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Quality-Based Face Recognition System

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Quality-Based Face Recognition System

by

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Abstract

Quality assessment of a biometric sample is relatively difficult and understudied problem compared to the automated recognition and feature extraction in biometrics. More attention should be directed towards this problem since it has been found in many studies that the quality of samples significantly affects the performance of a biometric system. This thesis focuses on designing a unified framework which can adaptively compensate for different quality degradations of the facial images. The proposed quality estimation model determines the overall quality of a facial sample by considering the impact of quality degradation on the performance of the sample. Our proposed quality-based face recognition system utilizes this overall quality score to determine the appropriate preprocessing steps and facial representations for improved recognition performance. The proposed methodology employs a quality-based weighted score fusion to boost the recognition performance further. Extensive experiments with real and synthetic samples demonstrate the effectiveness of the proposed methodology.

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List of Symbols, Abbreviations and Nomenclature

Abbreviations	Definition
AAM	Active Appearance Model
CBFD	Compact Binary Face Descriptor
CLAHE	Contrast Limited Adaptive Histogram Equalization
DCT	Discrete Cosine Transform
DTCWT	Dual-Tree Complex Wavelet Transform
DWT	Discrete Wavelet Transform
EBGM	Elastic Bunch Graph Matching
FLD	Fisher's Linear Discriminant
FQI	Facial Image Quality Index
FW	Fuzzy Weight
GLQI	Global Luminance Quality Index
HE	Histogram Equalization
HH	High-High
HL	High-Low
HMM	Hidden Markov Models
HOG	Histograms of Oriented Gradients
IQ	Illumination Quality
KFLD	Kernel Fisher's Linear Discriminant
KNN	K-Nearest Neighbor
KPCA	Kernel Principal Component Analysis
LBP	Local Binary Pattern
LGBPHS	Local Gabor Binary Pattern Histogram Sequence
LH	Low-High

LL	Low-Low
LPQ	Local Phase Quantization
LQI	Luminance Quality Index
MH	Middle Halve
NN	Neural Network
OFIQ	Objective Facial Image Quality
PCA	Principal Component Analysis
PDV	Pixel Difference Vector
RFIQ	Relative Facial Image Quality
RMS	Root Mean Square
SALQI	Symmetrical Adaptive Local Quality Index
SVM	Support Vector Machine
UQI	Universal Quality Index
WT	Wavelet Transform
ZN	Z-score Normalization

Chapter 1

INTRODUCTION

1.1 Problem Statement

Biometric authentication is a reliable mechanism for an automatic person recognition. It is usually based on physiological or behavioral characteristics. Face, fingerprint, iris, hand and palm geometry are examples of physiological biometrics [47,49], while examples of behavioral biometrics are keystroke dynamics, gait, speech and signature [47]. According to the recent standard ISO/IEC 29794-1 [45], the quality of a biometric sample can be defined from three different perspectives: 1) character, 2) fidelity and 3) utility. In most of the biometric literature, utility is considered as the quality of a biometric sample [10, 32, 41]. It is a quantitative measure that indicates the performance of a biometric sample. A higher quality score of a biometric sample represents that the sample is more suitable for identifying an individual. Many studies have shown that biometric sample quality plays a vital role on the performance of a biometric system [14, 32, 35, 41]. However, there are very few studies that analyze the impact of different quality factors on facial samples, and introduce a system for estimating the overall quality of the facial image considering various quality factors [1, 2, 19, 20, 28, 51, 55]. In this thesis, I intend to fill this gap. I analyze the impact of different quality factors on the performance of a face recognition system and build a model that will estimate the overall quality of a biometric sample consolidating different quality scores into a single quality score. This quality score is a strong indicator of the performance of the sample and it indicates whether the facial sample will be correctly identified or not. I also propose a quality-based face recognition system which will minimize the adverse effects of quality degradations based on the introduced overall quality score. This quality-based approach improves the overall performance of the face recognition system.

Among all the biometric techniques, face biometric-based identification is one of the most popular and highly accepted biometric traits due to the non-invasive nature of its acquisition process [47, 49]. Automatic face recognition has established itself as a key research area in computer vision and pattern recognition over the past few decades. In general, every face recognition system is comprised of three essential components: data collection, feature extraction, and classification. Facial images collected from various sensors are used for feature extraction. These extracted features are used by the classifier for identifying or verifying an individual based on the facial traits. Automatic face recognition becomes a convenient person identification tool due to the availability of the low-cost hand-held devices, which makes it possible to acquire the facial images from a distance. As a result, face recognition is being used in many real-world applications such as access control [16], security [44], law enforcement [47], intelligent surveillance system [90], human-computer interaction [44], e-learning [4], and virtual reality [93]. However, despite a growing application domain, an automated face recognition remains a challenging task in uncontrolled environments. Uncontrolled environments may introduce quality degradation of the facial images due to the changes in lighting conditions, occlusion, and poor sensor quality. Similarly to other biometrics, automated face recognition system also suffers from poor quality samples. Recent studies show that variations in lighting conditions, contrast, brightness, focus, occlusion, and other quality factors have a major impact on the performance of a face biometric system [1, 2, 20, 69, 80]. Intra-class variations introduced by the degradation of these quality factors may lead to higher identification errors and lower the overall performance of the biometric system.

It was established that the quality of facial images during enrollment and verification stages significantly affects the performance of an automated face recognition system [1, 2, 80]. Therefore, an efficient method is needed which can capture the impact of different quality factors on the performance of a facial sample and can minimize the adverse effects of these quality factors on that facial image. In this thesis, I focus on face recognition under quality degradation of the facial images. I analyze the impact of different quality factors on the recognition performance and build an efficient and effective method for consolidating different quality scores of a sample into a single score which will reflect the overall performance of that sample. Moreover, I propose a quality-based face recognition system which will compensate for low facial quality using an overall quality score of the facial image. The primary research questions that I plan to answer in this thesis are as follows:

1. Can a system be created that estimates various quality factors and consolidates different quality factors into a single score to determine an overall quality of a facial image?

2. Is it possible to introduce some preprocessing steps and select appropriate facial representations based on the overall quality of the facial image that will compensate for quality degradation introduced by different quality factors?

3. Can an adaptive system be built based on the overall quality of a facial image that will minimize the adverse effects of different quality degradation and improve the overall performance of the face recognition system?

1.2 Motivation

Face recognition is one of the highly accepted physiological biometrics due to its non-intrusive nature and ease of acquisition of the samples [47, 49]. Over the years, many benchmark face recognition approaches have been introduced that can efficiently and reliably recognize faces in a controlled environment [5, 58, 59, 95, 101]. As a result, face recognition-based authentication has become very popular. It is now used in various real-world applications such as law enforcement, border control, video surveillance, forensic investigation, as well as in social media [9, 44, 47, 85, 86, 90]. However, like all the prominent biometric modalities, face recognition systems are also affected by quality degradation of the biometric samples [14, 36]. In biometric, quality of a sample can be defined as a measure of the performance of the biometric sample for identifying an individual [10, 32, 41]. There are different factors that affect the quality of face biometric samples, and as a result, affect the overall performance of the face recognition system.

Facial quality factors can be categorized in many ways. According to face data standards ISO/IEC 19794-5 [46], the facial quality factors can be categorized into four types: 1) Formatting factors represent the digital specification and organization of the images; 2) Digital factors represent spatial resolution, conversion, compression, contrast of gray-scale images; 3) Photographic factors include positioning of the head in the image and different camera attributes, such as exposure, brightness, and focus, and 4) Scenic factors incorporate various lighting conditions and attributes related to image and subjects, such as head rotation, state of eyes and mouth. Another categorization of the quality factors is image-based which includes illumination, blurriness, optical distortions and noise related to compression [14]. Poor quality of facial images introduced by the degradation of these quality factors may lead to higher identification errors in the systems [2, 14, 36, 80].

Automatic quality assessment of a face biometric sample is a relatively difficult problem. However, it is a strong indicator of the performance of the sample for biometric recognition. Moreover, there are many other applications of the automatic quality assessment model. We can summarize the various application scenarios as follows:

1. Quality-based Sample Selection:

   (a) Enrollment Stage: Quality check during enrollment stage is very important for ensuring high-quality gallery of images. Based on the quality score, we can decide whether to 'accept' or to 'reject' the sample.

   (b) Verification Stage: Feature extraction and verification are computationally expensive. Therefore, in the verification stage, the facial samples can be discarded based on the quality of the samples. If the overall quality of the sample is below some threshold values, then we can reject that sample for alleviating false alarms in the system.

2. Quality-based Preprocessing: Image enhancement techniques can be applied during the preprocessing step for improving the image quality. Instead of blindly selecting the image enhancement parameters, the quality score of the facial sample can be used to select the image

enhancement parameters.

3. Quality-based Recognition:

   (a) Unimodal approach: In a unimodal approach, different classifiers or feature extraction methods can be applied based on the quality of the facial samples. Moreover, the decision of different classifiers can be fused based on the overall quality of the facial samples. The regions of the facial image may vary in quality. Therefore, regions with high-quality scores can be selected or preferred for mitigating the identification errors.

   (b) Multimodal approach: In a multimodal approach, involving several biometrics traits, a more reliable system can be built by assigning more weights to the modality with better image quality. Therefore, the quality of the modalities can be used for assigning weights for a reliable multimodal biometric system.

We can see that the facial image quality is not only a good indicator of the performance of the biometric sample, but also the quality score can be used to minimize the adverse effects of various quality factors and improve the performance of the recognition system. There are very few studies in the literature that consider various quality factors and associate the relationship between quality factors and the performance of an individual sample [1, 2, 19, 20, 28, 51, 55]. Moreover, most of the face recognition systems perform well only under a controlled environment. There are some recent quality-based face recognition techniques that can handle quality degradation while recognizing faces. However, they are limited to handling one or two quality factors at a time [25, 80, 84]. Therefore, a unified framework which can evaluate the overall quality of the facial image considering various quality factors is needed. Moreover, a face recognition technique should be proposed that will compensate for quality degradations based on this overall quality score. This has motivated me to build a system for quality estimation of the facial sample, as well as a quality-based face recognition system for improved recognition performance. I aim to determine the overall quality of the facial samples which will be a significant indicator of the impact of different qual-

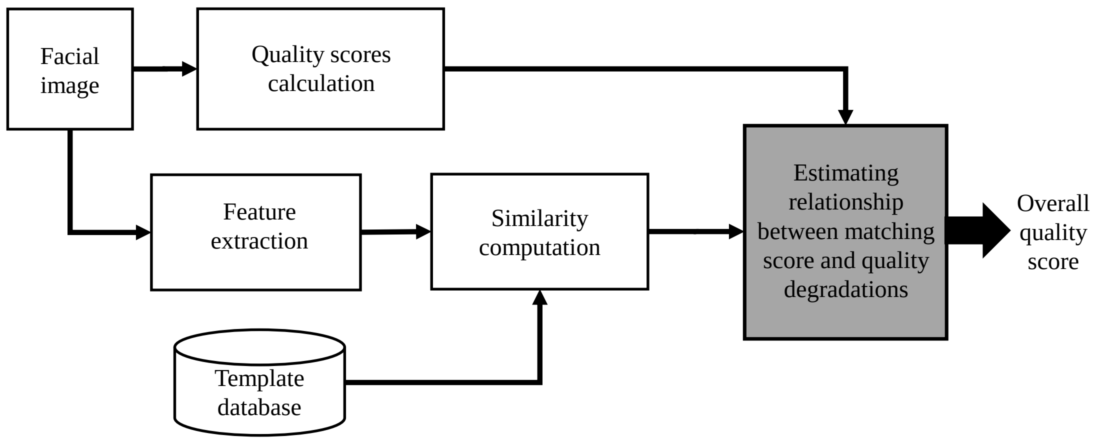


Figure 1.1: General block diagram of the proposed quality assessment system for the facial images.

ity degradations on matching performance. Figure 1.1 depicts a high-level view of the quality assessment model. Under the same framework, I intend to design a quality-based recognition system that will minimize the impact of various quality factors, and improve the overall performance of the face recognition system. Figure 1.2 represents a high-level view of the quality-based face recognition system.

1.3 Objectives

In this thesis, my primary goal is to estimate the overall quality of the facial image which will reflect the impact of quality degradations. This unified quality score can be used to compensate for different quality degradations without considering individual quality scores. This fact helps to design a unified framework for minimizing the impact of various quality factors and improve the overall performance of the face recognition system while working with facial images affected by different quality factors. This unified framework will handle various quality degradations based on the overall quality of the facial samples. The primary objectives of this thesis are summarized below:

1. Image quality can significantly affect recognition performance. However, there are very few studies in the literature that systematically analyze the impact of different quality factors on

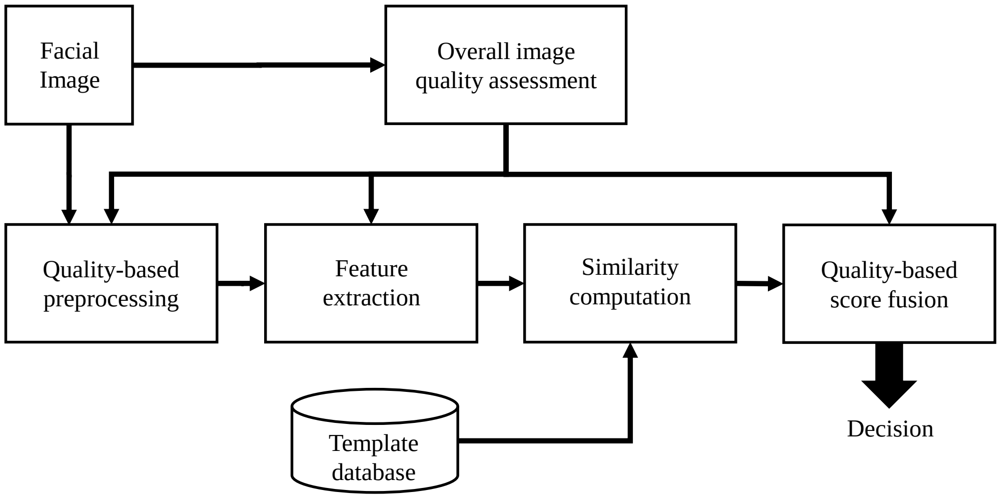


Figure 1.2: General block diagram of the quality-based face recognition system.

face recognition performance [2, 20, 28, 51, 55]. Therefore, in this thesis, I intend to analyze the impact of different quality factors on the face recognition performance and design a way to estimate the quality of the facial sample.

2. Different quality factors can affect the recognition system differently. There should be a way to estimate the impact of different quality factors and combine them to calculate the overall quality of a facial image. Therefore, I aim to propose a method that will determine the overall quality of the facial image while taking into account different quality factors, such as illumination, contrast, brightness, and focus. This unified quality score will be a reliable indicator of the intra-class variations introduced by the degradation of different quality factors.

3. There is a need for an automated face recognition systems to become more computationally intelligent and adaptive. However, very few current systems are designed this way. Traditional recognition systems are tested under strictly controlled conditions or with single quality impact (i.e. illumination) [25, 80, 84]. There are very few attempts made to date to jointly consider various quality factors under a unified framework. In this thesis, I intend to design a fully functional system that will estimate the overall quality of the facial images considering different quality factors, and improve the overall performance of the face recognition system

based on this score.

4. For minimizing the impact of quality degradation, some preprocessing steps should be introduced based on the quality of the facial samples. Also, we need to investigate the appropriate feature extraction methods to improve the performance of the system while recognizing faces with degraded facial samples.

1.4 Contributions

In this thesis, I analyze the impact of different quality factors on face recognition performance, as well as develop a new methodology for quality-based adaptive face recognition. I introduce a linear regression model to integrate different quality factors into a single quality score, and this unified quality score is used to adaptively handle different quality factors while recognizing faces. The research was conducted under the supervision of Professor Marina L. Gavrilova, Head of the Biometric Technologies Laboratory at the University of Calgary. The list of our contributions to the biometric research domain is presented below:

1. We conduct a rigorous study to investigate the taxonomy of quality-based methods in face recognition. Our study points out that quality-based adaptive face recognition is a relatively understudied topic in biometric. To the best of our knowledge, there are very few studies that incorporate the individual impact of different quality factors while integrating them into a unified quality score and adapt the uncertainty of the quality degradation during operation. In this thesis, a systematic survey is conducted on the quality-based methods in face recognition.

2. We present a new method that consolidates different quality scores into a single evaluation score to estimate the overall quality of the facial images. The proposed model considers various quality factors, such as illumination, contrast, brightness, and focus of the facial images. A linear regression-based approach is used to capture the relationship between these quality factors and corresponding matching performance of a facial image (Published

in ICCI*CC'17 Conference [105] and its extended version is accepted to Special Issue of IJCINI [107]).

3. We design a fully functional face recognition system that uses quality-based preprocessing and feature selection, and adaptively handles the quality degradation of the facial images. The proposed discrete wavelet transform (DWT)-based face recognition system compensates for different quality degradations based on the overall quality score with a very small number of training samples available. A preprocessing step based on the overall facial quality using contrast limited adaptive histogram equalization (CLAHE) and discrete cosine transform (DCT) based normalization is used to minimize the image distortions. We use a weighted score fusion of low and high-frequency sub-bands from the DWT-based feature extraction method to recognize the faces in the presence of quality degradations. Fuzzy membership functions are used to calculate the fusion parameters based on the overall quality of the facial images (Published in CW'17 Conference [106] and its extended version is accepted to Special Issue of TCS Journal [108]).

4. We design a case study to analyze the impact of other quality factors, in particular, occlusion on face recognition performance. We propose a occlusion localization method based on the depth information provided by the Kinect RGB-D camera. The face recognition system considers the occluded area localized from Kinect depth images while identifying the users from the gallery images. The proposed face recognition system reduces the number of misclassification, and as a result, improves the recognition performance of the biometric system by considering only the non-occluded facial parts to find the best possible match (Published in CW'16 Conference [103] and in Special Issue of TCS Journal [104]). The case study is presented in Appendix A.

The proposed quality assessment method and the quality-based adaptive system are validated on Yale database B, and Extended Yale database B [39, 54]. The Yale database B consists of 10 subjects, and the extended Yale database B consists of 28 subject images under 64 different lighting conditions. To the best of our knowledge, there are no publicly available databases that consolidated or addressed various quality issues, such as illumination, contrast, brightness and focus in their databases. The Yale Database B considered a wide range of illumination conditions which makes it an appropriate database for validating the impact of illumination on the face recognition performance. For validating the impact of other quality factors, we have synthetically generated other quality effects by automatically changing or adjusting contrast, brightness and focus. These synthetically created samples provide a sufficient number of instances to analyze the impact of different quality factors. For analyzing the impact of occlusion as a quality factor on the face recognition performance, we consider the EURECOM Kinect Face Dataset [62]. This database is publicly available and contains depth images acquired using Kinect, which incorporate different types of occlusion. Therefore, it is an appropriate database for determining the impact of occlusion on face recognition performance. The database is comprised of 52 subjects: 14 females and 38 males. The images are captured in two sessions, and there are nine types of variations in the images.

The analysis of the methodologies presented in this thesis will validate that the quality of the facial image has a significant impact on the face recognition performance. Therefore, the adaptive face recognition system based on image quality can be used to improve the recognition performance in the presence of a quality degradation. Moreover, a unified technique for handling different quality factors will save the preprocessing time of a recognition system. The overall quality score introduced in the proposed method can be used to discard the poor-quality facial images at the enrollment phase for improving the performance of the system. This score can also be used to assign weights while integrating the matching scores of several facial samples. Moreover, the quality factors that we have used in our proposed method are independent of biometric identifiers. Therefore, the proposed method is applicable to any image-based biometric system, such as ear-based person identification system. We can also incorporate the overall quality score for assigning weights to the matching scores from different modalities. It will result in an adaptive multimodal system where image quality for different modalities (for example, ear and face) will be assessed and scores will be weighted accordingly.

1.5 Thesis Outline

The organization of the rest of the thesis is as follows. Chapter 2 presents an overview of the biometric system, face biometric system and various quality factors that affect the recognition performance of the system. We also investigate the related works on facial quality assessment methods, and quality-based face recognition approaches, and discuss the limitations of some of the existing methods. In chapter 3, the quality assessment model is presented. The model includes estimation of different quality factors, calculation of the matching score for individual facial images and the linear regression model for estimating the overall quality. The quality-based adaptive face recognition system is presented in chapter 4 which comprises quality-based preprocessing steps, DWT-based feature extraction, and quality-based fusion methods. Chapter 5 presents the detailed experimental results for validating the effectiveness of the proposed quality estimation model and the proposed quality-based face recognition system. This chapter also includes database description, experimental setup, analysis of the impact of different quality factors on face recognition performance, analysis of the regression model, and comparison of the quality-based face recognition system with the state-of-the-art methods. Finally, the conclusions of the thesis, limitations of the proposed methods and possible future works are discussed in chapter 6.

Chapter 2

LITERATURE REVIEW

In this thesis, our primary objective is to estimate the overall quality of the facial image considering various quality degradation. This will allow us to build an adaptive face recognition system based on the overall quality score, which will compensate for various quality degradation. In this chapter, we present an overview of the biometric authentication systems and state-of-the-art face recognition techniques. In addition, the impact of quality factors on biometric samples and different facial quality factors are described. Finally, different quality assessment methods and reviews of face recognition systems that consider quality are presented at the end of this chapter.

2.1 Overview of the Biometric Systems

Biometric authentication is used for verifying the claim of a person's identity in a various real-life applications. In a biometric authentication system, a person is identified based on his/her physiological and/or behavioral characteristics, rather than by traditional methods of authentication, such as passwords, ID cards, etc. Face, fingerprint, iris, hand and palm geometry are examples of physiological biometrics [47, 49]. Examples of behavioral biometrics are keystroke dynamics, gait analysis, speech and signature [47]. Any biometric system is comprised of four basic modules, namely data collection module, feature extraction module, matching module, and decision module [37, 48]. In addition, multimodal biometric systems have the information fusion module [37, 72].

1. Data collection module: In this module, data is collected from the desired biometric traits of an individual. Biometric data can be collected through various sensors, such as camera, scanner, microphone etc. The output of these sensors becomes input to the feature extraction module. However, environmental conditions and different human factors affect the data

collected through various sensors. Therefore, quality assessment of these biometric data is needed before extracting the features. Many biometric systems add this quality assessment module to estimate the quality of the biometric samples before enrolling the data to the system database and/or before identifying or verifying the individual. Normally, if the data is of a poor quality, the sample is rejected or retaken.

