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Conception et Implémentation d'Architectures Modulaires et Hiérarchiques en Reconnaissance Biométrique

Thèse présentée par :

Meryem Regouid

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Soutenue devant le jury composé de :

KHABABA	Abdallah	Prof. Université de Ferhat Abbas Sétif 1	Président
BESSOU	Sadik	MCA. Université de Ferhat Abbas Sétif 1	Directeur
NOUIOUA	Farid	MCA. Université de Bordj Bou Arreridj	Examinateur
AKROUF	Samir	MCA. Université de M'sila	Examinateur
BENOUIS	Mohamed	MCB. Université de M'sila	Invité
TOUAHRIA	Mohamed	Enseignant Chercheur Retraité	Invité

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Design and implementation of modular and hierarchical architecture for biometric recognition

A dissertation by :

MERYEM REGOUID

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Board of examiners :

KHABABA	ABDALLAH	Prof. University of Ferhat Abbas Setif 1	President
BESSOU	SADIK	Assoc Prof. University of Ferhat Abbas Setif 1	Advisor
AKROUF	SAMIR	Assoc Prof. University of M'Sila	Examiner
NOUIOUA	FARID	Assoc Prof. University of Bordj Bou Arreridj	Examiner
BENOUIS	MOHAMED	Assis Prof. University of M'Sila	Invited
TOUAHRIA	MOHAMED	Retired Researcher Teacher	Invited

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Abstract

Unimodal biometric recognition systems have been widely used in various fields. The use of a single modality makes the developed system suffering from many challenges. Combination of multiple information extracted from different biometric modalities in emergent biometric recognition system is the best-proposed solution up till now. These systems aim to solve different drawbacks encountered in a unimodal biometric system. The search for suitable data sources that build a robust and secure system is ongoing.

Electrocardiogram (ECG or EKG) provides an inherent characteristic of the liveness of a person, making it hard to spoof compared to other biometric traits. This new technology has been recently employed in several unimodal and multimodal systems. Ear biometrics is another emerging modality, it presents a rich and stable source of information over an acceptable period of human life. Iris is one of the oldest biometrics that was used in literature. Because of its higher accuracy and reliability, iris biometrics has been embedded with different biometric modalities such as fingerprint, face and palm print.

In this dissertation, we aim to solve the existing problems encountered by the unimodal systems by analyzing existed works and then proposing a novel multimodal biometric system. Two contributions have been introduced. In the first contribution, we implement two systems. Firstly, we develop an ECG biometric system based on Shifted One Dimensional Local Binary Patterns (Shifted-1D-LBP). In this system, we investigate the impact of the preprocessing step by applying three different techniques named Savitzky-Golay Finite impulse response (SG-FIR), Butterworth and 1D digital filters. The second system consists of combining ear and ECG modalities in a bimodal biometric system based on 1D Multi-Resolution Local Binary Patterns (1D-MR-LBP).

The second contribution employs ear, ECG and iris to develop a novel multimodal system. Local texture descriptors (1D-LBP, Shifted-1D-LBP and 1D-MR-LBP) are used to extract the important features from the ECG signal and the converted ear and iris images to 1D signal. An augmented vector was generated by fusing the three set features. KNN and RBF are used for matching to classify the unknown user into genuine or impostor. The experimental results demonstrate that the proposed approach outperforms unimodal biometric systems, our bimodal biometric system and existing multimodal systems.

Keywords: Multimodal Biometric, ECG, Ear, Iris, Local Descriptors, 1D-LBP, Shifted-1D-LBP, 1D-MR-LBP.

Résumé

Les systèmes de reconnaissance biométrique unimodaux sont largement utilisés dans divers domaines. L'utilisation d'une seule modalité fait que le système développé souffre de nombreux défis. La combinaison de plusieurs informations extraites de différentes modalités biométriques dans un nouveau système de reconnaissance biométrique est la meilleure solution proposée jusqu'à présent. Ces systèmes visent à résoudre différents inconvénients rencontrés dans un système biométrique unimodal. La recherche de sources de données appropriées pour construire un système robuste et sécurisé est en cours.

L'électrocardiogramme (ECG ou EKG) offre une caractéristique inhérente à la vivacité d'une personne, ce qui le rend difficile à usurper par rapport à d'autres modalités biométriques. Cette nouvelle technologie a été récemment utilisée dans plusieurs systèmes unimodaux et multimodaux. L'oreille biométrique est une autre modalité émergente. Elle présente une source d'informations riche et stable sur une période acceptable de la vie humaine. L'iris est l'une des plus anciennes biométries utilisées dans la littérature. En raison de sa précision et de sa fiabilité supérieure, l'iris a été intégré avec des différentes modalités biométriques tels que l'empreinte digitale, le visage et la paume.

Dans cette thèse, nous visons à résoudre les problèmes existants rencontrés par le système unimodal en analysant les travaux existants puis en proposant un nouveau système biométrique multimodal. Deux contributions ont été introduites. Dans la première contribution, nous implémentons deux systèmes. Tout d'abord, nous développons un système biométrique pour l'ECG basé sur Shifted 1D-LBP. Dans ce système, nous étudions l'impact de l'étape de prétraitement en appliquant trois techniques différentes (SG-FIR, Butterworth et filtres numériques 1D). Le deuxième système consiste à combiner l'oreille et l'ECG dans un système biométrique bimodal basé sur 1D-MR-LBP.

La deuxième contribution utilise l'oreille, l'ECG et l'iris afin de développer un nouveau système multimodal. Des descripteurs de texture locaux (1D-LBP, Shifted 1D-LBP et 1D-MR-LBP) sont utilisés pour extraire les caractéristiques importantes du signal ECG et des images converties de l'oreille et de l'iris en signal 1D. Un vecteur augmenté a été généré en fusionnant l'ensemble des trois caractéristiques. KNN et RBF sont utilisés pour l'appariement afin de classer un utilisateur inconnu comme un authentique ou un imposteur. Les résultats expérimentaux démontrent que l'approche proposée surpasse les systèmes biométriques unimodaux, le système bimodal proposé et les systèmes multimodaux existants.

Mots-clés: Biométrie Multimodale, ECG, Oreille, Iris, Descripteurs Locaux, 1D-LBP, Shifted-1D-LBP, 1D-MR-LBP.

ملخص

تستخدم الأنظمة البيومترية وحيدة النمط على نطاق واسع في مختلف المجالات. استخدام صفة بيومترية واحدة يجعل النظام المطور يعاني من العديد من التحديات. يعد الجمع بين العديد من المعلومات المستخرجة من صفات بيومترية مختلفة في نظام بيومتري جديد هو أفضل حل مقترح حتى الآن. يهدف هذا النظام إلى حل العيوب المختلفة التي تواجهها الأنظمة البيومترية وحيدة النمط. وقد تم الدمج بين العديد من الصفات البيومترية مثل الوجه وبصمات الأصابع وقزحية العين ... إلخ. البحث عن مصادر البيانات المناسبة التي تبني نظام قوي وآمن مازال مستمر.

يوفر التخطيط الكهربائي للقلب (ECG أوEKG) خاصية متأصلة في حياة الشخص، مما يجعله صعب المحاكاة مقارنة مع الصفات البيومترية الأخرى. لقد استخدمت هذه التقنية الحديثة مؤخرًا في عدة أنظمة وحيدة ومتعددة الأنماط. الأذن البيومترية هي صفة واعدة أخرى. فهي تحتوي على معلومات مهمة وثابتة خلال فترة مقبولة من حياة الإنسان. القزحية هي واحدة من أقدم الصفات البيومترية التي استخدمت. بسبب دقتها العالية وموثوقيتها ، فقد تم دمج القزحية مع عدة صفات بيومترية أخرى مثل بصمات الأصابع والوجه وطبعة راحة اليد.

في هذه الأطروحة ، نحن نهدف إلى حل المشاكل القائمة التي يواجهها النظام وحيد النمط من خلال تحليل الأعمال الحالية ثم اقتراح نظام بيولوجي جديد متعدد الأنماط. بالنسبة للطريقة الأولى، تم تنفيذ نظامين. أولا، نقوم بتطوير نظام تخطيط القلب ECG على أساس Shifted-1D-LBP (أنماط ثنائية المحلية). في هذا النظام ، نتحقق من تأثير خطوة المعالجة المسبقة من خلال تطبيق ثلاث تقنيات مختلفة (SG-FIR ، Butterworth و 1D-digital). يتمثل النظام الثاني في دمج الأذن و ECG في نظام بيومتري ثنائي يعتمد على 1D-MR-LBP (متعدد الدقة).

في الطريقة الثانية، تم تطوير نظام متعدد الأنماط قائم على دمج ECG ،الأذن والقزحية حيث يتم استخدام واصفات الملمس المحلية (1D-MR-LBP, Shifted 1D-LBP, 1D-LBP) لاستخراج الميزات الهامة من إشارة ECG وكذا من الأذن وقزحية العين بعد تحوليهما من صور الى شعاع ذو بعد واحد .يتم إنشاء شعاع جديد عن طريق دمج مجموعة الميزات الثلاثة. كما تم استخدام KNN و RBF للمطابقة لتصنيف المستخدم الغير معروف إلى أصلي أو محتال. أظهرت النتائج التجريبية أن النظام المقترح يتفوق على الأنظمة البيومترية وحيدة النمط، والنظام الثنائي المطور وكذا الأنظمة متعددة الأنماط الحالية.

كلمات مفتاحية: البيومترية متعددة الأنماط ، تخطيط القلب ECG ، الأذن ، القزحية ، الواصفات المحلية ،1D-LBP ، Shifted-1D-LBP، 1D-MR-LBP.

