الجمهورية الجزائرية الديمقراطية الشعبية

REPUBLIQUE ALGERIENNE DEMOCRATIQUE ET POPULAIRE

وزارة التعليم العالي والبحث العلمي

MINISTERE DE L'ENSEIGNEMENT SUPERIEUR ET DE LA RECHERCHE SCIENTIFIQUE

جامعة فرحات عباس سطيف 1

UNIVERSITE FERHAT ABBAS SETIF1

THESE

Présentée à la Faculté de Technologie

Pour Obtenir le Diplôme de

Doctorat LMD 3ème Cycle

Domaine : Sciences et Technologie
Filière : Electronique
Option : Systèmes Embarqués et Technologie

Par

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Sécurisation des transactions et des déplacements des personnes par la biométrie multi-modale

Soutenue le : 25/07/2019 devant un jury composé de :

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PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

FERHAT ABBAS SETIF 1 UNIVERSITY

A thesis

presented to the University of Setif 1

in fulfilment of the

thesis requirement for the degree of

Doctor of third cycle LMD

in embedded system and technologies

by

CHENITI Mohamed

Securing transactions and moving people using multimodal biometric

Presented in 25/07/2019

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Acknowledgments

First of all, I thank from the bottom of my heart ALLAH, the almighty, for enlightening me on the right path.

Taking this opportunity I would like to express my gratitude to my very helpful principal supervisor Pr. **Naceur-Eddine Boukezzoula** for his supervision, guidance and support. This excellent support and guidance have indeed helped me find a proper direction in my work. His valuable advice and technical guidance have encouraged me to understand research methodology.

I would like to express my appreciation to my thesis committee members:
Pr. **HASSAM Abdelouahab,** Pr**. FERHAT-HAMIDA Abdelhak**, Pr. **TOUMI Salah** for their discussions, suggestions, and feedbacks to improve my thesis.
Taking this opportunity I would like to express my gratitude to Pr. **Zahid Akhtar** for his help. Also, I thank all my friends.

Last, but not least, I would like to express my gratitude and appreciation to all of my family (specially my mother and father) for their support, encouragement, faith, understanding and help. Without them, this work would not have been possible.

Glossary of Important Terms

BSIF : Binarized Statistical Image Features.

CLAHE: Contrast limited Adaptive Histogram Equalization

DFT : Discrete Fourier Transform.

EER : Equal Error Rate.

EP: Einstein product,

FAR : False Acceptance Rate.

FRR : False Rejection Rate.

FFT: fast Fourier transform.

FLD : Fisher Linear Discriminant.

GAR : Genuine Acceptance Rate.

GMM : Gaussian Mixture Model.

HTER : Half Total Error Rate.

HOG : Histogram of Oriented Gradient.

HMM: Hidden Model Markov.

ICA: Independent Component Analysis.

ID: Identification Card.

KPCA: kernel Principal Component Analysis.

KLDA : kernel Linear Discriminate Analysis.

KNN: k-nearest neighbor.

LBP : Local Binary Patterns.

LDA : Linear Discriminate Analysis.

LTP: Local Ternary Patterns.

LPQ: Local Phase Quantization.

MLE : Maximum Likelihood Estimation.

MCC : Minutia Cylinder-Codes.

MLP: Multi-Layer Perceptron.

NIST: National Institute of Standards and Technology.

OPT (order preserving tree).

PCA : Principal Component Analysis.

PIN : Personnal Identification Number.

POC: Phase only correlation.

PSO: Particle Swarm Optimization.

PUT: Poznan University Of Technology

QDA: Quadratic Discriminant Analysis.

ROC: Receiver Operating Characteristic.

ROI: Region Of Interest.

RBF: Radial Basis Function.

SVM: Support Vector Machine.

SRC: Sparse Representation Classifier.

STFT: Short-term Fourier transform.

S-norm: symmetric sum.

Std: standard deviation.

Tanh: tanh-estimators.

TER : Total Error Rate. T-norm: triangular norm, t-conorm: triangular norm.

UC3M: University Carlos III of Madrid.

Abstract

Multibiometric systems that fuse information from different sources are able to alleviate limitations of the unimodal biometric systems. In this thesis, we propose a multibiometric framework to identify people using their left and right wrist vein patterns. The framework uses a fast and robust preprocessing and feature extraction method. A generic score level fusion approach is proposed to integrate the scores from left and right wrist vein patterns using Dubois and Parad triangular norm (t-norm). Experiments on the publicly available PUT wrist vein dataset show that the proposed multibiometric framework outperforms the unimodal systems, their fusion using other t-norms techniques, and existing wrist vein recognition methods. Also, a new framework for score level fusion based on symmetric sums (s-sums) has been presented. These s-sums are generated via triangular norms. The proposed framework has been tested on two publicly available benchmark databases. In particular, the authors used two partitions of NIST-BSSR1, i.e. NIST-multimodal database and NIST-fingerprint database. The experimental results show that the proposed method outperforms the existing approaches for the NIST-multimodal database and NIST-fingerprint database.
Keywords—Biometrics, Authentication, Multibiometrics, Data fusion, Wrist vein, Triangular norms, Symmetric sums, Fuzzy logic.

Résumé

Les systèmes biométriques multimodaux qui fusionnent des informations provenant de différentes sources peuvent atténuer les limitations des systèmes biométriques uni-modaux. Dans cette thèse, nous proposons un cadre multi-biométrique pour identifier les personnes à l'aide de leurs modèles de veines du poignet droit et gauche. La structure utilise une méthode d’extraction et de prétraitement rapide et robuste. Une approche générique de fusion au niveau des scores est proposée pour intégrer les scores des modèles de veines du poignet droit et gauche en utilisant les normes de Dubois et Parad triangulaires (t-norm). Des expériences sur la base de données de veine de poignet PUT disponible au public montrent que le cadre multi-biométrique proposé surpasse les systèmes uni-modaux, leur fusion à l'aide d'autres techniques de normalisation et les méthodes de reconnaissance de veine de poignet existantes. Un nouveau cadre pour la fusion de niveaux de score basé sur des sommes symétriques (s-sum) a été présenté. Ces sommes sont générées via des normes triangulaires. Le cadre proposé a été testé sur deux bases de données de référence disponibles au public. Les auteurs ont notamment utilisé deux partitions de NIST-BSSR1, à savoir la base de données multimodale (NIST-multimodal) et la base de données d'empreintes digitales (NIST-fingerprint). Les résultats expérimentaux montrent que la méthode proposée surpasse les approches existantes pour la base de données multimodale (NIST-multimodal) et la base de données d'empreintes digitales (NIST-fingerprint).

Mots-clés: Biométrie, Authentification, Multi-biométrie, Fusion de données, Veine du poignet, Normes triangulaires, Sommes symétriques, logique floue.

ملخص

الجمع بين اثنين أو أكثر من طرائق البايومتري في التطبيقات يرفع من معدل التعرف على الأشخاص, لهذا قمنا باقتراح طريقة جديدة تعتمد على الدمج بين الشرايين الدموية المتواجدة في معصم اليد اليمنى مع نظيرتها في اليد اليسرى لبناء نظام بيومتري متعدد المقاييس، لقد قمنا باختيار الشرايين المتواجدة في المعصم لأنها توفر جميع الشروط المتطلبة لبناء نظام بيومتري قوى، في هذه الأطروحة قمنا ببناء خوارزمية جديدة لتوضيح شكل الشرايين المتواجدة فى معصم اليد، لأنها عادة ما تكون مشوشة بسبب عدة عوامل خارجية مثل الجهاز المستخدم لالتقاط صورة الشرايين، بعدها قمنا بدمج (scores) الأنظمة أحادية الواسطة (نظام يعتمد على شرايين نتائج المعصم الأيمن و الأيسر) مع بعضهما لتكوين نظام متعدد الوسائط, قمنا بصهر النتائج باستخدام نهج جديد يسمى (triangular norm) أجريت تجربة هذه التقنيات على قاعدة بيانات اسمها (PUT)، من خلال النتائج بينا تفوق الطريقة المقترحة مقارنة مع الأنظمة الأحادية من جهة، و على النتائج المتحصل عليها باستخدام طرق منتهجة من طرف عدة باحثين آخرين من جهة أخرى.

فى سياق اخر لقد قمنا بتبنى طريقة جديدة لدمج نتائج الأنظمة البيومترية الأحادية باستخدام نظرية جديدة تسمى الجمع المتناظرولقد قمنا بتجربة هذه الطريقة على قاعدتين بيانيتين (NIST-Multimodal و NIST-Fingerprint) اظهرت النتائج المحصل عليها تفوق النهج المقترح على جميع طرق الدمج المقترحة من طرف عدة باحثين.

الكلمات الدلالية : شرايين المعصم الايمن و الايسر,المجاميع المتناظرة, الانظمة البيومترية متعددة الوسائط المنطق الغامض.

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Chapter 1: Introduction to Biometric systems

1.1.Introduction

The need of robust user authentication is increasing day by day owing to exponential growth in digital information and communication technologies. Several efforts have been made to develop systems that can identify and authenticate genuine users. Conventional person identification methods are based on "what you have" (such as an ID card) or "what you know" (such as a password) paradigms. However, they can be easily lost, forgotten or stolen [1.1]. To mitigate some issues of traditional authentication techniques, recently biometrics, which is based on "who you are", has been widely employed in diverse applications ranging from border crossing to mobile authentication [1.2], [1.3]. Biometrics is used to recognize users based on their physiological and behavior characteristics, such as face, palm-print, fingerprint, voice, vein, keystroke, gait, etc. *Figure 1.1* shows physiological and behavioral characteristics which can be used in biometric systems for person authentication.

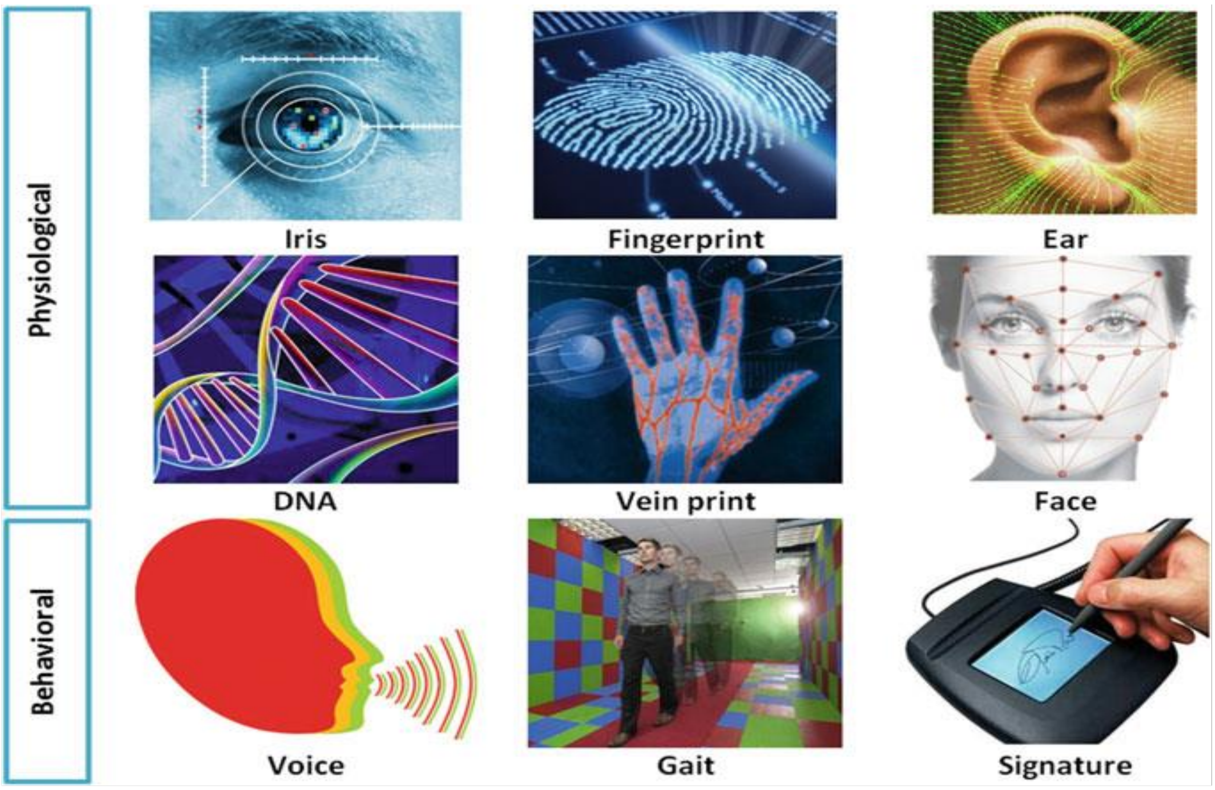

Figure 1.1. Various physiological and behavioral biometric trait [1.4].

1.2. Comparison of Traditional Biometric Trait

Table 1.1 lists the essential physical and behavioral biometric modalities (traits) in use currently (exist in real world applications) with their famous advantages and limitations.

Table 1.1. Advantages and Limitations of different biometric modality [1.5].

Biometric Modality	Advantages	Limitations and Considerations
Iris	✓ Considered the most accurate modality ✓ High stability of characteristics over time ✓ Works well with either verification or identification applications ✓ Hand-free operation ✓ Moderate data storage requirements for templates	✓ Expensive implementation costs data ✓ Requires more training and attentiveness than other ✓ Can be obscured by eyelashes, eye lenses, and reflections from the cornea
Facial recognition	✓ Can operate without user interaction ✓ Only current technology capable of identification over distance ✓ Existing image databases ✓ 3D offers increased precision as images capture surface texture of the face on three axes ✓ Can provide a record of potential imposters ✓ Easy for humans to see the results	✓ Facial traits vary over time ✓ Uniqueness is not maintained ex. in case of twins ✓ Not proper recognition if person has different expression like slight smiling can affect recognition ✓ Highly dependent on lightning
Hand geometry	✓ Operates well in challenging environments; ✓ Biometric is considered highly stable ✓ Widely used; established ✓ Very low storage requirements for its templates	✓ Not accurate for moderate to large populations; human hands are not unique ✓ Readers are bulky and can seem complicated ✓ Perception of passing germs; unhygienic ✓ Not intuitive; require training
Retina recognition	✓ Among the most accurate of biometrics ✓ Moderate storage requirements for templates ✓ Error rate is 1 out of 10,000,000 (almost 0%) ✓ Highly reliable	✓ Considered intrusive; public has never warmed up to it ✓ Not usable in populations with high incidence of eye disease (e.g., elderly) ✓ Can have high cost; special hardware is required

Table 1.1. (Continued)

Fingerprint/ palm print	✓ Most widely used biometric system ✓ Relatively inexpensive ✓ Even twins have unique fingerprint patterns so highly secure ✓ Small template size so matching is also fast ✓ An effective biometric for large-scale systems	✓ Cuts, scars can produce obstacle for recognition ✓ Not privacy enhancing; high level of latency ✓ Approximately 2% to 5% of a given population cannot be enrolled ✓ dirty, dry, or damaged finger affect use
Vein pattern recognition	✓ Highly private; no properties of latency ✓ Highly secure; not possible to lift or steal the vein pattern ✓ Very accurate ✓ Small to moderately sized readers ✓ Near contactless, hygienic ✓ Difficult to circumvent ✓ No cultural stigmas to overcome	✓ Newer biometric; not yet widely used
Keystroke dynamics	✓ Very easy to use and to implement ✓ Except keyboard no additional hardware required ✓ Cost effective	✓ Dynamic changes in timing pattern ✓ Injury ✓ Changes in keyboard hardware
Voice verification	✓ Reliable ✓ Inexpensive ✓ Easy to use and no special instructions required ✓ Readily available component parts (e.g.,microphone, etc.)	✓ Affected by noisy environment ✓ Very large database ✓ Changes if person suffering from cold ✓ Depend on emotional condition of individuals
Gait recognition	✓ Details can be captured from distance ✓ Difficult to conceal ✓ Can be extracted without knowing user	✓ Time to time it persons walking style changes ✓ Not necessarily unique
Dynamic signature verification	✓ Readily integrates into e-business applications ✓ An accepted biometric in banking and financial applications ✓ Low total error ✓ Low storage required	✓ Professional forgers may able to reproduce signatures ✓ From time to time person's style of signature changes ✓ Changes based on emotional and medical condition of person
DNA recognition	✓ It is highly unique feature ✓ Performance is high ✓ Its universality is very high	✓ More informative so privacy issues ✓ More storage required ✓ Not automatic technique

Whereas *Table 1.1* focuses on the characteristics of each biometric trait, *Table 1.2* compares the traditional physiological and behavioral biometric modalities against the original seven criteria for what makes a good biometric. Generally, the following evaluation criteria can help to define a good biometric modality for a given application: (1) uniqueness, (2) permanence, (3) universality, (4) collectability, (5) acceptability, (6) performance, and (7) resistance.

1) **Uniqueness:** is the degree to which a biometric identifier distinguishes one person from another. It should be noted that most scientists believe that all persons are unique in terms of distinctive features such as their vein patterns, fingerprints, retinas, and irises.
2) **Permanence:** refers to stability of the biometrics' trait over time, aging significantly effects some biometric trait (e.g., facial recognition). Some biometric identifiers remain generally constant over one's life (e.g., vein pattern recognition).
3) **Universality:** a useful biometric trait is one that is found in all human beings. If every individual is qualified to provide a specific biometric identifier for recognition purposes, then that biometric trait would be considered truly universal. However, no biometric modality is totally universal.
4) **Collectability:** the biometric modality must be appropriate for capture and measurement, and should be comfortable for the individual to present to the biometric sensor
5) **Acceptability:** indicates the degree of public acceptance and approval for a given biometric modality. Generally, nonintrusive biometric techniques tend to garner greater levels of user acceptance (e.g., Gait recognition). This is a significant factor because user acceptance is critical to the success of any biometric implementation.
6) **Performance:** refers to accuracy, speed, and robustness of the system. Accuracy of biometric systems is usually defined by their false accept and false reject rates. Accuracy is influenced in the data collection process by environmental (e.g., lighting, shadows, background noise).

7) **Resistance to circumvention:** indicates the degree of resistance against spoofing attack. Spoofing is the process by which a fraudulent user can subvert or attack a biometric system by masquerading as registered user and thereby gaining illegitimate access and advantages.

Table 1.2. Comparison of Traditional Biometric Modalities (L: Low, M: Moderate, H: High) [1.5].

Modality	**Universality**	**Uniqueness**	**Permanence**	**Performance**	**Acceptability**	**Resistance to circumvention**
DNA	H	H	H	H	L	L
Iris	H	H	H	H	L	H
Voice	M	L	L	L	H	L
Signature	L	L	L	L	H	L
Fingerprint	M	H	H	H	M	H
Retina	H	H	M	H	L	H
Face	H	L	M	L	H	L
Veine pattern	H	H	H	M	H	H
Ear	M	M	H	M	H	M
Hand geometry	M	M	M	M	M	M
Gait	L	L	L	L	H	M
Keystroke	L	L	L	L	H	L

1.3. Unimodal Biometric Systems

A biometric system based on a single source of biometric information, e.g. single fingerprint or face, is known as a unimodal system. These unimodal systems contain problems like noise in sensed data, non-universality, lack of individuality of the chosen biometric trait, absence of an invariant representation for the biometric trait and susceptibility to circumvention [1.6].

1) **Noisy Data**

   Noise is usually present inside biometric data when sensors are not properly preserved. A typical example is the presence of dirt on the sensor of a fingerprint scanner, which cause a noisy fingerprint. Failure to output the right voice during enrollment is also a form of noisy data. Moreover, not being able to localize a camera properly can lead images of the face and iris that are not very clear [1.6].

2) **Non-universality**

   Universality is one of the fundamental needs for a biometric trait. A biometric system is said to be universal if all users are able to present a biometric trait for identification. Not all biometric traits are truly universal. For example, a blind person cannot present his/her iris or retina in front of the sensors or an unlettered individual cannot give signature for biometric authentication [1.1].

3) **Lack of individuality**

   This problem happens with all of the biometrics traits used in person authentication. If the feature sets of a specific biometric trait obtained from two different subjects are similar, then it is hard to make distinction between those two subjects. This is called lack of individuality problem in biometrics domain and as a result false recognition rate can be higher in this situation. For example, the facial appearance of a father and a son can be quite similar [1.2].

4) **Intra-class variation**

   This problem occurs when a biometric data sets acquired from a user for enrollment phase are not similar to the biometric data sets acquired from the same user during verification stage. This can happen due to the changes in the environmental conditions and inherent changes in the biometric trait, poor user interaction with the sensor [1.1],[1.2].

5) **Susceptibility to circumvention**

This problem occurs when an impostor provides a fake biometric sample to the system. For example, circumventing a biometric system is possible by using gummy fingers. Generally, Behavioral biometric modalities such as signature and voice are more sensitive to this kind of attack than physiological biometric modalities [1.6].

1.4. Aims and Objectives

Among the various biometric traits, vein patterns as a biometric characteristic is now gaining more momentum because it is able to provide several advantages compared to other traits [1.7],[1.8]. Beside fundamental properties such as stability, universality, uniqueness, vein biometric trait has several vital characteristics, e.g., (i) the vein images are obtained in a contact-less manner; thus users may find it less intrusive compared to iris or retina scanning systems [1.7], plus it may also lead to hygienic to the user who then is more likely to adopt it, (ii) due to being touch-less no latent prints are left unintentionally as opposed to finger marks left on the sensor in fingerprint recognition [1.9], (iii) vein patterns are stable and remain unchanged over time, which means vein patterns have strong immunity to ageing [1.10]. While, other biometric traits change over people age thereby making it hard to match the stored templates for that individual after a certain time [1.3],(iv) unlike most physical biometric traits (e.g., face), vein patterns differ between identical twins [1.11], [1.12], (v) vein recognition comparatively requires low cost equipment and a shorter time to verify individuals [1.13], [1.14], (vi) since vein pattern is beneath the skin and invisible to the human eye, thus it is difficult for impostors to steal, replicate or spoof [1.15], [1.16]. Spoofing is the process by which a fraudulent user can subvert or attack a biometric system by masquerading as registered user and thereby gaining illegitimate access and advantages [1.17].