2. Feature extraction module: In the next step, a set of discriminating features is extracted from the biometric data to uniquely identify an individual. Some feature extraction methods, such as image processing or signal processing methods are applied to the biometric data to extract meaningful representations. The extracted biometric features are stored in the template database for further processing.

3. Matching module: In the matching module, the degree of similarity between the template stored in the database and the test sample is calculated. The features extracted from the test sample are compared against the template stored in the database based on different similarity measures. Various matching algorithms exist in the literature for efficiently calculating the similarity or dissimilarity scores, which are commonly known as matching scores [47]. The scores are then passed to the decision module for determining the identification or verification results.

4. Decision module: Decision module verifies or establishes the claim of a user's identity based on the matching score determined in the matching module. The outcomes can be binary (yes or no), or fuzzy (ranked user identity or a confidence percentage) [63].

5. Information fusion module: In a multimodal biometric system, information from different modalities are fused together to improve the recognition performance. There is a number of fusion techniques based on the number of modalities, feature sets, and level at which information fusing is taking place. The major fusion techniques are sensor-level fusion, feature-level fusion, match score-level fusion, rank level-fusion, and decision level-fusion [37].

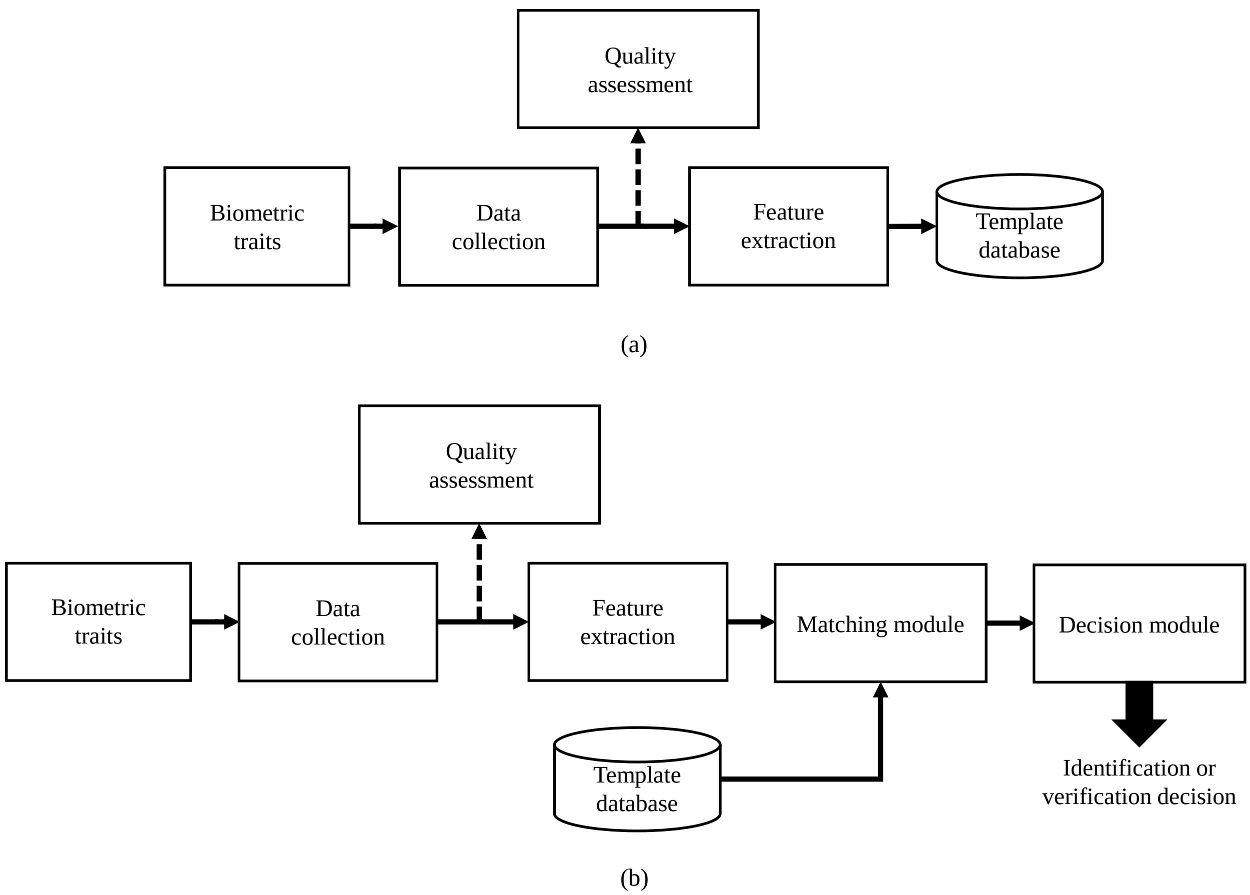


Figure 2.1: (a) Enrollment, and (b) identification/verification stages of a biometric system.

Biometric authentication means identifying or verifying a person based on his/her biometric traits. Before identification or verification, the biometric features of a person need to be enrolled in the template database. In the enrollment phase, biometric features are extracted from the captured biometric data, and the extracted features are stored in the template database for future use. Figure 2.1(a) shows the steps for the biometric enrollment process. Biometric verification means verifying the identity claim of a user. Biometric verification is a one-to-one comparison, that is, it compares biometric features of the users with the biometric features of the claimed identity from the template database and decides whether it is a true claim or not. Many real-life applications use person verification for validating a person, such as banking, border crossing, access to secure premises, providing social services, and so on. On the other hand, biometric identification is establishing the identity of a person. It is a one-to-many comparison of the person's biometric features against all the biometric features enrolled in the template database for identifying the person. One of the applications of biometric identification is in law enforcement for identifying the convict. Figure 2.1(b) shows the steps of the biometric identification or verification process.

2.2 Overview of Face Recognition Systems

Face recognition is a very popular means of authenticating a person using facial biometric traits and is being highly used in many real-life applications due to its non-invasive nature. Over the years, many face recognition techniques have been introduced in the literature to successfully recognize faces from images [49, 70, 102]. The face recognition approaches in the literature are mainly divided into two categories: geometrical feature-based approaches and holistic feature-based approaches.

Geometrical feature-based approaches consider the geometry of the facial local features, such as nose, mouth, and eyes. An initial approach to geometric feature-based face recognition was introduced in 1977 by Kanade [50]. The author located some feature points, such as the top of the head, cheeks and sides of the face, nose, mouth, and chin etc., and extracted more precise features from them. Euclidean distance was used to determine the correlation between these features on a database of 20 people. The authors in [15] proposed a similar approach for recognizing faces based on geometrical features. Relative positions and other parameters were extracted from the facial local features, and Bayes classifier was used to recognize faces from a database of 47 persons. Samaria and Young [73] used Hidden Markov Models (HMM) to automatically segment facial images and extract features from them. This HMM-based method can handle small orientation, illumination changes and variations in facial attributes. Active Appearance Model (AAM) based face recognition was proposed by Edwards et al. in [29]. AAM is a photo-realistic statistical model containing a shape model and a gray-level appearance model. The model parameters are derived from the shape and gray-level parameters and used for face recognition. The model is used to synthesize a very close approximation of the target facial image. Summary of the geometrical feature-based approaches is presented in Table 2.1.

Holistic feature-based approaches are more advanced rather than the geometrical feature-based approaches due to their ease of implementation and robustness. Eigenfaces is one of the very popular holistic feature-based approaches. Turk and Pentland [88] proposed to transform the facial images into a face space known as eigenfaces. Principal Component Analysis (PCA) was used for selecting the discriminating feature images that best describe the variation among the known faces. PCA [27] is a very well-known dimensionality reduction and feature extraction approach which is also known as Karhunen-Loeve expansion. Another variation, a derivative of Fisher's Linear Discriminant (FLD) known as Fisherfaces was introduced by Belhumeur et al. [12]. The advantage of FLD is that it can maximize the between-class scatter, as well as minimize the within-class scatter, which represent the classes well separately in a lower dimensional subspace. A non-linear representation of PCA named as kernel principal component analysis (KPCA) was proposed by Schölkop in 1998 [76]. Kernel PCA exploits higher order correlations of samples for efficient face recognition. The non-linear generalization of Fisher's discriminant known as kernel FLD was proposed by Mika et al. in 1999 [61]. The proposed method employed a non-linear variant of the Fisher's discriminant and extracted the most discriminant non-linear features in the input space. Yang investigated on the KPCA and KFLD for face recognition and compared the performance with other baseline face recognition algorithm [94]. Summary of the holistic feature-based approaches is presented in Table 2.2.

There are some other face recognition approaches developed more recently in the literature for efficiently recognizing faces. In 2004 and 2006, Ahonen et al. [5, 6] presented a face recognition approach based on the well-known texture analysis approach known as Local Binary Pattern (LBP) [64, 65]. The proposed approach considered both the shape and texture information by dividing the facial image into smaller subparts and extracting LBP histograms from those small regions. In 2005, Zhang et al. in [99] proposed a combination of Gabor filters and LBP operator

Table 2.1: Summary of the geometrical feature-based approaches.

Approaches	Ref.	Year	Methods	Database	Limitations
Geometry feature-based	[50]	1977	located some facial feature points and extracted precise facial features from them.	experimented on a database of 20 people; total samples 40.	• depend on the accurate detection of the facial features, such as eyes, nose, mouth, and chin [49]. • ignore the facial texture and appearance-based information [49].
	[15]	1993	extracted relative positions and other parameters from the facial local features.	experimented on a database of 47 persons; total samples 188.	
	[73]	1994	used Hidden Markov Models (HMM) to automatically segment facial images and extract features from them.	experimented on a database of 24 people; total samples 150.	
	[29]	1998	used a photo-realistic statistical model, namely Active Appearance Model (AAM) to recognize faces.	experimented on a database of 20 people; total samples 400.	

known as Local Gabor Binary Pattern Histogram Sequence (LGBPHS) to enhance the local spatial representation. Local binary patterns are extracted from the non-overlapping regions of the Gabor magnitude images, and the final histogram is built by concatenating the local histograms. Albiol et al. used Histograms of Oriented Gradients (HOG) for face recognition [8]. In their method, they used elastic bunch graph matching (EBGM) to localize the facial landmarks and extracted the facial features using histogram of orientation in a local neighborhood. In 2015, Lu et al. [59] introduced a binary face descriptor which computed the difference between each pixel and its neighboring pixels. The pixel difference vectors (PDVs) are projected into a low-dimensional binary vector and compact binary face descriptor (CBFD) was obtained. Summary of the local feature-based approaches is presented in Table 2.3.

All the above-mentioned face recognition approaches can efficiently recognize faces under a controlled environment. However, uncontrolled environments may introduce quality degradation of the facial images due to the changes in lighting conditions, facial expressions, occlusion, and

Table 2.2: Summary of the holistic feature-based approaches.

Approaches	Ref.	Year	Methods	Database	Limitations
Holistic feature-based	[88]	1977	transformed the facial images into a face space known as eigenfaces.	experimented on a database of 2500 samples.	• sensitive to severe local changes, such as acute illumination changes, facial expression and pose variations, and occlusions [43].
	[15]	1993	used Fisher's Linear Discriminant to obtain well separated classes in a low-dimensional subspace.	experimented on Harvard and Yale face database.	
	[73]	1994	used kernel principal component analysis (KPCA) for face recognition.	experimented on AT&T and Yale face database.	
	[23]	1996	used kernel Fisher's discriminant (KFLD) for face recognition.	experimented on AT&T and Yale face database.	

Table 2.3: Summary of the local feature-based approaches.

Approaches	Ref.	Year	Methods	Database	Limitations
Local feature-based approaches	[5]	2004	extracted LBP histograms from the small facial regions.	experimented on FERET face dataset.	• create high-dimensional feature sets. • sensitive to severe illumination changes, and to blurred and noisy images [43].
	[99]	2005	used a combination of Gabor filters and LBP operator to enhance the local spatial representation.	experimented on AR and FERET face dataset.	
	[8]	2008	used HOG descriptors for face recognition.	experimented on Yale and CVL face database.	
	[59]	2015	introduced a binary face descriptor which computed the difference between each pixel and its neighboring pixels.	experimented on FERET, CAS-PEAL-R1, LFW, PaSC, and CASIA NIR-VIS 2.0 face datasets.	

poor sensor quality [49, 102]. Many state-of-the-art face recognition techniques will result in degraded performance due to the intra-class variations introduced by the degradation of the quality factors.

2.3 Image Quality of Biometric Samples

According to the recent standard ISO/IEC 29794-1 [45], the quality of a biometric sample can be defined from three different perspectives: 1) character, 2) fidelity and 3) utility. In the ISO/IEC 29794-1,

- Character is defined as “inherent features of the source”.
- Fidelity is defined as “how accurately a biometric sample represents its source biometric characteristic”.
- Utility is defined as “observed performance of a biometric sample or set of samples in one or more biometric systems”.

In most of the literature, utility is considered as the quality of a biometric sample [10, 32, 41]. It is a quantitative measure that indicates the performance of a biometric sample. A higher quality score of a biometric sample represents that the sample is suitable for identifying an individual. Various external effects, such as varying illumination, brightness, contrast and occlusions may introduce degradation of the biometric samples. A low-quality sample will perform poorly while matching it with the gallery biometric samples due to these external effects. Therefore, the matching performance of a biometric sample will indicate the suitability of the biometric sample for identifying an individual [14, 41]. In this thesis, for estimating the overall quality of a facial sample, we determine the matching performance of the sample. This overall quality score is a strong indicator of the performance of the biometric sample.

2.3.1 Impact of Image Quality on a Biometric System

Many studies have shown that biometric sample quality plays a vital role on the performance of a biometric system [14,32,41]. Various factors related to external influences and poor sensor quality may affect the quality of the biometric samples. Youmaran and Adler [98] addressed that with the decrease in a sample's quality, the quantity of discriminating information in the biometric sample also decreases. Therefore, high-quality biometric samples are needed for a more reliable recognition system. For ensuring a more reliable system, the impact of these quality factors on biometric samples should be measured and represented as a quantitative quality which can characterize the overall quality of the biometric sample.

Bharadwaj et al. [14] presented a survey on the role of sample's quality on fingerprint, iris, and face biometrics. The authors claimed that for building a robust large-scale biometric system, consideration of the impact of different quality factors is necessary. They presented different architectures for using the quality assessment module at different stages of the biometric system. They also described various quality factors that affect the biometric samples and degrade the biometric system's performance. The authors had classified the biometric quality factors into three main categories, namely user traits, user-sensor interactions and operational factors. They had also classified the quality degradation as image-based and modality-based degradations.

The authors of [32] also investigated the role of a sample's quality and studied different quality assessment algorithms for different biometric samples, such as iris, face, and fingerprint. The authors also provided a framework indicating different ways of incorporating a sample's quality score in the biometric system. The quality factors were classified in user-related, user-sensor interaction, acquisition sensor, and processing-system factors. The authors stated that quality degradation introduced by uncontrolled environments greatly affect the performance of a face recognition system. They also showed that the matching scores degrade with the degree of quality degradation of the biometric samples.

Grother and Tabassi [41] formalized that biometric matching performance is directly related to the quality of the biometric samples. They had investigated the roles of quality assessment at the different biometric modules. They had also described some processing steps that can be adapted to incorporate the quality information for improving the recognition performance.

Quality assessment is a relatively challenging and under-researched problem compared to the automated recognition and feature extraction approaches in biometrics. It has been found in many studies that the quality of biometric samples significantly affects the performance of a biometric recognition system.

2.3.2 Facial Image Quality Factors

As we established above, the face biometric system suffers from the quality degradation of the biometric samples. Recent studies show that various external factors, such as variations in lighting conditions, contrast, brightness, occlusion, and some behavioral factors, such as facial expressions and gestures have a major impact on the performance of a face biometric system [2, 20, 69, 80]. According to data standards ISO/IEC 19794-5 [46], the factors that affect the quality of a facial biometric sample can be categorized into four classes.

1. Formatting factors represent the digital specification and organization of the images;

2. Digital factors represent spatial resolution, conversion, compression and contrast of gray-scale images;

3. Photographic factors are position of the head in the image, and different camera attributes, such as exposure, brightness, and focus; and

4. Scenic factors are different lighting conditions and attributes related to image and subjects, such as head rotation, state of eyes and mouth.

Gao et al. [36] categorized the factors that affect the quality of facial samples into four groups.

1. Environmental factors: asymmetric lighting, unevenly illuminated facial area and cluttered background;

2. Factors related to camera conditions: resolution, contrast, and geometric distortion;

3. Factors related to user's conditions: eyes with glass/no glass, makeup, accessories and facial expressions; and

4. Factors related to user-camera positioning: out of focus, occlusion, deviation from the frontal pose, and the distance between an object and camera.

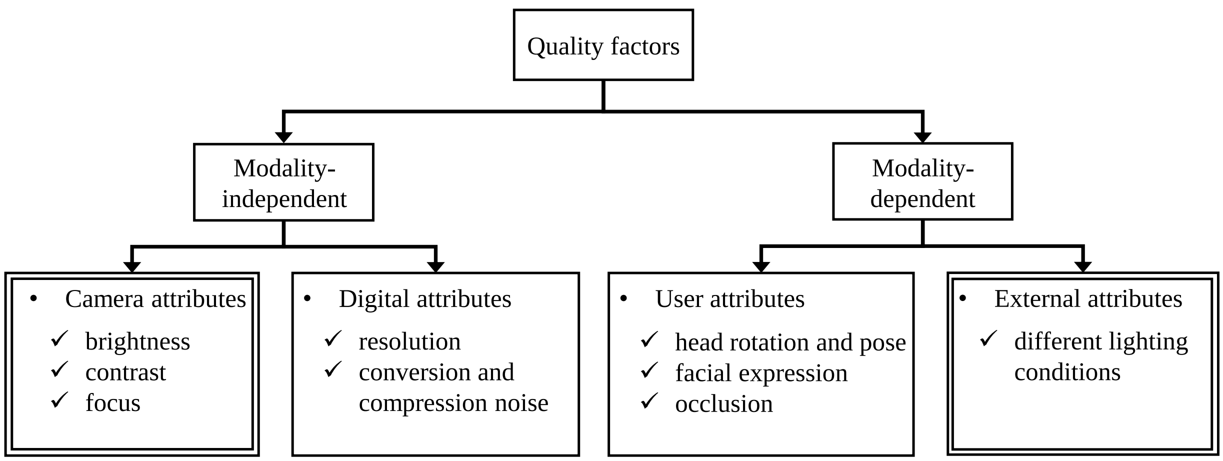


Figure 2.2: Proposed classification of the factors that affect the quality of an image-based biometric sample. Double frame identifies factors studied in this thesis.

After reviewing the factors that affect biometric sample quality, and specifically the above classifications for the facial quality factors, we have classified the facial image quality factors into two main groups: modality-dependent and modality-independent quality factors. Modality-independent quality factors can be further categorized into camera attributes and digital attributes. On the other hand, modality dependent quality factors can be categorized into two groups namely, user attributes and external attributes. Figure 2.2 shows the proposed classification of the facial quality factors.

Poor quality of facial images, introduced by the degradation of these quality factors, may lead to higher identification errors in the systems [2, 14, 36, 80]. Therefore, it is needed to evaluate the quality of the facial samples to determine the relationship between the quality score and the performance of a face recognition system.

2.4 Facial Quality Assessment Methods

Despite its obvious importance, up until recently, only a few attempts have been made to jointly consider a wide range of quality factors under one framework for estimating the overall quality of the facial image [19,28]. Chen et al. presented a quality assessment model in [19] to reduce the influence of quality factors that degrade the overall quality of a facial image. In the proposed method, the authors had considered different quality factors, such as occlusion, pose, distance from the camera and variations in illumination. The overall quality of the facial image was calculated by simply multiplying different quality scores, and based on this quality score the bad quality samples were discarded. However, quality scores integration scheme employed by the proposed method is not a reliable indicator of the overall quality of the facial image as it does not consider the relationship between the matching performance and the quality of the facial samples. A statistical learning-based quality assessment method was proposed by Liao et al. in [55]. The proposed method used multi-scale Gabor filters to extract the features from the facial images and built a hierarchical decision tree based on support vector machine (SVM) to classify the images into five different classes. For reliable training, a large database of various facial images was used. The drawback of this method is that for classifying the images into m classes, $(m-1)$ binary classifiers are needed. Abaza et al. in [2] evaluated a variety of facial image quality measures, such as contrast, sharpness, focus, brightness, and illumination. The authors proposed a new facial image quality index (FQI) that combined multiple quality scores using Neural Network (NN) and classified a facial image as good or bad. From the NN approach, it is impossible to infer the impact of different quality factors on recognition performance. The proposed method classifies the images into two categories. However, it does not provide any quantitative value to indicate the overall quality of the facial images. The method in [28] presented a Bayesian model to describe the relationship between image quality and corresponding face recognition performance. The model considered pose and illumination variations for predicting face recognition performance. The model relied solely on image quality information and did not require similarity scores to make predictions about recognition performance. The main limitation of this model is that it requires a sufficiently large number of training samples spread densely in the quality space, hence constraining the variety of qualitative measurements that can be performed in testing. Moreover, it estimates the recognition performance of a large group of facial samples considering that all of them have the same quality.

The method proposed by Kim et al. in [51] designed a learning-based model considering the visual quality, and the mismatch between training and test facial images as the two main quality factors. For representing the visual quality, the authors computed objective facial image quality (OFIQ), and relative facial image quality (RFIQ). A facial image quality assessor using AdaBoost algorithm [33, 34] was learned based on these two factors to label the facial images as '+1' or '-1'. It also had some drawbacks. The quality assessment model did not provide any quantitative value which can be used for adaptive threshold selection. The authors only used the quality assessment model to reject the low-quality facial samples. Subramanyam et al. in [83] classified images into four groups, namely illuminated, dull, shadow and dark based on illumination and contrast quality. The proposed method estimated the illumination and contrast-based quality, and classified the facial images based on some predefined threshold values.

Table 2.4: Summary of the quality assessment methods.

Ref.	Year	Quality Factors	Methods	Database	Limitations
[19]	2011	occlusion, pose, distance from the camera and illumination variations.	calculated the overall quality by multiplying different quality scores.	experimented on CAS-PEAL face database.	does not consider the relationship between the recognition performance and the quality of the facial samples.

Table 2.4 : Summary of the quality assessment methods.

