FACE RECOGNITION IN UNCONTROLLED INDOOR ENVIRONMENT

by

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Abstract

Face recognition (FR) is one of the most convenient biometric systems even though it is not currently the most reliable one. Especially when images for (FR) system are captured by surveillance cameras, such cameras often produce low quality images which make recognition more difficult and less reliable. This study uses a recently published database called 'SCface database' which emphasizes the challenges of face recognition in uncontrolled indoor conditions such as lighting conditions, face pose, facial expression and distance to camera. More specifically, the recognition is done using different cameras of different resolutions and imaging sensors. The aim of this study is to examine the effect of camera quality and distance from the camera with regards to face recognition rates by analyzing different face recognition schemes such as Eigenfaces, Discrete Cosine Transform (DCT), Wavelet Transform, Gray Level Concurrence Matrix (GLCM) and Spatial Differential Operators (SDO). Principal Component Analysis (PCA), Zonal coding and spectral regression were also investigated as various dimensionality reduction approaches. At the classification stage a variety types of classifiers were tested and compared such as: Linear Discriminant Function (LDF), KNN classifier, polynomial classifiers and Neural Networks. As a result we developed a reliable face recognition system that recognizes faces captured by different cameras in terms of quality and resolution at different distances in surveillance conditions. In our proposed algorithm, face images are preprocessed by means of; skin segmentation, color transformation, cropping, normalization and filtering. Then both Spatial Differential Operators (SDO) and Discrete Cosine Transform (DCT) are applied to extract features, and Principal Component Analysis (PCA) is employed to reduce dimensionality. Linear Discriminant Function (LDF) is utilized as a classifier. The proposed system is compared with the well-known eigenfaces recognition solution. Experimental results show that the proposed system yields superior recognition rates compared to those obtained by the recently published solutions.

Search Terms: ***Face Recognition, Spatial Differential Operators (SDO), Eigenfaces, Discrete Cosine Transform (DCT), Grey Level Co-occurrence Matrix (GLCM), Principle Component Analysis (PCA), Linear Discriminant Function (LDF).***

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ASM	Active Shape Model
DCT	Discrete Cosine Transform
DWT	Discrete Wavelet Transform
EBGM	Elastic Bunch Graph Matching
EFM	Enhanced Fisher Model
FAR	False Accept Rate
FLDA	Fisher’s Linear Discriminant Analysis
FMR	False Match Rate
FNMR	False Non-Match Rate
FR	Face Recognition
FRR	False Reject Rate
FTE	Failure To Enroll
GLCM	Grey Levels Co-occerrence Matrix
HCI	Human Computer Interface
HPF	High Pass Filter
IR	Infra Red
KNN	K Nearest Neighbours
LDF	Linear Discriminant Function
LPF	Low Pass Filter
PCA	Pricipal Component Analysis
RLDA	Regularized Linear Discriminant Analysis
SDO	Spatial Differntial Operators
SFDCF	Spatial and Frequency Domains Combined Features
SR	Spectral Regression
STFT	Short Time Fourier Transform
SVDD	Support Vector Data Description

LIST OF SYMBOLS

α	Regularization Coefficients
B_e	Subset of biological characteristics or behavioral qualities that are enrolled.
B_p	Represents all biological characteristics or behavioral qualities for all persons.
C	Set of recognized classes
C	Covariance matrix of the training images after subtracting the mean
Cam	Camera
Cb	Chrominance blue difference
cdf	Cumulative distribution function
Cr	Chrominance red difference
d	Differential operator
Dist	Distance
F(u,v)	Frequency domain value
h	Pixel's equalization value
K	Number of Training images
L	Number of grey levels
$M \times N$	Image size
Ne	Number of selected Eigen vectors
$P(x_i)$	Probability density function
S_B	Between-class scatter
S_m	Set of biometric samples
S_p	Set of processed samples
S_w	Within-class scatter
T	Set of templates or extracted features from the processed samples.
Tq	Subset of T represents features suitable for recognition after quality control.

Tr	Training Image
Ts	Testing Image
v	Pixel's value
w_j	Linear Classifier weights
Y	Luminance
φ_i	Training Image after subtracting the mean
μ	Average
μ_i	Eigen vector

1. INTRODUCTION

This chapter introduces the necessary background of biometrics technology. It also defines and describes the face recognition problem and presents the face recognition system and its applications. Then, it proceeds to the objectives and main contribution of this research. Finally, it outlines the organization of the remaining parts of this thesis report.

1.1. Biometrics

Biometrics can be defined as identifying people based on their physiological characteristics which are genetically implied or behavioral qualities which are acquired during person's life [1].

1.1.1. Introduction to biometric technologies

In order for a biometric system to be reliable the chosen biometric characteristic must exist in each person (Universality). Not only should this biometric characteristic differ from one person to another (Distinctiveness) but also it should not vary for the same person (Permanence). Moreover, it should be measured quantitatively (Collectability) and accepted by the public (Acceptability) [2]. In general biometrics can be classified into two categories; physiological and behavioral. Table 1 shows some biometrics examples:

Table 1 Biometrics examples

Physiological characteristics	Behavioral qualities
• Facial recognition • Fingerprint recognition • Hand geometry • Iris recognition • Retina recognition	• Signature recognition • Keystroke recognition • Voice recognition • Gait recognition • Human-Computer Interaction

1.1.2. Biometric system's modes of operation

A biometric system mainly includes three modes of operation; these modes are Enrollment, Verification and Identification. In the Enrollment mode of operation the system collects information about the person to be identified by sensing and measuring a certain characteristic and then it generates a template for this person. This template is added to the database of the biometric system. Verification is known as one to one matching, it simply answers the question "am I the person whom I claim to be?" However, Identification is one-to-many matching, in which the system selects the best template that matches the test sample [3]. Figure 1 shows biometric systems modes of operation.

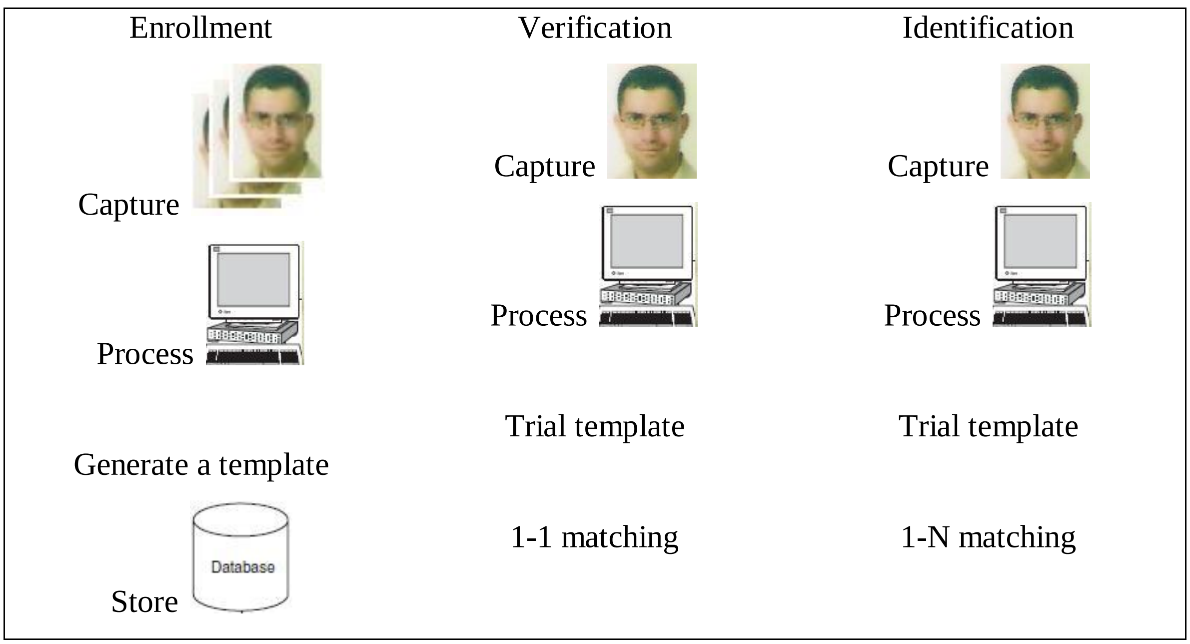


Figure 1 Biometric systems modes of operation

Seven sets can be formalized to show how biometric systems work [1] These sets are:

B_p Represents all biological characteristics or behavioral qualities for all persons.

B_e Subset of B_p biological characteristics or behavioral qualities that are enrolled.

S_m , S_p Sets of biometric samples and processed samples respectively.

T Set of templates or extracted features from the processed samples.

T_q Subset of T represents features suitable for recognition after quality control.

C Set of recognized classes. The relation between these sets can be established as follows:

$$B_p \xRightarrow{Enroll} B_e \xRightarrow{Sampling} S_m \xRightarrow{proessing} S_p \xRightarrow{Feature\ \ extraction} T \xRightarrow{Quality\ \ control} T_q \xRightarrow{Classification} C$$

1.1.3. Performance of biometric systems

Biometric systems vary in complexity, quality and efficiency. However; measuring the efficiency of any biometric system is not easy but there are some key measures that show the performance of a biometric system. These measures are False Match Rate (FMR- probability of being matched incorrectly) and False Non-Match Rate (FNMR- probability of being wrongly not matched). These two errors are identification errors at algorithmic level; they are related to 1-N matching process. While False Accept Rate (the probability of being accepted incorrectly) and False Reject Rate (the probability of being rejected incorrectly) are verification errors at the system level, they are related to 1-1 matching. Failure To Enroll (FTE- probability of being not able to enroll) and Failure To Acquire are acquisition errors [4]. In this research the 1-N matching process is considered and recognition rates are calculated based on FMR.

$$\boldsymbol{Face\ recognition\ rate\ =\ 100\%\ -\ FMR} \qquad 1\text{-}1$$

1.1.4. Face versus other biometric characteristics

In fact there is a trade-off between the accuracy of any biometric system and how convenient and acceptable is that system. In fingerprint mainly two types of features are extracted and used for classification: global features which are the integral flow of ridges, and local features such as minutiae matching which focuses on details such as ridge ending, delta and island [5]. Each person’s fingerprints are unique and the technology of fingerprint is easy to use and it gives high recognition rates. There are some limitations with fingerprint systems; fake fingerprints can beat this technology [4]. Moreover this technology might fail if finger tissues change because of damage, age or any other reason. One more issue to be considered is that user interaction is required in fingerprint systems.

Iris recognition is considered to be one of the most reliable biometric systems because of the high textural variation in irises. There are several ways to extract iris features either in binary representation such as Gabor filter and Gaussian filter or in real value features such as Discrete Cosine Transform (DCT), and wavelet transformations [6]. Data acquisition is not easy for iris it has low acceptability among people, similar to fingerprint user intention is required, iris recognition equipment are expensive.

In sound identification the implementation cost is very low but voice patterns are not highly repeatable and it can easily affected by noise [7].

On the other hand, in face recognition based biometrics, face image capturing can be done without the person's attention or interaction using low cost cameras. One more advantage for face recognition is that face images are already collected and stored in databases when issuing ID cards or passports and that is socially and culturally accepted. There are so many feature extraction schemes used in face recognition systems such as Eigenfaces, Fisherfaces, Laplacianfaces and Elastic Bunch Graph Matching (EBGM) [8].

Face recognition has many challenges associated with it including lighting conditions, pose, image capturing distance, facial expression and changes in faces during the lifetime [4]. These challenges should be studied and considered in the design phase of any face recognition system.

Table 2 compares biometric technologies. It is clear from this table that there is a trade-off between the accuracy of any biometric system and how convenient and acceptable is that system.

Table 2 Comparison of biometrics technologies [3]

Biometrics	Uniqueness	Permanence	Collectability	Performance	Acceptability
Face	Low	Medium	High	Low	High
Fingerprint	High	High	Medium	High	Medium
Keystrokes	Low	Low	Medium	Low	Medium
Hand Vein	Medium	Medium	Medium	Medium	Medium
Iris	High	High	Medium	High	Low
Retinal Scan	High	Medium	Low	High	Low
Signature	Low	Low	High	Low	High
Voice Print	Low	Low	Medium	Low	High
Odor	High	High	Low	Low	Medium
DNA	High	High	Low	High	Low
Gait	Low	Low	High	Low	High
Ear	Medium	High	Medium	Medium	High

1.2. Face recognition system

Human face is a 3-D non-rigid object which is usually photographed under uncontrolled environment. Face recognition has drawn the attention of researchers because it is one of the easiest and most convenient biometrics that can be utilized in security, psychology and computer vision [3].

A general face recognition system model starts with a face detection stage. At this stage a face is located and extracted from a background. Change in illumination, camera quality, and facial expression are important factors that affect performance of face recognition (FR) systems[9]. These variations can be combated by preprocessing. Preprocessing is used to alleviate uncontrolled lighting conditions and to eliminate unwanted details in the face that could harm FR performance. After preprocessing comes feature extraction; a feature extractor converts the input face image into a reduced and representative set of parameters. These parameters vary among the different known feature extraction algorithms; some algorithms follow appearance-based methods while others follow model-based approaches. Feature selection may be used within or after feature extraction to further reduce the number of extracted parameters. The last stage in an FR system is classification, which has two modes of operation; training mode and testing mode. In the training mode, features extracted form a training set are processed to generate face models. While in the testing mode, features extracted from faces to be recognized are matched against the previously generated face models. Figure 2 shows a typical block diagram of a FR system.

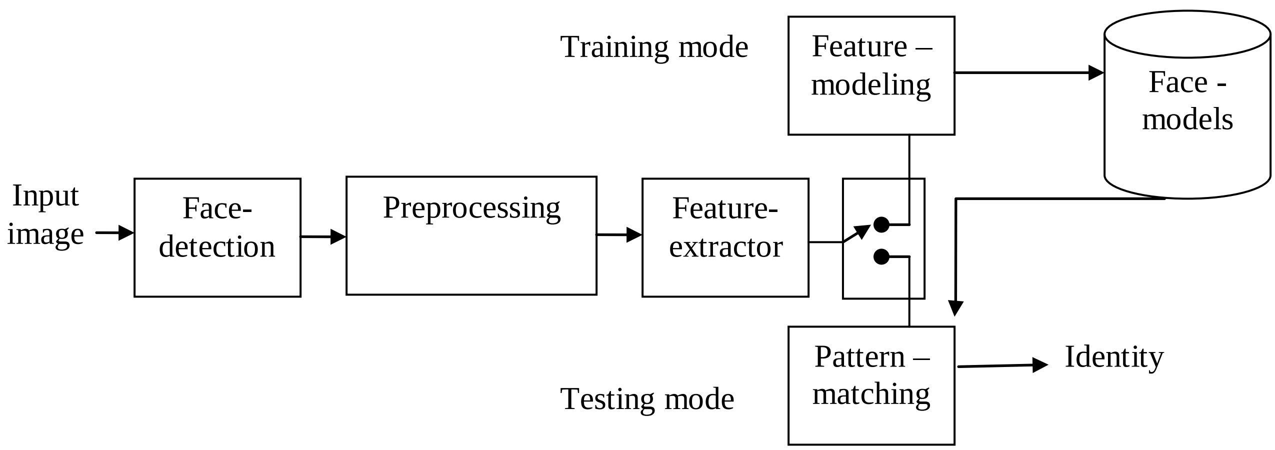


Figure 2 Face recognition system model

1.3. Face recognition applications

Potential applications for face recognition systems include ATM machines, online access, elections and Human Computer Interface (HCI). These applications can be summarized as follows [10]:

- Access control: in some systems a combination of both password and physical security is used for PC logins. This physical security access could be achieved by a finger print or face recognition software add-ons.
- Identification Systems: to prevent people from getting multiple identity cards or driving licenses.
- Surveillance: Face recognition is perhaps the most convenient system in such application since it does not need a person's interaction or even his awareness.

1.4. Thesis Objectives and Contribution

Face recognition is considered to be a solved problem when relatively high resolution cameras are used at almost fixed and close distance with slight changes in lighting and pose. Researchers have achieved more than 97% recognition rate for such conditions. For example, in the Yale face database five human faces were selected as training samples, then wavelet transformation was applied to extract features, and the recognition rate of 97% was achieved [11]. Applying wavelet faces and PCA on Essex Grimace database and ORL database gives recognition rate of 98.5% and 94.5% respectively, while using Curvelet Based PCA gives 98.5% and 96.6% [12].

SCface database presents a challenging face recognition problem, because images were taken using different quality cameras at different distances to mimic real-world surveillance conditions. The researchers who produced and published the SCface database declared that their recognition rates never exceeded 10% when the well-known Eigen faces standard FR recognition algorithm was used [13].

The main objective of this research is to examine the effect of having images taken by different camera qualities of low resolution at different distances on several face recognition schemes (i.e. under surveillance application). Accordingly, the SCface database was used in this thesis.

In this thesis we aim to develop a face recognition system (a set of algorithms) that recognizes faces captured by different cameras of varying qualities and resolutions at different distances in uncontrolled indoor conditions. We intend to develop a set of algorithms that yield superior recognition rates to the state-of-the-art results published on the SCface database.

To examine the effect of camera quality and distance from the camera with regards to face recognition rates different face recognition schemes were analyzed in this work, the following feature extraction methods were examined: Eigenfaces, Discrete Cosine Transform (DCT), Wavelet Transform, Gray Level Concurrence Matrix (GLCM), Spatial Differential Operators (SDO), and a combination of both spatial domain features with frequency domain features. Principal Component Analysis (PCA), Zonal coding and spectral regression were also investigated as various dimensionality reduction approaches. At the classification stage a variety types of classifiers were tested and compared such as: Linear Discriminant Function (LDF), KNN classifier, polynomial classifiers and Neural Networks.

The main contribution of this research is presenting and applying a novel technique for (FR) that combines spatial domain features and frequency domain features. Experimental results show that skin segmentation, color transformation, normalization, and filtering images via low pass filter as preprocessing techniques then using (SDO) followed by PCA with (DCT) as feature vectors improves face recognition rate for images taken at different distances. In our proposed method the recognition rates obtained when different quality cameras are used reach 99.23% while the highest published rate obtained was 91.78% [35]. More importantly, our recognition rate across different distances reaches 93.8% as compared to the best published rate of 62.78% [34].