Though hand palm vein is the obvious choice to be exploited in biometric systems, wrist vein provides much more detailed patterns (namely more distinctive features) than hand palm vein [1.7]. There exist several biometrics studies based on wrist vein [1.18], [1.7], [1.19]. However, all prior works are unimodal systems, i.e., they only use single wrist vein, e.g., of right hand, to authenticate the user. But, it is well documented that unimodal biometric systems are unable to provide a high accuracy and security performances mainly due to noise in the sensed data, intra-class variations, inter-class similarities, and attacks [1.1]. Several above-mentioned problems can be solved or at least their impact reduced by fusing several biometric information sources, any such system is known as multibiometric systems [1.2]. Multibiometric systems offer many advantages over unimodal systems, such as significant improvement in the overall accuracy, mitigation of the effect of noisy input data, population coverage larger than the unimodal system [1.19], and greater resistance to spoofing such that they can be more robust than each corresponding unimodal system, even in the case when all biometric traits are spoofed [1.17]. Few works have been focused on palm vein based multibiometric system, e.g., [1.11], [1.20]. To the best of our knowledge, no wrist vein based multibiometric system, particularly integrating right and left wrist vein patterns, has been studied in the literature.

In this thesis, we propose a method to increase the performance of a multimodal biometric security system which uses multiple biometric trait. The main contribution lies in the efficient consolidation of information obtained from different biometric traits. We propose a novel score level fusion method based on triangular norm (t-norm) and symmetric sum based fusion method for multibiometric information fusion. The detailed contributions of this thesis are summarized below:

In this doctoral thesis, we develop a multimodal biometric system based on left and right wrist vein biometric traits to meet the recent extensive security requirements and demands for high performance. This system can alleviate most of the drawbacks associated with unimodal biometric systems mentioned above.

In this doctoral thesis, we proposed a new algorithm for extracting wrist vein features using a fast and resilient preprocessing technique that does not require either user-cooperation or prior learning.

In this doctoral thesis, we proposed a new score level fusion approach for a multimodal biometric system based on symmetric sum (s-sum). These s-sums do not require any learning or training procedure, thus making our system simple, efficient and computationally less expensive.

1.5.Thesis Organization

The thesis has been structured in the following way. Chapter 1 describes the general problem statement and the thesis contributions along with description of biometric systems.

Multimodal biometric systems and their possible fusion strategies are described in chapter 2. This chapter also discusses the designing issues involved in multimodal system development process.

Chapter 3 presents a review of previous investigations into multimodal biometrics.

The proposed fusion method including symmetric sum and triangular norm are described in chapter 4.

Chapter 5 shows the outcomes of the experiments performed on different database frameworks. The experimental overview and the databases are also discussed.

Chapter 6 summarizes the thesis and the contribution and presents some concluding remarks. Possible future directions of this research are also discussed at this chapter.

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Chapter 2: Multimodal biometric systems

2.1. Introduction

In this chapter we introduce the basics of multimodal biometric systems including common performance measures, and we outline some of the common multimodal biometric databases used in the practice.

2.2. Functionality of Biometric Systems

Any biometric systems can provide three modes of operation: (1) enrollment, (2) ongoing transactions (both verification and identification), and (3) updates (re-enrollments).

2.2.1. Enrollment

Enrollment records a person to a biometric database for the first time, see *Figure 2.1*. The user offers a sample (e.g., fingerprint, face, and iris) for the biometric system to transform to a reference template and to store it in the system database [2.1], [2.2].

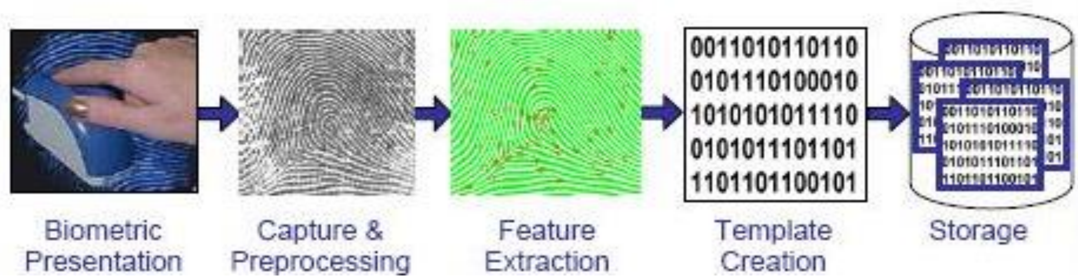

Figure 2.1. Biometric Enrollment Process [2.3].

2.2.2. Verification and Identification

Verification systems seek to answer the question "Is this person who they say they are?" Under a verification system, an individual presents himself or herself as a specific person. The system checks his or her biometric against a biometric profile that already exists in the database linked to that person's file in order to find a match. Verification systems are generally described as a 1-to-1 matching system because the system tries to match the biometric presented by the individual against a specific biometric already on file. Because verification systems only need to compare the presented biometric to a biometric reference stored in the system, they can generate results more quickly and are more accurate than identification systems, even when the size of the database increases. In simple terms it is 1-1 matching with the database [2.2]. See *Figure2.2*.

Identification systems are different from verification systems because an identification system seeks to identify an unknown person, or unknown biometric. The system tries to answer the questions "Who is this person?" or "Who generated this biometric?" and must check the biometric presented against all others already in the database. Identification systems are described as a 1-to-n matching system, where n is the total number of biometrics in the database. Forensic databases, where a government tries to identify a latent print or DNA discarded at a crime scene, often operate as identification systems. In simple terms, it is 1-n Matching within the database [2.4]. See *Figure 2.2*.

2.2.3. Re-enrollments

Nearly all biometric systems preserve stability (permanence) over time; however, changes can occur. The mean reasons for change include adaptation in sensor characteristics (e.g., new biometric reader models), variations in the biometric trait itself (e.g., scars, cuts, or disease).

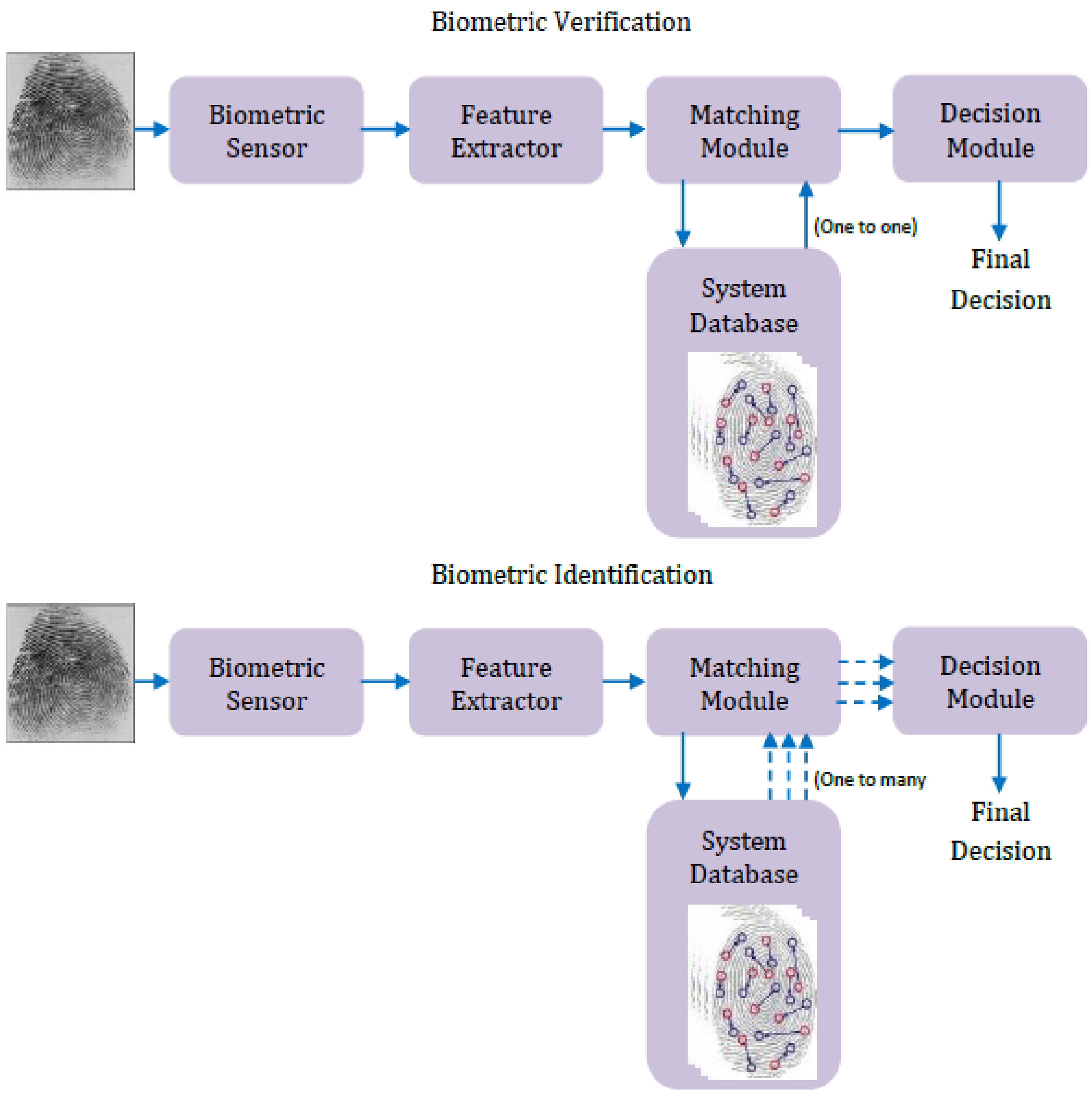

Figure 2.2. Biometric Verification and Biometric Identification.

2.3. Multimodal Biometric System

2.3.1. Advantages of Multimodal Biometric Systems

Some limitations of unimodal systems can be alleviated by multimodal biometric systems that consolidate evidence from multiple biometric sources [2.5, 2.6]. The advantages of multimodal biometric systems are; increased and reliable recognition performance, fewer enrolment problems and enhanced security.

1) **Increased Recognition Performance**

Since multimodal biometric systems rely on more than one biometric trait, as a consequence each of those traits can provide further evidence about the genuineness of any identity claim. For example, the faces of two persons of the same family (or coincidentally of two different persons) can be similar, In this situation, unimodal biometric system based only on face pattern analysis may result in false recognition, If the same biometric system also contains fingerprint matching, the system would results in increased recognition rate as it is impossible that two different persons have same face and fingerprint [2.7].

2) **Fewer Enrolment Problems**

As we state before, unimodal biometric system suffer from the problem of non-universality. Biometric system is said to be universal if all users are able to present a biometric trait for identification, however, not all biometric traits are universal. It has been revealed that about 2% of population are not able to offer a good quality fingerprint, i.e. there are individuals with disabilities [2.8], and thus reduce the failure to enroll rate significantly. A lot of multimodal biometric systems can perform matching even in the absence of one of the biometric samples. For example, in a fingerprint and iris based multimodal system, a person cannot enroll his fingerprint information to the system due to the scars in his fingerprint. In this case, the multimodal system can still perform authentication using the iris characteristics of that person.

3) **Enhanced Security**

It is almost impossible to spoof multimodal biometric system, because the impostor would have to be able to spoof more than one biometric trait simultaneously [2.9].

2.3.2. Fusion Scenarios

A multibiometric system can be based on one or a combination of the following fusion scenarios [2.10] (see *Figure 2.3)*:

1) **Multiple sensors:** In these systems, many sensors are used for capturing different illustrations of the same biometric trait to extract different information. For example, a biometric system can use 2D, 3D images.
2) **Multiple algorithm:** In these systems, a single biometric trait but multiple algorithm are used in order to create templates with different information. For example a system may use minutiae- and texture-based representations.
3) **Multiple instances:** In these systems, a single biometric trait but multiple parts of human's body are used, for example, the use of multiple finger in fingerprint identification, the use of right and left eye in retina recognition system.
4) **Multiple samples:** In these systems, the same biometric modality and instance is acquired with the same sensor multiple times.
5) **Multiple modalities:** In these systems, many biometric modalities are combined, this also known as multimodal biometric.

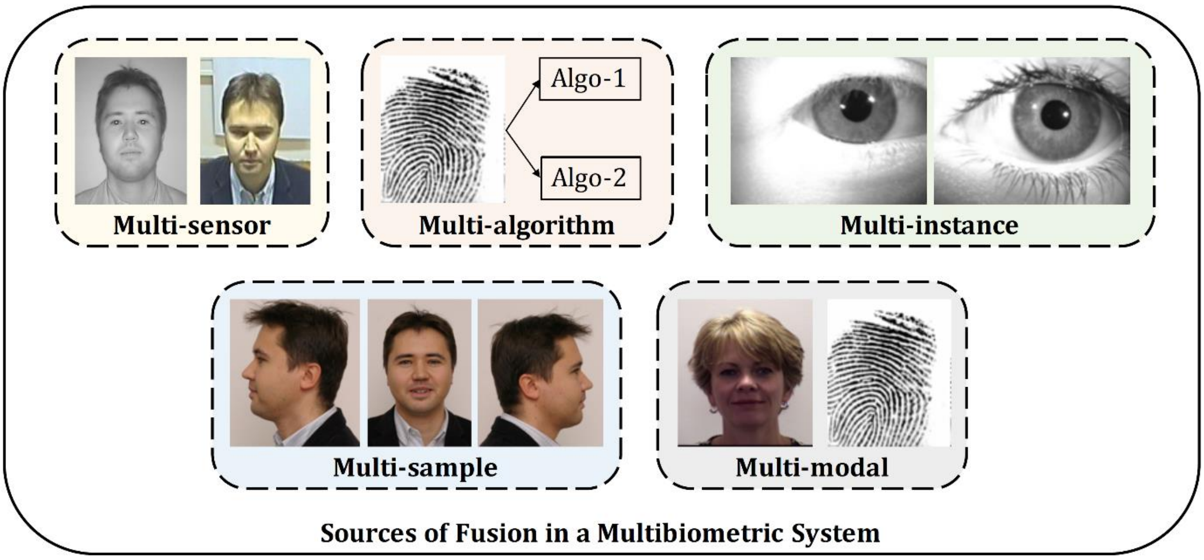

Figure 2.3. Different sources of information that can be exploited by a multibiometric system. Information from multiple se.nsors (infrared and visible spectra) or multiple algorithms (minutiae-based and texture-based) or multiple instances (left and right irises) or multiple samples (left, frontal and right facial profiles) or multiple modalities (face and fingerprint) can be fused [2.10].

2.4. Performance Metrics of Biometric Systems

Several quality performance metrics measure the performance of any biometric authentication system (unimodal or multimodal). A judgment made by a biometric system is either a “genuine individual” type of decision or an “impostor” type of decision [2.11]. For each type of decision, there are two reasonable results, true or false. Therefore, there are only four possible outcomes: a genuine individual is accepted or a genuine match occurred, a genuine individual is rejected or a false rejection occurred, an impostor is rejected or a genuine rejection occurred and an impostor is accepted or a false match occurred [2.12].

2.4.1. The Various Types of Operating Points

Generally, the following operating points are the most used to measure the confidence related with different decisions made by a biometric system (unimodal or multimodal).

1) **FAR** (*False Acceptance Rate*): Witch is defined as the probability of an impostor being accepted as a genuine individual. The FAR is defined in equation (2.1)

   Where FA is total number of forgeries accepted and N_i is total number of forgeries submitted to the system test [2.13].

$$FAR = \frac{FA}{N_i} \tag{2.1}$$

2) **FRR**: (*False Rejection Rate)*: which is defined as the probability of a genuine being rejected as an impostor individual. The FRR is defined in equation (1.2), where FR is total number of genuine rejected and N_c is total number of genuine submitted to the system test [2.13].

$$FRR = \frac{FR}{N_c} \tag{2.2}$$

3) **TER**: (*Total Error Rate)*: is the total error rate of a biometric system. This measure is calculated by the following relation [2.13]:

$$TER = FAR + FRR \quad \textbf{(2.3)}$$

4) **HTER** :(*Half Total Error Rate)*: is the average error rate of a biometric system. This measure is calculated by the following relation [2.13]:

$$HTER = \frac{FAR + FRR}{2} \quad \textbf{(2.4)}$$

5) **EER**: (*Equal Error Rate)*: For a simple empirical measure, it is used to summarize the performance of a biometric system that is defined at the point where False Reject Rate (FRR) and False Accept Rate (FAR) are equal. System with the lower EER, is the more accurate and precise [2.13].
6) **GAR**: (*Genuine Accept Rate*) is the likelihood that a genuine individual is recognized as a match. The GAR is defined in equation (2.5) :

$$GAR(T) = 1 - FRR(T) \quad \textbf{(2.5)}$$

2.4.2. The Performance Curves

For applications, we need to set a threshold with which we make decisions (acceptance or rejection of the user). *Figure 2.4* illustrates the genuine and impostor distributions. Regulating the threshold t changes both false acceptance rate (FAR) and false rejected rate (FRR). For applications that need a high level of security we should increase threshold *t*, also FRR increases. If the threshold *t* is decreased to make the system more tolerant, FAR increases (see *Figure 2.5*). The most commonly used plotting curve is the Receiver Operating Characteristics (ROC) curve [2.14], which is used mostly for biometric verification. ROC curves plot FAR against the corresponding FRR for any threshold. In *Figure 2.5*, every ROC curve represents the performance of a given biometric system, from the same curve we can notice that ROC 3 provides the best performance.

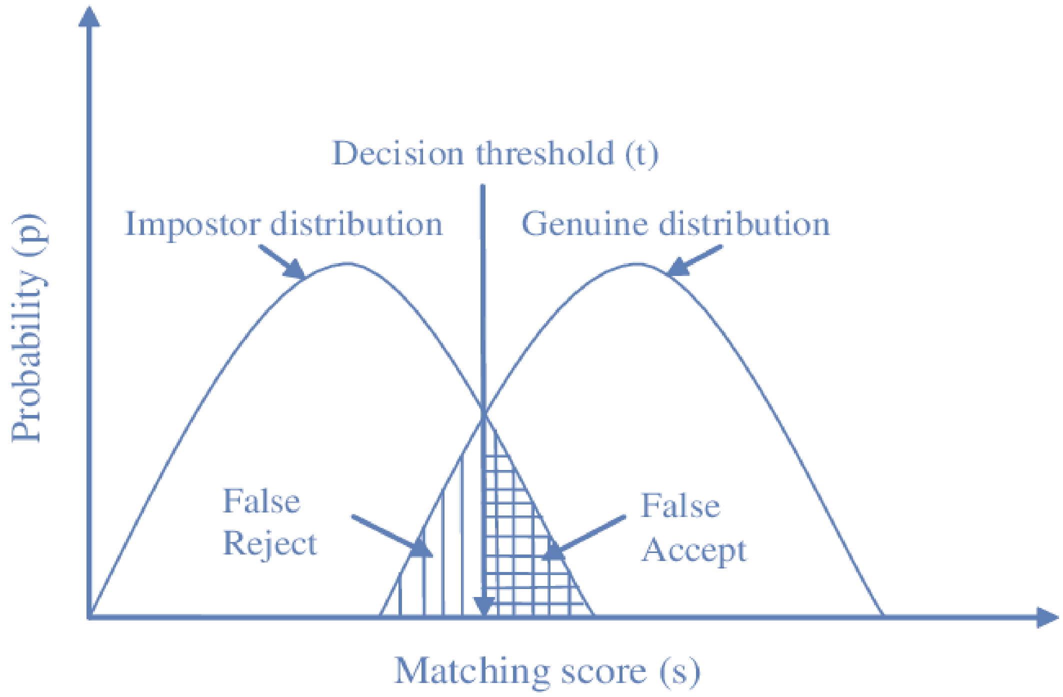

Figure 2. 4. Error rate FAR, FRR for a given threshold over genuine and impostor score distribution.

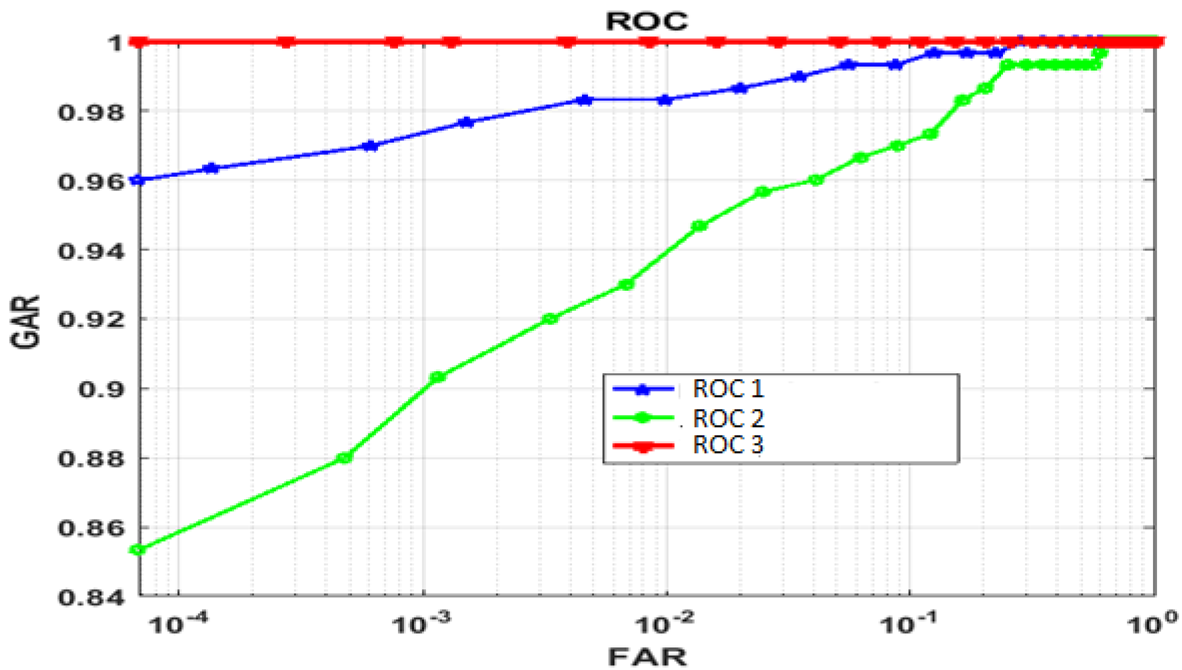

Figure 2.5. Comparison of ROC's.

