then projected onto the face space. This is basically the dot product of each image with one of the Eigenfaces. Combining the vectors of matrices a weight matrix M x N can be computed, where N is the dimension of the database

$$\omega_k = \mu_k(\Gamma_{new} - \Psi) \tag{11.10}$$

$$\Omega^T = [\omega_1 \omega_2 \ldots \omega_{M'}] \tag{11.11}$$

$$WeightMatrix = \begin{pmatrix} \omega_{11} & \cdots & \omega_{1n} \\ \vdots & \ddots & \vdots \\ \omega m'1 & \cdots & \omega m'n \end{pmatrix} \tag{11.12}$$

An input image can similarly projected onto the face space which will yield a vector of M dimensional space. Now the recognition is simply a matter of finding the closest match in the database which is mathematically computed using simple Euclidian distance between and a database point

$$\varepsilon_k = \sqrt{\| \Omega_{new} - \Omega_k \|^2} \tag{11.13}$$

Due to the overall similarities of facial structures, the face pixels follow an overall face distribution. By combining this distribution with PCA dimension can be reduced significantly. The computational complexity is extremely reduced this way.

11.3 Averaging Technique

The above mentioned method can be further refined by averaging together the weight vectors of a like person. This creates a class of faces where an even smaller weight matrix can represent the general faces of the entire dataset. Upon the arrival of an input image a weight vector is created by projecting onto the face space. The face is than matched against the face class than minimizes the Euclidian distance. A hit is counted if the image matches correctly its own face class. A miss occurs if the minimum distance of a face class of another person.

Chapter 12

Implementation

12.1 Overview

This chapter describes the proof of concept implementation developed during this thesis.

These are:

- Faceprint, a Visual Basic 6 implementation of an automatic facial recognition
- Process using Histogram Equalization, Eigenface, and Averaging technique.
- A Math Module that returns sigmoid values and computes Inverse Cosine.

- A front interface (Interface.frm) that loads (loadFace) equal sized grayscale images from the directory, initialize (init) and add faces to the training set and after when the eigenvectors are computed run the identification routine once template created out of samples
- First of two class modules, FaceProcessingEngine, implements HE and Eigenface functions described in Development section, a blurring technique is used (diffuseEdges) which diffuses edges information which allows edge tracing to be more noise tolerant.
- The second of two class module, FaceRecognitionEngine, simply makes use of the FaceProcessingEngine to update an average face template as soon as a new image added to the face space and then simply matches the face with the highest eigenvector value after a sort has been conducted.

The specific content of the CD-ROM is listed in Appendix c.

12.2 Faceprint

Faceprint is a VB6 implementation of an automatic facial recognition system developed on Visual Studio Platform. Faceprint is implemented for the face recognition task (one-to-many search) and is not expected to encounter unknown persons. Faceprint uses HE for light correction, Masking and Circular Tracing for face detection and Eigenfaces for face recognition.

A screen shot of Faceprint is displayed in Figure 12.1. A quick user guide is provided in Appendix D.