1.5. Thesis Outline

This thesis consists of eight chapters which are organized as follows: Chapter 1 Introduces the necessary background in biometrics. Chapter 2 describes SCface database and emphasizes its importance as a challenging face recognition problem, this chapter also compares SCface database with some other well known face databases. Chapter 3 summarizes work done by researchers on FR. Face detection and preprocessing techniques for FR and the consequences of image enhancement are discussed in Chapter 4. Different feature extraction schemes are presented in Chapter 5. Dimensionality reduction and features manipulation are discussed in chapter 6. Pattern recognition and various classification techniques are investigated in chapter 7. Our proposed face recognition system and the experimental results obtained are analyzed in chapter 8. Finally, conclusions and future work are presented in Chapter 9. Main Algorithms used in this research are presented in appendix A, B and C.

2. FACE RECOGNITION DATABASES

This chapter describes SCface database and explains how images were collected using different surveillance cameras, it emphasizes the importance of this database as a challenging face recognition problem, since images were taken from different quality cameras at different distances and it compares SCface database with some other well known face databases.

2.1.Scface database

SCface [13] is a database of static images of 130 different people. Earlier, images were taken by five different video surveillance cameras (cam1, cam2… cam5) those cameras are of various i quality and resolution. Each person was asked to walk in front of the surveillance cameras and stop at previously marked positions as shown in Figure 3 (at distances of 4.20, 2.60 and 1.00 meters). In this way 15 images per subject were taken. The only illumination source was outdoor light coming from a window on one side. All cameras were placed at height of 2.25m.

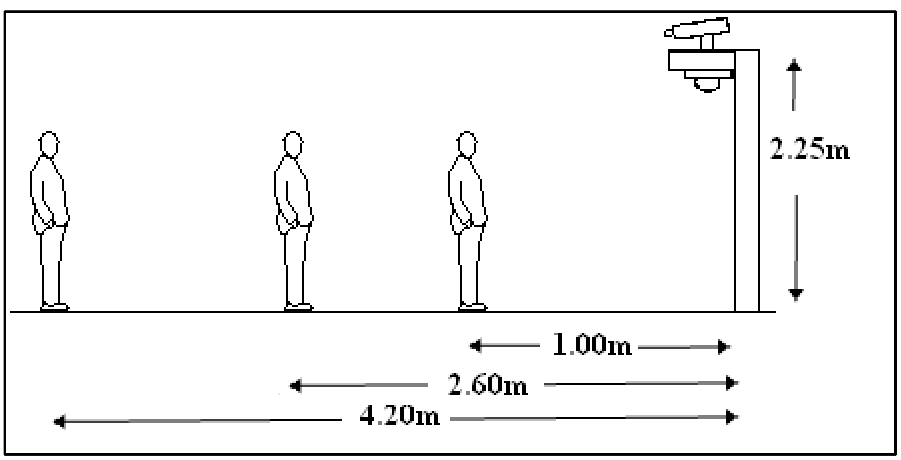


Figure 3 Capturing distances

Figure 4 shows images taken by the five mentioned cameras (cam1, cam2… cam5) for Subject 1 at distance 1 which is 4.2m. Size of images taken at this distance is 100×75:

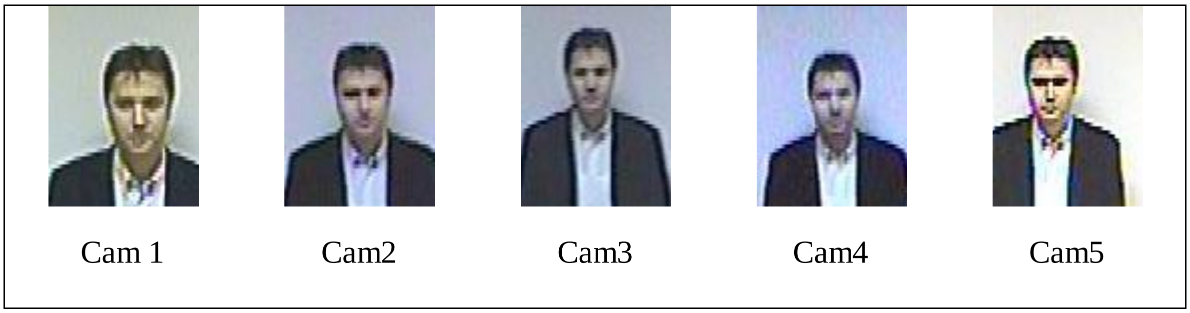


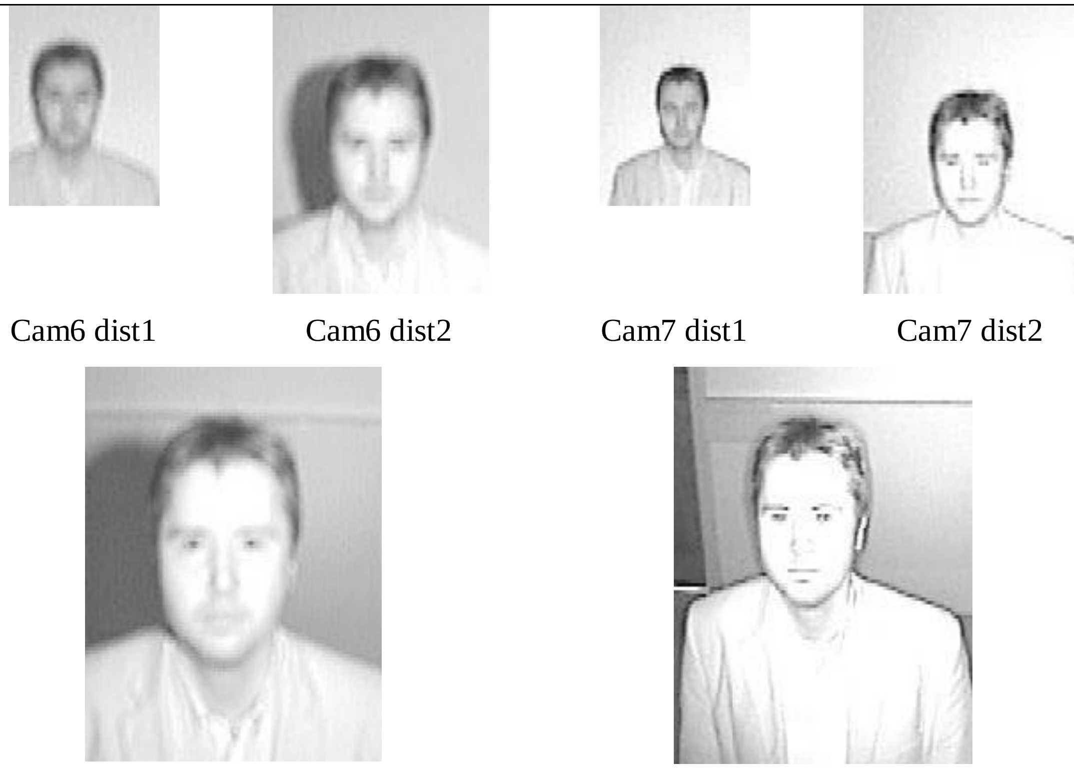
Figure 4 Images for subject 1 at distance of 4.2m [13]

Figure 5 shows images taken by the five mentioned cameras for Subject 1 at distance 2 which is 2.6m; Size of images taken at this distance is 144×108, while Figure 6 shows images taken by the five mentioned cameras for Subject 1 at distance 3 which is 1.0m; Size of images taken at this distance is 224×168:

Figure 5 Images for subject 1 at distance of 2.6m [13]

Figure 6 Images for subject 1 at distance of 1.0m [13]

Cam1 and cam5 were used also in IR night vision mode to produce two more images per subject; new names were given for these cameras in IR night mode. Cam 6 is the new name for cam1 in IR mode while cam 7 is the new name for cam5 in IR mode. Same procedure was followed but this time in dark room; each person was asked to walk in front of the surveillance cameras and stop at previously marked positions (at distances of 4.20, 2.60 and 1.00 meters). Six images per subject were taken as shown in Figure 7.

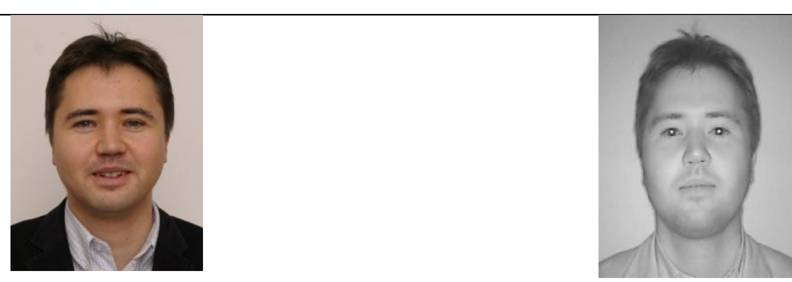


Cam6 dist1 Cam6 dist2 Cam7 dist1 Cam7 dist2

Cam6 dist3 Cam7 dist3

Figure 7 Images for subject 1 using IR night vision mode [13]

A high-quality photo camera was used to take a mug shot image in controlled light environment and IR image as shown in Figure 8. Images were scaled by15%



Mug shot IR – cam8

Figure 8 Images for subject 1 mug shot and IR [13]

Finally each person was photographed with a digital camera at a closer distance in standard indoor lighting at different views varying from -90 to 90 with a step of 22.5 degrees. Nine images per subject are shown in Figure 9. Total number of images per subject is 15+6+2+9=32.

Figure 9 Images for subject 1 different views [13]

2.2. Olivetti Research Lab (ORL) database

The ORL database was collected between 1992 and 1994 [14] It contains ten different images for each subject of 40 distinct subjects. Some images were taken at different times, slight variations in illumination, and little facial expression variations, the conditions were not varied systematically [15]. All the images were taken against a dark homogeneous background and all are frontal with slight tilt. Images are in grey scale with 256 grey levels per pixel, and all are of the size 92 x 112. Figure 10 shows samples of ORL images.

Recognition rate reaches 99.5% when this database is tested using FR system based on pseudo 2D Hidden Markov Model and DCT features [16]. While using PCA base Immune Networks (PCA-IN) gives a recognition rate of 99.70% [17].

Figure 10 Face images from ORL database [14]

2.3. Yale face database

The Yale Face database contains 11 images of 15 subjects, facial expression varies and light is centered in all images [15], 165 grayscale images in GIF format, and the size of each image is 243×320 with 256 gray levels per pixel. Recognition rate is 84% when using discrete orthogonal moments [18]. Gradientfaces method achieves 93.94% on Yale database [19]. Sample of Yale face database is shown in Figure 11.

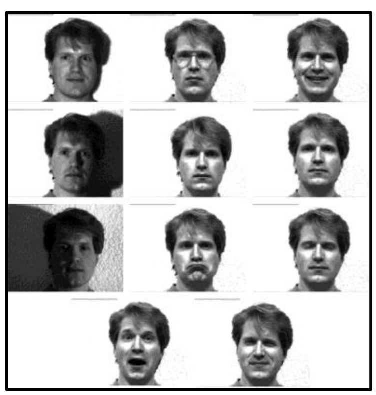


Figure 11 Face images from Yale face database [18]

2.4.AR database

4,000 color images corresponding to 126 people's faces (70 men and 56 women). All Images are frontal view faces with different facial expressions, and different illumination conditions [15], sample is shown in Figure 12. A combination of Trace transform and Fourier transform is applied on AR database to detect faces followed by hamming distance, the recognition rate found to be higher than 88% [20].

Figure 12 Face images from AR face database [20]

2.5.FERET database

The Facial Recognition Technology (FERET) database was collected at George Mason University wide set of pose variations and frontal images with slight expression variations are there in FERET database [15], sample is shown in Figure 13. Radon Transform was applied for enhancement followed by DCT to extract face features, the recognition rates obtained for two different sets of FERET database are 97.75% and 98.93% [21].

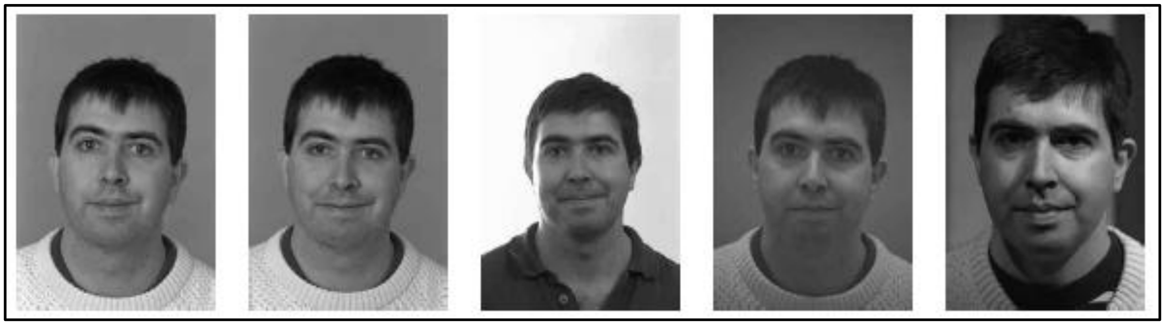


Figure 13 Face images from FERET face database [15]

2.6. Summary of some well-known face databases

The following tables summarize the challenges in some of the well known face databases, it is very clear that SCface database is one of the most challenging face recognition problem.

Table 3 FR challenges

Challenge ID	Challenge description
(1)	Facial expression
(2)	Pose to camera
(3)	Illumination
(4)	IR images (night mode vision)
(5)	Distance from camera,
(6)	Camera quality (low resolution images)
(7)	Different cameras,
(8)	w/no glasses, w/no scarf,
(9)	Aging

Table 4 some well known face databases

Database	Color	Image size	Subjects	Challenges
AR face database	Yes	576x768	126	(1),(3),(8)
Yale face database	No	320x243	15	(1),(3),(8)
Yale (B) face database	No	640x480	10	(1),(2),(3),(8)
PIE face database	Yes	640x486	68	(1),(2),(3),(8)
ORL face database	No	92 x 112	40	(1),(2),(3),(8)
The Human scan database	No	384 x 286	23	(1),(2),(3),(8)
FERET database	Yes	256 x 384	1199	(1),(2),(3),(7),(8),(9)
SCface database	Yes	Different sizes	130	(1),(2),(3),(4),(5),(6),(7),(8)

2.7.SCface as a challenging FR problem

When SCface database is compared to other databases like ORL, AR, and Yale face databases, many challenges come into sight; these challenges can be summarized as follows: different cameras were used in SCface database, those cameras were of low quality (commercially used cameras) [13], obtained images are very low in resolution, images were taken at different distances illumination was not controlled, pose was not fixed; some images were taken in the dark using IR night vision mode. Figure 14 shows samples of images taken from ORL, Yale, and SCface databases.

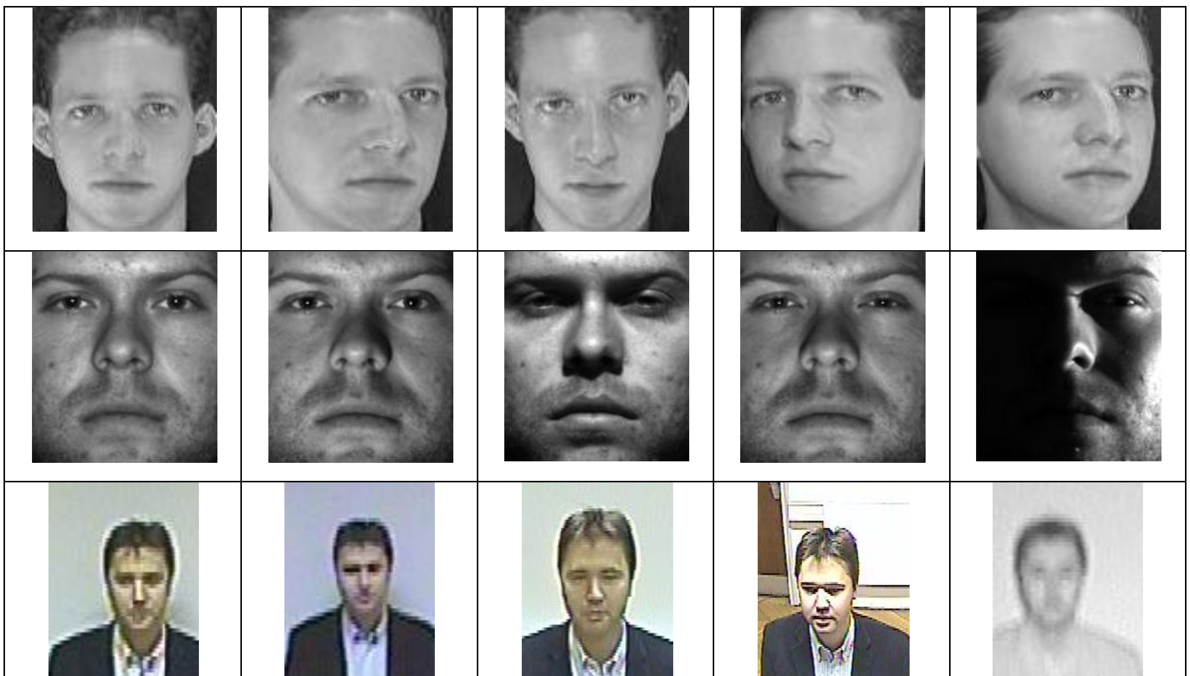


Figure 14: Samples taken from ORL database (1st row), YALE FACES (2nd row) and SCFACE database (3rd row) [13][14][15]

3. LITERATURE REVIEW

In this chapter a review of work done on FR is presented. This chapter focuses on the different challenges faced by FR researchers and the approaches used to overcome each challenge. It also reviews the work done on SCface database.

3.1. Illumination problem

Changing the light conditions such as light intensity level and light source direction affects face images significantly; dark areas such as shadows' shapes and locations vary accordingly, FR is an illumination dependant problem. A range of different approaches have been used to handle the illumination problem such as illumination invariant feature extraction like edge maps. Another way to beat uncontrolled lighting conditions problem is to implement illumination normalization such as histogram mapping. A third approach is modeling illumination variations using 3D face models [22].

For instant illumination normalization methods such as Laplacian-of-Gaussian filters, edge-maps and various wavelet-based filters are commonly used to enhance the performance of any (FR) system [23] especially when light intensity is not controlled. Xudong and Kin [24] considered the human face as a sequence of small and flat facets. They applied a local normalization technique to model each facet by multiplicative noise and additive noise, and then Principle Component Analysis (PCA) was utilized on both YaleB database and AR database. Zhiming and Chengjun [25] proposed a new color space (RIQ) called hybrid color space, Where R is the red component from RGB space I, and Q are the chromatic components from YIQ space. Enhanced Fisher Model(EFM) was applied for feature extraction. Chun-Nian and Fu-yan [26] normalized the brightness across an image and increased contrast using a homomorphic filtering technique. They separated illumination which represents the low frequency components and reflectance which represents the high frequency components by taking the logarithm transform for each pixel in the spatial domain followed by filtering the image in the frequency domain back to the spatial domain for histogram equalization. Both Yale face database B and CMU PE face database were experimented.