2.5. Multimodal Biometric Database

2.5.1. The Various Types of Multimodal databases

This section provides an insight into various databases that are reported in the literature.

1. **BIOMET**

This database includes five modalities: audio, face images, hand images, fingerprint and signature of 91 subjects. The database was acquired in three different sessions (8 months between the first and the last one) [2.15].

2. **MyIDEA**

This database includes six modalities: face, audio, fingerprint, signature, handwriting, hand geometry and two synchronized recordings were also performed: face-voice and writing-voice. The data was collected from 104 subjects [2.16].

3. **BIOSEC**

This database was acquired under BioSec integrated project. It includes four modalities: fingerprint images from three different sensors, frontal face images from webcam, iris images from an iris sensor and voice utterances. This corpus comprises of 200 subjects. The extended version of the BIOSEC database comprises 250 subjects with four sessions per subject [2.17].

4. **BiosecurID**

This database was collected at six different sites in an office like uncontrolled environment. It includes eight modalities: speech, iris, face, signature, handwriting, fingerprints, hand geometry and keystroking. The data was collected from 400 subjects [2.18].

5. **BANCA**

The data was collected in three scenarios: controlled, degraded and adverse. This work reported a well-defined protocol for testing and validation.208 subjects were involved in providing data for the database [2.19].

6. XM2VTSDB

This database containing video data of 295 subjects is reported in [2.20]. This simultaneously provides data of face and speech as videos were recorded. Data acquisition was done in four sessions.

2.5.2. NIST BSSR l (Biometric Scores Set)

NIST-BSSR 1 database (NIST 2004) developed by the National Institute of Standards and Technology [2.1]. The database includes similarity scores from two commercial face recognizers and one fingerprint system and is partitioned into three sets.

1. NIST- Multimodal Database

It contains of fingerprint and face match scores of 517 subjects. It is important to Note that face and fingerprint images of the subject are not offered. One fingerprint score was acquired by comparing a pair of impressions of the left index finger and another score was obtained by comparing impressions of the right index finger. Two different face matchers (referred toes 'C and 'G') were useful to calculate the similarity between two frontal face images. So, there are four match scores for each subject (one for each modality).

2. NIST- Fingerprint Database

The content of NIST-fingerprint database is left-index fingerprint score and right-index fingerprint score obtained from same individuals. This database consists of 6,000users, and therefore there are 6,000 genuine scores and 6,000 x 5,999=35,994,000 impostor scores that can be generated.

3. NIST- Face Database

NIST-face database contains face scores of 3,000 users obtained by two different systems labeled by matchers C and G. In this database, each user has 2 face images.
The organization used a certain algorithm to compare the images and generate the scores. In order to generate a genuine face score, they compare the images of a same person (because there are 2 images per person). Likewise, in order to generate an

impostor face score, they compare an image of a person with an image of another person. Since there are 2999 persons who are different with a certain person, then they have generated 2999 impostor scores for every person. Thus, in total they have generated 3000 genuine scores and 3,000 x 2,999 = 8,997,000 impostor scores.

2.6. Conclusion

In this chapter, we discussed the types and architecture of a biometric system, we have discussed advantages of multimodal systems compared to single biometric systems, as well as the two main factors involved in multimodal biometric system development and finally we discussed the evaluation of a biometric system. In the next chapter, we present a state of the art on approaches to build multimodal biometric systems and the recognition of wrist vein.

2.7. References

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Chapter 3: Literature Review

3.1. Introduction

As we discussed in the previous chapter, biometric system based on single biometric trait (unimodal system) suffers from limitation such as lack of uniqueness, non-universality and noisy data. Multimodal biometric system based on the information extracted from multiple biometric traits. Generally, multimodal biometric can overcome the limitations possessed by single biometric trait and give better classification accuracy.

Information fusion is the key to the success of multimodal biometric system, In the case of biometric system, fusion of information can be done at four different levels: sensor level, feature level, matching score level and decision level.

This chapter discusses some of the previous research done on different biometric and multimodal biometric systems as well as research on information fusion approaches for combining multimodal information with the main focus is given to score level fusion. Further, some of the previous research on vein modality has also been discussed in this chapter.

3.2. Levels of Fusion in Multimodal Biometric Systems

Multimodal biometric systems can be defined as one that combines the outcome acquired from more than one biometric feature for the aim of identification. When we use the information (data) from the output of any modules discussed i.e. sensor, feature, matching and decision-making module. The different levels of fusion are therefore sensor, feature, matching score and decision level fusion (see *Figure 3.1*).

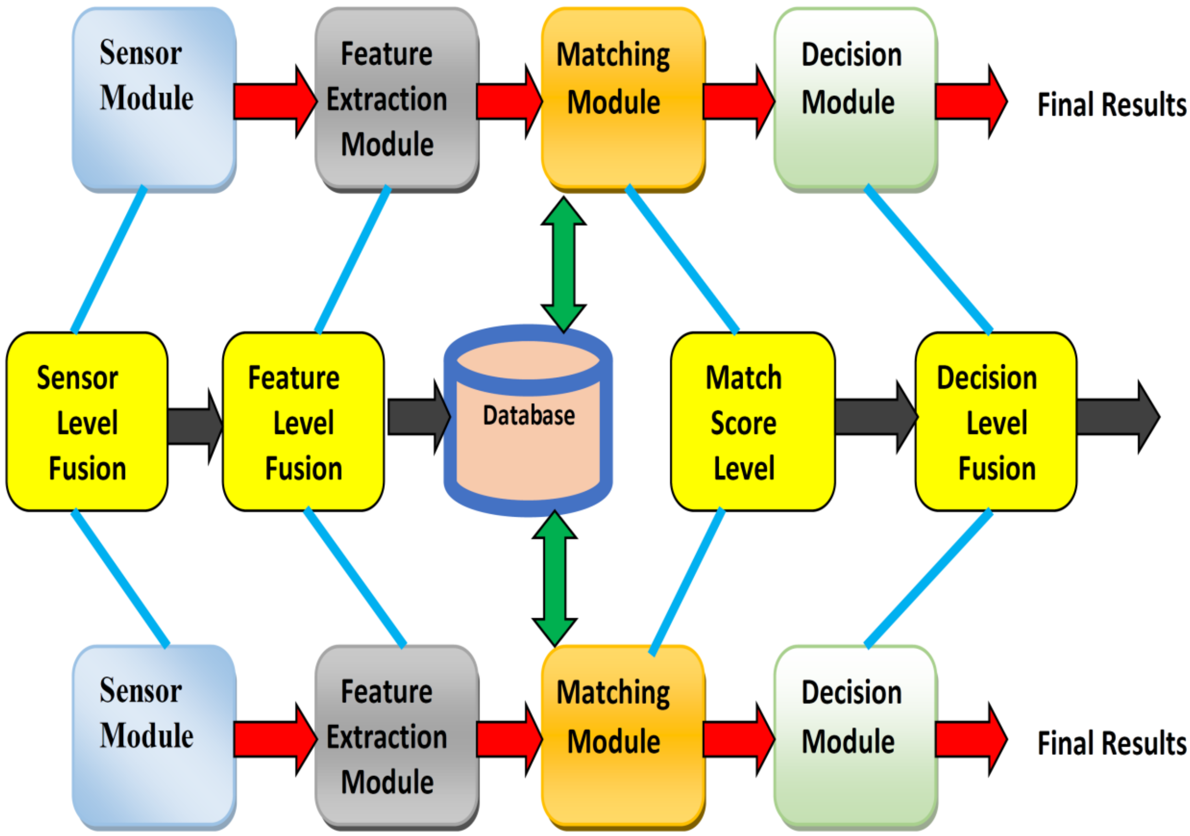


Figure 3.1. The different Levels of fusion.

3.2.1. Sensor Level Fusion

Figure 3.2 illustrates fusion at the sensor level, this level of fusion means bringing together different sensors' raw data. Raw data refers to any data that hasn't subjected thorough processing, e.g. from the fingerprint sensor, video camera, etc. From every single sensor raw information is extracted and combined at the very first level of fusion (sensor) to build raw fused information [3.1, 3.2]. Sensor level fusion could occur if the various traits are sorts of the same biometric trait acquired from multiple sensors or multiple values of the same biometric acquired from a single sensor. An example is the presentation of images containing various fingerprints to become a full fingerprint image. Other examples include facial images taken from various cameras put together to become a 3D model of a face [3.3, 3.4]. Usually, Sensor level fusion has been classified into three categories, namely: [i] Single sensor-multiple instances where different instances acquired from a single sensor are fused to build the information in a reliable and illustrative mode. [ii] Intra-class multiple sensors: where multiple instances obtained from various sensors are fused to detail the information location of a similar sensor or variability of different sensors and [iii] Inter-class multiple sensors, few studies have been undertaken of this sensor fusion mode. *Table 3.1* represents a summary of the three categories.

Table 3.1. *Sensor level fusion summary.*

Research Works	Category of Sensor Level Fusion	Biometric Traits
Ratha et al. [3.5]	Single sensor-multiple instances	Fingerprint
Jain et al. [3.6]	Single sensor-multiple instances	Fingerprint
Yang et al. [3.7]	Single sensor-multiple instances	Face
Xiaoming et al. [3.8]	Single sensor-multiple instances	Face
Ross et al. [3.9]	Single sensor-multiple instances	Fingerprint
Singh et al. [3.10]	Single sensor-multiple instances	Face
Ghouti et al. [3.11]	Single sensor-multiple instances	Iris
Jaisakthi et al. [3.12]	Single sensor-multiple instances	Face
Godil et al. [3.13]	Intra-class multiple sensors	Face
Xiaoguang et al. [3.14]	Intra-class multiple sensors	Face
BenAbdelkader et al. [3.15]	Intra-class multiple sensors	Depth and texture cues of Face
Bebis et al. [3.16]	Intra-class multiple sensors	Thermal and visible face
Kong et al. [3.17]	Intra-class multiple sensors	Visible and thermal IR face
Singh et al. [3.18]	Intra-class multiple sensors	Visible and infrared face image
Raghavendra et al. [3.19]	Intra-class multiple sensors	Visible and infrared face
Froba et al. [3.20]	Inter-class multiple sensors	Voice, Lip motion and still image
Chang et al. [3.21]	Inter-class multiple sensors	Ear and Face
Jing et al. [3.22]	Inter-class multiple sensors	Face and Palmprint
Noore et al. [3.23]	Inter-class multiple sensors	Fingerprint, face ,iris and signature

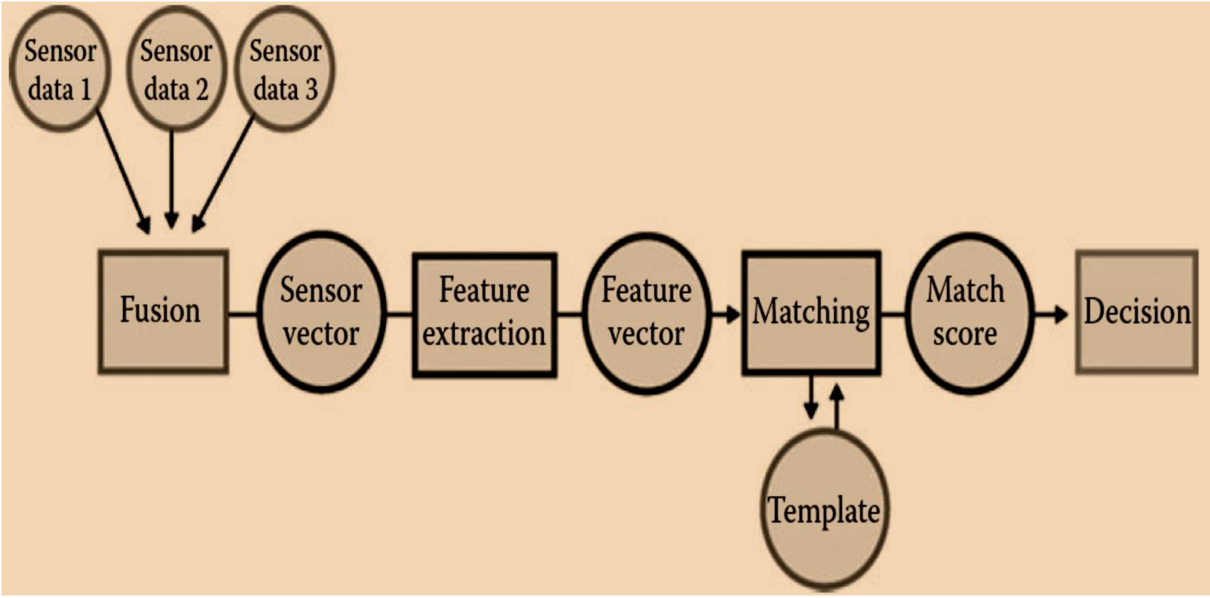


Figure 3.2. Sensor Level Fusion.

3.2.2. Feature Level Fusion

Figure 3.3 illustrates fusion at the feature level, feature level fusion consolidates information from multiple biometric feature sets of the same individual. When the feature vectors are from the same kind (e.g., multiple fingerprint impressions of a user's finger), the feature vector can be calculated as a weighted average of the individual feature vectors. When the feature vectors are not compatible (e.g., feature vectors acquired using different feature extraction techniques, or feature vectors of different biometric modalities like face and iris), these feature vectors can be concatenated to form a single feature vector. Because a lot of information regarding the identity of a person is available at this level, so feature level fusion is expected to perform better than match score level or decision level fusion methods [3.24]. Integration at the feature level should provide better recognition results than other levels of integration. However, integration at the feature level is difficult to achieve in practice because of the following reasons: (i) the relationship between the feature spaces of different biometric systems may not be known. In the case where the relationship is known in advance, care needs to be taken to discard those features that are highly correlated. This requires the application of feature selection algorithms prior to classification. (ii) Concatenating two feature vectors may result in a feature vector with very large dimensionality leading to the 'curse of dimensionality' problem [3.25]. Although, this is a general problem in most pattern recognition applications, it is more severe in biometric applications because of the time, effort and cost involved in collecting large amounts of biometric data. (iii) Most commercial biometric systems do not provide access to the feature vectors which they use in their products. Hence, very few researchers have studied integration at the feature level and most of them generally prefer score fusion schemes. *Table 3.2* showing related works done using the features level fusion method.

Table 3.2. Feature Level Fusion Research Work.

Research Work	Method of Fusion	Biometric Modalities
Ahmad et al. [3.24]	Discrete cosine Transform(DCT)	Face and Palmprint
Sharifi et al. [3.25]	Feature fusion (BSA)	Face and iris
Azom et al. [3.26]	Hybridized fusion Strategy	Iris and face
Yao et al. [3.27]	Custom Defined Rule	Face and Palmprint
Tong et al. [3.28]	Bayesian Inference	Face and Fingerprint
Arif et al. [3.29]	Dempster-Shafer Theory	Hand written signature and Hand geometry
Jing et al. [3.30]	pixel level fusion	Face and Palmprint
Gawande et al. [3.31]	Support Vector Machine	Iris and Fingerprint

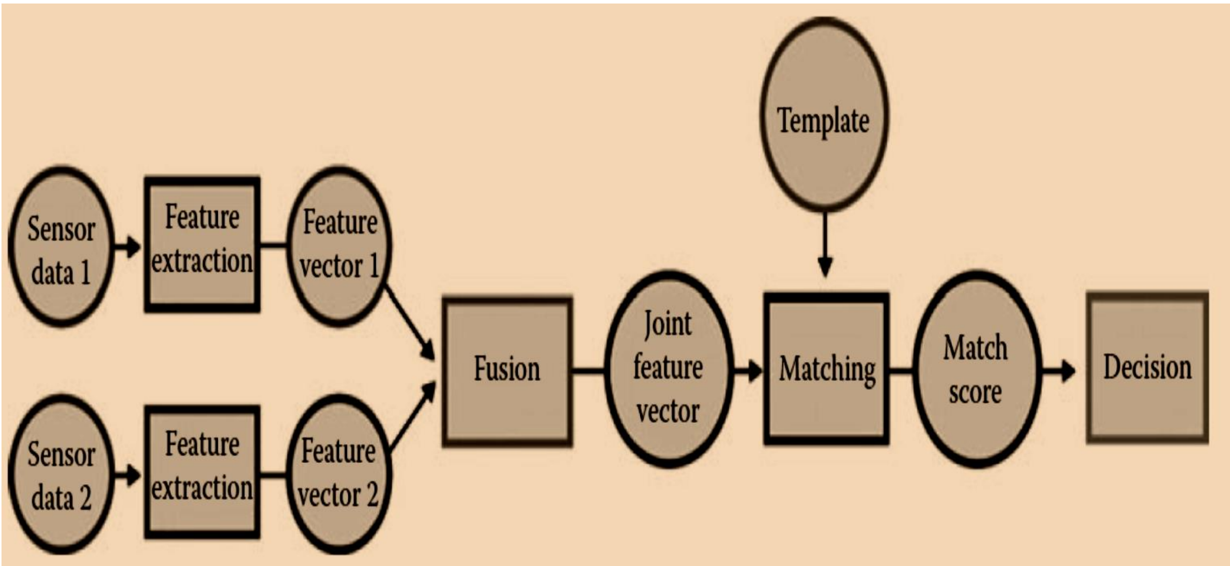


Figure 3.3. Feature Level Fusion.

3.2.3. Decision Level Fusion

On decision level, the joining of different information from multiple biometric modalities happens when the individual system makes an individualistic decision about the identity of the user of a claimed identity. Here, each biometric type is pre-classified individually and the final classification is based on the fusion of the outputs of the various modalities (see *Figure 3.4*). Furthermore, a decision is given for each biometric type at a later stage which reduces the reason for improving the system accuracy through the fusion process [3.32, 3.33]. This fusion level makes use of the final output of the individual modalities with methods such as 'AND' or 'OR' making it the simplest form of fusion. The dempster-dhafer theory of evidence, behavior knowledge space and bayesian decision fusion are other methods used at this level of fusion. *Table 3.3* showing related works done using the decision level fusion method.

Table 3.3. Decision Level Fusion Research Work.

Research Work	**Method of Fusion**	**Biometric Modalities**
Yazdanpanah et al. [3.32]	Linear Weighted Fusion	Face, Ear and Gait
Yu et al. [3.33]	Majority Voting Rule	Palmprint Fingerprint and finger geometry
Poh et al. [3.34]	Bayesian Inference	Fingerprint and face image
Singh et al. [3.35]	Dempster-Shafer Theory	Fingerprint
Kumar et al. [3.36]	Neural Network	Palmprint and Hand Geometry
Vora et al. [3.37]	Support Vector Machine	Fingerprint and Palmprint

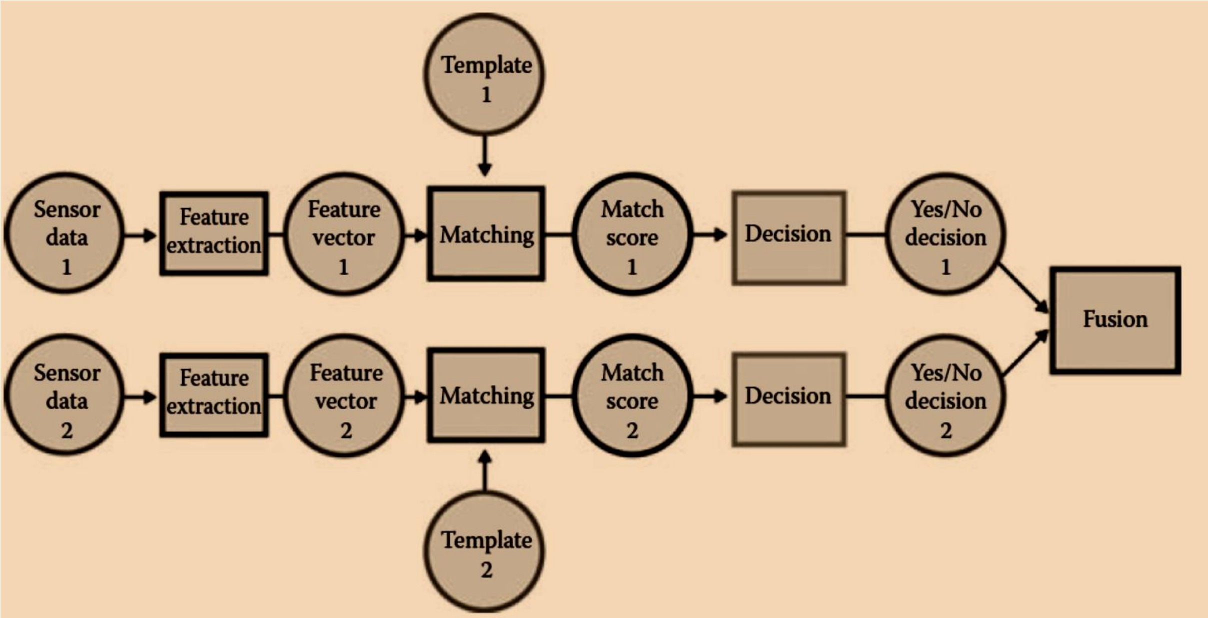


Figure 3.4. Decision Level Fusion.

3.2.4. Score Level Fusion

In multimodal systems, information fusion can be carried out at the sensor, feature extraction, matching score, or decision level [3.37]. Owing to ease in accessing and combining of scores (see *figure 3.5*), fusion at the matching score level is the most commonly adopted approach in the literature [3.38].There exist ample of studies to empirically show the efficacy of multimodal biometric systems. More specifically. The authors in [3.39] have proposed score level fusion schemes using triangular norms (t-norms) and fuzzy logic, respectively. The multimodal fusion methods published in the literature can be classified into three categories: transformation-based, classifier based and density-based fusion [3.38–3.64].

