New Multimodal Biometric Systems with Feature-Level and Score-Level Fusions

Waziha Kabir

A Thesis

in

The Department

of

Electrical and Computer Engineering

Presented in Partial Fulfillment of the Requirements

For the Degree of

Doctor of Philosophy (Electrical and Computer Engineering) at

Concordia University

Montréal, Québéc, Canada

February, 2020

©Waziha Kabir, 2020

CONCORDIA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Waziha Kabir

Entitled: New Multimodal Biometric Systems with Feature-Level and Score-Level Fusions

and submitted in partial fulfillment of the requirements for the degree of

Doctor Of Philosophy (Electrical and Computer Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

____ Chair
Dr. Luis Amador-Jimenez

____ External Examiner
Dr. Henry Leung

____ External to Program
Dr. Chun-Yi Su

____ Examiner
Dr. William E. Lynch

____ Examiner
Dr. Wei-Ping Zhu

____ Thesis Co-Supervisor
Dr. M. Omair Ahmad

____ Thesis Co-Supervisor
Dr. M.N.S.Swamy

Approved by ____
Dr. Rastko Selmic, Graduate Program Director

April 9, 2020 ____
Dr. Amir Asif, Dean
Gina Cody School of Engineering and Computer Science

Abstract

New Multimodal Biometric Systems with Feature-Level and Score-Level Fusions

Waziha Kabir, Ph.D.

Concordia University, 2020

In recent years, biometric-based authentication systems have become very important in view of their ability to prevent identity theft by identifying an individual with high accuracy and reliability. Multimodal biometric systems have now drawn some attention in view of their ability to provide a performance superior to that provided by the corresponding unimodal biometric systems by utilizing more than one biometric modality. The existing multimodal biometric systems fuse multiple modalities at a single level, such as sensor, feature, score, rank or decision, and no study to fuse the modalities at more than one level that may lead to a further improvement in the performance of multimodal biometric systems, has been hitherto undertaken. In this thesis, multimodal biometric systems, wherein fusions of the modalities are carried out at more than one level, are investigated.

In order to improve the performance of multimodal biometric systems over unimodal biometric systems, normalization and weighting of scores from multiple matchers are essential tasks. In view of this, in the first part of the thesis, a number of normalization and weighting techniques under the score level fusion are investigated. Unlike the existing normalization techniques that are based only on the genuine scores, four new techniques based on both the genuine and impostor scores, are proposed. Two weighting techniques that are based on confidence of the scores, are proposed. Extensive experiments are conducted to evaluate the performance of the multimodal biometric system under the score-level fusion (MBS-SL) using the proposed normal-

ization and weighting techniques.

The focus of the second part of this thesis is on the development of multimodal biometric systems, wherein fusions of the modalities are carried out at multiple levels. Specifically, two multimodal biometric systems, in which three modalities are used for their fusion both at the feature level and the score level, are proposed. In the first multimodal biometric system, referred to as the multimodal biometric system with feature level and score level (MBS-FSL) fusions, the features of the three modalities are encoded using the binary hash encoding technique. Unlike the existing techniques for feature level fusion that use unencoded features, this encoding technique allows the neighbourhood feature information to be taken into account. The score-level fusion is carried out on the score obtained from the feature-level fusion and the score from the matching module of the modality that has the lowest equal error rate.

In the proposed MBS-FSL, the border values of raw features could not participate in the encoding in view 4-connected neighbors not being available. In order to take both the border and non-border information as well as the neighbourhood information into consideration, a second multimodal biometric system, referred to as the multimodal biometric system with modified feature level and score level (MBS-MFSL) fusions, is proposed, wherein both the raw and encoded features are taken into account. In this system, the feature-level fusion is carried out in a manner similar to that for the MBS-FSL system. The score-level fusion is then carried out between the score obtained from the feature-level fusion, the score from the matching module of the modality that was not utilized in the feature-level fusion, and the scores from individual modalities by using their raw features.

Extensive experiments are performed to evaluate the performance of the two proposed multimodal biometric systems. The results of these experiments demonstrate that both of the proposed multimodal biometric systems provide performance superior to that provided by the existing multimodal biometric systems in which fusion of modalities is carried out at a single level, namely, the score level. Experimental results also show that, in view of both the border and neighbourhood feature information being considered in the proposed MBS-MFSL system, it provides a performance superior to that provided by MBS-FSL system.

The investigation undertaken in this thesis is aimed at advancing the present knowledge in the field of human biometric identification by considering, for the first time, the fusion of the modalities at two levels, namely, the feature and score levels, and it is hoped that the findings of this study would pave the way for further research in the development of new multimodal biometric systems employing fusion of modalities at multiple levels.

Acknowledgments

I would like to express my sincere gratitude and thanks to my supervisors Dr. M.N.S. Swamy and Dr. M. Omair Ahmad for their support, encouragement and guidance to successfully complete this PhD thesis. I feel extremely privileged to be able to work under their supervision for my masters and doctoral theses.

I am very grateful to my supervisors and University of Concordia for the financial support that I received from their grants awarded by Natural Sciences and Engineering Research Council (NSERC) of Canada and the Regroupement Stratégique en Microsystèmes du Québec (ReSMiQ). My special thanks to all my fellow colleagues at the Center for Signal Processing and Communications, Concordia University, specially, Homa Tahvilian, Dr. Mohamed Naiel, Dr. Mahdi Yektaii, Dr. Hossein Kourkchi, Dr. Hamed Abdzadeh-Ziabari and Dr. Omid Saatlou.

I would like to thank many researchers for their support throughout this journey. Special thanks to Dr. Mohammad Rafiqul Alam, Dr. Carsten Gootschlich and Dr. Zohaib Khan for sharing their knowledge and expertise in the field of biometrics, and to guide me for writing the codes of this thesis.

I would like to offer my deep admiration and gratitude to my undergrad thesis supervisor (Dr. Satya Prasad Majumder), my instructor (Dr. Md Hossam-e-Haider) and my cousin (Dr. Sabreena Anowar) for their motivation and encouragement towards my higher studies. Much respect and appreciation to my best friends, Dr. Rokshana Hossain and Dr. Bushra Sarwat for their unlimited support.

My deepest gratitude goes to my parents (Hena Parveen and Rezaul Kabir), my sister (Wasifa Kabir) and my brother-in-law (Ataur Rahman) for their unconditional love and continuous support in my life. Last, but not the least, I would like to express my deep love and respect for my wonderful husband (Mouad El Kasemi) whose presence has given me the happiness and peace of mind.

Finally, all praises and thanks to my Creator Who has given me the strength to complete every work of my life successfully.

Contents

List of Figures

List of Tables

List of Symbols

$A(k)$	Anchor value for the modality k
$C(k)$	Confidence factor
η	Maximum feature value or total number of bits
$\boldsymbol{F}(k)$	Feature image for the modality k
$f_{xy}(k)$	Feature value at the position (x, y) for the modality k
$G(k)$	Genuine scores for the modality k
$h_{xy\lambda}(k)$	Encoded feature value at the position (x, y) for the modality k
$h_{xy\lambda}(1, 2)$	Fused encoded value at the position (x, y)
$I(k)$	Impostor scores for the modality k
i	i^{th} person
j	j^{th} person
k	Total number of modalities
l	Parameter
λ	Bin position
m	Total number of modalities
M	Total number of persons
$max(G(k))$	Maximum value of the genuine scores
$max(I(k))$	Maximum value of the impostor scores
$min(G(k))$	Minimum value of the genuine scores
$min(I(k))$	Minimum value of the impostor scores

$\mu(G(k))$	Average value of the genuine scores
$\mu(I(k))$	Average value of the impostor scores
N	Total number of samples per person
n_R	Total number of elements in $\sum_{\forall i,j,p,q} R^{i,j}_{p,q}(k)$
n_s	Total number of elements in $\sum_{\forall i,j,p,q} s^{i,j}_{p,q}(k)$
$\nu(k)$	Parameter
$\oplus$	Logical OR operation
p	p^{th} sample of the i^{th} person
q	q^{th} sample of the j^{th} person
$R(k)$	Reliability for the matching scores of a modality k
$R^{i,j}_{p,q}(k)$	Individual reliability for the matching scores of the modality k
$S_R(k)$	Repeated score set for the modality k
$S_{Ravg}(k)$	Average of $S_R(k)$
$S_{Rstd}(k)$	Standard deviation of $S_R(k)$
$\boldsymbol{S}(k)$	The matching scores from the matching module k
$\boldsymbol{S}(l)$	The matching scores from the matching module l
$\boldsymbol{S}(t)$	The matching scores from the matching module t
$\boldsymbol{S}_N(k)$	The normalized value of $\boldsymbol{S}(k)$
$\boldsymbol{S}_N(l)$	The normalized value of $\boldsymbol{S}(l)$
$\boldsymbol{S}_N(t)$	The normalized value of $\boldsymbol{S}(t)$
$\boldsymbol{S}^{1,1}$	The matrix of $\boldsymbol{S}$ at the position (1,1)
$\boldsymbol{S}^{1,2}$	The matrix of $\boldsymbol{S}$ at the position (1,2)
$\boldsymbol{S}^{1,3}$	The matrix of $\boldsymbol{S}$ at the position (1,3)
$\boldsymbol{S}^{2,1}$	The matrix of $\boldsymbol{S}$ at the position (2,1)
$\boldsymbol{S}^{2,2}$	The matrix of $\boldsymbol{S}$ at the position (2,2)
$\boldsymbol{S}^{2,3}$	The matrix of $\boldsymbol{S}$ at the position (2,3)
$(\boldsymbol{S}^{1,2})^T$	The transpose matrix of $\boldsymbol{S}^{1,2}$

$(\boldsymbol{S}^{1,3})^T$	The transpose matrix of $\boldsymbol{S}^{1,3}$
$(\boldsymbol{S}^{2,3})^T$	The transpose matrix of $\boldsymbol{S}^{2,3}$
$s_{p,q}^{i,j}(k)$	Individual matching scores for the modality k
$\boldsymbol{S}_{FSL}$	The fused score from the multimodal biometric system with feature and score level (MBS-FSL) fusions
$\boldsymbol{S}_{MFSL}$	The fused score from the multimodal biometric system with modified feature and score level (MBS-FSL) fusions
$sf_{p,q}^{i,j}$	Individual fused matching scores for the modality k
$std(\mathrm{G(k)})$	Standard deviation of the genuine scores
$std(\mathrm{I(k)})$	Standard deviation of the impostor scores
$\bar{s}_{p,q}^{i,j}(k)$	Individual normalized scores for the modality k
t	Parameter
$Th(k)$	Threshold value for the modality k
$TH_{EER}(k)$	Threshold value at the EER for the modality k
$w(k)$	The weight attached to the score from matching module k
$w(l)$	The weight attached to the score from matching module l
$w(t)$	The weight attached to the score from matching module t
$\boldsymbol{X}(k)$	Biometric image for the modality k
ζ	Parameter

List of Abbreviations

CBW-1	Confidence-based weighting technique 1
CBW-2	Confidence-based weighting technique 2
DET	Detection error tradeoff
DPW	D-prime weighting
DS	Decimal scaling
EER	Equal error rate
EERW	Equal error rate weighting
EP	Earprint
FAI	Falsely accepted impostor
FAR	False acceptance rate
FDRW	Fisher discriminant ratio weighting
FP	Fingerprint
FRG	Falsely rejected genuine
FRR	False rejection rate
FVC	Fingerprint Verification Competition
GAR	Genuine acceptance rate
IAMM	Improved anchored min-max
MAD	Median absolute deviation
MBS	Multimodal biometric system
MBS-SL	Multimodal biometric system under the score-level fusion

MBS-FSL	Multimodal biometric system with feature and score level fusions
MBS-MFSL	Multimodal biometric system with modified feature and score level fusions
MM	Min-max
MOEBA	Mean-to-overlap extrema-based anchor
MOEBAMM	Mean-to-overlap extrema-based anchored min-max
OEBA	Overlap extrema-based anchor
OEBAMM	Overlap extrema-based anchored min-max
OEVBA	Overlap extrema-variation-based anchor
OEVBAMM	Overlap extrema-variation-based anchored min-max
OLR	Overlap region
PAN-MM	Performance anchored min-max
PP	Palmprint
RHE	Reduction of high-scores effect
ROC	Receiver operating characteristic
SL	Score-level
SS	Simple sum
TARC	Threshold alignment and range compression
QQ	Two-quadric
ULPGC	Universidad de Las Palmas de Gran Canaria
VMD-1	Virtual multi-biometric database-1
VMD-2	Virtual multi-biometric database-2
WS	Weighted sum
ZS	Z-score

Chapter 1

Introduction

1.1 General

Accurate human recognition is an important task for designing a reliable identity management system in the context of several applications, such as performing online financial transactions, forensic investigations, granting access to nuclear facilities, or boarding a commercial flight [2]. Biometrics is defined as the physiological and/or behavioural attributes of an individual, and is considered as the most reliable identifier for authentication of a person in recent years. Various applications of a biometric-based authentication system, such as airport security, online banking, education, e-voting, healthcare, gaming, have been implemented successfully using different traits, such as face, fingerprint, iris and/or heart rate. Typically, a biometric-based authentication system uses a single biometric information and such a system is known as unimodal biometric system [3]. Although most of the biometric systems are unimodal, since they are cost-effective, they sometimes fail to provide the desired recognition accuracy due to the following reasons. (1) *Poor-quality data*: Low quality of a biometric image is one of the limitations for a unimodal system, since it may degrade the recognition rate. For example, capturing a fingerprint image of moist, greasy or dirty finger will result in a poor-quality biometric image, or an elderly person has inferior quality of ridges in comparison with that of a younger person. As a result, the person may not be recognized by the unimodal system. (2) *Intra-class variation*: In this case, a single individual may be identified as more than one different individuals due to changes in the environmental conditions while capturing the biometric data. For example, a facial recognition system may not recognize a person who has face images captured from different directions. (3) *Inter-class similarity*: In this case, two individuals can be identified as one individual, since features extracted from those two individuals may not be distinguishable. For example, a facial recognition system may identify monozygotic twins as the same (i.e., a single) person. (4) *Non-universality*: Unimodal biometric systems are not universal, since they sometimes cannot cover the entire population. For example, an iris-based biometric system cannot enrol a blind person or an illiterate person cannot be enrolled in a signature-based biometric system. (5) *Spoof attacks*: A unimodal biometric system suffers from spoofing attacks, since it is easy to counterfeit a single source of biometric information. (6) *Changes of biometric traits*: Some biometric traits change over time, and as a result the person may not be recognized by the unimodal system. For example, a cancer patient loses his fingerprint ridges due to having drugs for a long period of time. As a result, the person may not be recognized by the unimodal system over time.

In order to obtain the desired recognition accuracy as well as to further improve the security of a biometric-based authentication system, one can employ multiple biometric information. Such a system is known as a multimodal biometric system [1]. A multimodal biometric system offers several benefits such as: (a) the consolidation of multiple biometric information, which could possibly increase the overall recognition rate, (b) improving the population coverage, since multiple biometric traits are utilized, and (c) less susceptibility to spoof attacks, since it is not easy to attack multiple biometrics at the same time. In recent years, multimodal biometric systems have received much attention in view of these benefits.

In a multimodal biometric system, it is possible to have multiple information under five scenarios in which the first four scenarios are based on a single biometric trait (e.g., fingerprint), while the fifth scenario is based on multiple biometric traits (e.g., fingerprint and face). These five scenarios are described as follows. 1) *Multi-sensor*: in this scenario, different images are acquired from a single biometric trait by using multiple sensors. For example, two different fingerprint images of the same finger are captured by using an optical sensor and a capacitive sensor. 2) *Multi-instance*: in this scenario, different images are acquired from a single biometric trait by using multiple instances. For example, ten different fingerprint images of ten different fingers of a person. This scenario does not necessarily require multiple sensors. 3) *Multi-snapshot*: in this scenario, different images are obtained from a single biometric trait by using multiple snapshots. For example, two different fingerprint images from two different regions, such as top and bottom of the same finger, are captured with a small sized sensor. This scenario also does not necessarily require multiple sensors. 4) *Multi-algorithm*: in this scenario, different feature images are obtained from a single biometric trait by using multiple algorithms. For example- two different fingerprint feature images of the same finger are obtained by using a texture-based algorithm and a minutiae-based algorithm. This scenario does not necessarily require multiple sensors. 5) *Multi-trait*: in this scenario, different images are obtained from different biometric traits. For example- fingerprint and face images. In order to make the final decision to identify a person, multiple information obtained under the above mentioned scenarios, are required to be fused. Therefore, it is essential to develop a suitable fusion technique to investigate as to which of the multiple information are needed to be fused and how they are to be fused in multimodal biometric systems.

Fusion of multiple information in a multimodal biometric system can be done at five levels, namely, sensor, decision, rank, feature or score level. Sensor-level has too much redundant information that can degrade the performance of a multimodal biometric system. In the decision-level fusion, the information is too abstract and is not sufficient to improve the performance of a multimodal biometric system. Therefore, these two levels of fusion have not drawn much interest of researchers. Rank-level fusion has also not drawn much attention, since it cannot be used for the purpose of verification of a person. Feature-level fusion has drawn much attention for improving the performance of a multimodal biometric system, since the feature set contains information about the raw biometric data that is richer than the matching score or the final decision does. Score-level fusion has also drawn much attention, since it is easy to access and easy to combine the matching scores as well as the amount of information for fusion is more suitable for improving the performance of a multimodal biometric system.

In score-level fusion, multiple scores obtained from multiple matching modules give rise to three different issues in a multimodal biometric system [4]. First, these scores from different matching modules may be non-homogeneous in the sense that one matching module may measure similarity, while another may measure dissimilarity scores. Second, the matching scores may be on different numerical scales, e.g., one matching module may have the range of [0.15, 0.9], while another matching module may have the range of [-200, 200]. Third, the matching scores may be following different statistical distributions, e.g., one matching module may provide Gaussian, while another one may provide Weibull distribution. Normalization of scores can take care of these issues. Therefore, developing a suitable normalization technique is of crucial importance in a multimodal biometric system.

In score-level fusion, the overall performance of a multimodal biometric system can be affected by the performance of multiple matching modules, since one matching module may provide a higher error rate than that provided by another [5]. As a result, the overall recognition accuracy of a multimodal biometric system may not be higher than that of the unimodal biometric systems using one of the biometric sources from the former system. Therefore, estimation of weights of multiple matching modules in order to improve the recognition rate of multimodal biometric systems is an essential task.

1.2 A Brief Literature Review on Fusion, Normalization, and Weighting Techniques for Multimodal Biometric Systems

Many techniques of fusion, normalization, and weighting have been recently proposed for multimodal biometric systems.

It has been shown in the literature that techniques for fusion play an important role for improving the recognition rate of a multimodal biometric system [6–98]. There exist several fusion techniques for consolidating multiple biometric sources at sensor [6–8], rank [9–25], decision [26–33], feature [34–68], or score [69–98] level. In sensor-level fusion, multiple biometric sources are fused before extracting the features from them. There are a few techniques that have been proposed for this level of fusion based on texture, depth, or mosaicking method [8]. The sensor-level fusion is not popular for multimodal biometric systems, since it requires additional cost or time to develop new feature extraction and matching algorithms for the fused biometric data. In a rank-level fusion, ranking lists obtained from the individual matching modules are consolidated to form a fused ranking list for final decision. A few rank-level fusion techniques have been developed based on fuzzy logic [16], logistic regression [19], Markov chain, the highest rank methods, or Borda count method [25]. Rank-level fusion has not drawn much attention, since this level of fusion can only be applied for the purpose of identification. Multiple decisions are consolidated in order to make a final decision for identifying an individual under decision-level fusion. Some work based on "AND"/"OR", voting methods, Bayesian decision, Dempster-Shafer theory of evidence [1], hyperbolic functions [28], and posterior probability [29] has been done for decision-level fusion. This level of fusion has not drawn much attention of the researchers, since the information at the decision-level fusion is not sufficient for improving the recognition rate of the multimodal biometric system. In a feature-level fusion, features extracted from multiple biometric sources are consolidated to create a fused feature set. Many feature-level fusion techniques based on multi-resolution Log-Gabor filter [34], discriminant correlation analysis [39], shapes extracted from features [50], particle swarm optimization [51], and transformation of features [67] have been proposed. Since features contain richer information about a biometric data, feature-level fusion has drawn much attention of the researchers. However, in the existing feature-level fusion techniques, it is required to find a relationship between multiple feature sets, normalize the feature values if their ranges are different, and/or reduce the dimension of the fused feature set. In the score-level fusion, the scores obtained from the multiple matching modules are consolidated to obtain a fused score set. Many score-level fusion techniques based on arithmetic operations, such as addition, subtraction, maximum, minimum, or median [1] have been developed. Score-level fusion has also drawn much attention of the researchers, since scores are easy to combine and most of the vendors allow to access the scores, and the recognition rate of a multimodal biometric system can be improved significantly under the score-level fusion. However, the score-level fusion techniques fail to improve the recognition rate of a multimodal biometric system in cases where scores are non-homogeneous, have different statistical distributions or have different numerical scales [1]. In view of the advantages of the feature-level and score-level fusions over the other levels of fusion and in order to improve the recognition accuracy over that of the existing schemes, there is a need to investigate new fusion schemes for a multimodal biometric system involving these two levels of fusion.

It is known that the recognition accuracy of a multimodal biometric system is highly dependent on normalization of the scores obtained from multiple matching modules [99]. Many normalization techniques have been developed for normalizing scores in a multimodal biometric system [4, 99–111]. In the min-max (MM) normalization technique [4], the minimum and maximum values of the raw matching scores are utilized to transform multiple scores into a common range of [0, 1]. Although the

MM technique is the most commonly used normalization technique due to its simplicity and good performance in a multimodal biometric system, it is highly sensitive to outliers. In order to overcome the limitation of MM, a new normalization technique has been developed based on median and median absolute deviation (MAD) which are insensitive to outliers [4]. However, this technique cannot transform the raw matching scores obtained from individual biometric systems of a multimodal biometric system into a common numerical range. Decimal scaling (DS) normalization technique [4] has been developed to normalize scores based on a logarithmic scale. The limitation of the DS normalization technique is that it requires raw matching scores to be on a logarithmic scale. The z-score (ZS) normalization technique [4] utilizes the average and standard deviation to normalize the raw matching scores. However, it does not guarantee a common numerical range of normalized scores obtained for individual biometric systems of a multimodal biometric system. Some normalization techniques, such as TanH [4], have been developed based only on the genuine scores of the matching scores for normalizing the scores. However, the TanH normalization technique requires the estimation of some parameters using Hampel influence function [112]. And, it does not consider the impostor scores of the matching scores for normalizing the raw scores. Most recently, normalization techniques based on threshold values have been developed [109, 110]. For example, the performance anchored min-max (PAN-MM) normalization technique utilizes the threshold values based on the errors of the individual biometric matching modules to normalize the scores [110]. However, these techniques require a prior knowledge of the errors of each of the individual biometric matching modules of a multimodal biometric system. It is to be noted that the error in recognition results from the scores common to both the genuine and impostor scores [101]. In the existing normalization techniques, the scores that are common to both the genuine and impostor score sets have not been taken into consideration. Therefore, it is worth taking into account the information provided by these common score values for developing new normalization techniques that could possibly improve the overall recognition accuracy of a multimodal biometric system.

It is known that the recognition accuracy of a multimodal biometric system is highly dependent on the weights assigned to the various matching modules [101, 113–119]. There exist several weighting techniques for estimating the weights of the multiple matching modules of a multimodal biometric system [101, 113–119]. The equal error rate weighting (EERW) technique is one of the most popular techniques in which the errors of the corresponding individual unimodal systems are considered to estimate the weights of multiple matching modules [101]. However, EERW fails to improve the recognition rate in the case, where there is significant difference between the highest and lowest errors provided by the various matching modules. Most of the weighting techniques such as D-prime weighting (DPW) and Fisher discriminant ratio weighting (FDRW) techniques, have been developed based on the genuine and impostor scores, in which the separability of the genuine and impostor score distributions are considered [101, 118]. However, in these techniques, the common values between the genuine and impostor scores that may reduce the recognition accuracy of a multimodal biometric system are not taken into consideration. In the existing weighting techniques, the reliability of the individual matching scores is not considered in order to estimate the weights of the matching modules. Therefore, the reliability of the matching scores can be utilized for developing new weighting techniques for improving the recognition accuracy of multimodal biometric systems.

1.3 Objectives and Organization of the Thesis

The objective of this thesis is to study techniques for feature-level and score-level fusions, and apply these techniques in multimodal biometric systems for reducing the error rate and improving the overall recognition accuracy. For this purpose, in this thesis, we focus on developing new fusion techniques by integrating feature-level and score-level fusions for the first time to the best of our knowledge. As mentioned earlier in this chapter, normalization and weighting play an important role for improving the accuracy of a multimodal biometric system under the score-level fusion. Hence, we first develop new normalization and weighting techniques. These normalization and weighting techniques are then employed to the existing and the proposed fusion schemes in order to show their effectiveness in improving the performance of multimodal biometric systems.

In Chapter 2, a brief review of multimodal biometric systems is presented. Various levels of fusion for multimodal biometric systems are discussed. Most commonly used fusion rules, namely, simple-sum and weighted-sum fusion rules, for combining multiple matching scores at score-level fusion are also discussed. The standard metrics for evaluating the performance of a biometric system are introduced. Finally, the design of two multi-biometric databases using unimodal biometric databases for evaluating the performance of a multimodal biometric system for this thesis is presented.

In Chapter 3, methods for constructing matching scores for each of the samples of an individual of a unimodal biometric database is discussed. The procedure to separate the genuine and impostor scores from the matching scores is also discussed. Four normalization techniques based on these scores for a multimodal biometric system under score-level fusion are proposed. The performance of the multimodal biometric system under the score-level fusion (MBS-SL) is investigated utilizing the proposed normalization techniques and compared to that using the existing normalization techniques in terms of equal error rate, genuine acceptance rate, receiver operating characteristics, and detection error tradeoff curve.

In Chapter 4, two weighting techniques are proposed for a multimodal biometric system under score-level fusion. In order to assign appropriate weights for the matching scores using the proposed weighting techniques that are based on the matching scores without any distinction or with distinction of their being genuine or impostor, are presented. The performance of the MBS-SL using the proposed weighting techniques is compared to that using the existing weighting techniques in terms of equal error rate, genuine acceptance rate, receiver operating characteristics, and detection error tradeoff curve. Finally, this experiment is repeated by incorporating the various proposed and existing normalization techniques.

In Chapter 5, a new multimodal biometric system, referred to as the multimodal biometric system with feature level and score level (MBS-FSL) fusions, based on incorporating both the feature-level and score-level fusions is proposed. In this system, we first encode the features of individual modalities, and based on these encoded features, we then determine the modalities that should be used for the feature-level fusion. Next, for the feature-level fusion, a technique to fuse the encoded features of the selected modalities is devised. A score-level fusion is then carried out to fuse the score obtained from the feature-level fusion and that from the modality that was not utilized in the feature-level fusion. The performance, in terms of the various metrics, provided by this multimodal biometric system, MBS-FSL, is then compared to that provided by the existing MBS-SL, under different normalization and weighting techniques.

In Chapter 6, another multimodal biometric system, referred to as the multimodal biometric system with modified feature level and score level (MBS-MFSL) fusions, is developed for further improving the recognition accuracy. This system is implemented in two stages. In the first stage of this system, the feature-level fusion is carried out in a manner similar to that of MBS-FSL system, described in the previous chapter. In the second stage, a score-level fusion is carried out to fuse the score obtained from the feature-level fusion, the score from the modality that was not utilized in the feature-level fusion, and the scores from individual modalities by using their raw features. The performance provided by this multimodal biometric system, MBS-MFSL, is then compared to that provided by MBS-FSL, proposed in Chapter 5, under various normalization and weighting techniques in terms of the various metrics.