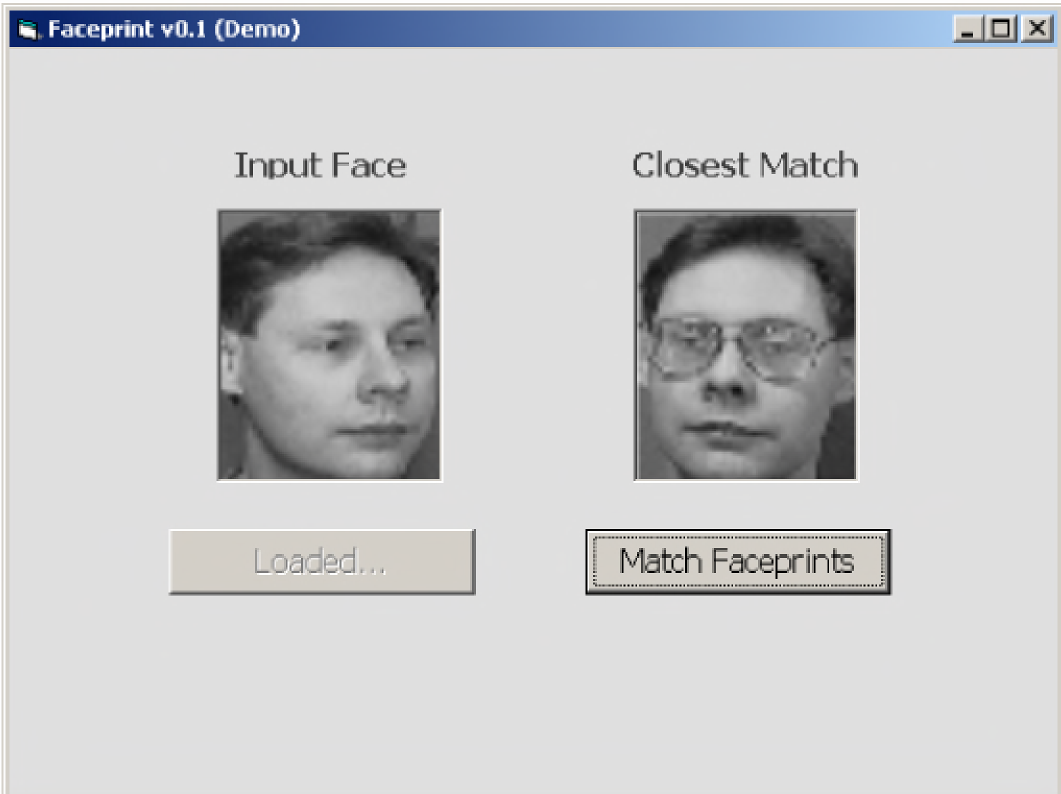


Figure 12.1: The main window of the Faceprint application, which contains an input from a directory, and, the image of the recognized person.

Faceprint application is a naïve approach to facial recognition. So, sophisticated settings and equipment have not been used implementing it. Figure 12.2 displays a case where the application fails to identify the person.

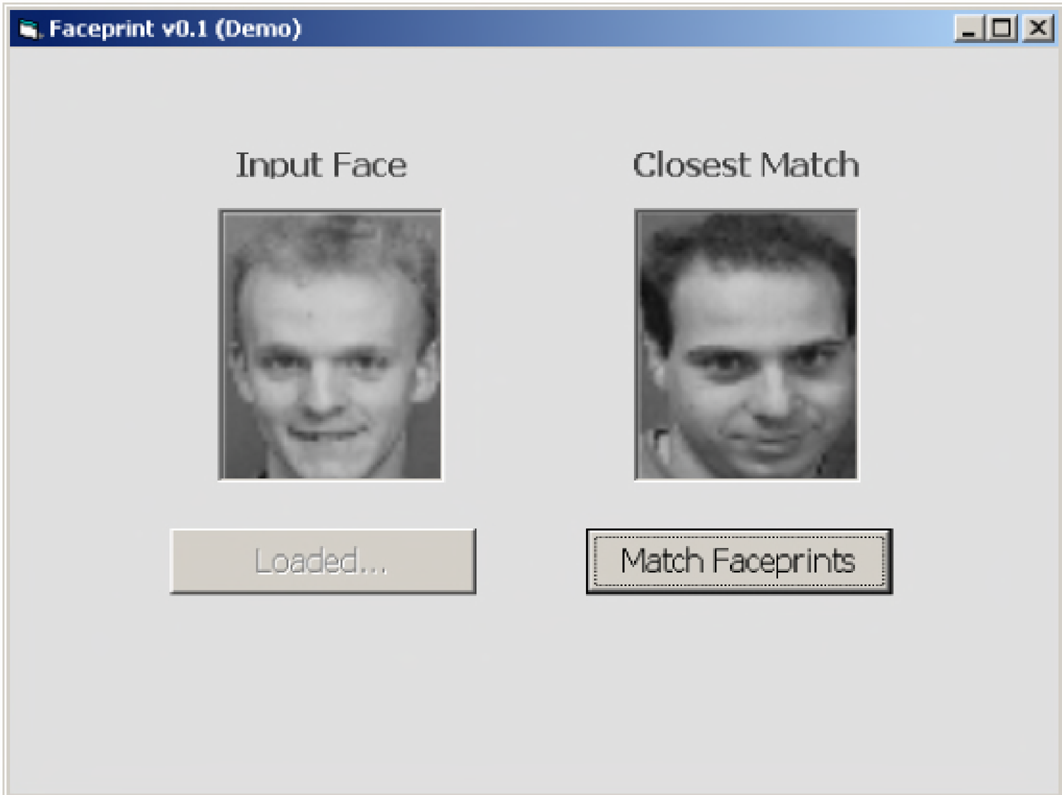


Figure 12.2: The Faceprint application obtaining a false recognition.