3.2. Different pose to camera

Spatial features in facial images (such as eyes, mouth, nose, chin and eyebrows) are key elements in FR. When the pose changes these features are not only affected dramatically but also some of these features might not be visible to the camera. Different poses of images per subject is another challenge that has been investigated by researchers. Jyh-Bin et. al [27] converted non-front viewing face to front viewing face by determining the triangle constructed between eyes and mouth, then slant (rotation) and tilt (depression) angles were estimated using parallel projection, lastly the 2D face was transformed using a 3D head model. Xiaozheng and Yongsheng [28] reviewed many techniques proposed to tolerate and/or reimburse variations caused by pose changes. They classified these techniques into three categories: general algorithms (such as Principal component analysis, Fisher discriminant analysis), 2D algorithms (such as Parallel deformation, Pose parameter manipulation) and 3D approaches (such as Cylindrical 3D pose recovery and probabilistic geometry assisted face recognition) They found that 3D approaches are more promising than the others.

3.3. In-plane rotation

Randon Transform was applied to enhance low frequency components followed by DCT to extract face features. 25% of the DCT coefficients were utilized to recognize faces in both FERET and ORL databases. The approach used showed that the recognition rate is invariant to in-plane rotation, and the recognition rates obtained for two different sets of FERET database are 97.75% and 98.93% [21]. A similar approach was applied [29] based on Kernel Fisher Discriminant.

Researchers also applied PCA and LDA in the DCT domain, Recognition rates were the same as in spatial domain [30]. The effect of using different gray scale or color space conversions was studied along with the degree of compression on FR performance of color-based FR system [31].

3.4. Low resolution images

Low resolution of images taken by surveillance cameras makes face recognition more difficult, some researchers [32] applied both Principle Component Analysis and Elastic Bunch Graph Matching (EBGM) to compare the effect of three super-resolution techniques on FR. Support Vector Data Description was used to solve low resolution problem. Researchers extracted faces from the Asian Face Database then normalized them and convert all images into gray scale followed by their projection onto SVDD balls [33].

3.5. Work done on SCface database

All the aforementioned challenges are there in SCface database; face images taken by five different commercial cameras at different distances. PCA was applied to recognize faces in SCface database; Eigenfaces were obtained from a different database. SCface Images were normalized and aligned, such that eyes lie on a straight line. Faces were then cropped to 64 ×64 and masked with an elliptical mask [13]. The researchers who published SCface database declared that results never exceed 10% recognition rate [13]. Table 5 shows the results obtained by the team that produced the SCface database team.

Table 5 Results obtained by SCface database team [13]

Camera	Recognition rate%
Cam1_1	2.30%
Cam1_2	7.70%
Cam1_3	5.40%
Cam2_1	3.10%
Cam2_2	7.70%
Cam2_3	3.90%
Cam3_1	1.50%
Cam3_2	3.90%

Camera	Recognition rate%
Cam3_3	7.70%
Cam4_1	0.70%
Cam4_2	3.90%
Cam4_3	8.50%
Cam5_1	1.50%
Cam5_2	7.70%
Cam5_3	5.40%

A new method for improving FR performance on the SCface database was proposed by Jae Young et. Al [31, 34]. In this proposed method, 36 color components of 12 color spaces were used and an adaptive boost technique which focuses on weak learners to select the best color component features was applied. Three different feature extraction methods were used; namely, PCA, Fisher's Linear Discriminant Analysis (FLDA) and Regularized Linear Discriminant Analysis (RLDA). Only 16 images per subject were selected from the SCface database, mug shoot images and images taken by cameras 1, 2,3,4,5 (excluding IR images) at distance 3 were used as the training set while images taken by same cameras at distances 1 and 2 were up-sampled and used as the testing set.

Figure 15 shows the performance obtained by Jae Young et. al. on the SCface daytabse where 62.78% was the highest recognition rate obtained therein.

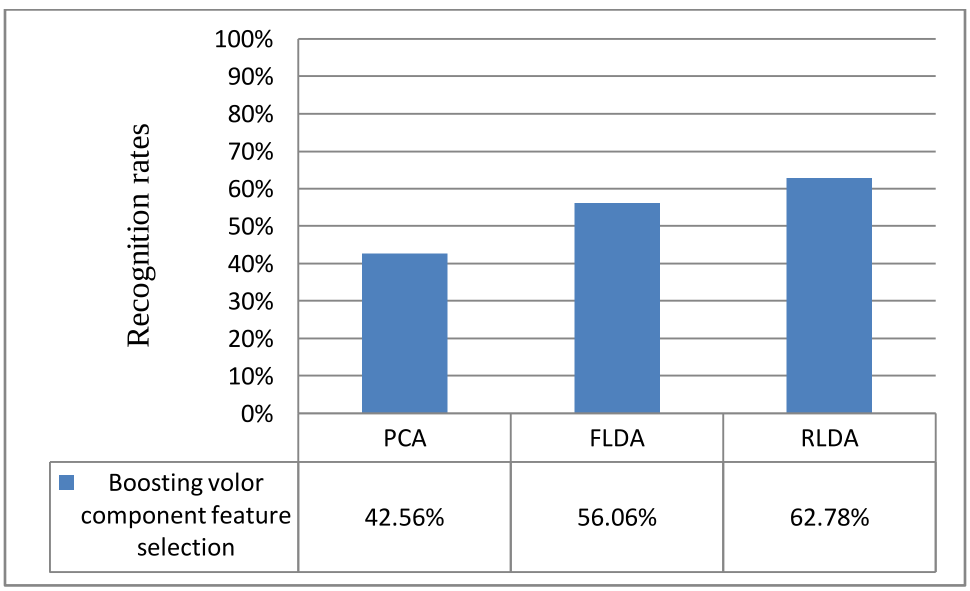


Figure 15 Boosting color component feature selection [31]

SCface database was also experimented by Yew and Shahrel [35]. AdaBoost algorithm was utilized as a face detection technique followed by Holistic feature extraction approach. Support Vector Machine is used for classification. Seven subjects were removed from the database to increase the recognition rates. The highest recognition rate obtained using this method was 91.87% when different camera qualities are considered. However, when the experiments were done across different distances, this approach yielded very low recognition rates. The maximum recognition rate obtained for different distances was 33.64%. Figure 16 shows the recognition rates obtained for different distances.

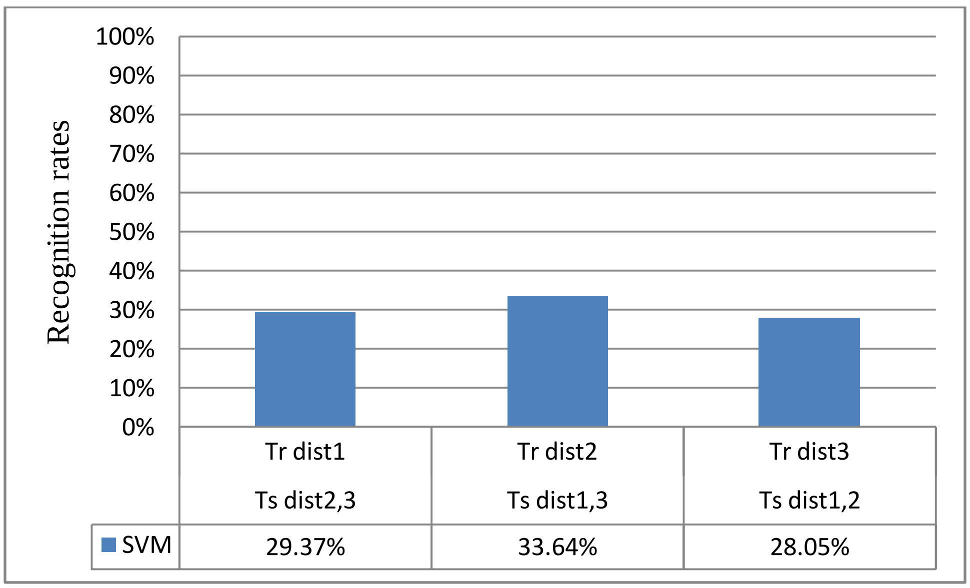


Figure 16 Multiclass Support Vector Machine [35]

4. PREPROCESSING TECHNIQUES FOR FACE RECOGNITION

This chapter presents face detection and preprocessing techniques for FR and the consequences of face image enhancement such as face detection, histogram equalization, normalization, de-noising and filtering.

4.1.Face detection

Face detection is to locate and extract a face form an image background. While extracting a face from an image some factors should be considered; like face-pose to the camera , face shape, size, color, and orientation, another important factor is appearance variation because of the change in illumination or camera quality or even change in facial expression [9]. Mainly there are two approaches for face detection; these are: feature based approach and image based approach. In feature based approach detection can be done based on three types of analysis; these are: low level analysis (edges, gray levels, or colors) feature analysis (like pair of dark regions indicates eyes) and active shape models (contours are used to locate head boundary). In image based models a window scanning technique is applied using linear subspace methods or statistical approaches [36].

Viola-Jones method for face detection is one of the most famous and efficient ways, it finds Haar features first by subtracting the average dark-region pixel value from the average light-region pixel value and comparing it with a threshold value as shown in

Figure 17. An integral image technique is used for rapid feature selection; which reduces image preprocessing steps, followed by AdaBoost classifier [37].

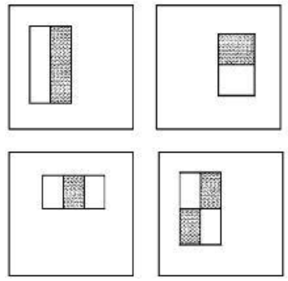


Figure 17 Rectangle features for face detection [37].

In this research we used three different approaches for face detection; these are: cropping using fixed mask size; cropping using dynamic mask size and color segmentation. Cropping is required to extract a face from an image and to eliminate unnecessary background details; we cropped the face in each gray scale image with a mask that is centered at the nose; the size of the cropping mask affects the recognition rates significantly as discussed in chapter 8. Increasing the size of the cropping mask leads to more information that could be irrelevant while small mask size could leave out some relevant information. Therefore, an empirically determined optimum mask size is used to maximize the recognition rate. Figure 18 shows how the nose coordinates in each image was used to locate and crop the face:

Figure 18 Using nose coordinates for cropping

Figure 19 shows few face images cropped with fixed mask size at different distances, row1 for images captured at distance 1, row 2 for images captured at distance 3 and row 3 for images captured at distance 3:

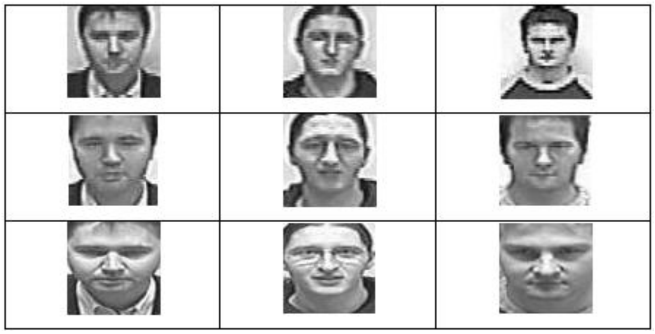


Figure 19 Cropped faces using fixed mask size

Since face pose is not fixed and faces are of different sizes using fixed mask size centered at the nose is not the best solution for face detection, the best mask size found to be 75×75, 61×61 and 41×41 at distances 1,2 and 3 respectively. Moreover; face images were taken at three different distances which could leave some important information such as face limits at the cheeks and chin or could include irrelevant information when the face image is small. Dynamic mask size beats the problem of having different face sizes, and it also takes into account that face images are taken at different distance, but when dynamic mask is used for cropping still we assume that the nose is almost located at the center in each face image. The dimensions of the dynamic mask size are function of both distance between eyes and eyes to moth distance, Figure 20 shows a sample of cropped faces with dynamic mask size.

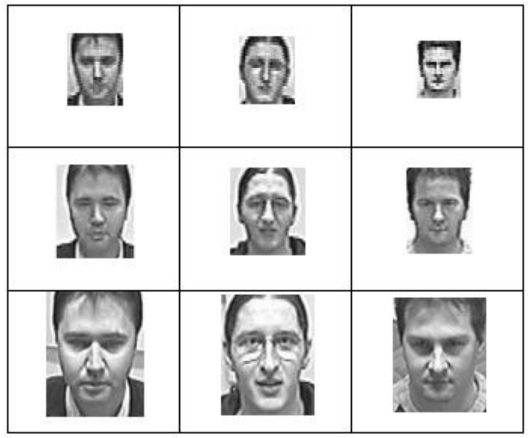


Figure 20 Cropped faces using dynamic mask size

Using skin segmentation is more efficient in face detection; since no assumption about the nose location should be made. The only problem with skin segmentation method is that faces in images taken in the dark using night vision mode can't be detected. Figure 21 shows the output skin segmentation process.

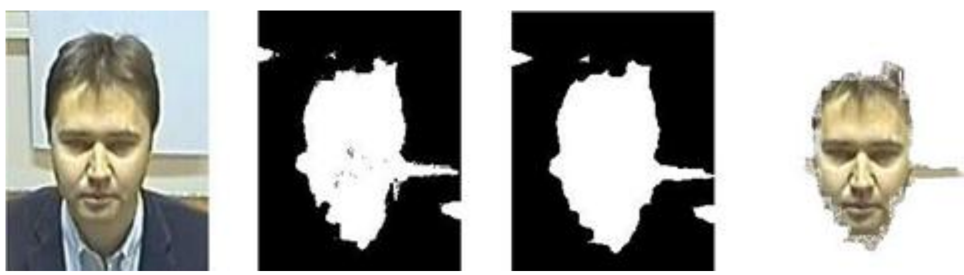


Figure 21 Face detection using skin segmentation

In skin segmentation image is transformed from RGB color space into YCbCr color space, Y is luminance Cb and Cr are the chrominance values; blue difference and red difference components respectively. Chai and Ngan conclude in their research that skin pixel should satisfy the following conditions [38]:

$77 \leq Cb \leq 127$ and $133 \leq Cr \leq 173$

Each pixel in the YCbCr is checked against the previous conditions, and replaced by zero if it does not meet those conditions, then a dilation followed by an erosion are applied as a morphological operation to close the image. Another approach can be utilized for skin segmentation, in this regard the system learn the mean value of the three color components RGB from the training images and calculate the standard deviation for each component in both skin and non-skin areas, this approach gives almost similar results to the results obtained when YCbCr color space is used, but it takes more time, since the algorithm should learn and calculate the average and standard deviation values for each color component.

4.2. Preprocessing for uncontrolled lighting conditions

As discussed in the previous chapter uncontrolled lighting conditions can affect face recognition dramatically. To minimize the effect of illumination variation on face recognition rates images should be preprocessed. One of the simplest and easiest techniques in this regard is histogram equalization. For $M \times N$ image cumulative distribution function (cdf) at each pixel value (v) is used to find the pixel's equalization value over L grey levels as follows:

$$\boldsymbol{h} = \left(\frac{\boldsymbol{cdf}(\boldsymbol{v}) - \boldsymbol{cdf}_{\boldsymbol{min}}}{\boldsymbol{M} \times \boldsymbol{N} - \boldsymbol{cdf}_{\boldsymbol{min}}}\right)(\boldsymbol{L} - \mathbf{1}) \qquad \text{4-1}$$

Figure 22 shows the effect of histogram equalization on images taken under uncontrolled light conditions; histogram equalization increases the contrast of an image by mapping each grey level value in the spatial domain to another value so that the histogram of the output image has a uniform distribution.

Figure 22 Histogram equalization, original face image to the left

Figure 23 shows the histogram of the original image, there are few pixels with high light level intensity and few pixels with low level light intensity, after applying histogram equalization almost a uniform distribution of pixel values is obtained as shown in Figure 24, this improves the image contrast.

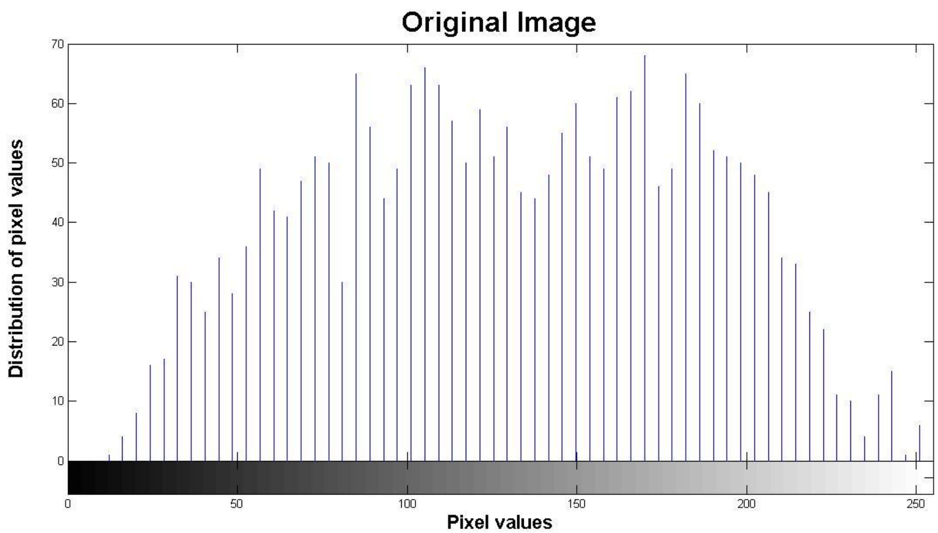


Figure 23 Original image histogram

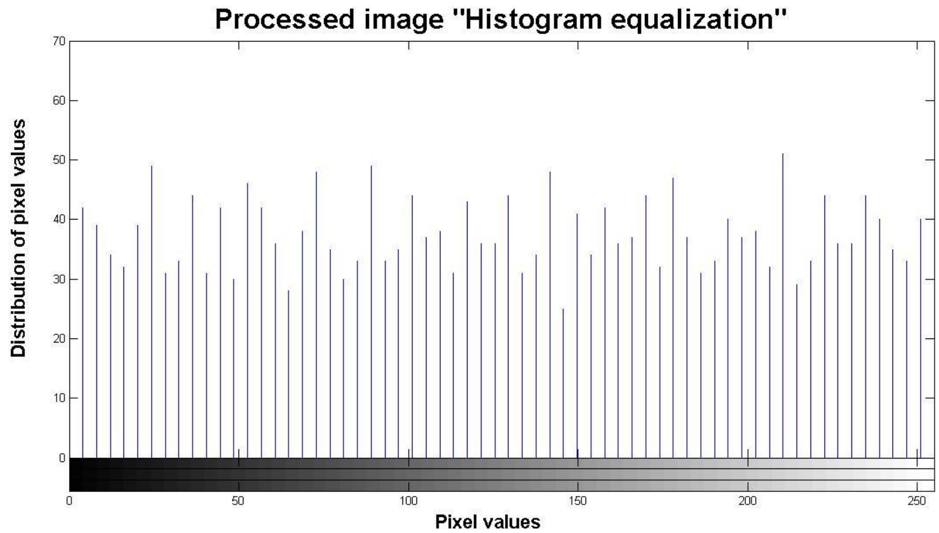


Figure 24 Histogram equalization

4.3. Pose effect on face recognition

A slight change in face pose might affect the recognition rate considerably; this change in pose could be in-plane rotation or out-of-plane rotation. In-plane rotation is much easier to deal with; researchers has shown that using DCT coefficients to recognize faces in both FERET and ORL databases is invariant to in-plane rotation [21].