Ref.	Year	Quality Factors	Methods	Database	Limitations
[55]	2012	features extracted using Gabor wavelet filters.	built a hierarchical decision tree based on support vector machine (SVM) to classify the images into five different classes.	experimented on AR and FERET face dataset.	needs (m-1) binary classifiers for classifying the images into m classes.
[2]	2014	contrast, sharpness, focus, brightness and illumination.	combined multiple quality scores using neural network (NN).	experimented on Yale, QFIRE and FTMC data set.	difficult to interpret the impact of different quality factors on recognition performance and does not provide any quantitative value to indicate the overall quality.
[28]	2014	pose and illumination variations	used a Bayesian model to describe the relation between image quality and corresponding face recognition performance.	experimented on subset of the MultiPIE data set.	estimates the recognition performance of a large group of facial samples considering that all of them have the same quality.
[51]	2015	visual quality, and the mismatch between training and test samples.	learned the facial image quality assessor using AdaBoost algorithm [33, 34] for labeling the images.	experimented on FRGC 2.0 DB.	does not provide any quantitative value which can be used for adaptive threshold selection.
[83]	2016	illumination and contrast	estimated the illumination and contrast-based quality, and classified the facial images into four classes.	experimented on Yale Extended Face database.	does not provide any scaler quantity for the overall quality score.

Several biometric applications would require to have a general quality index which can indicate the overall quality of the input data. There are some researches in the literature that proposed to estimate the quality of a biometric sample by consolidating different quality factors into a single quality score. However, most of them used facial quality assessment model for discarding the low-quality samples. It is not always a good choice to discard the low-quality samples. In a real-life scenario, the test samples are collected from uncontrolled environments, such as video surveillance and CCTV footage. In most of the cases, the quality of these facial samples is very low and it is impossible to recapture the facial samples. Moreover, there are quality estimation models in the literature that classify the facial samples in a large group, considering that all of them have the same quality. Processing of the individual samples based on the precise quality scores will avoid the undesired artifacts and will build a more reliable face recognition approach. Also, the individual quality score for each sample can be used to determine the sample-specific fusion parameters. Therefore, in this thesis, our goal is to design a quality assessment model which will integrate different quality scores into a single quality score for providing the overall quality of a facial image. We will also analyze the impact of different quality factors on the recognition performance and will build an adaptive face recognition approach based on this overall quality scores.

2.5 Quality Dependent Face Recognition Systems

Despite an ongoing research over the past few decades, automated face recognition remains a challenging task when operated in uncontrolled environments [49, 102]. As established before, uncontrolled environments may introduce quality degradation of the facial images due to the changes in lighting conditions, facial expressions, occlusion and poor sensor quality. Similarly to other biometrics, automated face recognition system also suffers from poor quality samples. Recent studies show that variations in lighting conditions, contrast, brightness, focus, occlusion, facial expressions and other quality factors have a major impact on the performance of a face biometric system [1, 69, 80]. Intra-class variations introduced by the degradation of these quality factors may lead to higher identification errors and lower the performance of the overall system. The most common approaches employed to solve the variability in image quality include the use of robust face descriptors [30, 31, 40, 100], and application of preprocessing and normalization approaches [68, 75, 92, 109]. However, authors in [80] showed that application of preprocessing steps without considering the degree of quality changes may degrade the quality of a good sample. Therefore, considering the quality of the image while compensating for the quality degradation may improve the recognition performance. The recent research showed that the design of an adaptive identification system based on facial biometrics has advantage over a traditional face biometric system and can lead to a more intelligent decision-making [3, 79, 80]. Both theoretical studies on formal knowledge-based representation systems [87] and emerging studies on information fusion in biometric systems [38] demonstrated a significant advantage of this approach.

There are very few studies in the literature that have considered a set of quality factors, responsible for degrading the recognition performance and improved the performance by compensating for those quality degradations based on the quality information [79, 80]. Abboud et al. in [3] proposed a face recognition approach that considered the quality degradation introduced by varying illumination conditions. The authors presented two quality measures for estimating the different lighting conditions of the facial image, namely symmetrical adaptive local quality index (SALQI) and middle halve (MH). The proposed method used these two quality measures to select the best way for image normalization. Sellahewa and Jassim proposed a quality-based face recognition approach in 2009 [79]. Two image normalization approaches based on global and regional image quality indices were introduced in the proposed method. Histogram equalization (HE) is applied to the image if the global luminance quality index (GLQI) is less than some predefined threshold. In the regional quality-based approach, the luminance quality index (LQI) is calculated for every region and the HE is applied to those regions where the LQI is lower than some predefined thresholds. The authors proposed another approach for a quality-based face recognition system in 2010 [80]. In this approach, different lighting conditions were considered as image quality factor, and the quality score was used to select various fusion parameters. Sultana et al. in [84] proposed an illumination invariant face recognition system using the Dual-Tree Complex Wavelet Transform (DTCWT). The authors had calculated the illumination score and used that score for assigning weights to the low and high-frequency sub-bands extracted from DTCWT. This quality-based approach was used to recognize faces under different lighting conditions. All of these methods only investigated the use of varying illumination as an image quality factor for designing a quality-based face recognition system.

An illumination and expression invariant face recognition approach was proposed by Sellahewa and Jassim [78]. The proposed method investigated the different sub-bands from wavelet transform (WT) and found that low-frequency sub-band is a good feature descriptor for well-lit facial images and facial expression invariant recognition. The authors also investigated the importance of quality-based fusion against fixed fusion parameters. The authors in [60] proposed two quality indices for estimating pose and illumination. The proposed method used the quality indices for discarding the facial samples if they are below some pre-defined threshold values. The authors also suggested that the two quality indices can be integrated to decide the suitability of the facial samples. These approaches considered multiple quality factors. However, they did not use the quality information for adaptively handling the quality degradation.

There are very few face recognition systems that consider a quality-based approach for recognizing faces. To the best of our knowledge, none of these above approaches considered the overall quality of the facial samples by integrating different quality factors into a single quality index. Therefore, our goal is to build an adaptive face recognition approach, which will determine the appropriate image quality-based preprocessing steps and find an efficient face descriptor to handle the quality deviation of the facial samples introduced by different quality factors. This quality-based approach will also set the system's parameters based on the overall quality for a more reliable recognition system.

2.6 Summary

Facial image quality has a strong influence on the performance of the biometric recognition system. Therefore, the quality scores can be used to adaptively minimize the adverse effects of various quality factors and to improve the performance of the recognition system. From the above discussion, it is clear that there are very few researches in the literature that propose a unified framework for estimating the facial image quality incorporating various quality factors. This overall quality score has a wide range of applications, ranging from selecting the fusion parameters to selecting the appropriate modality in a multimodal approach. The advantage of using the overall quality score for an adaptive face recognition approach is many folds.

1. It is a strong indicator of the overall performance of the biometric samples, therefore it can be used to discard the low-quality samples in the training phase, or to trigger recapture.

2. A preprocessing step based on the overall quality will reduce the computational complexity by replacing the consecutive preprocessing steps for different quality factors.

3. Also, selecting the fusion parameters based on the overall quality would be more realistic rather than selecting them using different quality scores.

In this thesis, our goal is to investigate the effectiveness of a unified framework which can adaptively compensate for the quality degradation introduced by various factors based on the overall quality of the facial image. Therefore, we build a system for quality estimation of the facial images considering different quality factors. In the process of designing a quality-based face recognition system for improved recognition performance, the estimated overall quality score is used to determine the preprocessing steps and to assign the fusion parameters. The estimated overall quality of the facial image is a significant indicator of the impact of different quality degradation on the matching performance of the biometric sample. In this thesis, our goal is to explore the effectiveness of a quality-based adaptive face recognition system.

Chapter 3

METHODOLOGY FOR FACIAL QUALITY ASSESSMENT

In this chapter, we provide the detailed description of the proposed facial quality assessment method that considers different quality factors while estimating the overall quality of a facial sample. The overview of the proposed method is presented in the first section, and the remaining sections describe all the components of the proposed method in details. The proposed quality assessment method presented in this chapter has been published in [105] and its extended version is accepted to the International Journal of Cognitive Informatics and Natural Intelligence (IJCINI) [107]. Some methods presented in this chapter appeared in the research article [105] under explicit publisher copyright agreement.

3.1 Overview

We propose a quality estimation method that will consolidate different quality scores into a single evaluation score to indicate the overall quality of a facial image. The proposed model considers various modality-independent and modality-dependent quality factors, such as illumination, contrast, brightness and focus, and generates a unified evaluation score. We use a linear regression based approach to capture the relationship between various quality scores and the corresponding matching performance of a facial image. This model will adjust the coefficients while integrating different quality factors based on the relationship between the quality factors and the impact of those factors on the facial sample. Due to the imaging conditions, different lighting conditions, and the interaction between the user and the sensor, two samples from the same user are not identical. Matching score is a measure of the similarity between the test and the template biometric sample. More formally, matching score $S = (X_Q, X_I)$ between feature derived from the test X_Q and the template X_I represents the similarity between these two samples [47]. High value for a matching score indicates high probability for identifying an individual from that sample. Therefore, it is a strong indicator of the performance of a biometric sample. Fig. 3.1 shows sample of template and test facial images with their corresponding matching scores.

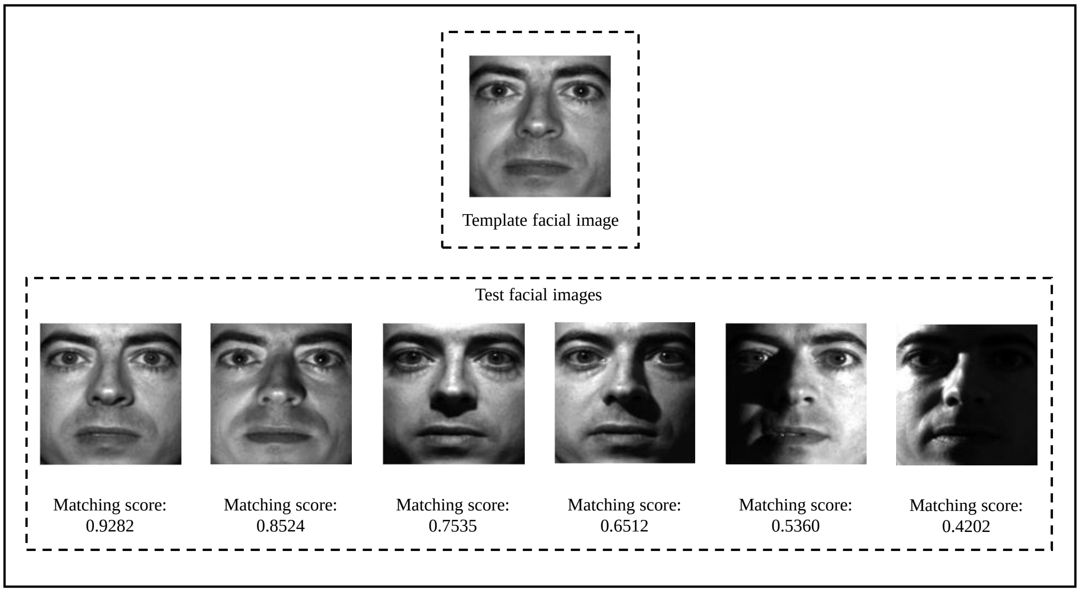


Figure 3.1: Sample of template and test facial images with their corresponding matching scores.

Some existing quality estimation methods trained the model using the relationship between quality scores and recognition performance considering that a large group of facial samples has the same recognition performance [28]. This relationship will reflect the quality of a large group of data rather than individual quality. On the other hand, the matching score of a sample is a strong indicator of the performance of that sample for identifying an individual. Moreover, biometric applications may benefit from having a quantitative value which can indicate the overall quality of the input facial sample. Processing of the individual sample based on the precise quality scores may avoid the undesired artifacts and help to build a more reliable face recognition system. Also, an individual quality score for each sample can be used to determine the sample-specific system parameters. The proposed method uses a linear regression model to estimate the overall quality of a facial sample by analyzing the relationship between different quality factors and the matching performance of that sample. The main advantage of the linear regression-based quality assessment method is that it reveals the relationship between the quality factors and the performance of the sample. The regression model determines the coefficients in such a way that it reflects the correlation between different quality factors and the matching performance of the facial sample. Most of the existing quality assessment methods classify the images as "bad" and "good" quality samples and propose to discard the "bad" quality samples to improve the recognition performance [2, 51]. However, in a real-life scenario, the test samples are collected under uncontrolled environment or from video surveillance and CCTV footage. These samples are of low quality, and there is sometimes no option for recapturing the images.

In the proposed method, the quality scores for various quality factors are measured using some very well-known techniques. Discrete Wavelet Transform (DWT)-based feature extraction technique is used to extract the facial features from the samples. Typically, the low-frequency subbands extracted using DWT, contain the discriminating features of faces. Moreover, they are less sensitive to quality degradation than some existing holistic and local feature-based approaches. Therefore, we extract the facial features from the images using a DWT-based feature extraction technique. A matching score between the gallery facial image and the low-quality facial sample is calculated by comparing the template and the probe image. We train the linear regression model using the matching scores and the corresponding quality scores for predicting the overall quality of the facial image. Given the quality scores, the regression model can predict the overall quality of the facial sample which will reflect the performance of the facial sample for identifying an individual. Fig. 3.2 shows the basic components of the proposed quality assessment method. A detailed description of the method is presented in the following sections.

3.2 Quality Score Estimation for Different Quality Factors

There are many quality factors that significantly affect the performance of a face recognition system. According to the classification that we provided in section 2.3.2, the quality factors can be broadly classified into two groups: modality-dependent and modality-independent. In our thesis,

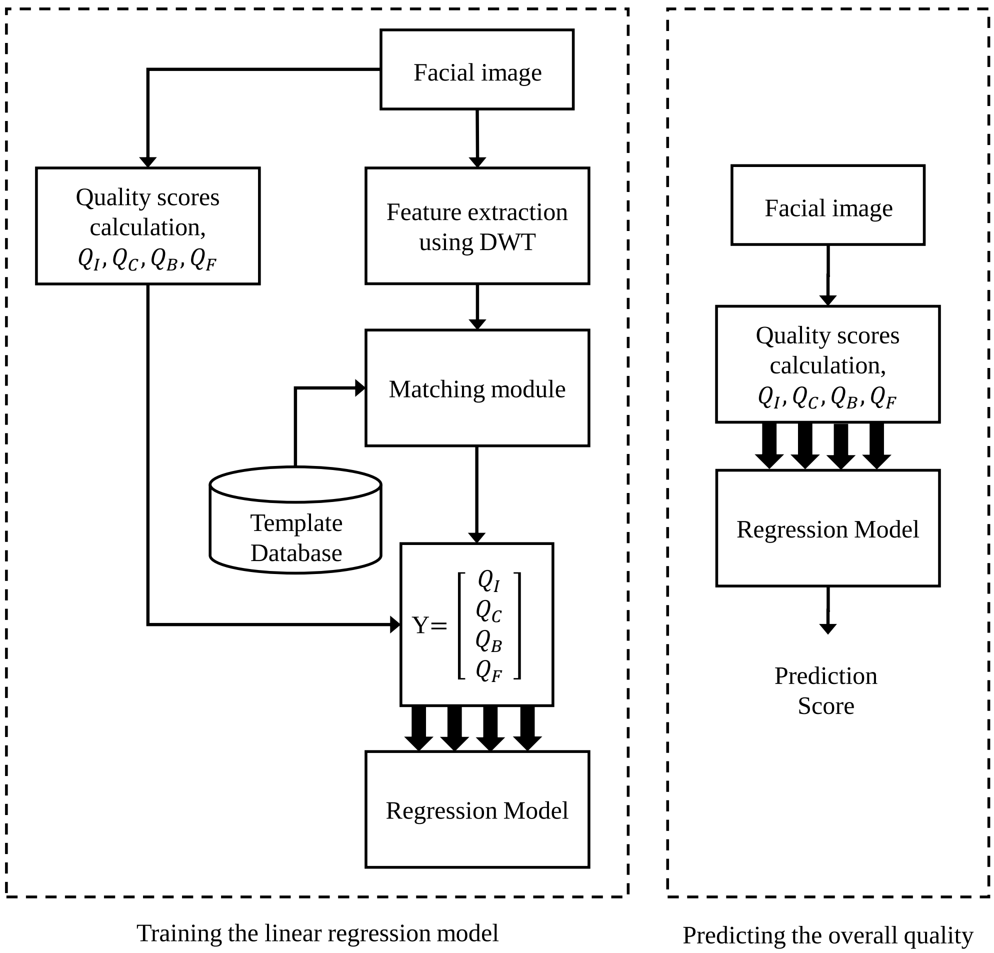


Figure 3.2: Overview of the proposed regression model to estimate the overall quality of a facial image.

we focus on some modality-independent quality factors, such as brightness, contrast, and focus. Also, we take into account illumination as a quality factor which is a modality-dependent quality factor. The reason for considering these quality factors is that most of the existing literature consider illumination as a quality factor due to the large intra-class variation introduced by it in the system [19, 28, 83]. And, the other three modality-independent quality factors were chosen so that it is possible to investigate the impact of different quality factors on some other modalities, such as ear-based person identification system. Moreover, these quality factors are considered to have a significant impact on the quality of a biometric sample in the context of face recognition.

Various techniques have been reported in the literature for measuring different quality factors. We use the methods that have been reported in the literature and were heavily used for quantifying the quality factors that affect a facial image [13, 36, 91, 97]. The methods that we have considered in our thesis for measuring the quality factors are as follows:

1. **Illumination**: Illumination is one of the facial image quality factors that is heavily investigated in the literature. In most of the face biometric systems, the enrolled or template facial images are taken under uniform lighting conditions. However, this is not the case for the test samples. The test samples can be obtained from an uncontrolled environment, having uncertain illumination conditions. Intraclass variations introduced by illumination distortion lead to higher identification errors in the system. For the proposed method, the illumination quality (I) is calculated by determining the luminance distortion between the reference image and the test sample. The Universal Quality Index (UQI) proposed by Wang and Bovik [91], is a combination of three main factors: loss of correlation, luminance distortion, and contrast distortion. The luminance distortion between two images $x = x_i | i = 1, 2, ..., N$ and $y = y_i | i = 1, 2, ..., N$ can be determined using Equation 3.1 [91], which represents how close the mean luminance is between these two images. This is a widely accepted quality measure for estimating illumination [2, 79, 80, 84] . Equation 3.2 defines $\bar{x}$ and $\bar{y}$ that is the average intensity of the reference image and the test image.

$$I = \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \tag{3.1}$$

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \ \ , \ \ \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{3.2}$$

2. **Contrast**: Contrast is a modality-independent image quality factor. It is one of the camera attributes that can adversely affect the quality of an image. We use the Root Mean Square (RMS) contrast for estimating the contrast score. It is measured by calculating the standard deviation of the pixel intensities. In the proposed method, we consider RMS contrast since it is commonly used for non-periodic targets, such as noise, textures, and images.The RMS contrast of a facial image is calculated using Equation 3.3 [36, 66]:

$$C_{RMS} = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_{(i,j)} - \bar{I}\right)^2} \tag{3.3}$$

where $\bar{I}$ is the mean intensity value of the test facial image I of size $M \times N$.

3. **Brightness**: Brightness is another modality-independent image quality factor. In the proposed method, we use arithmetic mean model for estimating the brightness score. Arithmetic mean model is a very popular brightness measure algorithm [13]. The brightness denoted by B of an image of size $M \times N$ can be calculated using Equation 3.4 [13]. In this equation, r, g, and b are the RGB (red, green and blue) coordinates.

$$B = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[(r,g,b)/3] \tag{3.4}$$

4. **Focus**: Focus or blurriness is another highly investigated image quality factor. Pertuz et al. described several image focus measures in [67]. Among these approaches, energy of image

gradient presented by Subbarao et al. [82], is a commonly used approach for measuring focus. The energy of image gradient can be defined using the Equation 3.5 [82]. Here, I_x and I_y are the first derivative in the x and y directions.

$$F = \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_x(i,j)^2 + I_y(i,j)^2 \right) \tag{3.5}$$

3.3 Matching Score Calculation

A very well-known approach for face recognition is the wavelet-based approach. Wavelet-based face recognition approaches are used for dimensionality reduction, as well as for extracting facial features [30, 77, 96]. The low and high-frequency sub-bands extracted from discrete wavelet transform (DWT) of the facial image can be used as a facial descriptor for the recognition purpose. Typically, the low-frequency sub-bands contain the most discriminating features of faces. Therefore, the low-frequency sub-bands can be used as face descriptors for recognizing faces. The authors in [30, 77] used DWT as multi-resolution feature descriptor. Some existing literature used wavelet-based approaches for reducing the image dimensionality prior to the recognition process [21, 52]. DWT decomposes the input images into low and high-frequency sub-bands, such as Low-Low (LL), High-Low (HL), Low-High (LH), and High-High (HH). In the proposed method, DWT is applied to the facial images to extract the low-frequency sub-bands (LL) from the facial images. Matching scores are calculated by comparing the probe and template images, and these matching scores and various quality scores are used to train the data-driven model for predicting the overall quality of the facial image. Euclidean distance is used to determine the matching scores between features derived from the test and the template facial images. Fig. 3.3 shows the steps for matching score calculation using DWT-based feature extraction.

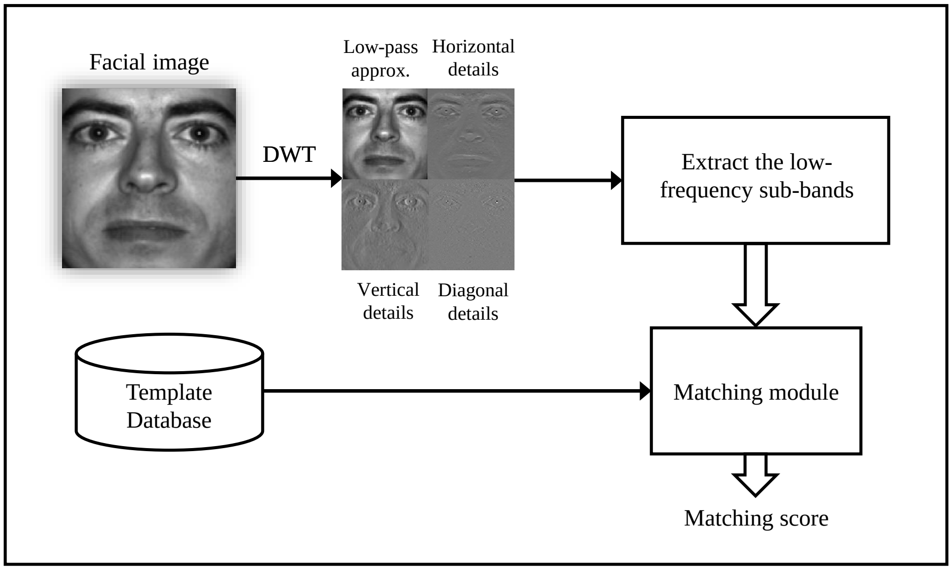


Figure 3.3: Steps for matching score calculation using DWT-based feature extraction.