12.2.1 Faceprint Requirements

The Faceprint application is designed for the windows platform and is fully tested on a Windows-XP machine. For face detection and recognition MathsModule.bas; FaceProcessingEngine.cls and FaceRecognitionEngine.cls must be provided. The complete source code is included on the enclosed CD-ROM.

Part IV

Test Results

Chapter 13

Recognition Results

13.1 Undistorted input results

For averaging technique undistorted duplicate of the original images were fed into the system for recognition in order to determine the best-case rate for recognition. For all there datasets (Rice, AT&T and Yale) rates of recognition stabilized as the number of Eigenfaces used in the recognition scheme increased.

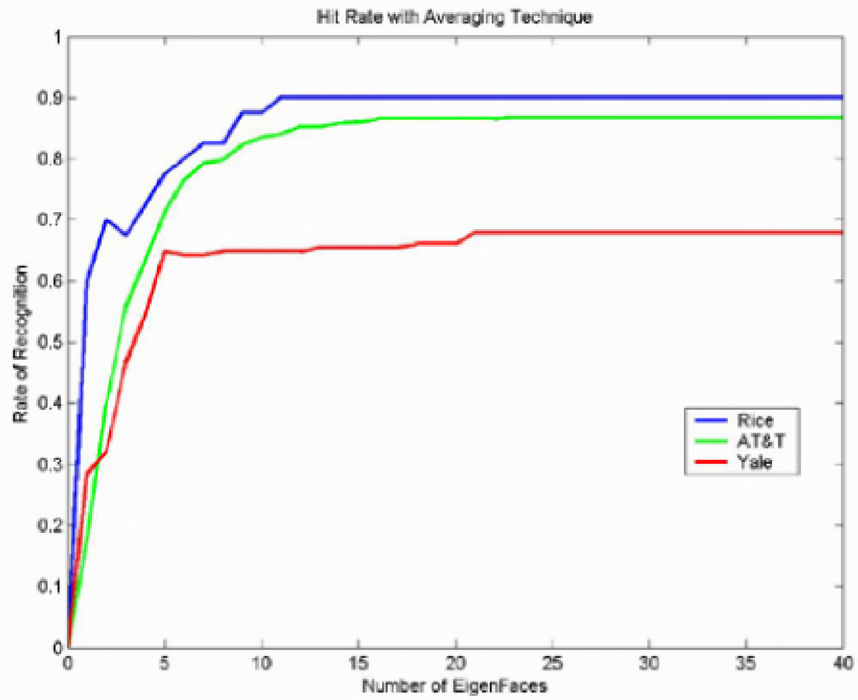


Figure 13.1: Rate of identification of the correct individual using undistorted inputs for the averaging technique.

Using averaging technique, for each image set, stability was reached at the following hit rate and for the specified number of Eigenfaces:

Image Set	**Stable Hit Rate**	**Number of Eigenfaces**
Rice	90%	11
AT&T	86%	17
Yale	68%	21

Table 13.1. Number of Eigenfaces for Hit Rate Stability for All Image Sets

For detection tests using a number of Eigenfaces greater than that specified in Table 13.1 no significant improvement in detection success rate was achieved. These tests suggest that averaging techniques do not achieve greater detection rates with numbers of Eigenfaces greater than the minimum number needed for stability.

13.2 Occluded Input Results

For averaging technique, Rice image sets were tested for detection rates with horizontal and vertical occlusions centered on the vertical and horizontal axes respectively. Results show that hit rate stability, as before, is achieved as the number of Eigenfaces used increases.