In [39] face pose was estimated using the relative locations of the eyes and the center of the face then eyes were aligned; an assumption was made that is face has a circular shape. Out-of-plane rotation is more serious issue in face recognition; such rotation might lead to difficulty in estimating eyes location in a face image. Moreover; some important features might disappear and cause a drop in face recognition rates. Figure 25 shows some images with uncontrolled pose from SCface database.

Figure 25 Uncontrolled pose

4.4.Facial expression variation

One of the most important challenges in face recognition for images captured by surveillance cameras is facial expression variation; such as happiness, anger, sadness, fear and surprise. Most of the feature extraction schemes are affected by facial muscles contraction, hence they generate different feature vectors for that might be of different natures for the same subject when facial expression changes. Researchers have used different approaches to overcome the facial expression variation, in [40] researchers studied the effect of facial expression variation on face recognition by comparing different approaches such as: motion based approach, model based approach, muscle based approach and hybrid based approach. The following Figure 26 shows some images with facial expression variation from SCface database.

Figure 26 Facial expression variation

4.5. De-noising and filtering

Face images may degrade by noise while being captured because of the camera quality or during the transmission; a common noise distribution is Gaussian noise. There are various types of local based filters that act on each pixel to enhance the image quality and reduce noise such as: Gaussian filter, mean and median filters.

The idea of using a Low Pass Filter (LPF) is to enhance the low frequency component in DCT. Randon transform was used for the same purpose by some researchers, training images from FERET database were normalized first then Randon projections were found followed by DCT. It was found that when 25% of DCT coefficients are used the recognition rate reaches 88.5% and it jumps to 95.5% when Randon projections are used [21]. In this research images were filtered using low pass filter (LPF) to retain the low frequency information since noise change rapidly from one pixel to another this filter is very helpful to get rid of high frequency noise. A sample of an original image and a filtered image is shown in Figure 27.

Figure 27 Original and filtered image - filtered image to the right

An efficient normalization technique can be done by replacing each pixel in the spatial domain by its Z score value. Image normalization should take place after cropping otherwise the image mean and the image standard deviation will be affected by the image background.

5. Feature extraction schemes

This chapter shows the different feature extraction schemes used in this research. It explains how features are extracted in each scheme and what factors might affect the reliability of the extracted features. Features discussed in this chapter are: Landmarks, Eigenfaces, Fisher faces, Discrete Cosine Transform (DCT) coefficients, Wavelet transform, Gray Level Co-occurrence Matrix (GLCM), and Spatial Differential Operators (SDO).

In pattern recognition there are two types of features; first type is features with clear physical meaning like statistical features, the second type is mapping features without clear physical meaning. In the first case feature selection is required while on the second case feature extraction is needed [41].

Features used for face recognition vary among the different known algorithms; some face recognition systems extract landmarks [42] and analyze the relative size, position and or shape of eyes, nose, mouth and jaw and then a testing image is compared to a set of training images (gallery) using the same landmarks for identification. Another type of features could be a compressed global representation of each image in the database like in (PCA) eigenfaces are used to represent the entire image rather than the local features [43]. In skin texture analysis face lines and spots are converted into mathematical space.

5.1. Landmarks

Facial landmarks are used for both face detection and face recognition; landmarks with either biological meaning or just mathematical model can be used for face modeling as in [42]. There are so many distinguishable facial landmarks that can be used for FR, such as eyes' limits, eyebrows' ends and shape, nose, mouth and different peaks and valleys that make up facial features as shown in Figure 28. Elastic Bunch Graph Matching (EBGM) is one of the algorithms that uses landmarks for FR. EBGM uses Gabor wavelets of different frequencies to estimate landmarks locations. Active Shape Model (ASM) is another technique that uses also landmarks for FR but these two methods are very sensitive for both facial expression variation and uncontrolled light conditions [44].

Figure 28 Facial Landmarks [45]

5.2.Eigenfaces

Another set of features used in FR is the eigenfaces, it is one of the most famous appearance based approaches. PCA is used to extract eigenfaces; eigenvectors of the covariance matrix derived from a set of facial images are then calculated [46]. The following steps explain how eigen faces are used in FR:

First of all face images should be of the same size and face in each image is centered, an $N \times M$ image is converted to column vector:

$$\boldsymbol{Image\ v(x,y)} = \begin{bmatrix} \boldsymbol{x_{11}} & \boldsymbol{x_{12}} & .. & \boldsymbol{x_{1M}} \\ .. & .. & .. & .. \\ \boldsymbol{x_{N1}} & \boldsymbol{x_{N2}} & .. & \boldsymbol{x_{NM}} \end{bmatrix} \rightarrow \boldsymbol{\gamma_i} = \begin{bmatrix} \boldsymbol{x_{11}} \\ \boldsymbol{x_{12}} \\ .. \\ \boldsymbol{x_{1M}} \\ \boldsymbol{x_{21}} \\ \boldsymbol{x_{22}} \\ .. \\ \boldsymbol{x_{2M}} \\ .. \\ .. \\ \boldsymbol{x_{NM}} \end{bmatrix}$$

5-1

The average matrix (μ) for (K) training images (Tr_i) is found and subtracted from each image to have a zero mean images this removes any common information, the obtained images are(φ_i),

$$\mu = \frac{1}{K}\sum_{i=1}^{K} Tr_i \qquad 5\text{-}2$$

$$\varphi_i = Tr_i - \mu \qquad 5\text{-}3$$

$$A = [\varphi_1\ \varphi_2\ \varphi_3 \cdots \varphi_K]$$

The covariance matrix (C) is found:

$$C = AA^T \qquad 5\text{-}4$$

Eigen vectors (u_i) associated with the N_e largest Eigen values are then selected to form the set of Eigenfaces $N_e < N$. Figure 29 shows an example of extracted Eigenfaces.

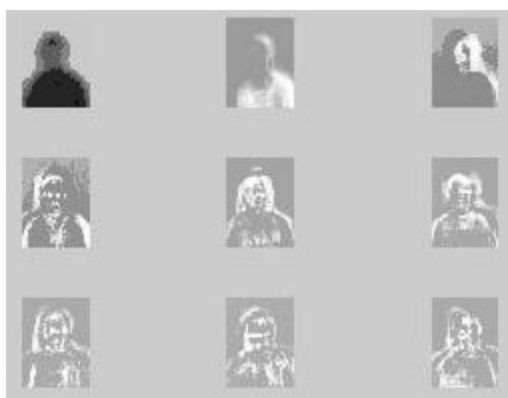


Figure 29 Sample of extracted Eigenfaces from SCface database

The weights can be calculated using the following formula:

$$w_j = u_j^T \varphi_i \qquad 5\text{-}5$$

The feature vector for each image is a set of these weights $\begin{bmatrix} w_{1i} \\ w_{2i} \\ .. \\ w_{Ki} \end{bmatrix}$

In the recognition procedure testing image is projected in the direction of the Eigen vectors of the training images, the weights are calculated $[w_1 \quad w_2 \quad \cdot\cdot \; w_K \;]^T$ the same way then the following argument could be used for classification:

$$\mathbf{Min} \left\| \begin{bmatrix} \mathbf{w_{1i}} \\ \mathbf{w_{2i}} \\ \cdot\cdot \\ \mathbf{w_{Ki}} \end{bmatrix} - \begin{bmatrix} \mathbf{w_1} \\ \mathbf{w_2} \\ \cdot\cdot \\ \mathbf{w_K} \end{bmatrix} \right\| \qquad 5\text{-}6$$

One draw back for this approach is that both scatters are maximized within- class scatter and between -classes scatter.

5.3. Fisher faces

Fisher faces can be extracted from a set of training images using Linear Discriminant Analysis (LDA) by creating a linear combination of the features to achieve the largest mean differences between the desired classes. This method selects the optimum Eigen vectors in a way that the ratio of the between-class scatter (S_B) and within-class scatter (S_W) is maximized [46].

$$\boldsymbol{W_{opt}} = \mathbf{arg\,max} \frac{|\boldsymbol{W^T S_B W}|}{|\boldsymbol{W^T S_w W}|} \qquad \mathbf{5\text{-}7}$$

Fisher faces and Eigen faces are good methods when there is no change in face expression or pose to camera [46].

5.4. DCT coefficients

The Discrete Cosine Transform (DCT) transforms spatial domain images into decoupled frequency domain images, therefore the information becomes in the form of DCT coefficients. Also it reveals excellent energy compaction [47]. High values of DCT coefficients are located in the upper left corner of the DCT matrix. These coefficients are the most important in terms of image representation. The definition of DCT for an N×N image is as follow:

$$\boldsymbol{F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} v(x,y) \cos\frac{\pi(2x+1)u}{2N} \cos\frac{\pi(2y+1)v}{2N}} \qquad 5\text{-}8$$

$$\boldsymbol{u, v = 0, 1, 2, 3, \dots, N-1}$$

$$\boldsymbol{\alpha}(\mathbf{u}) = \begin{cases} \sqrt{\frac{1}{N}} & \mathbf{u} = \mathbf{0} \\ \sqrt{\frac{2}{N}} & \mathbf{u} \neq \mathbf{0} \end{cases} \qquad 5\text{-}9$$

Figure 30 shows both the original image in the spatial domain and the discrete cosine transformed image:

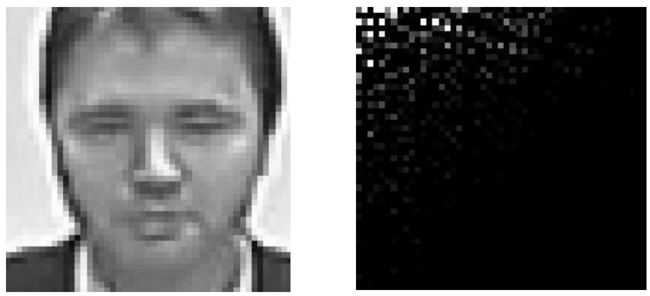


Figure 30Input face image and its DCT coefficients

5.5.Discrete wavelet transform

Spectral content of stationary signals can be analyzed using Fourier Transform (FT), but for non stationary signal to investigate exactly where each frequency component appears some other transforms can be used such as Short Time Fourier Transform (STFT) or Wavelet Transform (WT); in these transforms spectral is analyzed per time. For discrete signals Discrete Wavelet Transform (DWT) is given by:

$$\boldsymbol{DWT}[\boldsymbol{n}] = \sum_{\boldsymbol{k}=-\infty}^{\infty} \boldsymbol{x}[\boldsymbol{k}]\boldsymbol{h}\,[\boldsymbol{n}-\boldsymbol{k}] \qquad 5\text{-}10$$

Low Pass Filter (LPF) generates the approximation of the desired signal and High Pass Filter (HPF) produces the details as shown in Figure 31:

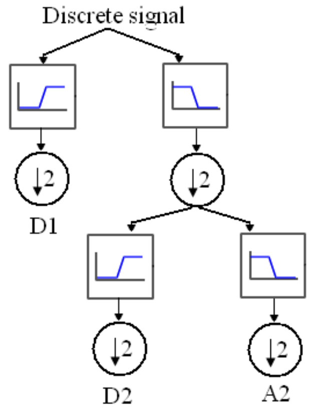


Figure 31Two level Discrete Wavelet Transform

Face features can be extracted using Wavelet Transform in different ways; the simplest one is to use DWT coefficients direct as face features. When LPF is applied on both rows and columns an approximation of a face image is obtained, while diagonal details are the output of HPF on rows and columns [48], the following figure shows an example of extracted features using DWT:

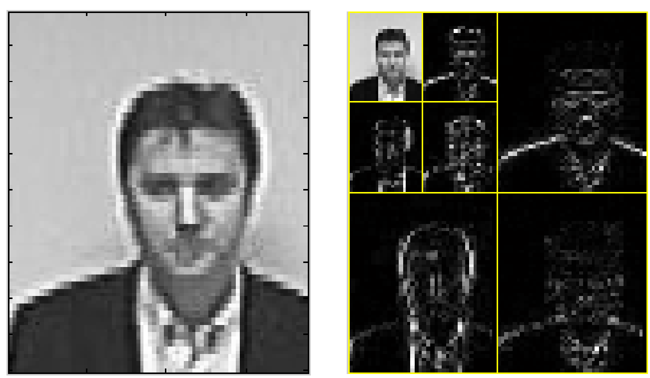


Figure 32 Wavelet Transform decomposition at level 2

It was found that facial expression variations affect only high frequency spectrum while change in pose and light conditions affect low frequency spectrum [49].

5.6.Grey Level Co-occurrence Matrix (GLCM)

Textural features for image classifications were introduced first by Haralick when he introduced 14 statistical measures [50]. Textural features for face image can be extracted using Grey Level Co-occurrence Matrix (GLCM), GLCM calculates how frequently a pixel with value k appears in a certain direction in the spatial domain with respect to another pixel valuel. Figure 33 explains this idea for binary image:

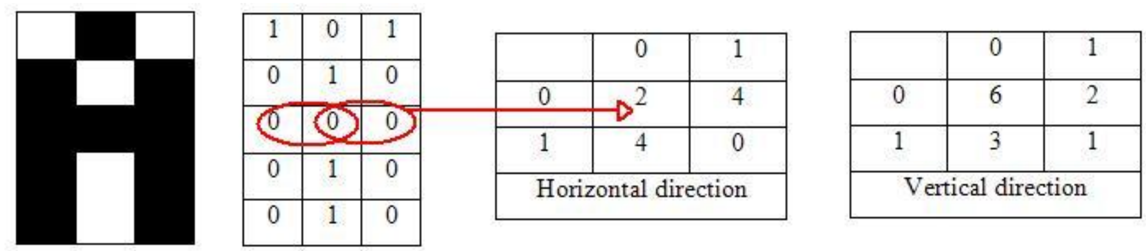


Figure 33 GLCM

Figure 33 shows the GLCM in both horizontal and vertical directions, in this figure the off diagonal values in horizontal direction are bigger than the diagonal values while in the vertical direction it is the opposite, this indicates more texture variations in horizontal direction.

GLCM can be used to evaluate image contrast:

$$\mathbf{f_{contrast}} = \sum_{i,j} |\mathbf{i} - \mathbf{j}|^2 \, \mathbf{v}(\mathbf{i}, \mathbf{j}) \qquad 5\text{-}11$$

While homogeneity can be found using the following equation:

$$f_{\mathbf{homogeneity}} = \sum_{i,j} \frac{v(i,j)}{1+|i-j|} \qquad 5\text{-}12$$

$\boldsymbol{v}(\boldsymbol{i},\boldsymbol{j})$ is the pxel value at $(\boldsymbol{i},\boldsymbol{j})$

Three factors should be considered and selected wisely when applying GLCM, these factors are:

- The radius which represents how many adjacent pixels should be counted

- The direction: with respect to the location of the desired value in the spatial domain
- The number of quantization levels.

In many cases GLCM matrix is sparse matrix, the following figure shows GLCM matrix for a face image taken from SCface database.

Figure 34 GLCM for a face image taken from SCface database

5.7. Spatial Differential Operators (SDO)

There are several distance measures can be used as Spatial Differential Operators to extract face features such as: Euclidean distance, city clock and cosine distance. Euclidean distance is one of the most commonly used distance in multidimensional space because of simplicity in calculations, for two vectors of n-dimensions:

$$\mathbf{d}(\mathbf{x},\mathbf{y}) = \sqrt{\sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{n}}(\mathbf{x_i} - \mathbf{y_i})^{\mathbf{2}}} \qquad \text{5-13}$$

This distance is very sensitive for changes and it calculates the summation of squared pixels intensity differences [51]. Standardized Euclidean distance is given by the formula:

$$\mathbf{d}(\mathbf{x},\mathbf{y}) = (\mathbf{X} - \mathbf{Y})\mathbf{D}^{-\mathbf{1}}(\mathbf{X} - \mathbf{Y})' \qquad \text{5-14}$$

D is the variances diagonal matrix.

Standardized Euclidean has the advantage of making sure that huge differences in pixels intensity are not dominating.

City block distance is similar to Euclidian distance. However the effect of large differences in a single dimension is dampened because the pixels intensity differences are not squared.

$$\mathbf{d}(\mathbf{x},\mathbf{y}) = \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{n}} |\mathbf{x_i} - \mathbf{y_i}| \qquad 5\text{-}15$$

Cosine distance is used in classification for clustering. Euclidean distance and cosine distance are very similar when the dimensionality is very high. Cosine distance is calculated using the following:

$$\mathbf{d}(\mathbf{x},\mathbf{y}) = \mathbf{1} - \frac{\mathbf{XY'}}{\sqrt{\mathbf{XX'}}\sqrt{\mathbf{YY'}}} \qquad 5\text{-}16$$

In our proposed solution Spatial and Frequency Domains Combined Features (SFDCF) we extracted two types of features; spatial domain features using SDO and frequency domain features using DCT, each feature extraction scheme was followed by dimensionality reduction process, PCA was implemented to reduce the dimensionality of SDO features while Zonal coding was applied on DCT coefficients. The obtained reduced features are then concatenated to form a face feature vector. Figure 35 shows the steps of transforming an input face image into a feature vector. Linear discriminant function is used to classify the extracted features.