3.4 The Linear Regression Model

In the proposed method, we use linear regression to interpret the relationship between various quality scores and the corresponding matching score of a facial image. Linear regression reveals the relationship between predictor and response variables. In our approach, we consider different quality scores as the predictor variables and the performance of the facial sample is used as the response variable. The regression model determines the coefficients in such a way that it reflects the correlation between different quality factors and the matching performance of the facial sample. On the contrary, quality estimation methods, such as minimum, maximum, mean and geometric mean of the quality scores cannot effectively describe the relationship between the quality of samples and matching performance. Neural network (NN) and other classifiers, such as support vector machine (SVM) can be used to classify the images into different classes. However, it is difficult to interpret the impact of different quality factors on the recognition performance using these approaches, and they do not provide any quantitative value to indicate the overall quality. Therefore, for the proposed quality estimation method, we consider a linear regression model to compute the overall quality of a facial sample.

Let Q denote the image quality set consisting of different image quality parameters, such as illumination, contrast, brightness, and focus. Therefore, $Q = [Q_I, Q_C, Q_B, Q_F]$. And, for a particular face recognition system, Y represents the performance of the probe facial images where the performance is determined by calculating the matching score between the test and the gallery images. Regression generates an equation that describes the relationship between one or more predictor variables and the response variable. In this paper, we propose a linear regression model for interpreting the interaction between image quality Q and matching performance Y. The regression model is trained using the quality scores of a sample for different quality factors, Q as predictor variables and matching score of that sample, Y as the response variable. The model can be represented using Equation 3.6 [57]:

$$Y = m + w_1 Q_I + w_2 Q_C + w_3 Q_B + w_4 Q_F \tag{3.6}$$

Where Q_I, Q_C, Q_B and Q_F are the quality scores of a particular facial image affected by different quality factors. Y denotes the matching performance of the probe images compared to the template images. $w1$, $w2$, $w3$ and $w4$ represent the corresponding regression coefficients. Here, m is the regression constant. In this thesis, we want to interpret the relationship between the quality scores and the matching performance of a sample from the linear regression model. And, the relationship can be described using the regression coefficients. The value of the regression coefficients will be determined by the linear regression model in such a way that can reflect the relationship between different quality factors and the matching performance of the test facial images. In most of the cases, the constant term, m (i.e the y-intercept) does not convey any meaningful information for the model.

However, proper analysis of different quality scores and corresponding matching performance shows that variations in a particular quality factor have an impact on the performance of a sample, as well they affect other quality factors. Therefore, the inclusion of interactions or correlations between quality factors can more accurately reflect the relationship between different quality factors and the matching performance. Some additional terms will be then included in the model in which two factors are multiplied. In the proposed method, we consider interactions regression model to interpret the relationship between the quality factors and the matching performance of a biometric sample. The model contains an intercept (or regression constant), linear terms of individual quality scores, and all products of pairs of distinct quality factors. Therefore, the regression model can be represented using Equation 3.7 [57]. Here, all the terms that multiply two quality factors represent the relation of interaction between those two quality factors.

$$\begin{aligned} Y = m + w_1 Q_I + w_2 Q_C + w_3 Q_B + w_4 Q_F + w_5 Q_I Q_C \\ + w_6 Q_I Q_B + w_7 Q_I Q_F + w_8 Q_C Q_B + w_9 Q_C Q_F + w_{10} Q_B Q_F \end{aligned} \tag{3.7}$$

The quality scores for different quality factors such as illumination, contrast, brightness, and focus are calculated using the quality measures described in section 3.2. We use DWT for extracting the low-frequency sub-bands from the facial images and calculate the matching scores between the template and probe images. The linear regression model is trained using the quality scores and the matching performance of the facial samples. The quality scores are normalized before feeding to the linear regression model using Z-score normalization (ZN). The model generates an equation using the predictor variables Q_I, Q_C, Q_B and Q_F, and the response variable Y. It also provides the regression coefficients which reflect the impact of each quality factor on the matching performance of the facial sample. Given the quality scores of a facial sample, the regression model can predict the matching performance of that sample which is a strong indicator of the overall performance of the facial sample. The prediction scores range from 0 to 1, representing the overall quality of the facial image.

3.5 Summary

Our proposed method develops a new quality estimation method that reflects the impact of different quality factors on the performance of a facial sample. An appropriate set of methods is used to measure various quality factors, such as illumination, contrast, brightness, and focus. We extract the facial discriminating features using DWT-based feature extraction technique and determine the matching score between the template and probe facial images. The relationship between different quality factors and the matching performance is modeled using an interactions linear regression model where corresponding weights of these quality factors are unknown. The estimated coefficients of the predictor variables reflect the impact of various quality factors on the performance of the biometric sample. Therefore, the proposed quality estimation model results in a face quality index, which can characterize the overall quality of a facial image in correlation with the matching performance of a facial sample. The extensive experiments presented in chapter 5 demonstrate that the proposed method performs better than several existing quality scores integration schemes.

Chapter 4

METHODOLOGY FOR ADAPTIVE FACE RECOGNITION SYSTEM BASED ON IMAGE QUALITY

In this chapter, we present the proposed quality-based face recognition approach that utilizes the overall quality of a facial sample to improve the performance of a face recognition system in the presence of quality degradation. The overview of the proposed method is presented in the first section and the remaining sections describe all the components in details. An initial approach of this proposed quality-based face recognition system has been published in Cyberworlds 2017 [106] and its extended version is accepted to the Special issue on Cyberworlds 2017 in Transactions on Computational Science (TCS) [108]. Some methods presented in this chapter appeared in these research articles under explicit publisher copyright agreement.

4.1 Overview

Uncontrolled environments may introduce quality degradation to the facial images due to the changes in lighting conditions, orientation, and variations in different camera attributes. Recent studies show that variations in lighting conditions, contrast, brightness, focus, occlusion, and different user's attributes have a major impact on the performance of a face biometric system [14,36]. Intra-class variations introduced by the degradation of these quality factors may lead to higher identification errors and lower the performance of the overall system. The recent research showed that the design of an adaptive identification system based on facial biometrics has an advantage over a traditional face biometric system and can lead to a more intelligent decision-making [3,79,80]. An adaptive system can consider different quality factors, and handle the quality degradation based on the quality of the sample. However, there are very few studies that consider a quality-based ap-

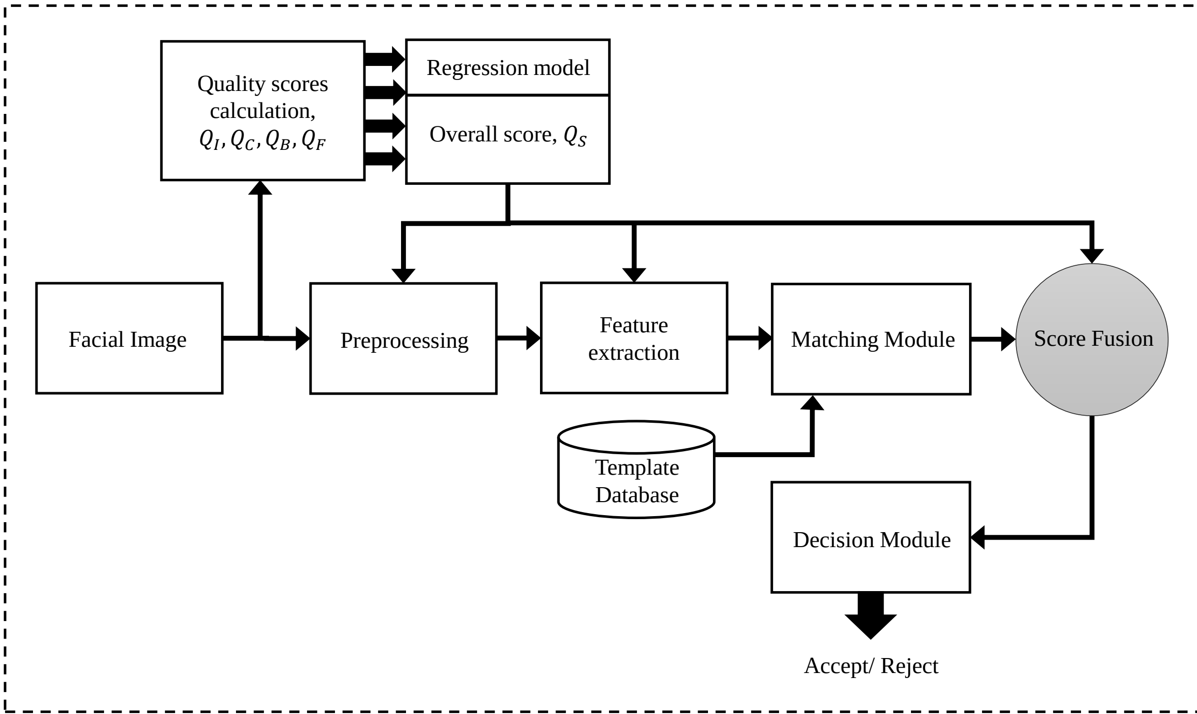


Figure 4.1: High-level overview of the unified framework.

proach for recognizing faces. In this thesis, our goal is to investigate the effectiveness of a unified framework that will integrate different quality factors into a single overall quality, and compensate for the quality degradation based on this overall quality of the samples. In chapter 3, we proposed a linear regression-based quality assessment method which estimates the overall quality of a sample. In this chapter, we present a quality-based face recognition approach for determining the appropriate quality-based preprocessing steps, and to find an efficient face descriptor to handle the quality deviation of the facial samples introduced by different quality factors. The matching scores calculated from the different representation of faces will be fused together based on the overall quality to determine the final decision. Fig. 4.3 presents a very high-level overview of the unified framework.

In this thesis, we consider the overall quality score of a sample to compensate for a quality degradation instead of considering individual quality score. There can be two different face recognition approaches based on the individual scores for different quality factors. For example, a facial sample is affected by three different quality factors. The quality estimation module will calculate the quality scores, (Q_1), (Q_2) and (Q_3) for these three quality factors. The first approach is a sequential system where the system will compensate for different quality factors sequentially. The facial sample can be processed sequentially based on (Q_1), (Q_2) and (Q_3). At every step, the system will check whether the quality is lower than some predefined threshold, and quality enhancement techniques will be applied based on specific quality degradation for the low-quality samples. However, this sequential approach will increase the complexity of the system, and introduce some redundant steps in the system. The second approach is to consider the lowest of these three quality scores and to handle different quality degradation based on a single quality factor. In this approach, the individual quality score (lowest of the three different quality factors) will not be able to represent the overall quality of the sample, as different quality factors affect the facial sample differently. Even a small change in lighting condition may heavily affect the facial sample resulting in identification error, whereas a small change in contrast will not impair the recognition. Therefore, preprocessing steps based on this individual score will introduce undesired artifacts in the facial sample, as well as this individual score is not a strong indicator of the overall quality of the sample.

Therefore, in this thesis, we choose to use a unified framework that will estimate the overall quality of a sample and utilize this overall quality to improve the performance of a face recognition system. In this chapter, we present a quality-based face recognition approach that will compensate for different quality factors based on the overall quality of a sample. This quality-based system determines the appropriate preprocessing steps and selects an efficient face descriptor to handle the quality deviation of the facial samples introduced by different quality factors. This adaptive system also assigns the fusion parameters based on the quality of the sample for a more reliable recognition performance. In the proposed method, the input images are preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE) and Discrete Cosine Transform (DCT) based normalization. The facial features are extracted using Discrete Wavelet Transform (DWT).

DWT decomposes the images into low and high-frequency sub-bands. Matching scores are calculated by comparing the test sample with every sample from the template database. For the good quality facial images, e.g. images higher than some predefined threshold, we extract only the low-frequency sub-band and decision is made based on the matching score calculated from this sub-band. On the other hand, for the low-quality samples, both low and high-frequency sub-bands are extracted and matching scores are calculated by comparing these sub-bands with the template database. The identification decision is made based on the weighted fusion of the matching scores from these sub-bands. This process improves the recognition performance in the presence of quality degradation. The fusion parameters are selected based on the overall quality of the samples to ensure the appropriate selection of weights for the different sub-bands. We use fuzzy membership functions to calculate the weights based on the overall quality of the sample. Fig. 4.2 shows the basic components of the proposed quality-based face recognition approach. A detailed description of the method is presented in the following sections.

4.2 Quality-based Preprocessing of the Facial Image

The most common approach for quality enhancement is to preprocess the biometric samples using image normalization techniques, such as histogram equalization (HE) [68], histogram matching, contrast limited adaptive histogram equalization (CLAHE) [109], gamma intensity correction [81], and discrete cosine transform (DCT) based normalization [18]. However, quality enhancement using image normalization techniques depends on the degree of quality degradation. It has been shown that normalizing good quality samples may degrade the identification accuracy [3, 80]. Therefore, an adaptive normalization approach is needed that will preprocess the facial samples based on the overall quality of the sample.

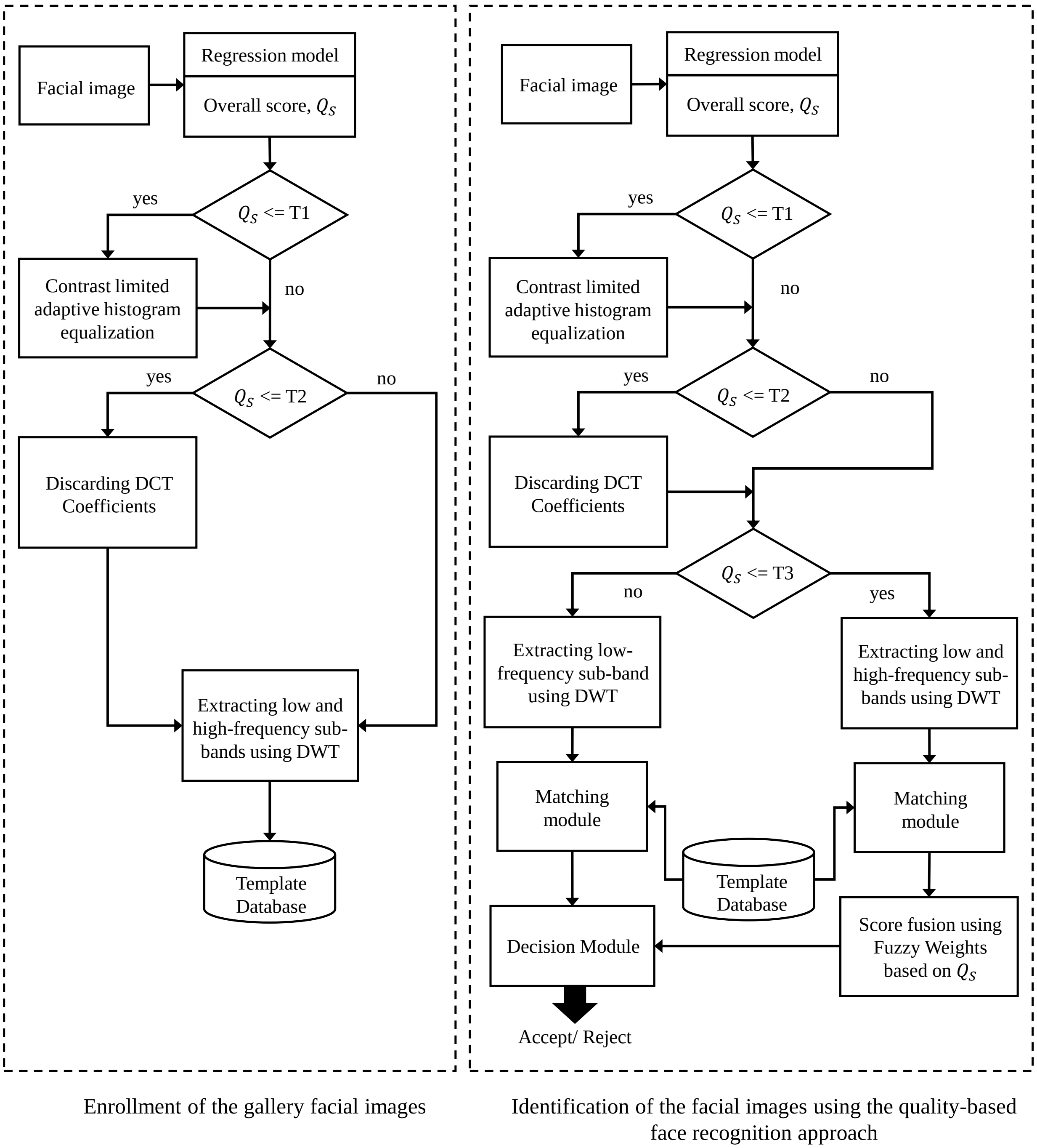


Figure 4.2: Overview of the proposed quality-based face recognition approach.

4.2.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Histogram equalization is a contrast enhancement technique which can significantly improve the visual quality of an image. In many automatic face recognition algorithm, this technique is applied to enhance the facial features. Histogram equalization accumulates the intensity distribution of the entire image and transforms the image based on the global intensity. However, the facial images can be affected by regional quality variations. In those cases, histogram equalization may over enhance the content of the whole image instead of focusing on the local regions [56]. Therefore, in the proposed method, we adopt contrast limited adaptive histogram equalization (CLAHE) [68, 109] for normalizing the facial samples. It is one of the variants of histogram equalization which considers the local processing of the images while enhancing the quality. CLAHE works on the small non-overlapping regions and enhances the contrast of each region separately. It also applies an interpolation method to eliminate the undesired block artifacts introduced by the local processing [68]. In the proposed method, the normalization process is applied to those samples whose quality score is lower than a predefined threshold. In this way, we ensure that the good quality samples are unaffected by the normalization process, and normalization is applied to only the bad quality samples. The contrast limit is set based on the quality information using Z-shaped fuzzy membership function.

4.2.2 Normalization in the DCT Domain

In our proposed method, to further enhance the quality of the facial images, we apply an illumination normalization approach. Chen et al. proposed a Discrete Cosine Transform (DCT) based technique for illumination normalization [18]. In this normalization process, low-frequency DCT coefficients are discarded as they are highly related to illumination changes. In the proposed method, DCT-based normalization approach is used because we want to normalize the illumination to enhance the quality of the facial image without impairing the facial features. Moreover, it is relatively easy to discard the low frequency components in the DCT domain. To minimize the illumination variations, we can simply set an appropriate number of low-frequency DCT coefficients to zero in the logarithm domain, as the low-frequency band contains most of the illumination variations [18].

After the preprocessing step using CLAHE, the facial images are transformed into the logarithm domain. The logarithm image is then converted into the DCT domain to get the DCT coefficients. The 2D-DCT for an input image, I of size $M \times N$ can be defined using Equation 4.1 [18]. Here, the values $C_{(u,v)}$ is called the DCT coefficients of I. The appropriate number of DCT coefficients for normalizing the illumination variations is selected based on the quality of a sample using Z-shaped fuzzy membership function.

$$\begin{aligned} C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I(x,y) \\ \times cos\left[\frac{\pi(2x+1)u}{2M}\right] cos\left[\frac{\pi(2y+1)v}{2N}\right] \end{aligned} \tag{4.1}$$

where $0 \leq u \leq M-1$ and $0 \leq v \leq N-1$, and

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{M}}, & u = 0 \\ \frac{2}{\sqrt{M}}, & u = 1,2,...,M-1 \end{cases}$$

$$\alpha(v) = \begin{cases} \frac{1}{\sqrt{N}}, & v = 0 \\ \frac{2}{\sqrt{N}}, & v = 1,2,...,N-1 \end{cases}$$

Fig. 4.3 shows example facial images before and after the normalization steps. Fig. 4.3(a) is the original facial images. It shows the quality scores before the normalization process. Fig. 4.3(b) is the output facial image after the CLAHE and Fig. 4.3(c) is the output facial image after discarding the DCT coefficients in the logarithm domain. From the figure, it is clear that the normalization process improves the quality of the facial sample.

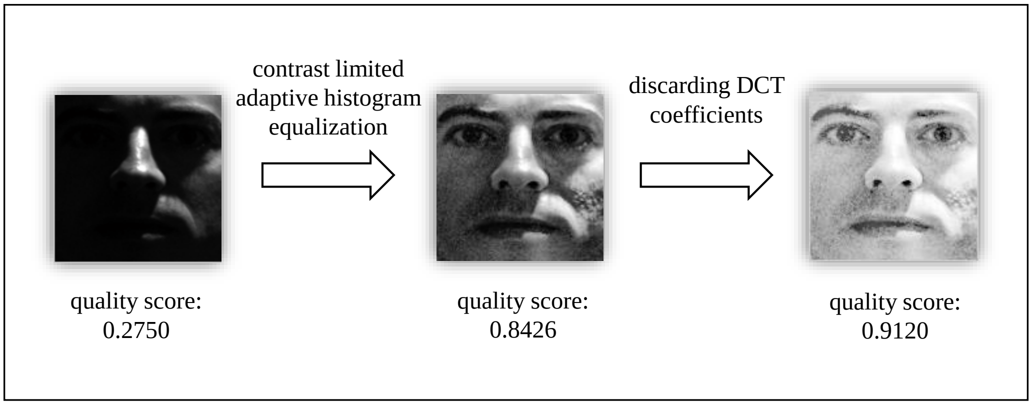


Figure 4.3: Example of facial images before and after the normalization steps. (a) input facial image, and output facial images after (b) CLAHE and (c) discarding DCT coefficients.

4.3 DWT-based Face Recognition

Discrete wavelet transform (DWT) is a well-known approach for face recognition. DWT is a signal or image processing tool that segments the signal or image into low and high-frequency sub-bands at different scales. DWT decomposes the input images into low and high-frequency sub-bands, such as Low-Low (LL), High-Low (HL), Low-High (LH), and High-High (HH). The low and high-frequency sub-bands extracted from discrete wavelet transform (DWT) of the facial image can be used as a facial descriptor for the recognition purpose. In the proposed method, we apply DWT to extract the facial features from the images. Other face recognition approaches, such as the holistic feature-based approaches are sensitive to sever local changes, such as acute illumination changes, facial expression and pose variations. Also, the local feature-based face recognition approaches are subtle to the severe illumination and blurriness of the facial images. On the other hand, authors of [77, 78] showed that low-frequency sub-bands (LL) from the DWT can be used as an efficient face descriptor for the facial images. This is because the low-frequency sub-bands contain the most prominent facial features. However, they are severely sensitive to quality degradation, such as variations in lighting conditions. On the contrary, the high-frequency sub-bands perform relatively well under different quality degradations. It is because high-frequency components contain the geometry-based facial features, such as the shapes and relative positions of the eyes, nose, mouth, and chin, and are less affected by the variations in different quality factors.