Finally, some concluding remarks followed by scope for further research are presented in Chapter 7.

Chapter 2

Background Material

In security applications, biometric has become the most reliable and efficient identifier for authentication of a person. An optimal biometric system aims to satisfy some properties such as permanence, universality, collectivity, acceptability, distinctiveness and security [3]. Unimodal biometric systems are not optimal, since there is no single biometric trait that has all of the above mentioned properties. In order to design an optimal authentication system, multimodal biometric systems are introduced in which multiple biometric sources of information are integrated.

In this chapter, first, multiple biometric sources of information and levels of fusion for multimodal biometric systems are discussed. Then, fusion rules and performance evaluation metrics that are commonly utilized in multimodal biometric systems are described. Finally, databases used in this thesis for evaluating the performance of multimodal biometric systems are discussed in detail.

2.1 Multimodal Biometric Systems

Multimodal biometric systems consolidate multiple sources of biometric information. Therefore, there are several issues for implementing a multimodal biometric system, such as availability of sources of information, selection of biometric traits, techniques for fusion, cost, processing time, and so on. In order to improve the recognition accuracy of a multimodal biometric system, sources of information and techniques for fusion are considered as the two main factors [25]. These two factors are discussed below in detail.

2.1.1 Sources of information for multimodal biometric systems

A multimodal biometric system may have five categories of sources of information as shown in Fig. 2.1. They are described as below.

Multiple sensors-single biometric trait: Under this category, multiple images of a single biometric trait captured using different sensors are used for authentication. For example, a multimodal biometric system may utilize fingerprint images captured using optical and capacitance sensors for identifying a person as shown in Fig. 2.1.

Multiple instances-single biometric trait: Under this category, an individual can be identified using multiple instances of a single biometric trait. For example, a multimodal biometric system can identify a person using his/her left and right palmprint images as shown in Fig. 2.1.

Multiple snapshots-single biometric trait: Under this category, multiple snapshots of an individual are used for authentication. For example, palmprint images with multiple rotations can be utilized to identify a person in a multimodal biometric system as shown in Fig. 2.1.

Multiple algorithms-single biometric trait: Under this category, an individual is identified using multiple algorithms for a single biometric trait. For example, a multimodal biometric system may use minutiae and texture based fingerprint matching modules to identify a person as shown in Fig. 2.1.

Multiple biometric traits: Under this category, multiple traits are used for person authentication. For example, a multimodal biometric system may use finger-

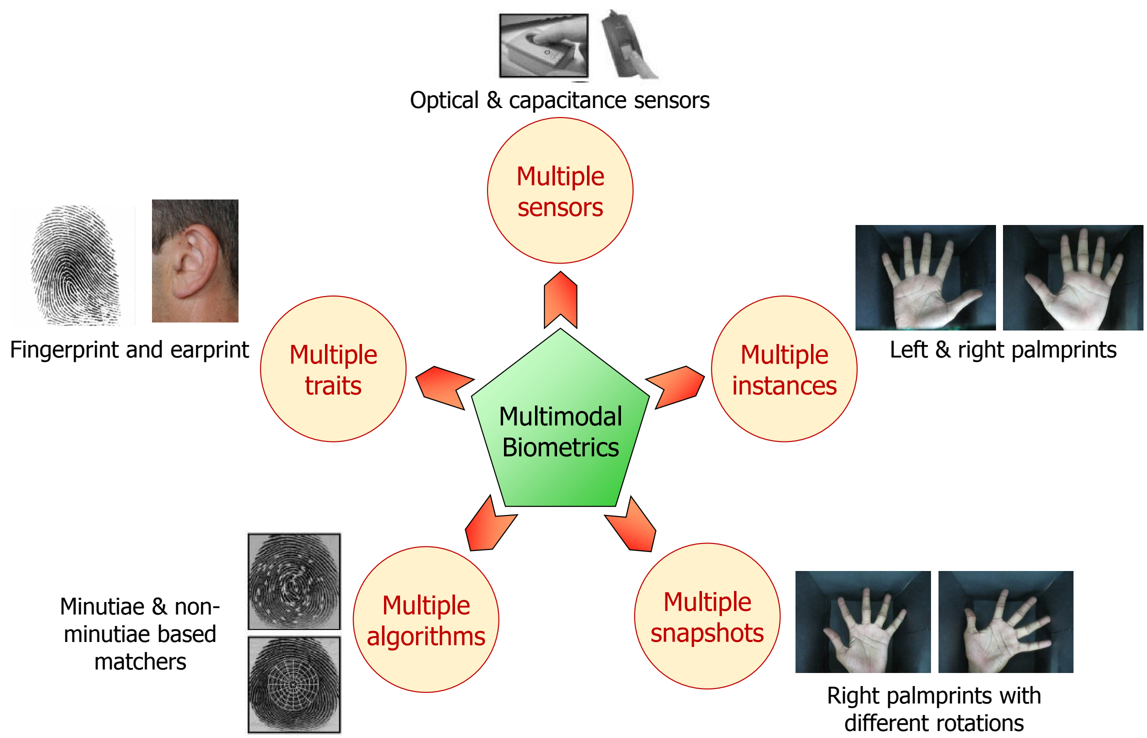

Figure 2.1: Sources of information in a multimodal biometric system

print and earprint for identifying a person as shown in Fig. 2.1.

2.1.2 Levels of fusion for multimodal biometric systems

Fusion is the main key in multimodal biometric systems, since it relies on the evidence from multiple sources of biometric information. In [120], authors categorized fusion methods into two main categories: pre-classification fusion and post-classification fusion. Pre-classification fusion is done before matching at sensor or feature level. Post-classification fusion is done after matching at score, rank or decision level. Fig. 2.2 shows these five levels of fusion for a multimodal biometric system using two sources of information.

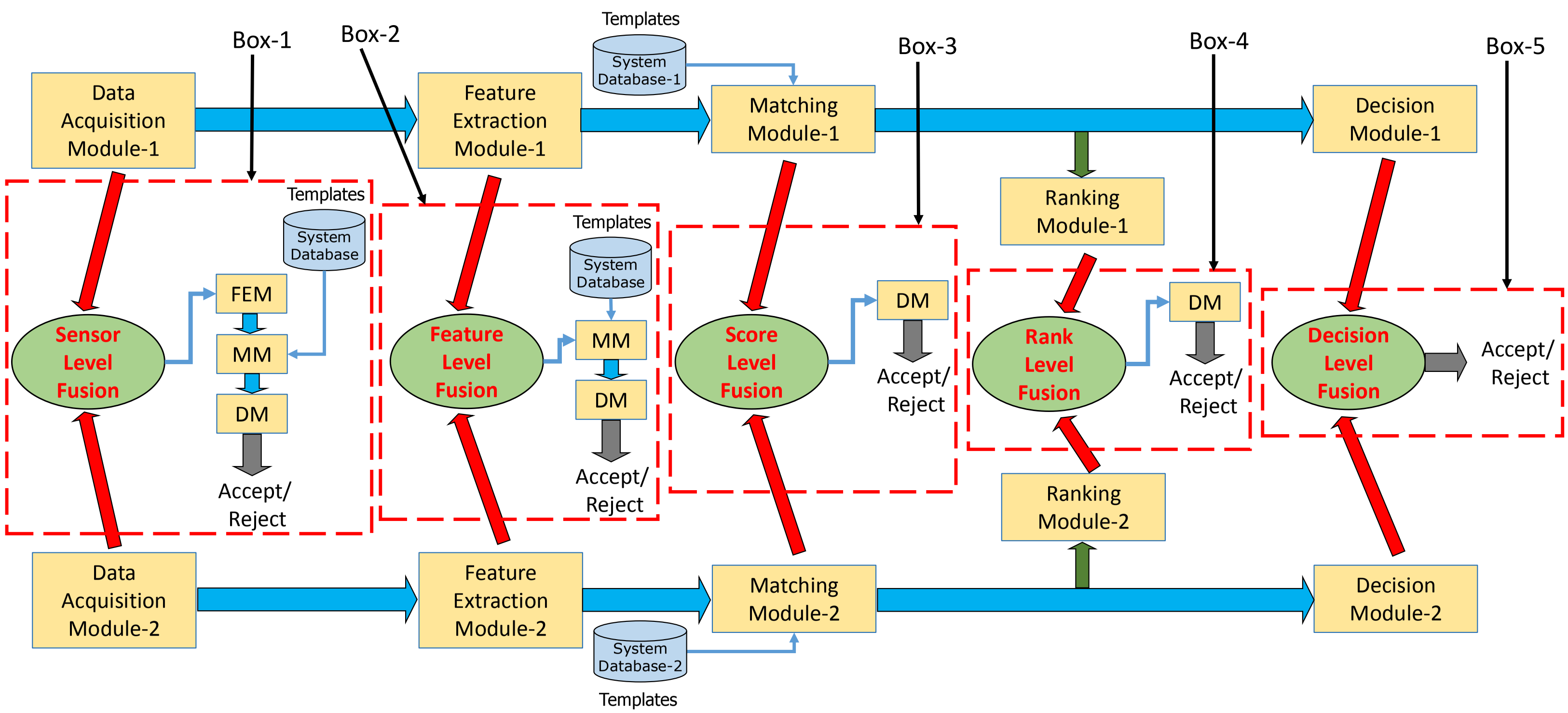

Figure 2.2: Levels of fusion in a multimodal biometric system for two sources of information (FEM-feature extraction module, MM-matching module, DM-decision module)

Sensor-level fusion: Biometric information obtained from different acquisition modules are consolidated under sensor-level fusion. The fused image obtained under sensor-level fusion is then passed through feature extraction and matching modules in order to make a final decision for identifying a person. Under this category, a multimodal biometric system requires one feature extraction module, one matching module, one decision module, and multiple sensors as can be seen from Box-1 of Fig. 2.2.

Feature-level fusion: Features obtained from multiple feature extractors are consolidated under this level of fusion. The fused feature set obtained under feature-level fusion is then passed through a matching module in order to make a final decision for identifying a person. As can be seen from Box-2 of Fig. 2.2, a multimodal biometric system requires one matching module, one decision module, and multiple feature extraction modules under feature-level fusion.

Score-level fusion: Scores obtained from multiple matching modules are consolidated under this level of fusion. The fused score set obtained under score-level fusion is then passed through a decision module in order to make a final decision for identifying a person. It can be seen from Box-3 of Fig. 2.2, a multimodal biometric system requires one decision module, and multiple matching modules under score-level fusion.

Rank-level fusion: In this case, ranks are assigned to scores obtained from multiple matching modules in order to form ranking lists. These ranking lists are then consolidated in order to obtain a fused ranking list under rank-level fusion. The fused ranking list obtained under this fusion level is then passed through a decision module in order to make a final decision for identifying a person. Under rank-level fusion, a multimodal biometric system requires one decision module, multiple matching modules, and multiple ranking modules as can be seen from Box-4 of Fig. 2.2.

Decision-level fusion: Decisions obtained from multiple decision modules are consolidated under this level of fusion. The fused decision obtained under decision-level fusion is the final decision for identifying a person. As can be seen from Box-5 of Fig. 2.2, a multimodal biometric system requires multiple decision modules under decision-level fusion.

2.2 Fusion Rules

In general, the matching scores obtained from multiple matching modules in a multimodal biometric system are combined using simple or weighted summation fusion rules. These rules are discussed below.

2.2.1 Simple sum rule-based fusion

The simple-sum (SS) fusion rule utilizes arithmetic summation to combine the matching scores obtained from multiple matching modules. The weights of multiple matching modules are not required to be estimated under SS fusion rule. The fused score $sf_{p,q}^{i,j}$ using the matching scores $s_{p,q}^{i,j}(k)$ for the k ($k = 1, 2, ...m$) modalities under SS fusion rule is computed as

$$sf_{p,q}^{i,j}(k) = \sum_{k=1}^{m} s_{p,q}^{i,j}(k) \tag{2.1}$$

where p corresponds to the p^{th} sample of the i^{th} person, q corresponds to the q^{th} sample of the j^{th} person, $(i, j = 1, 2, ..., M)$, and $(p, q = 1, 2, ..., N)$.

2.2.2 Weighted sum rule-based fusion

The weighted sum (WS) fusion rule utilizes the raw matching scores and the estimated weights of multiple matching modules to compute the fused score. The fused score $sf_{p,q}^{i,j}$ for the k ($k = 1, 2, ...m$) modalities under WS fusion rule is computed as

$$sf_{p,q}^{i,j}(k) = \sum_{k=1}^{m} w(k) s_{p,q}^{i,j}(k) \tag{2.2}$$

where $w(k)$ is the estimated weight for the modality k.

2.3 Metrics for Performance Evaluation of Biometric Systems

In a biometric system, the matching module provides a score value that is used by the decision module to identify an individual person. Based on a threshold value, a person is identified as a "genuine" or "impostor" if his score is higher or lower, respectively, than the selected threshold value. Therefore, the decision module in a biometric system may provide four possible outcomes based on the score and threshold values for a person: 1) the score value is higher than the threshold for a genuine individual and the person is identified as a genuine, 2) the score value is lower than the threshold for an impostor individual and the person is identified as an impostor, 3) the score value is higher than the threshold for an impostor individual and the person is identified as a genuine, or 4) the score value is lower than the threshold for a genuine individual and the person is identified as an impostor. The following error rates are established based on the above mentioned four possible decisions for identifying an individual [3].

1) *Genuine accept rate (GAR)* is computed as the ratio of the number of genuine people accepted as genuine ones to the total number of enrolled people for a predefined threshold [1].

2) *False accept rate (FAR)* is computed as the ratio of the number of impostor people accepted as genuine ones to the total number of enrolled people for a predefined threshold [1].

3) *False reject rate (FRR)* is computed as the ratio of the number of genuine people rejected as impostor ones to the total number of enrolled people for a predefined threshold [1].

4) *Equal error rate (EER)* is the point where FAR and FRR have the same

value [1]. The lower the EER value, the better is the biometric system.

In order to represent the recognition accuracy of a biometric system, GAR, FAR and FRR are used to plot different curves. The most commonly used curves are the receiver operating characteristic (ROC) and detection error tradeoff (DET) for evaluating the performance of a biometric system [1]. ROC curves are plotted in terms of GAR as a function of FAR. DET curves are plotted in terms of FRR as a function of FAR. Higher the value of GAR and lower the value of FRR, the better is the performance of a biometric system. Example ROC and DET curves are shown in Fig. 2.3. It can be seen from Fig. 2.3 (a) that ROC curve provides a higher value of GAR for a higher value of FAR. Fig. 2.3 (b) shows that DET curve provides a lower value of FRR for a higher value of FAR.

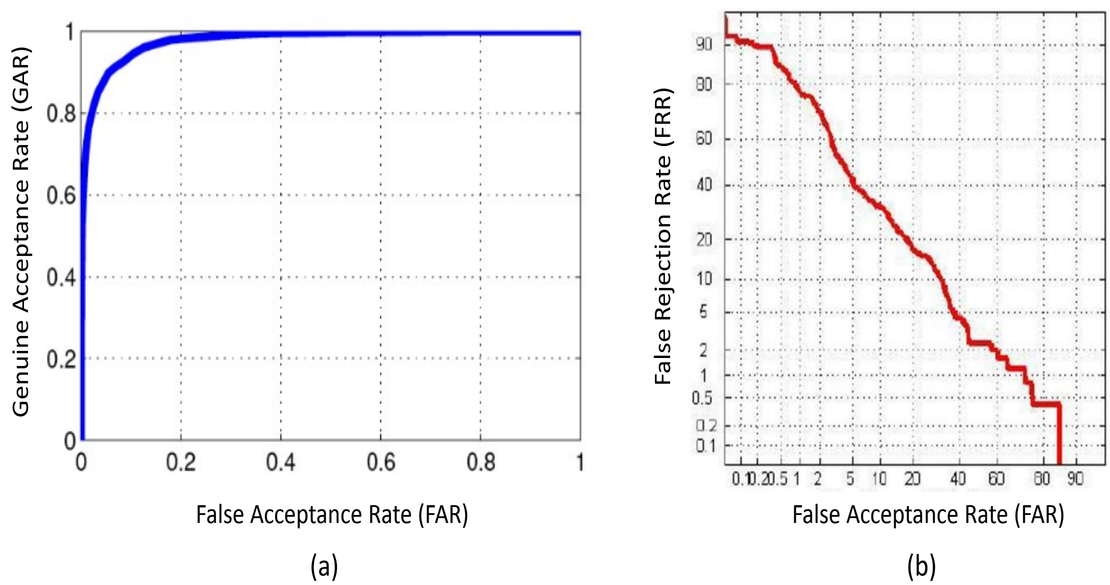

Figure 2.3: Example (a) Receiver Operating Characteristic (ROC) curve in terms of GAR as a function of FAR, and (b) Detection Error Tradeoff (DET) curve in terms of FRR as a function of FAR

2.4 Databases

Selection of a modality for a biometric system is an important task. Biometric modalities have varying amounts of the characteristics, such as universality, distinctiveness, collectability, and acceptability. Table 2.1 lists different modalities with the amount of their characteristics classified as high (H), medium (M) or low (L). Therefore, in the design of a biometric system one needs to choose a modality or modalities having these characteristics in the amounts as high as possible.

In some cases, there may be a situation in which the features of a given single modality of two different persons are correlated. However, the features of the same two individuals are likely to have lower probability to be correlated if more than two modalities are used. For example, the face features of monozygotic twins are generally correlated, whereas their fingerprint features may not be as correlated. Therefore, the use of more than one modality in a multimodal biometric system should increase the identification accuracy of the individuals.

We use three different modalities in order to show the improvement in the performance of a multimodal biometric system using the proposed normalization, weighting and fusion schemes of this thesis. In order to select three modalities, we first sort those biometric traits that have only high and medium amounts of the characteristics from Table 2.1. This sorting results in 4 biometric traits, namely, earprint, fingerprint, hand geometry and palmprint. It is to be noted that only the earprint amongst these 4 biometric traits is not from the same part of a human body. In addition, earprint can be easily captured from a distance without the full cooperation of the person. Thus, we consider earprint as one of the three modalities in this thesis. Next, we select two traits from fingerprint, hand geometry and palmprint, based on the total number of H amount of the characteristics. This sorting results in 2 traits, namely, fingerprint and palmprint, that have three H's whereas hand geometry has only one H. Therefore, we finally select earprint, fingerprint, and palmprint as the three modal-

Table 2.1: The characteristics of the various biometric identifiers with the amount High (H), Medium (M), or Low (L) [1]

Biometric identifier	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	M
Face	H	L	M	H	L	H	H
Facial thermogram	H	H	L	H	M	H	L
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand geometry	M	M	M	H	M	M	M
Hand vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Palmprint	M	H	H	M	H	M	M
Retina	H	H	M	L	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

ities in this thesis for evaluating the performance of a multimodal biometric system using the proposed normalization, weighting and fusion schemes.

The images of fingerprint, palmprint and earprint are obtained from four databases, namely, FVC2002-DB1-A fingerprint database [121], COEP and IITD palmprint databases [122–124] and AMI earprint database [125], respectively. These databases are described below.

2.4.1 FVC2002-DB1-A fingerprint database

This database was created for Second International Competition for Fingerprint Verification Competition (FVC) Algorithms. It contains fingerprints of 100 subjects and 8 samples per subject. In total, there are 800 gray-level images acquired through an optical sensor. The size and resolution of the images are 388 x 374 and 500 dpi, respectively. Fig. 2.4 shows some examples of fingerprint images from this database for a subject with six samples as follows: full fingerprint image in Fig. 2.4 (a), fingerprint images with partial top in Fig. 2.4 (b), with partial top and bottom in Fig. 2.4 (c), with rotation and scar in Fig. 2.4 (d), with pore and without core features in Fig. 2.4 (e), and partial fingerprint image with pore features in Fig. 2.4 (f).

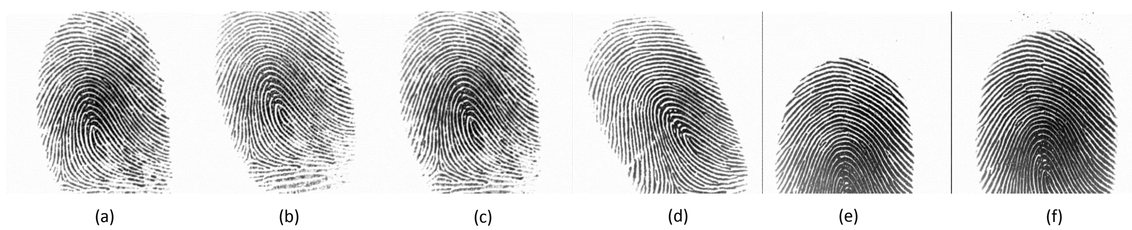

Figure 2.4: Example images from FVC2002-DB1-A fingerprint database for one subject with 6 samples

2.4.2 COEP palmprint database

This database contains palmprint images of 168 subjects in RGB-levels. Each subject has 8 samples of palmprints. The images are captured with a digital camera. The resolution of the images is 1600 x 1200 pixels. Fig. 2.5 shows some examples of palmprint images for a subject with six samples from this database.

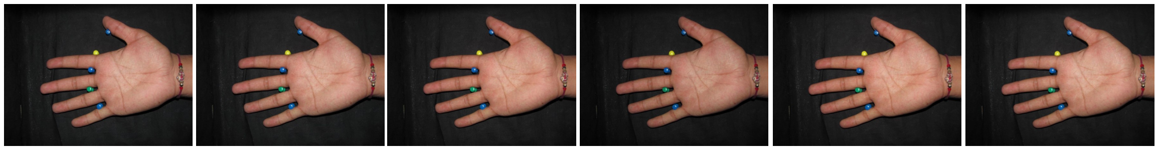

Figure 2.5: Example images from COEP palmprint database for one subject with 6 samples

2.4.3 IITD palmprint database

This database contains the hand images those are collected from the students and staffs of IIT Delhi, New Delhi, India. Images of this database are captured in an indoor environment with the employment of fluorescent illumination around the camera lens. It contains palmprint images of left and right hands of 235 users, with seven images from each subject with the variation of hand poses. The resolution of these palmprint images is 800×600 pixels. Fig. 2.6 shows some examples of palmprint images from this database for a subject with six samples: the first sample is without any rotation of the palm of the person as shown in Fig. 2.6 (a), the second, fifth and sixth samples are captured by rotating the palm of the person to the left direction as shown in Figs. 2.6 (b), (e) and (f), and the third and fourth samples are captured by rotating the palm of the person to the right direction as shown in Figs. 2.6 (c) and (d).

Figure 2.6: Example of images from IITD palmprint database for one subject with 6 samples with the variation of hand poses

2.4.4 AMI earprint database

This database contains ear images collected from students, teachers, and staff of the Computer Science department at Universidad de Las Palmas de Gran Canaria (ULPGC), Las Palmas, Spain. Images of this database are captured in an indoor environment. It contains earprint images of 100 subjects with 7 samples per subject in RGB-level. These 7 samples are as follows: right side profile of the person 1) facing forward, 2) looking up, 3) looking down, 4) looking left, 5) looking right, 6) zoomed earprint of the person facing forward, and 7) the left side profile of the person facing forward. The resolution of these earprint images is 492 x 702 pixels. Fig. 2.7 shows some examples of earprint images from this database for a subject with six samples: image of left ear that is named as 'back ear' in Fig. 2.7(a), and images of right ear of the person looking down that is named as 'down ear' in Fig. 2.7(b), facing forward that is named as 'front ear' in Fig. 2.7(c), looking left that is named as 'left ear' in Fig. 2.7(d), looking right that is named as 'right ear' in Fig. 2.7(e), and looking up that is named as 'up ear' in Fig. 2.7(f).

(a) (b) (c) (d) (e) (f)

Figure 2.7: Example images from AMI earprint database for one subject with 6 samples (a) back ear , (b) down ear, (c) front ear, (d) left ear, (e) right ear, and (f) up ear

2.4.5 Merged datasets of fingerprint, palmprint and earprint

Since we aim to evaluate the performance of a multimodal biometric system using the proposed normalization, weighting and fusion schemes of this thesis considering fingerprint, palmprint and earprint, it is necessary to have a dataset that contains features and scores of these three modalities. But, to the best of our knowledge, there is no such public-domain dataset that provides the features and matching scores of fingerprint, palmprint and earprint of the same individual. Therefore, we form two chimeric datasets in which the subjects are virtual, and refer these datasets as virtual multi-biometric dataset-1 (VMD-1) and virtual multi-biometric dataset-2 (VMD-2). We select 25 subjects and 6 samples per individual from FVC2002-DB1-A, COEP and AMI databases to build VMD-1. We select 25 subjects and 6 samples per individual from FVC2002-DB1-A, IITD and AMI databases to build VMD-2. Therefore, there are 150 images for each of the modalities in each virtual multi-biometric datasets. Since the palmprint images of the IITD database used to create the dataset VMD-2 have more variations of hand poses and less resolution than that of the COEP database used in the dataset VMD-1, the dataset VMD-2 is more challenging than the dataset VMD-1.

2.5 Summary

In this chapter, the two main factors, sources of information and levels of fusion for multimodal biometric systems are discussed with examples and block diagrams. Then, the simple-sum and weighted-sum rule-based fusions that are most commonly used for multimodal biometric systems are discussed. Various error rates and curves for evaluating the performance of a biometric system are also discussed. Finally, uni-biometric databases followed by the construction of multi-biometric datasets used for evaluating the performance of multimodal biometric systems by employing the proposed normalization, weighting and fusion schemes in this thesis are discussed in detail.

Chapter 3

Normalization Techniques for a Multimodal Biometric System under Score Level Fusion

3.1 Introduction

In score-level fusion, the fused score set is obtained by consolidating multiple scores from different matching modules using the simple-sum (SS) rule in a multimodal biometric system. These multiple scores from different matching modules may be non-homogeneous in the sense that one matching module may provide scores based on similarities between features, while another may provide scores based on dissimilarities between features. The multiple scores may be on different numerical scales, e.g., one matching module may provide score with the range of [0.58, 0.98], whereas another may provide score with the range of [-300, 300]. These multiple scores may also have different statistical distributions, e.g., one matching module may provide scores that follow Gaussian distribution while another one logarithmic distribution. The above mentioned three issues of score-level fusion can be solved by normalizing the multiple scores from different matching modules in order to improve the recognition rate of a multimodal biometric system. A general block diagram of a multimodal biometric system using two matching modules with the normalization of scores at the score-level fusion is shown in Fig. 3.1. This figure shows that scores

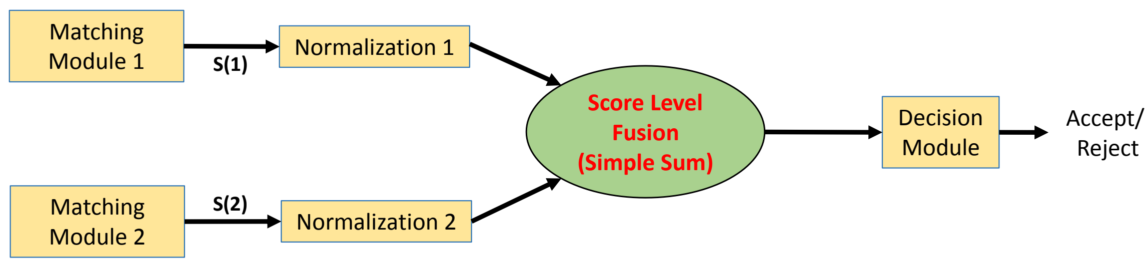

Figure 3.1: Score-level fusion for a multimodal biometric system using two matching modules with normalization of scores

from the two matching modules are normalized before applying simple arithmetic summation in score-level fusion for making a final decision. Many normalization techniques have been proposed for improving the recognition rate of a multimodal biometric system for the score-level fusion [4, 99–111]. Some of these [4, 99–105] have been developed based on the matching scores that are obtained from a matching module, such as min-max (MM) [4] and two-quadrics (QQ) [101]. The advantage of such normalization techniques is that they are simple. Limitations of these matching score-based normalization techniques are that they are sensitive to outliers, or require matching scores to be on a logarithmic scale, or cannot transform matching scores into a common range. A few normalization techniques [4, 106] have been developed based on the genuine scores, such as TanH [4] and reduction of high-scores effect (RHE) [106]. The advantage of such normalization techniques is that they are not sensitive to outliers. However, normalization techniques based on the genuine scores require Hampel influence function for estimating parameters. Some of the normalization techniques [107–111] have been developed based on threshold values, such as threshold alignment and range compression (TARC) [109] and performance anchored min-max (PAN-MM) [110]. The advantage of such normalization techniques is that they provide better recognition rate as compared with that provided by the first two categories of normalization techniques for a multimodal biometric system. Limitations of these techniques are that they require equal error rates (EER), false acceptance rates (FAR) or false rejection rates (FRR) of each unimodal biometric system in a multimodal biometric system. From the above discussion, it can be concluded that the existing normalization techniques have not made use of the impostor scores. Therefore, we investigate new normalization techniques that utilize not only the genuine scores, but also the impostor scores for improving the recognition rate of a multimodal biometric system at the score-level fusion.