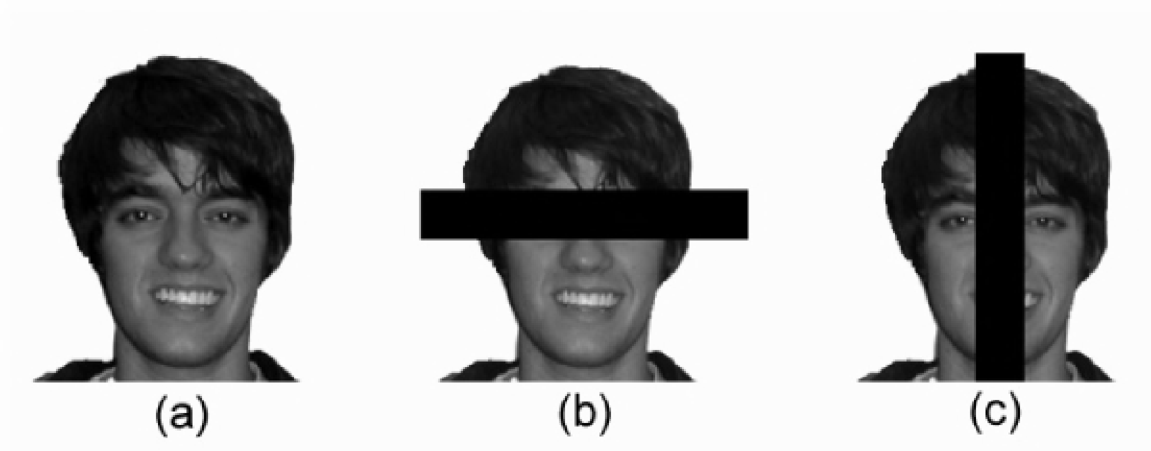


Figure 13.2: (a) the undistorted base image. (b) The image with a horizontal occlusion. (c) The image with a vertical occlusion.

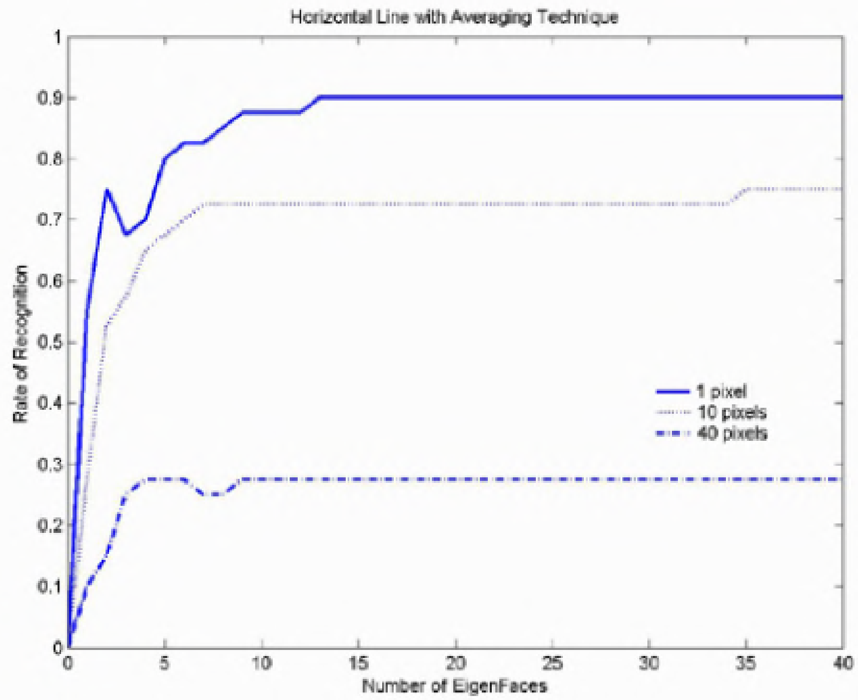


Figure 13.3: Rate of identification of the correct individual using horizontally occluded training set with the averaging technique.