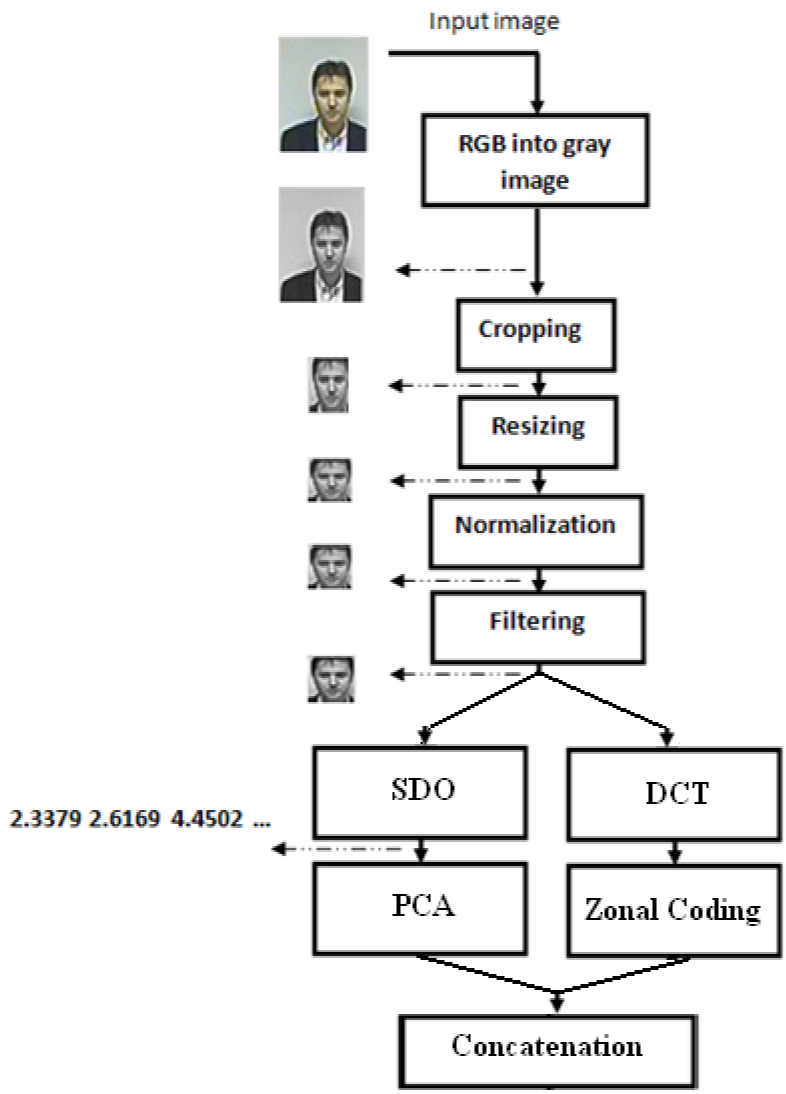


Figure 35 Proposed Solution (Concatenation of SDO and DCT)

6. DIMENSIONALITY REDUCTION AND FEATURE MANIPULATION

In this chapter we discuss various dimensionality reduction techniques such as PCA, Zonal Coding and Spectral regression. After that we talk about feature manipulation using polynomial expansion technique.

6.1. Dimensionality reduction

One of the most common challenges in classification problems is Curse of dimensionality; in this regard the number of extracted features is extremely high in comparison with the number of classes. There are several ways to overcome this problem such as: PCA, Zonal coding and Spectral regression.

6.1.1. Principal component analysis

Large datasets usually include huge number of variables. It may be possible to reduce the number of variables significantly and retaining a large amount of the information in the original dataset. A number of dimension-reducing techniques exist for doing this, Principal Component Analysis is one of them. The basic idea of principal component analysis (PCA) is to minimize the dimensionality of a data set that contains a large number of variables, while retaining as much as possible of the variation present in the data set. This can be done by projecting the data set in the direction of the maximum variation. One draw back for this approach is that both scatters are maximized within-class scatter and between -classes scatter. PCA calculations and algorithm are discussed in 5.2.

6.1.2. Zonal coding

Zonal coding technique considers one particular zone at a time unlike other coding techniques; typically zone of interest. As discussed in 5.4 in Discrete Cosine Transform coefficients the most important information of a face image is located at the upper lift corner; Figure 30 shows that the previous mentioned area is lighter than other areas which means high coefficients are located there. Moreover; the variations in this area is much more than other areas. Zonal coding is implemented to select the most representative DCT coefficients as shown in figure 38:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n-1} & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n-1} & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n-1} & a_{3n} \\ a_{41} & a_{42} & a_{43} & \cdots & a_{4n-1} & a_{4n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & a_{m3} & \cdots & a_{m-1n-1} & a_{mn} \end{bmatrix}$$

Figure 36 Zonal coding

6.1.3. Spectral regression

Spectral regression method has recently become known as a powerful tool for dimensionality reduction. This method uses information contained in the eigenvectors to reveal low dimensional structure in high dimensional data.

More specifically, for a set of m feature vectors x1, x2, · · · , xm, belonging to c classes, the objective function of LDA is as follows:

$$a^* = \arg_a \max \frac{a^T S_b a}{a^T S_w a} \qquad \text{6-1}$$

Where s_w is the within-class scatter matrix and s_b is the between-class scatter matrix.

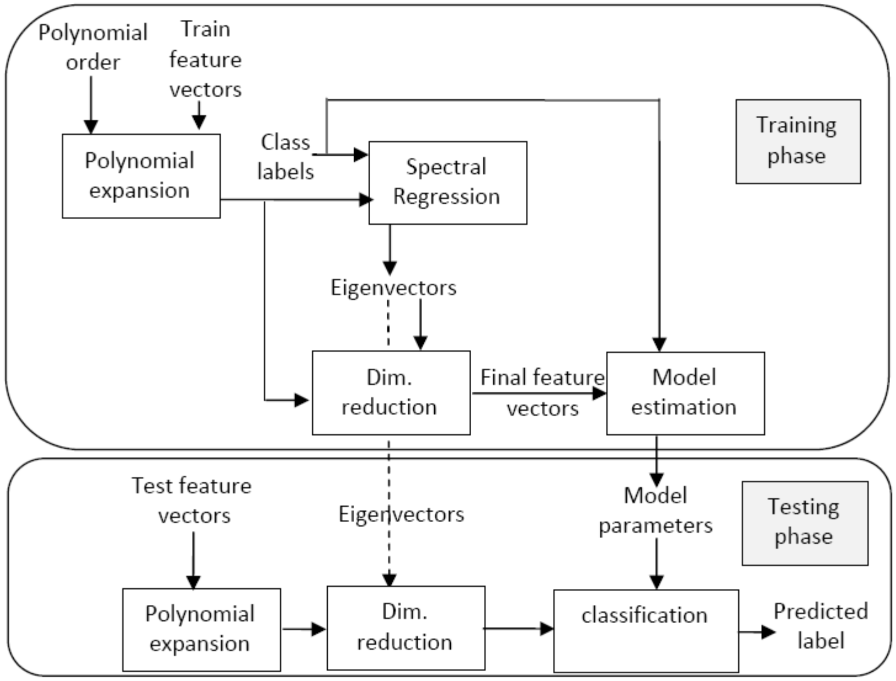


Figure 37 Polynomial expansion followed by spectral regression for classification [52]

To solve the LDA eigen-problem efficiently; Let $\bar{y}$ be the eigenvector of eigen-problem, $W\bar{y} = \lambda\bar{y}$ with eigenvalue λ. If $\bar{X}^T a = \bar{y}$ then a is the eigenvector of eigen-problem with the same eigenvalue λ. Where $\bar{X}$is the centered data matrix, $W^{(k)}$ is a $m_k \times m_k$ matrix with all elements equal to $1/m_k$, m_k is the number of data points in kth class, m is the number of total training data points, n is the number of features, c is the number of classes [52]. The LDA basis functions can be obtained by solving the eigen-problem to get $\bar{y}$ then finding a which satisfies $\bar{X}^T a = \bar{y}$. A possible way is to find a is:

$$a = \arg_a \min \sum_{i=1}^{m} (a^T \bar{x}i - \bar{y}i)^2 + \propto \|a\|^2 \qquad 6\text{-}2$$

Where $\bar{y}i$ is the ith element of $\bar{y}$.

For a large number of features, this technique produces more stable and meaningful solutions. Figure 37 shows the process of Polynomial expansion followed by spectral regression for classification.

6.2. Feature manipulation using Polynomial expansion

Polynomial expansion of an M-dimensional feature vector $x_i = [x_{i,1}\ x_{i,2}\ x_{i,3} \dots x_{i,N}]$ is achieved by combining the vector elements with multipliers to form a set of basis functions, p(x). The elements of p(x) are the monomials of the form $\prod_{j=1}^{M} x_j^{k_j}$, where k_j is a positive integer, and $0 \le \sum_{j=1}^{M} k_j \le P$. Therefore, the Pth order polynomial expansion of an M-dimensional vector x generates an $O_{M,P}$ dimensional vector $p(x)$. $O_{M,P}$ is a function of both M and P and can be expressed as

$$\mathbf{O_{M,P} = 1 + PM + \sum_{l=1}^{P} C(M,l)} \qquad 6\text{-}3$$

Where $C(M,l) = \binom{M}{l}$ is the number of distinct subsets of l elements that can be made out of a set of M elements. Therefore, for class i the sequence of feature vectors $x_i = [x_{i,1}\ x_{i,2}\ x_{i,3} \dots x_{i,N}]$ is expanded into $V_i = [p(x_{i,1})\ p(x_{i,2})\ p(x_{i,3})\ \dots\ p(x_{i,N})]$ Expanding all the training feature vectors results in a global matrix for all K classes obtained by concatenating all the individual matrices V_i such that $V = [V_1\ V_2\ \dots\ V_K]^T$

7. CLASSIFICATION TECHNIQUES

Classification is to assign each input to one set of given classes; this can be done using either linear or non-linear classifiers. When data is linearly separable in the feature space linear classifiers, such as linear discriminant function (LDF), are the best choice because they are very fast, simple and robust against noise. They split a high-dimensional input space with hyperplane boundaries. In some applications features are not linearly separable, in such cases the need of a nonlinear classifiers such as neural networks or polynomial classifiers become essential to deal with the nonlinearity of the data. The back propagation algorithm in multilayer non linear neural networks works fine for classification problems. However, thousands of iterations affect the efficiency of the system and lead to many problems like time in real time applications, storage space and the probability of divergence. On the other hand polynomial expansion classifier does not require iterations, it has been approved that this classifier is very efficient nonlinear classifier which can be used in different fields such as speaker and speech recognition, Extraction of Fetal ECG and Arabic sign language recognition [53] In this research we used three different classifiers: linear discriminant functions (LDFs), KNN classifier and polynomial classifier. We have also used dimensionality reduction based on spectral regression. In this chapter, pattern recognition is introduced. And some classification techniques are discussed.

7.1. Pattern Recognition

Pattern recognition is a subfield of Artificial Intelligence; it has various applications in different aspects of engineering and science. Pattern recognition is a process of identifying and recognizing a correspondence between features that represent samples or data points [54].

There is a wide a range of applications where pattern recognition is needed; like in junk mails are classified as either junk or non-junk. Similarly, in speech recognition, an input sound wave is classified as a spoken word. In industries, a fruit sorter uses images taken on conveyor belt and sorts them based on their quality. Another example is computer aided diagnosis where a microscopic image can be identified as either healthy or cancerous. In all cases, pattern recognition system is a machine learning system that tries to match a new data point (test data) with a certain class based on a set of data points that is either stored in the database or seen online.

Pattern recognition has four stages as shown in figure 38; Data acquisition is the first stage, transducers are used at this stage to collect physical quantities from the environment and are transformed into electrical signals. Collected data must be sufficient for the system to learn. Preprocessing is the next stage- in this stage the system tries to get rid of noise and outliers. Next feature extraction comes; in this stage the system generates a representative template for each data point by removing redundancy and irrelevant data. Features should be representative, which means they should be similar within the class and different for different classes. Last stage is the modeling stage or classification stage at this stage the system maps features with their classes [55].

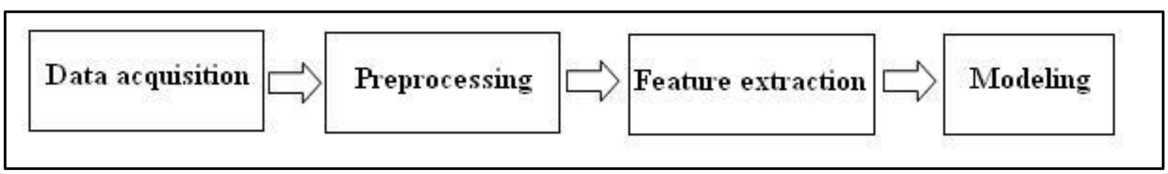


Figure 38 Pattern recognition system model

In Pattern recognition system design the system needs to be trained using either supervised learning or unsupervised learning (clustering). And it can be evaluated based on classification rate and system reliability, memory, time, ease of data acquisition.

7.2.Bayesian decision theory

In Bayesian decision theory measure (y) is taken for the following classes $\{x_1, x_2, x_3, \dots, x_n\}$ if both priors' probabilities $P(x_i)$ and the probability density functions

$P(y/x_i)$ (likelihood) are known, and y is noticed then decision can be made based on the following argument $\max P(x_i/y)$, where:

$$P(x_i/y) = \frac{P(y/x_i)P(x_i)}{P(y)} \quad 7\text{-}1$$

$$P(y) = \sum_{i=1}^{n} P(y/x_i)P(x_i) \quad 7\text{-}2$$

7.3.Linear discriminant function

Linear classifier which is shown in Figure 39 achieves classification based on a linear combination of the extracted features, it is very simple to use comparing to other classification techniques; linear classifier is optimal for Gaussian distributions with equal covariance even though, it still can be used for other distributions. In case of non- linearly separable data, transformations can linearize the problem [55].

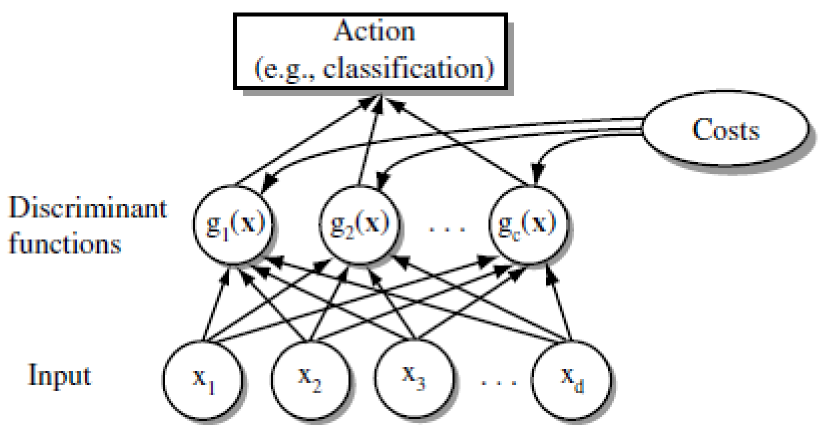


Figure 39 Discriminant Functions [55]

Let X be the feature vector of a training sample, this X contains d features $\boldsymbol{X} = [\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \dots, \boldsymbol{x_d}]$. All training feature vectors can be combined in one matrix called training matrixTr, if n feature vectors are available for training. Then the training matrix is: $\mathrm{Tr} = [\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \dots, \boldsymbol{X_n}]^{\mathrm{t}}$ for classification the weights (W) matrix should be evaluated first:

$$\mathbf{W} = (\mathbf{Tr^tTr})^{-\mathbf{1}}\mathbf{Tr^t}(\mathbf{Y}) \qquad 7\text{-}3$$

The number of rows in the target matrix Y is equal to the number of classes while the number of columns is the same as the number of feature vectors in the training data. All elements in a row of target matrix are zeros except for the desired class it must be one. Then decision can be made based on the maximum $(\mathrm{y_i})$, where:

$$(\mathbf{y_i}) = \sum_{\mathbf{i=1}}^{\mathbf{d}} \mathbf{x_i w_i} \qquad 7\text{-}4$$

For multidimensional problems the boundaries of the classified regions are hyper-plane.

7.4.K nearest neighbors

K Nearest Neighbor (KNN) classifier is a simple classifier that predicts the class label of a given point by selecting the k nearest neighbors to that point and uses a majority vote to determine the class of that point [56]. In Figure 40 shown below 10-NN classifier classifies the test point as green because five points vote to green out of ten while three vote to blue and only two vote to red.

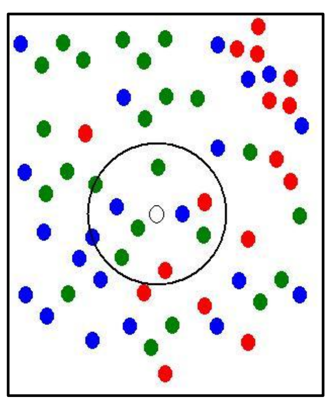


Figure 40 KNN Classifier

KNN uses Euclidean distance 2-5 or Manhatten distance 2-6

$$\mathbf{d}(\mathbf{a_1}, \mathbf{a_2}) = \sum_{\mathbf{i=1}}^{\mathbf{k}} \sqrt{(\mathbf{a_{1i}} - \mathbf{a_{2i}})^{\mathbf{2}}} \qquad 7\text{-}5$$

$$\mathbf{d}(\mathbf{a_1}, \mathbf{a_2}) = \sum_{\mathbf{i=1}}^{\mathbf{k}} |\mathbf{a_{1i}} - \mathbf{a_{2i}}| \qquad 7\text{-}6$$

Other Similarity Measures are cosine 2-7 and correlation 2-8

$$\mathbf{d}(\mathbf{a_1}, \mathbf{a_2}) = \frac{\mathbf{a_1 a_2^t}}{\|\mathbf{a_1}\|\|\mathbf{a_2}\|} \qquad 7\text{-}7$$

$$\mathbf{d}(\mathbf{a_1}, \mathbf{a_2}) = \frac{\sum_{\mathbf{i=1}}^{\mathbf{k}}((\mathbf{a_{1i}} - \overline{\mathbf{a_1}})(\mathbf{a_{2i}} - \overline{\mathbf{a_2}}))}{\sqrt{\sum_{\mathbf{i=1}}^{\mathbf{k}}(\mathbf{a_{1i}} - \overline{\mathbf{a_1}})^2 \sum_{\mathbf{i=1}}^{\mathbf{k}}(\mathbf{a_{2i}} - \overline{\mathbf{a_2}})^2}} \qquad 7\text{-}8$$

The performance of a KNN classifier is primarily determined by the choice of K as well as the distance metric applied. Choosing the best k may be difficult; KNN is considered to be computationally heavy, and it needs large number of samples for accuracy.