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Contents

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List of Abbreviations

ECG / EKG	Electrocardiogram
Shifted-1D-LBP	Shifted One Dimensional-Local Binary Patterns
SG-FIR	Savitzky-Golay Finite Impulse Response
1D-MR-LBP	One Dimensional-Multi-Resolution-Local Binary Patterns
AI	Artificial Intelligence
ML	Machine Learning
PCA	Principal Component Analysis
LDA	Linear Discriminant Analysis
LPQ	Local Phase Quantization
BSIF	Binarized Statistical Image Features
IoT	Internet of Things
ATM	Automated Teller Machine
KNN	K-Nearest Neighbors
NN	Neural Network
FTA	Failure To Acquire
FTE	Failure To Enroll
FAR	False Accept Rate
FRR	False Reject Rate
GAR	Genuine Accept Rate
EER	Equal Error Rate
CRR	Correct Recognition Rate
HMM	Hidden Markov Models
NLP	Natural Language Processing
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
SVM	Support Vector Machines
SETI	Extra-Terrestrial Intelligence

IIT-Delhi	Indian Institute of Technology Delhi
UND	University of Notre Dame
PIE	Pose, Illumination and Expression
CP	Carreira Perpiñán
USTB	University of Science and Technology in Beijing
AMI	Mathematical Analysis of Images
ULPGC	University of Las Palmas of Gran Canaria
WPUT	West Pomeranian University of Technology
AWE	Annotated Web Ears
WLD	Weber Local Descriptor
CCA	Canonical Correlation Analysis
SA	Sinoatrial Node
AV	Artio-Ventricular
SIMCA	Soft Independent Modeling of Class Analogy
DWT	Discrete Wavelet Transform
HRV	Heart Rate Variability
IQR	Interquartile Ranges
BFS	Greedy Best First Search
NSR	MIT-BIH/Normal Sinus Rhythm
PTB	Physikalisch Technische Bundesanstalt
MIT-BIH-A	MIT-BIH Arrhythmia Database
INCART	Institute of Cardiological Technics
AC	Auto-Correlation
DCT	Discrete Cosine Transform
SAECG	Signal Averaged-ECG
ZMCP	Ziv-Merhav Cross Parsing
PAR	Pulse Active Ratio
NCBFSU	Nonlinear Correlation-Based Filters using Symmetrical Uncertainty
RPCANET	Robust Principal Component Analysis Network
PCG	Phonocardiography

EEG	Electroencephalogram
UAE	United Arab Emirates
RAIC	Restricted Area Identity Card
WFP	World Food Program
CHT	Circular Hough Transform
LG	Log-Gabor
CT	Contourlet Transform
GLAC	Gradient Local Auto-Correlation
KELM	Kernel Extreme Learning Machine
NIR	Near-Infrared
VW	Visible Wavelength
CASIA	Institute of Automation, Chinese Academy of Sciences
UPOL	University of Palackeho and Olomouc
IFO	Indexing-first-One
KPCA	Kernel Principal Component Analysis
SR	Spectral Regression
ECIREA	ECG- Iris-Ear Multimodal System

General Introduction

In the past several decades, the human being a source of inspiration for many researchers. His intelligence and his way of thinking and making decisions in addition to how he interacts with the external environment, stimulated scientists to develop machines that will be able to mimic his actions and behaviours. Understanding human falls under the science of Artificial Intelligence (AI) that builds smart machines. Defining all rules and data that an AI-based expert system needs is quite impossible especially if the data changed over time.

A possible solution to the problem at hand is to give machines a set of data and try to make it able to learn from it which is known as Machine Learning (ML). The latter is sub-field of AI. It is based on mimicking the human brain. ML makes machines capable to learn data and make rules by its self through its experiences instead of giving it all possible data which is sometimes impossible. Machine learning has a high potential to analyze, interpret and secure large data. For these reasons, pattern recognition and in particular biometric recognition was considered as one of the biggest beneficiaries of this progress.

For a long time, one of the most popular ideas in literature is allowing access to only authorized personnel. Password, tokens, keys, access card and other types of authorization methods have been invented and used for decades. There are different attacks that can be launched against authentication systems based on these traditional methods. Hence it is necessary to find other advanced techniques to solve these problems. Recently, the biological, behavioural and morphological characteristics of humans can be used to find the identity of an individual which is known as biometric traits. Biometrics is a technique that allows the identification of a person based on his body measurements and calculations.

There are some properties that can be distinguished for determining the suitability of biometric traits such as uniqueness, universality and permanence. These properties may be changed from one biometric traits to another which makes it more reliable. The choice of the appropriate modality depends on various factors such as the nature, requirements, variety of issues and the matching performance of an application. Several biometric characteristics have been already integrated. Based on the natures of the extracted biometric features, the latter can be subdivided into three main types including the biological (i.e. DNA, EEG, ECG...etc.), morphological (i.e. fingerprint, face, ear...etc.) and behavioural characteristics (i.e. gait, voice, keystroke dynamics...etc.).

These human characteristics are used in many civilian and commercial applications for recognition purpose. It can be adopted in the forensic domain which helps in criminal investigations, financial transactions, airport check-in and homeland security or access control. The high-security level achieved based on this type of authentication reassures privacy and safety of clients. Accordingly, numerous countries exploit their different strengths on critical fields such as voter registration and national ID such as India's national ID program called Aadhaar.

The biometric system can perform in verification or identification mode depending on the application contexts. In verification mode, the biometric systems validate the user's identity by comparing the input traits with one template that exists in the database. Whereas, in identification mode, the biometric systems validate the user's identity by comparing the input traits with all templates that exist in the database. The first use of the biometric system by a client is called enrolment. In this stage, the user must introduce his biometric information using a suitable sensor (e.g. cameras for face image). The captured data will be processed and stored as a template in the database.

The biometric system consists of three major steps. The first step called preprocessing step which has the aim of improving and enhancing the quality of collected data and removing deferent artifacts and noises that can be accrued during the acquisition. Secondly, a set of features will be extracted from the preprocessed data. This step called features extraction step, it is considered as the heart of the biometric system. The more the extracted features were accurate and unique for each individual, the better the system performs.

Global, local or even both features can be extracted. Both approaches were widely applied in the literature. For the global approaches, PCA (Principal Component Analysis) and LDA (Linear Discriminant Analysis) are the most used in this field. Whereas LBP, LPQ (Local Phase Quantization) ,BSIF (Binarized Statistical Image Features) and other techniques were applied for detecting the local features. Finally, the extracted pattern will be compared with the stored templates to identify the claimed identity. This process will be performed by estimating the distance between them based on a chosen classifier such as hamming distance. This phase is called classification.

Local texture descriptors have proven their efficiency in Biometric domains which have been applied in a 3D shape, 2D image and also recently 1D signal. Researchers have demonstrated the robustness of local texture descriptors in the multimodal biometric system especially in real-world applications as well as easy data acquisition. In this dissertation, we have investigated more on the extraction step which aims to reduce the data and select the significant features.

The extracted set must be invariant against multiple issues that may appear in biometric task. Furthermore, feature extraction is one of the crucial steps of the biometric system. It is related to dimensionality reduction and abstraction data (i.e., image, signal, etc.) to get features that will be useful in the decision and identification of subjects.

Although many studies on handcrafted features have appeared in recent years, local binary patterns remain an interesting feature extraction technique. LBPs keep attracting the researchers particularly after its remarkable performance on biometric applications such as face, iris and ear. In this purpose, three local texture descriptors namely 1D-LBP, Shifted 1D-LBP and 1D-MR-LBP have been implemented and detailed in this document in an attempt to evaluate our unimodal and multimodal biometric systems.

When a biometric system uses a single biometric modality, it holds the name of monomodal biometric system. Many mono-modal biometric systems have been proposed in various areas, providing only one biometric trait. A single biometric trait does not have the ability to meet all the requirements of an application. However, every separate biometric remains facing the problems of improving accuracy, robustness, security and privacy. It can be affected during its acquisition by noises or illumination changes which lead to a poor quality of collected data. These problems will decrease the performance of the system. Further efforts are needed to develop efficient approaches that can be used for personal identification in different contexts and applications.

To date, state-of-the-art methods for biometric authentication are being incorporated into various access control and personal identity management applications. Physically-based biometrics has been the most commonly used technology. There is a growing evidence that the combination of different biometric traits can be used for solving the pitfalls faced by unimodal system and building reliable person recognition. The fusion of two or more biometric modalities in the same biometric system falls under the name of a multimodal biometric system.

In this dissertation, we aim to overcome the challenges encountered by unimodal biometric systems by developing a robust and secure multimodal system. The use of multiple sources of data implies its fusion at a defined level. In the biometric field, the information of the biometric traits can be merged at different levels of fusion: sensor-level fusion, feature extraction-level fusion, score-level fusion and decision level fusion. Moreover, the first two stages occur before the matching stage and the remaining ones take place after the matching stage. The nature of the merged data and the requirements of the system determine the appropriate level. In this present work, feature extraction level fusion is performed.

Latterly, ear biometric has received many attentions in various domains, especially in forensic science. The human ear has a stable structure a little change with age and no change with the pose and facial expression over an acceptable period of human life. Ear is larger than conventional modalities like iris or fingerprint providing more important information increasing efficiency and therefore is more easily captured from a distance. In some cases, the system may suffer from difficulties during the acquisition of ear modality. It can be hidden by hair, headphones, a scarf or curls. Additional research has been applying 2D ear images for recognition.

In the biomedical engineering field, biological or behavioral data may be captured directly from diverse sensors (ECG sensor, microphone for voice, etc.). To capture high-quality data, quite a few capturing sensors have been developed. Early sensors were generally less comfortable and expensive. Indeed, they required a high degree of cooperation from the users. With the development and popularization of healthcare technology, ubiquitous smart sensors have become more compact, affordable and friendly. They make it possible to embed them in smartwatches, mobile phones and wearable devices (e.g., Google glass 6).

To solve serious challenges, recently, mobile health objects and the Internet of Things (IoT) provide new concepts involving the use of smart mobile devices to create efficient healthcare/smart-life services and solutions. Thus, we intend to investigate the benefit of these emerging biometric methods. These include a number of advantages which allow us to improve the overall performance of a biometric system while maintaining strong user authentication and is biometrically-based smart and replaceable as a privacy concern.