In view of the requirement of genuine and impostor scores for implementing new normalization techniques at the score-level fusion for a multimodal biometric system, in this chapter, we first propose a method to separate these scores from the matching scores. Next, we propose various normalization techniques, using these genuine and impostor scores, for a multimodal biometric system [126–129]. The performance of the multimodal biometric system under the score-level fusion (MBS-SL) is then investigated utilizing the proposed normalization techniques and compared to that using the existing normalization techniques.

3.2 Separation of Genuine and Impostor Scores from Matching Scores

Information from the matching scores is an essential requirement for the score-level fusion in a multimodal biometric system. The matching scores can be divided into two types, namely, genuine and impostor scores. In this section, we develop a method to separate the genuine and impostor scores. First, the features of an image of an individual is compared with the other images of the individual, as well as with all the images of all the other individuals in order to construct the matching scores for a given modality k used in a multimodal biometric system. This comparison produces the matching scores denoted by $s_{p,q}^{i,j}(k)$, $p{\neq}q$ when $i{=}j$, where p corresponds to the p^{th} sample of the i^{th} person, q corresponds to the q^{th} sample of the j^{th} person, $(i, j = 1, 2, ..., M)$, and $(p, q = 1, 2, ..., N)$. Thus, $s_{p,q}^{i,j}(k)$ is undefined when p=q and i=j.

A genuine score is defined as the matching score obtained by comparing the features of an image of an individual with the other images of the same individual. Therefore, the genuine score set, $G(k)$, for the k^{th} modality is obtained as follows

$$G(k) = \{s_{p,q}^{i,j}(k)\} \; where \; p \neq q \tag{3.1}$$

An impostor score is defined as the matching score obtained by comparing the features of an image of an individual with all the images of all the other individuals. Therefore, the impostor score set, $I(k)$, for the k^{th} modality is obtained as follows

$$I(k) = \{s_{p,q}^{i,j}(k)\} \; where \; i \neq j \tag{3.2}$$

The matching scores are obtained by comparing the features of an image with the features of all other images in the dataset including the features of the image itself. Therefore, such a comparison occurs two times for each individual image in the dataset. The genuine and impostor scores can be separated easily by arranging the matching scores in a particular way. Such an arrangement is shown in Table 3.1 with an example in which we consider the matching scores for modality k (say, the fingerprint) of 3 individuals ($i, j = 1, 2, 3$) each having 2 samples ($p, q = 1, 2$).

Table 3.1: Matching scores of 3 persons each having 2 samples for the fingerprint modality ($i, j = 1, 2, 3; p, q = 1, 2$)

$$\mathbf{S}(\text{k}) \Longrightarrow \begin{array}{cc|cc|cc} - & \boldsymbol{s_{1,2}^{1,1}} & s_{1,1}^{1,2} & s_{1,2}^{1,2} & s_{1,1}^{1,3} & s_{1,2}^{1,3} \\ \boldsymbol{s_{2,1}^{1,1}} & - & s_{2,1}^{1,2} & s_{2,2}^{1,2} & s_{2,1}^{1,3} & s_{2,2}^{1,3} \\ \hline s_{1,1}^{2,1} & s_{1,2}^{2,1} & - & \boldsymbol{s_{1,2}^{2,2}} & s_{1,1}^{2,3} & s_{1,2}^{2,3} \\ s_{2,1}^{2,1} & s_{2,2}^{2,1} & \boldsymbol{s_{2,1}^{2,2}} & - & s_{2,1}^{2,3} & s_{2,2}^{2,3} \\ \hline s_{1,1}^{3,1} & s_{1,2}^{3,1} & s_{1,1}^{3,2} & s_{1,2}^{3,2} & - & \boldsymbol{s_{1,2}^{3,3}} \\ s_{2,1}^{3,1} & s_{2,2}^{3,1} & s_{2,1}^{3,2} & s_{2,2}^{3,2} & \boldsymbol{s_{2,1}^{3,3}} & - \end{array}$$

The matching score can be represented as a partitioned matrix for this example as follows.

$$\boldsymbol{S(k)} = \begin{bmatrix} \boldsymbol{S^{1,1}} & \boldsymbol{S^{1,2}} & \boldsymbol{S^{1,3}} \\ (\boldsymbol{S^{1,2}})^{\boldsymbol{T}} & \boldsymbol{S^{2,2}} & \boldsymbol{S^{2,3}} \\ (\boldsymbol{S^{1,3}})^{\boldsymbol{T}} & (\boldsymbol{S^{2,3}})^{\boldsymbol{T}} & \boldsymbol{S^{3,3}} \end{bmatrix} \tag{3.3}$$

where

$$\boldsymbol{S^{1,1}} = \begin{bmatrix} - & \boldsymbol{s^{1,1}_{1,2}} \\ \boldsymbol{s^{1,1}_{2,1}} & - \end{bmatrix} \tag{3.4}$$

$$\boldsymbol{S^{2,2}} = \begin{bmatrix} - & \boldsymbol{s^{2,2}_{1,2}} \\ \boldsymbol{s^{2,2}_{2,1}} & - \end{bmatrix} \tag{3.5}$$

$$\boldsymbol{S^{3,3}} = \begin{bmatrix} - & \boldsymbol{s^{3,3}_{1,2}} \\ \boldsymbol{s^{3,3}_{2,1}} & - \end{bmatrix} \tag{3.6}$$

$$\boldsymbol{S^{1,2}} = \begin{bmatrix} \boldsymbol{s^{1,2}_{1,1}} & \boldsymbol{s^{1,2}_{1,2}} \\ \boldsymbol{s^{1,2}_{2,1}} & \boldsymbol{s^{1,2}_{2,2}} \end{bmatrix} \tag{3.7}$$

$$\boldsymbol{S^{1,3}} = \begin{bmatrix} \boldsymbol{s^{1,3}_{1,1}} & \boldsymbol{s^{1,3}_{1,2}} \\ \boldsymbol{s^{1,3}_{2,1}} & \boldsymbol{s^{1,3}_{2,2}} \end{bmatrix} \tag{3.8}$$

and

$$\boldsymbol{S^{2,3}} = \begin{bmatrix} \boldsymbol{s^{2,3}_{1,1}} & \boldsymbol{s^{2,3}_{1,2}} \\ \boldsymbol{s^{2,3}_{2,1}} & \boldsymbol{s^{2,3}_{2,2}} \end{bmatrix} \tag{3.9}$$

The elements of the transpose matrices, $(\mathbf{S}^{1,2})^T, (\mathbf{S}^{1,3})^T$, $(\mathbf{S}^{2,3})^T$ are not included in the impostor scores, because of their symmetrical nature. Similarly, $s^{1,1}_{2,1}$, $s^{2,2}_{2,1}$ and $s^{3,3}_{2,1}$ are not included in the genuine scores, since $\mathbf{S}^{1,1}$, $\mathbf{S}^{2,2}$ and $\mathbf{S}^{3,3}$ are symmetric. Therefore, the genuine score set is $G(k) = \{s^{1,1}_{1,2}, s^{2,2}_{1,2}, s^{3,3}_{1,2}\}$ and the impostor score set is $I(k) = \{s^{1,2}_{1,1}, s^{1,2}_{1,2}, s^{1,2}_{2,1}, s^{1,2}_{2,2}, s^{1,3}_{1,1}, s^{1,3}_{1,2}, s^{1,3}_{2,1}, s^{1,3}_{2,2}, s^{2,3}_{1,1}, s^{2,3}_{1,2}, s^{2,3}_{2,1}, s^{2,3}_{2,2}\}$ for the fingerprint modality for this example.

3.3 Proposed Normalization Techniques

A score value that aligns the score distributions, named as anchor value, was introduced in [110]. In this work, the authors considered the score threshold value at the equal error rate (EER) as the anchor value. Therefore, their proposed method requires the score threshold value and EER of individual biometric systems for normalizing the scores. The MM normalization technique [4] transforms the matching scores into the common range of [0,1]. The authors in [110] have extended the range of the MM normalization technique by anchoring the middle point of the score range at $TH_{EER}(k)$ to obtain the normalized scores as

$$\bar{s}^{i,j}_{p,q}(k) = \begin{cases} \frac{s^{i,j}_{p,q}(k) - min\{G(k), I(k)\}}{2(TH_{EER}(k) - min\{G(k), I(k)\})}, & if\ s^{i,j}_{p,q}(k) \leq TH_{EER}(k) \\ 0.5 + \frac{s^{i,j}_{p,q}(k) - TH_{EER}(k)}{max\{G(k), I(k)\} - TH_{EER}(k)}, & if\ s^{i,j}_{p,q}(k) > TH_{EER}(k) \end{cases} \tag{3.10}$$

where $TH_{EER}(k)$ is the threshold value at the EER for the modality k. The first part of (3.10) provides a value of zero for $s^{i,j}_{p,q}(k) = min\{G(k), I(k)\}$, and a value of 0.5 for $s^{i,j}_{p,q}(k) = TH_{EER}(k)$, whereas the second part of (3.10) provides a value of 0.5 for $s^{i,j}_{p,q}(k) = TH_{EER}(k)$, and a value of 1.5 for $s^{i,j}_{p,q}(k) = max\{G(k), I(k)\}$. Therefore, the normalization technique presented in [110] using (3.10) transforms the matching scores into the common range of [0,1.5].

In our proposed normalization techniques, the anchor values are computed based on the matching scores, genuine and impostor scores as described in Sec. 3.2. Therefore, our proposed normalization techniques do not require score threshold value and EER of individual biometric systems for normalizing the scores. Our proposed normalization techniques are discussed below in detail.

3.3.1 Improved Anchored Min-max Normalization Technique

In this technique [126, 127], a new score set, $S_R(k)$, is constructed by selecting only those values of $G(k)$ and $I(k)$ that occur more than once, and refer it as repeated score set as shown in Fig. 3.2. Now, the mean and standard deviation of $S_R(k)$ are computed. The mean and standard deviation provide the information about the average and variation of the repeated scores of $G(k)$ and $I(k)$. Next, an anchor value is obtained by considering the summation of the mean and the standard deviation of $S_R(k)$. Finally, the normalized score is computed with this anchor value. The steps to compute the final fused score using the above mentioned anchor value are as follows.

(a) Select the score values that occur more than once in $G(k)$ and $I(k)$, construct a score set with those score values denoted by $S_R(k) = \{S_{R1}, S_{R2},....\}$. An example of matching scores with numerical values for modality k (say, the fingerprint) of 3 individuals (i.e., $i, j = 1, 2, 3$) each having 2 samples (i.e., $p, q = 1, 2$) is given in Table 3.2. Based on this example, the genuine score set is $G(k) = \{100, 100, 100\}$, and the impostor score set is $I(k) = \{40, 30, 44, 33, 20, 10, 25, 15, 40, 30, 20, 11\}$ for the fingerprint modality for this example. And, the repeated score set $S_R(k)$ is $S_R(k) = \{100, 40, 30, 20\}$.

(b) Compute the average and standard deviation of the set, $S_R(k)$, and denoted by $S_{Ravg}(k)$ and $S_{Rstd}(k)$, respectively,

$$S_{Ravg}(k) = mean(S_R(k)),\ S_{Rstd}(k) = std(S_R(k)) \tag{3.11}$$

(c) The anchor value for the modality k is then computed as follows

$$A(k) = S_{Ravg}(k) + S_{Rstd}(k) \tag{3.12}$$

(d) The above anchor value is then utilized as an operating point in (3.10) for

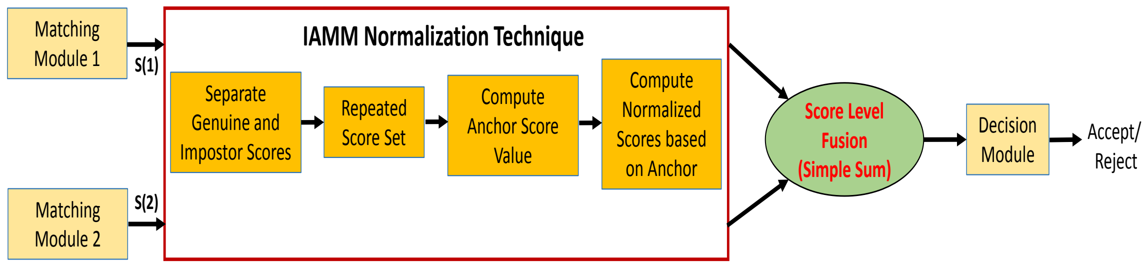

Figure 3.2: Score-level fusion for a multimodal biometric system using two matching modules with the proposed improved anchored min-max (IAMM) normalization technique

Table 3.2: Values of matching scores of 3 persons each having 2 samples for the fingerprint modality $(i, j = 1, 2, 3; p, q = 1, 2)$

-	100	40	30	20	10
100	-	44	33	25	15
40	44	-	100	40	30
30	33	100	-	20	11
20	25	40	20	-	100
10	15	30	11	100	-

normalizing the scores as

$$\bar{s}_{p,q}^{i,j}(k) = \begin{cases} \frac{s_{p,q}^{i,j}(k) - min\{G(k), I(k)\}}{2(A(k) - min\{G(k), I(k)\})}, & if\ s_{p,q}^{i,j}(k) \leq A(k) \\ 0.5 + \frac{s_{p,q}^{i,j}(k) - A(k)}{max\{G(k), I(k)\} - A(k)}, & if\ s_{p,q}^{i,j}(k) > A(k) \end{cases} \tag{3.13}$$

where $\bar{s}_{p,q}^{i,j}(k)$ is the normalized scores for the modality k, and $p \neq q$, if $i = j$. It is to be noted that the normalized scores obtained using the above steps with the anchor value in (3.12) is referred to as the *improved anchored min-max (IAMM)* normalization technique [126, 127].

The final fused score set of the multimodal biometric system is obtained using the SS rule at the score-level fusion. Then, this fused score is passed through the decision module for identifying an individual as shown in Fig. 3.2.

In general, the genuine and impostor scores have some common values in a multimodal biometric system. Therefore, there is an overlap region (OLR) between the genuine and impostor scores as shown in Fig. 3.3. The region of the genuine and impostor scores can be divided into three parts, such as A, B and C. The matching scores in parts A and C are clearly impostor and genuine scores, respectively, and these scores are shown as the non-overlap scores in Fig. 3.3. The matching score values in part B are common between the genuine and impostor scores, and these scores are shown as the overlap scores in Fig. 3.3. The overlap scores indicate that these values exist in both the genuine and impostor score sets. The recognition errors arise due to this overlap region of the genuine and impostor scores [101]. Therefore, the recognition accuracy of a multimodal biometric system can be improved by considering the information contained in the overlap scores of the genuine and impostor sets. In view of this, we consider two choices for the anchor values, and refer to them as the *overlap extrema-based anchor (OEBA)* and *mean-to-overlap extrema-based anchor (MOEBA)* values, which are obtained from the genuine and impostor scores. In order to obtain these anchor values, four parameters of the genuine and impostor scores, namely, $\min(G(k))$, $\mu(G(k))$, $\max(I(k))$ and $\mu(I(k))$, which are the minimum and mean values of the genuine scores, and maximum and mean values of the impostor scores, respectively, are utilized. We assume that a biometric source with high performance produces genuine scores that have a wide mean-to-max range and a wide mean-to-min impostor score range.

3.3.2 Overlap Extrema-Based Anchored Min-max Normalization Technique

In this technique [128], the anchor value is computed from the overlap region of the genuine and impostor scores. A low performance biometric system has a wide overlap area between the genuine and impostor scores. The lowest correct score values in the genuine and impostor sets are represented, respectively, by their minimum and maximum values. In order to obtain the anchor value taking the overlap region, more

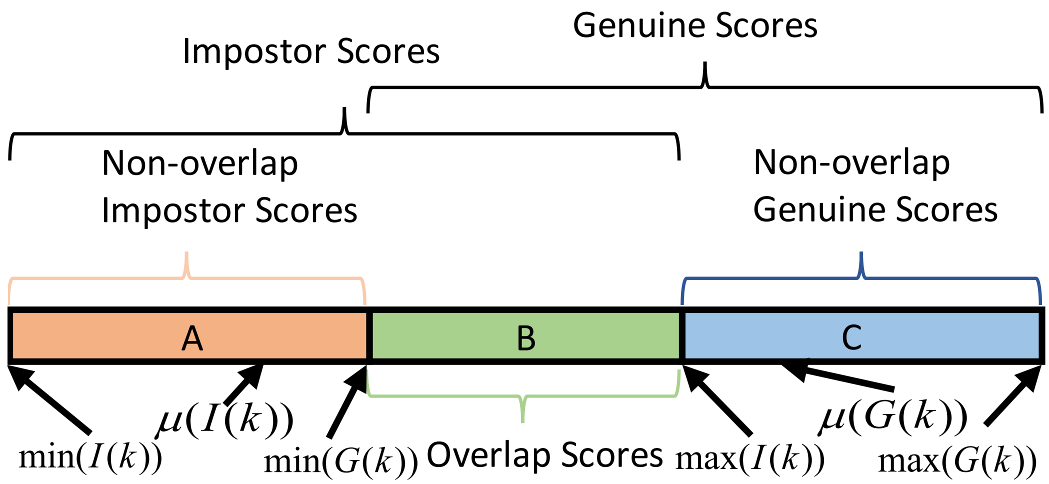

Figure 3.3: Genuine and impostor scores of a biometric system with overlap and non-overlap regions

precisely, overlap extremas into consideration, we compute the difference between the maximum of the impostor scores and the minimum of the genuine scores. Finally, the normalized score is computed with this anchor value. The steps to compute the final fused score using the above mentioned anchor value are as follows.

(a) First, separate the genuine $G(k)$ and impostor $I(k)$ scores from the matching scores for the modality k, as shown in Fig. 3.4, using the method described in Sec. 3.2.

(b) Compute the width of the OLR by taking the difference between the maximum of the impostor scores and the minimum of the genuine scores. The overlap extrema-based anchor (OEBA) value for the modality k, denoted by $A(k)$, in a multimodal biometric system is formulated as

$$A(k) = max(I(k)) - min(G(k)) \tag{3.14}$$

(c) The above anchor value is then utilized as an operating point in (3.10) for normalizing the scores as

$$\bar{s}_{p,q}^{i,j}(k) = \begin{cases} \frac{s_{p,q}^{i,j}(k) - min\{G(k),I(k)\}}{2(A(k) - min\{G(k),I(k)\})}, & if\ s_{p,q}^{i,j}(k) \leq A(k) \\ 0.5 + \frac{s_{p,q}^{i,j}(k) - A(k)}{max\{G(k),I(k)\} - A(k)}, & if\ s_{p,q}^{i,j}(k) > A(k) \end{cases} \tag{3.15}$$

where $\bar{s}_{p,q}^{i,j}(k)$ is the normalized scores for the modality k, and $p \neq q$, if $i = j$.

It is to be noted that the normalized scores obtained using the above steps with the anchor value $A(k)$ in (3.15) is referred to as the *overlap extrema-based anchored min-max (OEBAMM)* normalization technique [128].

The final fused score set of the multimodal biometric system is obtained using the SS rule at the score-level fusion. Then, this fused score is passed through the decision module for identifying an individual as shown in Fig. 3.4.

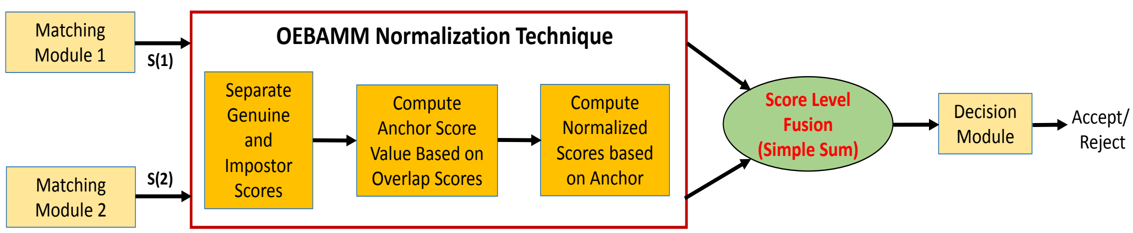

Figure 3.4: Score-level fusion for a multimodal biometric system using two matching modules with the proposed overlap extrema-based anchored min-max (OEBAMM) normalization technique

3.3.3 Mean-to-Overlap Extrema-Based Anchored Min-max Normalization Technique

In this case [128], the anchor value is computed considering the overlap scores and its neighbors in both the genuine and impostor scores. The region between the mean of the imposter scores and its maximum value, as well as that between the mean of the genuine scores and its minimum value are considered for computing the anchor value. Finally, the normalized score is computed with this anchor value. The steps to compute the final fused score using the above mentioned anchor value are as follows.

(a) First, separate the genuine $G(k)$ and impostor $I(k)$ scores from the matching scores for the modality k, as shown in Fig. 3.5, using the method described in Sec. 3.2.

(b) Compute the two differences as follows: i) the difference between the maximum and mean values of the impostor scores, and ii) the difference between the mean and minimum values of the genuine scores. The overlap extrema-based anchor (OEBA) value for the modality k, denoted by $A(k)$, in a multimodal biometric system is then computed by taking the summation of these two differences as

$$A(k) = \{max(I(k)) - \mu(I(k))\} + \{\mu(G(k)) - min(G(k))\} \tag{3.16}$$

(c) The above anchor value is then utilized as an operating point in (3.10) for normalizing the scores as

$$\bar{s}_{p,q}^{i,j}(k) = \begin{cases} \frac{s_{p,q}^{i,j}(k) - min\{G(k), I(k)\}}{2(A(k) - min\{G(k), I(k)\})}, & if\ s_{p,q}^{i,j}(k) \leq A(k) \\ 0.5 + \frac{s_{p,q}^{i,j}(k) - A(k)}{max\{G(k), I(k)\} - A(k)}, & if\ s_{p,q}^{i,j}(k) > A(k) \end{cases} \tag{3.17}$$

where $\bar{s}_{p,q}^{i,j}(k)$ is the normalized scores for the modality k, and $p \neq q$, if $i = j$.

It is to be noted that the normalized scores obtained using the above steps with the anchor value $A(k)$ in (3.17) is referred to as the *mean-to-overlap extrema-based anchored min-max (MOEBAMM)* normalization technique [128].

The final fused score set of the multimodal biometric system is obtained using the SS rule at the score-level fusion. Then, this fused score is passed through the decision module for identifying an individual as shown in Fig. 3.5.

3.3.4 Overlap Extrema-Variation-Based Anchored Min-max Normalization Technique

It is known that the lowest correct score values in the genuine and impostor score sets are represented by the minimum and maximum values of the corresponding sets [113].

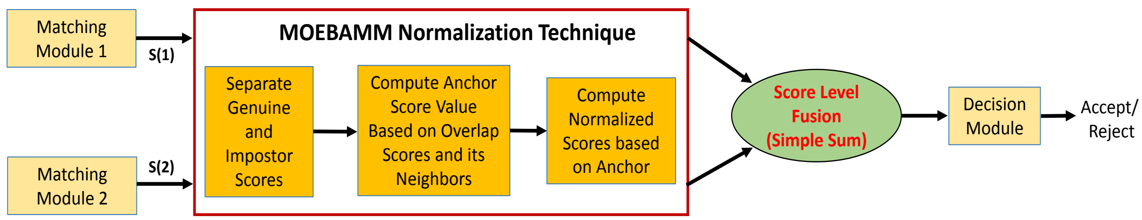

Figure 3.5: Score-level fusion for a multimodal biometric system using two matching modules with the proposed mean-to-overlap extrema-based anchored min-max (MOEBAMM) normalization technique

The variations of the genuine and impostor scores can be represented by the standard deviations in their corresponding sets. In this case [129], the anchor value is computed from the extrema and the standard deviations of the genuine and impostor score sets. It is assumed that a biometric source with high performance produces a small overlap area between the genuine and impostor scores, and the value of the standard deviations of these scores are smaller than the value of $\min(G(k))$. Based on this assumption, the ratio of the width of the overlap area and the difference between the standard deviations of the impostor and genuine scores would provide a smaller value than $\min(G(k))$ for a high performance biometric source. This ratio is considered as the anchor value for normalizing the scores. The steps to compute the final fused score using the above mentioned anchor value are as follows.

(a) First, separate the genuine $G(k)$ and impostor $I(k)$ scores from the matching scores for the modality k, as shown in Fig. 3.6, using the method described in Sec. 3.2.

(b) Compute the two differences as follows: i) the difference between the maximum value of the impostor scores and minimum value of the genuine scores, and ii) the difference between the standard deviations of the impostor and genuine scores. The overlap extrema-variation-based anchor (OEVBA) value for modality k, denoted by $A(k)$, in a multimodal biometric system is then computed by taking the ratio of these two differences as

$$A(k) = \frac{max(I(k)) - min(G(k))}{std(I(k)) - std(G(k))} \tag{3.18}$$

(c) The above anchor value is then utilized as an operating point in (3.10) for normalizing the scores as

$$\bar{s}^{i,j}_{p,q}(k) = \begin{cases} \frac{s^{i,j}_{p,q}(k) - min\{G(k),I(k)\}}{2(A(k) - min\{G(k),I(k)\})}, & if\ s^{i,j}_{p,q}(k) \leq A(k) \\ 0.5 + \frac{s^{i,j}_{p,q}(k) - A(k)}{max\{G(k),I(k)\} - A(k)}, & if\ s^{i,j}_{p,q}(k) > A(k) \end{cases} \tag{3.19}$$

where $\bar{s}^{i,j}_{p,q}(k)$ is the normalized scores for the modality k, and $p \neq q$, if $i = j$.

It is to be noted that the normalized scores obtained using the above steps with the anchor value $A(k)$ in (3.19) is referred to as the *overlap extrema-variation-based anchored min-max (OEVBAMM)* normalization technique [129].

The final fused score set of the multimodal biometric system is obtained using the SS rule at the score-level fusion. Then, this fused score is passed through the decision module for identifying an individual as shown in Fig. 3.6.