In transformation-based fusion methods, the matching scores need preliminary to be in the same domain, thus require to be normalized before fusion. In classifier-based fusion, the scores obtained from multiple matchers are concatenated to form a feature vector. Then a suitable classifier is used to attain the final label whether the use is genuine or impostor (e.g. support vector machine (SVM)-based score level fusion in [3.37]). In density-based fusion, the densities of genuine and impostor matching scores are clearly and unambiguously estimated. Then the final output is achieved by employing the likelihood ratio test. In [3.40], it was observed that modelling the genuine and impostor similarity score distribution as a finite Gaussian mixture model gives high performance compared with a kernel density estimator onXM2VTS and WVU databases. *Table 3.4* showing related works done using score level fusion method.

The transformation-based fusion rules can be broadly divided into two classes as fixed and trained [3.41]. The methods in the former category do not require any specific training procedure. While, techniques in the latter class require learning or training processes, e.g. trained rules such as weighted sum, where the model parameters are estimated from the training data subset to be latter used in the testing phase. The fixed fusion approaches, such as max, min, and sum rules, have been observed to be performing weak since they do not account much for the distribution distance of different biometric modal matching scores. The trained fusion approaches, such as weighted sum, weighted product rules, require large training or evaluation subsets because the model's parameters (e.g. weights) are data-dependent. Also, classifier-based score fusion algorithms suffer from an unbalanced training set, cost of misclassification, and choice of the classifier. Likewise, though density-based methods could provide optimal performance, the density function of scores need to be estimated accurately, which is a difficult task because these score densities are usually unknown and need a large database. The natural solution to overcoming the above-mentioned limitations of classifier- and density-based fusion methods is to devise novel and computationally inexpensive techniques based on the score level fusion method.

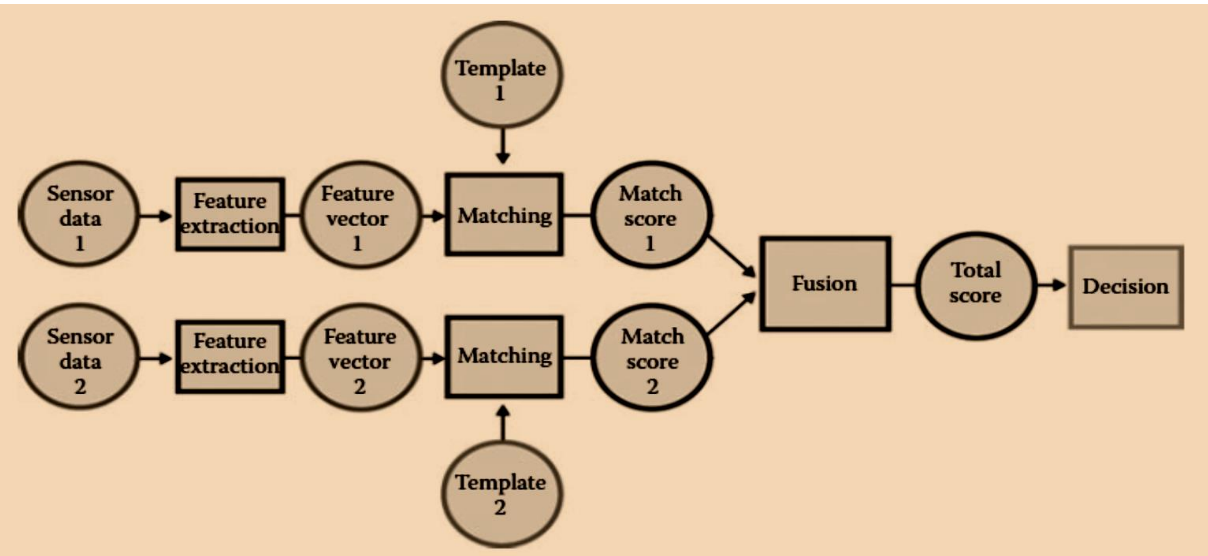


Figure 3.5. Score Level Fusion**.**

Table 3.4. Score Level Fusion Research Work.

Research Work	Method of Fusion	Biometric Modalities
Moeen et al. [3.38]	entropy function	left index, left middle, right index, and right middle
Hanmandlu et al. [3.39]	triangular norms	Palmprint, hand veins, hand geometry
Nandakumar et al. [3.40]	Likelihood ratio- based score fusion	Face, fingerprint, iris,speech
Sim et al. [3.41]	Weighted sum rule	Face and iris
Eskandar et al. [3.42]	Weighted sum rule	Face and iris
Benaliouche et al. [3.43]	Weighted sum rule	Iris and Fingerprint
Peng et al. [3.44]	Weighted sum rule and triangular norms	finger vein, fingerprint, shape, knuckle print
Mezai et al. [3.45]	Weighted sum rule and triangular norms	Face and voice
Farmanbar et al. [3.46]	Sum Rule	Face and palmprint
Nigam et al. [3.47]	Phase only correlation(POC)	Palmprint, finger-knuckle-print
Fakhar et al. [3.48]	fuzzy combination rule	Face and iris
Assaad et al. [3.49]	Weighted sum rule	Voice and face
Azom et al. [3.50]	Weighted sum rule	Face and iris
Kumar et al. [3.51]	Weighted sum rule	Palmprint and iris
Liang et al. [3.52]	O P T (order preserving tree)	Fingerprint and face
Sharifi et al. [3.53]	Weighted sum rule	Face and iris
George et al. [3.54]	Gaussian Radial Basis Function Network	Eye movement
Matin et al. [3.55]	Weighted score	Face and iris
Ghulam et al. [3.56]	Sum, Product rule	Fingerprint and palmprint
Liau et al. [3.57]	Svm based feature selection	Face and iris
Meraoumia et al. [3.58]	Weighted score	Palmprint, finger-knuekle- print
Hossain et al. [3.59]	Sum Rule	Face and gait
Mezai et al. [3.60]	Dempster-Shafer based	Face and voice
Meraoumia et al. [3.61]	Weighted score	Palmprint, finger-knucklc- print
Raghavendra et al. [3.62]	Weighted score	Face and palmprint
Anzar et al. [3.63]	Sum Rule	Fingerprint and voice
Wang et al. [3.64]	SVM based fusion	Face and iris

3.3. Methods of Fusion

This section provides an overview of the different fusion methods used in multimodal biometric systems. Fusion methods can be divided into three categories namely: rule-based method, classification-based method and estimation-based method.

Many theoretical framework has been developed for merging the evidence collected from various classifiers using methods such as sum, product, max and min rules. These methods are also called unsupervised methods of fusion as there is no training process because learning rules are most suitable for physical applications that work for pre-decided target marks. Based on this theory, the posterior probabilities obtained from matching scores of real or fake identities can be fused using sum, product, max and min rules. Hence, if $\overrightarrow{x_i}$ is the feature vector of the input pattern X, the output will be the posterior probability i.e.$P[(Wj|\overrightarrow{x_i})]$, where Wj is the class given to the feature vector $\overrightarrow{x_i}$ [3.63].

3.3.1. Sum Rule

This is seen as one of the most effective rules as it eliminates the issue of noise that could lead to difficulty during classification. In the sum rule, to obtain the final score, transformed scores of every class (R classifiers) are added together to obtain the final score. For example, one can assume the input pattern is delegated to class α such that

$$\alpha = \arg\max_j \sum_{i=1}^{R} P[(Wj|\overrightarrow{x_i})] \qquad (3.1)$$

3.3.2. Product Rule

This rule yields fewer results compared to the sum rule, as it is based on the statistical independence of the feature vectors. Hence, the input class (we have R classifiers) delegated to class α such that

$$\alpha = \arg\max_j \prod_{i=1}^{R} P[(Wj|\overrightarrow{x_i})] \qquad (3.2)$$

3.3.3. Max Rule

The max rule approximates the average of the posterior probability by the maximum value of the input pattern, thus, the input pattern designated to class a is given by

$$\alpha = \arg\max_{j} P[(Wj|\vec{x_i})] \quad (3.3)$$

3.3.4. Min Rule

In the min rule, a minimum posterior probability is collected from of all classes. Thus, the input pattern designated to class a is such that

$$\alpha = \arg\max_{j} \min P[(Wj|\vec{x_i})] \quad (3.4)$$

Other strategies of the Rule Based fusion methods are linear weighted fusion, Majority voting Rule and Custom defined Rule. Linear weighted fusion is a method that combines the information derived from various biometric modalities in a linear form using normalized weights. Based on literature, weight normalization can be done using various techniques such as decimal scaling, z score methods, tanh estimators and min-max [3.63]. Majority voting rule is a method that combines information where all the weights are equal. In this method, at the final decision is where most of the classifier reaches a similar decision [3.33].

3.4. Classification-Based Fusion Method

Several classifiers have been used to consolidate the matching scores and arrive at a decision. Liang et al. [3.52] use order preserving tree decision for combining the scores of face and fingerprint modalities. Wang et al [3.64] use a support vector machine classifier to combine the scores of face and iris experts. They show that the performance of such a classifier deteriorates under noisy input conditions. To overcome this problem, they implement structurally noise-resistant classifiers like a piece-wise linear classifier and a modified Bayesian classifier. Verlinde and Chollet [3.65] combine the scores from two face recognition experts and one speaker recognition expert using three classifiers: k-NN classifier using vector quantization, decision-tree based classifier and classifier based on a logistic regression model. Chatzis et al. [3.66] use fuzzy k-means and fuzzy vector quantization, along with a median radial basis function neural network classifier for the fusion of scores obtained from biometric systems based on visual (facial) and acoustic features.

1. Fisher Linear Discriminant (FLD)

FLD is a simple linear projection of the input vector x on a uni-dimensional space so that a linear boundary between classes can be satisfactorily obtained. The Equation for the linear boundary is given as [3.67]

$$h(x) = w^T x + b \tag{3.5}$$

where, w is a transformation vector obtained on the development data using a Fisher criterion (described in the next section), T is the transpose operation, and b is a threshold determined on the development data to give the minimum error of classification in respective classes. The rule for class allocation of any data vector is given by

$$x \in \begin{cases} c1 \\ c2 \end{cases} if \ w^T x + b \begin{cases} > \\ < \end{cases} 0 \tag{3.6}$$

Where, c_1, c_2 are the client and impostor classes respectively.

2. Fisher Linear Discriminant for the Data from Two Classes

Given a set of N_1 points for class c_1 and N_2 points for class c_2, with the statistics $[\mu_i, S_i]$, where S_i and μ_i are the scatter (covariance) matrix and mean for the particular class i obtained on the development data, the scatter matrix is given as [3.68].

$$S_i = \sum_{k \in C_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{3.7}$$

Where, T indicates the transpose operation.

The overall within class scatter matrix S_W is given by

$$S_W = \sum_{i=1}^{2} S_i \tag{3.8}$$

The transformation vector w is obtained using the equation

$$w = S_W^{-1}(\mu_2 - \mu_1) \tag{3.9}$$

3. Quadratic Discriminant Analysis (QDA)

This technique is similar to FLD but is based on forming a boundary between two classes using a quadratic equation given as [3.67]

$$h(x) = x^T \mathrm{A}\, x + B^T x + c \tag{3.10}$$

For training data 1 and 2 from two different classes, which are distributed as

$M[\mu_i, S_i], i \in 1$ and 2, the transformation parameters A and B can be obtained on the development data as:

$$A = -\frac{1}{2}(S_1^{-1} - S_2^{-1}) \tag{3.11}$$

$$B = S_1^{-1}\mu 1 - S_2^{-1}\mu 2 \tag{3.12}$$

Where, c is a constant that depends on the mean vectors and covariance matrices and is computed as follows

$$c = \mu_1^T S_1^{-1}\mu_1 - \mu_2^T S_2^{-1}\mu_2 + \ \ln \frac{|S_1|}{|S_2|} \tag{3.13}$$

4. K-Nearest-Neighbor (KNN)

Is a simple classifier that requests no explicit training phase. The single information needed is reference data points for both classes (clients, impostors). An unidentified (test) data point x is then assign the same class label as the label of the majority of its k nearest (reference) neighbors. To locate these k nearest neighbors the Euclidean distance between the test point and every reference points is calculated, the acquired distances are grouped in ascending order and the reference points corresponding to the smallest Euclidean distances are taken. This exhaustive distance calculation step during the test phase leads rapidly to important computing times, which is the major drawback of this otherwise very simple algorithm [3.65].

Let $k_1,\ k_2$ respectively be the number of client and impostor neighbors the decision rule is then given by:

$$k_1 - k_2 \underset{<\,Impostor}{\overset{>Client}{}} 0 \quad \textbf{(3.14)}$$

3.5. Research on Vein Recognition

Though wrist vein is a promising biometric characteristics, there exist very few works on wrist vein recognition system [3.68], [3.69]. The authors of [3.69] demonstrated that the wrist vein pattern can be utilized for biometric user authentication. A dataset of wrist vein in infrared band of 30 individuals was collected in [3.68], where also a prototype for vein image capturing based on quality measurement was proposed. The first work that reported performance of wrist vein algorithms on a large database is [3.70]. The study used PUT vein images with binarization and correlation for enhancement and recognition, respectively. In [3.71], different segmentation techniques were analyzed such that DFT (Discrete Fourier Transformation) was employed for enhancement and correlation for classification. While, a technique based on Gaussian filter was used for enhancement and feature extraction in [3.72]. Uriarte-Antonio et al. [3.73] and Hartung et al. [3.74], [3.75] proposed minutia feature and spectral minutia, chain code fusion-based wrist vein recognition systems, respectively. A method to extract vein minutiae and transforming them into a fixed-length vector that represents translation, rotation and scale invariant features was proposed in [3.76]. Uriarte-Antonio et al. [3.77] explored possibility of performing wrist vein biometric recognition using crossing number of minutiae. Pflug et al. [3.78] presented vein pattern feature encoding based on spatial and orientation properties of veins and obtained 0.67% of EER. The works in [3.79], [3.80], [3.81] and [3.82] extracted wrist vein features with minutia cylinder-codes, local binary patterns, FFT with PCA and scale invariant feature transform, while utilizing correlation, SVM, RBF, MLP, and Euclidean distance to compute matching scores, respectively. A summary with relevant features of the most representative works in wrist vein biometrics is presented in *Table 3.5*.

Table 3.5. Previous works on wrist vein based biometric authentication. EER: Equal Error Rate, Acc: Accuracy, SVM: Support Vector Machine, MLP: Multi-Layer Perceptron, RBF: Radial Basis Function, SRC: Sparse Representation Classifier.

Study	Features	Classification	Dataset	Users	Performance	Year
Akhloufi et al. [3.69]	Morphological filtering	Distance	Private	---	Acc= 80.10%	2008
Pascual et al. [3.68]	Maximum variation of energy per pixel	2D correlation	Private	30	---	2010
Kabacinski et al. [3.70]	Discrete Fourier Transformation	2D correlation	PUT	95	EER= 3.51%	2010
Kabacinski et al. [3.71]	Frequency high-pass filtration and local minima analysis	2D correlation	PUT	50	EER= 2.19%	2011
Kabacinski et al. [3.72]	Gauss filtering	Minutiae comparison	PUT	50	EER= 3.8%	2011
Uriarte-Antonio et al. [3.73]	Relative location and orientation of the minutiae	Minutiae comparison	UC3M	29	EER= 2.27%	2011
Uriarte-Antonio et al. [3.77]	Crossing number based minutiae extraction and classification	correlation	UC3M	29	EER= 15.75 %	2011
Hartung et al. [3.74]	Location-based spectral minutiae	Points parallelism	UC3M	29	EER= 6.13%	2011
Hartung et al. [3.75]	Chain codes using spacial and orientation properties of vein patterns	correlation	UC3M	29	EER= 1.38%	2012
Hartung et al. [3.76]	Spectral minutiae	Local error distance	UC3M	29	EER= 4.48%	2012
Pflug et al. [3.78]	Chain code using spatial and orientation properties of vein patterns	correlation	UC3M	29	EER= 0.67%	2012
Hartung et al. [3.79]	Minutia Cylinder-Codes (MCC)	SVM	UC3M	29	EER= 0.31%	2013
Das et al. [3.80]	Local binary patterns	SVM, MLP	PUT	50	EER= 0.79%	2014
Kurban et al. [3.81]	FFT-based low-pass filtering with Principal component analysis (PCA)	RBF	Private	34	Acc= 94.11%	2016
Raghavendra et al. [3.83]	9 local and global feature representations	Correlation, SRC	Private	50	EER= 1.63%	2016
Fernandez et al. [3.82]	Scale invariant feature transform	Euclidean distance	Private	30	EER= 0.15%	2017

3.6. Feature extraction for wrist vein

For feature extraction, there exist various methods but for simplicity and low computational cost, four local textural descriptors namely: LPQ, LBP, BSIF, and LTP are employed.

3.6.1. Local Phase Quantization (LPQ)

This descriptor is based on quantizing the Fourier transform phase in local neighborhoods by computing a short-term Fourier transform (STFT) over a rectangular M^2 neighbourhood N_x at each position x of the image f(x) as follows [3.84]**:**

$$F_{u,x} = w_u^T f_x \tag{3.15}$$

Where w_u denote the basis vector of the 2-D DFT at frequency u, and f_x is a vector containing all M^2 image pixels fromN_x.

3.6.2. Local Binary pattern (LBP)

It is an efficient textural descriptor that labels every pixel of an image based on thresholding the neighborhood of each pixel with the center pixel value. Then obtained binary number is converted to a decimal value [3.85]. The histogram of the labels from non-overlapping blocks is used to form the texture descriptor. The LBP code of a pixel I_c is defined by:

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(I_p - I_c) 2^p \tag{3.16}$$

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.17}$$

Where, I_c and I_p refer the center pixel and neighboring pixels, respectively. The use of uniform rotation invariant $LBP_{P,R}$ reduces the length of feature vector.

3.6.3. Binarized Statistical Image Features (BSIF)

BSIF is a recent descriptor which is based on a set of filters of the same size [3.86]. The filter response s_i by applying a filter $\varphi_i^{l\times l}$ on a given image X of size $m \times n$ pixels is given by:

$$s_i = \sum_{m,n} \varphi_i^{l\times l} X(m,n) \qquad (3.18)$$

The binarized feature b_i is defined as:

$$b_i = \begin{cases} 1 & if\ s_i > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (3.19)$$

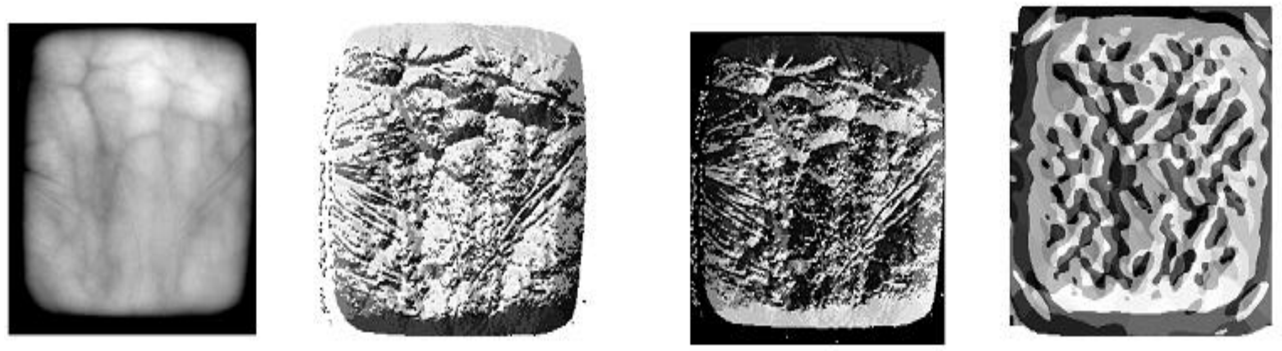
1. **Local Ternary Patterns (LTP):**

In this descriptor, the LBP code is extended into 3-valued codes [3.86], which is a ternary code at each pixel. The indicator $s'(I_p)$ is given by:

$$s'(I_p, I_c, t) = \begin{cases} 1 & I_p \geq I_c + t \\ 0 & |I_p - I_c| < t \\ -1 & I_p \leq I_c - t \end{cases} \qquad (3.20)$$

Here I_p , I_c and t are neighborhood pixels, enter pixel and a user-specified threshold value, respectively.

Figure 3.6 shows normalized vein images of wrist and the corresponding LBP, LTP, LPQ and BSIF.



a) **b)** **c)** **d)**

Figure 3.6. Normalized wrist vein images, LBP, LTP , LPQ , from left to right respectively .

3.7. Conclusion

In this chapter, we have presented a brief description of research conducted on different fusion schemes for multimodal biometric information consolidation, also we have presented the main rules used for fusion. As individual biometric identifiers, we have used wrist vein. Therefore, previous research conducted. Features extraction from wrist vein biometric are also discussed in this chapter.

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Chapter 4: Score level fusion based on triangular norms and symmetric sum methods

4.1. Introduction

The most important part in a multimodal biometric system improvement is information fusion. We debated the pros and cons of diverse multimodal biometric fusion methods in chapter three; and in this doctoral research, we choose to employ score level fusion based on triangular norms and symmetric sum methods in our multimodal biometric system development process. The following two sections describe a detailed explanation of the proposed fusion approach.

4.2. Information Fusion Using Fuzzy logic

The power of fuzzy sets for information fusion, particularly in diverse combination fusion methods fall into the following categories:

- The possibility of representing very heterogeneous information.
- The flexibility of the combination operators, which makes it possible to fuse elements of information that are different in nature, in very different situations.
- The various possible semantics.

The next two sub-sections describe the basic concepts of fuzzy logic and the fuzzy fusion mechanism for the new multimodal biometric system.

4.2.1. Fuzzy Logic

Fuzzy logic refers to the generalization of the classical set theory, and to all of the theories and technologies that employ fuzzy sets, which are classes with un-sharp boundaries [4.1]. The idea of fuzzy sets was introduced in 1965 by Professor Lotfi A. Zadeh from the Department of Electrical Engineering and Computer Science at the University of California, Berkeley [4.2]. The core technique of fuzzy logic is based on following three basic concepts:

1. Fuzzy sets

A fuzzy set [4.3] is a set in which the members of the set can have partial membership, meaning they can have a membership value of any number between 0 and 1 unlike the ‘crisp' set where the members can have only two membership value, i.e. 0 and 1.