In contrast to the approaches found in the literature and detailed above, analysis of electrocardiogram (ECG) is a new biometric measure for human identity recognition. The activity recorded by the ECG comes from extracellular currents related to the propagation of a depolarization front (atrial P wave, then ventricular QRS complex) across the heart. The strength of ECG based biometric authentication systems is that ECG can be directly utilized as a liveness detector. A remote login process by ECG signal captured from a finger, which improves security and privacy. This promising biometric is chosen to be one among the three used modalities in this dissertation.

To the best of our knowledge, among the most popular biometric technologies, the iris recognition system is considered to be one of the most confident techniques for security in numerous fields. The use of the iris as the third biometric modality makes our system more robust and achieves a high level of security. Iris has unique characteristics that can differentiate between individuals, twins or even between the left and right irises of the same person. Despite its promising performance for these biometric tasks, iris-based biometric requires full cooperation on the part of the user and also has often not been fully accepted by them.

Due to the unimodal biometric systems limitations, as well as problems concerning missing data and unreliable identification, some challenges commonly encountered by such systems remain. These include:

- Environmental (e.g. it may affect the system during authentication due to changes in the prevailing conditions).
- Noise in sensed data (e.g. dirty sensor, poorly illuminated or problems modalities like several ear or face poses).
- Intra-class variations (e.g. multiple differences between enrolled and authenticated templates).
- Interclass similarities (e.g. significant similarity between data acquired from different subjects).
- Non-universality (e.g. some people may do not have the desired modality due to disabilities or illness).
- Spoof attacks (e.g. the use of a single biometric modality makes it easier to mimic, also some biometric modalities are easy to spoof because of their use in public like face).
- Upper bound on identification accuracy (e.g. cannot continuously improve the recognition rate).

To overcome these problems, we propose a new multimodal recognition system integrating ear, iris and ECG biometric technologies. Our approach was implemented using local texture descriptors in order to extract features from each modality and fuse the extracted features at features level fusion. There have been considerable variants of multi-biometric strategy schemes proposed for human identification and recognition. As for ECG with conventional biometric, there are fewer studies. For this reason, a comparison was done with existing multimodal systems that use one or two out of three modalities. The overall goal of this work is to develop a multimodal biometric system that will be able to:

- Take advantage of the strengths and reduce the chance of the false alarm of each approach while increasing the accuracy of the biometric authentication process.
- Achieve better performance and high-security level (minimum Equal Error Rate).
- Reduce the complexity weaknesses of a multimodal system by applying 1d-LBPs.
- Hard to imposer to spoof ear, iris and ECG traits at the same time.
- The uses of liveness measurements are not easily mimicked.

- Remote login process by ECG signal captured from a finger which improves security and privacy.
- Combination of hidden (ECG) and visible (ear and iris) modalities in a multimodal system leads to form a robust and secure system.
- Make our biometric system become more robust against many various factors where are usually linked to diseases factors, accident, age and life conditions.
- Meet the specific requirements expected in different contexts such as border control, mobile application, IoT and healthcare application.

Dissertation outline

The manuscript is divided into two parts; the first part presents a state of the art for biometric recognition and basic concepts of pattern recognition. It also describes a background for each modality used in our approaches. The second part presents the proposed contributions. Each part contains the following chapters:

Part I: BACKGROUNDS AND LITERATURE REVIEW

Chapter 1: STATE OF THE ART

This chapter presents the basic concepts of biometric recognition including its definition, types and properties besides describes both identification and verification mode of a biometric recognition system. The structure of the biometric system will be explained starting from the sensor module to the database module. We also present basic concepts of multimodal system and its fusion techniques.

Chapter 2: PATTERN RECOGNITION

We present in the second chapter a second state of the art for pattern recognition. This chapter is subdivided into three main parts. The first part consists of giving the definition of Artificial Intelligence, an overview of its history besides a discussion on its application areas. Secondly, we talk about machine learning which is considered as a branch of AI. The last part will be reserved for giving the necessary background of pattern recognition by presenting its based structure followed by some of the well-known pattern recognition techniques.

Chapter 3: Ear BIOMETRIC

We present through this third chapter the essential elements for ear based recognition by explaining its external anatomy and reviewing the existing works related to the application of ear on unimodal systems on both 2D and 3D. Beside to present the limitations that lead us to use the 1D space in this dissertation. We discuss some of the well-known used algorithms on ear biometrics. In the last part, we mention some of the recent multimodal systems that merge ear biometric with other modality.

Chapter 4: ECG BIOMETRIC

The fourth chapter presents a state of the art for ECG biometric. We firstly give a definition of this novel modality besides its anatomy. Next, we present the motivation of using this biometric modality as the main biometric traits in our dissertation by giving the different ECG strengths and advantages. Thereafter, we detail the ECG biometric system architecture starting from preprocessing step to the matching.

Chapter 5: Iris BIOMETRIC

This chapter followed the same structure of the previous two chapters by giving a definition of the iris as biometric recognition beside its anatomy. We also talk about the challenges of iris biometric and its influence on the cost-effectiveness of the system. We review in the next part some of the related researches. Where the iris is widely used in recognition, we present some multimodal systems where iris is fused with other modalities.

Part II: PROPOSED MULTIMODAL BIOMETRIC SYSTEMS

Chapter 6: Ear-ECG BASED MULTIMODAL SYSTEM

This chapter is subdivided into three main sections. Firstly, an explanation of the proposed local descriptors will be described which will be used to extract features from data. The next part will present the first approach which consists of developing two biometric systems. The first represents an ECG biometric system using shifted 1D-LBP, where we will study the importance of the preprocessing step by applying different normalization techniques and investigating its impact on the performance of the system. Part two will present an ear-ECG based multimodal biometric system based on 1D-MR-LBP descriptor.

Chapter 7: ECIREA MULTIMODAL BIOMETRIC SYSTEM

The last chapter will present the second approach which consists of a novel multimodal biometric system. ear, ECG and iris biometric modalities were combined together at features fusion level. Three local descriptors namely 1D-LBP, Shifted 1D-LBP and 1D-MR-LBP techniques will be introduced. The extracted features will be normalized and fused in a single vector aiming to provide a more robust representation for persons. Statistical comparisons will be performed to see how far the proposed multimodal system overcomes the unimodal system weaknesses.

By the end of this dissertation, we will summarize our proposed work in a general conclusion. In addition to the limitatons encountered by our approaches besides to some perspectives that will be also presented. The last part is dedicated to the used bibliography.

Part I

BACKGROUNDS AND LITERATURE REVIEW

CHAPTER 1

STATE OF THE ART

1.1 Introduction

In this chapter, a state of the art will be presented, including basic concepts and terminologies of biometric technology. A biometric definition was introduced, including the biometric system. Besides an explanation in details about the difference between identification and verification modes will be introduced. Also, the different characteristics that make human biometric traits being able to use for a recognition purpose were discussed, in addition, to mention the biometric applications domains. The different modules of the biometric system architecture will be discussed in details.

Another point consists of the performance measures that allow computing error rates and plotting curves which make the comparison and the evaluation of a biometric system easier. A considerable portion is dedicated to explain the definition of an unimodal biometric system, its robustness and its weakness. An introduction to the multimodal biometric system as a solution to problems faced by the unimodal biometric system will be presented. Subsequently, fusion techniques have considerable importance in a multimodal biometric system. For this reason, we concentrate on the existed level fusion and clarify the robustness and the weakness of them. Finally, some of related works will be analyzed.

1.2 Biometric Definition

The etymology of the term biometric is taken from two Greek words “bio” which means life and “metrics” which mean measure. Idiomatically, biometric is a quantitative study of biological, morphological or behavioral human traits. It can be defined also as a set of measurable, robust, distinctive and uniquely human features. These traits can be used to identify or verify the claimed identity of an individual.

Because of the different attacks that can be launched against authentication systems based on passwords and tokens, Biometric recognition is considered as a real alternative to passwords, signatures and other identifiers. Biometric has the ability to solve several problems faced by authentication systems based on traditional methods. For example, an imposter can guess passwords or stealing tokens. Many modalities were used for recognition such as blood, DNA, ECG, urine, odor, saliva which they are used as biological features. Fingerprint, face, iris, hand geometric or ear can be used as morphological features. In addition to behavioral features like signature, voice, gait, keystroke dynamics…etc (Jain et al., 2007). Figure 1.2.1 shows the biometric type's.

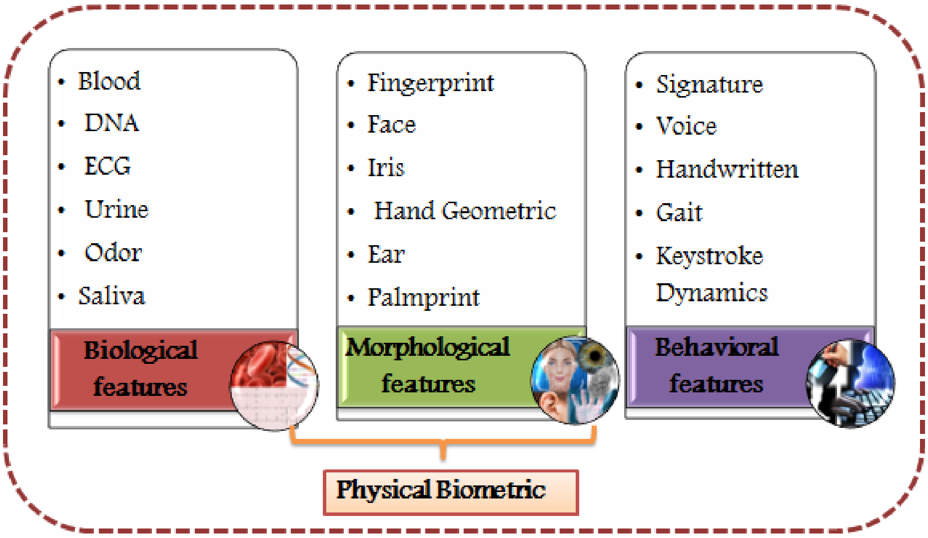

Figure 1.2.1: Examples of biometric features types (Jain et al., 2007).