7.5. Artificial neural networks

One of the most common non-linear system identification approaches is based on the application of Artificial Neural Networks (ANNs) [57]. In 1943, a paper was presented by W. McCulloch and W. Pitts in which they used math and algorithms to construct the first model for neural network. After six years D. Hebb, initiated the first theory of learning. In 1959, B. Widrow and M. Hoff applied neural network to eliminate echoes in phone lines. Two years after M. Minsky and S. Pappert assumed that only linearly separable functions can be used with multilayer neural networks. A transition took place in 1982 when the back propagation algorithm was discovered [52]. In general, a neural network consists of input layer, one hidden layer at least and an output layer as shown in Figure 41. Input layer should be nonlinear otherwise the net work can deal only with linearly separable data. At each hidden node the net value is calculated through an activation function at the output layer a linear or nonlinear activation function could be used to map the output of the hidden layer with the desired classes.

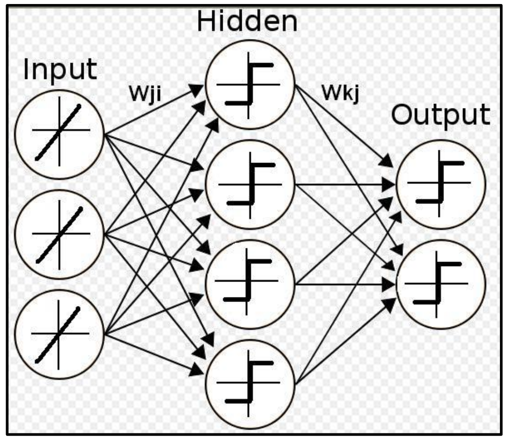


Figure 41 Neural Network system model [55]

$$\mathbf{y_j} = \mathbf{f}\left(\sum_{i=1}^{d} \mathbf{x^k w_{ji}} + \mathbf{w_{j0}}\right) \tag{7-9}$$

$$\mathbf{g_j(x)} = \mathbf{f}\left(\sum_{i=1}^{d} \mathbf{w_{kj}}\,\mathbf{f}\left(\sum_{i=1}^{d} \mathbf{x^k w_{ji}} + \mathbf{w_{j0}}\right) + \mathbf{w_{k0}}\right) \tag{7-10}$$

Activation function could be one of the following:

- Log-Sigmoid Function
- Tan-Sigmoid Function
- Softmax Function
- Unit step function

Two modes of operation are used in neural Network; in feed forward mode inputs are fed through the network to obtain outputs. Those outputs are then subtracted from a desired output to measure the error generated by the network. This will start the learning mode since network parameters (weights) are updated based on the calculated error. Training Protocols vary according to the application it could be Stochastic, Batch, or online back propagation.

$$\mathbf{J(w, v)} = \frac{1}{2} \sum_{i=1}^{n} \sum_{c=1}^{m} \left(\mathbf{t_c^i} - \mathbf{z_c^i}\right)^2 \tag{7-11}$$

ANN system starts by collecting input and output data, and then it selects a network structure which could be either feedforward or recurrent structure, last is training and Verification of the trained network. The Polynomial Neural Network PNN is a single-layer neural network that uses polynomial terms of the input features in addition to the linear terms (L.L.Huang, A.Shimizu, Y.Hagihra, H.Kobatake, 2003).

7.6. Polynomial Classifiers model and algorithm

Polynomial classifiers are used when the classification problem is non-linearly separable. It provides an efficient way of describing the input output relation using polynomials. The higher the degree of the polynomial, the more flexible the model but then the memory size is a critical issue. The second order polynomial model can be expressed as follows:

$$\boldsymbol{\varphi}(\mathbf{x}) = \mathbf{w_0} + \sum_{i=1}^{l} \mathbf{w_i x_i} + \sum_{i=1}^{l} \sum_{m=i+1}^{l} \mathbf{w_{im} x_i\, x_m} + \sum_{i=1}^{l} \mathbf{w_{ii} x_i^2} \qquad 7\text{-}12$$

The offset and the first sum describe a linear model, the second sum describes the interaction terms while the last sum represents the second order terms. Least squares (LS) can be used to estimate the polynomial model parameters (Liu, 2001). The second order polynomial classifier algorithm takes input training feature vectors $\mathbf{Tr} = [\boldsymbol{X_1}, \boldsymbol{X_2}, \boldsymbol{X_3}, \dots, \boldsymbol{X_n}]^{\mathbf{t}}$ and then it expands these features as in 2-13

$$\boldsymbol{Tr_{expanded}} = \begin{bmatrix} \mathbf{1} & \mathbf{x_{11}} & \mathbf{x_{12}} & .. & \mathbf{x_{11}x_{12}} & \mathbf{x_{11}x_{13}} & .. & \mathbf{x_{11}}^{\mathbf{2}} & \mathbf{x_{12}}^{\mathbf{2}} & .. & \mathbf{x_{1d}}^{\mathbf{2}} \\ .. & .. & .. & .. & .. & .. & .. & .. & .. & .. & .. \\ \mathbf{1} & \mathbf{x_{N1}} & \mathbf{x_{N2}} & .. & \mathbf{x_{N1}x_{N2}} & \mathbf{x_{N1}x_{N3}} & .. & \mathbf{x_{N1}}^{\mathbf{2}} & \mathbf{x_{N2}}^{\mathbf{2}} & .. & \mathbf{x_{Nd}}^{\mathbf{2}} \end{bmatrix}$$

7-13

The weights are calculated as in 12-14, where Y is the target matrix as described in 7.3

$$\mathbf{W} = (\boldsymbol{Tr_{expanded}}^{\mathbf{t}} \boldsymbol{Tr_{expanded}})^{-\mathbf{1}} \boldsymbol{Tr_{expanded}}^{\mathbf{t}} (\mathbf{Y}) \qquad 7\text{-}14$$

Using the calculated weights, the testing data Ts can be classified based on the following argument $\boldsymbol{Max}(\boldsymbol{Y})$ where:

$$\boldsymbol{Y} = (\boldsymbol{Ts})(\boldsymbol{W}) \qquad 7\text{-}15$$

Neural networks as classifiers are excellent learners they do not require previous knowledge of the subjects being identified, they just extract the required information from the given training inputs and outputs. Moreover, they can solve linear and non-linear classification problems. But the drawbacks of neural networks are mainly: 1) Selecting the proper neural network structure for a given classification problem is not easy. 2) Iterations in neural networks are not always efficient as it might lead to divergence. On the other hand, polynomial classifiers are easy to implement and iteration is not required in polynomial expansion calculation. One disadvantage for polynomial classifiers is that high orders need huge storage space.

8. EXPERIMENTAL RESULTS AND DISCUSSION

This chapter presents the experimental results obtained. It compares the recognition rates for various feature extraction techniques and it evaluates the different classifiers used in this research. Figure 35 in section 5.7 shows the steps of transforming an input face image into a feature vector.

8.1. Effect of preprocessing steps on FR rates

Image processing plays a significant role in improving face recognition performance. It not only increases the recognition rate but also reduces time and memory space required to run any face recognition algorithm. Row images were fed into various feature extraction schemes as training images and testing images to determine the sensitivity of each scheme for different image preprocessing steps such as face detection, normalization and noise filtering. The following figures show the effect of preprocessing on Spatial and Frequency Domains Combined Features (SFDCF), Eigenfaces and DCT coefficients. Training (Tr) and testing (Ts) images are captured at different distances:

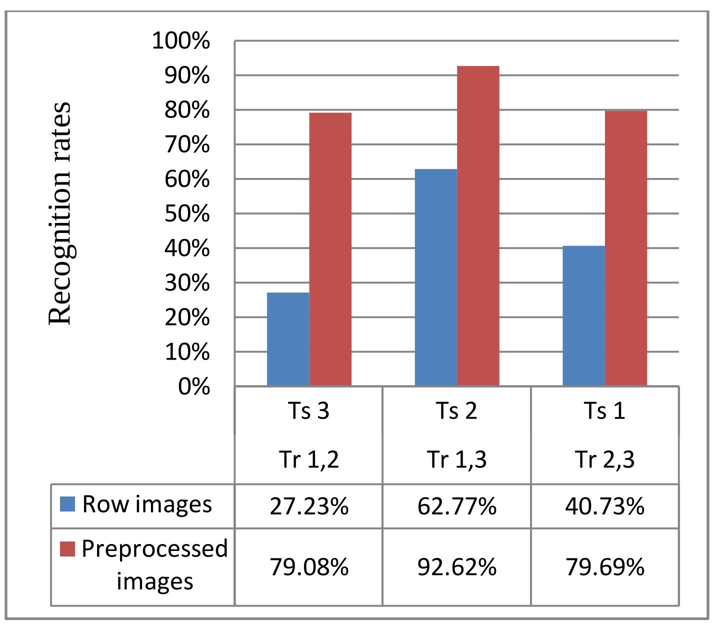
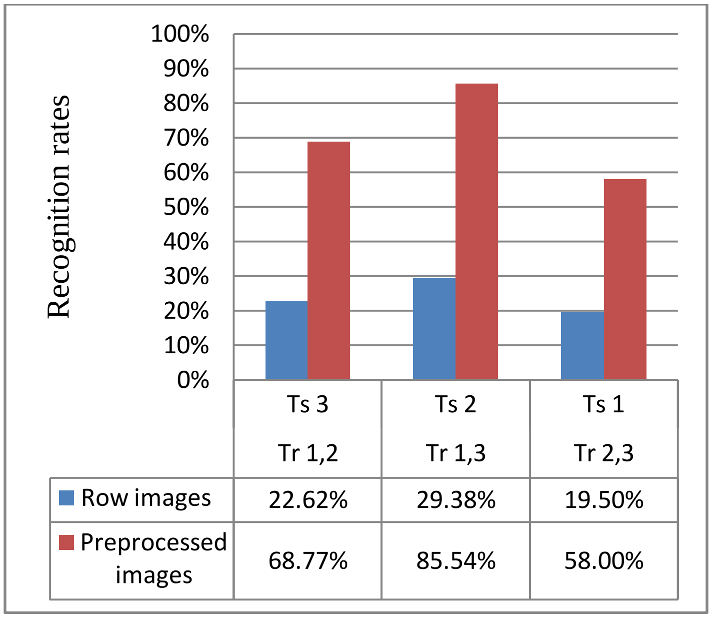
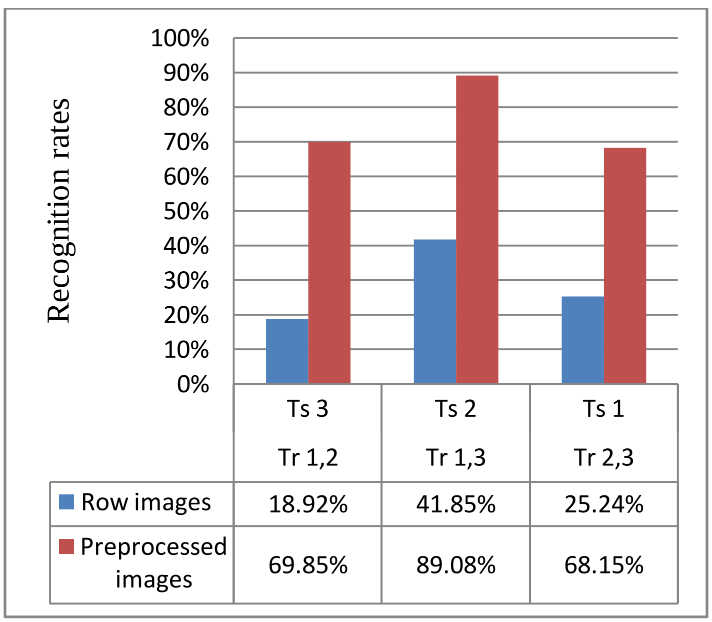


Figure 42 Effect of preprocessing steps on FR rates (SDO)



	Ts 3 Tr 1,2	Ts 2 Tr 1,3	Ts 1 Tr 2,3
Row images	22.62%	29.38%	19.50%
Preprocessed images	68.77%	85.54%	58.00%

Figure 43 Effect of preprocessing steps on FR rates (Eigenfaces)



	Ts 3 Tr 1,2	Ts 2 Tr 1,3	Ts 1 Tr 2,3
Row images	18.92%	41.85%	25.24%
Preprocessed images	69.85%	89.08%	68.15%

Figure 44 Effect of preprocessing steps on FR rates (DCT)

As shown in Figure 45 after preprocessing on SFDCF extraction scheme, face recognition rates improve by an average of 48%, while on DCT and on Eigenfaces schemes, rates improve by an average of 62.1% and 66.3% respectively. This means that SFDCF extraction scheme is less sensitive to image preprocessing steps.

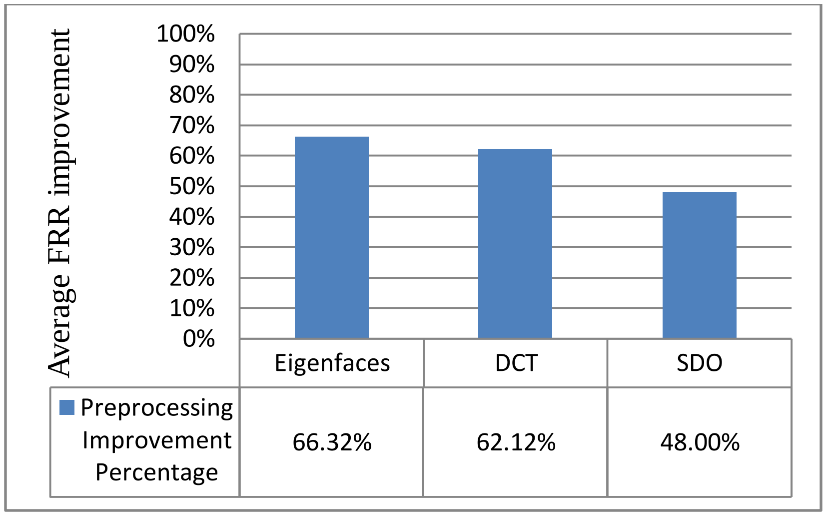


Figure 45 Effect of preprocessing steps on FR rates

Cropping is required to extract a face from an image and to get rid of unnecessary background details, Face detection using different cropping techniques such as fixed mask size, dynamic mask size and color segmentation play a significant role in improving face recognition rates. The size of the cropping mask affects the face recognition rates significantly. Increasing the size of the cropping mask leads to more details, while small mask size leads to fewer details, hence low recognition rates. In Figure 46 it is clear that increasing the cropping mask size has irrelevant information while small mask skips some important details such as eyebrow and chin.

Figure 46 Cropping with different mask sizes

The following figure shows the average recognition rates obtained using different cropping techniques with SFDCF. In this regard the total number of experiments done is fifteen, five at each distance. In every five experiments one image was kept for testing and the other four images were used as training images and later the average of recognition rates was calculated.

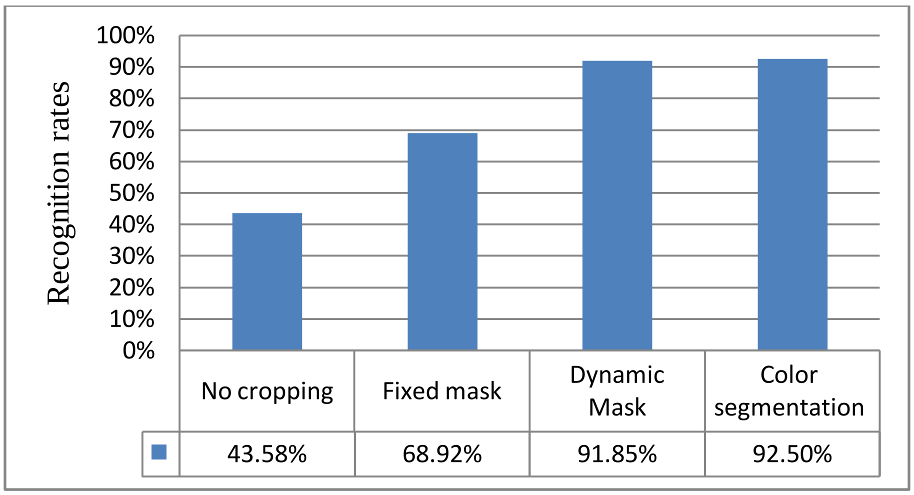


Figure 47 Different cropping techniques

It is very clear form the previous figure that cropping face using dynamic mask size or color segmentation technique improves the recognition rates significantly. Image normalization should take place after cropping, otherwise the mean and the standard deviation of the image will be affected by the image background as shown in Figure 48.

Figure 48 Original image (a), Normalized image (b), Cropped and normalized image (c)

An efficient normalization technique can be done by replacing each pixel in the spatial domain by its Z score value. This process increases the average recognition rate from 76.6% to 83.8%. These values are the averages of sets of fifteen experiments each. In the first five experiments images captured at distances 1 and 2 were treated as training images, while images captured at distance 3 were considered testing images. Then we took images captured at distance 2 for testing and kept images taken at distance 1 and 3 for training. Finally images taken at distance 1 were utilized for testing and images captured at distance 2 and 3 for training.

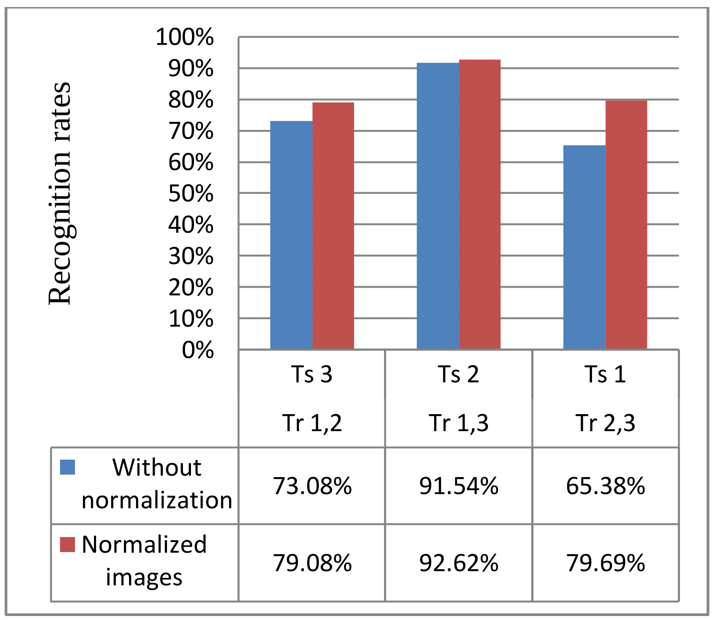
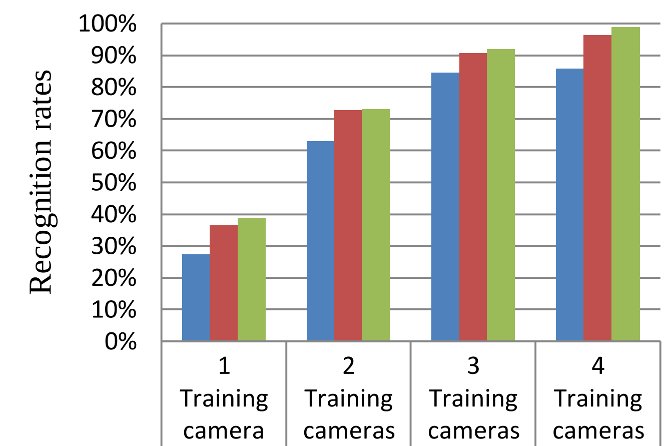


Figure 49 Normalization effect on FRR

Figure 49 shows that normalization has no significant effect when testing images are at the mid range distance from the captured cameras (Distance 2), while training images are at close and far distances from the cameras (Distance 3 and Distance 1 respectively). On the other hand normalization makes the difference when testing images are at close or at far distances from the cameras.