2. Linguistic variable

A linguistic variable is a novel concept in fuzzy logic where a variable can have values in linguistic terms of words or sentences rather than numbers, which allows reasoning be done at the fuzzy level rather than that of crisp numeric variables [4.4].

3. Possibility Distribution

During an assignment of a fuzzy set to a linguistic variable, the fuzzy sets put constrains on the value of the variable. This process is called possibility distribution [4.5].

4.2.2. Fuzzy rules

Fuzzy rule is the most widely used technique developed using fuzzy sets and has been applied to many disciplines. Some of the applications of fuzzy rules include control (robotics, automation, tracking, and consumer electronics), information systems (information retrieval), pattern recognition (image processing, machine vision), decision support (sensor fusion).

4.2.2.1. Preliminaries of the triangular norms (t-norm)

In this section, we introduce our proposed score-level fusion method based on triangular norm. Triangular norms (t-norms) are the general families of binary functions that satisfy the requirements of the conjunction and disjunction operators [4.6]. T-norms are considered as most suitable general candidates for generalized intersection operations of fuzzy sets in the mathematical fuzzy community [4.7]. T-norms are the functions that map the unit square into the unit interval:

$$T\,(x, y): [0, 1] \times [0, 1] \rightarrow [0, 1] \qquad \textbf{(4.1)}$$

A t-norm is a function that satisfies the following conditions:

1. Commutativity : $t(x, y) = t(y, x)$.
2. Associativity: $t(t(x, y), z) = t(x, t(y, z))$.
3. Monotonicity: if ($x \leq$ a) and ($y \leq$ b) then $t(x, y) \leq t$ (a, b).
4. Boundary Conditions: t (0, 0) = 0 and t (x, 1) = x

Additionally, we have: $t(O, 1) = t(0,0) = t(1,0) = 0$, $t(1,1) = 1$ and 0 is a zero element ($\forall x \in [0,1], t(x, 0) = 0$) .

Continuity is often added to this list of properties.

The operators $\min(x, y), xy, \max(O, x + y - 1)$ are examples of t-norms, which are by far the most commonly used.

T-norms generalize to fuzzy sets the concept of intersection as well as the logical "and".

The following result is easy to prove. For any t-norm, we have:

$$\forall(x, y) \in [0,1]^2, t(x, y) \leq \min(x, y) \tag{4.2}$$

This shows that the "min " is the highest t-norm and that any t-norm has a conjunctive behavior.

On the other hand, any t-norm is always higher than t_0, which is the smallest t-norm, defined by:

$$\forall(x, y) \in [0,1]^2, t_0(x, y) = \begin{cases} x \; if \; y = 1 \\ y \; if \; x = 1 \\ 0 \; otherwise \end{cases} \tag{4.3}$$

Some of the t-norms which we have implemented for our work are:

1. Einstein product: $(\frac{x \quad y}{(2-(x+y-xy))})$

2. Hamacher: $(\frac{xy}{(x \quad +y \quad -xy)})$

3. Yager ($p > O$): $\max(1 - ((1 - x \quad)^p + (1 - y)^p)^{1/p}, 0)$

4. Schweizer and sklar ($p > O$): $(\max(x^p + y^p - 1,0))^{1/p}$

5. Frank $(p > 0)$: $\log_p(1 + \frac{(p^x-1)(p^y \ \ -1)}{p-1})$

Based on a t-norm and a complementation c, another operator t, referred to as the t-conorm, can be defined by duality:

$$\forall(x, y) \in [0,1]^2, t(x, y) = c[t(c(x), c(y))]. \quad \textbf{(4.4)}$$

Therefore, a t-conorm is a function $t : [0,1] \times [0,1] \rightarrow [0,1]$ such that:

1. Commutativity : $t(x, y) = t(y, x)$.
2. Associativity: $t(t(x, y), z) = t\big(x, t(y, z)\big)$.
3. Monotonicity: if $(x \leq a)$ and $(y \leq b)$ then $t(x, y) \leq t$ (a, b).
4. Boundary Conditions: t (0, 0) = 0 and t $(x$, 1) = x.

The most common examples of t-conorms are: $\max(x, y)$, $\min(1, x + y)$.

For any t-conorm, we have:

$$\forall(x, y) \in [0,1]^2, t(x, y) \geq \max(x, y). \quad \textbf{(4.5)}$$

This shows that the max " is the smallest t-conorm and that any t-conorm has a disjunctive behavior. On the other hand, any t-conorm is smaller than T0, which is the highest t-conorm, defined by:

$$\forall(x, y) \in [0,1]^2, T_0(x, y) = \begin{cases} x \ if \ y = 0 \\ y \ if \ x = 0 \\ 1 \ otherwise \end{cases} \quad \textbf{(4.6)}$$

If t is a t-norm, then S(x,y)=1-t(1-x,1-y) is a t-conorm, and vice versa. We obtain a dual pair (t,S) of a t-norm and a t-conorm.

Table 4.1 shows a few typical examples of t-conorms. They are obtained by using various t-norms.

Table 4.1. Typical examples of t-conorms [4.13].

T-norm	**T-conorm**	**Name of rule**
$\min(x+y,1)$	$\min(x,y)$	Zadah
$x.y$	$x+y-x.y$	Product
$\max(x+y-1{,}0)$	$\min(x+y,1)$	Lukasiewicz
$T_0(x,y)=\begin{cases} x \; if \; y=1 \\ y \; if \; x=1 \\ 0 \; otherwise \end{cases}$	$T_0(x,y)=\begin{cases} x \; if \; y=0 \\ y \; if \; x=0 \\ 0 \; otherwise \end{cases}$	Weber

4.2.2.2. Preliminaries of symmetric sums

Here, we introduce the proposed score-level fusion method based on Symmetric sums (S-sums). Though, recently the use of triangular norms in the score level fusion is prevalent in the literature [4.8, 4.9, 4.10], but use of S-sums in the score level fusion does not exist in the literature. Symmetric sums were introduced by Silvert in 1979 [4.11, 4.12, 4.13], and they are a kind of binary functions that are used as a rule of combination for fuzzy sets. S-sums are characterized by an auto-duality property, which means the invariance of the result of the operation by inverting the scale of values to combine. More precisely, s-sum is a function S: $[0,1] \times [0,1] \rightarrow [0,1]$ such that:

1. $S(0,0) = 0$;
2. $S(1,1) = 1$;
3. S is commutative;
4. S is increasing with respect to the two variables;
5. S is continuous;
6. S is self-dual: $\forall(x,y) \in [x,y]^2, S(x,y) = 1 - s(1-x,1-y)$;

The general form of symmetric sums is given by:

$$S(x,y) = \frac{g(x,y)}{g(x,y)+g(1-x,1-y)} \tag{4.7}$$

Where g is a continuous, positive, increasing function of $[0,1] \times [0\ ,1]$ into $[0,1]$, such that $g(0,0) = 0$. Typically, a continuous t-norm or t-conorm can be chosen as g.

Table 4.2 shows a few typical examples of symmetric sums. They are obtained by using various t-norms and t-conorms as generating function g.

Table 4.2: Examples of symmetric sums (s-sum), defined based on t-norms and t-conorms [4.14].

g(x, y)	**S(x, y)**	**Property**
xy	$\frac{xy}{1-x-y+2xy}$	associative
$x+y-xy$	$\frac{x+y-xy}{1+x+y-2xy}$	non-associative
$\min(x,y)$	$\frac{\min(x,y)}{1-\lvert x-y\rvert}$	mean
$\max(x,y)$	$\frac{max(x,y)}{1+\lvert x-y\rvert}$	mean

4.3. Score Fusion Using Fuzzy logic Rule

Figure 4.1 shows the block diagram of the proposed approach, here we extend the fusion rules such as product and sum rules to general class of fuzzy aggregation operators (t-norms and s-sums) to enhance the score level fusion.

The proposed score level fusion module, which is a fuzzy rule-based system. The score level fusion is viewed as the combination problem. Here, the scores are combined using the t-norm and s-sums. Since the concept of these norms is applicable mainly in the fuzzy logic, so scores from all the modalities must be first converted to the common fuzzy domain [0,1] to guarantee a meaningful combination of the scores.

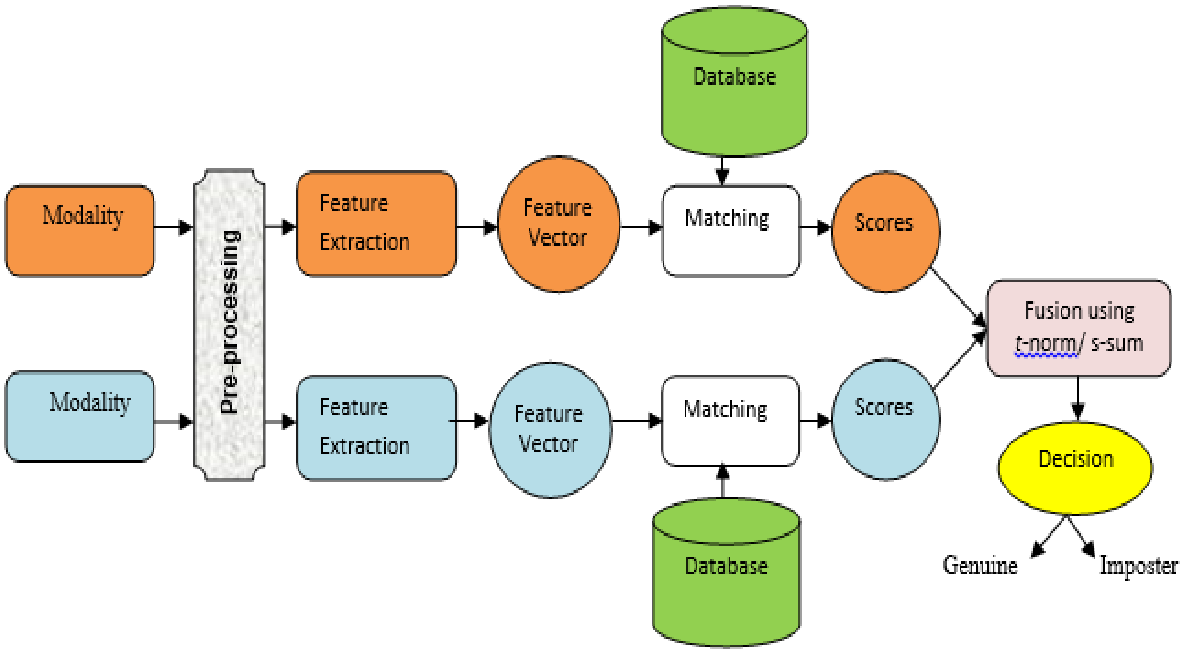

Figure 4.1. A schematic diagram the block diagram of the proposed approach.

4.3.1. Various normalization schemes

Let X denote the set of raw matching scores from a specific matcher (unimodal system), and let $x \in X$. The normalized score of x is then denoted by x'.

4.3.1.1. Min-Max normalization

This normalization maps the raw matching scores to interval [0, 1] and retains the original distribution of matching scores except for a scaling factor [4.15]. Given that max(X) and min(X) are the maximum and minimum values of the raw matching scores, respectively, the normalized score is calculated as

$$x' = \frac{x - \min(X)}{\max(x) - \min(x)} \qquad \mathbf{(4.8)}$$

Suppose that a matcher has a set of matching scores as listed below:

Genuine	15	17	17	19	19	22	25
Impostor	5	5	7	9	14	15	17

After equation (4.8) is applied to the matching scores in the list, matcher will get this result:

Genuine	0.5	0.6	0.6	0.7	0.7	0.88	1
Impostor	0	0	0.1	0.2	0.45	0.5	0.6

4.3.1.2. Z-score normalization

Z-score normalization method calculates normalized scores using arithmetic mean and standard deviation of the given data [4.16]. The normalized scores will have a distribution with mean of 0 and standard deviation of 1. Let mean (X) denote the arithmetic mean of X and std (X) denote the standard deviation of X, then the formula for z-score normalization is

$$x' = \frac{x - \text{mean}(X)}{\text{std}(X)} \qquad \textbf{(4.9)}$$

4.3.1.3. Tanh-estimators normalization

Introduced by Hampel et al. [4.17] are robust and highly effective [4.18]. The normalization is given by

$$x' = \frac{1}{2}\left\{tanh\left(0.01\left(\frac{x - \mu}{\sigma}\right)\right) + 1\right\} \qquad \textbf{(4.10)}$$

Where x' is the normalized score, μ and σ are the mean and standard deviation estimates, respectively, of the genuine score distribution as given by Hampel estimators.

4.3.2. Score-level fusion method based on t-norm and s-sum

T-norms can be regarded as a generalization of the two-valued logical conjunction such that the norms monotonicity property makes sure that the truth of conjunction degree does not decrease if the truth values of conjuncts increase. Usually, considering correlation among the information sources in fusion avoids under or over estimates [4.9], since multi-valued t-norms are a generalization of the Boolean intersection operation, thus they are better suited to handle the correlation [4.10]. Contrary to the AND operation that only gives the minimum, t-norms attain the infimum of information (e.g., matching scores) leading thereby to yielding a better representation of the product of the information. Due to the t-norms associative and commutative properties, the order of fusion of three or more biometric sources/modalities is immaterial. Moreover, t-norms do not require the assumption of evidential independence of the information sources being fused. In this work, the t-norms were selected for score level fusion because generally they produce performance better than the classification techniques such as SVM, MLP, and logistic regression [4.11].

Let S_1, S_2 represented the scores derived from each unimodal biometric systems.

Let S represented the result fusion of the two scores S_1, S_2 using t-norms, we take Yager t-norm to build the fusion score rule, so we will have:

$$S = \max\left(1 - ((1 - S_1)^p + \left(1 - S_2)^p\right)^{\frac{1}{p}}, 0\right) \qquad (p > O) \tag{4.8}$$

The real number ‘p’ spans the space of t-norms.

The fused score is compared with a threshold, t which assigns the user.

$$\begin{cases} \text{the user is imposter if } S < t \\ \text{the user is genuine if } S > t \end{cases}$$

Combination of scores emanating from different modalities plays a central role in the score-level fusion. The challenge involved here is how to deal with the uncertainty and imperfection from the scores of different modalities. In this sense, we analyze the t-norms of Einstein product, Frank with p = 0.4, Hamacher, Yager with p = 0.5, and Schweizer–Sklar with p = −0.1, Weber Sugeno with p = 0.8. As shown in figures (4.2 to 4.7), respectively.

Except for Yager t-norm, the Einstein product, Frank, Hamacher, and Schweizer–Sklar t-norms maximize the fusion of genuine scores while they fail to further minimize the imposter scores simultaneously.

Let $S = (x, y)$ denote the fusion of two normalized matching scores using s-sums. Let $s'_1, s'_2, \ldots . s'_n$ denote the normalized matching scores of n modalities, the two scores s'_1, s'_2 are first combined to yield $S = (s'_1, s'_2)$ which is in turn combined further with s'_3 to yield $S = (S(s'_1, s'_2), s'_3)$ until all normalized scores are combined. If the fused score S is below a given acceptance threshold T, the user is classified as an impostor, otherwise it is classified as a genuine user.

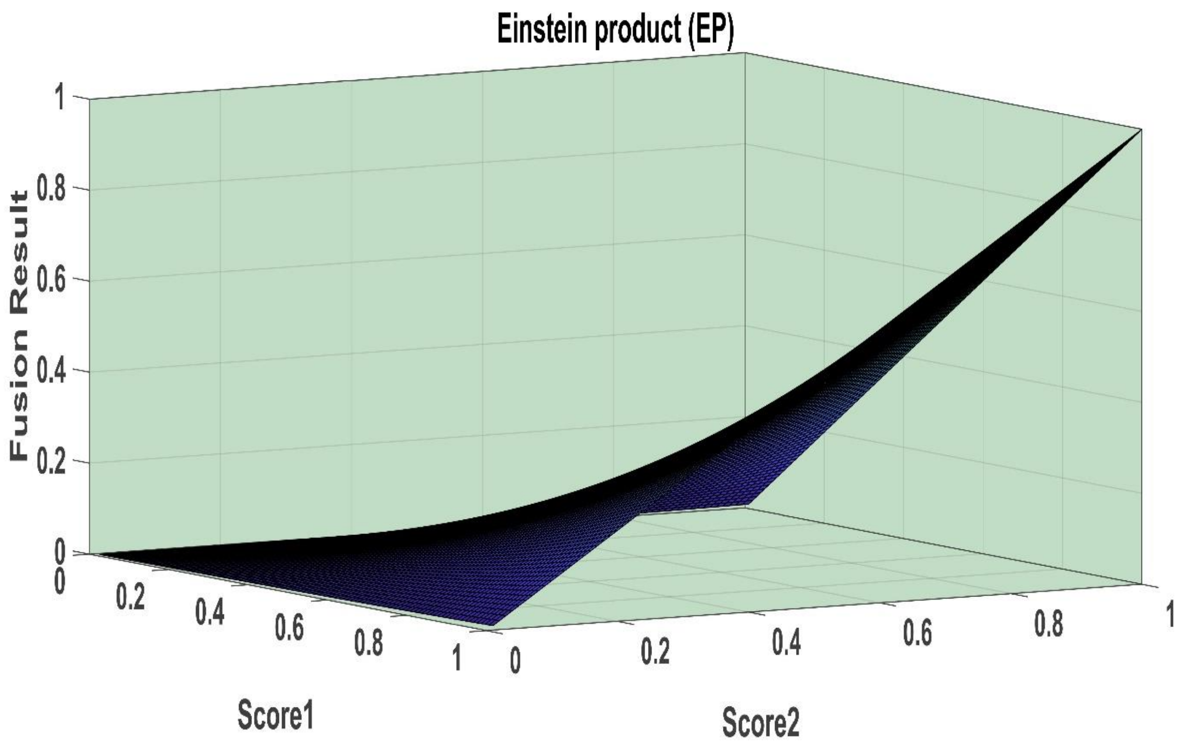

Figure 4.2. T-norms of Einstein product.

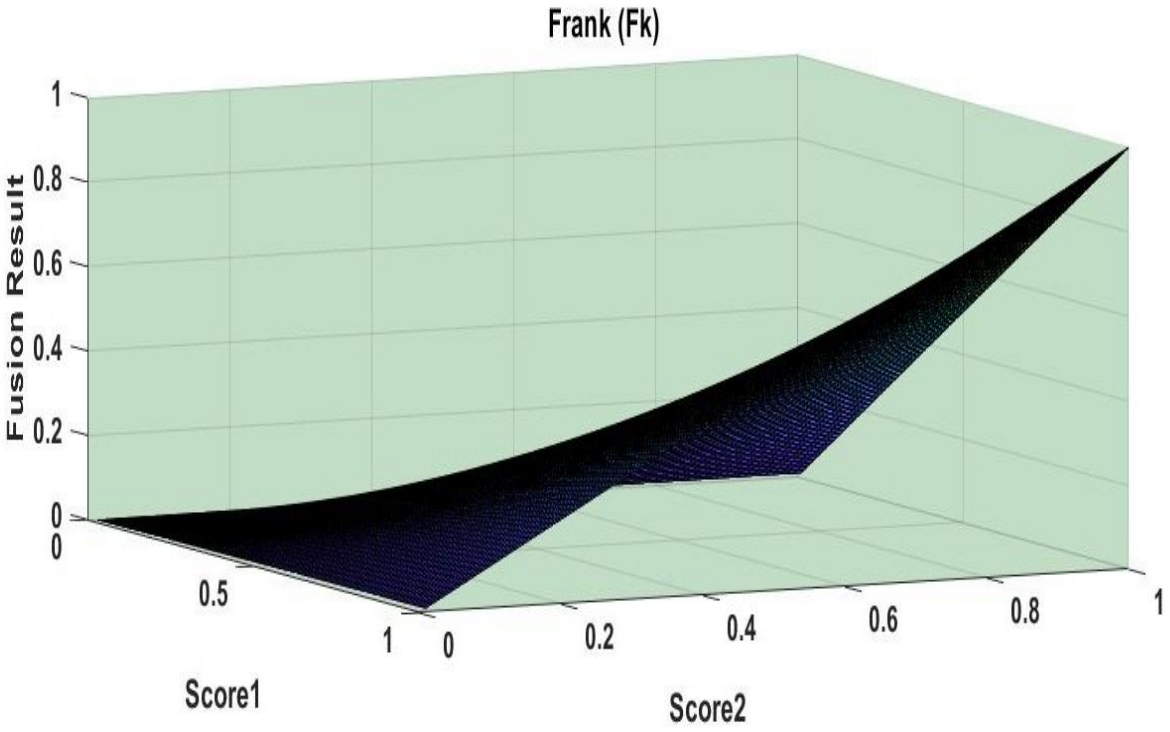

Figure 4.3. T-norms of Frank with p = 0.4.