1.3 Identification versus Verification

Many techniques were proposed theoretically for security, even thousands of years ago. Last decades, Biometric has big attention due to its efficiency and its power especially in security and forensic domains. Because of computer's processing advance, various automated biometric systems were available and many techniques were investigated. Obviously, biometric systems are made to identify or verify certain individuals automatically based on their biometric data.

Biometric systems may run in two modes: verification and identification. In the verification mode, the system must answer the question: "are you who you are claiming?"; by comparing the input data with its own biometric template (s) stored in the system database. A one-to-one comparison is applied to validate the person's identity and check if the claim is true or not. Whereas, in the identification mode, the system must answer a different question: "who are you?"; by comparing the input data with all biometric template(s) stored in the system database. A one-to-many comparison is applied to achieve the individual's identity (Lumini and Nanni, 2007). Figure 1.3.1 shows the two modes steps.

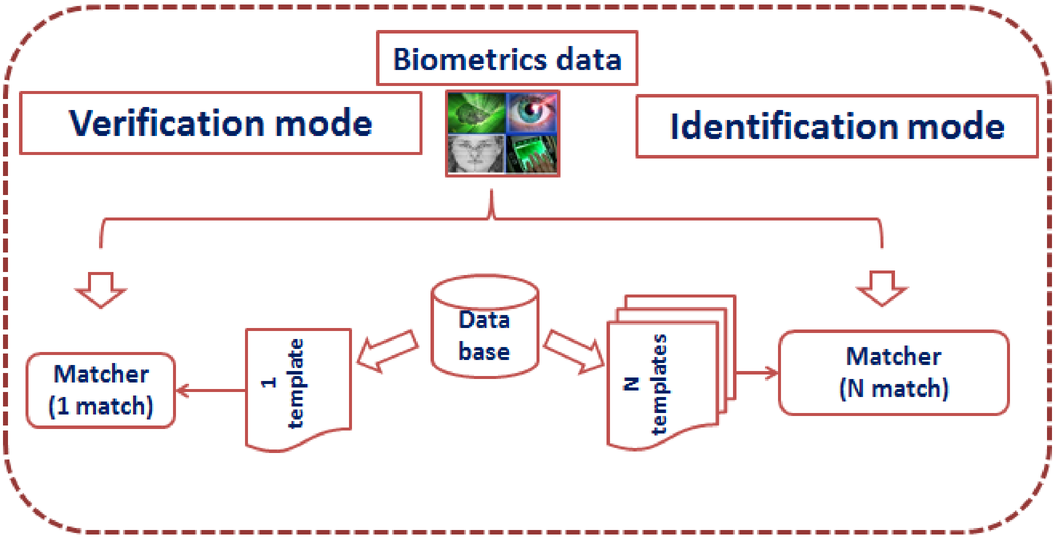

Figure 1.3.1: The verification and identification modes (Maltoni et al., 2003).

1.4 Biometric Properties

The biometric human data are referred to as traits, indicators, identifiers or modalities. It must be noted that each biometric modality has its strengths and its drawbacks which means that no biometric is reliable at 100%. To use our biological, morphological or behavioral features as modalities to be exploited on automated recognition system, they must respect seven factors that determine its suitability:

- Universality (user's application must have the proposed modality).
- Uniqueness (each user has its unique traits compared with other individuals).
- Permanence (the stability of the biometric trait over a period of time).
- Measurability (the acquisition of the biometric trait using the adequate device in order to extract the representative feature sets).
- Performance (the constraints imposed by the application should be accepted when calculating the recognition accuracy).

- Acceptability (users do not disturb presenting their biometric trait to the system).
- Circumvention (the possibility of imitating trait of individual using fake traits).

Biometric systems demonstrate its effectiveness and robustness to various types of malicious attacks in various areas in modern society. The most used biometric characteristics are the face, fingerprint, Palm print, iris, Keystroke, Signature, Voice, Gait. . . etc. The choice of a biometric modality depends on its strength and weakness besides to the application's requirements (Jain et al., 2007).

1.5 Applications of Biometric

The need for reliable automatic identification and authentication systems was always the purpose of most applications. With the development of technology, smartphones, social network and communication, achieving high security were required in order to protect user privacy. Using biometric as a technique for authentication or identification was investigated by several applications in the place of traditional authentication methods to increase performance and security. While the biometric has used in various domains that need high security, ensuring the security of the biometric template is of utmost importance (Benaliouche and Touahria, 2014). These applications can be divided into 3 types; cited as bellow:

1. **Forensic applications:** used in a criminal investigation, to recognize the corpse of someone, to determine the parenthood of persons.
2. **Government applications:** used in many cards that allows the recognition of the cardholder such as national ID card, passport, driver's license or social security. Also in monitoring operations: border control, passport control or camera control.
3. **Commercial applications:** used in control access to an application or devices such as e-commerce (Jain et al., 2011), computer network login, Internet access, Automated Teller Machine (ATM) or credit card, mobile phone, medical records management and company login.

Table 1.1: Some application areas of biometrics (Jain et al., 2007).

FORENSICS	GOVERNMENT	COMMERCIAL
Corpse Identification	National ID Card	ATM
Criminal Investigation	E-passport Drivers Licence	Access Control
Parenthood Determination	Voter Registration	Computer Login
Missing Children	Illegal Immigration	Mobile Phone
	Border Crossing and Control	E-commerce
	Surveillance in Critical Infrastructures	Telephone Banking
	Ambient Intelligence	Internet Banking
	Physical Access to Military Facilities	Smart Card
	Hospitals	
	Nuclear Power Stations	

1.6 Biometric System Structure

The biometric system is based generally on four modules. The first module, named sensor module, consists of the acquisition of biometric personal data. The acquired biometric data was scanned and read using an adequate electronic device. This latter depends on the used biometric modality (for example camera for face and ear, fingerprint sensor, electrodes for ECG…etc.). The scanned data will be processed to generate a biometric template. A biometric template is a collection of discriminant information that will be used for recognition.

The sensor module has a critical impact on the system; any effect in the captured data may reduce the performance rate of all the system. Therefore, it is important to improve the quality of the scanned biometric data and remove any irrelevant and redundant information presented or noisy and unreliable traits which were due to sensor problems. The next module consists of preprocessing the captured data. Several techniques can be applied such as normalization, transformation, filtering and segmentation and other algorithms of enhancement.

The third module named feature extraction. In this stage, the discriminants traits exist in the preprocessed data were extracted. Recently, many algorithms were developed and proposed depending on the used biometric modality in order to extract the representative characteristics which will be used to identify or verify the claimed identity. As long as the extracted characteristics are more discriminant in identification or verification purpose, the system will be more reliable with high performance. For all these reasons, features' extraction module considered as the heart of the biometric system.

The matching is the next module. It consists of comparing the extracted features of the input data against the stored templates existing in the database. Then, a final decision will be generated depending on the achieved match score to validate the claimed identity. Many algorithms can be applied in this stage such as K-Nearest Neighbors (KNN), Neural Network (NN) or deep learning...etc.

System database module is the final stage in the biometric system. In the enrollment mode, a database will be generated by storing a template for each client. It contains the extracted features of the client with some personal information like name, address, Personal Identification Number (PIN), etc. The stored template, called also gallery images, will be used next time for comparison on matching step with the input data, called also probe images, of the claimed client.

It must mentioned that all hardware (sensors, camera...etc.) and software (algorithms, databases...) have its impact and influence on the biometric system (Jain et al., 2011). Each one possesses its own advantages and limitations which will produce a good (increase performance, decrease the different errors rate...etc) or bad (decrease performance, increase errors rate, more computational, more time...etc.) influence on the obtained results. Figure 1.6.1 shows the architecture of a biometric system.