The low-frequency approximation image can be used as an efficient face descriptor for the facial images captured under ideal conditions. However, the effectiveness of this method will be lost under different quality degradation. Therefore, in the presence of variations in quality factors, the high-frequency components from the DWT can be used for the recognition purpose. However, the individual scores from the low or high-frequency sub-bands may not produce optimum results for the face recognition. A fusion of the low and high-frequency sub-bands may improve the recognition performance in the presence of quality degradation. Most importantly, we should consider the quality of the samples while fusing the low and high-frequency components. Because low-frequency components are ideal for recognizing good quality facial samples. On the other hand, more weights should be assigned to the high-frequency components in the presence of quality degradation. Therefore, an adaptive fusion of the low and high-frequency sub-bands based on the overall quality score of a sample is needed, which can improve the overall performance of a face recognition system.

4.3.1 Feature Extraction using DWT

In the proposed method, 2D-DWT is applied to the facial images. We have empirically found that the second-level DWT sub-bands perform well under varying lighting conditions for the face recognition. Therefore, the input image is decomposed up to the 2^{nd} level. We extract the 2^{nd} level low-frequency (LL2) sub-band for the facial image whose overall quality is higher than some predefined threshold. And, for the low-quality samples, 2^{nd} level low and high-frequency (LH2 and HL2) sub-bands are extracted. These sub-band coefficients are normalized using Z-score normalization (ZN). There are different methods for measuring the similarity between two samples, such as Principal Component Analysis (PCA), Support Vector Machine (SVM) and Neural Network (NN). However, due to its simplicity, Euclidean distance is the most common approach for similarity measure. In the proposed method, we use Euclidean distance to measure the similarity between the template and the test images. The Euclidean distance, $d_{(x,y)}$ between two vectors x and

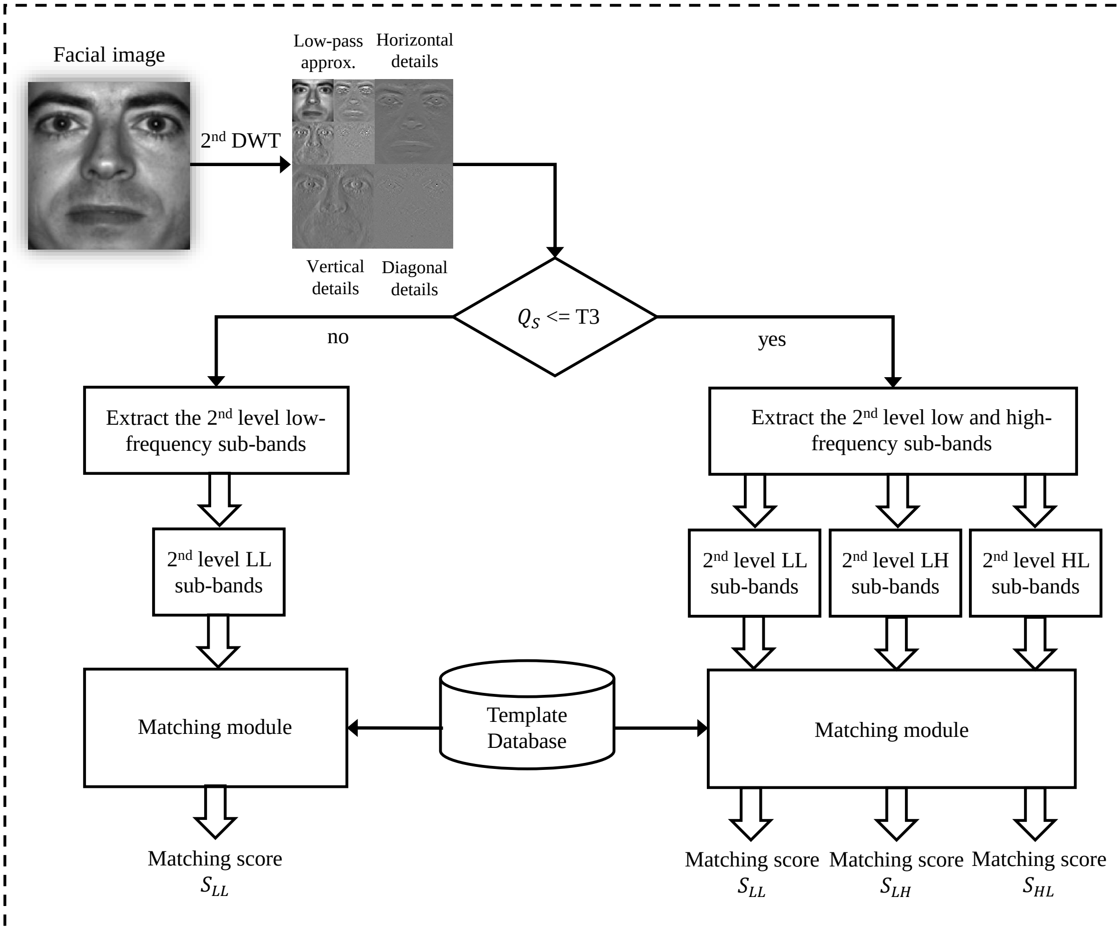


Figure 4.4: Steps for 2^{nd}-level DWT features extraction and matching scores generation.

y of size *N* can be expressed using Equation 4.2 [89]. The similarity between the test sample and every sample from the template database is computed. We calculated the matching scores for each of the sub-bands (LL2, HL2, and LH2) by comparing the sub-band coefficients of the template and the test facial images. Fig. 4.4 shows the steps for 2^{nd}-level DWT features extraction and the matching scores generation.

$$D_{(x,y)} = \sqrt{\sum_{k=1}^{N} (x_k - y_k)^2} \tag{4.2}$$

4.3.2 Quality-based Weighted Score Fusion for Face Recognition

For the good-quality samples, the low-frequency sub-bands are extracted and final decision is made based on the matching scores generated from these sub-bands. However, in the presence of quality degradation, the individual scores from the low or high-frequency sub-bands may not produce optimum results for the face recognition. Therefore, in the proposed method, we consider a match score-level fusion of the low and high-frequency sub-bands in the presence of quality degradation to improve the recognition performance. According to Jain et al. [47], the fusion approaches in biometric fall into two broad categories: before matching and after matching fusion. Data extracted from the biometric samples in the earlier stages is more discriminative than after processing. However, fusion approaches in this stages are computational expensive and complex. On the other hand, after matching fusion mechanisms, such as score-level approaches integrate information after the matching or comparison is done. And due to the ease of processing, score-level fusion is the most commonly used fusion approach in biometric. Therefore, we use quality-based score fusion to improve the recognition performance.

The matching scores can be fused together by calculating the weighted average of the individual scores. However, we should consider the quality of the samples while assigning weights to these sub-bands. Since in the presence of quality degradation, the performance of the low-frequency components will degrade and the high-frequency components will perform relatively better than the low-frequency sub-bands. Therefore, an adaptive fusion of the low and high-frequency sub-bands based on the overall quality score of a sample is needed, which can improve the overall performance of a face recognition system. In the proposed method, we employ an adaptive approach to calculate the fusion weights using fuzzy membership functions based on the overall quality of a test image.

The matching scores are fused based on the overall quality of a sample. If the quality score is lower than a predefined threshold, matching scores calculated from the low and high-frequency sub-bands are fused, otherwise, only the low-frequency matching scores are considered for the

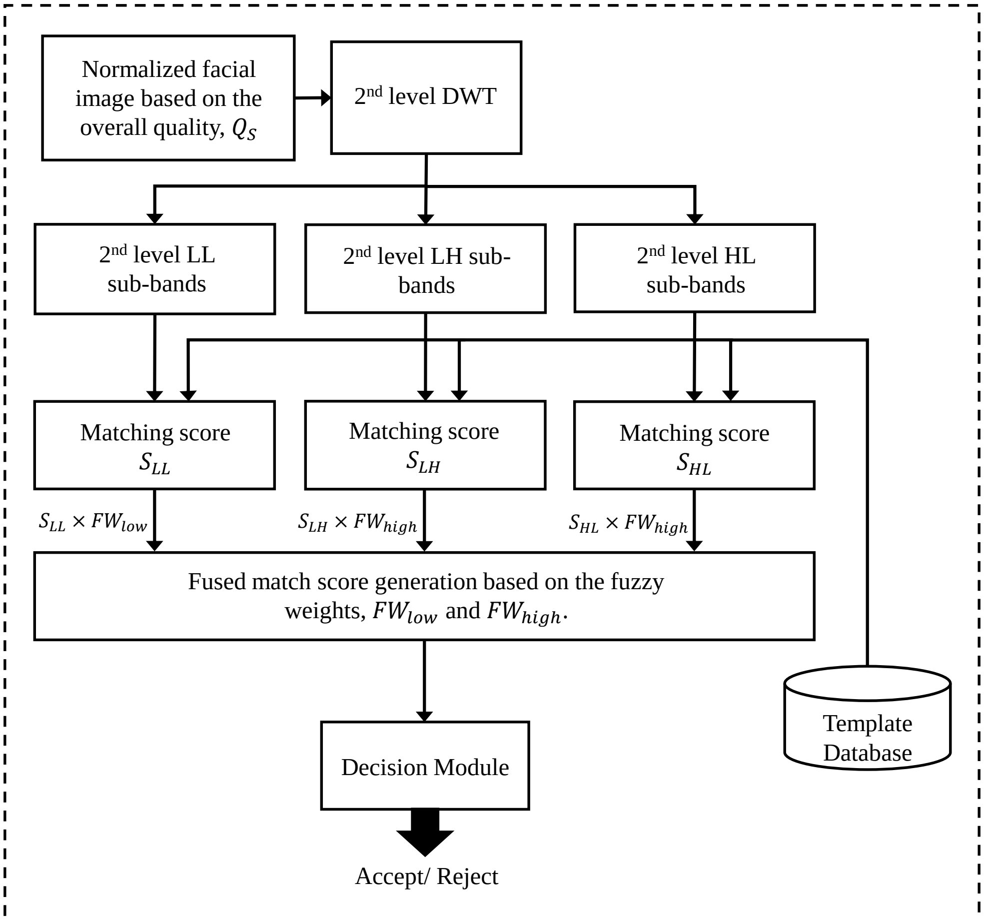


Figure 4.5: Steps for matching score calculation for the low-quality samples using DWT-based feature extraction.

identification purpose. Predefined fusion parameters will not be able to cope with the different degree of quality degradation. We need to assign appropriate weights for fusing the scores which will result in optimum results for the face recognition. Therefore, the fusion parameters are set adaptively based on the overall quality (Q_s). Two fuzzy weights $(FW_{low}$ and $FW_{high})$ respectively, for the low and high-frequency sub-bands are calculated using Sigmoid and Z-shaped fuzzy membership functions. Use of these fuzzy membership functions for the weights calculation was proposed by Sultana et al. in 2014 [84]. We employ these fuzzy membership functions to assign the weights of the low and high-frequency sub-bands. Equation 4.3 and Equation 4.4 describe the Sigmoidal and Z-shaped fuzzy membership functions for calculating $(FW_{low}$ and $FW_{high})$ [84].

$$FW_{low}(Q_S) = \frac{1}{1+e^{-a(Q_S-b)}} \tag{4.3}$$

$$FW_{high}(Q_S) = \begin{cases} 1 \ , & Q_S \leq c \\ 1-2\left(\frac{Q_S-c}{c-d}\right)^2, & c \leq Q_S \leq \frac{c+d}{2} \\ 2\left(\frac{Q_S-d}{d-c}\right)^2, & \frac{c+d}{2} \leq Q_S \leq d \\ 0 \ , & Q_S \leq d \end{cases} \tag{4.4}$$

Here, Q_S is the overall quality score of the test image, and a, b, c and d are parameters for the Sigmoidal and Z-shaped membership functions. The values of a, b, c and d should be real numbers, with $c < d$. We have empirically selected the values for a, b, c and d for the proposed method. Weighted sum rule is used to calculate the final match score using the matching scores from the low and high-frequency sub-bands. Equation 4.5 describes the equation used for the final match score calculation for the low-quality samples.

$$S = \frac{FW_{low} \times S_{LL} + FW_{high} \times S_{LH} + FW_{high} \times S_{HL}}{FW_{low} + FW_{high} + FW_{high}} \tag{4.5}$$

Here, S_{LL}, S_{LH}, and S_{HL} are the matching scores of LL2, LH2 and HL2 sub-bands, respectively. And, FW_{low} and FW_{high} are the weights for the low and high-frequency sub-bands. The weighted average of the matching scores calculated from these low and high-frequency sub-bands is computed, and the sample with the maximum matching score from the template database is selected as the class of a test sample. The final decision is made based on these selected classes. Fig. 4.5 depicts the score level fusion of the DWT sub-bands using fuzzy membership functions.

4.4 Summary

In this chapter, we presented the proposed quality-based face recognition approach. Our main goal is to investigate the effectiveness of a unified framework which can adaptively compensate for the quality degradation introduced by various factors based on the overall quality of the facial image. To make a robust and efficient face recognition system in the presence of quality degradation, we use image normalization techniques based on the overall quality of a sample. We apply CLAHE on those facial samples whose overall quality is lower than some pre-defined threshold. To further normalize the facial images, they are transformed into the logarithm domain and the low-frequency DCT coefficients are discarded. Moreover, we use DWT-based facial feature extraction method to recognize the faces. Instead of using only the low-frequency sub-bands from the wavelet transform, we consider a weighted average of the low and high-frequency sub-bands to improve the recognition performance of the low-quality samples. The fusion parameters are also selected based on the overall quality of the samples to assign appropriate weights for the different sub-bands. The extensive experiments presented in Chapter 5 demonstrate that the proposed quality-based face recognition approach performs better than the traditional face biometric systems.

Chapter 5

EXPERIMENTAL RESULTS

This chapter presents experimental results for the proposed quality estimation model and the quality-based face recognition approach. There are two independent sections which include the database description, experimental setup, analysis and results obtained from the proposed quality estimation model and the quality-based face recognition approach. The sections also present the performance comparison of the proposed methodologies against some state-of-the-art approaches.

5.1 Experimental Results for the Quality Estimation Method

In this section, we present the experimental results for the proposed linear regression-based quality estimation model. Publicly available facial datasets, namely Yale Face Database B and Extended Yale Face Database B [39, 54] are used to evaluate the proposed method. A detailed description of the dataset and the experimental setup is presented in section 5.1.1 and section 5.1.2, respectively. Next, the analysis of the impact of different quality factors on the performance of a face recognition system is presented in section 5.1.3. We also evaluated the performance of the proposed linear regression model and the results are presented in section 5.1.4. In section 5.1.5, we show the performance comparison of the proposed quality estimation model with some existing quality integration methods. The experimental results show that the proposed linear regression-based quality estimation model can predict the matching performance of the facial samples under various quality degradation, which is a strong indicator of the overall quality of the samples.

5.1.1 Database Description

To the best of our knowledge, there are no publicly available databases that consolidated or addressed different quality factors, such as illumination, contrast, brightness, and focus. The Yale

Database B considered a wide range of illumination conditions in their database. This database was first reported by Georghiades et al. in 2001 [39]. It contains 5760 images of 10 subjects under 9 different poses and 64 illumination conditions. The extended Yale Face Database B contains 16128 images of 28 human subjects under 9 poses and 64 illumination conditions and was first reported by Lee et al. in 2005 [54]. In this thesis, we validate the proposed linear regression-based quality estimation method and quality-based face recognition approach using the Yale database B and Extended Yale database B [39, 54]. The other quality effects are synthetically generated by automatically changing or adjusting contrast, brightness and focus. These synthetically created samples provide a sufficient number of instances to analyze the impact of different quality factors.

Illumination sets: From the Yale database B and Extended Yale database B, we have considered the frontal pose images of 38 subjects under 64 different lighting conditions. The image samples from the database are divided into five different illumination sets according to the angle, θ between the light source and the optical axis of the camera [39]. Set 1 to 5 has the illumination degradations in increasing order. Fig. 5.1 shows sample images from the five different illumination sets according to θ. It also shows the illumination scores for each of the facial samples.

Contrast sets: For analyzing the effect of contrast, we have considered 9 different sets of samples in different contrast scale. The samples are synthetically saturated at low and high intensities using histogram equalization within the range 10 to 90 with a step of 10%. Histogram equalization is an image processing method for adjusting the image contrast. Fig. 5.2 shows the histogram of intensity distribution before and after changing the contrast of a facial image by 50%. Some samples from the different set of contrast are shown in Fig. 5.3 with their corresponding contrast scores.

Brightness sets: Sample images from brightness sets are generated by shifting the histogram within the range -40 to $+120$ with a step of 20. This procedure creates 9 sets of brightness sam-

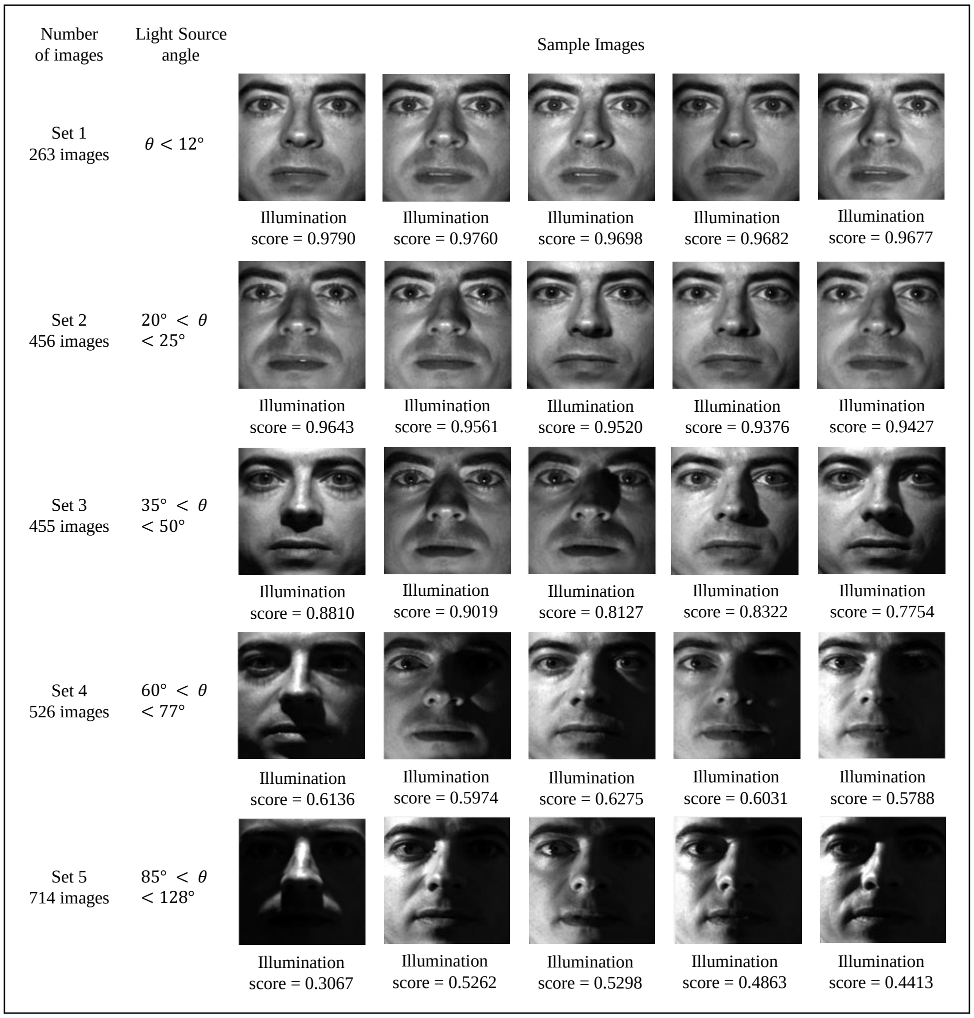


Figure 5.1: Sample images from the five different illumination sets for varied angles θ with corresponding illumination scores.

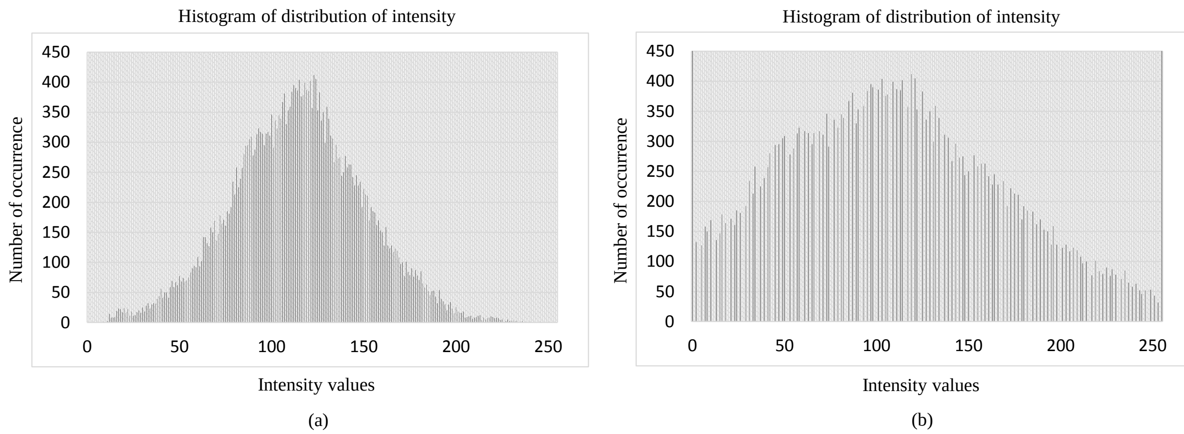


Figure 5.2: Histogram equalization for contrast adjustment: (a) distribution of intensity of the original image, and (b) distribution of intensity after imposing 50% histogram equalization.