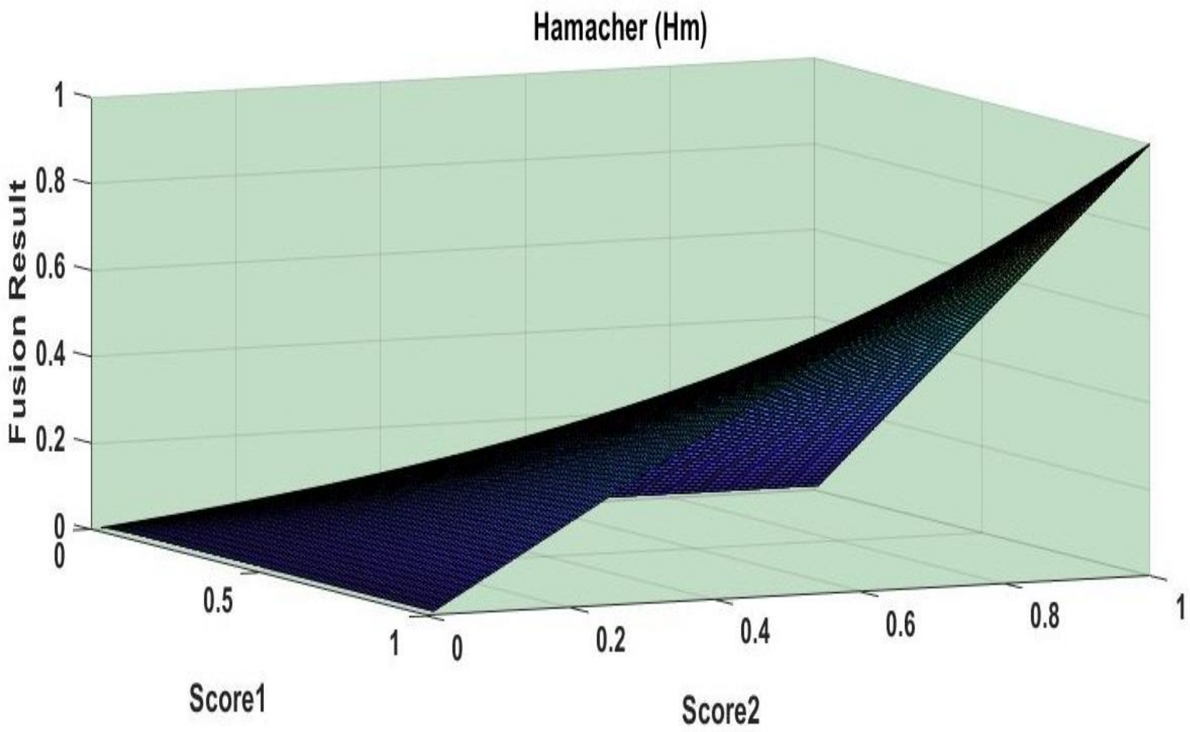

Figure 4.4. T-norms of Hamacher.

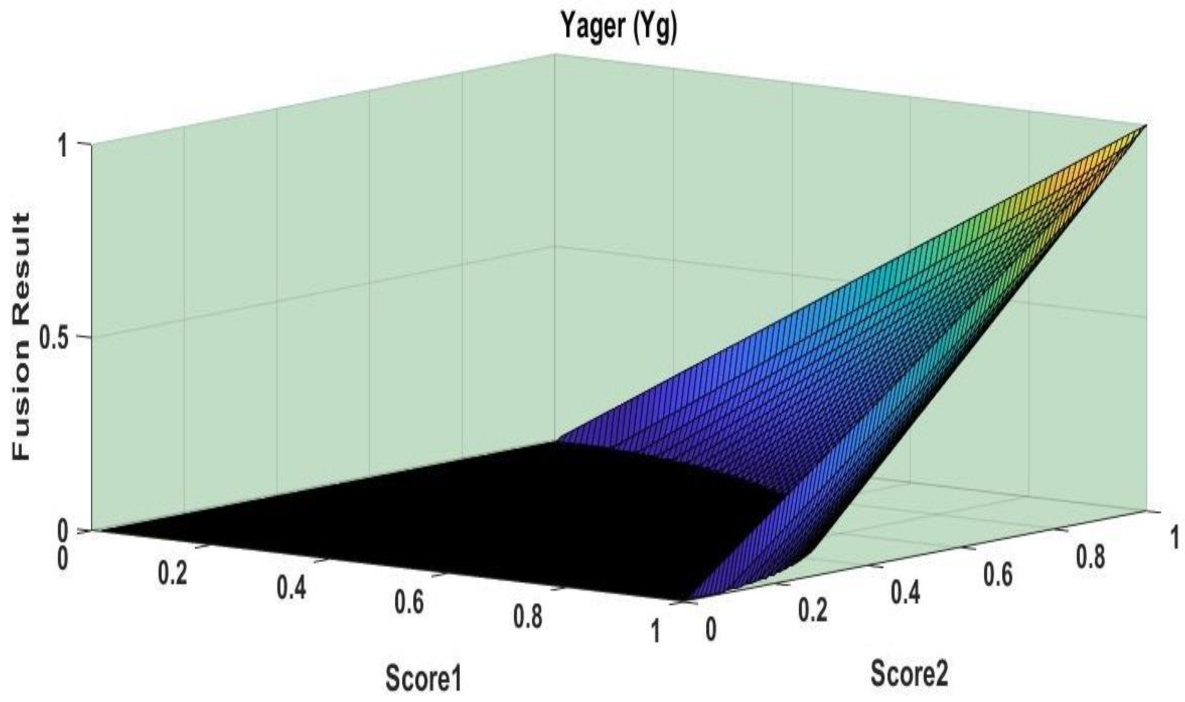

Figure 4.5. T-norms of Yager with p = 0.5.

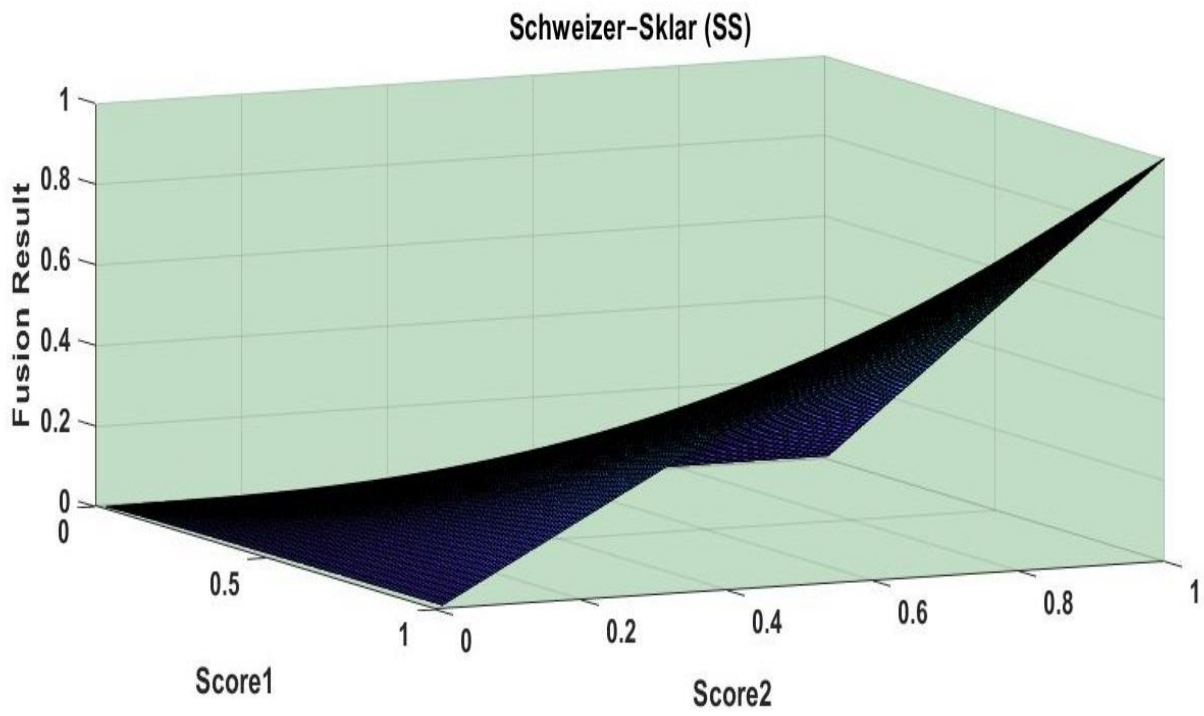

Figure 4.6. T-norms of Schweizer-Sklar with p = −0.1.

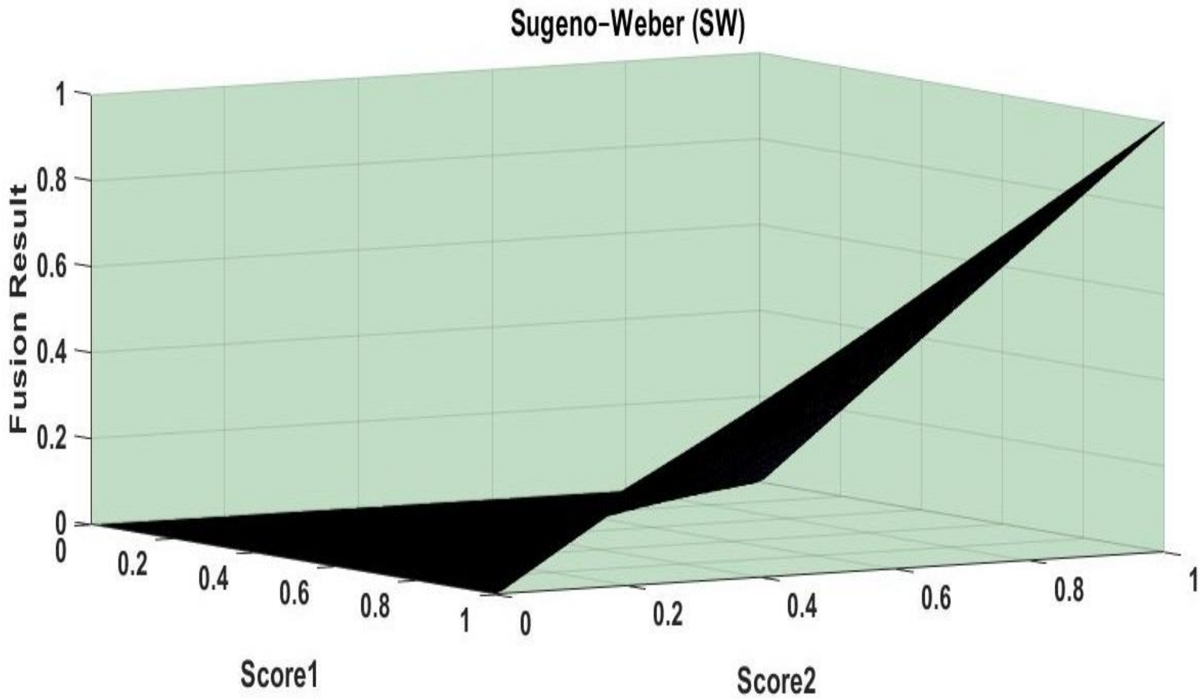

Figure 4.7. T-norms of Weber Sugeno with p = 0.8.

4.4. Conclusion

In this chapter, we present the methodology for the score fusion method and the fuzzy fusion method for the proposed multimodal biometric system. For score level fusion we define and discuss advantages and disadvantages of triangular norm and symmetric sum method. The chapter has given a brief description about the most effective and widely used score normalization techniques. These are min- max, z-score, and tanh-estimators normalization techniques. Then we discuss advantages of this method and show how this method could be applied. The next chapter discusses the results of applying the fusion methods.

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Chapitre 5 : Experimental Results

5.1. Introduction

Multimodal biometric systems that fuse information from different sources are able to alleviate limitations of the unimodal biometric systems. In this chapter, we propose a multimodal biometric framework to identify people using their left and right wrist vein patterns. The framework uses a fast and robust preprocessing and feature extraction method. A generic score level fusion approach is proposed to integrate the scores from left and right wrist vein patterns using the proposed method. Moreover, a new framework for score level fusion based on symmetric sums (s-sums) has been presented. These s-sums are generated via triangular norms. The proposed framework has been tested on two publicly available benchmark databases. In particular, we used two partitions of NIST-BSSR1, i.e. NIST-multimodal database and NIST-fingerprint database.

5.2. The proposed wrist vein multibiometric system

Figure 5.1 shows the schematic diagram of the proposed multibiometric person recognition algorithm based on left and right wrist vein patterns. The information coming from the two biometric sources/traits can be integrated at the sensor, feature, match score, and decision level. Fusion at match score level is generally preferred due to the ease in accessing and combining matching scores, and has been adopted in this work as well.

In a verification setting, each user presents his left and right wrist to the sensor, and claims his identity. First, left and right wrist vein images are processed using the proposed algorithm (explained in section 5.2.1 in detail). Then, the system separately matches the two images with respective templates of the claimed identity provided at enrollment phase in the database, and produces a left and a right wrist vein matching scores $S_{Left\_wrist\_Vein}$ and $S_{Right\_Wrist\_Vein}$, respectively. These scores are combined using a new t-norm based fusion [5.1] (explained in section 5.2.3 in detail).

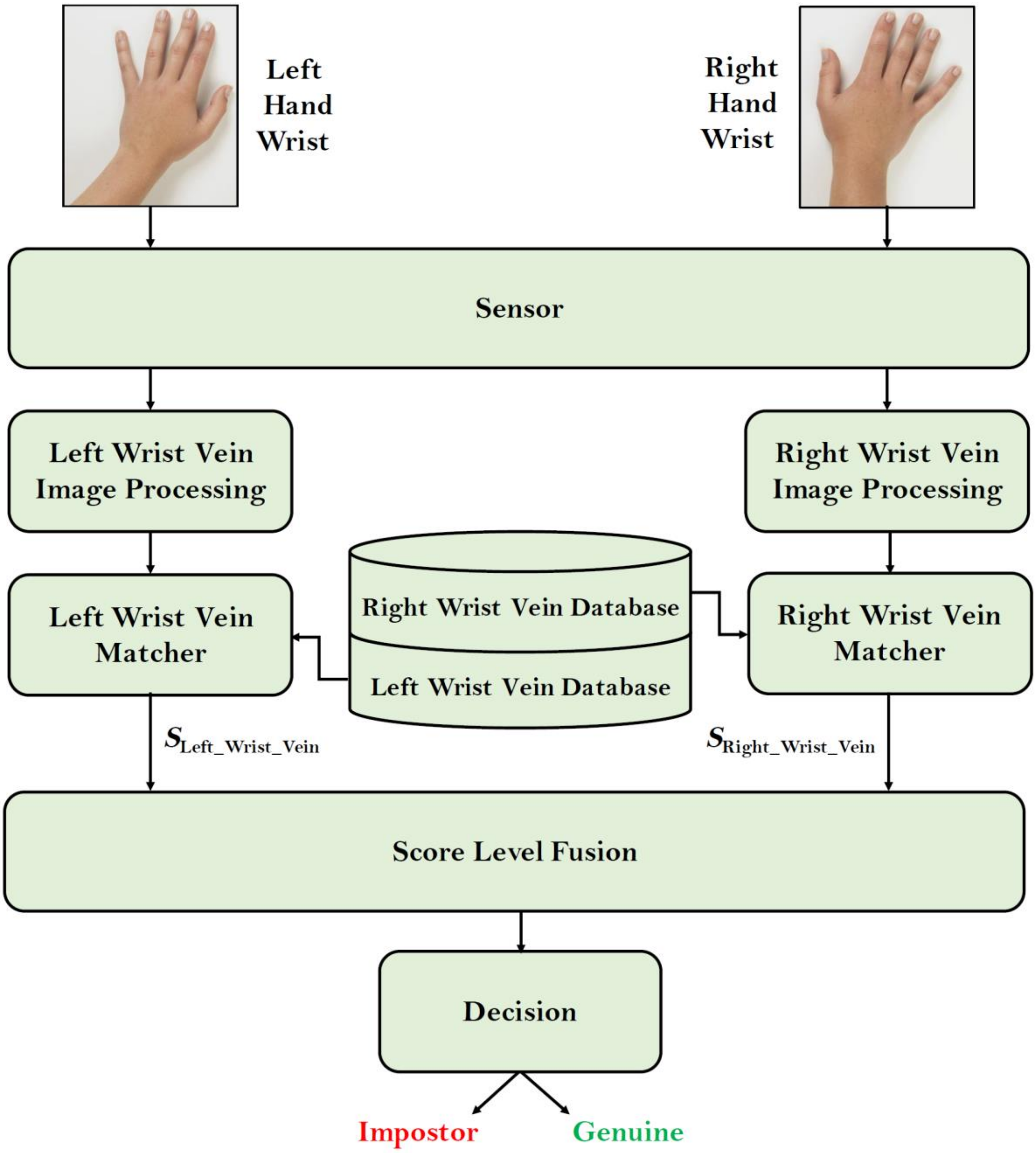

Figure 5.1. Proposed framework for wrist vein multibiometric system.

5.2.1. Pre-Processing captured wrist vein image

In particular, the captured left and right wrist vein images are separately processed to extract respective salient features. The steps followed for processing the wrist vein images are as follows: each captured image I_{Input} of size 768 x 1024 is normalized to 250 x 250 and converted to gray scale. After binarization and vein (wrist) centering, the median filter is used for noise reduction [5.2], which is independently followed by Global thresholding [5.3] and Contrast limited adaptive histogram equalization (CLAHE). The result obtained using CLAHE is further processed by local thresholding, i.e., by applying sequentially the average filter within window size of 31 x 31, and an arithmetic and morphological operations to remove more noise. Finally, the two binary images (one based on local and the other on global thresholding) are multiplied. *Figure 5.2* shows an example of a processed image. While, the procedure is summarized in Algorithm 1. It is worth mentioning that our algorithm is highly capable of extracting and enhancing the vein shape patterns even from low quality images. After pre-processing stage, we used the maximum value of the 2D correlation function as a measure of similarity between two patterns [5.4].

Algorithm 1 Pre-Processing captured wrist vein image

Input: A wrist vein image I_{Input}.

Output: A binary image I_{Output}, 1 for vein 0 otherwise.

1: Normalize I_{Input} and convert it to gray scale.

2: Centring the vein (wrist).

3: Apply median filter to remove noise, let I indicate the filtered image.

4: Apply CLAHE on I for contrast enhancement, let I_{Enh} indicate the enhanced image.

5: Apply global thresholding to obtain binarized image I_{Globa1}.

6: Apply average filter on I_{Enh} with threshold computed locally in 31×31 patch in order to obtain I_{Avr}.

7: Subtract element-wise I_{Enh} from I_{Avr} to obtain I_{Sub}.

8: Procure I_{Loca1} by binarizing I_{Sub} using a threshold, here 0 (black).

9: Compute the complement of the image I_{Loca1} for $\bar{I}$.

10: Remove noise from $\bar{I}$ using erosion followed by dilation operation.

11: Multiply element-wise $\bar{I}$ and I_{Globa1} for I_{Output}.

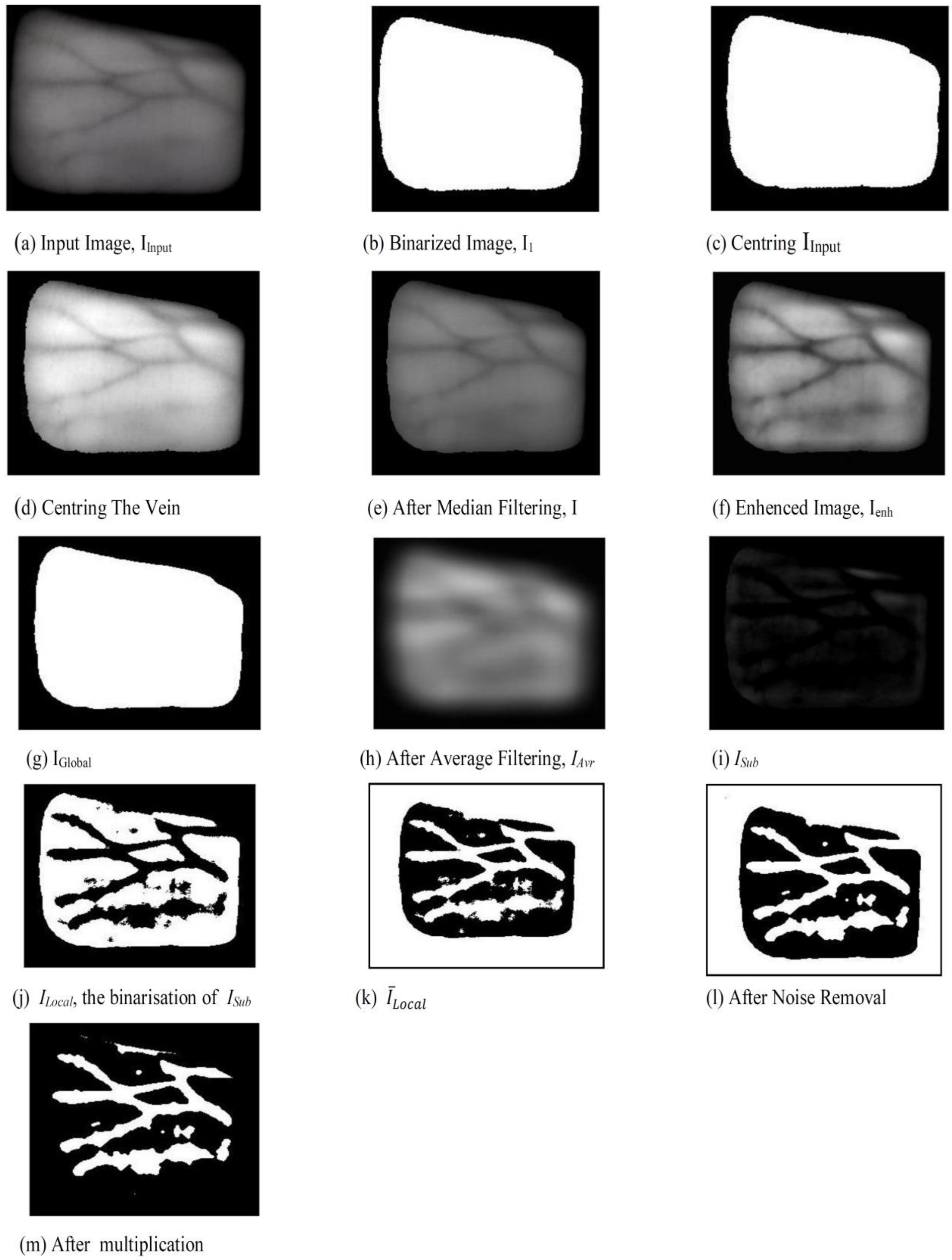

Figure 5.2. Results of preprocessing.

5.2.2. Measure of similarity

As mentioned above, we used the maximum value of 2D correlation function as a measure of similarity between two patterns (extracted wrist vein). In discrete form, normalized correlation can be defined in the following fashion.