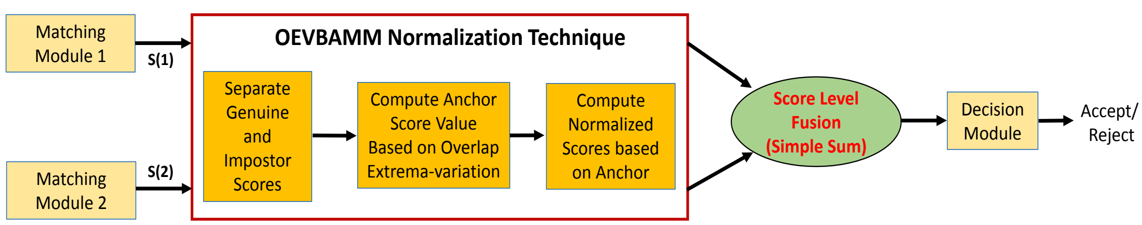

Figure 3.6: Score-level fusion for a multimodal biometric system using two matching modules with the proposed overlap extrema-variation-based anchored min-max (OEVBAMM) normalization technique

3.4 Experimental Results

The performance of the multimodal biometric system under the score-level fusion (MBS-SL) is evaluated by conducting experiments on the virtual multi-biometric datasets, namely, VMD-1 and VMD-2 discussed in Section 2.4.5. Then, a performance comparison is carried out between the unimodal biometric systems and MBS-SL using the proposed and existing normalization techniques. The values of equal error rate (EER) and GAR @0.5% FAR are used to provide quantitative evaluations of the unimodal biometric systems and of MBS-SL. Features and matching scores of the three modalities of the datasets are obtained by employing the techniques of feature extraction and matching as presented in [130–132].

Experiment 1: In this experiment, we study the performance of MBS-SL using the simple-sum (SS) rule without any normalization technique on the dataset VMD-1. Table 3.3 depicts EER(%) and GAR @0.5% FAR provided by the unimodal biometric systems and MBS-SL with no normalization. It is seen from this table that MBS-SL without normalization using the SS rule provides comparable or lower values of EER than that provided by the PP and EP unimodal biometric systems, respectively, but provides an EER value higher than that provided by the FP unimodal biometric system. It is also seen from this table that MBS-SL without normalization using the SS rule provides a higher value of GAR @0.5% FAR than that provided by the EP unimodal biometric system, but provides a GAR value lower than that provided by the FP and PP unimodal biometric systems. Therefore, it can be concluded that the FP unimodal biometric system is a better choice than MBS-SL without normalization technique using the SS rule.

Table 3.3: EER(%) and GAR @0.5% FAR provided by individual biometric systems and MBS-SL on the dataset VMD-1. (FP-Fingerprint, PP-Palmprint, EP-Earprint)

	Unimodal biometric systems			MBS-SL
	FP	PP	EP	SS Rule
EER(%)	3.47	6.64	45.01	6.67
GAR @0.5% FAR	89.33	88.53	8.27	81.6

Experiment 2: We now repeat Experiment 1 on the dataset VMD-2. Table 3.4 depicts the results of this experiment. It is seen from this table that MBS-SL without

normalization using the SS rule provides comparable or lower values of EER than that provided by the PP and EP unimodal biometric systems, respectively, but it provides an EER value higher than that provided by the FP unimodal biometric system. It is also seen from this table that MBS-SL without normalization using the SS rule provides a higher value of GAR @0.5% FAR than that provided by the PP and EP unimodal biometric systems, but provides a GAR value lower than that provided by the FP unimodal biometric system. Therefore, it can be concluded that the FP unimodal biometric system is a better choice than MBS-SL without normalization technique using the SS rule.

Table 3.4: EER(%) and GAR @0.5% FAR provided by individual biometric systems and MBS-SL on the dataset VMD-2. (FP-Fingerprint, PP-Palmprint, EP-Earprint)

	Unimodal biometric systems			MBS-SL
	FP	PP	EP	SS Rule
EER(%)	3.47	5.28	45.01	5.07
GAR @0.5% FAR	89.33	39.73	8.27	40.53

It is clear from these two experiments that there is no advantage of using MBS-SL over a unimodal biometric system, if no normalization is carried out.

Experiment 3: In this experiment, we study the performance of MBS-SL using

Table 3.5: EER(%) and GAR @0.5% FAR provided by MBS-SL using the proposed and existing normalization techniques under the SS rule on the dataset VMD-1

	MM	Z-score	PAN-MM	TanH	IAMM (proposed)	OEBAMM (proposed)	MOEBAMM (proposed)	OEVBAMM (proposed)
EER(%)	1.86	2.33	4.26	4.53	**0.56**	1.13	0.78	6.67
GAR @0.5% FAR	96.53	96.8	93.07	80.27	98.93	97.07	**99.2**	88.53

the proposed and existing normalization techniques on the dataset VMD-1. Table 3.5 depicts EER(%) and GAR @0.5% FAR provided by MBS-SL using the proposed and existing normalization techniques under the SS rule. It is seen from Tables 3.3 and 3.5 that MBS-SL using any of the proposed normalization techniques (except for OEVBAMM) provides an EER value lower and a GAR @0.5% FAR value higher than that provided by any of the unimodal biometric systems. It is also seen from Table 3.5 that MBS-SL using the proposed IAMM normalization technique provides the lowest EER value of 0.56% and the second highest GAR value of 98.93% @0.5% FAR, whereas the proposed MOEBAMM normalization technique provides the second lowest EER value of 0.78% and the highest GAR value of 99.2% @0.5% FAR.

Experiment 4: We now repeat Experiment 3 on the dataset VMD-2. Table 3.6 depicts the results of this experiment. It is seen from Tables 3.4 and 3.6 that MBS-SL using any of the proposed normalization techniques (except for OEVBAMM) provides an EER value lower and a GAR @0.5% FAR value higher than that provided by any of the unimodal biometric systems. It is seen from Table 3.6 that MBS-SL using the proposed IAMM normalization technique provides the lowest EER value of 1.6%, and the highest GAR value of 96.53% @0.5% FAR. Therefore, the proposed IAMM normalization technique is the best choice for MBS-SL in terms of EER and GAR @0.5% FAR.

Table 3.6: EER(%) and GAR @0.5% FAR provided by MBS-SL using the proposed and existing normalization techniques under the SS rule on the dataset VMD-2

	MM	Z-score	PAN-MM	TanH	IAMM (proposed)	OEBAMM (proposed)	MOEBAMM (proposed)	OEVBAMM (proposed)
EER(%)	3.47	2.66	6.89	6.2	**1.6**	3.19	2.72	5.6
GAR @0.5% FAR	87.2	95.73	41.87	76	**96.53**	91.73	94.4	72.27

We now further evaluate ROC and DET curves.

ROC and DET curves:

Figs. 3.7 and 3.8, respectively, show the ROC and DET curves of MBS-SL with the IAMM normalization technique on the datasets VMD-1 and VMD-2, and MBS-SL

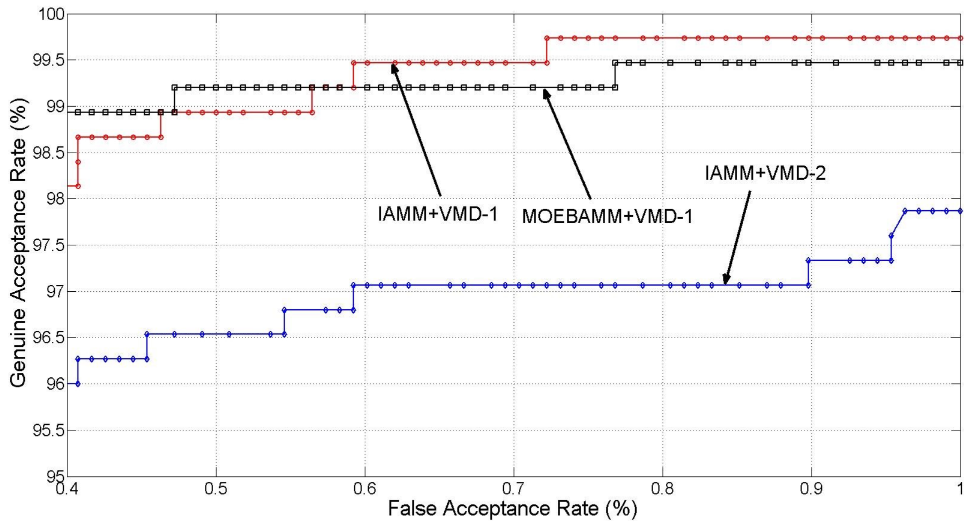

Figure 3.7: The best ROC curves of MBS-SL on the datasets VMD-1 and VMD-2

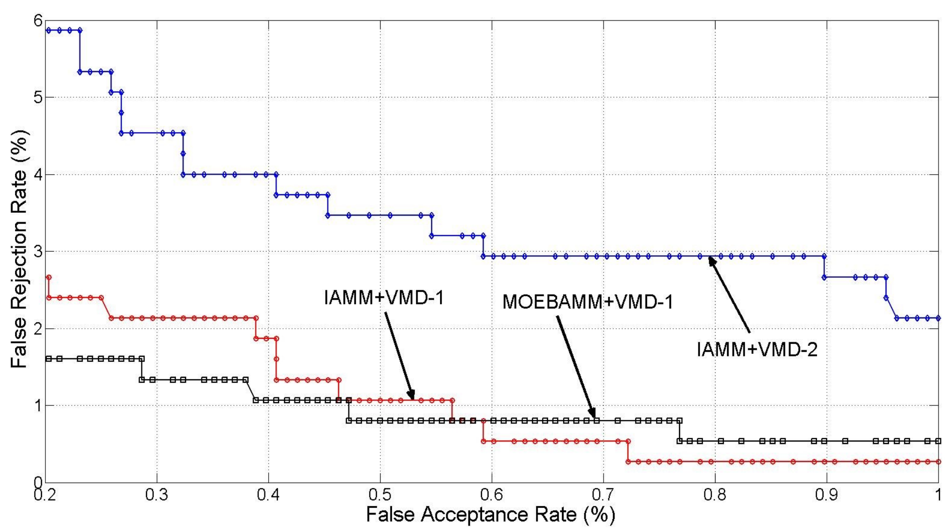

Figure 3.8: The best DET curves of MBS-SL on the datasets VMD-1 and VMD-2

with the MOEBAMM normalization technique on the dataset VMD-1. It is seen from these figures that MBS-SL with the IAMM normalization technique on the dataset VMD-1 provides GAR values higher and FRR values lower than MBS-SL with the MOEBAMM normalization technique. Since the dataset VMD-2 is more challenging dataset than the dataset VMD-1 as mentioned in Section 2.4.5, MBS-SL with the IAMM normalization technique provides a better performance on the latter dataset than that provided on the former.

The above finding in conjunction with the results already obtained based on Experiments 1 to 4 regarding EER and GAR @0.5% FAR, it can be concluded that the IAMM normalization technique is the best choice for MBS-SL irrespective of the dataset employed.

3.5 Summary

In this chapter, four new normalization techniques, namely, improved anchored min-max (IAMM), overlap extrema-based anchored min-max (OEBAMM), mean-to-overlap extrema-based anchored min-max (MOEBAMM) and overlap extrema-variation-based anchored min-max (OEVBAMM), have been developed based on the genuine and impostor scores. The performance of the multimodal biometric system under the score-level fusion (MBS-SL) with the simple-sum (SS) rule using the proposed normalization techniques has been studied in detail by conducting several experiments, and comparing the results with that using the existing normalization methods. The results have shown that a unimodal biometric system is a better choice than MBS-SL without normalization technique using the SS rule. Results have also shown that MBS-SL using the proposed IAMM normalization technique is the best choice in terms of EER, GAR @0.5% FAR, ROC curves and DET curves, irrespective of which dataset is considered.

In the next chapter, we will develop new weighting techniques for score level fusion, and evaluate the performance of a multimodal biometric system using these weighting techniques in conjunction with various normalization techniques including the ones developed in this chapter.

Chapter 4

Confidence-based Weighting Techniques for a Multimodal Biometric System under Score Level Fusion

4.1 Introduction

The error rates of different matching modules may not be the same in a multimodal biometric system. The recognition rate of such a multimodal system deteriorates due to the highest equal error rate (EER) or the lowest genuine acceptance rate (GAR) provided by a matching module under the simple-sum rule at the score-level (SL) fusion, as seen from the results of Chapter 3. It has been shown that for the SL fusion, the performance of a multimodal biometric system (MBS) can be improved over that of the simple-sum rule by using a sum of weighted scores from the various matching modules, and this has been referred to as the weighted-sum (WS) rule [114]. The main objective of a weighting technique is to assign appropriate weights for the scores of the various matching modules. A general block diagram of a multimodal biometric system with two matching modules using the estimated weights for the matching scores of the individual matching modules at the SL fusion is shown in Fig. 4.1. Many weighting techniques have been proposed for improving the recognition

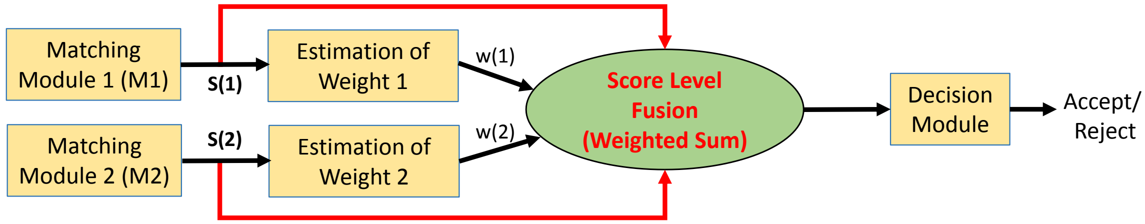

Figure 4.1: Score-level fusion for a multimodal biometric system using two matching modules with the estimation of their weights

rate of a multimodal biometric system [101, 113–119, 133]. These techniques have been developed based on the genuine and impostor scores or the equal error rate of individual matching modules. We now investigate new weighting techniques in order to improve the performance of a score level fusion [128, 134].

The first weighting technique uses the matching scores without any distinction of their being genuine or impostor, whereas the second one utilizes the scores with this distinction. The performance of the multimodal biometric system under the score-level fusion is compared to that using the existing weighting techniques.

4.2 Proposed Confidence-based Weighting Techniques

In this section, we first define reliability and confidence factors, and use these in proposing our weighting techniques. The reliability for the matching scores of a modality k is defined as

$$R^{i,j}_{p,q}(k) = \frac{|s^{i,j}_{p,q}(k) - \nu(k)|}{\nu(k)} \tag{4.1}$$

where $p \neq q$ when $i = j$, and the parameter $\nu(k)$ depends on the mean of the matching scores, or on the extremum and mean values of the genuine and impostor scores.

These scores are arranged in a particular way and this is illustrated through an example. Consider 3 individuals ($i, j = 1, 2, 3$) each having 2 samples ($p, q = 1, 2$) for modality k. This arrangement is given in Table 4.1 and is the same as that used for arranging the matching scores in Chapter 3 (see Table 3.1)

Table 4.1: Reliability of matching scores of 3 persons each having 2 samples for the fingerprint modality ($i, j = 1, 2, 3; p, q = 1, 2$)

$\mathbf{R}$(k) $\Longrightarrow$

-	$R_{1,2}^{1,1}$	$R_{1,1}^{1,2}$	$R_{1,2}^{1,2}$	$R_{1,1}^{1,3}$	$R_{1,2}^{1,3}$
$R_{2,1}^{1,1}$	-	$R_{2,1}^{1,2}$	$R_{2,2}^{1,2}$	$R_{2,1}^{1,3}$	$R_{2,2}^{1,3}$
$R_{1,1}^{2,1}$	$R_{1,2}^{2,1}$	-	$R_{1,2}^{2,2}$	$R_{1,1}^{2,3}$	$R_{1,2}^{2,3}$
$R_{2,1}^{2,1}$	$R_{2,2}^{2,1}$	$R_{2,1}^{2,2}$	-	$R_{2,1}^{2,3}$	$R_{2,2}^{2,3}$
$R_{1,1}^{3,1}$	$R_{1,2}^{3,1}$	$R_{1,1}^{3,2}$	$R_{1,2}^{3,2}$	-	$R_{1,2}^{3,3}$
$R_{2,1}^{3,1}$	$R_{2,2}^{3,1}$	$R_{2,1}^{3,2}$	$R_{2,2}^{3,2}$	$R_{2,1}^{3,3}$	-

The confidence factor is defined as

$$C(k) = \frac{\sum_{\forall i,j,p,q} R_{p,q}^{i,j}(k)}{n_R} \tag{4.2}$$

where $p \neq q$ when $i = j$, and n_R is the total number of elements in $\sum_{\forall i,j,p,q} R_{p,q}^{i,j}(k)$.

The weight for the matching scores of a modality k is computed as

$$w(k) = \frac{C(k)}{\sum_{k=1}^{m} C(k)} \tag{4.3}$$

where m is the total number of modalities. It is to be noted that, for the modality k, higher the reliability, larger is the confidence factor, since the denominator of (4.2) is constant for all values of k. It is also to be noted that, for the modality k, higher the confidence factor, larger is the weight assigned to that modality, since the denominator of (4.3) is constant for all values of k.

Now, we discuss the proposed confidence-based weighting techniques using equations (4.2) and (4.3).

4.2.1 Confidence Based Weighting Technique using the Mean Value of the Scores

In this section, we propose a weighting technique based on the matching scores without any distinction of their being genuine or impostor [134]. The general block diagram of the proposed weighting technique for the fusion of two modalities is shown in Fig. 4.2.

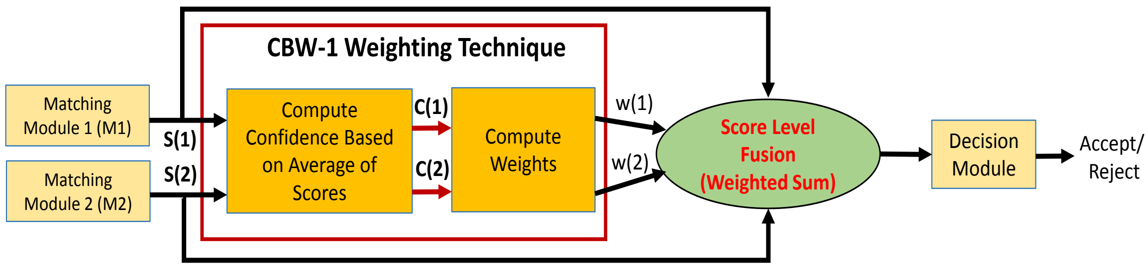

Figure 4.2: Score-level fusion for a multimodal biometric system using two matching modules with the proposed confidence-based weighting technique 1 (CBW-1)

First, the matching scores are obtained by utilizing the method described in Section 3.2. Then, the parameter $\nu(k)$ in (4.1) is chosen to be the average of the matching scores,

$$\nu(k) = \frac{\sum_{\forall i,j,p,q} s_{p,q}^{i,j}(k)}{n_s} \tag{4.4}$$

where $p \neq q$ when $i = j$, and n_s is the total number of elements in $\sum_{\forall i,j,p,q} s_{p,q}^{i,j}(k)$.

Next, the reliability for the matching scores of a modality k is obtained using (4.1). Then, the confidence factor and the weight for the matching scores of the modality k are computed using (4.2) and (4.3), respectively. We refer to this proposed weighting technique as *confidence-based weighting technique 1 (CBW-1)*.

The final score set for SL fusion of the multimodal biometric system is obtained using the WS rule. Then, this fused score is utilized by the decision module to identify the individual, as shown in Fig. 4.2.

To illustrate how the proposed CBW-1 weighting technique assigns appropriate weights to the individual matching scores, the following example is considered. Suppose the matching scores for modality 1 and modality 2 are as listed in Tables 4.2 and 4.3, respectively. The parameters $\nu(1)$ and $\nu(2)$ for the two modalities are obtained using (4.4) as 17.33 and 15.33, respectively. The reliabilities for the matching scores of the two modalities are obtained using (4.1), and these values are listed in Tables 4.4 and 4.5. The confidence factors $C(1)$ and $C(2)$ and the weights $w(1)$ and $w(2)$ for the matching scores for the two modalities are computed using (4.2) and (4.3), respectively, and these values are listed in Table 4.6. It is seen from this

Table 4.2: Matching scores of 3 persons each having 2 samples for modality 1 ($i, j = 1, 2, 3; p, q = 1, 2$)

$$
\mathbf{S}(1) \Longrightarrow
\begin{array}{cccccc}
\hline
- & \boldsymbol{s^{1,1}_{1,2}} & s^{1,2}_{1,1} & s^{1,2}_{1,2} & s^{1,3}_{1,1} & s^{1,3}_{1,2} \\
\boldsymbol{s^{1,1}_{2,1}} & - & s^{1,2}_{2,1} & s^{1,2}_{2,2} & s^{1,3}_{2,1} & s^{1,3}_{2,2} \\
\hline
s^{2,1}_{1,1} & s^{2,1}_{1,2} & - & \boldsymbol{s^{2,2}_{1,2}} & s^{2,3}_{1,1} & s^{2,3}_{1,2} \\
s^{2,1}_{2,1} & s^{2,1}_{2,2} & \boldsymbol{s^{2,2}_{2,1}} & - & s^{2,3}_{2,1} & s^{2,3}_{2,2} \\
\hline
s^{3,1}_{1,1} & s^{3,1}_{1,2} & s^{3,2}_{1,1} & s^{3,2}_{1,2} & - & \boldsymbol{s^{3,3}_{1,2}} \\
s^{3,1}_{2,1} & s^{3,1}_{2,2} & s^{3,2}_{2,1} & s^{3,2}_{2,2} & \boldsymbol{s^{3,3}_{2,1}} & - \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
- & \mathbf{50} & 30 & 20 & 10 & 5 \\
\mathbf{50} & - & 30 & 20 & 10 & 5 \\
\hline
30 & 30 & - & \mathbf{30} & 10 & 5 \\
20 & 20 & \mathbf{30} & - & 10 & 5 \\
\hline
10 & 10 & 10 & 10 & - & \mathbf{20} \\
5 & 5 & 5 & 5 & \mathbf{20} & - \\
\hline
\end{array}
$$

Table 4.3: Matching scores of 3 persons each having 2 samples for modality 2 ($i, j = 1, 2, 3; p, q = 1, 2$)

$$
\mathbf{S}(2) \Longrightarrow
\begin{array}{cccccc}
\hline
- & \boldsymbol{s^{1,1}_{1,2}} & s^{1,2}_{1,1} & s^{1,2}_{1,2} & s^{1,3}_{1,1} & s^{1,3}_{1,2} \\
\boldsymbol{s^{1,1}_{2,1}} & - & s^{1,2}_{2,1} & s^{1,2}_{2,2} & s^{1,3}_{2,1} & s^{1,3}_{2,2} \\
\hline
s^{2,1}_{1,1} & s^{2,1}_{1,2} & - & \boldsymbol{s^{2,2}_{1,2}} & s^{2,3}_{1,1} & s^{2,3}_{1,2} \\
s^{2,1}_{2,1} & s^{2,1}_{2,2} & \boldsymbol{s^{2,2}_{2,1}} & - & s^{2,3}_{2,1} & s^{2,3}_{2,2} \\
\hline
s^{3,1}_{1,1} & s^{3,1}_{1,2} & s^{3,2}_{1,1} & s^{3,2}_{1,2} & - & \boldsymbol{s^{3,3}_{1,2}} \\
s^{3,1}_{2,1} & s^{3,1}_{2,2} & s^{3,2}_{2,1} & s^{3,2}_{2,2} & \boldsymbol{s^{3,3}_{2,1}} & - \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
- & \mathbf{50} & 20 & 15 & 10 & 5 \\
\mathbf{50} & - & 20 & 15 & 10 & 5 \\
\hline
20 & 20 & - & \mathbf{30} & 10 & 5 \\
15 & 15 & \mathbf{30} & - & 10 & 5 \\
\hline
10 & 10 & 10 & 10 & - & \mathbf{20} \\
5 & 5 & 5 & 5 & \mathbf{20} & - \\
\hline
\end{array}
$$

Table 4.4: Reliability of matching scores of 3 persons each having 2 samples for modality 1 ($i, j = 1, 2, 3; p, q = 1, 2$) using the proposed CBW-1 weighting technique

$$
\mathbf{R}(1) \Longrightarrow
\begin{array}{cccccc}
\hline
\text{-} & R^{1,1}_{1,2} & R^{1,2}_{1,1} & R^{1,2}_{1,2} & R^{1,3}_{1,1} & R^{1,3}_{1,2} \\
R^{1,1}_{2,1} & \text{-} & R^{1,2}_{2,1} & R^{1,2}_{2,2} & R^{1,3}_{2,1} & R^{1,3}_{2,2} \\
\hline
R^{2,1}_{1,1} & R^{2,1}_{1,2} & \text{-} & R^{2,2}_{1,2} & R^{2,3}_{1,1} & R^{2,3}_{1,2} \\
R^{2,1}_{2,1} & R^{2,1}_{2,2} & R^{2,2}_{2,1} & \text{-} & R^{2,3}_{2,1} & R^{2,3}_{2,2} \\
\hline
R^{3,1}_{1,1} & R^{3,1}_{1,2} & R^{3,2}_{1,1} & R^{3,2}_{1,2} & \text{-} & R^{3,3}_{1,2} \\
R^{3,1}_{2,1} & R^{3,1}_{2,2} & R^{3,2}_{2,1} & R^{3,2}_{2,2} & R^{3,3}_{2,1} & \text{-} \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
\text{-} & 1.89 & 0.73 & 0.16 & 0.42 & 0.71 \\
1.89 & \text{-} & 0.73 & 0.16 & 0.42 & 0.71 \\
\hline
0.73 & 0.73 & \text{-} & 0.73 & 0.42 & 0.71 \\
0.16 & 0.16 & 0.73 & \text{-} & 0.42 & 0.71 \\
\hline
0.42 & 0.42 & 0.42 & 0.42 & \text{-} & 0.16 \\
0.71 & 0.71 & 0.71 & 0.71 & 0.16 & \text{-} \\
\hline
\end{array}
$$

Table 4.5: Reliability of matching scores of 3 persons each having 2 samples for modality 2 ($i, j = 1, 2, 3; p, q = 1, 2$) using the proposed CBW-1 weighting technique

$$
\mathbf{R}(2) \Longrightarrow
\begin{array}{cccccc}
\hline
\text{-} & R^{1,1}_{1,2} & R^{1,2}_{1,1} & R^{1,2}_{1,2} & R^{1,3}_{1,1} & R^{1,3}_{1,2} \\
R^{1,1}_{2,1} & \text{-} & R^{1,2}_{2,1} & R^{1,2}_{2,2} & R^{1,3}_{2,1} & R^{1,3}_{2,2} \\
\hline
R^{2,1}_{1,1} & R^{2,1}_{1,2} & \text{-} & R^{2,2}_{1,2} & R^{2,3}_{1,1} & R^{2,3}_{1,2} \\
R^{2,1}_{2,1} & R^{2,1}_{2,2} & R^{2,2}_{2,1} & \text{-} & R^{2,3}_{2,1} & R^{2,3}_{2,2} \\
\hline
R^{3,1}_{1,1} & R^{3,1}_{1,2} & R^{3,2}_{1,1} & R^{3,2}_{1,2} & \text{-} & R^{3,3}_{1,2} \\
R^{3,1}_{2,1} & R^{3,1}_{2,2} & R^{3,2}_{2,1} & R^{3,2}_{2,2} & R^{3,3}_{2,1} & \text{-} \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
\text{-} & 2.27 & 0.31 & 0.02 & 0.35 & 0.67 \\
2.27 & \text{-} & 0.31 & 0.02 & 0.35 & 0.67 \\
\hline
0.31 & 0.31 & \text{-} & 0.96 & 0.35 & 0.67 \\
0.02 & 0.02 & 0.96 & \text{-} & 0.35 & 0.67 \\
\hline
0.35 & 0.35 & 0.35 & 0.35 & \text{-} & 0.31 \\
0.67 & 0.67 & 0.67 & 0.67 & 0.31 & \text{-} \\
\hline
\end{array}
$$

Table 4.6: Confidence factors and estimated weights using the proposed CBW-1 weighting technique

Confidence factor C(1)=0.61	Confidence factor C(2)=0.55
Estimated weight w(1)=0.52	Estimated weight w(2)=0.47

table that the confidence factor for modality 2 is higher than that for modality 1, and hence, the estimated weight is larger for the former than that for the latter. Thus, the proposed weighting technique assigns a weight to the matching scores of modality 2 higher than that assigned to the matching scores of modality 1.