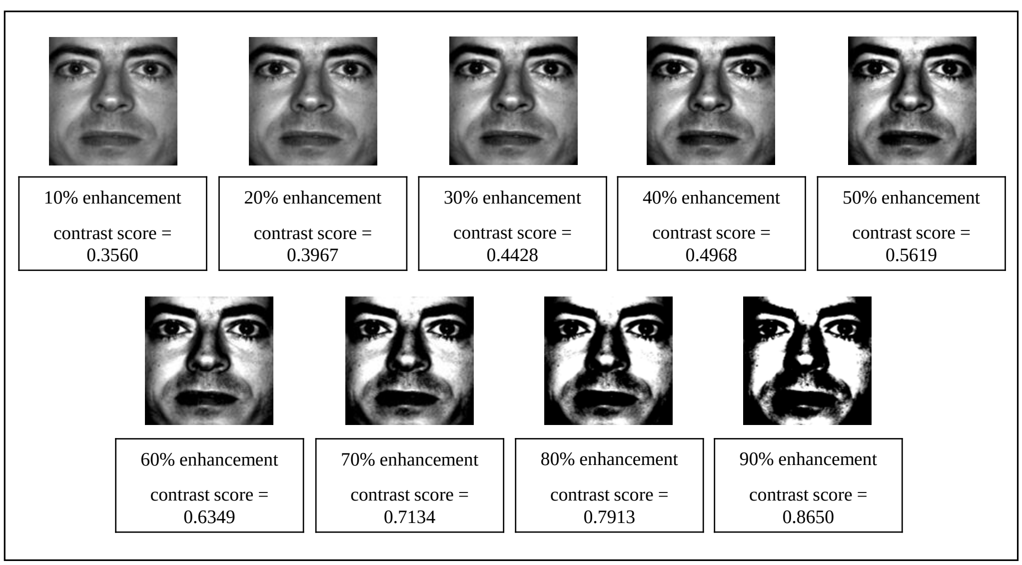
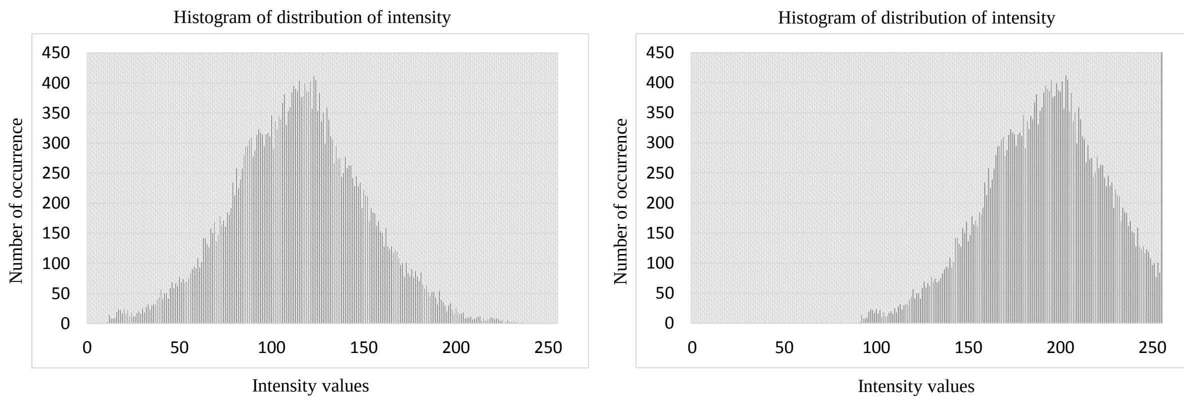


Figure 5.3: Sample images from the different sets of contrast conditions (contrast enhancement ranges from 10% to 90%) with corresponding contrast scores.



(a) (b)

Figure 5.4: Histogram shifting for Brightness changes: (a) distribution of intensity of the original image, and (b) distribution of intensity after shifting the distribution by 80 (the range is (-255 to +255)).

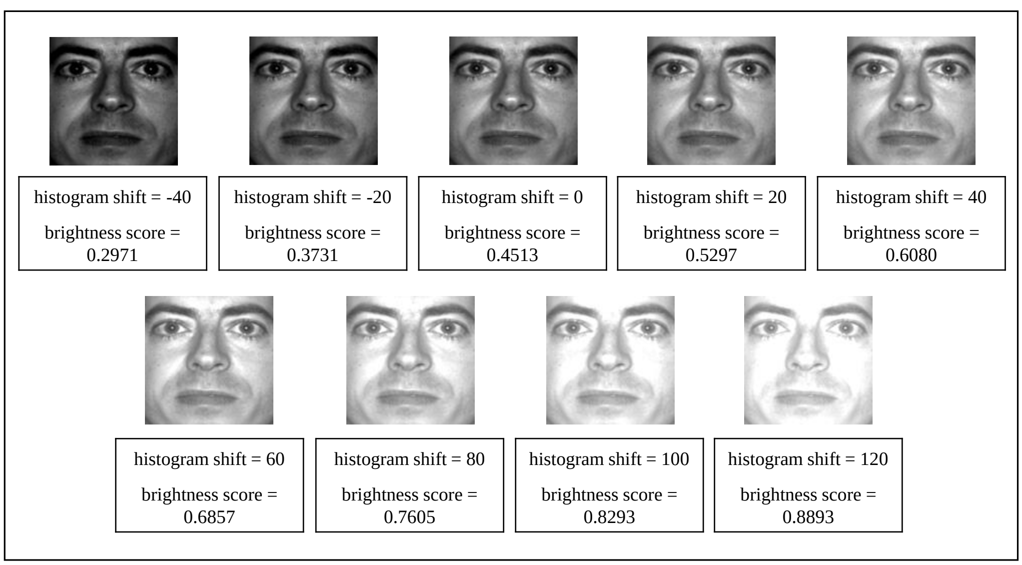


Figure 5.5: Sample images from the different sets of brightness conditions (histogram shifting ranges from -40 to +120) with corresponding brightness scores.

ples for the experiment. Example of shifting the distribution is presented in Fig. 5.4. The histogram can be shifted within $(-255\ to\ +255)$. Fig. 5.5 shows some sample images from different brightness sets with their corresponding brightness scores.

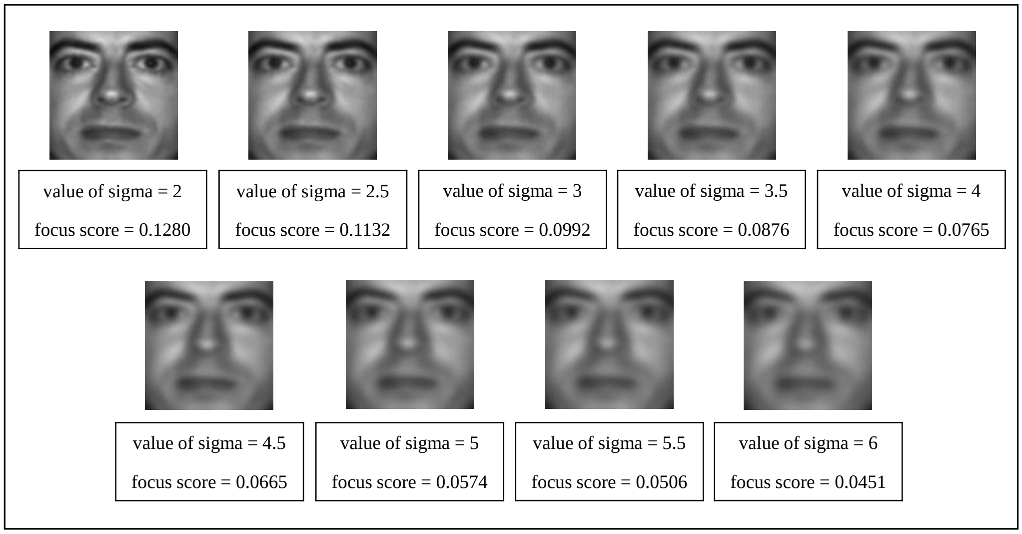


Figure 5.6: Sample images from the different sets of focus conditions (values of sigma range from 2 to 6 with a step of 0.5) with corresponding focus scores.

Focus sets: The focus samples are generated by convolving the facial images with a Gaussian mask where the value of sigma, σ ranges from 2 to 6 with a step of 0.5, resulting 9 different sets of focus samples. The size of the square filter is determined by $2 * ceil(2 * \sigma) + 1$. Gaussian filter or Gaussian blur mask is a popular tool for smoothing or blurring the images. This type of filtering is normally used for smoothing an image which will decrease the focus of the sample. Some sample images from different focus sets are shown in Fig. 5.6 with their corresponding focus scores.

The reasons for considering the Yale database B and Extended Yale database B [39, 54] for evaluating the proposed methods are as follows:

1. These databases are publicly available and consider a wide range of lighting conditions (64 different lighting conditions) which provides a sufficiently large number of instances to ana-

lyze the impact of illumination on the performance of a face recognition system.

2. We synthetically impose different quality factors, such as contrast, brightness and focus on the facial samples with frontal pose and under direct illumination which provide a sufficient number of facial samples under different quality degradations.

3. Most of the quality assessment methods and quality-based face recognition approaches utilized these databases as a baseline for performance evaluations.

Therefore, these databases are appropriate and sufficient to validate the performance of the proposed quality estimation method and the proposed quality-based face recognition approach.

5.1.2 Experimental Setup

Samples captured with frontal pose and under direct illumination (i.e., P00A+000E+00 image of each subject) are considered as the gallery facial samples for the 38 users (1 sample per user). The original images of size 168×192 are resampled to a fixed size of 128×128. Fig. 5.7 shows good quality facial samples of different users used as gallery facial images. The matching scores are determined for all the test facial images, that is 5 sets of samples for five different illumination conditions, 9 sets of samples for each of contrast, brightness and focus changes. The illumination sets contain a total of 2414 facial samples. There are 342 samples for each of the contrast, brightness and focus changes. Therefore, in total, we have 3440 facial samples. Before estimating the matching scores, we apply DWT on the facial images of size 128×128 to extract the low-frequency sub-bands (LL). The low-frequency sub-bands contain the discriminating facial features which can be used for recognizing faces. Euclidean distance is used to determine the matching scores between the probe and the template images.

To evaluate the performance of the proposed quality estimation method, we split the facial samples into two folds. Each fold contains facial samples of 19 users from 5 different illumination sets and 9 different contrast, brightness and focus sets. We use the first fold in the training

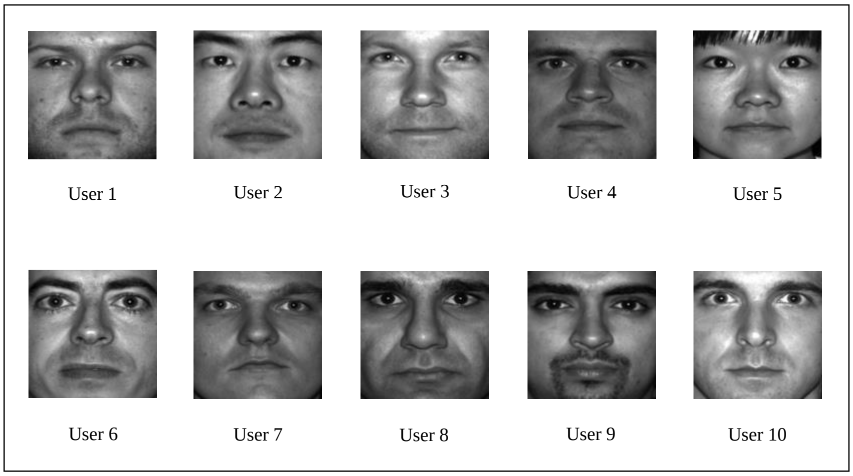


Figure 5.7: Good quality samples of different users used as gallery facial images.

phase to build the regression model, and the second fold is used to predict the matching performance using the model. There is no overlap between these two folds of facial images. We apply random sub-sampling cross-validation technique to properly estimate the performance of the prediction model [24]. Overall, 100 rounds of cross-validation are performed to assess the predictive accuracy, and the validation results are averaged to estimate the performance of the model. The four different quality scores of a facial sample are fed into the regression model and the model predicts the matching performance of the sample. We use different methods for measuring the quality scores, that generate values in different ranges. Therefore, all the scores are normalized using Z-score normalization (ZN) before feeding them to the regression model.

5.1.3 Analysis of the Impact of Quality Factors on the Performance of a Recognition System

We analyze the impact of different quality factors, such as illumination, contrast, brightness and focus on the performance of a face recognition system. Performance of the state-of-the-art face recognition approaches is considered under various quality degradation. Table 5.1 shows the recognition rates of different sets of facial images affected by different lighting conditions using principal component analysis (PCA), local binary pattern (LBP) and discrete wavelet transform (DWT). Table 5.1 indicates that illumination has a significant impact on different face recognition approaches.

From Table 5.1, we can see that the recognition performance degrades dramatically with minor changes in illumination while using LBP. Also, with severe illumination variation, PCA, LBP and DWT show very poor performance.

From Table 5.2, it is clear that for LBP-based method, recognition performance degrades sharply with the increase in contrast. However, changes in contrast have a small impact on the performance of PCA and DWT-based face recognition. Table 5.3 indicates that the changes in brightness highly affect the PCA and DWT-based face recognition. For the facial images with very low and high brightness scores, the recognition performance decreases dramatically. On the other hand, LBP can handle different brightness levels better than PCA and DWT-based face recognition approaches. Finally, we can see from Table 5.4 that performance of LBP degrades dramatically with the decrease in focus. LBP collects local features for texture analysis. Therefore, the quality factors that change the local pattern of a facial image have a significant impact on the recognition performance of an LBP-based system. However, the changes in focus level have very little impact on the performance of a PCA and DWT-based recognition system.

Table 5.1: Recognition performance (%) for the different illumination sets from the Extended Yale database B.

Yale database	Light source angle, θ	Average illumination score	Recognition performance (%) using PCA	Recognition performance (%) using LBP	Recognition performance (%) using DWT
Set 1	$\theta < 12°$	0.9483	95.05	85.17	95.05
Set 2	$20° < \theta < 25°$	0.9154	90.35	53.07	90.13
Set 3	$35° < \theta < 50°$	0.7731	20.65	17.76	20.65
Set 4	$60° < \theta < 77°$	0.5383	4.18	10.45	3.99
Set 5	$85° < \theta < 128°$	0.3172	2.8	5.32	2.8

5.1.4 Analysis of the Regression Model

For the proposed quality estimation model, we consider interactions model to interpret the relationship between quality and matching performance. The regression model tries to fit the relationship between quality factors and matching performance by adjusting the weights of different quality

Table 5.2: Recognition performance (%) for the different contrast sets from the Extended Yale database B.

Synthetic data from Yale database	Contrast Adjustment	Average contrast score	Recognition performance (%) using PCA	Recognition performance (%) using LBP	Recognition performance (%) using DWT
Set 1	10%	0.3432	100	100	100
Set 2	20%	0.3747	100	94.73	100
Set 3	30%	0.4122	100	84.21	100
Set 4	40%	0.4555	100	63.15	100
Set 5	50%	0.5052	100	34.21	94.73
Set 6	60%	0.5587	94.73	13.15	92.1
Set 7	70%	0.617	92.1	5.26	76.31
Set 8	80%	0.6806	81.57	5.26	71.05
Set 9	90%	0.7484	76.31	5.26	63.15

Table 5.3: Recognition performance (%) for the different brightness sets from the Extended Yale database B.

Synthetic data from Yale database	Value of histogram shifting	Average brightness score	Recognition performance (%) using PCA	Recognition performance (%) using LBP	Recognition performance (%) using DWT
Set 1	-40	0.2709	10.52	89.47	7.89
Set 2	-20	0.3463	100	100	100
Set 3	0	0.4241	100	100	100
Set 4	20	0.5022	100	100	100
Set 5	40	0.5798	28.94	97.36	18.42
Set 6	60	0.6563	5.26	89.47	5.26
Set 7	80	0.7308	2.63	78.94	2.63
Set 8	100	0.8014	2.63	52.63	2.63
Set 9	120	0.8648	2.63	21.05	2.63

Table 5.4: Recognition performance (%) for the different focus sets from the Extended Yale database B.

Synthetic data from Yale database	Value of sigma for the Gaussian filter	Average focus score	Recognition performance (%) using PCA	Recognition performance (%) using LBP	Recognition performance (%) using DWT
Set 1	2	0.1382	100	7.89	100
Set 2	2.5	0.1161	100	7.89	100
Set 3	3	0.0984	100	7.89	100
Set 4	3.5	0.0835	100	7.89	100
Set 5	4	0.0711	100	7.89	100
Set 6	4.5	0.061	97.36	5.26	100
Set 7	5	0.0529	97.36	5.26	100
Set 8	5.5	0.0465	94.73	5.26	100
Set 9	6	0.0417	92.1	5.26	100

factors. These weights are represented as regression coefficient in the model. Table 5.5 represents the regression coefficients given by the model. The coefficients that the regression provides are important because they show the impact of the quality factors in the model. From the Table 5.5, we can see the values of the regression coefficient. The regression coefficient for Q_I is $w_1 = 0.2676$, which represents the impact of illumination scores on the matching performance. From that table, we can see, for Q_F, the value of w_4 is positive and relatively lower than other regression coefficients. It indicates that the variations in focus conditions have very low impact on the matching performance. The positive value represents that the decrease in focus scores will result in degraded matching performance. The regression coefficient for Q_C is negative and very small. The negative relationship represents that the increase in contrast will decrease the matching performance, and the low value indicates that it has very low impact on the matching performance. The negative value of the regression coefficient for Q_B indicates that with high value for brightness scores the matching performance will decrease.

The most common way to analyze the prediction errors from the linear regression model is to analyze the distribution of residuals in linear regression. Examining the residuals is a key part of all statistical modeling. Residual (e) can be defined as the difference between the observed value

Table 5.5: Estimated coefficients of the linear regression model.

Variables	Regression coefficients
Q_I	0.2677
Q_C	-0.0194
Q_B	-0.0996
Q_F	0.0164
Q_IQ_C	-0.0085
Q_IQ_B	0.0677
Q_IQ_F	-0.0347
Q_CQ_B	0.0159
Q_CQ_F	0.0017
Q_BQ_F	0.0153

of the dependent variable (Y) and the predicted value $(\hat{Y})$ [71].

$$Residual = Observed\ value - Predicted\ value$$

$$e = Y - \hat{Y} \tag{5.1}$$

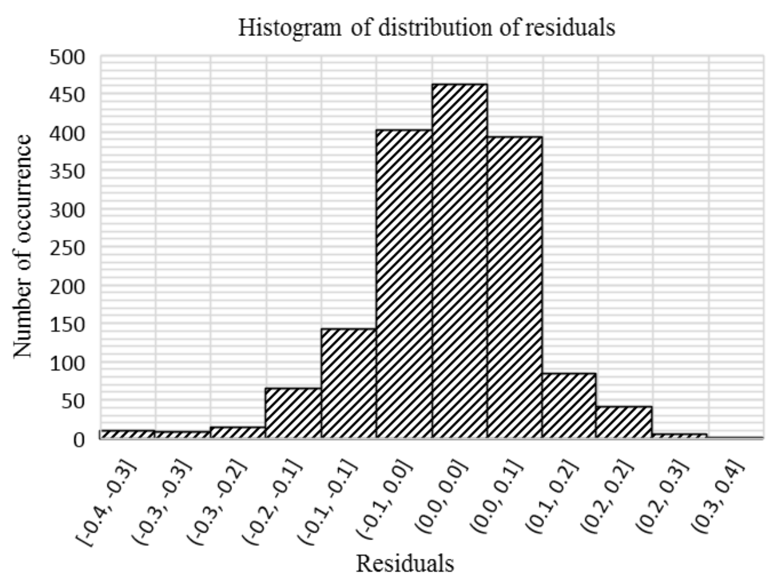


Figure 5.8: Histogram of distribution of residuals of the regression model.

Fig. 5.8 illustrates the histogram of the distribution of residuals produced by the interactions

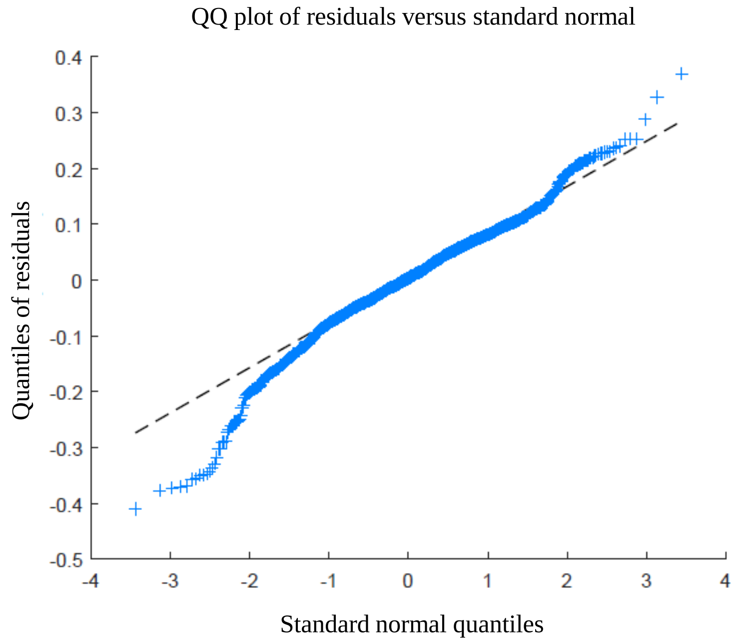


Figure 5.9: Quantile-quantile plot of the quantiles of residuals versus the theoretical quantiles from a normal distribution.