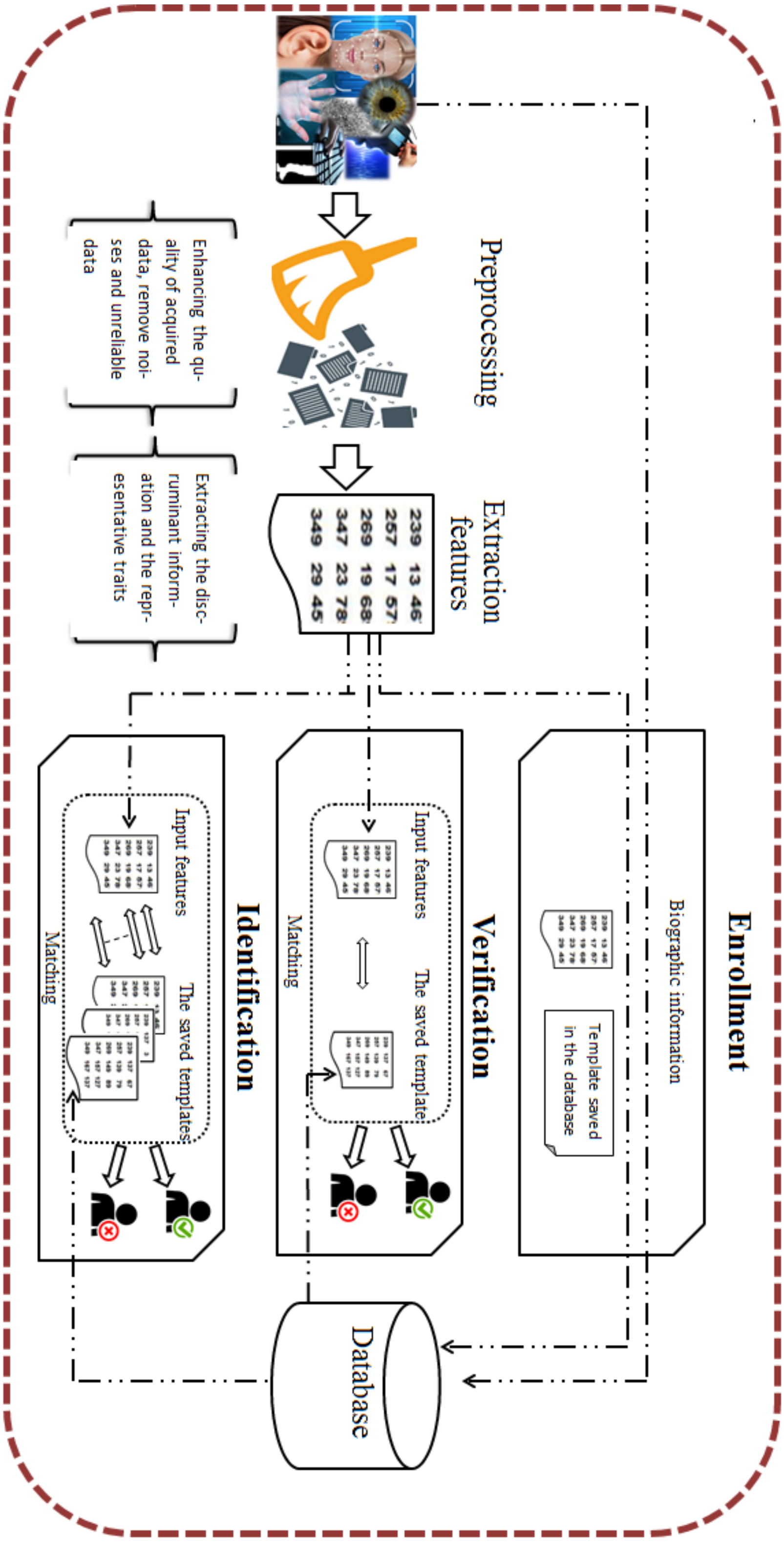

Figure 1.6.1: Enrollment, verification and identification steps of a biometric system (Jain et al., 2011).

1.7 Performance Measures

It is very important to perform quantitates studies in computing the different performance measures of any developed system. These measures allow us to know how far can we rely on this system. Also, it helps to reply to the asked question: does the system reply to the proposed question or no? Moreover, it used to compute the efficiency and reliability of the developed biometric system. For the biometric system, the different metrics should be referred to before addressing how to calculate them.

In the matching module, the input biometric features set of a user will be compared with the biometric template's features stored in the database and a similarity score will be calculated. If the input features find its similar template than the user will be known as a genuine. If not, then the user will be known as an imposter. Different errors rates can be distinguished. These measures are related to different factors like the correct/incorrect classification, complexity, processing time, memory occupancy and depending also on the executed module. Two different metric types can be used to validate a biometric system and compute its performance efficiency named error rate metrics and performance curve.

1.7.1 Error Rate Metrics

Some of the most types of failure are listed below:

Failure To Acquire (FTA) rate: denotes that the sensor is not able to capture the desired biometric traits from the user (Das, 2018). This kind of problems may be faced with sensors when the presented biometric trait possesses a poor quality (such as a contaminated or infected finger, occluded ear images with hair).

Failure To Enroll (FTE) rate: denotes that the biometric system is not able to enroll a user. This can happen when the user has not the required biometric traits. There are many cases prevents a person to present their biometric data. It can be found a person who has lost his finger due to an accident, or genetic reason. In some cases, users are unaware of how to register and provide the correct information and present the desired biometric traits correctly (Jain et al., 2007). To avoid this problem, developers must design interactive user interfaces which facilitate the enrollment stage thus decrease the FTE rate.

False Accept Rate (FAR): denotes that the biometric system considers an imposter as a genuine user.

False Reject Rate (FRR): denotes that the biometric system rejects a genuine user and considers him as an imposter.

Genuine Accept Rate (GAR): denotes the proportion of users that the biometric system considers as genuine and they are already well. Where:

$$GAR = 1 - FRR \tag{1.7.1}$$

Equal Error Rate (EER): denotes the point where the FAR is equal to FRR which means:

$$FRR - FAR = 0 \tag{1.7.2}$$

Correct Recognition Rate (CRR): denotes the accuracy of the biometric system. It can be calculated by:

$$CorrecteRecognitionRate = 100 - (FRR + FAR)/2 \tag{1.7.3}$$

FAR and FRR are linked together inversely according to a decision threshold. Depending on the application, if a minimum FAR is required so a high threshold must be assigned. In this case, the system will reject genuine users but it will be robust to imposters. Whereas, a low threshold for minimum FRR leads the system to accept genuine users and also imposters. Figure 1.7.1 illustrates the thresholding of FAR and FRR.

Generally, EER is commonly used to evaluate and test biometric systems' performance. In many cases, the use of EER alone is sufficient to compare and validate biometric systems' performance. This can be performed if these systems have different errors rate so it can easily determine which of these systems outperform the other systems (Giot et al., 2011). But in other cases, the EER become insufficient to use it alone as a metric performance where the compared systems have similar values. Such case entails applying additional performance metrics (FAR, FRR. . .) to make the comparison meaningful.

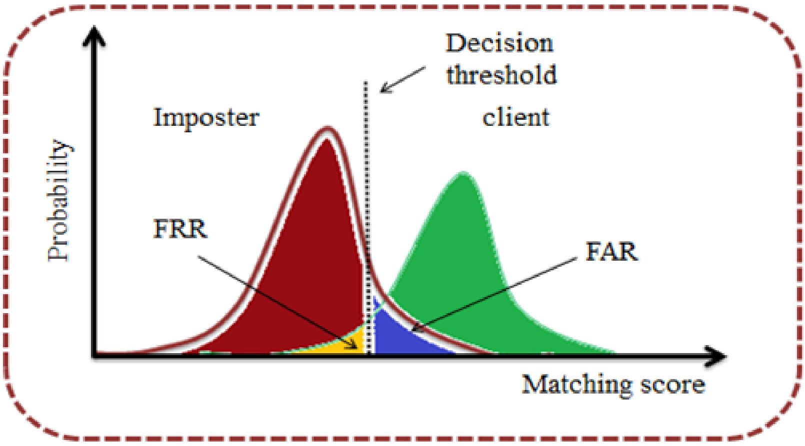

Figure 1.7.1: The thresholding of FAR and FRR (Jain et al., 2007).

1.7.2 Performance Curves

Another performance measures can be used called performance curves. Curves and schemes are known to be easier than tables and numerical values when analyzing and interpreting results. The most commonly used curves are:

Receiver Operating Characteristic (ROC) curve: it is the most used to evaluate the global performance of a biometric system. This curve allows visualizing its reliability and comparing several models to know the best one. ROC curve consists of representing the relation between FAR and FRR at various threshold values on a linear scale. If a logarithmic or semi-logarithmic scale is used than the ROC curves plots GAR against FAR (Ross et al., 2008). Figure 1.7.2 shows two examples for ROC curves one using the relation between FAR and FRR where the second plots GAR against FAR.

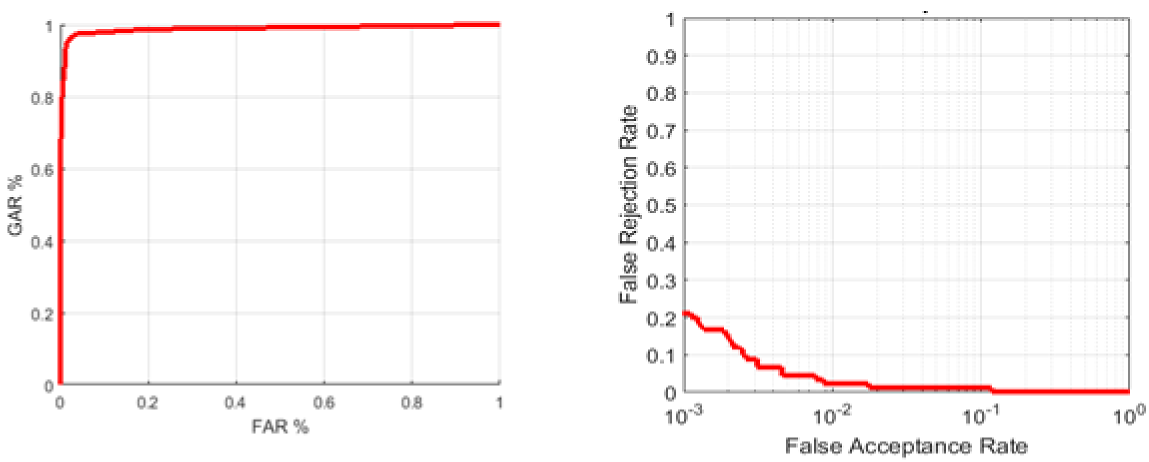

Figure 1.7.2: Examples of ROC curves.

Detection Error Tradeoff (DET) curve: there is a small difference between the ROC and DET curves. Where a ROC curve plots FRR against FAR at various threshold values on a linear scale, DET curve plots them on a normal deviate scale. This curve is used to comparing different biometric systems performances. It allows also achieving the EER value of the evaluated system which is obtained by the intersection of the curve with the line (x=y). An example of a DET curve is illustrated in subfigure 1.7.3 (a).

Cumulative Match Characteristic curve (CMC): in biometric systems, especially in the identification mode, with E represents the number of the enrolled users. The system generates a set of identities corresponding to the top k matches (1 $\leq$ k >=E). CMC can presented Rank-k performance by plotting R_k against k. CMC curves are used to compare biometric systems performances which they are based on identification mode. Subfigure 1.7.3 (b) shows an example of CMC curve.