4.2.2 Confidence Based Weighting Technique using the Extremum and Mean Values of Genuine and Impostor Scores

In this section, we propose a weighting technique based on the matching scores with distinction of their being genuine or impostor [128]. We reproduce Fig. 3.3 of Chapter 3 as Fig. 4.3 for the sake of convenience. Unlike the existing weighting techniques in which only the averages of the genuine and impostor scores are utilized [101, 116, 118], we utilize the non-overlap scores as shown in Fig. 4.3 for estimating the weights. The general block diagram of the proposed weighting technique is shown in Fig. 4.4 for the fusion of two modalities. First, the genuine and impostor scores are obtained by utilizing the method described in Section 3.2. Next, we assume that the difference between the maximum and mean values for the genuine scores is small with a similar assumption for the difference between the mean and minimum values for the impostor scores, for any modality k. Based on this assumption, we define the parameter $\nu(k)$ in (4.1) to be

$$\nu(k) = \{max(G(k)) - \mu(G(k))\} + \{\mu(I(k)) - min(I(k))\} \tag{4.5}$$

where $\max(G(k))$, $\mu(G(k))$, $\min(I(k))$ and $\mu(I(k))$ are the maximum and mean values of the genuine scores, and minimum and mean values of the impostor scores, respectively.

It should be noted that the parameter $\nu(k)$ excludes the non-overlap scores that are close to the overlap region and emphasizes those that are far removed. The reason behind this is that the impostor scores that are close to the overlap region have values higher than $\mu(I(k))$ and the genuine scores that are close to the overlap region have values lower than $\mu(G(k))$.

Next, the reliability for the matching scores of a modality k is obtained using (4.1). Then, the confidence factor and the weight for the matching scores of the modality k

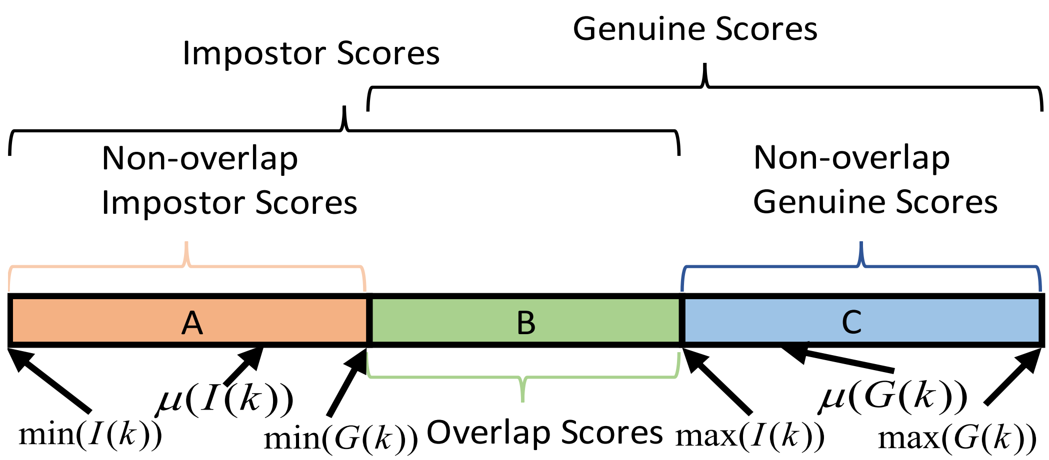

Figure 4.3: Genuine and impostor scores of a biometric system with overlap and non-overlap regions reproduced from Chapter 3

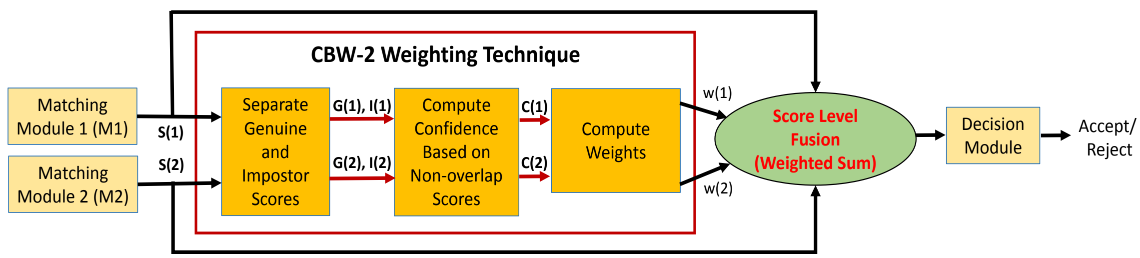

Figure 4.4: Score-level fusion for a multimodal biometric system using two matching modules with the proposed confidence-based weighting technique 2 (CBW-2)

are computed using (4.2) and (4.3), respectively. We refer to this proposed weighting technique as *confidence-based weighting technique 2 (CBW-2)*.

The final score set for SL fusion of the multimodal biometric system is obtained using the WS rule. Then, this fused score is utilized by the decision module to identify the individual, as shown in Fig. 4.4.

To illustrate how the proposed CBW-2 weighting technique assigns appropriate weights to the individual matching scores, the same matching scores for modality 1 and modality 2 that are listed in Tables 4.2 and 4.3, respectively, are considered. The genuine scores $G(1) = \{50, 30, 20\}$ and $G(2) = \{50, 30, 20\}$, and impostor scores

Table 4.7: Reliability of matching scores of 3 persons each having 2 samples for modality 1 ($i, j = 1, 2, 3; p, q = 1, 2$) using the proposed CBW-2 weighting technique

$$
\mathbf{R}(1) \Longrightarrow
\begin{array}{cccccc}
\hline
- & R_{1,2}^{1,1} & R_{1,1}^{1,2} & R_{1,2}^{1,2} & R_{1,1}^{1,3} & R_{1,2}^{1,3} \\
R_{2,1}^{1,1} & - & R_{2,1}^{1,2} & R_{2,2}^{1,2} & R_{2,1}^{1,3} & R_{2,2}^{1,3} \\
\hline
R_{1,1}^{2,1} & R_{1,2}^{2,1} & - & R_{1,2}^{2,2} & R_{1,1}^{2,3} & R_{1,2}^{2,3} \\
R_{2,1}^{2,1} & R_{2,2}^{2,1} & R_{2,1}^{2,2} & - & R_{2,1}^{2,3} & R_{2,2}^{2,3} \\
\hline
R_{1,1}^{3,1} & R_{1,2}^{3,1} & R_{1,1}^{3,2} & R_{1,2}^{3,2} & - & R_{1,2}^{3,3} \\
R_{2,1}^{3,1} & R_{2,2}^{3,1} & R_{2,1}^{3,2} & R_{2,2}^{3,2} & R_{2,1}^{3,3} & - \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
- & 1.0 & 0.2 & 0.2 & 0.6 & 0.8 \\
1.0 & - & 0.2 & 0.2 & 0.6 & 0.8 \\
\hline
0.2 & 0.2 & - & 0.2 & 0.6 & 0.8 \\
0.2 & 0.2 & 0.2 & - & 0.6 & 0.8 \\
\hline
0.6 & 0.6 & 0.6 & 0.6 & - & 0.2 \\
0.8 & 0.8 & 0.8 & 0.8 & 0.2 & - \\
\hline
\end{array}
$$

Table 4.8: Reliability of matching scores of 3 persons each having 2 samples for modality 2 ($i, j = 1, 2, 3; p, q = 1, 2$) using the proposed CBW-2 weighting technique

$$
\mathbf{R}(2) \Longrightarrow
\begin{array}{cccccc}
\hline
- & R_{1,2}^{1,1} & R_{1,1}^{1,2} & R_{1,2}^{1,2} & R_{1,1}^{1,3} & R_{1,2}^{1,3} \\
R_{2,1}^{1,1} & - & R_{2,1}^{1,2} & R_{2,2}^{1,2} & R_{2,1}^{1,3} & R_{2,2}^{1,3} \\
\hline
R_{1,1}^{2,1} & R_{1,2}^{2,1} & - & R_{1,2}^{2,2} & R_{1,1}^{2,3} & R_{1,2}^{2,3} \\
R_{2,1}^{2,1} & R_{2,2}^{2,1} & R_{2,1}^{2,2} & - & R_{2,1}^{2,3} & R_{2,2}^{2,3} \\
\hline
R_{1,1}^{3,1} & R_{1,2}^{3,1} & R_{1,1}^{3,2} & R_{1,2}^{3,2} & - & R_{1,2}^{3,3} \\
R_{2,1}^{3,1} & R_{2,2}^{3,1} & R_{2,1}^{3,2} & R_{2,2}^{3,2} & R_{2,1}^{3,3} & - \\
\hline
\end{array}
=
\begin{array}{cccccc}
\hline
- & 1.2 & 0.1 & 0.3 & 0.6 & 0.8 \\
1.2 & - & 0.1 & 0.3 & 0.6 & 0.8 \\
\hline
0.1 & 0.1 & - & 0.3 & 0.6 & 0.8 \\
0.3 & 0.3 & 0.3 & - & 0.6 & 0.8 \\
\hline
0.6 & 0.6 & 0.6 & 0.6 & - & 0.1 \\
0.8 & 0.8 & 0.8 & 0.8 & 0.1 & - \\
\hline
\end{array}
$$

$I(1) = \{30, 20, 30, 20, 10, 5, 10, 5, 10, 5, 10, 5\}$ and $I(2) = \{20, 15, 20, 15, 10, 5, 10, 5, 10, 5, 10, 5\}$ for the two modalities are obtained by utilizing the method described in Section 3.2. From these scores we obtain $max(G(1))$=50, $\mu(G(1))$=33.33, $\mu(I(1))$=13.33, $min(I(1))$=5 for modality 1, and $max(G(2))$=50, $\mu(G(2))$=33.33, $\mu(I(2))$=10.83, $min(I(2))$=5 for modality 2. Next, the parameters $\nu(1)$ and $\nu(2)$ for the two modalities are computed using (4.5) as 25 and 22.5, respectively. The reliabilities for the matching scores of the two modalities are obtained using (4.1), and these values are listed in Tables 4.7 and 4.8. The confidence factors $C(1)$ and $C(2)$ and the weights $w(1)$ and $w(2)$ for the matching scores for the two modalities are computed using (4.2) and (4.3), respectively, and these values are listed in Table 4.9. It is seen from this table that the confidence factor for modality 2 is higher than that for modality 1, and

Table 4.9: Confidence factors and estimated weights using the proposed CBW-2 weighting technique

Confidence factor C(1)=0.52	Confidence factor C(2)=0.53
Estimated weight w(1)=0.495	Estimated weight w(2)=0.505

hence, the estimated weight is larger for the former than that for the latter. Thus, the proposed weighting technique assigns a weight to the matching scores of modality 2 higher than that assigned to the matching scores of modality 1.

4.3 Experimental Results

The performance of the multimodal biometric system under the score-level fusion (MBS-SL) is evaluated by conducting experiments on the virtual multi-biometric datasets, namely, VMD-1 and VMD-2, as discussed in Section 2.4.5. Then, a performance comparison is carried out between MBS-SL using the proposed and existing weighting techniques. Next, the performance of MBS-SL using various normalization and weighting techniques is evaluated by conducting experiments on both VMD-1 and VMD-2. The values of EER and GAR @0.5% FAR are used to provide quantitative evaluations of MBS-SL.

Experiment 1: In this experiment, we study the performance of MBS-SL on the dataset VMD-1 using the two proposed weighting techniques, CBW-1 and CBW-2, as well as with the existing weighting techniques, but with no normalization. Table 4.10 depicts EER(%) and GAR @0.5% FAR provided by MBS-SL for the various weighting techniques. It is seen from this table that MBS-SL using the proposed CBW-2 weighting technique provides an EER value lower than that provided by MBS-SL using the existing weighting techniques. It is also seen that MBS-SL using the proposed CBW-2 and EERW provide a GAR @0.5% FAR value higher than that provided using the

Table 4.10: EER(%) and GAR @0.5% FAR provided by MBS-SL using the proposed and existing weighting techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
EER(%)	6.13	6.40	6.66	6.62	**5.86**
GAR @0.5% FAR	**89.87**	89.33	88.8	82.4	**89.87**

remaining weighting techniques. It is seen from Tables 4.10 and 3.3 that there is no advantage to be gained by using MBS-SL by simply employing a weighting technique without normalization over using unimodal biometric systems, since the lowest EER and the highest GAR @0.5% FAR are provided by the fingerprint unimodal biometric system in the present case.

Experiment 2: We now repeat Experiment 1 on the dataset VMD-2. Table 4.11 depicts the results of this experiment. It is seen from this table that MBS-SL using either of the proposed weighting techniques provides EER and GAR @0.5% FAR values lower and higher, respectively, than that provided by MBS-SL using the existing weighting techniques. It is seen from Tables 4.11 and 3.4 that there is no advantage to be gained by using MBS-SL by simply employing a weighting technique without normalization over using unimodal biometric systems, since the lowest EER and the highest GAR @0.5% FAR are provided by the fingerprint unimodal biometric system in the present case.

It is clear from these two experiments that there is no advantage of using MBS-SL

Table 4.11: EER(%) and GAR @0.5% FAR provided by MBS-SL using the proposed and existing weighting techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
EER(%)	5.27	5.28	5.27	**5.07**	**5.07**
GAR @0.5% FAR	39.73	39.73	39.73	40.53	**40.8**

over a unimodal biometric system, if no normalization is carried out.

Experiment 3: In this experiment, we study the performance of MBS-SL on the dataset VMD-1 using the various normalization and weighting techniques. Tables 4.12 and 4.13 depict EER(%) and GAR @0.5% FAR, respectively, provided by MBS-SL for the various normalization and weighting techniques. In these tables, individual columns correspond to EERs and GARs @0.5% FARs provided by MBS-SL using a given weighting technique for the various normalization techniques. The lowest EER and the highest GAR @0.5% FAR are indicated in boldface. It is seen from these tables that there are seven cases where MBS-SL provides the lowest EER value of 0.54% and the highest GAR value of 99.48% @0.5% FAR. These seven cases provide an EER value lower than and a GAR @0.5% FAR value higher than that provided

Table 4.12: EER(%) provided by MBS-SL using the various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	**0.54**	1.34	2.66	0.79	**0.54**
Z-score	2.93	0.86	0.54	2.93	2.67
PAN-MM	0.8	1.89	2.93	1.63	1.31
TanH	2.67	1.33	1.07	3.2	1.91
IAMM (proposed)	**0.54**	**0.54**	**0.54**	0.56	**0.54**
OEBAMM (proposed)	0.56	**0.54**	1.33	1.33	**0.54**
MOEBAMM (proposed)	0.56	**0.54**	1.34	1.07	**0.54**
OEVBAMM (proposed)	**0.54**	3.41	4.53	1.6	1.06

Table 4.13: GAR @0.5% FAR provided by MBS-SL using the various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	**99.47**	98.4	94.93	98.67	**99.47**
Z-score	94.13	96.8	99.2	94.13	95.47
PAN-MM	98.93	92.53	90.93	96.53	97.6
TanH	93.87	97.6	97.6	92.27	97.93
IAMM (proposed)	98.93	99.2	99.2	98.93	98.93
OEBAMM (proposed)	99.2	**99.47**	98.67	97.6	**99.47**
MOEBAMM (proposed)	99.2	**99.47**	98.67	97.33	**99.47**
OEVBAMM (proposed)	**99.47**	94.67	92.8	97.07	98.4

by any of the unimodal biometric systems, as seen from Tables 4.12, 4.13 and 3.3.

Experiment 4: We now repeat Experiment 3 on the dataset VMD-2. Tables 4.14 and 4.15 depict the results of this experiment. It is seen from Table 4.14 that MBS-SL using the proposed OEBAMM normalization technique and the CBW-2 weighting technique provides the lowest EER value of 1.12% and the highest GAR value of 97.33% @0.5% FAR. It is also seen from Tables 4.14, 4.15 and 3.4 that MBS-SL using the proposed OEBAMM normalization technique with the proposed CBW-2 weighting technique provides an EER value lower than and a GAR @0.5% FAR value higher than that provided by any of the unimodal biometric systems. By combining the results of EER and GAR @0.5% FAR of Tables 4.14 and 4.15, it is clear that the proposed OEBAMM normalization technique with the proposed CBW-2 weighting

Table 4.14: EER(%) provided by MBS-SL using the various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	1.33	1.33	1.33	2.39	1.33
Z-score	2.93	2.93	2.9	2.93	2.98
PAN-MM	1.33	1.35	1.33	2.67	1.29
TanH	2.93	2.69	2.67	3.68	3.197
IAMM (proposed)	3.46	1.33	1.33	2.46	1.35
OEBAMM (proposed)	2.13	1.87	1.87	2.67	**1.12**
MOEBAMM (proposed)	2.42	1.33	1.38	2.93	1.33
OEVBAMM (proposed)	1.33	1.64	1.87	2.87	1.92

Table 4.15: GAR @0.5% FAR provided by MBS-SL using the various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	96.53	96.3	96.27	94.93	95.47
Z-score	93.33	95.2	95.2	92.8	91.2
PAN-MM	97.33	97.33	96.53	95.47	96
TanH	91.2	91.73	90.93	90.93	91.47
IAMM (proposed)	91.2	96.53	96.3	95.2	96.8
OEBAMM (proposed)	95.47	96	95.73	94.67	**97.33**
MOEBAMM (proposed)	95.47	96.8	96.27	94.93	97.07
OEVBAMM (proposed)	96.8	93.6	93.07	91.73	96.53

technique is the best choice for MBS-SL in terms of EER and GAR @0.5% FAR.

From the above analysis of the results of Experiments 3 and 4, it is clear that the OEBAMM normalization technique with the CBW-2 weighting technique is the best choice for MBS-SL in terms of EER and GAR @0.5% FAR, irrespective of the dataset employed. We now further evaluate this case in terms of ROC and DET curves.

ROC and DET curves:

Figs. 4.5 and 4.6, respectively, show the ROC and DET curves of MBS-SL using the OEBAMM normalization technique and the CBW-2 weighting technique on the datasets VMD-1 and VMD-2. It is seen from these figures that MBS-SL using the OEBAMM normalization technique and the CBW-2 weighting technique on the dataset VMD-1 provides GAR values higher and FRR values lower than that provided on the dataset VMD-2. The reason for this could be attributed to the fact that the dataset VMD-2 is more challenging dataset than the dataset VMD-1 as mentioned in Section 2.4.5.

The processing time per image required by MBS-SL using the OEBAMM nor-

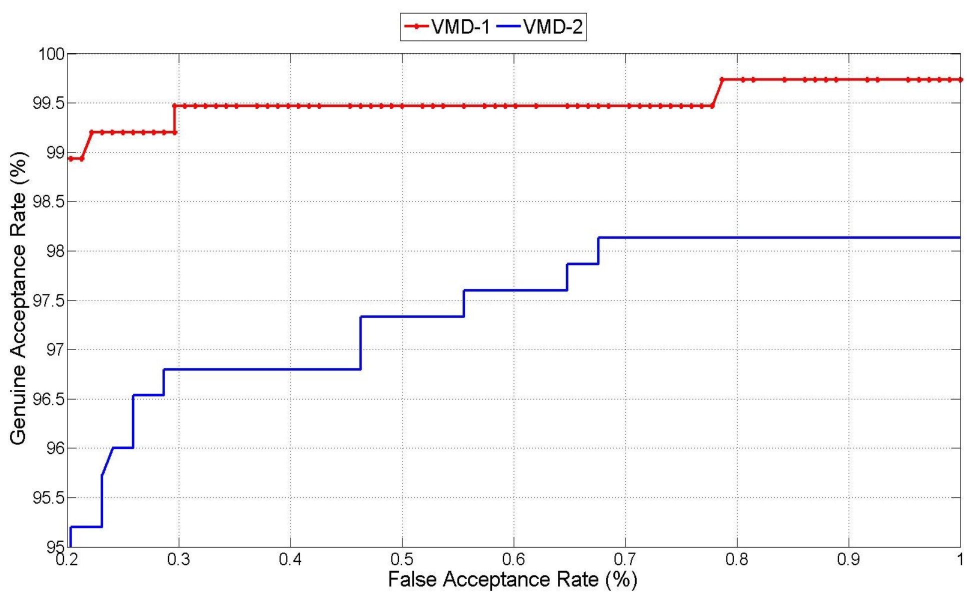

Figure 4.5: The best ROC curves of MBS-SL on the datasets VMD-1 and VMD-2

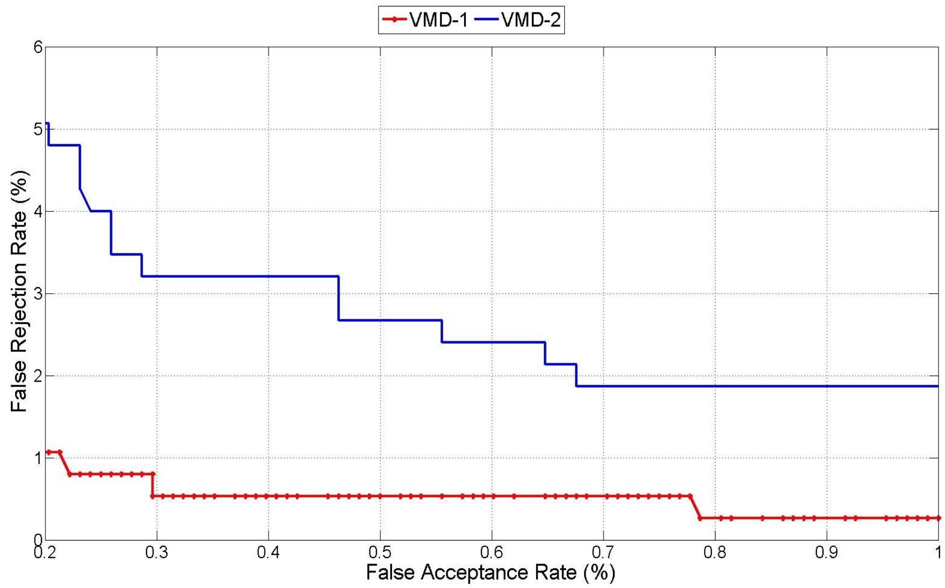

Figure 4.6: The best DET curves of MBS-SL on the datasets VMD-1 and VMD-2

malization technique with the CBW-2 weighting technique has been found to be 11.2 seconds using MATLAB 2014 in the environment of Windows PC platform with a 2.93 GHz Intel(R) Core(TM) i7 CPU and 8 GB RAM. It is to be noted that the processing time includes the time taken for feature extraction, feature encoding, matching, normalization and weighting of scores.

4.4 Summary

In this chapter, two weighting techniques, namely, confidence-based weighting 1 (CBW-1) technique and confidence-based weighting 2 (CBW-2) technique have been developed. The performance of the multimodal biometric system under the score-level fusion (MBS-SL) using the proposed weighting techniques have been studied in detail by conducting several experiments, and comparing the results with that using the existing weighting methods. The performance of MBS-SL using the proposed normalization and weighting techniques are compared to that using the existing normalization and weighting techniques. Experimental results have shown that MBS-SL using the proposed overlap extrema-based anchored min-max (OEBAMM) normalization technique with the proposed CBW-2 weighting technique is the best choice in terms of EER, GAR @0.5% FAR, ROC curves and DET curves, irrespective of the dataset. In Chapter 5, we develop a new fusion scheme, which consists of feature and score level fusions, and evaluate the performance of a multimodal biometric system using the various normalization and weighting techniques with the proposed fusion scheme.

Chapter 5

A Multimodal Biometric System with Fusions of Modalities at Feature and Score Levels

5.1 Introduction

In feature-level fusion, feature sets obtained from multiple feature extraction modules are fused, and this fused feature set is passed through the matching and/or ranking, and decision modules for identifying a person. Feature-level fusion is expected to provide better recognition rate, since features contain richer information about the biometric data than the matching scores or the decision of a matching module. Considerable work has been done in feature-level fusion based on concatenation of features [34–49, 51–67, 129], shapes of features [50], or encoded features [68]. In the existing feature-level fusion schemes [34–68, 129], the matching scores are obtained from matching modules by performing feature-by-feature comparison. These schemes cannot consider the neighbourhood information of a feature value at a given position to obtain the matching scores. Even though fusion at a single level such as the score-level or feature-level or rank-level has been discussed in the literature, there has been no study on multimodal fusion using more than one level. For this to be accomplished, information concerning at least three modalities would be required.

In this chapter, we propose a new multimodal biometric system [135], in which three modalities are fused both at the feature level and the score level. This is carried out by first performing a feature level fusion using the features of two of the modalities, followed by a score level fusion of the score obtained from the feature level fusion with the score of the remaining modality. A performance evaluation is conducted on this two-level multimodal biometric system under different normalization and weighting techniques.

5.2 Proposed Two-Level Fusion Scheme

In this section, we propose a multimodal biometric system in which by considering three different modalities, fusion is carried out at two distinct levels, namely, feature and score levels. We first take EERs of the individual biometric systems into consideration in order to find out as to which of the two modalities should be used for the feature-level fusion, and choose those two modalities for which the EER is not the least. The idea behind choosing such two modalities is that they need to be improved the most in order to enhance the recognition capacity through their feature-level fusion. We fuse the encoded features rather than the raw ones of these two modalities. The reason behind using encoded values of features is to reduce the processing time for the matching modules to identify a person as well as to utilize useful information from each of these two modalities. Finally, we fuse at the score-level the score obtained from the feature-level fusion with that of the modality for which the EER is the lowest under the weighted sum rule to improve the overall recognition rate of the multimodal biometric system.

A block diagram of the proposed fusion scheme is shown in Fig. 5.1. Let the biometric and feature images for the modality k $(k = 1, 2, 3)$ be denoted by $\mathbf{X}(k)$,

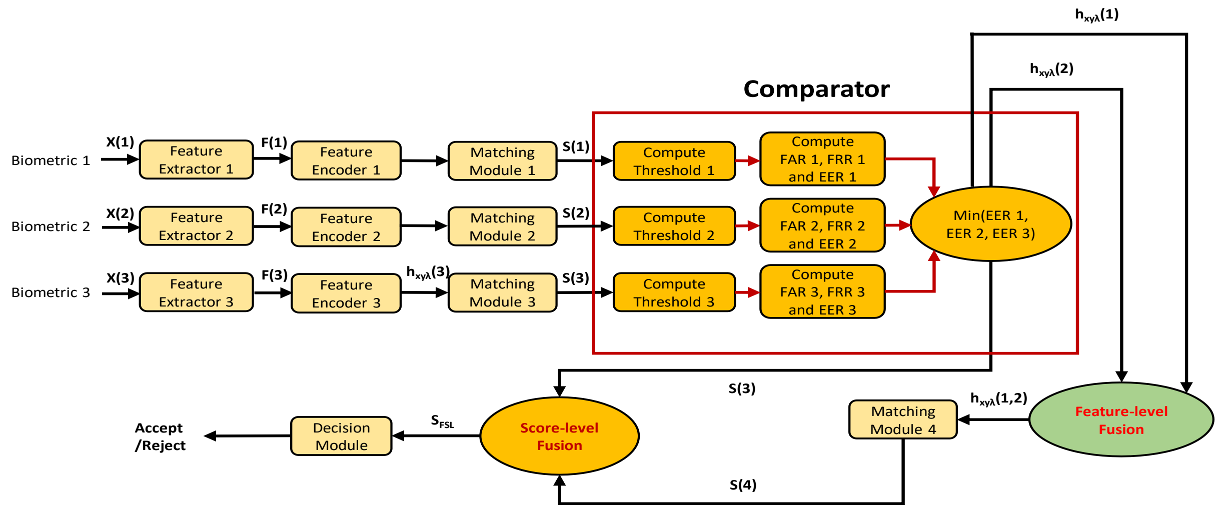

Figure 5.1: Schematic of the proposed two-level scheme (MBS-FSL)

and $\mathbf{F}(k)$, respectively. The feature image $\mathbf{F}(k)$ is now encoded by using a binary hash table encoding technique presented in [131] based on 4-connected neighbors of a feature value at a given position (x, y). Let the maximum feature value in $\mathbf{F}(k)$ be denoted by η. Then, the total number of bits required to assign a hash code for any feature value $f_{xy}(k)$ at the position (x, y) of $\mathbf{F}(k)$ is equal to η. For the feature value $f_{xy}(k)$, the hash function assigns it to the λ^{th} bin as

$$h_{xy\lambda}(k) = \begin{cases} 1, & \text{if } \lambda = f_{xy}(k) \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

where $h_{xy\lambda}(k)$ being the encoded form of $f_{xy}(k)$, and λ is the bin position. Fig. 5.2 shows an example of (a) the feature image $\mathbf{F}(k)$ for a palmprint, (b) two feature values in $f_{xy}(k)$ at the positions (23,21) and (23,22), i.e., $f_{23,21}$ and $f_{23,22}$, and (c) the corresponding hash table, where it is assumed that $\eta = 8$, and thus, 8 bits are required to encode f_{xy} in this example. Assuming the feature value $f_{23,21} = 8$, bins 1 to 7 are encoded as 0 and bin 8 as 1 for $f_{23,21}$. Further, if the feature value $f_{23,22}$ is assumed to be 4, then bin 4 is encoded as 1 and the rest of the bins as 0 for $f_{23,22}$.