8.2. Face recognition across different imaging sensors

Since SCface database contains 5 different cameras, two of them were used in the night vision mode- a total of 7 images at each distance were taken. There is a wide range of combinations for selecting the training and testing cameras. We examined many scenarios starting from one training image per subject to six training images per subject.



	1 Training camera	2 Training cameras	3 Training cameras	4 Training cameras
Dist 1	27.34%	62.88%	84.62%	85.69%
Dist 2	36.31%	72.63%	90.51%	96.15%
Dist 3	38.50%	73.14%	91.73%	98.92%

Figure 50 Effect of number of training cameras on FRR

What was found is that one training image of low resolution per subject is not enough for face recognition. The previous figure shows that for one training image the maximum average recognition rate is 38.5% when images captured at distance 3 are used as both training and testing images. As more training images are considered, face recognition rates improve. Figure 51 shows the relation between recognition rate and the testing cameras at each distance (without the use of infrared cameras).

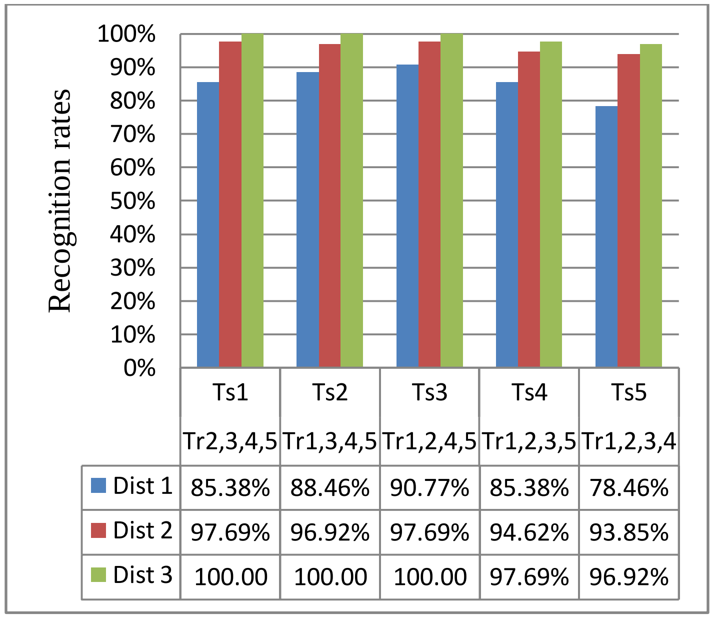
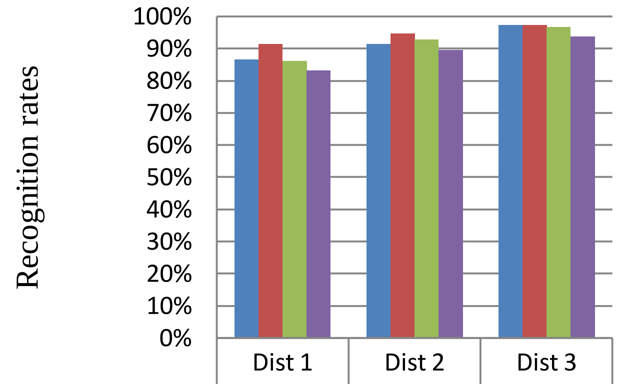


Figure 51 Effect of camera selection on FRR

In this experiment LDF is used to recognize faces after extracting SFDCF. We took four images out of five for training and the remaining image for testing. The average recognition rates using cameras at distance 3 are the highest in comparison to those of distance 1 and 2. The reason is that images taken at distance 3 are captured at a closer distance compared to the images taken at distances 1 and 2. Camera 5 has the least recognition rates across all distances hence it produces the least quality of the image compared with the other cameras; especially when images are captured at far distances.

8.3. SDO results

Four Spatial Differential Operators were used to extract features from each preprocessed image; those operators are: Euclidean, standardized Euclidean, City block and cosine distance. All measurements were taken between rows. It was found that standardized Euclidian gives the highest recognition rates when images are captured at far distance because this differential operator makes sure that huge differences in the pixel's intensity are not dominating, results are shown in Figure 52.



	Dist 1	Dist 2	Dist 3
Euclidean	86.62%	91.23%	97.32%
S-Euclidean	91.23%	94.77%	97.23%
City block	86.15%	92.62%	96.62%
Cosine disance	83.15%	89.52%	93.72%

Figure 52 Spatial Differential Operators

In this work we also examined the effect of using SDO across columns. We proved that SDO across rows gives higher recognition rates in comparison to SDO across columns, as shown in Figure 53. This is due to the symmetry between the left and right side of the head in a face image which gives less extracted details in columns compared to rows.

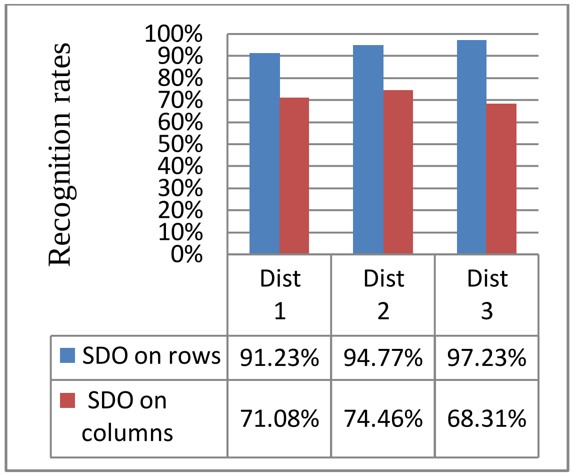


Figure 53 Rows and Columns SDO

Extracting face features using SDO leads to high dimensionality classification problem. We used PCA to reduce the dimensionality of the extracted feature vectors. Figure 54 shows that the optimum number of Eigen vectors that gives the maximum face recognition rates was empirically found to be 100 feature vectors.

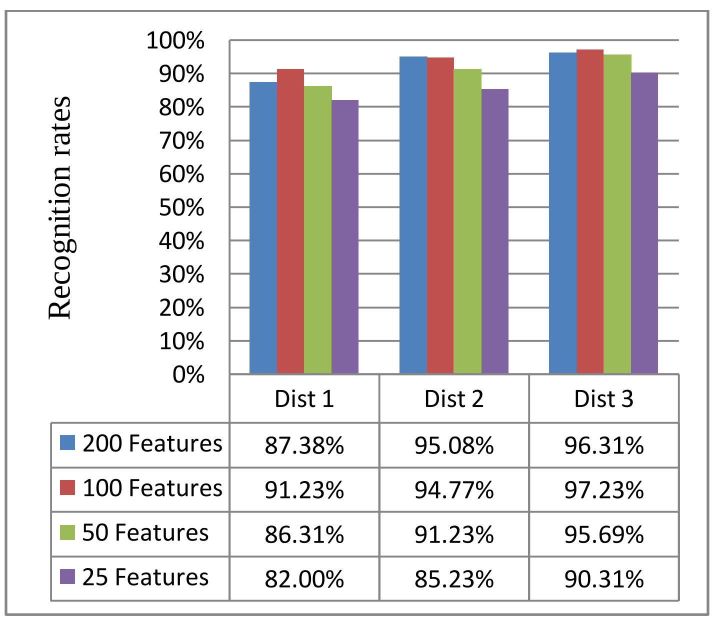


Figure 54 Optimum number of Eigen vectors

8.4. DCT and Eigenfaces results compared to SFDCF results

Each face image was transformed from the spatial domain to the frequency domain using the DCT method followed by Zigzag scanning to reduce the dimensionality of the face recognition problem. For maximum recognition rate we found that the best number of DCT coefficients to be used for images taken at distance 1 is 100 DCT coefficients, at distance 2 it is 70 and at distance 3 it is 50; that means for faces close to camera less number of DCT coefficients is needed to maximize face recognition rates, and the reason for that is discriminant details are not visible at far distance when few features are extracted.

In the Eigenfaces approach we extracted 130 Eigenfaces, hence the length of each feature vector is 130 coefficients. We have also confirmed that using the Eigenfaces approach with different cameras and variations in face pose at far distance results in poor recognition rates. Figure 55 shows that our proposed feature extraction scheme SFDCF gives better recognition rates in comparison with both Eigenfaces and DCT feature extraction techniques, especially when testing images are taken at a far distance from the cameras.

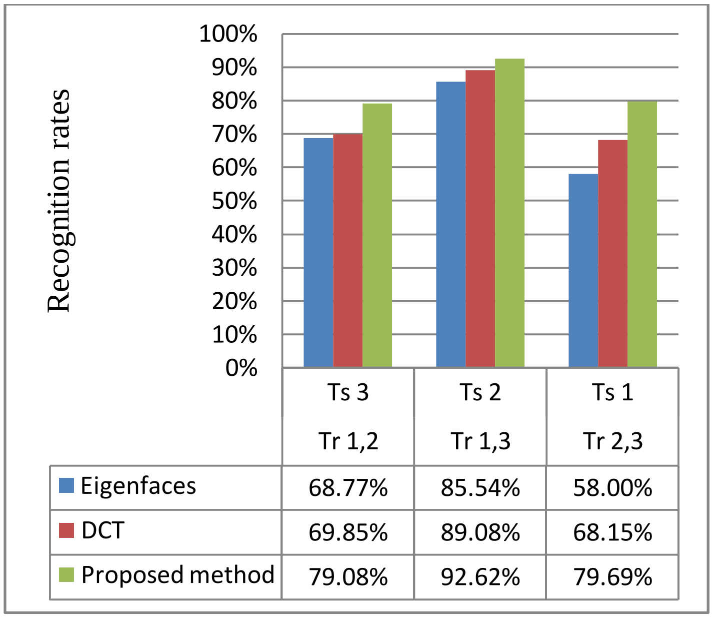


Figure 55 Eigenfaces , DCT and SDO

8.5.GLCM results

We used ORL database to test GLCM feature extraction scheme followed by PCA to reduce the dimensionality of the face recognition problem. Grey images were quantized, various quantization levels were investigated. Obtained results show that GLCM feature extraction scheme works fine with high resolution images. Figure 56 and Figure 57 shows the average recognition rates obtained. In this regard seven experiments were done for each quantization level; the number of training images varies from 4 to 9 while the number of testing images varies from 6 to 1.

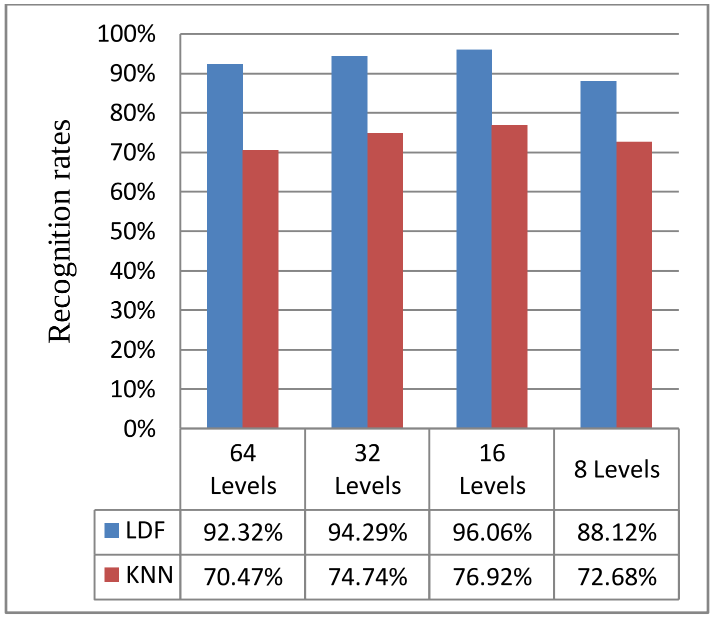


Figure 56 GLCM on ORL Database

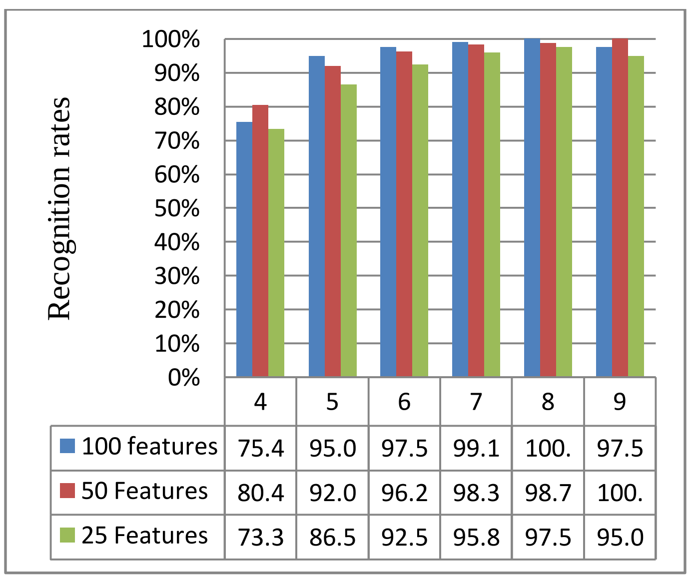


Figure 57 GLCM, Different number of training images (ORL)

At the classification stage we proved that LDF gives high recognition rates compared with KNN classifier when GLCM feature extraction scheme is used. Also we showed that 16 quantization levels is optimum. Moreover, Figure 57 shows that this approach requires at least five images per subject to achieve high recognition rates.

GLCM feature extraction scheme with LDF does not work with images captured with low resolution cameras, when this approach was applied on SCface database the obtained recognition rates were extremely low as shown in Figure 58.

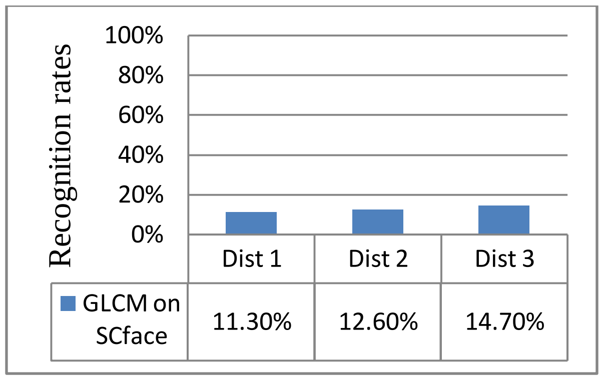


Figure 58 GLCM on SCface database

8.6. Wavelet decomposition results

Two wavelet decomposition feature extraction schemes were examined; in the first approach each face image is decomposed into two bands, this gives one image of approximation and six images of details. Then statistical measures of the wavelet coefficients along with 20 DCT coefficients were utilized as feature vector, in this method the recognition rates were very low. In the second approach Eigenfaces were extracted from the low frequency band that carries the face image approximation; here the recognition rates were higher than the first approach but lower than SFDCF scheme as shown in Figure 59.

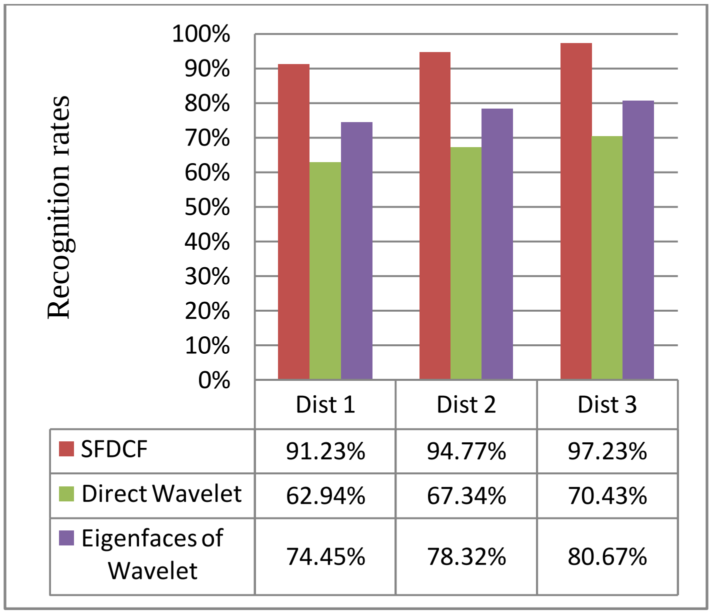


Figure 59 Wavelet results

Five experiments were done at each distance; in each experiment four training images were used as training images and one was kept for testing, Figure 59 shows the average recognition rates obtained for each wavelet approach compared with SFDCF scheme.

8.7.Effect of including images captured in the night vision mode

Images captured in the night vision mode in the training or testing process leads to almost 20% drop in face recognition rates. Those images usually do not add extra information to the training stage and they can hardly be recognized at the testing stage.

8.8.KNN classifier

First, 1-NN classifier was used. This classifier measures the distance between the testing feature vectors and training feature vectors. It labels the testing vectors according to the minimum distance found. Different K values were investigated, to see its impact on the recognition rates. The experiments were done using cam1 and cam4 as training cameras and cam2, cam3, and cam5 as testing cameras. Images taken in the night vision mode were disregarded just to investigate the best value of K that maximizes the recognition rate, as shown in Figure 60. It is clear from the graph that increasing K does not make any significant difference, instead the code consumes more time because more calculations are needed.