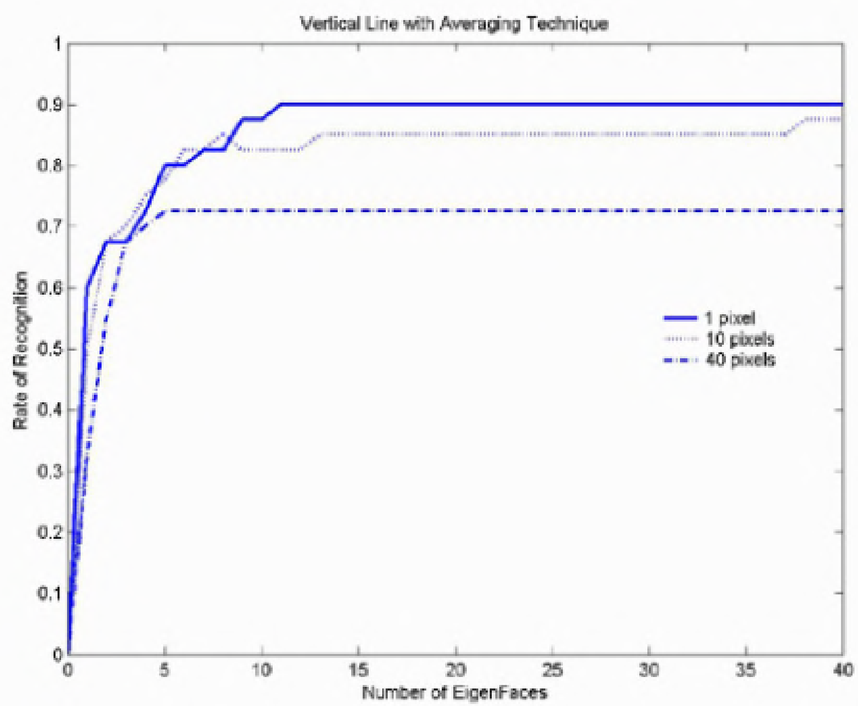


Figure 13.4: Rate of identification of the correct individual using vertically occluded training set with the averaging technique.

For each image set stability was reached at the following hit rate and for the specified number of Eigenfaces:

Occlusion	Stable Hit Rate	Number of Eigenfaces
Horizontal 1 pixel	90%	13
Horizontal 10 pixels	72%	7
Horizontal 40 pixels	28%	4
Vertical 1 pixel	90%	11
Vertical 10 pixel	83%	7
Vertical 40 pixel	71%	5

Table 13.2. Number of Eigenfaces for Hit Rate Stability for Rice Image Set, Averaging Technique

For detection tests using a number of Eigenfaces greater than that specified in Tables 13.2 no significant improvement in detection success rate was achieved. The occlusion tests suggest that averaging technique do not achieve greater detection rates with numbers of Eigenfaces greater than the minimum number needed for stability without occlusions.

Part V

Discussion/Conclusion

Chapter 14

Interpretation

Analysis of the eigenface method using averaging technique coupled with histogram equalization gives evidence that the system is 90% accurate. The recognition rates stabilized for a given number of Eigenfaces relatively quickly. This justifies that in any implementation of such a recognition system it is rather wasteful if not meaningless to using more Eigenfaces than optimal to achieve desired level of accuracy. Moreover, the measurements of accuracy with vertical, horizontal and 2D blurs also proves more than necessary number of Eigenfaces provide to added accuracy in sub-optimal conditions

So, it is logical to conclude that in order to assure higher success rates, refinements to the Eigenface concept must be made. Various other studies suggest profile size, complexion, ambient light and facial angle play significant parts in identification of a particular image. Effectiveness of using eigenface and weighing technique for varying illumination and facial angles should be investigated further.

Chapter 15

Future Work

The following sections describe interesting areas which could improve the facial recognition approach taken in this thesis

Light Normalization: One way to improve the robustness and flexibility of this implementation is to improve light normalization/correlation in the preprocess step since it does not need to be trained to be capable of handling multi-lighting conditions.

Face Detection: From an implementation point of view proper face detection is very important in a face recognition process. A very naïve approach is used in order to detect the edges with the images more sophisticated method such as

AdaBoost Learning-Based detection method which proved to be most successful could be used.

Skin Colour and Texture Modeling: Currently this implementation doesn't have any support for finer grained details such as skin colour and textures. Support for these will enable any face recognition system become more robust.

Chapter 16

Conclusion

The increase in complexity in security technologies provides for a new market for complementary technologies such as face recognition. Faced with security and safety mandate in public places; demands could be partially met by deployment of these technologies.

The four objectives of this thesis were: To discuss and summarize the process of facial recognition, to look at currently available facial recognition techniques, to design and develop a robust facial recognition system and finally an implementation and test result of this new system.

In Chapter 2 to Chapter 10 this thesis presents a comprehensive overview of the area of facial recognition, satisfying the two first objectives. The third objective of this thesis is satisfied by the work presented in Chapter 11 by the design and development of Faceprint. By tests, Chapter 13, the system demonstrated effectiveness and reliability. Finally, the last objective is satisfied by the work presented in Chapter 12.

With the completion of this thesis, an important step in addressing the quality and reliability of face recognition schemes has been completed

Appendix A

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Appendix B

CDROM Contents

1. Thesis Report
2. PowerPoint Presentation (Dec)
3. PowerPoint Presentation (Mar)
4. Faceprint Application (Executables, Using Dataset I & Dataset II)
5. Source Code