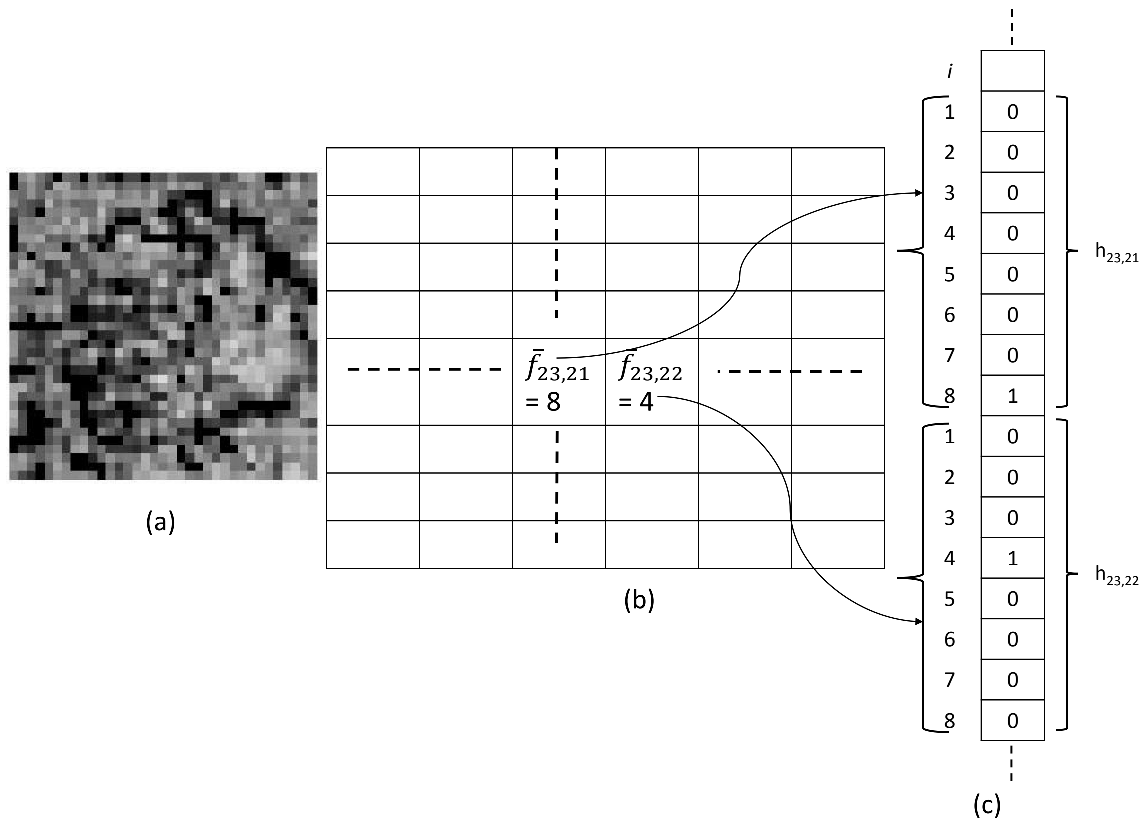

Figure 5.2: Binary hash table encoding: (a) the feature image, $\mathbf{F}(k)$ for a palmprint, (b) feature matrix $\mathbf{F}(k)$ with feature values $f_{23,21}$ and $f_{23,22}$ specified, and (c) corresponding hash table with the hash codes specified for $f_{23,21}$ and $f_{23,22}$

We utilize the genuine score, $G(k)$ and the impostor score, $I(k)$ for the modality k in order to select the matching module that provides the lowest EER in comparison with others in a multimodal biometric system using the comparator (see Fig. 5.1). The region of the genuine and impostor scores can be divided into four parts [128], as shown in Fig.5.3. In order to compute the threshold value for the modality k, two parameters of the genuine and impostor scores, namely, $\min(I(k))$, and $\max(G(k))$, which are the minimum value of the impostor scores, and the maximum value of the genuine scores, respectively, are utilized. The threshold value is computed for the

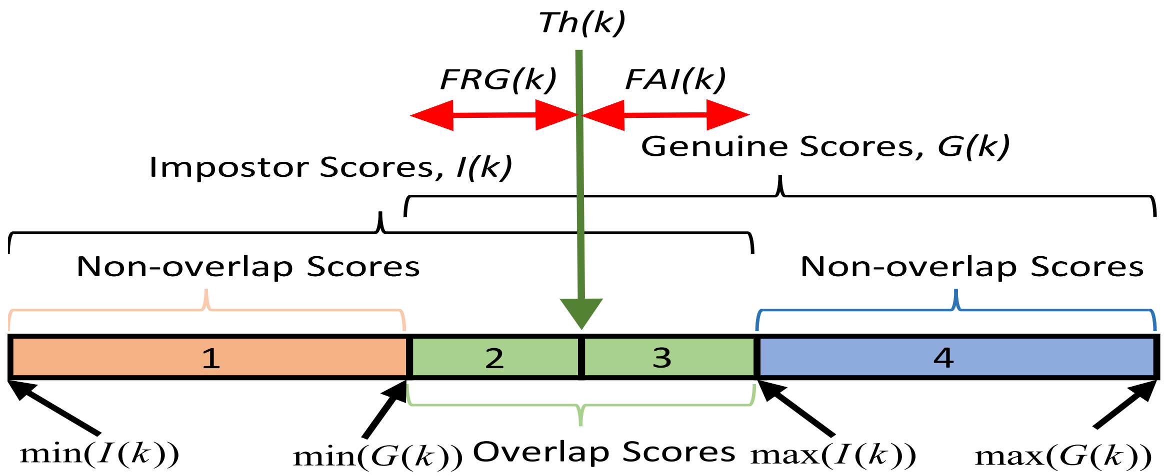

Figure 5.3: Genuine and impostor scores of a biometric system with falsely rejected genuine (FRG(k)) and falsely accepted impostor (FAI(k)) based on the threshold value $Th(k)$

modality k as follows.

$$Th(k) = [min(I(k)) : step\_size : max(G(k))] \tag{5.2}$$

where

$$step\_size = \frac{max(G(k)) - min(I(k))}{\zeta} \tag{5.3}$$

ζ being an empirical parameter. Next, we count the number of rejected genuine scores accepted falsely as impostor scores for which $G(k) < Th(k)$, and accepted impostor scores accepted falsely as genuine scores for which $I(k) \geq Th(k)$, and refer to them, respectively, as *falsely rejected genuine (FRG(k))* and *falsely accepted impostor (FAI(k))* scores for the modality k, as shown in Fig. 5.3. The parameter ζ controls the step size for the variable $Th(k)$ that is utilized to compute the number of falsely rejected genuine and falsely accepted impostor scores. The higher the value of ζ, the smaller is the step size for $Th(k)$. By running several experiments, it has been found that $\zeta = 10^3$ is the best value for the step size.

Now, the false acceptance rate (FAR), false rejection rate (FRR) and EER for the modality k are computed as follows

$$FAR(k) = \frac{FRG(k)}{length(G(k))} \tag{5.4}$$

$$FRR(k) = \frac{FAI(k)}{length(I(k))} \tag{5.5}$$

$$EER(k) = \frac{FAR(k) + FRR(k)}{2} \tag{5.6}$$

The EER of the matching module that provides the lowest value is given by

$$EER_{lowest} = \min_{k}(EER(k)) \tag{5.7}$$

We assume, without loss of generality, that it is matching module 3 that provides the lowest EER. Based on this assumption, we perform a feature level fusion of the encoded features obtained from the modalities 1 and 2. It is to be noted that the encoded features $h_{xy\lambda}(k)$ for the modality k are binary numbers in which '1' provides more information about the feature than '0' does. Therefore, this fusion can be done using the logical operators, such as XOR, AND, and OR in order to obtain the fused encoded feature. We utilize the logical OR operator for the fusion, since it considers encoded feature value of '1' at the position (x, y, λ) available from the modality 1 or 2. The fused encoded feature, $h_{xy\lambda}(1, 2)$ can be computed as [129]

$$h_{xy\lambda}(1, 2) = h_{xy\lambda}(1) \oplus h_{xy\lambda}(2) \tag{5.8}$$

at the position (x, y, λ), and the sign $\oplus$ indicates the logical OR operation. Next, the matching score $\mathbf{S}(4)$ corresponding to this fused feature is obtained using the matching module 4 (see Fig. 5.1).

Now, the matching score $\mathbf{S}(4)$ so obtained and the score $\mathbf{S}(3)$ from the matching module 3 are normalized and fused by the weighted sum rule at the score level fusion. Since the proposed fusion scheme is based on two levels of fusion, namely, feature-level and score-level, the fusion scheme is referred to as the multimodal biometric system with feature and score level (MBS-FSL) fusions. The final fused score $\boldsymbol{S}_{FSL}$ is given by

$$\boldsymbol{S}_{FSL} = \sum_{t=3}^{4} w(t)\boldsymbol{S}_N(t) \tag{5.9}$$

where $w(t)$ represents the weight attached to the score from matching module t and $\boldsymbol{S}_N(t)$ denotes the normalized value of $\boldsymbol{S}(t)$.

5.3 Experimental Results

The performance of the proposed two-level multimodal biometric system (MBS-FSL) using the various normalization and weighting techniques is evaluated by conducting experiments on the multi-biometric datasets, namely, VMD-1 and VMD-2, discussed in Section 2.4.5.

Experiment 1: In this experiment, we study the performance of MBS-FSL on the dataset VMD-1. Tables 5.1 and 5.2 depict EER(%) and GAR @0.5% FAR, respectively, provided by MBS-FSL for the various normalization and weighting techniques. In these tables, individual columns correspond to EERs and GARs @0.5% FARs provided by MBS-FSL using a given weighting technique for the various normalization techniques. The lowest EER and the highest GAR @0.5% FAR are indicated in boldface. It is seen from Tables 5.1, 5.2 and 3.3 that, irrespective of the normalization or weighting technique used, MBS-FSL provides an EER value lower and a GAR value @0.5% FAR higher than that provided by any of the unimodal biometric systems. It is seen from Tables 5.1 and 5.2 that MBS-FSL using the proposed OEVBAMM normalization technique and the proposed CBW-2 weighting technique provides the lowest EER value of 0.47%, and the highest GAR value of 99.73% @0.5% FAR. There-

Table 5.1: EER(%) provided by MBS-FSL with various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	3.15	1.07	1.34	2.39	0.83
Z-score	3.47	3.2	3.2	3.2	2.93
PAN-MM	3.2	1.08	1.39	2.39	0.8
TanH	3.2	1.86	2.12	2.66	1.34
IAMM (proposed)	3.2	2.13	2.39	2.93	1.08
OEBAMM (proposed)	3.2	2.4	2.67	2.94	1.33
MOEBAMM (proposed)	3.2	2.67	2.87	2.96	1.89
OEVBAMM (proposed)	2.67	1.03	0.8	1.11	**0.47**

Table 5.2: GAR @0.5% FAR provided by MBS-FSL with various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	92.8	96.53	96.27	96	98.67
Z-score	90.13	92.53	92.53	91.2	93.33
PAN-MM	92.8	96.53	96.53	95.47	98.67
TanH	92.27	95.47	95.2	94.4	97.6
IAMM (proposed)	92.53	96	95.47	93.87	96.53
OEBAMM (proposed)	92	96	95.2	93.87	96.27
MOEBAMM (proposed)	91.47	95.2	94.4	93.07	96
OEVBAMM (proposed)	94.93	98.67	98.67	96.53	**99.73**

fore, the CBW-2 weighting technique with the OEVBAMM normalization technique is the best choice for MBS-FSL in terms of EER and GAR @0.5% FAR.

Experiment 2: We now repeat Experiment 1 on the dataset VMD-2. Tables 5.3 and 5.4 depict the results of this experiment. It is seen Tables 5.3, 5.4 and 3.4 that, irrespective of the normalization or weighting technique used, MBS-FSL provides an EER value lower and a GAR value @0.5% FAR higher than that provided by any of the unimodal biometric systems. It is seen from Table 5.3 that MBS-FSL using the proposed OEVBAMM normalization method and the proposed CBW-2 weighting technique provides the lowest EER value of 1.07%. It is seen from Table 5.4 that MBS-FSL provides the highest GAR value of 97.6% @0.5% FAR for three cases.

Table 5.3: EER(%) provided by MBS-FSL with various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	2.88	2.13	1.63	2.93	1.54
Z-score	3.47	3.21	3.2	3.2	2.93
PAN-MM	2.93	2.13	1.85	2.93	1.09
TanH	2.67	2.66	2.67	2.93	2.39
IAMM (proposed)	2.93	2.66	2.13	2.94	1.39
OEBAMM (proposed)	2.94	2.71	2.47	2.93	1.83
MOEBAMM (proposed)	2.93	2.93	2.94	3.21	2.13
OEVBAMM (proposed)	2.14	1.33	1.09	2.64	**1.07**

Table 5.4: GAR @0.5% FAR provided by MBS-FSL with various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	94.13	96	96.53	93.33	95.47
Z-score	90.4	90.93	91.47	90.13	92.53
PAN-MM	94.13	95.47	96.53	92.8	**97.6**
TanH	90.93	91.2	91.47	90.93	91.47
IAMM (proposed)	92.53	94.93	95.73	92.27	96.8
OEBAMM (proposed)	92.27	94.13	94.93	91.73	96.53
MOEBAMM (proposed)	91.73	93.33	93.87	90.93	95.73
OEVBAMM (proposed)	95.73	97.33	**97.6**	94.93	**97.6**

It is clear from these two experiments that MBS-FSL using the CBW-2 weighting technique with the OEVBAMM normalization technique is the best choice not only in terms of EER, but also in terms of GAR @0.5% FAR, irrespective of which dataset is employed. We now further evaluate this case in terms of ROC and DET curves.

ROC and DET curves:

Figs. 5.4 and 5.5, respectively, show the ROC and DET curves of MBS-FSL using the OEVBAMM normalization technique and the CBW-2 weighting technique on the datasets VMD-1 and VMD-2. It is seen from these figures that MBS-FSL using the OEVBAMM normalization technique and the CBW-2 weighting technique on the dataset VMD-1 provides GAR values higher and FRR values lower than that provided

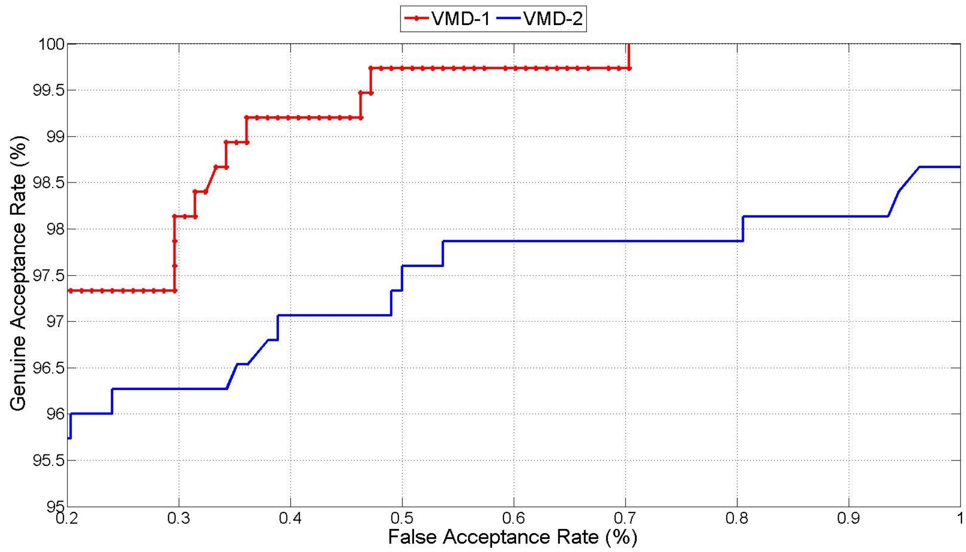

Figure 5.4: The best ROC curves of MBS-FSL on the datasets VMD-1 and VMD-2

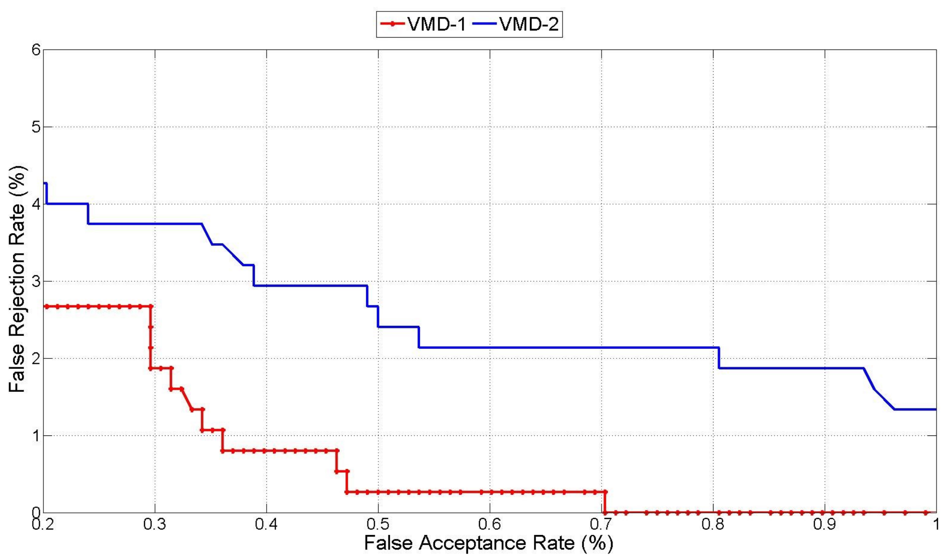

Figure 5.5: The best DET curves of MBS-FSL on the datasets VMD-1 and VMD-2

on the dataset VMD-2. As pointed out in Chapter 4, this inferior performance on the dataset VMD-2 is due to its challenging nature.

5.4 Comparison with MBS-SL Results

In this section, a performance comparison is presented between the best choices for MBS-SL and MBS-FSL on the datasets VMD-1 and VMD-2.

Tables 5.5 and 5.6 depict EER(%) and GAR @0.5% FAR provided by MBS-SL and MBS-FSL using the above mentioned choices on the datasets VMD-1 and VMD-2, respectively. It is seen from these tables that MBS-FSL using the OEVBAMM normalization technique and the CBW-2 weighting technique provides the lowest EER value and the highest GAR value, irrespective of which dataset is employed. Therefore, MBS-FSL using the OEVBAMM normalization technique is a better choice than MBS-SL using the OEBAMM normalization technique with the CBW-2 weighting technique in terms of EER and GAR value @0.5% FAR, irrespective of the dataset employed.

Table 5.5: The best results provided and the processing time (in seconds) required by MBS-SL and MBS-FSL on the dataset VMD-1

	EER	GAR @0.5% FAR	Processing time
MBS-SL+CBW-2+OEBAMM	0.54	99.47	11.2
MBS-FSL+CBW-2+OEVBAMM	**0.47**	**99.73**	**1.1**

Table 5.6: The best results provided and the processing time (in seconds) required by MBS-SL and MBS-FSL on the dataset VMD-2

	EER	GAR @0.5% FAR	Processing time
MBS-SL+CBW-2+OEBAMM	1.12	97.33	11.2
MBS-FSL+CBW-2+OEVBAMM	**1.07**	**97.6**	**1.1**

The processing time per image required by MBS-FSL using the OEVBAMM normalization technique along with MBS-SL using the OEBAMM normalization technique with the CBW-2 weighting technique is given in Tables 5.5 and 5.6 for the datasets VMD-1 and VMD-2, respectively. It is seen from these tables that MBS-FSL using the OEVBAMM normalization technique requires a processing time of 1.1 seconds per image, which is ten times lower than that required by MBS-SL using the OEBAMM normalization technique with the CBW-2 weighting technique, irrespective of which dataset is employed.

The above finding in conjunction with the results already obtained based on Section 5.3 regarding EER and GAR @0.5% FAR, it can be concluded that MBS-FSL using the CBW-2 weighting technique with the OEVBAMM normalization technique is the best choice not only in terms of EER and GAR @0.5% FAR, but also in terms of processing time, irrespective of which dataset is employed.

5.5 Summary

In this chapter, a new multimodal biometric system, MBS-FSL, in which three modalities are fused at the feature and score levels has been developed. In MBS-FSL, the two modalities with the lowest matching scores are first fused at the feature-level, followed by the normalization and fusion of the score obtained from the feature level fusion and the score of the remaining modality using the weighted sum rule for fusion at the score level. The performance of MBS-FSL using the various normalization and weighting techniques are evaluated on the datasets VMD-1 and VMD-2. Experimental results have shown that MBS-FSL using the proposed overlap extrema-variation-based anchored min-max (OEVBAMM) normalization technique with the proposed confidence-based weighting technique 2 (CBW-2) is the best choice in terms of EER, GAR @0.5% FAR, ROC curves, DET curves and processing time, irrespective of the dataset. In Chapter 6, we develop another two-level fusion scheme, in which features with and without being encoded are utilized to fuse three modalities at the feature and score levels, and evaluate the performance of a multimodal biometric system using the various normalization and weighting techniques with the proposed fusion scheme.

Chapter 6

A Multimodal Biometric System with Modified Fusions of Modalities at Feature and Score Levels

6.1 Introduction

Raw feature-based multimodal biometric systems [34–68, 129] make use of feature values in order to obtain the matching scores by using feature-by-feature comparison. However, in such systems, the neighbourhood information of a feature value at a given position cannot be taken into account. In the previous chapter, a multimodal biometric system with feature and score level fusions (MBS-FSL) has been proposed, wherein the raw features are encoded before the feature level fusion. In MBS-FSL, the encoded values of the raw features were obtained by using the binary hash table encoding technique presented in [131] based on 4-connected neighbors of a feature at a given position, which allowed the neighbourhood information to be included. However, in MBS-FSL, the border values of the raw features could not be encoded in view of the fact that the feature values of all 4-connected neighbours are not available; this was not the case when raw features were utilized for the feature level fusion. In view of the above discussion, one can expect the recognition accuracy of a multimodal biometric system to be further improved by carrying out fusion by taking into account the encoded features as well as the raw features, which will allow the border pixels to be taken into account as well.

In this chapter, we propose a new multimodal biometric system [136], in which three modalities are fused, wherein both the neighbourhood and border feature information are used. This is done by carrying out fusions taking into account the encoded features as well as the raw features. The performance of this multimodal biometric system is evaluated under different normalization and weighting techniques and compared with that of MBS-FSL of Chapter 5.

6.2 Proposed Modified Two-Level Fusion Scheme

In this section, we propose a new multimodal biometric system in which fusion is carried out at two distinct levels, namely, feature and score levels by taking into consideration both the encoded and raw features. A block diagram of the proposed fusion scheme for three modalities is shown in Fig. 6.1.

In order to perform the feature level fusion, we first encode the raw features and obtain the matching scores from the corresponding matching modules. Next, we utilize the comparator discussed in Section 5.2 in order to find out as to which of the two modalities should be used for the feature-level fusion, and choose those two modalities for which the EER is not the least. We then fuse the encoded features of these two modalities. In order to perform the score level fusion, we first obtain the matching scores from the matching modules by utilizing the corresponding raw features. The score obtained from the feature-level fusion, the score of the modality that was not used for the feature level fusion, and the scores from the three modalities

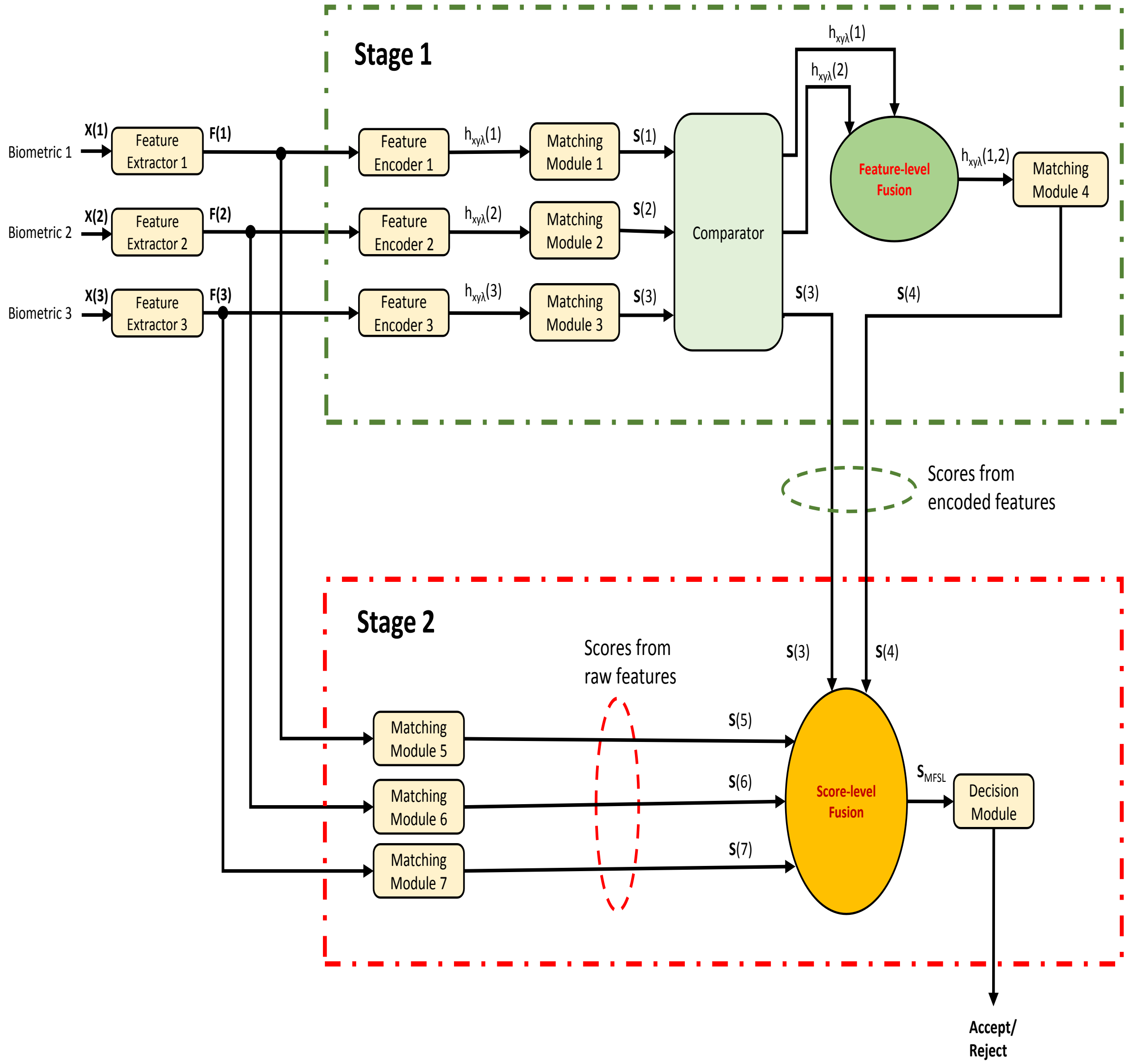

Figure 6.1: Schematic of the proposed modified two-level scheme (MBS-MFSL)

obtained from the matching modules by using their raw features are now fused at the score level under the weighted sum rule.