Let $p_1[i,j]$ and $p_2[i,j]$ be two image arrays of size $n \times m$. In our case the two images are the result of the pre-processing step.

$$\mu_1 = \left(\frac{1}{nm}\right) \Sigma_{i=1}^{n} \Sigma_{j=1}^{m} p_1[i,j] \tag{5.1}$$

$$\sigma_1 = [(1/nm) \Sigma_{i=1}^{n} \Sigma_{j=1}^{m} (p_1[i,j] - \mu_1)^2]^{\frac{1}{2}} \tag{5.2}$$

Where μ_1, σ_1 are the mean and standard deviation for the intensities of p_1. Also, let μ_2 and σ_2 be similarly defined with reference to p_2. Then the normalized correlation between p_1 and p_2 can be defined as:

$$c_{mn} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} (p_1[i,j] - \mu_1)(p_2[i,j] - \mu_2)}{nm\sigma_1\sigma_2} \tag{5.3}$$

We use the maximum value of c_{mn} to measure the similarity (score) between two patterns (wrists).

5.2.3. Score level fusion using t-norm

In this section, we introduce our proposed score-level fusion method based on triangular norm. Let x, y denote the matching scores derived from left and a right wrist vein, respectively. Let $\mathrm{t}(x, y)$ denote the fusion of two normalized matching scores using t-norm. As we see in the previous chapter, triangular norms (t-norms) are the general families of binary functions that satisfy the requirements of the conjunction and disjunction operators [5.1]. T-norms are considered as the most suitable general candidates for generalized intersection operations of fuzzy sets in the mathematical fuzzy community [5.5]. T-norms are the functions that map the unit square into the unit interval:

$$t(x, y) : [0,1] \times [0,1] \rightarrow [0,1] \quad \textbf{(5.4)}$$

As we see before t-norm is a function that satisfies the following conditions:

1. Commutativity : $t(x, y) = t(y, x)$.
2. Associativity: $t(t(x, y), z) = t\big(x, t(y, z)\big)$.
3. Monotonicity: if ($x \leq$ a) and ($y \leq$ b) then $t(x, y) \leq t$ (a, b).
4. Boundary Conditions: t (0, 0) = 0 and t (x, 1) = x.

Combination of scores emanating from different modalities plays a central role in the score-level fusion. The challenge involved here is how to deal with the uncertainty and imperfection from the scores of different modalities. In this sense, we analyze the t-norms of Einstein product, Frank (Fk) with p = 0.4, Hamacher (Hm), Yager (Yg) with p = 0.5, and Schweizer–Sklar (SS) with p = −0.1 (in chapter 4, section 4.3.2). Except for Yager t-norm, the Einstein product, Frank, Hamacher, and Schweizer–Sklar t-norms maximize the fusion of genuine scores while they fail to further minimize the imposter scores simultaneously. Our aim is to find a novel t-norm that can both maximize the fusion of genuine scores and farther minimize the imposter scores. Thus, the fusion function F need to make:

$$F(x, y) > \max\,(Ep(x, y), Fk(x, y), Hm(x, y)\ , Yg(x, y), SS(x, y)), \forall x, y > t \quad \textbf{(5.5)}$$

$$F(x, y) \leq \min\,(Ep(x, y), Fk < (x, y), Hm(x, y)\ , Yg(x, y), SS(x, y)), \forall x, y \leq t \quad \textbf{(5.6)}$$

The parameter $t \in [th + \nabla\, , \mathrm{th} - \nabla]$ is a threshold value, where th = (th1+ th2)/ 2, th1 and th2 are the threshold of unimodal biometric matching scores x, y for fusion, and ∇ is a bias acquiring from the experiments.

Dubois and Parade t-norm comes to our rescue by way of satisfying our requirement of equation **(**5.5) and (5.6). The family of Dubois and Parade t-norm was introduced in the early 1978s [5.1]. It is defined as

$$T(x,y) = \frac{x\,y}{\max(x,y,p)} \quad \text{where } p \in [0.1] \tag{5.7}$$

Dubois and Parade t-norm satisfies our requirement of equation (5.5) and (5.6), as shown in *Figure* 5.3. The better performance of multimodal biometric recognition can be obtained by this t-norm.

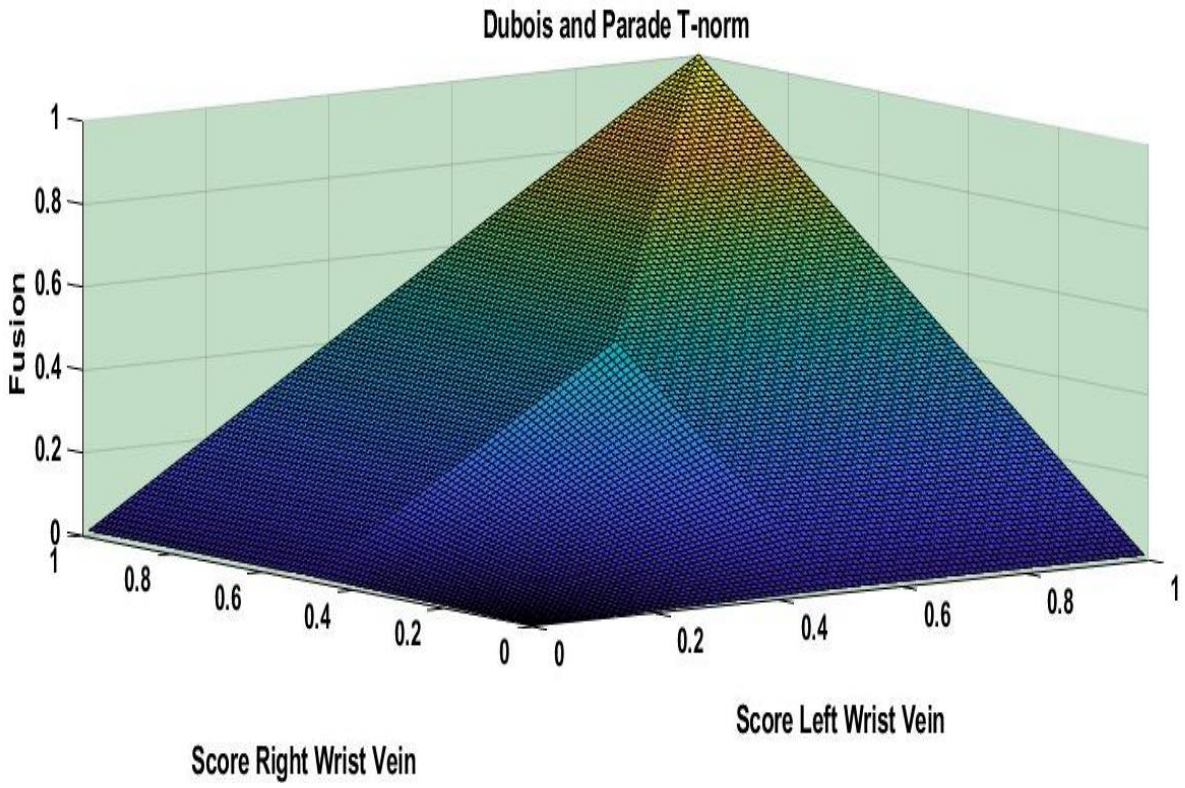

Figure 5.3. Graph of Dubois and Parade t-norm.

5.3. Experiments

Here, we provide an experimental evaluation of our proposed wrist vein multibiometrics for person authentication.

5.3.1. Dataset and Experimental Protocol

We used a publicly available dataset, called PUT vein pattern database [5.4], which is composed of 2400 images acquired from both hands of 50 users. The dataset contains images captured both for palm vein and wrist vein; we have only used images for wrist vein. For each subject, 12 samples are available. We used randomly selected 50% of the samples per user as training set, whereas the remaining 50% samples of the users were used to build the testing set, thus obtaining disjoint samples in training and testing sets. Experiments were performed in recognition mode and performance of the system is reported in Receiver Operating Characteristic (ROC) curves, EER (Equal Error Rate) and Decidability index (d').

5.3.2. Experimental Results

The results of both unimodal and multibiometric wrist vein person recognition systems using proposed method are presented in *Table 5.1* in terms of EER (%) [5.6] and corresponding ROCs are shown in *Figure 5.4*. In *Table 5.1*, it is easy to see that proposed multibiometric fusion method based on Dubois-Parade t-norm attains better performance than corresponding left and right wrist vein unimodal systems. For instance, using only left wrist vein features attained 4% EER, while fusion of left and right wrist vein features resulted into 0% EER. Similarly, we can observe in Figure 4 that at 1% FAR operating point, the GARs (Genuine Acceptance Rates) of left wrist vein, right wrist vein and their fusion using Dubois-Parade t-norm attained values up to 96%, 96%, and 100%, respectively.

Table 5.1 also reports the results of existing wrist vein recognition methods utilizing LBP [5.7] and LPQ and HOG [5.8] features. In addition, results using two largely adopted local image feature descriptions, i.e., LTP [5.9] and BSIF [5.10], are presented. Together with feature level fusion (here, feature concatenation), the most widely used sum rule as well as proposed combination technique based matching score level fusions were adopted to attain multibiometric results using existing methods. The results clearly show that the proposed method outperforms the existing methods. For example, the multibiometric (multi-instance) systems utilizing the method in [5.7] with sum fusion rule and the proposed approach yield 8.03 % and 0% EER, respectively.

Moreover, we can also notice that when the matching scores obtained by existing methods are fused using proposed combination technique, the accuracy is better than using sum rule, which further demonstrate the efficacy of the proposed fusion scheme. Similarly, feature level fusion of existing methods out performs the sum score fusion rule but underperforms when scores (from existing techniques) are integrated via proposed fusion method.

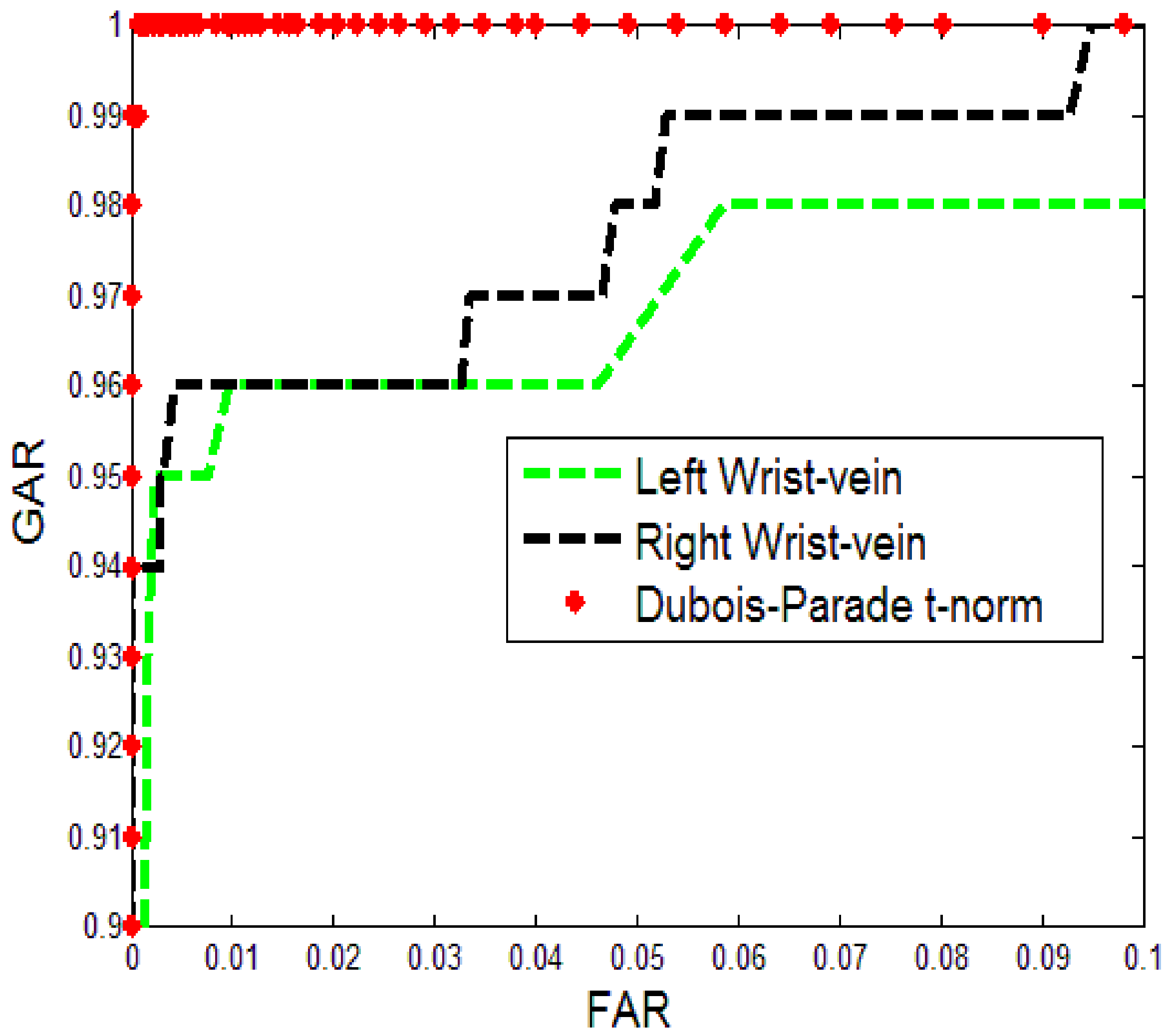

Figure 5.4. Comparison of ROC's curves of individual modality with Score Level Fusion.

Table 5.1. EER of both unimodal and multibiometrics systems. * Feature level fusion (here, feature concatenation). & Matching score level fusion using sum rule. # Matching score level fusion using proposed fusion technique.

Approach	**Left wrist vein**	**Right wrist vein**	**Fusion of left and right wrist veins**
*Local Binary Patterns (LBP) [5.7]	8.40 %	8.23 %	5.76 %
*Local Phase Quantization (LPQ) [5.8]	8.16 %	7.88 %	4.32 %
*Histogram of Gradients (HOG) [5.8]	5.14 %	4.61 %	3.41 %
*Local Ternary Patterns (LTP) [5.9]	7.43 %	7.29 %	4.19 %
*Binarized Statistical Image Features (BSIF) [5.10]	7.37 %	7.11 %	3.83 %
&Local Binary Patterns (LBP) [5.7]	8.40 %	8.23 %	8.08 %
& Local Phase Quantization (LPQ) [5.8]	8.16 %	7.88 %	7.56 %
&Histogram of Gradients (HOG) [5.8]	5.14 %	4.61 %	4.96 %
& Local Ternary Patterns (LTP) [5.9]	7.43 %	7.29 %	7.03 %
&Binarized Statistical Image Features (BSIF) [5.10]	7.37 %	7.11 %	6.68 %
# Local Binary Patterns (LBP) [5.7]	8.40 %	8.23 %	4.74 %
# Local Phase Quantization (LPQ) [5.8]	8.16 %	7.88 %	3.91 %
# Histogram of Gradients (HOG) [5.8]	5.14 %	4.61 %	0.28 %
#Local Ternary Patterns (LTP) [5.9]	7.43 %	7.29 %	3.05 %
# Binarized Statistical Image Features (BSIF) [5.10]	7.37 %	7.11 %	2.65 %
Proposed Fusion with Debois-Parade t-norm	**4.00 %**	**3.20%**	**0.00 %**

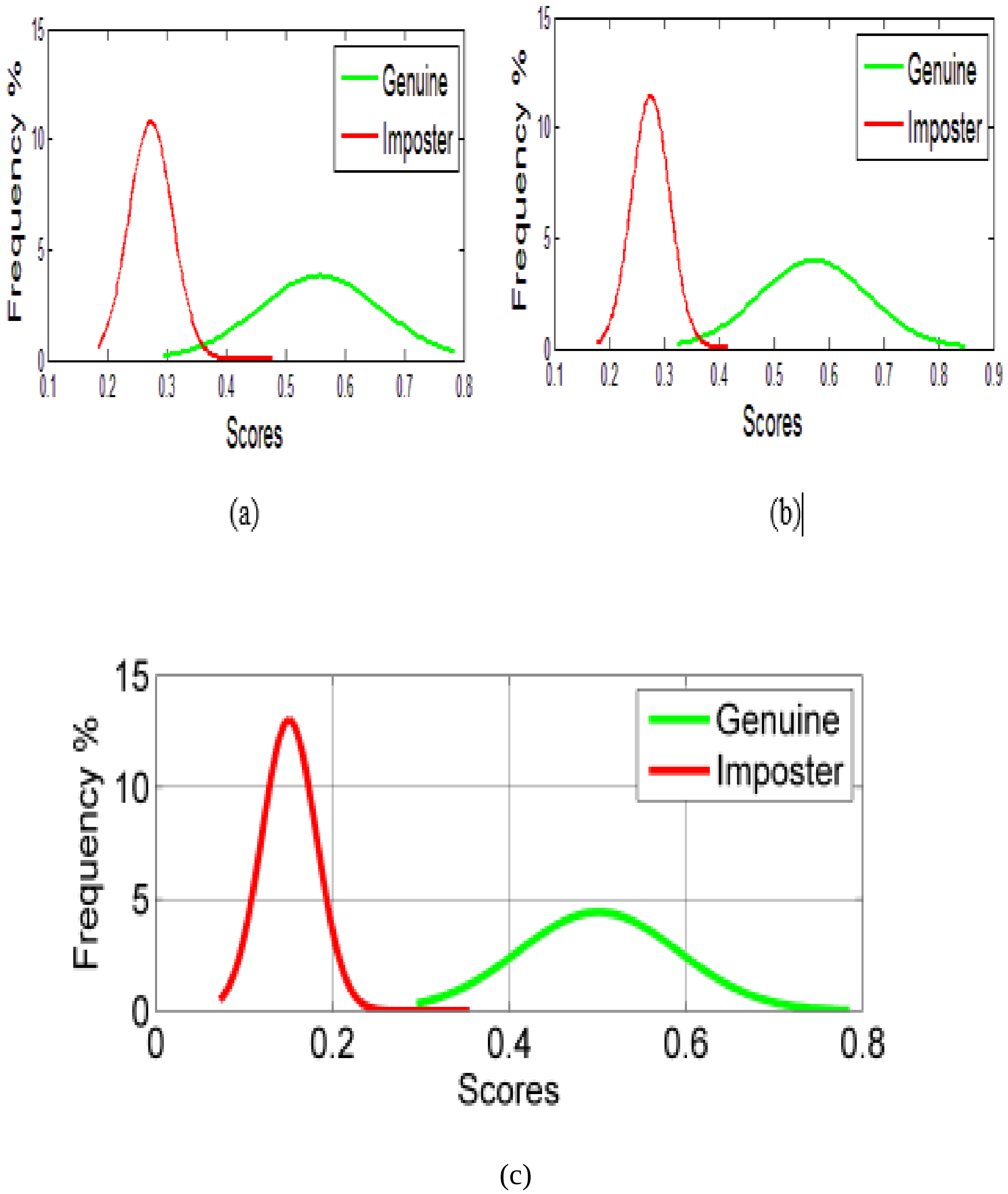

Figure 5.5. Score distribution: (a) Left wrist vein; (b) Right wrist vein; (c) Score level fusion result.

Figure 5.5 shows the probability density functions of unimodal and multibiometric systems. For unimodal systems, there is an overlap between the distributions of genuine and imposter scores. For better recognition, this overlap should be as minimum as possible [5.11], [5.12]. Thus, if we see *Figure 5.5* where both unimodal systems are fused via Dubois-Parade t-norm leads to almost no overlap between genuine and imposter score distributions thus ensuring better recognition.

The performance of a biometric system can also be evaluated using decidability index (d') [5.13]. It gives extent of overlap between two distributions and defined as:

$$d' = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2 - \alpha_2^2}{2}}} \tag{5.8}$$

Where μ1 and μ1 represent the mean of the genuine and imposter distributions, respectively, and σ_1, σ_2 represent the variances of the genuine and imposter distributions. A greater d' value means that the two distribution are more separable. *Table 5.2* gives d' values of the unimodal biometric modalities and multimodal fusion by various t-norms methods. We can notice that Dubois Parade t-norm has a higher d' value compared to the other t-norms, for Yager and Scheweizer-Sklar2 t-norm the value of d' is very small, that means the value of p is not suitable.

Table 5.2. A comparison of different fusion methodologies in terms of d'.

System	**d'**
Unimodal	
Right wrist vein	3.9471
Left wrist vein	3.595
Score-level multibiometric fusion	
Einstein product f-norm [5.5]	3.7231
Hamacher f-norm [5.5]	4.3010
Yager t-norm with p = 0.5 [5.5]	0.1414
Scheweizer-Sklarl t-norm with p = —0.1 [5.5]	4.1460
Scheweizer-Sklar2 t-norm p = 3 [5.5]	0.1416
Proposed Debois-Parade t-norm p = 0.5	**5.1926**

5.4. Proposed score-level fusion method

In this section, we first discussed preliminaries of symmetric sum(s-sum), then present the proposed multibiometric fusion scheme.

5.4.1. Preliminaries of symmetric sums

Here, we introduce the proposed score-level fusion method based on symmetric sums (s-sums). Though, recently the use of triangular norms in the score level fusion is prevalent in the literature [5.14], but use of s-sums in the score level fusion does not exist in the literature. Symmetric sums were introduced by Silvert in 1979 [5.15], and they are a kind of binary functions that are used as a rule of combination for fuzzy sets. s-sums are characterized by an auto-duality property, which means the invariance of the result of the operation by inverting the scale of values to combine. More precisely, s-sum is a function S: $[0,1] \times [0,1] \rightarrow [0,1]$ such that:

1. $S(0,0) = 0$;
2. $S(1,1) = 1$;
3. S is commutative;
4. S is increasing with respect to the two variables;
5. S is continuous;
6. S is self-dual: $\forall(x,y) \in [x,y]^2, S(x,y) = 1 - s(1-x, 1-y)$;

The general form of symmetric sums is given by:

$$S(x,y) = \frac{g(x,y)}{g(x,y) + g(1-x,\ 1-y)} \qquad (5.9)$$

Where g is a continuous, positive, increasing function of $[0,1] \times [0,1]$ into $[0,1]$, such that $g(0,0) = 0$. Typically, a continuous t-norm or t-conorm can be chosen as g.

Table 5.3 shows a few typical examples of symmetric sums. They are obtained by using various t-norms and t-conorms as generating function g.