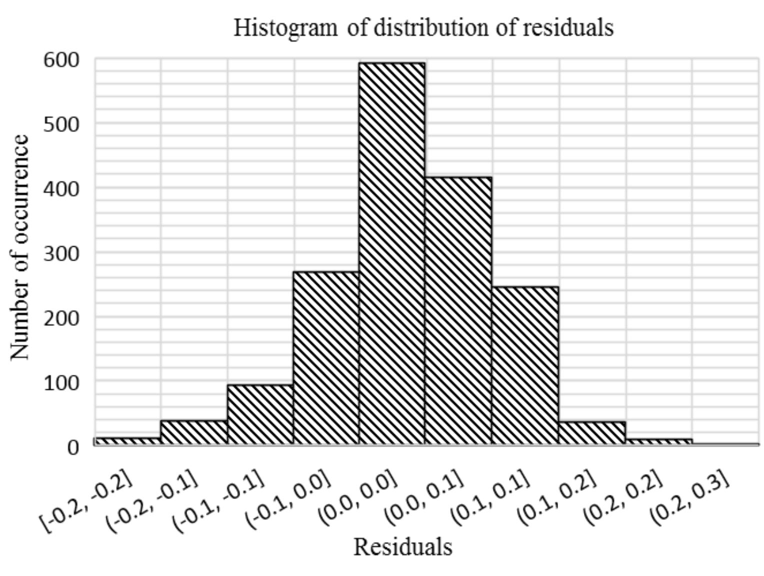


Figure 5.10: Histogram of distribution of residuals between original response values and the predicted values.

regression model. To check how good the linear regression model fits the data set, we need to analyze the normality of the residuals. The residuals should support normal distribution for a data set to be fitted by the linear regression model. We perform the normality test to determine whether the residuals are normally distributed. Fig. 5.9 shows the quantile-quantile plot (qq-plot) of the quantiles of residuals versus the theoretical quantiles values from a normal distribution. From Fig. 5.9, we can see that the resulting plot is approximately linear which validates the normal distribution of the residuals. If we observe the histogram of the distribution of residuals from Fig. 5.8, we can see that most of the residual errors fall in the range (-0.1,0.1). This indicates that the residual errors of our prediction model are very low. In most of the cases, this model will generate some prediction values with very low residual errors. There are some residuals with high values, but the frequency of occurrence of such values is very low. To estimate the performance of regression model, we run the experiment with 100 random partitions of the template and the probe facial images. The mean absolute residual error for the proposed model is 5.36 out of 100 which indicates that the regression model can generate an average prediction error of 5.36. And, the root mean square error (RMSE) is 9.19 out of 100. Fig. 5.10 shows the histogram of the distribution of residuals between the original response values and the predicted values generated from the model.

5.1.5 Transforming Response Variable for Classifying the Facial Images into Three Classes

For classifying the facial images into three classes, we transform the response variable (i.e. matching performance) to a new scale. Response variable in the range $(Y \geq 0.85 \ \& \ Y \leq 1.0)$ falls into class 1, $(Y \geq 0.6 \ \& \ Y{<}0.85)$ falls into class 2 and $(Y \geq 0 \ \& \ Y{<}0.6)$ represents class 3. The response variable predicted from the proposed model is also transformed to the same scale. If we consider the distance between original response value and the prediction value from the model as zero, the proposed method produces an accuracy of 84.03%. Based on the prediction score generated by the regression model, the images can be categorized into appropriate classes (i.e.1, 2, and 3). Fig. 5.11 shows the histogram of the distribution of the original response values and the predicted values generated after the piecewise transformation using the proposed quality estimation model.

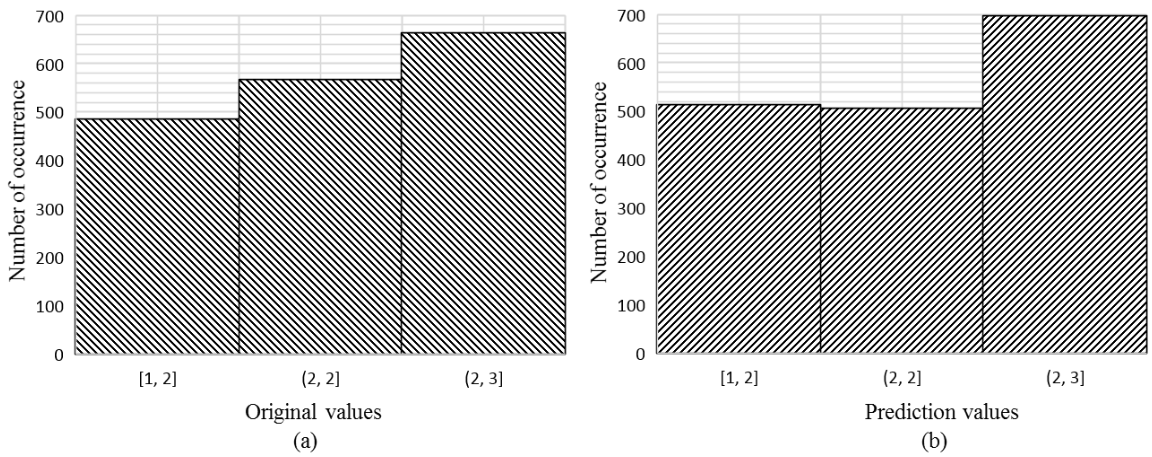


Figure 5.11: Histogram of distribution of (a) original response values and (b) prediction values after transforming the values into three classes.

5.1.6 Comparison with Other Quality Estimation Methods

We compare the performance of the proposed linear regression-based quality estimation model against the other methods for integrating the quality scores. We consider minimum, maximum, mean, geometric mean and regression model with recognition performance to estimate the overall quality of the facial images. Table 5.6 demonstrates that the accuracy of the proposed method is highest among several other quality scores integration schemes. Table 5.6 shows the residual error of the predicted scores and the accuracy of the integration method for classifying the images into three classes.

5.2 Experimental Results for the Quality-based Face Recognition System

In this section, we present experimental results for the proposed quality-based face recognition approach. The Yale Face Database B and Extended Yale Face Database B [39, 54] are used to evaluate the proposed method. A detailed description of the experimental setup is presented in section 5.2.1. This section also presents a comparison of the performance of each module of

Table 5.6: Comparison of different quality estimation schemes.

Integration scheme	residual error (%)	accuracy (%) for classifying the facial images into 3 classes
minimum	41.7	63.51
maximum	11.65	66.1
mean	24.15	63.45
geometric mean	27.33	63.51
prediction using recognition performance	26.28	72.19
proposed quality estimation method	**5.36**	**84.03**

the proposed system. We also show the performance comparison of the proposed quality-based face recognition system against state-of-the-art face recognition approaches. The experimental results show that the proposed method can significantly improve the recognition performance in the presence of quality degradation.

5.2.1 Experimental Setup

For the validation of the proposed quality-based face recognition approach, we consider the Yale database B and Extended Yale database B [39,54]. The similar setup is considered for the database as the quality estimation model. In the proposed method, some normalization steps are applied on the facial images based on the overall quality of the facial samples. After the normalization steps, 2D-DWT is applied on the facial images of size 128×128. We have empirically found that the second level DWT sub-bands perform well under varying lighting conditions for the face recognition. Therefore, the input image is decomposed up to the 2^{nd} level to obtain the LL2, HL2, LH2 sub-bands. These sub-band coefficients are normalized using Z-score normalization (ZN). A matching score for each of the sub-bands (LL2, HL2, and LH2) is computed by comparing the sub-band coefficients of the template and the test facial images. For simplicity, we use Euclidean distance to measure the similarity between the template and the test images. The final decision is made based on the weighted average of these matching scores for the low-quality samples.

Extensive experiments have been conducted to validate the proposed method. The first set of experiments is conducted to find the optimal level of decomposition for the low and high-frequency sub-bands. Next, we evaluate the performance of the proposed method on the Extended Yale database B. A set of experiments is conducted to compare the performance of the proposed quality-based method against other quality-based approaches. Also, we analyze the impact of the normalization approach and the fusion method that we have considered for the proposed quality-based face recognition approach. Finally, the performance of the proposed quality-based face recognition approach is compared against the state-of-the-art face recognition approaches.

5.2.2 Comparison of Low and High-frequency Sub-bands at Different Scales

Initially, we conduct some experiments to find the optimal sub-bands for the face recognition. Here, we only show the results for different illumination sets. Table 5.7 shows the recognition rates (%) for low and high-frequency sub-bands at different scales. We decompose the input up to 3^{rd} level DWT, and the recognition rates for LL1, LL2, LL3, LH1, LH2, LH3, HL1, HL2, HL3, HH1, HH2 and HH3 sub-bands are shown in the Table 5.7. From the table, it is clear that low-frequency sub-bands perform well for the well lit facial images. However, the recognition rate with low-frequency sub-bands degrades rapidly with the degree of quality distortion. On the other hand, high-frequency sub-bands perform better than the low-frequency sub-bands for highly distorted facial images. Also, from the table, we can observe that the low and high-frequency sub-bands at level 2 perform better than the frequency sub-bands at other levels. However, the recognition rates for the samples of illumination set 4 and 5 are relatively low for both the low and high-frequency sub-bands. Therefore, we compute the weighted fusion of the matching scores calculated from the three sub-bands (LL2, LH2 and HL2) for the low-quality samples. The weights for the low and high-frequency sub-bands are determined using the fuzzy membership functions. Table 5.8 shows the recognition rate for different sets of facial images with illumination, contrast, brightness and focus distortion using the proposed quality-based face recognition approach.

Table 5.7: Recognition performance (%) of the different illumination sets using low and high-frequency sub-bands at different scales.

Wavelet Subbands	Recognition rate (%)				
	Set 1	Set 2	Set 3	Set 4	Set 5
LL1	95.05	90.13	20.65	3.99	2.80
LH1	68.06	88.59	38.68	10.07	2.52
HL1	71.86	96.92	54.72	36.31	11.90
HH1	39.16	64.91	16.04	8.17	3.22
LL2	94.29	90.13	20	3.99	2.80
LH2	79.46	94.29	47.25	6.46	2.24
HL2	82.12	99.78	64.17	39.16	11.34
HH2	51.71	84.86	30.76	15.20	3.22
LL3	92.39	82.89	17.36	3.99	2.80
LH3	90.49	98.24	52.08	5.13	2.10
HL3	89.35	98.90	63.29	34.60	9.94
HH3	72.24	96.27	45.05	14.06	2.52

5.2.3 Comparison of Different Quality Normalization Process

In this section, we present experiments on the impact of the different normalization process on the recognition performance. Fig. 5.12 shows the recognition rate (%) using a bar chart for the different sets of images affected by illumination, contrast, brightness and focus. The facial images are normalized by applying the contrast adaptive histogram equalization (CLAHE) if the overall quality scores of the facial images are lower than a predefined threshold, T1 (value of T1 is set to 0.6). Similarly, the DCT-normalization is applied for those facial images whose overall quality scores are lower than a predefined threshold, T2 (value of T2 is set to 0.85). In this way, we ensure that the good quality samples are unaffected by the normalization process, and normalization is applied to only the bad quality samples. These threshold values are set empirically for minimizing the identification errors. We compare the recognition performance of the different quality sets us-

Table 5.8: Recognition performance (%) for different sets of images affected by quality degradation from the database.

	Illumination sets	Recognition performance (%)	Contrast sets	Recognition performance (%)	Brightness sets	Recognition performance (%)	Focus sets	Recognition performance (%)
Set 1	$\theta < 12°$	98.10	10%	100	-40	100	2	100
Set 2	$20° < \theta < 25°$	100	20%	100	-20	100	2.5	100
Set 3	$35° < \theta < 50°$	88.57	30%	100	0	100	3	100
Set 4	$60° < \theta < 77°$	93.16	10%	100	20	100	3.5	100
Set 5	$85° < \theta < 128°$	92.16	10%	100	40	100	4	100
Set 6			10%	100	60	100	4.5	100
Set 7			10%	100	80	100	5	100
Set 8			10%	100	100	100	5.5	100
Set 9			10%	100	120	100	6	100

ing DWT with no normalization process, DWT with DCT-normalization, DWT with CLAHE, and DWT with CLAHE and DCT normalization. From Fig. 5.12, we can see that image normalization using contrast limited adaptive histogram equalization (CLAHE) and DCT based normalization perform better than the other two normalizations (normalization using CLAHE and normalization using DCT). Face recognition without any normalization process in the presence of quality degradation shows lowest recognition performance among the other approaches. Also, from the figure, we can see that normalization process has no impact on the set with different focus values.

5.2.4 Comparison of the Face Recognition with Fusion vs. no Fusion using DWT

A set of experiment is conducted to analyze the impact of the fusion approach that we have considered in the proposed method. The proposed method employ a match score-level fusion of the low and high-frequency sub-bands in the presence of quality degradation to improve the recognition performance. The matching scores are fused based on the overall quality of a sample. If the overall quality score of a sample is lower than a predefined threshold (T3), the low and high-frequency sub-bands are fused, otherwise, identification decision is made based on the low-frequency match-

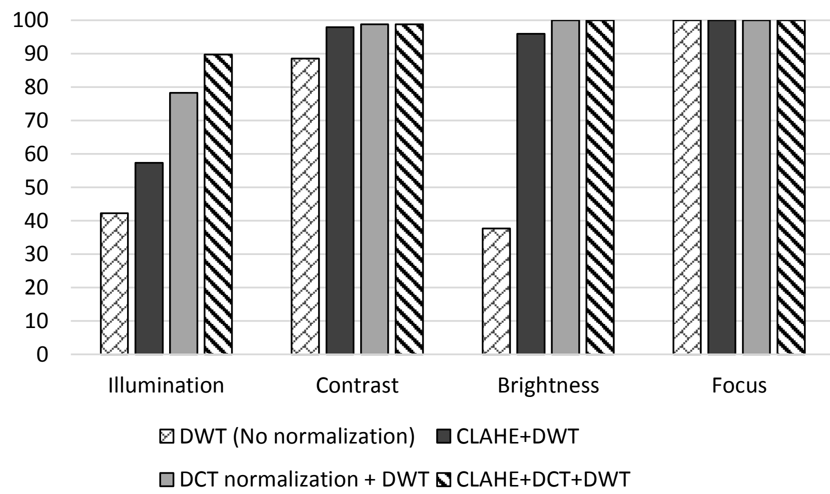


Figure 5.12: Comparison of the recognition rate (%) for different sets of illumination, contrast, brightness and focus using different quality normalization process.

ing scores. The value of T3 is set to 0.85. The threshold value is experimentally set in such a way that minimizes the identification errors. In the proposed method, the parameters (a, b, c and d) for the Sigmoidal and Z-shaped fuzzy membership functions, are also empirically selected to calculate the weights for the low and high frequency sub-bands. The values for these parameters are set to $a = 0.3$, $b = 0.6$, $c = 0.6$, and $d = 1.1$. We compare the result of the proposed face recognition approach against the face recognition approach with no fusion. For the face recognition approach with no fusion, we consider the low and high-frequency sub-bands as the facial features and compute the matching scores between the template and the probe images using the Euclidean distance. Table 5.9 shows the recognition performance of different sets of images using the face recognition approach with the weighted fusion of the low and high-frequency sub-bands and the face recognition approach with no fusion.

5.2.5 Comparison of Quality-based DWT vs. Quality-based PCA and LBP

We conduct a set of experiments to compare the performance of the proposed quality-based face recognition system against quality-based face recognition system using PCA and LBP. For the quality-based face recognition approach with PCA, we apply CLAHE and DCT-based normal-

Table 5.9: Recognition performance (%) with and without fusion using DWT for different sets of illumination, contrast, brightness and focus.

	Illumination		Contrast		Brightness		Focus	
	No fusion	Fusion	No fusion	Fusion	No fusion	Fusion	No fusion	Fusion
Set 1	98.47	98.09	100	100	100	100	100	100
Set 2	100	100	100	100	100	100	100	100
Set 3	88.54	88.57	100	100	100	100	100	100
Set 4	81.31	93.16	100	100	100	100	100	100
Set 5	80.57	92.16	100	100	100	100	100	100
Set 6			97.36	100	100	100	100	100
Set 7			97.36	100	100	100	100	100
Set 8			94.36	100	100	100	100	100
Set 9			94.73	100	100	100	100	100

ization to the low-quality facial images. After the preprocessing using CLAHE and DCT, PCA is used to identify the facial images in the presence of quality degradation. On the other hand, for the quality-based recognition with LBP, we apply quality-based normalization using CLAHE and DCT to the low-quality facial images. After that, the facial images are partitioned into small non-overlapping regions and LBP histogram is extracted from those local regions. These local histograms are then concatenated into the extended LBP histogram and used as the facial descriptor for the face recognition. Table 5.10 shows the results of the comparison among these quality-based face recognition approaches. From the table, it is clear that proposed quality-based approach using DWT performs better than the other two quality-based approaches.

Table 5.10: Comparison of the recognition performance (%) using quality-based PCA, quality-based LBP and quality-based DWT

Face recognition approaches	Illumination	Contrast	Brightness	Focus
Quality-based face recognition using PCA	72.93	96.19	100	100
Quality-based face recognition using LBP	48.70	65.78	95.02	11.40
Quality-based face recognition using DWT	**94.40**	**100**	**100**	**100**

5.2.6 Comparison of the Proposed Method with State-of-the-art Methods

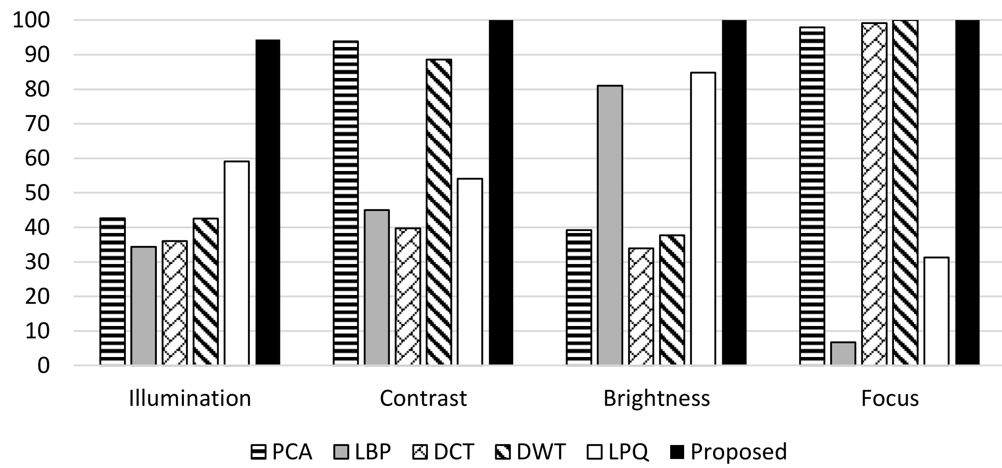


Figure 5.13: Performance comparison of state-of-the-art face recognition approaches against the proposed approach.

We evaluate the performance of our adaptive quality-based method with some state of the art face recognition approaches, such as Principal Component Analysis (PCA) [88], Local Binary Pattern (LBP) [6], Local Phase Quantization (LPQ) [7], Discrete Cosine Transform (DCT) [18] and Discrete Wavelet Transform (DWT) [21, 77] on the Extended Yale Database B. The recognition rate (%) for all these methods and the proposed method is shown in Fig. 5.13. From this bar chart, it is clear that the proposed method provides consistent results for the different sets of images with degraded quality. The well-known face recognition approaches, such as Eigenface, LBP, and LPQ obtain very poor results for the variations in lighting conditions. PCA shows good results for different contrast and focus sets. However, the recognition performance is poor for the different sets of brightness changes. On the other hand, LBP based face recognition can compensate for brightness changes. However, it fails to efficiently identify the facial images in the presence of illumination, contrast and focus changes. The case is similar for the LPQ-based face recognition. The recognition rate for the DCT and DWT based face recognition shows a similar pattern for recognizing different sets of facial images. DWT perform relatively well for the sets of images affected by contrast changes. For the contrast variations, Eigenface and DWT-based face recognition approach perform better than other approaches. LPQ and LBP-based approaches provide better recognition accuracy for the sets of images affected by brightness changes. And, LBP and LPQ show degraded performance for the sets of images affected by focus changes. On the other hand, the proposed method outperforms all these face recognition methods while considering images with illumination, contrast, brightness and focus changes. From Fig. 5.13, it is clear that the proposed method can handle different quality degradation, and the system consistently shows high recognition accuracy.

5.3 Summary

In this chapter, we presented the experimental results conducted to evaluate the performance of the proposed regression-based quality estimation method and the quality-based face recognition system. For both the quality estimation model and quality-based face recognition approach, we compared the performance of the proposed methods against some existing approaches. The proposed method achieves better performance than the existing approaches for quality estimation and some state-of-the-art face recognition approaches. The quality estimation model achieves an accuracy of 84.03% while predicting the matching performance of the facial samples which indicates the overall quality of the facial sample. On the other hand, our quality-based face recognition approach achieves an average accuracy of 98.6% while recognizing faces affected by quality degradation, where traditional methods (PCA, LBP, LPQ, DCT, and DWT) only achieve 50%-80%.

Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Summary of Thesis Contributions

In this thesis, we presented efficient methodologies for quality estimation of facial samples and a quality-based adaptive system for improved face recognition performance. The relationship between different quality factors and the matching performance is modeled using an interaction linear regression model to estimate the overall quality of a facial sample. Therefore, the proposed quality estimation model predicts an efficient face quality index, which can characterize the overall quality of a facial image in correlation with the matching performance of that sample. Moreover, we investigated the effectiveness of a unified framework which can adaptively compensate for the quality degradation introduced by various factors based on the overall quality of the facial image. We used quality-based preprocessing and feature selection for improving the recognition performance of the low-quality samples. A quality-based weighted average of the matching scores from the low and high-frequency DWT sub-bands are computed to determine the identification decision for the low-quality samples. This unified quality-based framework minimizes the impact of various quality factors and improves the overall performance of the face recognition system while working with facial images affected by different quality factors. A brief overview of the contributions of this thesis is following:

1. We conducted a rigorous study to investigate the taxonomy of quality-based methods in face recognition. Section 2.3.2 presented our proposed classification of the quality factors that affect the facial biometric samples. A systematic survey was conducted on the quality-based methods in face recognition in Chapter 2. Our study pointed out that the quality-based adaptive face recognition is a relatively understudied topic in biometric. To the best

of our knowledge, there are very few studies in the literature that incorporate the quality information in a face biometric system and adapt the uncertainty of the quality degradation during operation.

2. We presented a new method that consolidates different quality scores into a single evaluation score to estimate the overall quality of the facial images. The proposed model considered different quality factors, such as illumination, contrast, brightness, and focus of the facial images. A linear regression-based approach was used to capture the relationship between these quality factors and corresponding matching performance of a facial image. Experimental results from section 5.1.4 demonstrated that the proposed quality estimation model can effectively capture the relationship between quality factors and corresponding matching performance of a facial image, and can efficiently estimate the overall quality of the facial sample. Section 5.1.4 showed that the quality estimation model produced very low residuals error of 5.36%. From section 5.1.5, we can see that the prediction model achieved an accuracy of 84.03% for categorizing the facial images into three classes. Section 5.1.6 presented the comparison of the proposed quality estimation method against some existing quality estimation methods. From the section, it is clear that the proposed method performed better than the existing quality estimation methods.