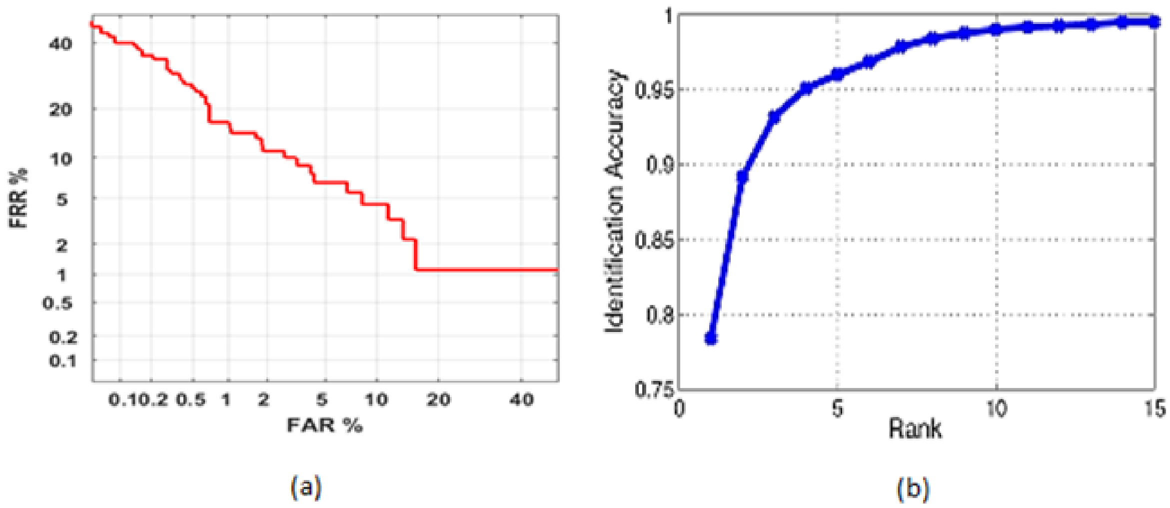

Figure 1.7.3: An example of a DET (a) and CMC (b) curves.

1.8 Unimodal Biometric System

When the biometric system uses a single biometric modality is called a unimodal biometric system. Many unimodal biometric systems have been proposed (Vezzetti and Marcolin, 2012)(Anwar et al., 2015)(Czajka et al., 2017)in various areas in modern society providing only one biometric trait. Each biometric modality has its advantages and inconvenient. No biometric is ideal which decreases the performance and makes the system still in need for more improvement.

- Environment: it may affect the system during authentication due to the different available conditions.
- Noise in sensed data: dirty sensor, poorly illuminated or problems modalities like several ear or face poses and while the performance of the biometric system is highly sensitive to the input data qualities, a significant reduction in performance rate can occur.
- Intra-class variations: Multiple differences between enrolled and authenticated templates which increase the FRR.
- Interclass similarities: traits extracted from different clients can be quite similar which increase the FAR.
- Non-universality: some people may do not have the desired modality due to disabilities or illness which increase the FTE.
- Spoof attacks: the use of a single biometric modality makes it easier to mimic, also some biometric modalities are easy to spoof because of their use in public such as the face.
- Unacceptable error rates using a single biometric in most of the cases.
- Fake biometric: an imposter can log in as a genuine to a system by using spoofed characteristics especially if the system uses behavioral features such as voice or gait which are more easier to mimic than biological features (Ross and Jain, 2003).
- Upper bound on identification accuracy: it cannot improve continuously the recognition rate (Wübbeler et al., 2007).

1.9 Multimodal Biometric System

The search for a perfect biometric system was the aim of many researchers. The first question posed was how these problems posed by a unimodal biometric system can be solved. The use of multiple sources of information for authentication can help to solve the majority of these limitations. These kinds of systems are appointed as Multimodal biometric systems. Generally, a multimodal biometric system uses two or more biometric modalities for recognition in order to overcome the drawbacks imposed by the unimodal system.

Multimodal systems are expected to be more reliable because most of the challenges suffered from using the unimodal biometric system can be overcome using multi-biometric information simultaneously. They address the problem of non-universality using more than one biometric, which decreases FTE error and increases the population coverage (Ross and Jain, 2003). Spoofing multiple biometric modalities will be very hard to an imposter which improves recognition accuracy and reduce FAR. It must be noted that the term multi-biometrics has several meanings not just the use of multiple modalities. It can be also referred to multiple sensors, multiple algorithms, multiple instances and multiple samples. Figure 1.9.1 shows different multi-biometric types.

Each term has its own mechanism and they are explained as below:

Multiple sensors: the use of diverse sensors to scan and capture the same biometric modality will be able to improve the recognition performance. For example, a multi-biometric system employs two sensors (cameras). If the captured biometric image from the first sensor has poor quality, while a better quality is captured with the second sensor. Therefore, the noisy data limitation will be eliminated and the matching accuracy can be enhanced.

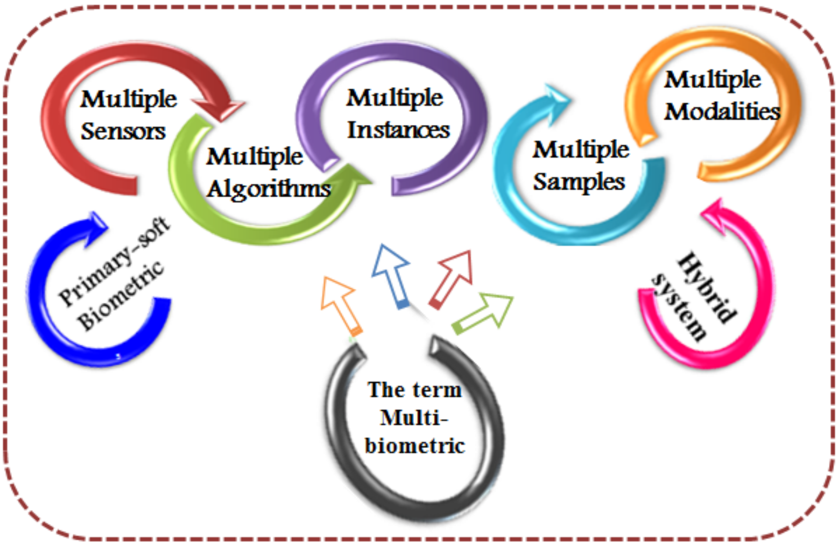

Figure 1.9.1: The various multi-biometric types.

Multiple algorithms: applying multiple algorithms on extracted features/matching module will be able to improve the system performance. Several algorithms can be applied for extracting features from the same biometric data. Then, a fused template will be generated to fuse all the extracted features from each algorithm. Another way consists of applying the first algorithm to extract features from the preprocessed biometric data. Then, a second algorithm will be applied to the obtained features of the first algorithm and so on. The same process can be applied for matching module by applying multiple algorithms on the same features data. This technique reduces the cost of the system. At the same time, adding new features and algorithms can increase the computational complexity.

Multiple instances: the use of many instances of the same body biometric data such as left and right ear or left and right iris. This technique increases the cost of the system if the person uses multiple sensors. Various discriminant features were extracted which improve the identification rate. The repetition of the same process several times may increase the computational complexity.

Multiple samples: the use of many samples for the same underlying biometric with different variations poses, sides, angles or lighting conditions depending on the application context which makes a system have a complete image of the processed biometric data. This technique imposes the use of a single sensor which reduces the cost system. Moreover, a high recognition rate can be achieved.

Multiple modalities: the use of two, three or more biological, morphological or behavioral traits for identification was investigated from several researchers. The massive diversity of the studied traits make the system more robust, secure, difficult to spoof, universal, high security and recognition rate. But a high cost will be obtained because of the use of different sensors depending on the chosen modalities. Besides to more computational complexity due to the variance applied algorithms, especially on preprocessing modules where we find that each modality has its own process and techniques.

Hybrid system: it consists of emerging different types of the multi-biometrics system discussed above on a single system. For example, use iris and face as a multimodal biometric system, besides applying many algorithms to extract features from iris biometric and use many samples for the face (Chang et al., 2005) (Jain et al., 2007). In this example, the hybrid system integrated three types namely: multimodal, multiple instances and multiple samples together. This term was introduced firstly by Chang et al. Many researches have been developed in this approach.

primary-soft biometric: it consists of fusing primary biometrics such as fingerprints, face, ECG which they respect the factors discussed above with soft biometric attributes such as height, weight or eye colour which cannot be used as a biometric identifier for individuals. The combination of identifier and non-identifier biometric traits on a multimodal biometric system can enhance the performance of the recognition system. The use of soft biometrics can reduce computational complexity using indexation. In place of comparing the input data with all database, soft biometric can shrinking search with just those that they have the same information which shortens a lot of time, especially with a large database.

Despite the different improvements included by the multimodal system, these systems suffer from some weaknesses such as complexity and cost that are increased because of the use of multiples sensors, besides to disturbance of using several modalities (Wübbeler et al., 2007). Recently, many studies have been proposed to solve these problems and achieve high accuracy and security and less complexity of multi-biometric systems.

1.10 Fusion Techniques

While different modalities are used in a multimodal biometric system, a fusion technique will be required to fuse various information in order to obtain the final decision. Different levels of fusion are possible. There are many rules have been proposed to fuse the heterogeneous and homogeneous data. Five fusion levels can be distinguished as shown in figure 1.10.1.

1.10.1 Sensor Fusion Level

Starting with the sensor level, which consists of fusing the captured biometric data in a single raw biometric. The raw data contains all the representative and richest information that can be used for recognition purpose. The acquired data captured from various sensors must be compatible. This imposed condition makes the fusion at this level does not choosed too much. It can be used just if the scanned data from many sensors are homogeneous or are from the same traits biometric. Also in the case of a multi-sample system and the multi-instance system which uses many samples from the same biometric modality and uses the same sensor.

1.10.2 Features Fusion Level

The second type of fusion named feature level. The features extracted from different extractions methods of the same biometric modality or multiple modalities are concatenated together. Various rules and techniques can be used to generate a single fusion vector feature. In this level, the extracted traits must be compatible and in some case, it must have the same size. The fused data may become a larger size which implies the use of redaction dimensionality techniques to avoid the problem of system performance degradation. Frequently, the features extraction requires normalization algorithms which increase the complexity of the biometric system (Yang and Zhang, 2012). The fused data preserve its discriminants and power which leads to considering feature level the best-used technique.

1.10.3 Score Fusion Level

Next fusion level named Score level. After extracting the discriminant characteristics form each biometric modality using the same extraction method, a comparison of two features sets gives the match score as a result. In this level, each biometric modality has its match score. A new match score will be generated by a combination of them. It must distinct two terms which are similarity score and distance score. While the first term's tests if the two comparative features are identical, the second term's tests if they are not. No data compatibility has required at this level. Simple algorithms can be used in this level for computing the match score which makes it very exploited and preferred in many multimodal biometric systems.