Table 5.3. Examples of symmetric sums (s-sum), defined based on t-norms and t-conorms [5.16].

g(x, y)	**S(x, y)**	**Property**
xy	$\frac{xy}{1-x-y+2xy}$	Associative
$x+y-xy$	$\frac{x+y-xy}{1+x+y-2xy}$	non-associative
$\min(x,y)$	$\frac{\min(x,y)}{1-\lvert x-y\rvert}$	Mean
$\max(x,y)$	$\frac{max(x,y)}{1+\lvert x-y\rvert}$	Mean

5.4.2. Score-level fusion method based on symmetric sums

Figure 5.6 illustrates the architecture of multimodal biometric system. To verify the claimed identity of a user, the user has to provide their biometric modalities to the corresponding sensors.

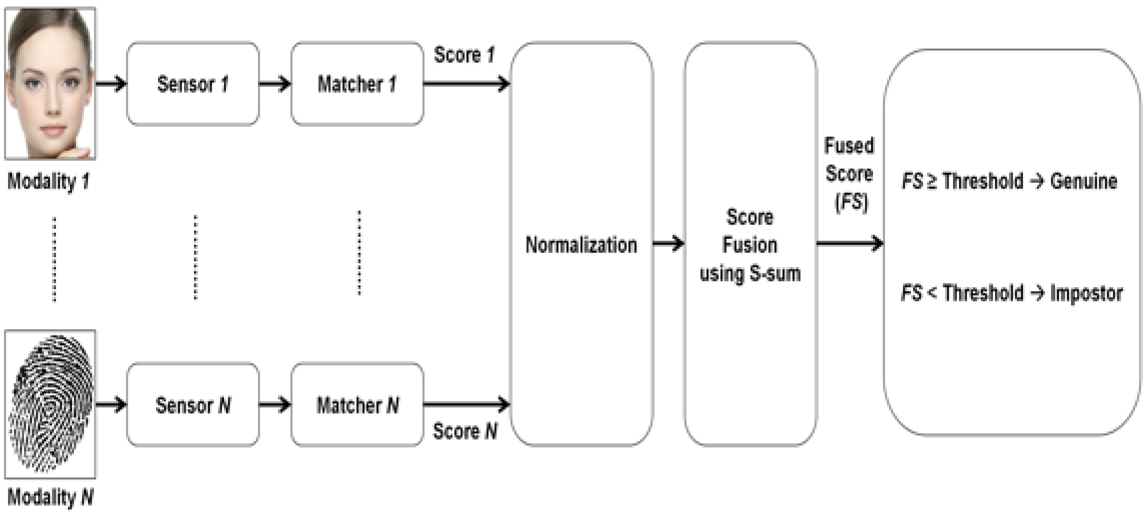

Figure 5.6. A schematic diagram of the score level fusion using S-sum.

The second step, the system individually compares the traits with their respective templates stored in database during the enrollment phase to produce the match score vector $S = [S_1, S_2, \ldots\ldots, S_N]$, where S_i is the scores provided by ith modality (corresponding to the *i*th sensors). As we mentioned before (chapter 4, section 4.3.1), the different matching scores should be first normalized into the domain [0, 1] before fixed Transformation-based fusion approaches can take place. Thus, min–max, and tanh-estimators normalization methods are used in this work as below:

$$S' = \frac{S - \min(S)}{\max(S) - \min(S)} \tag{5.10}$$

Equation (5.10) represents max-min normalization method [5.17], where S' is the normalized score and S denote the matching scores from a specific matcher.

$$x' = \frac{1}{2}\left\{tanh\left(0.01\left(\frac{x-\mu}{\sigma}\right)\right)+1\right\} \tag{5.11}$$

Equation (5.11) represents tanh-estimators normalization method [5.18], where x' is the normalized score, μ and σ are the mean and standard deviation estimates, respectively, of the genuine score distribution as given by Hampel estimators. After that, the normalized scores are combining using s-sum. In this work, we used t-norm functions to build s-sums because they can be represented by a general class of simple fusion rules, such as, min, max, product, and sum. Table 5.4 shows some of the t-norms, which we have used to generate s-sums.

Let $\mathrm{S} = (\mathrm{x}, \mathrm{y})$ denote the fusion of two normalized matching scores using s-sums. Let $\mathrm{s'}_1, \mathrm{s'}_2, \mathrm{s'}_3$ denote the normalized matching scores of three modalities, the two scores $\mathrm{s'}_1, \mathrm{s'}_2$ are first combined to yield $\mathrm{S} = (\mathrm{s'}_1, \mathrm{s'}_2)$ which is in turn combined further with $\mathrm{s'}_3$ to yield $\mathrm{S} = (\mathrm{S}(\mathrm{s'}_1, \mathrm{s'}_2), \mathrm{s'}_3)$ until all normalized scores are combined. If the fused score S is below a given acceptance threshold T, the user is classified as an impostor, otherwise it is classified as a genuine user.

Table 5.4. Examples of t-norms used to generate symmetric sums (s-sum).

T-norm	**Formulation**
Probabilistic	xy
Hamacher	$\frac{x\,y}{x+y-xy}$
Yager (p>0)	$max\left(1-((1-x)^{p}+(1-y)^{p})^{\frac{1}{p}},0\right)$
Schweizer & Sklar (p>0)	$\left(max(\,x^{p}+y^{p}-1,0)\right)^{\frac{1}{p}}$

5.4.3. Experimental results and analysis

In this section, we provide an experimental evaluation of the proposed fusion method on two publicly available datasets.

5.4.3.1. Databases

Our proposed score level fusion approach have been tested on two different partitions of the NIST-BSSR1 database. The two partitions are NIST-Multimodal database, NIST-Fingerprint database [5.19].

A. NIST-Multimodal database

NIST-Multimodal database contains four set of scores: two fingerprint scores from the left and right index fingers and two face matching scores using the same face images but generated by two different matchers labeled as matcher C and matcher G. The number of subjects in this database is 517, we have 517 genuine scores and 266,772 (517*516) impostor scores from each set of scores.

B. NIST- Fingerprint database

NIST- Fingerprint database contains two set of scores obtained from the left and right index fingers of the same users, the number of the users here is 6000, we have 6000 genuine scores and 35,994.000 (6000*599) impostor scores from each modality.

5.4.3.2. Performance of s-sum based fusion on NIST-Multimodal database

The matching scores of the face matcher C, face matcher G, left fingerprint and right fingerprint are normalized by tanh-estimators normalization method as in (5.11). Except for s-sum generated by Probabilistic t-norm, the s-sums generated by Hamacher, Yager, and Schweizer & Sklar t-norms are not associative, so, for non-associative s-sums the order of combination is as follow: let $x_1,\ x_2,\ x_3,\ x_4$ denote the normalized matching scores of face matcher C, face matcher G, left fingerprint and right fingerprint, respectively, the two scores $x_1,\ x_2$ are first combined to yield S= (x_1, x_2) which is in turn combined further with x_3 to yield S= ($S(x_1, x_2), x_3)$ until all normalized scores are combined.

The performance of the proposed system is evaluated using the ROC curve which is a plot of GAR vs FAR where GAR = 1- FRR is the genuine acceptance rate. FAR is the rate at which imposters are accepted as genuine and FRR is the rate at which genuine users are rejected as imposters, and GAR is the rate at which the correct person is accepted as a genuine user.

Figure (5.7) shows ROC's of individual modalities and of fused modalities by using s-sum generated by Schweizer & Sklar t-norm on NIST multimodal database. At FAR = 0.01 %, GAR's (1-FRR) [5.20] of face matcher C, face matcher G, left fingerprint, right fingerprint are 74.3%, 0.68%, 77.2% and 85.3% respectively. While, with s-sum generated by Schweizer & Sklar t-norm, GAR of 99.8% is obtained at 0.01% FAR operating point. As can be seen from table 5.5, other s-sums generated by Probabilistic, Yager, Hamacher t-norms are also used for score level fusion on NIST multimodal. Also, the performances attained by score level fusion using Likelihood ratio and SVM proposed in [5.21] (both requiring learning and training) have been reported. Besides, Entropy-with-frank and with Harmacher t-norms have reported as well. From table 5.5, it is easy to see that s-sums generated by Yager, Schweizer & Sklar outperforms the existing score level fusion in literature. Moreover, it can be observed that the s-sum using min and max rules outperforms the generating approaches (using min and max rules) thus making them superior.

Table 5.5. A comparison of fusion using different approaches on NIST multimodal database.

Score-level fusion method for FAR = 0.01 %	**GAR (%)**
S-sum using Probabilistic t-norm	97
S-sum uing Hamacher t-norm	95
S-sum using Yager t-norm with p= 1.2	99.8
S-sum using Schweizer & Sklar t-norm with p = 0.9	99.8
S-sum using Max rule	93.3
S-sum using Min rule	93.2
Max rule [5.5]	91.7
Min rule [5.5]	78
SVM [5.21]	98.8
Likelihood ratio [5.21]	99.1
Entropy-with-frank t-norm p=0.01[5.22]	96.62
Entropy-with- hamacher t-norm p=0.01 [5.22]	96.7

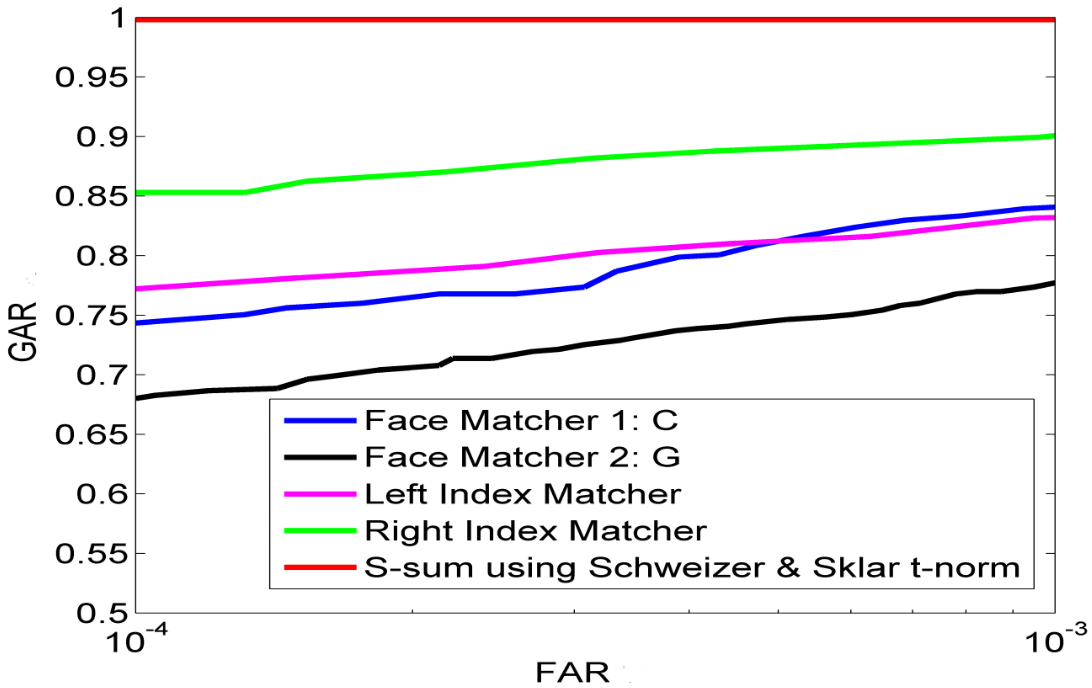

Figure 5.7. Comparison of ROC's curves of individual modality with score level fusion.

5.4.4.3. Performance of s-sum based fusion on NIST- Fingerprint database

For this dataset, the matching scores of left and right index fingers are normalized by min–max method as in equation (5.10). We used here the commutative property to fuse the two matching scores, so, the order of combination is not necessary.

Figure 5.8 depicts ROC's of individual modalities as well as of fused modalities using s-sum generated by max rule on NIST fingerprint database. At FAR = 0.01%, GAR's (1-FRR) of left index finger, right index finger are 75.5%, 83.5% respectively. But, with s-sum generated by max rule, GAR of 90.75% is obtained with the same FAR operating point.

We can observe in table 5.6, different s-sums generated by Probabilistic, Yager, Hamacher t-norms are also used for score level fusion on NIST fingerprint. The results obtained using score level fusion via Likelihood ratio and SVM learning-based methods of [5.21] are also presented for comparison. In the Table 5.6, we can notice that s-sums generated by Max rule and Yager t-norm give comparative performances. As in the previous section about multimodal system, we can state based on table 5.6 that s-sum using min, max rules outperforms the generating approaches (min, max rules). In addition, s-sum using max rule outperforms Entropy-with-frank and with harmacher t-norms.

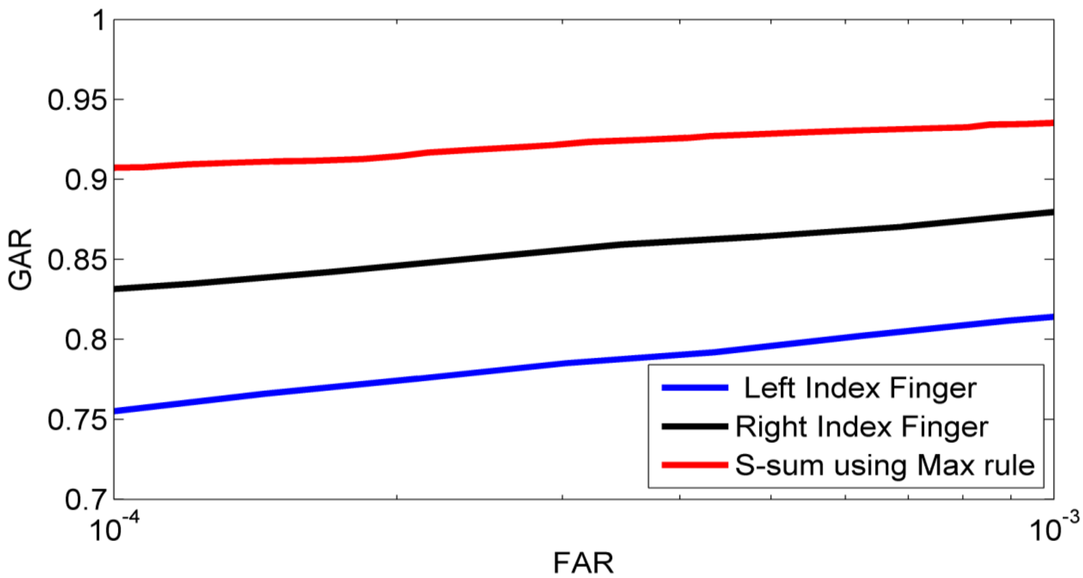

Figure 5.8. Comparison of ROC's curves of individual modality with score level fusion.

Table 5.6. A comparison of fusion using different approaches on NIST fingerprint database.

Score-level fusion method for FAR = 0.01 %	**GAR (%)**
S-sum using Probabilistic t-norm	89
S-sum uing Hamacher t-norm	75.5
S-sum using Yager t-norm with p= 10.3	90
S-sum using Schweizer & Sklar t-norm with p = 0.9	89
S-sum using Max rule	90.75
S-sum using Min rule	82.5
Max rule [5.5]	90.3
Min rule [5.5]	79.6
SVM [5.21]	91.4
Likelihood ratio [5.21]	91.4
Entropy-with-frank p=0.01 [5.22]	87.77
Entropy-with- hamacher p=0.01 [5.22]	85.42

5.4.4.4. Classifier fusion using s-sum rules

In this section, three classifier fusion methods are tested. These classifiers are, linear discriminant Analysis (LDA), quadratic discriminant analysis (QDA), and k-nearest neighbor (KNN) [5.23]. The two databases used in this paper have a massive number of scores in that it mainly contains impostor scores, for example, NIST fingerprint consists of 6000 genuine scores and 35994000 impostor scores (per matcher). The excessive number of impostor scores may cause a biased or over-trained modal [5.23]. To mitigate this problem, we select randomly two impostor scores per matcher per user for training as in [5.23]. The complete number of genuine scores plus reduced impostor scores are called "trimmed database." [5.23]. For each multimodal database, half of the genuine and half of the impostor scores were randomly selected to form the training set, and the other half (genuine, impostor) were used to form the test set [5.21], this partitioning of the scores was repeated 20 times, the mean of GAR values is considered as for performance evaluation of the system.

From table 5.7, it is clear that the two classifiers fusion (QDA and KNN) yield improvements compared to the corresponding fixed fusion rule (symmetric sum using Yager t-norm) on NIST trimmed multimodal database, whereas LDA fusion approach reduces the performance of the fixed fusion rule using the same database.

From table 5.8, the QDA classifier gives better performance compared to fixed fusion rule as well as other classifiers fusion (LDA and KNN) for NIST trimmed fingerprint database.

Table 5.7. Classifier fusion using (s-sum using Yager t-norm with) on NIST-multimodal database.

Classifier	S-sum using Yager t-norm with p = 1.2	LDA	QDA	KNN
GAR at 0.01 % FAR	99.8 %	99.6%	100%	100%

Table 5.8. Classifier fusion using (s-sum using Max rule) on NIST-fingerprint database.

Classifier	S-sum using Max rule	LDA	QDA	KNN
GAR at 0.01 % FAR	90.75%	91.76%	92.8%	89.7%

5.5. Conclusion

This chapter presents a novel algorithm for recognizing individuals based on their left and right wrist vein patterns. The algorithm extracts wrist vein features using a fast and resilient preprocessing technique that does not require either user-cooperation or prior learning. The left and right wrist vein patterns are fused at score level using Dubois-Parade t-norm. The experimental analysis on a publicly available PUT wrist vein dataset shows that proposed multibiometric system outperforms the unimodal systems, their fusion based on other t-norms and existing wrist vein recognition schemes.

Also, we have proposed a new score level fusion approach for a multimodal biometric system based on s-sums. These s-sums do not require any learning or training procedure, thus making our system simple, efficient and computationally less expensive. The experimental results are performed on two different partitions of the NIST-BSSR1 (NIST-multimodal and NIST-fingerprint). All in all, the presented experimental results demonstrate that our approach outperforms the generating approaches (i.e. min, max rules).

5.6. References

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General conclusion

General conclusion

Multimodal biometric systems, which combine information from multiple biometric sources, have shown to improve the identity recognition performance by overcoming the weaknesses and some inherent limitations of unimodal systems, For example, the problem of non-universality is addressed since multiple biometric modalities are able to provide sufficient information about the users. Also, multimodal biometric systems make it difficult for an intruder to simultaneously spoof the multiple biometric traits of a registered user. In multimodal systems, information fusion can be carried out at the sensor, feature extraction, matching score, or decision level. Owing to ease in accessing and combining of scores, fusion at the matching score level is the most commonly adopted approach in the literature.

To this aim, in this thesis, a new framework for score level fusion based on symmetric sums (s-sums) has been presented. To the best of our knowledge, no wrist vein based multi biometric system, particularly integrating right and left wrist vein patterns, has been studied in the literature. In this thesis, we propose a multibiometric user authentication framework that utilizes right and left wrist vein. Specifically, a recognition algorithm for wrist vein biometrics is presented, where the new score level fusion approach have been used to combine the scores originating from right and left wrist vein patterns is utilized.

The thesis starts by introducing biometric and its importance in the current world. Biometric systems and challenges for these systems are also presented in chapter 1. Multimodal biometric system has been thoroughly discussed to build the foundation for the rest of the thesis. Pros and cons of multimodal biometric systems along with various development issues have been discussed in chapter 2.

In chapter 3, previous related works in the areas of vein recognition and on different fusion approaches are reviewed. Due to the challenges with unimodal biometric systems and to meet the demanding security requirements, several approaches have been proposed and developed in literatures for multimodal biometric authentication system with different biometric traits and with different fusion mechanisms.

Among the available fusion methods, pre-matching fusion approaches, such as sensor level fusion and feature level fusion methods have not been used extensively due to limited access to the information. Match score level fusion methods are very popular with developers and also has been extensively investigated by biometric researchers as some of the earlier methods. Decision level fusion approaches are too abstract and used primarily in the commercial biometric system where only the final outcomes are available for processing. Thus in this doctoral research, we have used score level fusion which is common approach. The development procedures for the proposed multimodal system have been illustrated in the chapter 4.

Outcomes and experimentations have been presented and discussed in chapter 5. Firstly, A generic score level fusion approach is proposed to integrate the scores from left and right wrist vein patterns using Dubois and Parade triangular norm (t-norm). Experiments on the publicly available PUT wrist vein dataset show that the proposed multibiometric framework outperforms the unimodal systems, their fusion using other t-norms techniques, and existing wrist vein recognition methods. Furthermore, a new framework for score level fusion based on symmetric sums (S-sums) has been presented. These s-sums are generated via triangular norms. The proposed framework has been tested on two publicly available benchmark databases. In particular, the authors used two partitions of NIST-BSSR1, i.e. NIST-multimodal database and NIST-fingerprint database. The experimental results show that the proposed method outperforms the existing approaches for the NIST-multimodal database and NIST fingerprint database.

Author’s contributions

The major contributions of this research work can be summarized as follow:

- A novel algorithm for recognizing individuals based on their left and right wrist vein patterns. The algorithm extracts wrist vein features using a fast and resilient preprocessing technique that does not require either user-cooperation or prior learning.
- A novel score level fusion approach is proposed to integrate the scores from left and right wrist vein patterns using Dubois and Parade triangular norm (t-norm).
- A new framework for score level fusion based on symmetric sums (S-sums) has been presented. These s-sums are generated via triangular norms.

Future works

In the future, we aim to study cross-dataset and cross-sensor dorsal hand vein based biometric recognition systems.

Also, we will evaluate our method (symmetric sum-based biometric score fusion) at a large-scale including its robustness against spoofing attacks.

List of publications

The outcomes of this research have been published and presented through important venues, such as IET BIOMETRICS and 7th International Conference on Image Processing Theory, Tools and Applications (IPTA), At Montreal, Canada.

Journal Paper

Cheniti, M., Boukezzoula, N., Akhtar, Z.: 'Symmetric sum-based biometric score fusion', *IET Biometrics*, 2018, 7, (5), pp. 391–395.

Conference Paper

Cheniti, M., Akhtar, Z., Boukezzoula, N., Falk, T.H.: 'Combining left and right wrist vein images for personal verification', in '2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)' 2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA), (IEEE, 2017), pp. 1–6.