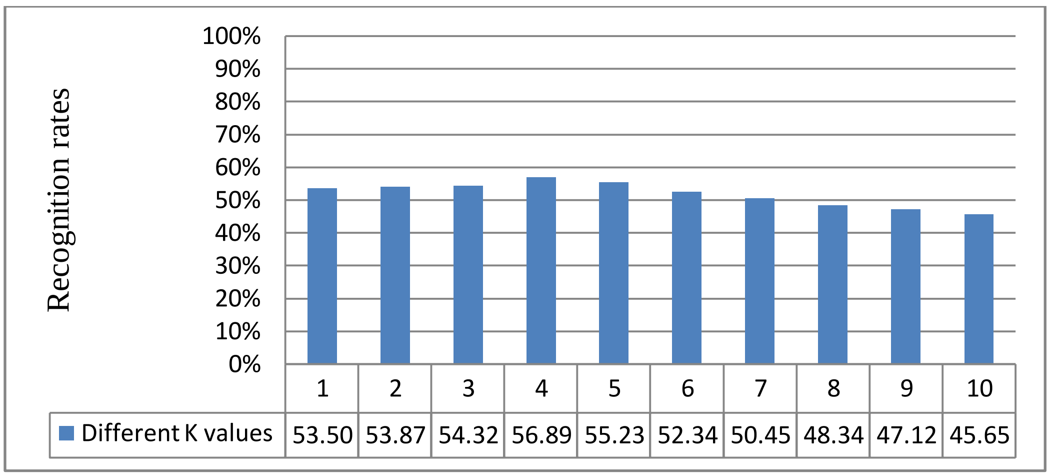


Figure 60 Optimum K in KNN classifier

For classification we found that LDF is more efficient than KNN classifier. Our proposed feature extraction scheme SFDCF was tested using both classifiers; results are shown in Figure 61:

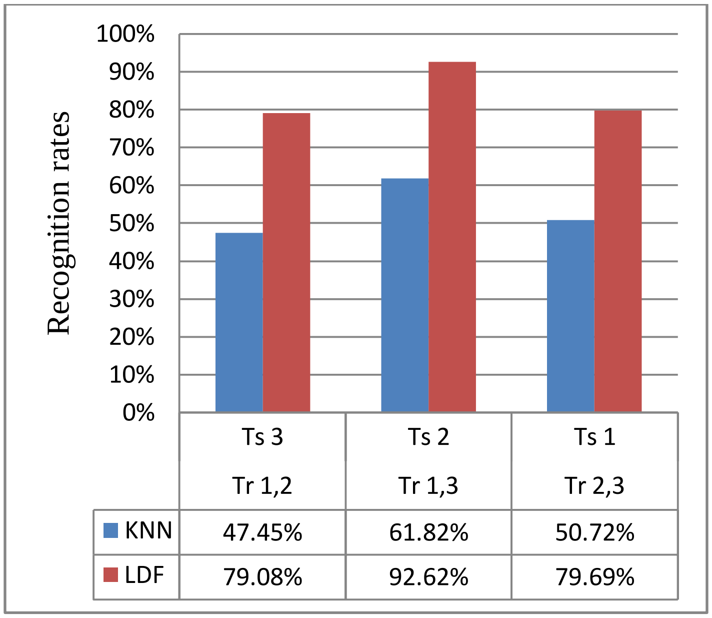


Figure 61 LDF and KNN classifier

8.9. Second order polynomial expansion followed by spectral regression

It is very common in classification problems to have non-linearly separable features; in this case a non-linear classifier is required. We expanded the DCT coefficients to obtain the second order polynomial expansion, each set of coefficients (linear, quadratic, interaction) were examined to see the amount of information carried by that set and how each set contributes to the recognition rates. We found that pure quadratic terms carry no additional information and its contribution to the recognition rate is minimal. We used second order polynomial followed by spectral regression to reduce the dimensionality of the feature vectors in the training and testing data. Spectral regression reduces the number of features to 129 (number of classes -1), so it saves memory space and reduces the required processing time; moreover it improves the recognition rate across each distance.

Figure 62 shows that second order polynomial expansion followed by SR improves the recognition rates for images taken at distance 1 by an average relative amount of 11%. At distance 2 and 3 the recognition rate increases by an average relative amount of 4% and 7% respectively when the second order polynomial expansion followed by spectral regression is used.

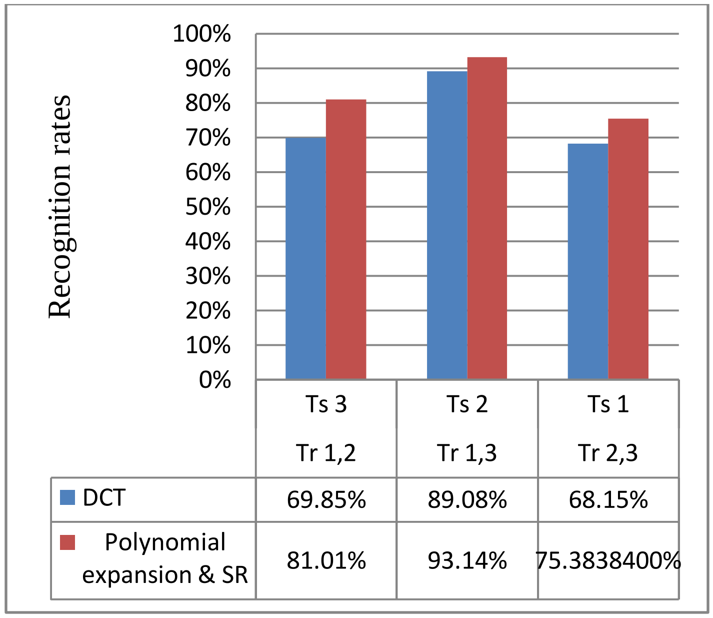


Figure 62 Polynomial expansion followed by SR for DCT coefficients

Polynomial expansion followed by spectral regression does not work with SDO as it works with DCT; further investigations need to be done.

8.10. Neural network results

Both DCT features and SFDCF were examined using two layers neural network with 20 hidden neurons; the obtained recognition rates are shown in Figure 63. SFDCF gives higher recognition rates in comparison to DCT approach. It was also found that linear classifier performs better than neural network for both feature extraction schemes.

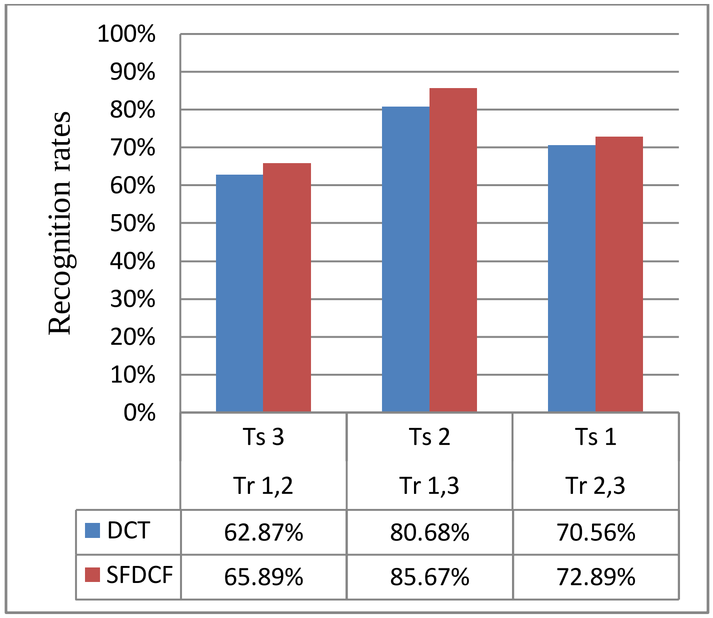


Figure 63 Neural network results

9. Conclusions and Future Work

Face recognition for images taken by commercial cameras of low resolution is an important and challenging research topic which has many applications. In this research we used a recently published database called “SCface Database” to emphasize the challenges of face recognition in uncontrolled indoor conditions. These challenges can be summarized as follows: illumination variation, different commercial camera qualities with low resolution, uncontrolled pose to cameras and different distances from cameras.

The total number of images we used in this research is 2730, taken at three different distances by five different commercial cameras. Seven hundred eighty images out of the total number were taken in the night vision mode. In this study we examined the effect of camera’s quality and distance from a camera with regards to face recognition rates by analyzing different face recognition schemes.

In this research, we developed a reliable face recognition system that recognizes faces captured by different cameras. We proposed two solutions: in the first proposed solution face images are preprocessed by means of: skin segmentation, color transformation, cropping, normalization and filtering. Then both Spatial Differential Operators (SDO) and Discrete Cosine Transform (DCT) are applied to extract features, and Principal Component Analysis (PCA) is employed to reduce dimensionality in the spatial domain, while zonal coding is employed to reduce the dimensionality in the frequency domain. Linear Discriminant Function (LDF) is utilized as a classifier. This solution gives better recognition rates in comparison with the state of arts feature extraction schemes such as Eigenfaces, (DCT), and Gray Level Co-occurrence Matrix (GLCM).

In the second proposed solution the same preprocessing steps are followed then (DCT) is applied to extract face features. These features are then exposed to second order polynomial expansion followed by spectral regression for dimensionality reduction. We have found that the latest proposed solution improves face recognition rates by 11%, 4% and 7% when testing images are captured at distances 4.20, 1.00, and 2.60m, respectively, comparing to the use of linear classifier with the same features.

We also studied the effect of having images captured in the night vision mode in relation to face recognition rates and found that this type of images lower the recognition rates. Also we showed that image preprocessing techniques such as face detection, de-noising and normalization enhance the face recognition rates.

I would recommend further research into utilizing Gaussian Mixture Model in order to extract face features; it might lead to better performance. Moreover, I would advise further research into why GLCM feature extraction scheme performs well with high resolution images but performs poorly with low resolution images. Finally the effect of including different number of hidden layers in Neural Networks classifier needs to be investigated in relationship to face recognition rates.

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Appendix A

Eigenfaces

Appendix A Eigenfaces

```
%%Eigenfaces
close all;
clear all;
clc;
all_coord;
nTr=10;
nTs=1;



Tr=[];%initiate feature vector

cd D:\thesis\SCface_database\surveillance_cameras_all
for subj=1:130
   for cam=[1 2 3 4 5]
            for dist=[2 3]



if subj<10
filename=['00',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end


if subj>9 && subj<100
filename=['0',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end

if subj>99
filename=[int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end



i=imread(filename);
i=rgb2gray(i);

d_eyes= coord(subj,3,cam,dist)-coord(subj,1,cam,dist);
d_eyes_mouth= coord(subj,8,cam,dist)-coord(subj,2,cam,dist);



i=imcrop(i,[(coord(subj,1,cam,dist)- d_eyes) (coord(subj,2,cam,dist)-1.5*d_eyes) 3*d_eyes
d_eyes_mouth+2.5*d_eyes]);

%figure;imshow(i);

i=imresize(i, [49 49]);
```

```
%figure;imshow(i);pause
%%%Zscore for the overall image
i=zscore(double(i(:)));


%figure;imshow(i,[]);pause
f=fspecial('gaussian');

i = imfilter(i,f);
%figure;imshow(i,[]);pause
%%%No Effect
%%%

%i=zscore(double(i));
%imshow(i)
%pause


%i=squareform(i);
%imshow(i./max(max((i))))
%pause

Tr=[Tr;i'];
        end
  end
end

coeff=princomp(Tr);
coeff=coeff(:,1:100);
u=mean(Tr);
x=Tr-repmat(u,nTr*130 ,1);
x=x*coeff;
Tr=x;


Ts=[];
for subj=1:130
  for cam=[5]
        for dist=[1]



if subj<10
filename=['00',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end


if subj>9 && subj<100
filename=['0',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end

if subj>99
```

```
filename=[int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end



i=imread(filename);
i=rgb2gray(i);
d_eyes= coord(subj,3,cam,dist)-coord(subj,1,cam,dist);
d_eyes_mouth= coord(subj,8,cam,dist)-coord(subj,2,cam,dist);



i=imcrop(i,[(coord(subj,1,cam,dist)- d_eyes) (coord(subj,2,cam,dist)-1.5*d_eyes) 3*d_eyes
d_eyes_mouth+2.5*d_eyes]);


%figure;imshow(i);

i=imresize(i, [49 49]);
%%%Zscore for the overall image
i=zscore(double(i(:)));

f=fspecial('gaussian');

i = imfilter(i,f);

%%%No Effect
%%%

%imshow(i);pause
%i=zscore(double(i));



%i=squareform(i);
%imshow(i./max(max((i))))
%pause

Ts=[Ts;i'];
        end
  end
end

y=Ts-repmat(u,nTs*130,1);
y=y*coeff;
Ts=y;



group=1:130*nTr;
group=fix((group-1)/nTr)+1;
class=knnclassify(Ts,Tr,group,10);
```

```
k=classify(Ts,Tr,group);

groupts=1:130*(nTs);
groupts=fix((groupts-1)/(nTs))+1;


results=class-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100


results=k-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100
```

APPENDIX B

DCT

Appendix B SDO and DCT

```
close all;
clear all;
clc;



cd D:\thesis\SCface_database\surveillance_cameras_all
all_coord;
Tr=[];%initiate feature vector
dct_Tr=[];
nTr=10;
nTs=1;

for subj=1:130
  for cam=[1 2 3 4 5]
        for dist=[1 2]



if subj<10
filename=['00',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end


if subj>9 && subj<100
filename=['0',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end

if subj>99
filename=[int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end



i=imread(filename);
i=rgb2gray(i);

d_eyes= coord(subj,3,cam,dist)-coord(subj,1,cam,dist);
d_eyes_mouth= coord(subj,8,cam,dist)-coord(subj,2,cam,dist);



i=imcrop(i,[(coord(subj,1,cam,dist)- d_eyes) (coord(subj,2,cam,dist)-1.5*d_eyes) 3*d_eyes
d_eyes_mouth+2.5*d_eyes]);

%figure;imshow(i);

i=imresize(i, [49 49]);
%figure;imshow(i);pause
```

```
%%%Zscore for the overall image
i=zscore(double(i(:)));
i=reshape(i, [49 49]);

%figure;imshow(i,[]);pause
f=fspecial('gaussian');

i = imfilter(i,f);
%figure;imshow(i,[]);pause
%%%No Effect
%%%

%i=zscore(double(i));
%imshow(i)
%pause


d=dct2(i);
f=zonal(d,80);
p=pdist(i);


%i=squareform(i);
%imshow(i./max(max((i))))
%pause

Tr=[Tr;p];
dct_Tr=[dct_Tr;f];
        end
  end
end

coeff=princomp(Tr);
coeff=coeff(:,1:100);
u=mean(Tr);
x=Tr-repmat(u,nTr*130 ,1);
x=x*coeff;
Tr=[x,dct_Tr];


Ts=[];
dct_Ts=[];
for subj=1:130
  for cam=[3]
        for dist=[3]



if subj<10
filename=['00',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end
```

```
if subj>9 && subj<100
filename=['0',int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end

if subj>99
filename=[int2str(subj),'_cam',int2str(cam),'_',int2str(dist),'.jpg'];
end



i=imread(filename);
i=rgb2gray(i);

d_eyes= coord(subj,3,cam,dist)-coord(subj,1,cam,dist);
d_eyes_mouth= coord(subj,8,cam,dist)-coord(subj,2,cam,dist);



i=imcrop(i,[(coord(subj,1,cam,dist)- d_eyes) (coord(subj,2,cam,dist)-1.5*d_eyes) 3*d_eyes
d_eyes_mouth+2.5*d_eyes]);

%figure;imshow(i);

i=imresize(i, [49 49]);
%figure;imshow(i);pause
%%%Zscore for the overall image
i=zscore(double(i(:)));
i=reshape(i, [49 49]);

%figure;imshow(i,[]);pause
f=fspecial('gaussian');

i = imfilter(i,f);
%figure;imshow(i,[]);pause
%%%No Effect
%%%

%i=zscore(double(i));
%imshow(i)
%pause


d=dct2(i);
f=zonal(d,80);
p=pdist(i);


%i=squareform(i);
%imshow(i./max(max((i))))
%pause
```

```
Ts=[Ts;p];
dct_Ts=[dct_Ts;f];
            end
   end
end




y=Ts-repmat(u,nTs*130,1);
y=y*coeff;
Ts=[y,dct_Ts];



group=1:130*nTr;
group=fix((group-1)/nTr)+1;
class=knnclassify(Ts,Tr,group,10);
k=classify(Ts,Tr,group);

groupts=1:130*(nTs);
groupts=fix((groupts-1)/(nTs))+1;


results=class-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100


results=k-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100
```

APPENDIX C

GLCM

Appendix C GLCM

```
close all;
clear all;
clc;

cd D:\thesis\faces
nTr=7;

Tr=[];
for sub=1:40
   newfolder=['D:\thesis\faces\s',int2str(sub)];
cd(newfolder)

   for k=1:nTr

filename=[int2str(k),'.pgm'];
i=imread(filename);
%imshow(i)

%i = histeq(i, 128);
%figure; imshow(i);
glcm=graycomatrix(i,'NumLevels',64);
%figure; imshow(glcm);

Tr=[Tr;glcm(:)'];
%pause
   end
end

coeff=princomp(Tr);
coeff=coeff(:,1:100);
u=mean(Tr);
x=Tr-repmat(u,nTr*40 ,1);
x=x*coeff;
Tr=x;


Ts=[];
for sub=1:40
   newfolder=['D:\thesis\faces\s',int2str(sub)];
cd(newfolder)

   for k=nTr+1:10

filename=[int2str(k),'.pgm'];
i=imread(filename);
%imshow(i)
```

```
%i = histeq(i, 128);
%figure; imshow(i);
glcm=graycomatrix(i,'NumLevels',64);
%figure; imshow(glcm);

Ts=[Ts;glcm(:)'];
%pause
   end
end

y=Ts-repmat(u,(10-nTr)*40 ,1);
y=y*coeff;
Ts=y;

group=1:40*nTr;
group=fix((group-1)/nTr)+1;
class=knnclassify(Ts,Tr,group,100);
k=classify(Ts,Tr,group);

groupts=1:40*(10-nTr);
groupts=fix((groupts-1)/(10-nTr))+1;


results=class-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100


results=k-groupts';
[m n]=size(results);
rec_rate=(m-nnz(results))/m*100
```

VITA

Kamal Abuqaaud was born on September 18, 1980, in Amman, Jordan. He studied in local public schools and graduated from high school in 1998. He received a scholarship from her Highness princess Alia Al-Faisal, to study at University of Jordan, from which he graduated with a bachelor degree of electrical engineering, in 2004. Then, He worked as a maintenance team leader at RUM Company for one year. In 2005, Kamal joined the Royal Scientific Society (RSS) as a conformity assessment officer he had the chance to travel to both UK and Sweden at that time for training. In 2007 he became project manager for electrical house hold appliances assessment at RSS. In 2007 he became a teacher at the Institute of Applied Technology (IAT) then electrical department head at the same institute in 2011. Mr. Kamal abuqaaud began a master's program in Electrical Engineering at the American University of Sharjah in 2009.