Let the biometric and feature images for the modality k ($k = 1, 2, 3$) be denoted by $\mathbf{X}(k)$, and $\mathbf{F}(k)$, respectively. The proposed fusion scheme can be divided into two stages and they are discussed below.

Stage 1: Feature-level fusion:

In this stage, the feature image $\mathbf{F}(k)$ is first encoded by using a binary hash table encoding technique presented in [131] based on 4-connected neighbors of a feature value at a given position (x, y), which allows the neighbourhood information to be included. Based on the scores obtained from these encoded features, the modalities for which the EER is not the least are chosen by employing the comparator, whose functionality was discussed in Section 5.2, for the feature level fusion. Next, the encoded features of these two modalities, say $h_{xy\lambda}(1)$ and $h_{xy\lambda}(2)$ are combined using (5.8) to obtain the fused encoded feature $h_{xy\lambda}(1, 2)$. The matching score $\mathbf{S}(4)$ is then obtained by passing $h_{xy\lambda}(1, 2)$ through the matching module 4 (see Fig. 6.1). Thus, the outputs of Stage 1 are the score of the modality that is not used in the feature level fusion $\mathbf{S}(3)$ and the score from the feature level fusion $\mathbf{S}(4)$. These scores are marked as *scores from encoded features* in Fig. 6.1.

Stage 2: Score-level fusion:

In this stage, the matching scores $\mathbf{S}(5)$, $\mathbf{S}(6)$ and $\mathbf{S}(7)$ corresponding to their raw features are obtained using feature-by-feature comparison from the matching modules 5, 6 and 7, respectively (see Fig. 6.1), which allow the border pixels to be included. These scores are marked as *scores from raw features* in Fig. 6.1. Next, these scores and the scores from Stage 1 are normalized and fused by the weighted sum rule at the score-level fusion. The final fused score $\boldsymbol{S}_{MFSL}$ is given by

$$\boldsymbol{S}_{MFSL} = \sum_{l=3}^{7} w(l)\boldsymbol{S}_N(l) \tag{6.1}$$

where $w(l)$ represents the weight attached to the score from matching module l and $\boldsymbol{S}_N(l)$ denotes the normalized value of $\boldsymbol{S}(l)$. Then, this fused score $\boldsymbol{S}_{MFSL}$ is passed through the decision module for identifying an individual as shown in Fig. 6.1.

This fusion scheme is referred to as the multimodal biometric system with modified feature and score level (MBS-MFSL) fusions.

6.3 Experimental Results

The performance of the proposed new two-level multimodal biometric system, MBS-MFSL, using the various normalization and weighting techniques is evaluated by conducting experiments on the multi-biometric datasets, VMD-1 and VMD-2.

***Experiment 1*:** In this experiment, we study the performance of MBS-MFSL on the dataset VMD-1. Tables 6.1 and 6.2 depict EER(%) and GAR @0.5% FAR, respectively, provided by MBS-MFSL for the various normalization and weighting techniques. In these tables, individual columns correspond to EERs and GARs @0.5% FARs provided by MBS-MFSL using a given weighting technique for the various

Table 6.1: EER(%) provided by MBS-MFSL with various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	1.01	0.27	0.48	0.82	0.06
Z-score	3.2	2.94	2.39	3.19	0.47
PAN-MM	0.27	0.31	0.74	0.22	**0.03**
TanH	3.2	1.33	1.1	2.73	1.37
IAMM (proposed)	0.57	0.47	0.47	0.56	0.48
OEBAMM (proposed)	2.37	0.26	0.27	1.88	0.32
MOEBAMM (proposed)	2.63	0.28	0.29	2.4	0.51
OEVBAMM (proposed)	0.28	0.49	0.54	0.49	0.24

Table 6.2: GAR @0.5% FAR provided by MBS-MFSL with various weighting and normalization techniques on the dataset VMD-1

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	97.07	**100**	99.73	98.13	**100**
Z-score	92.27	95.2	96	92.53	99.73
PAN-MM	**100**	**100**	98.4	**100**	**100**
TanH	92.8	96.53	96.8	94.93	96.53
IAMM (proposed)	98.93	99.73	99.73	99.2	99.73
OEBAMM (proposed)	96	**100**	**100**	96.53	**100**
MOEBAMM (proposed)	96	**100**	**100**	96	99.73
OEVBAMM (proposed)	**100**	99.73	99.47	99.73	**100**

normalization techniques. The lowest EER and the highest GAR @0.5% FAR are indicated in boldface. It is seen from Tables 6.1, 6.2 and 3.3 that, irrespective of the normalization or weighting technique used, MBS-MFSL provides an EER value lower and a GAR value @0.5% FAR higher than that provided by any of the unimodal biometric systems. It is seen from Tables 6.1 and 6.2 that there is only one combination, namely, the PAN-MM normalization technique with the CBW-2 weighting technique, which provides simultaneously both the lowest EER value of 0.03% and the highest GAR value of 100% @0.5% FAR. Therefore, MBS-MFSL using the CBW-2 weighting technique with the PAN-MM normalization technique is the best choice for the dataset VMD-1 in terms of both EER and GAR @0.5% FAR.

Experiment 2: We now repeat Experiment 1 on the dataset VMD-2. Tables 6.3 and 6.4 depict the results of this experiment. It is seen from Tables 6.1, 6.2 and 3.4 that, irrespective of the normalization or weighting technique used, MBS-MFSL provides an EER value lower and a GAR value @0.5% FAR higher than that provided by any of the unimodal biometric systems. It is seen from Tables 6.3 and 6.4 that there is only one combination, namely, the OEVBAMM normalization technique with the CBW-2 weighting technique, which provides simultaneously both the lowest EER value of 1.07% and the highest GAR value of 97.87% @0.5% FAR. Therefore, MBS-MFSL using the CBW-2 weighting technique with the OEVBAMM normalization technique is the best choice for the dataset VMD-2 in terms of both EER and GAR @0.5% FAR.

Table 6.3: EER(%) provided by MBS-MFSL with various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	1.91	1.32	**1.07**	2.43	1.85
Z-score	2.93	2.93	2.94	3.21	2.67
PAN-MM	2.12	1.33	1.09	2.67	1.92
TanH	2.93	2.67	2.67	3.18	2.67
IAMM (proposed)	2.93	2.93	2.93	3.20	2.93
OEBAMM (proposed)	2.88	1.87	1.89	2.66	1.08
MOEBAMM (proposed)	2.94	2.16	2.13	2.93	2.92
OEVBAMM (proposed)	1.33	**1.07**	1.09	1.89	**1.07**

Table 6.4: GAR @0.5% FAR provided by MBS-MFSL with various weighting and normalization techniques on the dataset VMD-2

	EERW	DPW	FDRW	CBW-1 (proposed)	CBW-2 (proposed)
MM	96	97.6	97.07	95.47	96
Z-score	91.73	93.33	93.6	91.47	94.67
PAN-MM	96.27	97.33	97.6	94.67	96.53
TanH	91.2	91.73	91.47	92	91.73
IAMM (proposed)	92	93.33	93.33	91.2	93.33
OEBAMM (proposed)	94.67	96	96.27	93.87	97.33
MOEBAMM (proposed)	93.87	95.73	95.47	93.07	94.13
OEVBAMM (proposed)	97.6	97.33	96	95.73	**97.87**

6.4 Comparison with MBS-FSL Results

In this section, a performance comparison between the best choices for MBS-FSL and MBS-MFSL on the datasets VMD-1 and VMD-2 is presented. For this purpose, we first evaluate these cases in terms of ROC and DET curves.

Figs. 6.2 and 6.3, respectively, show the ROC and DET curves for the best choices of MBS-FSL and MBS-MFSL on the dataset VMD-1. It is seen from these figures that MBS-MFSL using the PAN-MM normalization and CBW-2 weights provides GAR values higher and FRR values lower than that provided by MBS-FSL using the OEVBAMM normalization and CBW-2 weights for the dataset VMD-1.

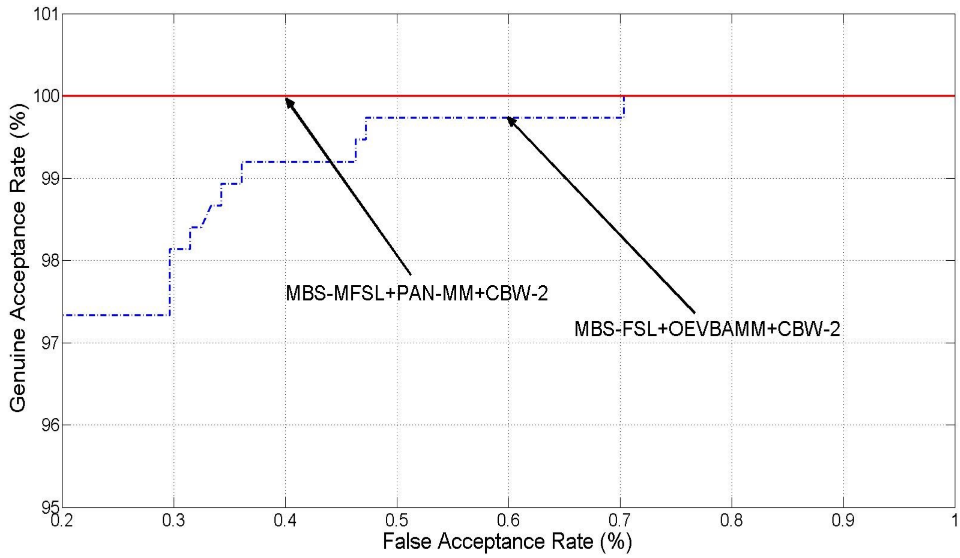

Figure 6.2: The best ROC curves of MBS-FSL & MBS-MFSL on the dataset VMD-1

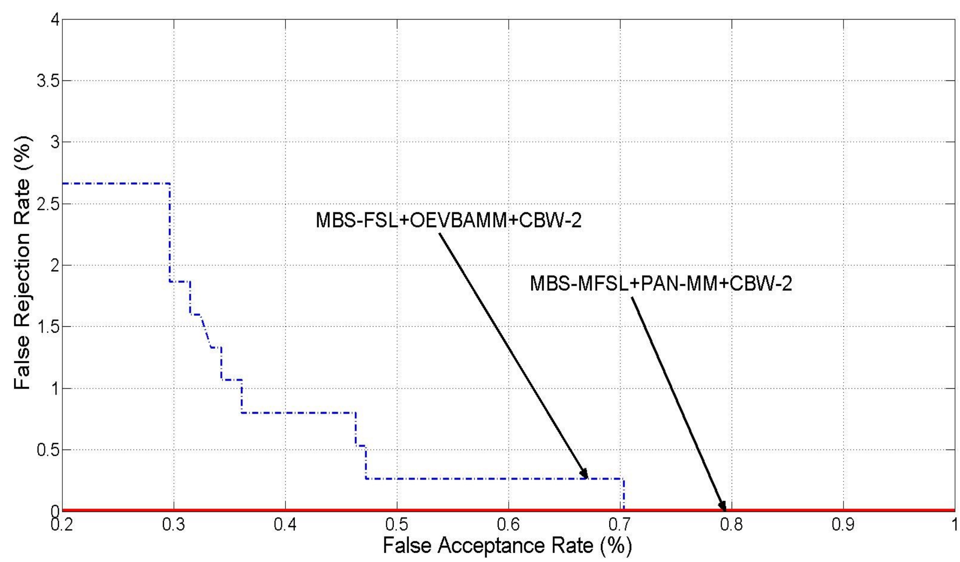

Figure 6.3: The best DET curves of MBS-FSL & MBS-MFSL on the dataset VMD-1

Figs. 6.4 and 6.5, respectively, show ROC and DET curves for the best choices of MBS-FSL and MBS-MFSL on the dataset VMD-2. It is seen from these figures that MBS-FSL using the OEVBAMM normalization and CBW-2 weights provides GAR values and FRR values almost similar to that provided by MBS-MFSL using the OEVBAMM normalization and CBW-2 weights for the dataset VMD-2.

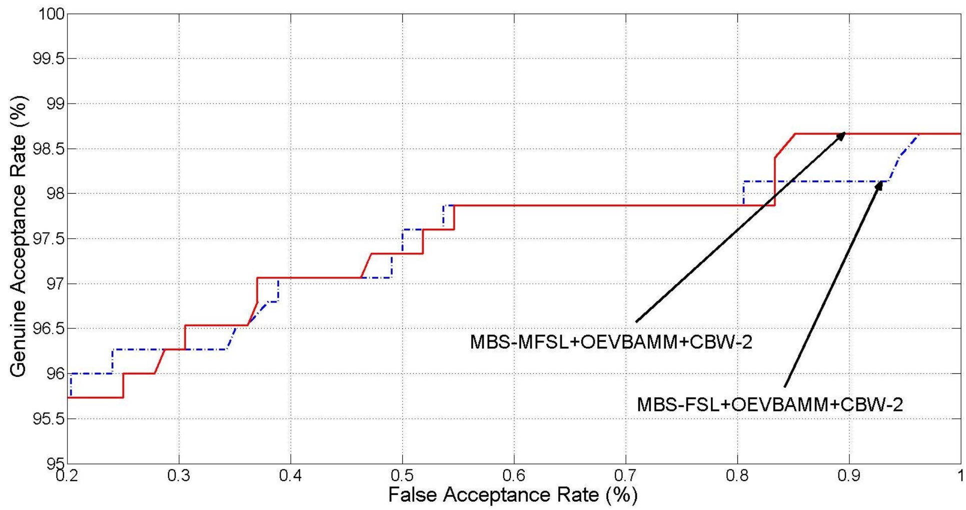

Figure 6.4: The best ROC curves of MBS-FSL & MBS-MFSL on the dataset VMD-2

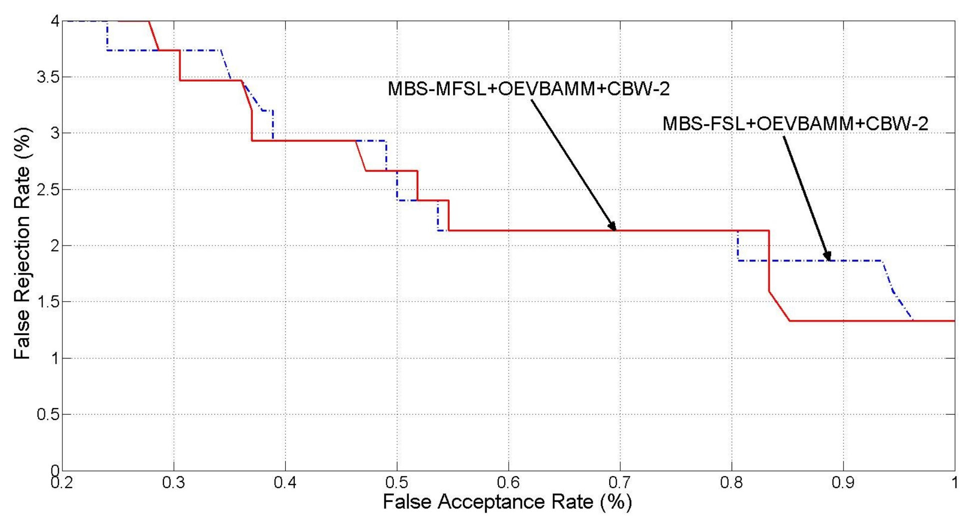

Figure 6.5: The best DET curves of MBS-FSL & MBS-MFSL on the dataset VMD-2

Tables 6.5 and 6.6 depict EER(%) and GAR @0.5% FAR provided by MBS-FSL and MBS-MFSL using the above mentioned choices on the datasets VMD-1 and VMD-2, respectively. It is seen from these tables that MBS-MFSL using the PAN-MM normalization and CBW-2 weights provides an EER value lower than and a GAR value higher than that provided by MBS-FSL using the OEVBAMM normalization and CBW-2 weights for the dataset VMD-1. However, MBS-FSL and MBS-MFSL with the OEVBAMM normalization and CBW-2 weights provide the same EER, with the latter providing a slightly higher GAR than that provided by the former for the dataset VMD-2.

The processing times per image required by the best choices for MBS-FSL and MBS-MFSL on the datasets VMD-1 and VMD-2 are also given in Tables 6.5 and 6.6, respectively. It is seen from these tables that MBS-MFSL requires a processing time of 12.3 seconds per image, which is eleven times higher than that required by MBS-FSL, irrespective of which dataset is employed.

Table 6.5: The best results provided and the processing time (in seconds) required by MBS-FSL and MBS-MFSL on the dataset VMD-1

	EER	GAR @0.5% FAR	Processing time
MBS-FSL+CBW-2+OEVBAMM	0.47	99.73	**1.1**
MBS-MFSL+CBW-2+PAN-MM	**0.03**	**100**	12.3

Table 6.6: The best results provided and the processing time (in seconds) required by MBS-FSL and MBS-MFSL on the dataset VMD-2

	EER	GAR @0.5% FAR	Processing time
MBS-FSL+CBW-2+OEVBAMM	**1.07**	97.6	**1.1**
MBS-MFSL+CBW-2+OEVBAMM	**1.07**	**97.87**	12.3

The above findings regarding EER and GAR @0.5% FAR, it can be concluded that MBS-MFSL using the PAN-MM normalization with CBW-2 weights is a better choice than MBS-MFSL using the OEVBAMM normalization with CBW-2 weights at the cost of an increased processing time for the dataset VMD-1. However, MBS-FSL using the OEVBAMM normalization with CBW-2 weights is a better choice than MBS-MFSL using the OEVBAMM normalization with CBW-2 weighting technique with a slightly lower value of GAR @0.5% FAR, but with a substantially reduced processing time for the dataset VMD-2.

6.5 Summary

In this chapter, a new multimodal biometric system, MBS-MFSL, in which three modalities are fused at the feature and score levels that takes both the raw and encoded features into account, has been developed. In MBS-MFSL, the two modalities with the lowest matching scores are first fused at the feature-level, followed by the normalization and fusion of the score obtained from the feature level fusion, the score of the modality that was not used in the feature level fusion, and the scores obtained from the matching modules by using the raw features at the score level. The performance of MBS-MFSL using the various normalization and weighting techniques have been evaluated on the datasets VMD-1 and VMD-2. Experimental results have shown that MBS-MFSL using the PAN-MM normalization technique with the CBW-2 weighting technique is the best choice for the dataset VMD-1 at an increased cost of processing time, whereas MBS-FSL using the OEVBAMM normalization technique with the CBW-2 weighting technique is the best choice for the dataset VMD-2 with a slightly lower GAR @0.5% FAR, but with a substantially lower processing time.

Chapter 7

Conclusion

7.1 Concluding Remarks

Accurate and reliable person identification is an important task in many real-life applications such as in criminal investigations, and border and access control. In recent years, biometric-based authentication systems have been successfully deployed in such applications in view of their ability to identify a person with high accuracy and reliability. Most of the biometric-based authentication systems are unimodal in that they utilize only one biometric modality to identify a person. However, such a unimodal biometric system may fail or wrongly identify a person in the case of the noisy input data, or changes in the biometric trait over time, or because of the inter-class similarity or intra-class dissimilarity. In an effort to address these limitations, multimodal biometric systems have been developed, in which fusion of multiple modalities is carried out at a given level, such as sensor, feature, score, rank or decision. There are only a few techniques that have been developed for the sensor level fusion, since an additional cost or time is required to develop new feature extraction and matching algorithms to fuse the data obtained from multiple sensors. Rank level fusion has not drawn much attention, since this level of fusion can only be applied for the purpose of identification. Decision level fusion has not drawn much attention, since the information at this level is not sufficiently adequate to improve the performance of a multimodal biometric system. Many techniques for the feature level fusion have been developed, since features contain richer information about biometric data, and therefore, lead to an improved performance of a multimodal biometric system. Many techniques for the score level fusion have also been developed, since it is easy to combine scores, and it can improve the performance of a multimodal biometric system over that of unimodal biometric systems. However, there does not seem to exist any study for the fusion of modalities at multiple levels in multimodal biometric systems, despite the progress made in achieving performance improvement by such systems when modalities are fused at a single level. This thesis, for the first time, has investigated the problem of developing multimodal biometric systems by considering fusions of the modalities both at the feature level and the score level.

It has been observed that when the scores of the individual modalities are fused without normalization or weighting, the performance of the resulting multimodal biometric systems cannot be improved over that of the corresponding unimodal systems. Therefore, in order to benefit from multimodal biometric systems in providing an improved performance, it is imperative to have suitable normalization and weighting techniques for the fusion of the modalities. Hence, to start with, this thesis has developed a number of normalization and weighting techniques for the score level fusion in multimodal biometric systems. Four normalization techniques, referred to as improved anchored min-max (IAMM), overlap extrema-based anchored min-max (OEBAMM), mean-to-overlap extrema-based anchored min-max (MOEBAMM), and overlap extrema-variation-based anchored min-max (OEVBAMM) have been developed. These techniques have been developed based on the genuine and impostor scores. Two weighting techniques, referred to as confidence-based weighting technique 1 (CBW-1) and confidence-based weighting technique 2 (CBW-2) have been developed. The first one has been developed based on the mean value of the scores, whereas the second one developed based on the extremum and mean values of genuine and impostor scores. Extensive experiments have been conducted on two multi-biometric datasets in order to evaluate the performance of the multimodal biometric system under the score-level fusion (MBS-SL) using various normalization and weighting techniques including those developed in this thesis. It has been shown that if no normalization or no weighting technique is used for MBS-SL, this multimodal biometric system cannot provide a performance superior to that provided by a unimodal biometric system. It has also been shown that MBS-SL using the OEBAMM normalization technique and the CBW-2 weighting technique is a better choice than MBS-SL using the existing weighting and normalization techniques or the corresponding unimodal biometric systems, in terms of equal error rate, genuine acceptance rate, receiver operating characteristics and detection error tradeoff curves.

The focus of the second part of this thesis has been on the development of multimodal biometric systems, wherein fusions of the modalities are carried out at multiple levels. Specifically, two multimodal biometric systems, in which three modalities are used for their fusion at the feature level as well as at the score level, have been developed. In the first multimodal biometric system, referred to as the multimodal biometric system with feature level and score level (MBS-FSL) fusions [129, 135], the features of three modalities are encoded using the binary hash encoding technique. Unlike the existing techniques for feature level fusion, this encoding technique allows the neighbourhood feature information to be taken into account. Among the three modalities, the features of the two modalities that do not have the lowest equal error rate are made to participate in the feature level fusion. The score-level fusion of the score obtained from the feature-level fusion and the score from the matching module of the modality that was not utilized in the feature-level fusion, i.e., the modality with the lowest equal error rate, is then carried out. Extensive experimentation have shown that, irrespective of the normalization or weighting technique used, MBS-FSL is a better choice than that of any of the corresponding unimodal biometric systems. More importantly, the results have also shown that MBS-FSL using the OEVBAMM normalization technique with the CBW-2 weighting technique is a better choice than MBS-SL, not only in terms of the various metrics but also in terms of the processing time.

In the proposed MBS-FSL multimodal biometric system, the encoded features, which allow the neighbourhood information to be taken into account, are used. However, the border values of the raw features could not be encoded in view of the fact that for the border pixels the feature values of 4-connected neighbours were not available to be used, and as such, the border features are not taken into consideration for the feature level fusion. Hence, a second multimodal biometric system, referred to as the multimodal biometric system with modified feature level and score level (MBS-MFSL) fusions [136] is developed. In this system, both the raw features that include both the border and non-border information and the hash encoded features that include the neighbourhood information are taken into consideration. In this system, the feature-level fusion is carried out in a manner similar to that of MBS-FSL system. The score-level fusion is then carried out between the score obtained from the feature-level fusion, the score from the matching module of the modality that was not utilized in the feature-level fusion, and the scores from individual modalities by using their raw features. Extensive experimentations have shown that, irrespective of the normalization or weighting technique used, MBS-MFSL is a better choice than any of the unimodal biometric systems. But more importantly, the results have shown that MBS-MFSL using the existing anchored min-max (PAN-MM) normalization technique with the CBW-2 weighting technique is the best choice for one of the two datasets used at an increased cost of the processing time, whereas MBS-FSL using the OEVBAMM normalization technique with the CBW-2 weighting technique is the best choice for the other dataset with a slightly lower performance, but with a substantially lower processing time.

It is concluded that the performance of either of the two multimodal biometric systems proposed in this thesis is superior to any of the unimodal biometric systems or to the multimodal biometric system in which fusion of modalities are carried out only at the score level.

As a final note, it needs to be pointed that the investigation undertaken in this study has attempted to move the state-of-the art ahead in human biometric identification and authentication by introducing the notion of fusion of biometric modalities at multiple levels and its findings have paved the way for further innovations in the development of new multimodal biometric systems.

7.2 Scope for Future Work

The multimodal biometric systems proposed in this thesis have been developed using three modalities and fused at two levels, feature level and score level. There are a number of additional studies that can be undertaken based on the ideas developed in this thesis. Some of the possible studies that can be pursued are as follows:

- A study can be undertaken to investigate how the proposed multimodal biometric systems can be adopted to fuse only two modalities or extended to more than three modalities.
- New multimodal biometric systems can be investigated to take the advantages of feature level or score level along with any of the other levels of fusion. For example, a multimodal biometric system can be studied to investigate as to how to fuse multiple modalities at the sensor and feature levels, or at the sensor and score levels.
- Studies can be undertaken to investigate multi-level multimodal biometric systems to fuse multiple modalities at more than two levels, such as fusions at sensor, feature and score levels.
- An investigation can be conducted to explore the possibilities of fusing multiple modalities at a given single level in multiple stages.
- Subject to the availability of large multimodal biometric databases in future, a study can be undertaken to investigate the performance of multimodal biometric

systems in which fusion of modalities can be carried out at single or multiple levels by developing and employing techniques of machine learning or artificial intelligence.

- Statistical approaches can also be investigated for their suitability to separate the genuine and impostor scores from the matching scores, which can then be used in the proposed multimodal biometric systems.

References

[1] A. Ross, K. Nandakumar, and A. Jain, *Handbook of Multibiometrics*. New York: Springer-Verlag, 2006.

[2] A.T.S. Ho and S. Li, *Handbook of Digital Forencics of Multimedia Data and Devices*. Wiley-IEEE Press, 2015.

[3] A. Jain, P. Flynn, and A. Ross, *Handbook of Biometrics*. New York: Springer, 2007.

[4] A. Jain, K. Nandakumar, and A. Ross, "Score normalization in multimodal biometric systems," *Pattern Recognition*, vol. 38, no. 12, pp. 2270–2285, Dec. 2005.

[5] J. Czyz, J. Kittler, L. Vandendorpe, "Multiple classifier combination for face-based identity verification," *Pattern Recognition*, vol. 37, no. 7, pp. 1459–1469, Jul. 2004.

[6] E.F. Garcia et al., "Fusing actigraphy signals for outpatient monitoring," *Information Fusion*, vol. 23, pp. 69–80, May. 2015.

[7] C. Haynes and M. Todd, "Enhanced damage localization for complex structures through statistical modeling and sensor fusion," *Mechanical Systems and Signal Processing*, vol. 54-55, pp. 195–209, Mar. 2015.