1.10.4 Rank Fusion Level

Another fusion level named rank level. In identification mode, the output of each matcher can be transformed as a set of possible matching identities sorted in decreasing order of confidence. Each unimodal subsystem generates a rank to each enrolled client. A combination of ranks obtained from all unimodal subsystems is performed to assign a new rank for each identity. The newly generated rankings are compatible which simplify its comparison and the normalization process will be not required.

1.10.5 Decision Fusion Level

Finally, the decision level named also the abstract fusion level. Each unimodal subsystem executes all steps Independent of other unimodal subsystems. Then, a final decision is assigned using fusion decision methods such as: "AND" and "OR" rules, majority voting, weighted majority voting or Bayesian decision fusion (Jain et al., 2007). This level is mostly used.

In most cases, the choice of fusion level depends on the nature of used biometric data. Improvement of discussed fusion levels for a multimodal biometric recognition system has attracted a lot of attention in our day in order to solve different existing drawbacks of unimodal systems. Hong and Anil (Hong and Jain, 1998) have developed a prototype biometric authentication system using faces and fingerprints at decision fusion level.

Ross and Jain (Ross and Jain, 2003) propose a Multimodal biometrics system that includes the face, fingerprint and hand geometry at the matching score level. After that, many modalities were fused to full varied application needs (Annapurani et al., 2015) (Pietikäinen et al., 2011) (Barpanda et al., 2018). Ear, ECG or iris biometric modalities fusions are introduced with different modalities and different fusion strategies using various levels of fusion in several works in litterateur because of their various advantages and strengths. For these reasons, this dissertation presents our contributions that introduce a novel multimodal biometric system based feature level fusion.

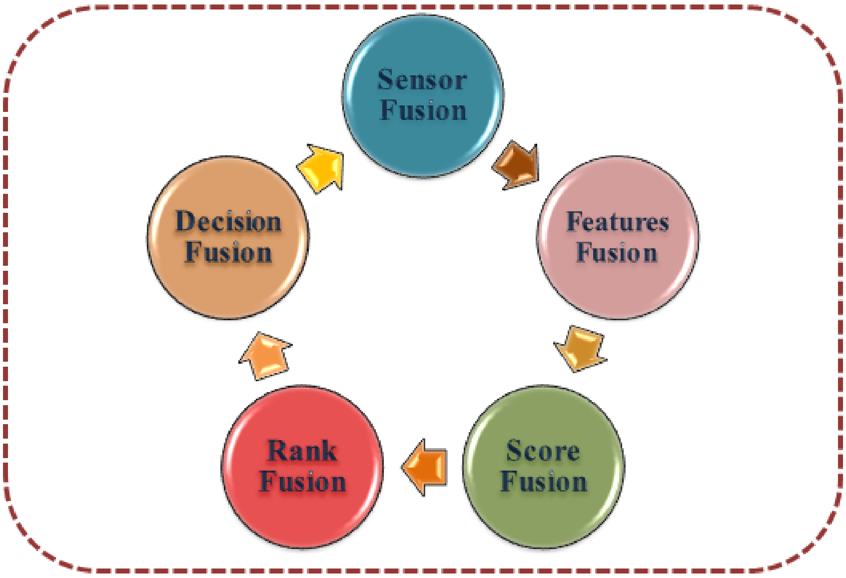

Figure 1.10.1: The different types of fusion level.

1.11 Conclusion

This chapter summarizes the basic concepts of a biometric system. A definition of biometric was given, besides the different conditions and properties that make human biometric traits can be used for recognition purpose were explained. We have presented also the architecture of the biometric system and explained each module.

The unimodal system gained much attention in several applications domains but it faced some challenges which decreased the performance of the developed system. The multimodal system was the solution to solve these problems and deal with its weaknesses.

While the multimodal biometric system used multiple modalities, instances, algorithms, samples or sensors, a technique of fusion was irreplaceable. Techniques of fusion can be applied on different modules (sensors/ feature extraction/matching) depending on the biometric data nature. The next chapters are reserved to discuss biometric traits used in our dissertation.

CHAPTER 2

PATTERN RECOGNITION

2.1 Introduction

For decades, researchers develop machines in several fields which help humans in their life. The invention of computers offers various devices and many manual machines had been automatized. With the revolution of digital computing, many physical and mathematical systems have been available. Recently, scientists have passed the stage of developing systems that can reason only on numbers, they aim to build systems that can also reason on symbols. In other words, they aim to translate human intelligence to AI.

In this chapter, an overview of AI will be presented; starting with defining the meaning of artificial intelligence besides a discussion will be introduced about its history will be introduced. Another part will be reserved for talking about the different artificial intelligence branches and applications. A state of the art for both machine learning and pattern recognition will be also presented.

2.2 Artificial Intelligence

2.2.1 Definition

AI is the science that makes the machine works like human intelligence processes. In other words, AI attempts to make the machine able to use a language, to form a concept, to learn information, to solve problems that are usually done with human intervention, perceive, reason and act beside to improve themselves. This science aims to solve real-world problems utilizing artificial intelligence based on the representation and the use of knowledge. AI is based on four concepts or ideas: Thinking humanly, Thinking rationally, Acting humanly and Acting rationally. It should be noted that humans were and still the most intelligent creators.

We can define AI as the context of human. It is the study that allows the simulation of human thinking intelligently with learning. The goal of AI is to create systems that can function intelligently and independently. It is based on developing smart agents (computers). AI aims to get systems thinking rationally by developing techniques that include automated reasoning, proof planning, constraint solving and case-based reasoning. Another goal consists of making programs have the ability to learn, discover and predict by developing techniques which include machine learning, data mining (search) and scientific knowledge discovery (Panesar, 2019). Artificial Intelligence gained much attention because it is related to several fields that need human's behavioral simulation.

2.2.2 History

After the invention of the programmable digital computer in the 1940s, many questions were posed by mathematicians and philosophers about how the machine can learn, think and improve itself. The first use of the term Artificial Intelligence was in the Dartmouth College Artificial Intelligence Conference in 1956. The conference was organized by John McCarthy at Dartmouth College, Hanover, New Hampshire, United States. Ten researchers who participated in the conference were considered as the fathers of AI are John McCarthy, Marvin Minsky, Claude Shannon, Ray Solomonoff, Alan Newell, Herbert Simon, Arthur Samuel, Oliver Selfridge, Nathaniel Rochester and Trenchard More (Moor, 2006). The main points processed in this meeting were describing every aspect of learning and every feature of intelligence that a machine can be made to simulate it.

From 1956 to 1980 was considered the golden period for AI. Researchers faced many problems and difficulties of some of the remaining tasks. Many algorithms and techniques were developed in order to solve complex problems such as the Geometry Theorem Prover, made machines able to learn to speak English (1968) and LISP language. This latter was defined by John McCarthy and considered as the second oldest language. The belief network formalism was invented. It produces efficient reasoning about the combination of uncertain evidence. The proposed technique solves the probabilistic reasoning problems. Various approaches and architectures in the fields of speech recognition were introduced since 1970. But they were demonstrated in limited examples

A few years later, Hidden Markov Models (HMM) have gained many attentions especially rigorous mathematical theory based aspect. Beside another aspect that generates speech researchers based on a process of training on a large corpus of real speech data. In 1975, many representation languages were developed (LUNAR, PLANNER...etc). Since 1980, various successful commercial expert systems were developed. Microwords was the term introduced to the limited problems that need intelligence. After the years 1990s, AI achieved the majority of selected goals and researchers start applying intelligent behavior in different ways (Russell and Norvig, 1995). AI becomes international in several fields.

In our days, AI has emerged in many applications and systems such as IBM's question answering system in 2011. The proposed system combines information retrieval and Natural Language Processing (NLP) fields. It consists of giving an answer to a question posed by human using natural language. In 2012, deep learning gained more attention and its methods which based on the artificial neural network become a solution to multiples difficulties. A few years later, Google has seen a qualitative leap by increasing the number of software projects based on AI to more than 2,700 projects while it was used sporadically before (Wikipedia contributors, 2018). Improvement algorithms and techniques based AI were greatly increased. Figure 2.2.1 shows the main developments of AI.

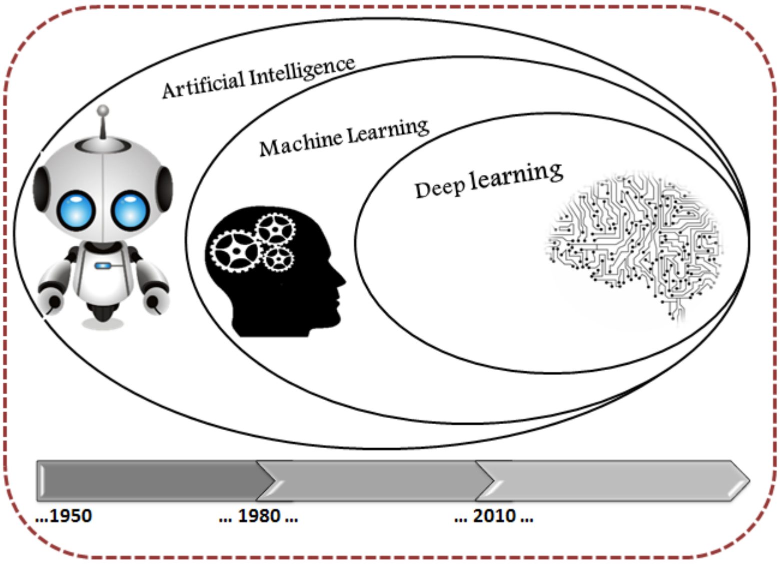

Figure 2.2.1: The main developments of AI (Panesar, 2019).

2.2.3 Artificial Intelligence Applications

AI research has been divided into subfields that often fail to communicate with each other. Each field has the goal of mimicking some human behaviors. AI is a broad branch of computer science. humans can speak and listen to communicate through language. This is known as speech recognition field. Much of speech recognition have a statistically base, hence, it's called statistical learning. Humans can write and read the text in a specific language; this is the field of NLP.