3. We designed a fully functional face recognition system that used quality-based preprocessing and feature selection, and adaptively handled the quality degradation of the facial images. The proposed discrete wavelet transform (DWT)-based face recognition system compensated for different quality issues based on the overall quality score with a very small number of training samples available. We used a quality-based weighted fusion of low and high-frequency sub-bands from the DWT-based feature extraction method to recognize the faces in the presence of quality degradation. Experimental results from section 5.2.4 showed that the preprocessing steps based on the overall facial quality using contrast limited adaptive histogram equalization (CLAHE) and discrete cosine transform (DCT) based normalization

improved the recognition performance by 31.39% on average for all the sets of illumination, contrast, brightness and focus changes for the DWT-based face recognition. According to the experimental results in section 5.2.4, the quality-based fusion of different sub-bands for the low-quality samples further boosted the recognition performance by 1.6% on average. This weighted fusion of the low and high-frequency sub-bands improved the recognition rate for the facial images affected by variations in lighting conditions by 4.62%. The proposed quality-based face recognition approach achieved an average accuracy of 98.6% while recognizing faces affected by quality degradation. Experimental results from section 5.2.6 demonstrated that the proposed quality-based face recognition approach outperformed many state-of-the-art face recognition approaches.

4. We designed a case study to analyze the impact of occlusion on face recognition performance. We proposed an occlusion localization and detection method based on the depth information provided by the Kinect RGB-D camera. The face recognition system excluded the occluded area localized from Kinect depth images while identifying the user from the gallery images. Appendix A showed that the proposed method improved the recognition performance by 5.28% on average while considering only the non-occluded facial parts for face recognition in the presence of occlusion.

6.2 Conclusions

We established that quality assessment of a biometric sample is a relatively difficult area that received less attention compared to the automated recognition and feature extraction approaches in biometrics. More attention should be directed towards this problem since it has been found in many studies that the quality of biometric samples significantly affects the performance of a biometric recognition system [1, 2, 20, 80]. Therefore, in this thesis, we investigated the effectiveness of a unified framework which can adaptively compensate for different quality degradation based on the overall quality of the facial images. We designed a quality estimation model for the facial images which determines the overall quality of a facial sample by considering the impact of different quality degradation on the matching performance of a biometric sample. In the process of designing a quality-based face recognition system for improved recognition performance, we used this estimated overall quality score to determine the preprocessing steps and to select the facial features for identifying a user. For the low-quality samples, matching scores from the different sub-bands were fused together based on the quality scores to improve the recognition performance.

To validate the performance of the proposed linear regression-based quality estimation method and the proposed quality-based face recognition approach, we considered Yale database B and Extended Yale database B [39, 54]. The Yale Database B considers a wide range of illumination conditions in their database. For our experiments, the other quality effects were synthetically imposed on the facial samples by automatically changing or adjusting contrast, brightness and focus. We evaluated the performance of the proposed quality estimation model by analyzing the distribution of residuals and the mean residuals error. Also, we showed that the proposed quality estimation model achieved an accuracy of 84.03% for classifying the facial images into three classes. The proposed method effectively captured the relationship between the quality factors and the impact of quality degradation on the facial images, and predicted the overall quality of the facial samples.

We also presented a quality-based face recognition approach for improved recognition performance than a traditional face recognition system in the presence of quality degradation. The proposed face recognition approach resulted in 98.6% identification rate on average, which outperformed many state-of-the-art face recognition approaches. The quality-based approach showed better performance than a traditional face recognition approach due to the quality-based selection of the preprocessing steps and the quality-based features selection. Moreover, we used quality-based score fusion of the different sub-bands to improve the recognition performance further.

6.3 Limitations and Future Work

In this thesis, we considered different camera attributes and external attributes, such as lighting conditions, contrast, brightness and focus that adversely affect the facial biometric samples. There are several other quality factors that affect the performance of a face recognition system. One of the future directions of research is to design a more robust face biometric system that will incorporate some other quality factors while estimating the overall quality of a facial sample. In this thesis, we presented a case study where an investigation is conducted to analyze the impact of occlusion on face recognition performance. From that study, we concluded that occlusion of different facial parts significantly affects the quality of the facial samples, and degrades the recognition performance. We proposed an occlusion detection and localization method based on Kinect depth information and built a face recognition approach that improves the performance by excluding the occluded facial parts while recognizing faces. As a future extension of this work, occlusion can be incorporated as a quality factor in the proposed quality estimation model. Also, integrating the occlusion detection and localization method with the proposed quality-based face recognition approach may be successful to compensate for the occluded facial parts based on the overall quality. Due to the lack of the availability of any public database that captures facial images affected by various quality factors, such as different lighting conditions, brightness, contrast, and focus, we synthetically generated facial samples affected by different factors. A large database containing facial samples affected by different quality factors would be very helpful for fine-tuning the threshold values used in the system.

In this thesis, we incorporated the quality information into the different stages of the system to improve the performance of the biometric recognition system. One possible future direction is to design a module for checking the quality of the gallery images before enrolling them in the system. Based on the decision of the quality estimation model, the low-quality facial samples can be discarded from the gallery images. As feature extraction and verification are computationally expensive, in the verification stage, the facial samples can be rejected based on the quality of the samples for alleviating false alarms in the system. Another possible direction for using the quality information is to select appropriate classifier or feature extraction methods based on the quality of the facial samples in a unimodal approach.

One of the exciting possibilities for future research, that this thesis enables, is incorporating quality information in a multimodal system. For example, involving several biometrics traits, a more reliable system can be built by assigning more weights to the modality with better sample quality. The confidence of the system's decision can then be predicted by assigning fewer weights to the modalities with low-quality samples.

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Appendix A

Case Study: Face Recognition using Occluded Area Localization Method from the Kinect Depth Images

Recently, RGB-D cameras such as Kinect sensor have received a vast amount of attention from diverse research communities as it is a low-cost device which can effectively extract the depth mapping from the object in front of the camera. The Kinect sensor can capture 2D and 3D data simultaneously with a promising acquisition time. Our goal is to investigate whether we can improve the face recognition performance in the presence of occlusion using the Kinect depth images. We localize the occluded regions from the facial images using the depth information. If the probe image contains an occluded region, then the face recognition system will match only the non-occluded facial parts with the gallery images to find the best possible match. This will reduce the number of misclassification, and as a result, will improve the recognition performance of the biometric system. We extract the local features from the facial images using Local Binary Pattern (LBP) analysis and feed those features to the k-nearest neighbor (KNN) classifier to identify the occluded faces. For detecting and localizing the occluded facial areas we used the depth information provided by Kinect RGB-D camera. For the evaluation of the proposed method, we consider EURECOM Kinect Face dataset [62].

Database and Experimental Setup

For this case study, we considered the EURECOM Kinect Face Dataset [62] which is composed of 52 subjects: 14 females and 38 males. The images are captured in two sessions and there are nine types of variations in the images: neutral, smiling, open mouth, illumination variation, occlusion of half of the face by paper, occlusion of the mouth by hand, occlusion of the eyes by glasses, and left and right profile of the facial images. From these sets of images, we considered neutral, illumination variation, occlusion of half of the face and occlusion of the mouth for ex-

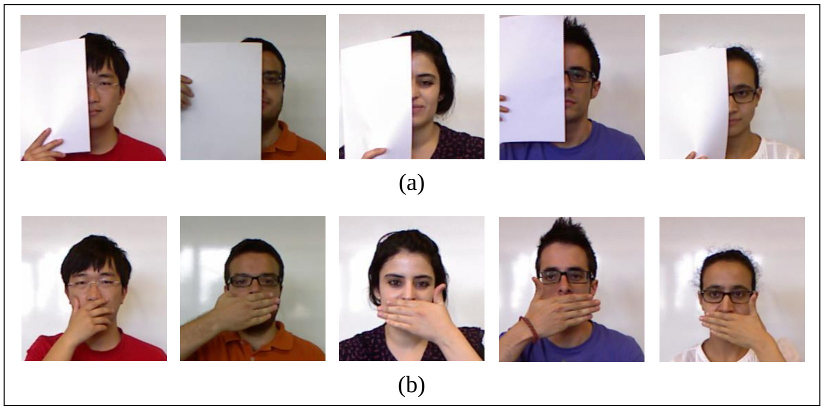


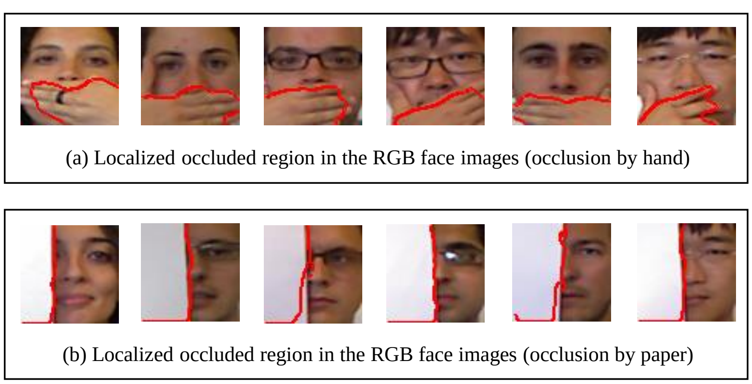
Figure .1: Example of occluded RGB facial images from EURECOM Kinect Face dataset [62]. (a) occlusion by paper, and (b) occlusion by hand.

perimental purpose. For classifying the images in occluded and non-occluded classes, we use a nonlinear support vector machine (SVM) classifier with radial basis kernel to classify front face and occluded face. For the generalization of the implemented method, 5-fold cross-validation was applied where the training fold contains images of 160 front and 160 occluded faces and the testing fold contains images of 40 front and 40 occluded faces from the database. For the recognition task, K-Nearest Neighbor (KNN) classifier is used with the distance defined as *'cityblock'*. The neutral facial images from session 1 and session 2 were used as gallery images. $LBP^{u2}_{(8,2)}$ operator is used for extracting features from 8×8 non-overlapping regions of the facial images. Fig. .1 shows an example of occluded RGB facial images from the EURECOM Kinect Face dataset.

Experimental Results on Occlusion Detection and Localization

For detecting occluded facial images, we consider neutral, light on, occlusion of mouth by hand, and occlusion of the face by a paper from the database. We extract the facial features using $LBP^{u2}_{(8,2)}$ operators and the facial features are fed to the SVM classifier to detect the occluded facial images. We achieve an accuracy of 98.50% for classifying the facial images. From the detected occluded facial images, we localize the occluded regions.

Investigation on depth images shows that if the face is occluded, then there must be some regions other than the nose area in the face that is closer to the camera. The pixel intensity is disproportional to the distance from the camera. Based on this hypothesis, we apply a threshold-based approach to extract high-intensity values from the occluded depth images. The facial images are filtered based on an empirically set threshold value, T. After that morphological opening operation is applied to the threshold image to remove all the small objects from binary images. Next, a component with the maximum energy (i.e. highest pixel intensities) is selected as the potential candidate for the occluded region after connected component analysis on the binary image. The selected occluded area is then corrected using the reference front face image. In creating the reference image, we have considered the 200 front face images from the database. The absolute difference between the reference image and the occluded facial image will result in an image that has higher pixel values in the area where the difference between the reference and occluded facial image is higher. The resulting images are then binarized to get images with edges at the boundary of the occluded region. In our proposed method, we referred to these images as edge images. In the next step, the selected occluded area after connected component analysis is corrected using the edge images. The edge image contains the boundary of the occluded area. Based on this boundary, the connected component is adjusted to find the accurate occluded area of the facial image. Finally, we apply canny edge detection to fine tune the boundary of the occluded region. Fig. .2 shows the localized region of occlusion (occluded by hand and paper) in the RGB facial images.



(a) Localized occluded region in the RGB face images (occlusion by hand)

(b) Localized occluded region in the RGB face images (occlusion by paper)

Figure .2: Example of localized occluded area in the RGB facial images (red marked area), (a) occluded by hand, and (b) occluded by paper (the resolution of the images are 64×64).

Experimental Results on Face Recognition using Occluded Area Localization Method

After localizing the occluded area, we extract the non-occluded region from the facial images. Facial features are extracted from these non-occluded regions using $LBP^{u2}_{(8,2)}$ operator. The feature vectors are then fed to the KNN classifier for determining the face recognition performance. Table .1 shows the Rank-1 identification rate for the 2D face recognition in the presence of occlusion with and without using the occluded area localization method. The images contain occlusion of mouth by hand and occlusion of the face by paper. From the table, we can see that the average identification rate for occlusion of mouth by hand images from the two sessions is 90.39% and the average identification rate for occlusion of the face by paper is 83.66%. For the images containing occlusion of mouth, the average identification rate improves to 95.19%, and for the images containing occlusion of the face by paper, the average identification rate improves to 89.42% after using the proposed area localization method. Therefore, the proposed face recognition technique improves the recognition performance by using the depth information from the Kinect depth images. The proposed method exploits the depth information for localizing the occluded area in the facial images and discard the occluded area while matching the probe images to the gallery images.

Table .1: Identification rate for recognizing faces in the presence of occlusion.

Identification rate (%) in the presence of occlusion			Identification rate (%) with the occluded area localization method		
Session	Occlusion by hand	Occlusion by paper	Session	Occlusion by hand	Occlusion by paper
Session 1	92.31	84.62	Session 1	96.15	90.38
Session 2	88.46	82.69	Session 2	94.23	88.46
Average	90.39	83.66		95.19	89.42

Findings from the case study:

- We can detect the occluded facial images from the Kinect RGB images using the depth information.

- This localized occluded regions can be used to improve the face recognition performance.

- We can estimate the quality score for occlusion by simply calculating the ratio of occluded and unoccluded regions in the facial images. This score can be used to adaptively compensate for the quality degradation due to occlusion. Also, this score can be used to discard the facial samples for alleviating false alarms in the system.

Appendix B

The Yale Databases:

The image datasets used in for validating the quality estimation model and the quality-based face recognition system are created by the authors of articles [39, 54]. The databases are publicly available at:

Yale database B: `http://vision.ucsd.edu/content/yale-face-database` and, Extended Yale database B: `http://vision.ucsd.edu/content/extended-yale-face-database-b-b`.

I have attached the screen-shot of the websites where it explicitly says that the databases are free to use for research purposes (Fig. .3 and Fig. .4).

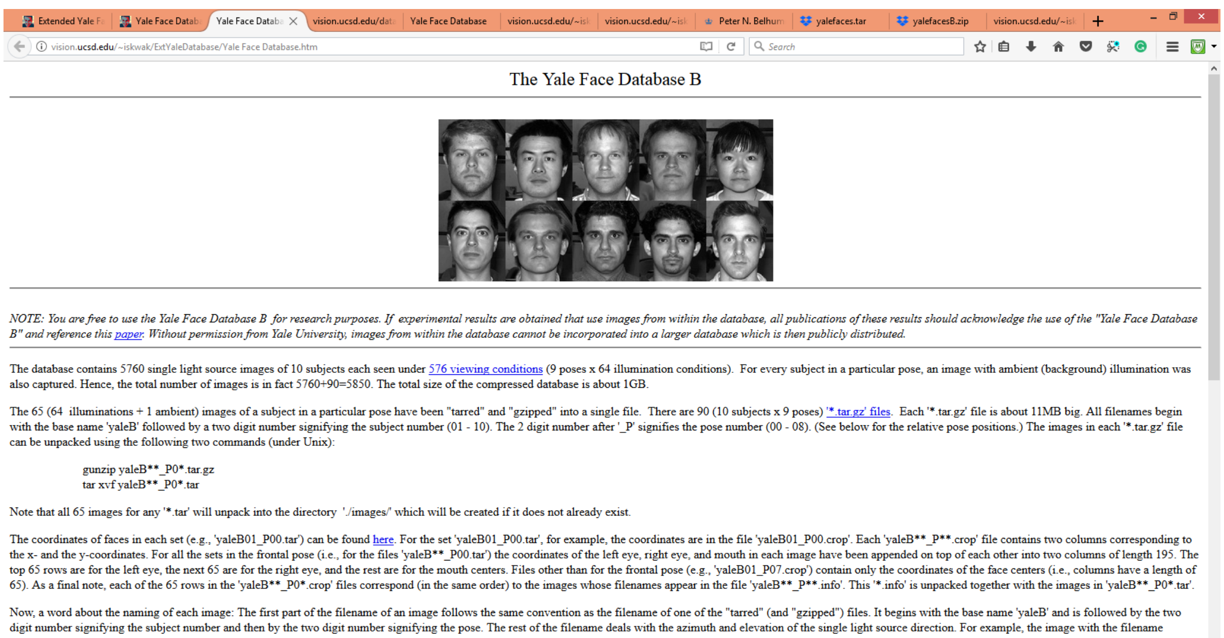
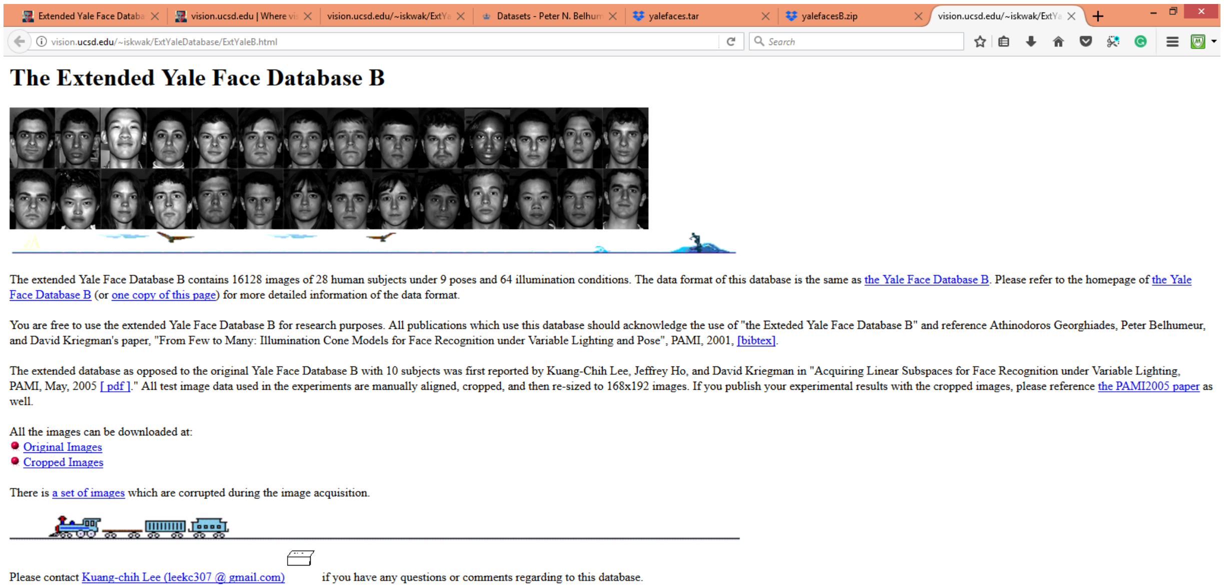


Figure .3: Yale Database B.

The EURECOM Kinect Face Dataset:

For analyzing the impact of occlusion on face recognition performance, we use the EURECOM Kinect Face Dataset [62]. The dataset is available upon request at `http://rgb-d.eurecom.fr/`. We sent an email for requesting the dataset and the dataset was provided to us. The email communication is attached below (Fig. .5).


The Extended Yale Face Database B

The extended Yale Face Database B contains 16128 images of 28 human subjects under 9 poses and 64 illumination conditions. The data format of this database is the same as the Yale Face Database B. Please refer to the homepage of the Yale Face Database B (or one copy of this page) for more detailed information of the data format.

You are free to use the extended Yale Face Database B for research purposes. All publications which use this database should acknowledge the use of "the Exteded Yale Face Database B" and reference Athinodoros Georghiades, Peter Belhumeur, and David Kriegman's paper, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose", PAMI, 2001, [bibtex].

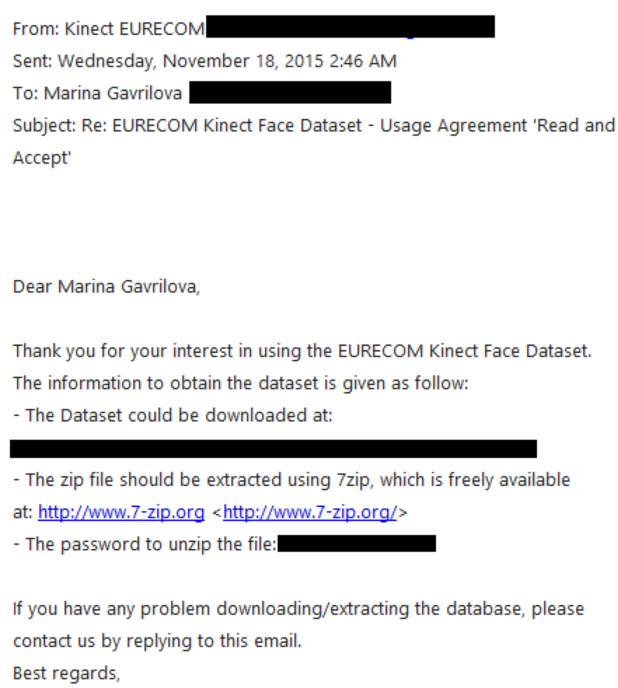
The extended database as opposed to the original Yale Face Database B with 10 subjects was first reported by Kuang-Chih Lee, Jeffrey Ho, and David Kriegman in "Acquiring Linear Subspaces for Face Recognition under Variable Lighting, PAMI, May, 2005 [pdf]." All test image data used in the experiments are manually aligned, cropped, and then re-sized to 168x192 images. If you publish your experimental results with the cropped images, please reference the PAMI2005 paper as well.

All the images can be downloaded at:
- Original Images
- Cropped Images

There is a set of images which are corrupted during the image acquisition.

Please contact Kuang-chih Lee (leekc307 @ gmail.com) if you have any questions or comments regarding to this database.

Figure .4: Extended Yale Database B.


From: Kinect EURECOM [redacted]
Sent: Wednesday, November 18, 2015 2:46 AM
To: Marina Gavrilova [redacted]
Subject: Re: EURECOM Kinect Face Dataset - Usage Agreement 'Read and Accept'

Dear Marina Gavrilova,

Thank you for your interest in using the EURECOM Kinect Face Dataset.
The information to obtain the dataset is given as follow:
- The Dataset could be downloaded at:
[redacted]
- The zip file should be extracted using 7zip, which is freely available at: http://www.7-zip.org <http://www.7-zip.org/>
- The password to unzip the file: [redacted]

If you have any problem downloading/extracting the database, please contact us by replying to this email.
Best regards,

Figure .5: EURECOM Kinect Face Dataset.

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Author: Fatema Tuz Zohra

Publisher: IEEE

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