[8] X. Liu and T. Chen, "Geometry-assisted statistical modeling for face mosaicing," in *2003 International Conference on Image Processing (ICIP)*, vol. 2, Barcelona, Spain, Spain, Sep. 2003, pp. 883–886.

[9] M.W. Rahman, F.T. Zohra, and M.L. Gavrilova, "Rank level fusion for kinect gait and face biometrie identification," in *IEEE Symposium Series on Computational Intelligence (SSCI)*, Honolulu, HI, USA, Nov-Dec. 2017, pp. 1–7.

[10] N. Susyanto, "Pool adjacent violators based biometric rank level fusion," in *International Conference of the Biometrics Special Interest Group (BIOSIG)*, Darmstadt, Germany, Sept. 2017, pp. 1–3.

[11] S.B. Jemaa and M. Hammami, "Human identification based on the palmar surface of the hand," in *13th International Conference on Computer Graphics, Imaging and Visualization (CGiV)*, Beni Mellal, Morocco, Mar-Apr. 2017, pp. 51–56.

[12] H. Talebi and M.L. Gavrilova, "Prior resemblance probability of users for multimodal biometrics rank fusion," in *IEEE International Conference on Identity, Security and Behavior Analysis (ISBA 2015)*, Hong Kong, China, Mar. 2015, pp. 1–7.

[13] P.P. Paul and M.L. Gavrilova, "Rank level fusion of multimodal cancelable biometrics," in *IEEE International Conference on Identity, Security and Behavior Analysis (ISBA 2014)*, London, UK, Aug. 2014, pp. 80–87.

[14] E. Marasco and C. Sansone, "Exploiting cohorts information in multibiometric identification systems via graph-based fusion," in *IEEE International Conference on Identity, Security and Behavior Analysis (ISBA 2013)*, Naples, Italy, Sep. 2013, pp. 34–40.

[15] A. Kumar, M. Hanmandlu, and S. Vasikarla, "Rank level integration of face based biometrics," in *Ninth International Conference on Information Technology - New Generations*, Las Vegas, NV, USA, April. 2012, pp. 36–41.

[16] M.M. Monwar, M. Gavrilova, and Y. Wang, "A novel fuzzy multimodal information fusion technology for human biometric traits identification," in *IEEE 10th International Conference on Cognitive Informatics and Cognitive Computing (ICCI-CC'11)*, Banff, AB, Canada, Aug. 2011, pp. 112–119.

[17] A. Abaza and A. Ross, "Quality based rank-level fusion in multibiometric systems," in *IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems*, Washington, DC, USA, Sep. 2009, pp. 1–6.

[18] M.M. Monwar and M.L. Gavrilova, "Multimodal biometric system using rank-level fusion approach," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 39, no. 4, pp. 867–878, Aug. 2009.

[19] M.M. Monwar and M. Gavrilova, "Integrating monomodal biometric matchers through logistic regression rank aggregation approach," in *37th IEEE Applied Imagery Pattern Recognition Workshop*, Washington DC, USA, Oct. 2008, pp. 1–7.

[20] M.M. Monwar and M. Gavrilova, "Fes: A system for combining face, ear and signature biometrics using rank level fusion," in *Fifth International Conference on Information Technology: New Generations (itng 2008)*, Las Vegas, NV, USA, April. 2008, pp. 922–927.

[21] A. Kumar and S. Shekhar, "Personal identification using multibiometrics rank-level fusion," *IEEE Transactions on Systems, Man and Cybernetics-PART C: Applications and reviews*, vol. 41, no. 5, pp. 743–752, Sep. 2011.

[22] M.R. Alam et al., "A confidence-based late fusion framework for audio-visual biometric identification," *Pattern Recognition Letters*, vol. 52, pp. 65–71, Jan. 2015.

[23] H. S. Bhatt, R. Singh, and M. Vatsa, "On recognizing faces in videos using clustering-based re-ranking and fusion," *IEEE Transactions on Information Forensics and Security*, vol. 9, no. 7, pp. 1056–1068, Jul. 2014.

[24] M. R. Alam et al., "An efficient reliability estimation technique for audio-visual person identification," in *8th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, Melbourne, Australia, Jun. 2013, pp. 1631–1635.

[25] M. Monwar, "A multimodal biometric system based on rank level fusion," Ph.D. dissertation, Univ. of Calgary, Calgary,Alberta, Dec. 2012. [Online]. Available: https://prism.ucalgary.ca/handle/11023/385

[26] P.P. Paul, M.L. Gavrilova, and R. Alhajj, "Decision fusion for multimodal biometrics using social network analysis," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 44, no. 11, pp. 1522–1533, Nov. 2014.

[27] K. Veeramachaneni, L.A. Osadciw, and P.K. Varshney, "An adaptive multimodal biometric management algorithm," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 35, no. 3, pp. 344–356, Jul. 2005.

[28] K.-A. Toh and Wei-Yun Yau, "Combination of hyperbolic functions for multimodal biometrics data fusion," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 34, no. 2, pp. 1196–1209, April. 2004.

[29] A. Das et al., "A decision-level fusion strategy for multimodal ocular biometric in visible spectrum based on posterior probability," in *IEEE International Joint Conference on Biometrics (IJCB)*, Denver, CO, USA, Oct. 2017, pp. 794–798.

[30] K. Aizi, M. Ouslim, and A. Sabri, "Remote multimodal biometric identification based on the fusion of the iris and the fingerprint," in *2015 4th International Conference on Electrical Engineering (ICEE)*, Boumerdes, Algeria, Dec. 2015, pp. 1–6.

[31] T. Barbu, A. Ciobanu, and M. Luca, "Multimodal biometric authentication based on voice, face and iris," in *E-Health and Bioengineering Conference (EHB)*, Iasi, Romania, Nov. 2015, pp. 1–4.

[32] L. Marfella, E. Marasco, and C. Sansone, "Liveness-based fusion approaches in multibiometrics," in *IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS)*, Salerno, Italy, Sep. 2012, pp. 1–7.

[33] Y.H. Park et al., "A multimodal biometric recognition of touched fingerprint and finger-vein," in *International Conference on Multimedia and Signal Processing*, Guilin, Guangxi, China, May. 2011, pp. 247–250.

[34] B. Ammour, T. Bouden, and L. Boubchir, "Face–iris multi-modal biometric system using multi-resolution log-gabor filter with spectral regression kernel discriminant analysis," *IET Biometrics*, vol. 7, no. 5, pp. 482–489, Aug. 2018.

[35] Y. Xin et al., "Multimodal feature-level fusion for biometrics identification system on IoMT platform," *IEEE Access*, vol. 6, pp. 21 418–21 426, Mar. 2018.

[36] N. Hezil and A. Boukrouche, "Multimodal biometric recognition using human ear and palmprint," *IET Biometrics*, vol. 6, no. 5, pp. 351–359, Aug. 2017.

[37] F.M. Algashaam et al., "Elliptical higher-order-spectra periocular code," *IEEE Access*, vol. 5, pp. 6978–6988, Apr. 2017.

[38] S. Veluchamy and L.R. Karlmarx, "System for multimodal biometric recognition based on finger knuckle and finger vein using feature-level fusion and k-support vector machine classifier," *IET Biometrics*, vol. 6, no. 3, pp. 232–242, Apr. 2017.

[39] M. Haghighat, M.A. Mottaleb, and W. Alhalabi, "Discriminant correlation analysis: Real-time feature level fusion for multimodal biometric recognition," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 9, pp. 1984–1996, Sep. 2016.

[40] A. Nagar, K. Nandakumar, and A.K. Jain, "Multibiometric cryptosystems based on feature-level fusion," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 1, pp. 255–268, Feb. 2012.

[41] R.M. Jiang, A.H. Sadka, and D. Crookes, "Multimodal biometric human recognition for perceptual human–computer interaction," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 6, pp. 676 – 681, Nov. 2010.

[42] V. Conti et al., "A frequency-based approach for features fusion in fingerprint and iris multimodal biometric identification systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 40, no. 4, pp. 384 – 395, Jul. 2010.

[43] S. Taheri, and Ö. Toygar, "On the use of DAG-CNN architecture for age estimation with multi-stage features fusion," *Neurocomputing*, vol. 329, no. 15, pp. 300–310, Feb. 2019.

[44] Z. Golrizkhatami and A. Acan, "ECG classification using three-level fusion of different feature descriptors," *Expert Systems with Applications*, vol. 114, no. 30, pp. 54–64, Dec. 2018.

[45] D. Peralta et al., "Distributed incremental fingerprint identification with reduced database penetration rate using a hierarchical classification based on feature fusion and selection," *Knowledge-Based Systems*, vol. 126, no. 15, pp. 91–103, Jun. 2017.

[46] M.I. Ahmad, W.L. Woo, and S. Dlay, "Non-stationary feature fusion of face and palmprint multimodal biometrics," *Neurocomputing*, vol. 177, no. 12, pp. 49–61, Feb. 2016.

[47] P. Perakis, T. Theoharis, and I.A. Kakadiaris, "Feature fusion for facial landmark detection," *Pattern Recognition*, vol. 47, no. 9, pp. 2783–2793, Sep. 2014.

[48] J. Yang, and X. Zhang, "Feature-level fusion of fingerprint and finger-vein for personal identification," *Pattern Recognition Letters*, vol. 33, no. 5, pp. 623–628, Apr. 2012.

[49] W. Yang et al., "Comparative competitive coding for personal identification by using finger vein and finger dorsal texture fusion," *Information Sciences*, vol. 268, no. 1, pp. 20–32, Jun. 2014.

[50] K. Annapurani, M.A.K. Sadiq, and C. Malathya, "Fusion of shape of the ear and tragus – a unique feature extraction method for ear authentication system," *Expert Systems with Applications*, vol. 42, no. 1, pp. 649–656, Jan. 2015.

[51] P.H. Silva et al., "Multimodal feature level fusion based on particle swarm optimization with deep transfer learning," in *IEEE Congress on Evolutionary Computation (CEC)*, Rio de Janeiro, Brazil, Jul. 2018, pp. 1–8.

[52] S. Soleymani et al., "Generalized bilinear deep convolutional neural networks for multimodal biometric identification," in *25th IEEE International Conference on Image Processing (ICIP)*, Athens, Greece, Oct. 2018, pp. 763–767.

[53] B.H. Guo, M.S. Nixon, and J.N. Carter, "Supervised generalized canonical correlation analysis of soft biometrie fusion for recognition at a distance," in *8th International Conference on Imaging for Crime Detection and Prevention (ICDP 2017)*, Madrid, Spain, Dec. 2017, pp. 49–54.

[54] V. Talreja, M.C. Valenti, and N.M. Nasrabadi, "Multibiometric secure system based on deep learning," in *IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Montreal, QC, Canada, Nov. 2017, pp. 298–302.

[55] H. Naderi, B.H. Soleimani, and S. Matwin, "Manifold learning of overcomplete feature spaces in a multimodal biometric recognition system of iris and palmprint," in *14th Conference on Computer and Robot Vision (CRV)*, Edmonton, AB, Canada, May. 2017, pp. 191–196.

[56] M.K. Bashar, "Integrated biometrics for human identification integrated biometrics," in *2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, Okinawa, Japan, Nov. 2017, pp. 96–100.

[57] X. Zhang, Y. Dai, and X. Xu, "Android-based multimodal biometric identification system using feature level fusion," in *International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, Xiamen, China, Nov. 2017, pp. 120–124.

[58] S. Soviany et al., "An optimized biometric system with intra-and inter-modal feature-level fusion," in *9th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, Targoviste, Romania, Jul. 2017, pp. 1–8.

[59] Y. Bouzouina and L. Hamami, "Multimodal biometric: Iris and face recognition based on feature selection of iris with GA and scores level fusion with svm," in *2017 2nd International Conference on Bio-engineering for Smart Technologies (BioSMART)*, Paris, France, Sep. 2017, pp. 1–7.

[60] P.A. Kumari and G.J. Suma, "An experimental study of feature reduction using PCA in multi-biometric systems based on feature level fusion," in *International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES)*, Putrajaya, Malaysia, Nov. 2016, pp. 109–114.

[61] V.V. Dakre and P.G. Gawande, "An efficient technique of multimodal biometrics using fusion of face and iris features," in *Conference on Advances in Signal Processing (CASP)*, Pune, India, Jun. 2016, pp. 231–236.

[62] D. Brown and K. Bradshaw, "A multi-biometric feature-fusion framework for improved uni-modal and multi-modal human identification," in *IEEE Symposium on Technologies for Homeland Security (HST)*, Waltham, MA, USA, May. 2016, pp. 1–6.

[63] M. Garau et al., "Experimental results on multi-modal fusion of EEG-based personal verification algorithms," in *International Conference on Biometrics (ICB)*, Halmstad, Sweden, Jun, 2016, pp. 1–6.

[64] I.S. Oveisi and M Modarresi, "A feature level multimodal approach for palmprint and knuckleprint recognition using adaboost classifier," in *International Conference and Workshop on Computing and Communication (IEMCON)*, Vancouver, BC, Canada, Oct. 2015, pp. 1–7.

[65] X. Meng, M. Chen, and Z. Wang, "Improved locality preserving projections for multimodal biometrics," in *Third International Conference on Robot, Vision and Signal Processing (RVSP)*, Kaohsiung, Taiwan, Nov. 2015, pp. 228–231.

[66] K.B. Raja et al., "Fusion of face and periocular information for improved authentication on smartphones," in *18th International Conference on Information Fusion (Fusion)*, Washington, DC, USA, Jul. 2015, pp. 2115–2120.

[67] M. Modarresi and I.S. Oveisi, "A contourlet transform based for features fusion in retina and iris multimodal biometric system," in *International Workshop on Biometric Authentication*, Sofia, Bulgaria, Nov. 2014, pp. 75–90.

[68] R.H. Jeng, and W.S. Chen, "Two feature-level fusion methods with feature scaling and hashing for multimodal biometrics," *IETE Technical Review*, vol. 34, no. 1, pp. 91–101, 2017.

[69] M. Cheniti, N.-E. Boukezzoula, and Z. Akhtar, "Symmetric sum-based biometric score fusion," *IET Biometrics*, vol. 7, no. 5, pp. 391 – 395, Aug. 2018.

[70] M. Sultana et al., "Social behavioral information fusion in multimodal biometrics," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 48, no. 12, pp. 2176 – 2187, Dec. 2018.

[71] N. Kihal et al., "Efficient multimodal ocular biometric system for person authentication based on iris texture and corneal shape," *IET Biometrics*, vol. 6, no. 6, pp. 379–386, Nov. 2017.

[72] K. Roy et al., "Multibiometric system using fuzzy level set, and genetic and evolutionary feature extraction," *IET Biometrics*, vol. 4, no. 3, pp. 151–161, Aug. 2015.

[73] K. Nguyen et al., "Score-level multibiometric fusion based on dempster–shafer theory incorporating uncertainty factors," *IEEE Transactions on Human-Machine Systems*, vol. 45, no. 1, pp. 132 – 140, Feb. 2015.

[74] V. Kanhangad, A. Kumar, and D. Zhang, "Contactless and pose invariant biometric identification using hand surface," *IEEE Transactions on Image Processing*, vol. 20, no. 5, pp. 1415 – 1424, May. 2011.

[75] B.J. Kang and K.R. Park, "Multimodal biometric method based on vein and geometry of a single finger," *IET Computer Vision*, vol. 4, no. 3, pp. 209–217, Sep. 2010.

[76] N. Poh, J. Kittler, and T. Bourlai, "Quality-based score normalization with device qualitative information for multimodal biometric fusion," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 40, no. 3, pp. 539–554, May. 2010.

[77] F.A. -Fernandez et al., "Quality-based conditional processing in multi-biometrics: Application to sensor interoperability," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 40, no. 6, pp. 1168–1179, Nov. 2010.

[78] A. Kumar, V. Kanhangad, and D. Zhang, "A new framework for adaptive multimodal biometrics management," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 1, pp. 92–102, Mar. 2010.

[79] S. Ribaric ; D. Ribaric ; N. Pavesic, "Multimodal biometric user-identification system for network-based applications," *IEE Proceedings - Vision, Image and Signal Processing*, vol. 150, no. 6, pp. 409–416, Dec. 2003.

[80] G.S. Walia et al., "Robust multimodal biometric system based on optimal score level fusion model," *Expert Systems with Applications*, vol. 116, pp. 364–376, Feb. 2019.

[81] R. Dwivedi and S. Dey, "Score-level fusion for cancelable multi-biometric verification," *Pattern Recognition Letters*, Apr. 2018.

[82] Y. Liang et al., "Combining multiple biometric traits with an order-preserving score fusion algorithm," *Neurocomputing*, vol. 171, no. 1, pp. 252–261, Ja. 2016.

[83] H.M. Sim et al., "Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images," *Expert Systems with Applications*, vol. 41, no. 11, pp. 5390–5404, Sep. 2014.

[84] Y. Kim et al., "An online learning network for biometric scores fusion," *Neurocomputing*, vol. 102, no. 15, pp. 65–77, Feb. 2013.

[85] N. Poh, T. Bourlai, and J. Kittler, "A multimodal biometric test bed for quality-dependent, cost-sensitive and client-specific score-level fusion algorithms," *Pattern Recognition*, vol. 43, no. 3, pp. 1094–1105, Mar. 2010.

[86] F. Alsaade et al., "Qualitative fusion of normalised scores in multimodal biometrics," *Pattern Recognition Letters*, vol. 30, no. 5, pp. 564–569, Apr. 2009.

[87] B.H. Guo, M.S. Nixon, and J.N. Carter, "A joint density based rank-score fusion for soft biometric recognition at a distance," in *24th International Conference on Pattern Recognition (ICPR)*, Beijing, China, Aug. 2018, pp. 3457 – 3462.

[88] M.W. Rahman and M.L. Gavrilova, "Emerging eeg and kinect face fusion for biometrie identification," in *IEEE Symposium Series on Computational Intelligence (SSCI)*, Honolulu, HI, USA, Dec. 2017, pp. 1–8.

[89] J.P. Hube, "Formulae for consistent biometric score level fusion," in *IEEE International Joint Conference on Biometrics (IJCB)*, Denver, CO, USA, Oct. 2017, pp. 329–334.

[90] L. Lu, X. Zhang, and X. Xu, "Fusion of face and visual speech information for identity verification," in *International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, Xiamen, China, Nov. 2017, pp. 502 – 506.

[91] L. Mezai and F. Hachouf, "Adaptive multimodal biometric fusion algorithm using particle swarm optimization and belief functions," in *4th International Conference on Biometrics and Forensics (IWBF)*, Limassol, Cyprus, Mar. 2016, pp. 1–6.

[92] L. Mezai and F. Hachouf, "Score level fusion algorithm using differential evolution and proportional conflict redistribution rule," in *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Budapest, Hungary, Oct. 2016, pp. 001 051–001 056.

[93] R.M. Jomaa, M.S. Islam, and H. Mathkour, "Enhancing the information content of fingerprint biometrics with heartbeat signal," in *2015 World Symposium on Computer Networks and Information Security (WSCNIS)*, Hammamet, Tunisia, Sep. 2015, pp. 1–5.

[94] A.Meraoumia, S. Chitroub, and A. Bouridane, "Robust multimodal biometric identification system using finger-knuckle-print features," in *3rd International Conference on Control, Engineering and Information Technology (CEIT)*, Tlemcen, Algeria, May. 2016, pp. 1–6.

[95] M. Derawi and I. Voitenko, "Fusion of gait and ecg for biometric user authentication," in *International Conference of the Biometrics Special Interest Group (BIOSIG)*, Darmstadt, Germany, Sep. 2014, pp. 1–4.

[96] Y. Kumar et al., "An automated multimodal biometric system and fusion," in *IEEE Symposium on Computational Intelligence in Biometrics and Identity Management (CIBIM)*, Orlando, FL, USA, Dec. 2014, pp. 16–21.

[97] S. Mukherjee et al., "Differential evolution based score level fusion for multi-modal biometric systems," in *IEEE Symposium on Computational Intelligence in Biometrics and Identity Management (CIBIM)*, Orlando, FL, USA, Dec. 2014, pp. 38–44.

[98] H. Aronowitz et al., "Multi-modal biometrics for mobile authentication," in *IEEE International Joint Conference on Biometrics*, Clearwater, FL, USA, Oct. 2014, pp. 1–8.

[99] K. Shanmugasundaram, A.S.A. Mohamed, and N.I.R. Ruhaiyem, "An overview of hand-based multimodal biometrie system using multi-classifier score fusion with score normalization," in *International Conference on Signal Processing and Communication (ICSPC)*, Coimbatore, India, Jul. 2017, pp. 53–57.

[100] P. Ejarque and J. Hernando, "Score bi-gaussian equalisation for multimodal person verification," *IET Signal Processing*, vol. 3, no. 4, pp. 322–332, Jul. 2009.

[101] R. Snelick et al., "Large-scale evaluation of multimodal biometric authentication using state-of-the-art systems," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 3, pp. 450–455, Mar. 2005.

[102] P. Moutafis and I.A. Kakadiaris, "Can we do better in unimodal biometric systems? a rank-based score normalization framework," *IEEE Transactions on Cybernetics*, vol. 45, no. 12, pp. 2654–2667, Dec. 2015.

[103] M. Hanmandlu et al., "Score level fusion of multimodal biometrics using triangular norms," *Pattern Recognition Letters*, vol. 32, no. 14, pp. 1843–1850, Oct. 2011.

[104] R. Cappelli, D. Maio, and D. Maltoni, "Combining fingerprint classifiers," in *International Workshop on Multiple Classifier Systems*, Cagliari, Italy, Dec. 2000, pp. 351–361.

[105] Y.N. Singh and P. Gupta, "Quantitative evaluation of normalization techniques of matching scores in multimodal biometric systems," in *International Conference on Biometrics (ICB)*, Seoul, Korea, Aug. 2007, pp. 574–583.

[106] M. He et al., "Performance evaluation of score level fusion in multimodal biometric systems," *Pattern Recognition*, vol. 43, no. 5, pp. 1789–1800, May. 2010.

[107] Q.D. Tran and P. Liatsis, "A modified equal error rate based user-specific normalization for multimodal biometrics," in *Sixth International Conference on Developments in eSystems Engineering*, Abu Dhabi, United Arab Emirates, Dec. 2013, pp. 286–290.

[108] N. Poh and S. Bengio, "F-ratio client dependent normalisation for biometric authentication tasks," in *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Philadelphia, PA, USA, Mar. 2005, pp. I/721 – I/724 Vol. 1.

[109] K. Tiwari, A. Nigam and P. Gupta, "TARC: A novel score fusion scheme for multimodal biometric systems," in *IEEE Symposium on Computational Intelligence in Biometrics and Identity Management (CIBIM)*, Florida, USA, Dec. 2014, pp. 53–59.

[110] N. Damer, A. Opel, and A. Nouak, Ed., *Performance anchored score normalization for multi-biometric fusion.* Berlin, Heidelberg: Springer-Verlag, 2013, vol. 8034.

[111] R.L.V. Hsu, J. Shah, and B. Martin, "Quality assessment of facial images," in *2006 Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference*, Baltimore, MD, USA, Aug. 2006, pp. 1–6.

[112] F.R. Hampel et al., *Robust Statistics: The Approach Based on Influence Functions.* Wiley, 2011.

[113] N. Damer, A. Opel, and A. Nouak, "Biometric source weighting in multi-biometric fusion: Towards a generalized and robust solution," in *22nd European Signal Processing Conference (EUSIPCO)*, Lisbon, Portugal, Nov. 2014, pp. 1382–1386.

[114] C. Chia, N. Sherkat, and L. Nolle, "Towards a best linear combination for multimodal biometric fusion," in *20th International Conference on Pattern Recognition*, Istanbul, Turkey, Aug. 2010, pp. 1176 – 1179.

[115] N. Poh and S. Bengio, "Non-linear variance reduction techniques in biometric authentication," in *Workshop on Multimedia User Authentication (MMUA)*, Idiap-RR-26-2003, 2003, pp. 123–130.

[116] N. Poh et al., "Benchmarking quality-dependent and cost-sensitive score-level multimodal biometric fusion algorithms," *IEEE Transactions on Information Forensics and Security*, vol. 4, no. 4, pp. 849–866, Dec. 2009.

[117] R. Raghavendra, G. H. Kumar, A. Rao, "Seventh international conference on advances in pattern recognition," in *Workshop on Multimedia User Authentication (MMUA)*, Kolkata, India, Feb. 2009, pp. 193–196.

[118] N. Poh and S. Bengio, "A study of the effects of score normalisation prior to fusion in biometric authentication tasks," IDIAP Research Report, Martigny, Switzerland, Tech. Rep. IDIAP-RR-04-69, Dec 2004.

[119] A.C. Lorena and A.C.P.L.F. de Carvalho, "Building binary-tree-based multiclass classifiers using separability measures," *Neurocomputing*, vol. 73, no. 16-18, pp. 2837–2845, Oct. 2010.

[120] A. Ross and A. Jain, "Information fusion in biometrics," *Pattern Recognition Letters*, vol. 24, no. 13, pp. 2115–2125, Sep. 2003.

[121] [FVC2002] The 2nd Fingerprint Verification Competition. Available from: http://bias.csr.unibo.it/fvc2002/.

[122] COEP Palm Print Database from College of Engineering Pune-411005 (An Autonomous Institute of Government of Maharashtra). Available from: https://www.coep.org.in/resources/coeppalmprintdatabase.

[123] IIT Delhi Palmprint Image Database version 1.0. Available from: http://www4.comp.polyu.edu.hk/csajaykr/IITD/ Database_Palm.htm.

[124] A. Kumar, “Incorporating cohort information for reliable palmprint authentication,” in *Sixth Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP)*, Bhubneshwar, India, Dec. 2008, pp. 583–590.

[125] AMI ear database. Available from: http: //www.ctim.es/ research_works/ ami_ear_database/.

[126] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “A new anchored normalization technique for score-level fusion in multimodal biometric systems,” in *IEEE International Symposium on Circuits and Systems (ISCAS)*, Montreal, Quebec, Canada, May. 2016, pp. 93–96.

[127] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “A novel normalization technique for multimodal biometric systems,” in *IEEE 58th International Midwest Symposium on Circuits and Systems (MWSCAS)*, Fort Collins, CO, USA, Aug. 2015, pp. 145–148.

[128] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “Normalization and weighting techniques based on genuine-impostor score fusion in multi-biometric systems,” *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 8, pp. 1989–2000, Aug. 2018.

[129] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “A two-stage scheme for fusion of hash-encoded features in a multimodal biometric system,” in *16th IEEE International New Circuits and Systems Conference (NEWCAS)*, Montréal, QC, Canada, Jun. 2018, pp. 340–343.

[130] Nonsubsampled Contourlet Toolbox. Available from: https:// www.mathworks.com/ matlabcentral/ fileexchange/ 10049-nonsubsampled-contourlet-toolbox.

[131] Z. Khan, A. Mian, and Y. Hu, “Contour code: robust and efficient multispectral palmprint encoding for human recognition,” in *ICCV*, 2011.

[132] J. Abraham, P. Kwan, and J. Gao, “Fingerprint matching using a hybrid shape and orientation descriptor,” *State of the art in Biometrics*, pp. 25–56, 2011.

[133] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “Weighted hybrid fusion for multimodal biometric recognition system,” in *IEEE International Symposium on Circuits and Systems (ISCAS)*, Florence, Italy, May. 2018, pp. 1–4.

[134] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “Score reliability basedweighting technique for score-level fusion in multi-biometric systems,” in *IEEE Winter Conference on Computer Vision (WACV)*, New York, USA, Mar. 2016, pp. 1–7.

[135] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, “A multi-biometric system based on feature and score level fusions,” *IEEE Access*, vol. 7, pp. 59 437–59 450, May. 2019.

[136] W. Kabir, M.O. Ahmad, and M.N.S. Swamy, "A two-level fusion scheme for multimodal biometric recognition," *IEEE Transactions on Information Forensics and Security*, (under review).