Humans can see with their eyes and process what they see; this is the field of computer vision. This latter fold under the symbolic way for computers process information. Recently, there has been another way which outcomes to the later, named image processing. This field is not directly related to AI, but is required for computer vision. It based on what humans see around themselves through their eyes which create images of that world. Using the assumption that humans can understand their environment, advanced robotic arms and other industrial robots were widely proposed in modern factories. They can learn from experience how to move efficiently.

The tradition of the ability of persons to see different patterns and group these objects into different groups according to specific conditions falls under the field of pattern recognition. Machines considered even better than humans in pattern recognition because they can use more data and dimensions of data, we talk now about machine learning. Another important field is the Neural Network. This field aims to produce the same structure and functions of the human brain that may be able to get cognitive capabilities in machines (Gero, 2012). When we have more complex data to learn and the networks will be more complex and deeper, then we talk about deep learning.

There are many types of deep learning in the machine which are essentially different techniques that simulate what the human brain does such as CNN and Recurrent Neural Network (RNN). CNN is most commonly applied to analyze visual imagery that can be used to solve problems in computer vision and object recognition is accomplished through AI (Panesar, 2019). From figure 2.2.2, it can be noticed that AI works in two different ways. One is symbolic learning and the second is machine learning or database.

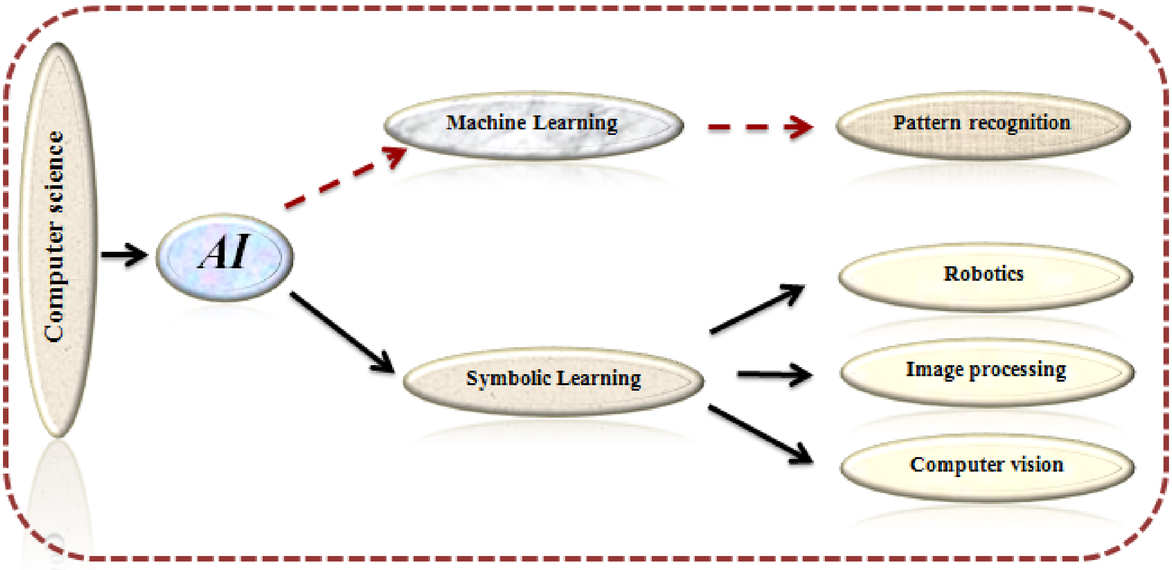

Figure 2.2.2: AI main fields (Gero, 2012).

2.3 Machine Learning

2.3.1 Definition

The term of machine learning was introduced by Arthur Samuel of IBM. In 1959, Arthur Samuel proposed the possibility of teaching computers to learn what they need to know about their environments and how to carry out tasks for themselves (Panesar, 2019). Moreover, this type of machine can learn to perform the desired tasks without the intervention of the human.

ML can also define the techniques that program computers to learn from data. It is working to solve problems that require many long lists of rules to find the solution by simplify the implemented algorithms and improving the performance. ML was used especially in unstable environments' where requirements were variable (Russell, 2018). The objective of such type of machine is the application of practical and scientific consideration and bases in order to develop techniques and algorithms so that systems approach human performance in several tasks.

It is necessary to distinguish between artificial intelligence and machine learning terms. Where the first is based on developing intelligent machines using multiple approaches, the second term consists of using one approach making machines learn how to perform tasks (Rebala et al., 2019). So there are AI approaches that were not based on learning such as expert systems.

2.3.2 Types of Machine Learning systems

Learning algorithms can be categorized according to the used learning model. As shown in figure 2.3.1, four categories can be distinguished depending on whether they have been trained with humans or not:

- Supervised Learning
- Unsupervised Learning
- Semi-supervised Learning
- Reinforcement Learning

Before detailing each learning model, we must clearly differentiate between labels and unlabels terms. Labeled pattern referred to the desired solution of the new input data which means that it is correctly predicted or classified (Rebala et al., 2019). Whereas the unlabeled pattern referred to the false result of the new input data which means that the machine learning has failed to predict which category belongs to it.

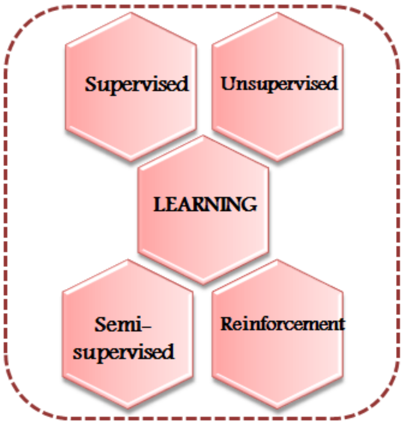

Figure 2.3.1: Learning methods (Panesar, 2019).

2.3.2.1 Supervised Learning

The stored representative information of the used data in the database called labeled data or training data. ML aims to learning a set of rules that generate a model through the training dataset. Based on this model, the machine will be able to predict the new input data point, called data test points, which they are not in the dataset. In the case of associating the data to multiple classes with a probability of belonging to each class, the type of machine learning called supervised probabilistic learning.

Classification and regression are the most used form in the supervised learning category. The classification problem predicts the class of the new input data (output) based on the build models which they are created using the trained dataset. A class is a set of objects having some important properties in common. This problem emerges in virtually any pattern recognition task. For example, the recognition of number exists in an input image into '0' to '9'. The task is to find a function which maps this input image to their corresponding class (our example finds the number of the input image by assigning it to one of the ten classes). The regression problem is very similar to classification. The only difference between them is that regression predicts a numeric value. In other words, the output variable in the regression form is in the form of real values like the price of a flat, body temperature and weight or number of transactions for an e-commerce site. It is possible to use some regression algorithms for classifications as well and vice versa.

The most important supervised algorithms are KNN, linear regression, NNs, Support vector machines (SVM), Decision trees and random forests.

2.3.2.2 Unsupervised Learning

In unsupervised learning, the system must learn from themselves. There are no models or prerequisites which allow the prediction of the output. The learning algorithms of this category have the role of finding the structure from the input data. Where the supervised learning uses the term 'class' to classify the dataset which means that it has known categories, the unsupervised learning has the term 'cluster' which means that it has unknown categories. This type of machine learning uses unlabeled data. The algorithm must extract the attributes and the hidden structure of objects. Next, it groups the objects that share the same structure in the same cluster (Herbrich, 2001). When the similarity of objects that belong to the same cluster is much greater than the similarities among objects from different clusters, then the used unsupervised algorithm was successfully grouping the data.

Revisiting the example of recognizing the number in an input image, suppose that a machine is given a set of images that have the numbers '1', '3' and '8'. The data is not labeled to identify which number is in the image. The task is to find the similarity of these images. Then, images that have the same structure and much similarity will be grouped on the same cluster. The machine could successfully identify all inputs numbers and groups it in 3 different clusters. But, it must be noticed that the machine still not know which group is '1', which group is '3' and which group is '8'. It will just know that there are three distinct groups or clusters.

2.3.2.3 Semi-Supervised Learning

Semi-supervised Learning is a hybrid where the machine uses a mixture of labeled and unlabeled data in the input. This type of learning is most applied where we have a very high number of unlabeled data points, compared to the labeled data points. This technique is less computationally expensive and doesn't spend a lot of time and effort in labeling each data point which can be a highly manual process. The algorithm consists of applying clustering techniques to identify groups within the given dataset. The few labeled data points will be used within each group to provide labels to other data points in the same cluster. So that all similar data points will get the same label derived from the labeled data points (Rebala et al., 2019). Finally, all data points in the machine have labeled to be used in future learning.

2.3.2.4 Reinforcement Learning

If you give an algorithm a goal and expect the machine through error and feedback to achieve that goal, then it's called reinforcement learning. Reinforcement learning consists of learning what to do to maximize a given reward. In this type of problem, the machine must map situations to action from it because the used learning algorithm is not told which actions to take in a given situation. The machine learns by itself based on previous actions and observations. By learning behaviors that will maximize the reward, the machine (agent) will decide the best and the optimal actions. This category is mostly used for robotics which attempts to learn how to walk, speak, avoid collisions, work or other tasks until its success (Herbrich, 2001). Reinforcement learning is also used in multiplayer games, driving or game of chess.

2.4 Pattern Recognition

2.4.1 Definition

The definition of pattern recognition can be deduced from the definition of each term "pattern" and "recognition" separately. The word "pattern" could be an object, process or event that can be given a name. Typically, it represented by a vector x of numbers. Whereas, the recognition term can be referred to as classification by assigning given objects to prescribed classes (Koutroumbas and THEODORIDIS, 2018). In other words, pattern recognition is the classification of objects, which can be images, signals or any types of data, into a number of categories or classes.

Due to AI and ML technologies' emergence and evolution, various data became available in more credible sources and can be analyzed and understood. For these reasons, pattern recognition was considered as one of the biggest beneficiaries of this progress. It is an integral element of machine learning technology. One or two or even 3D is easy for humans to understand and learn, the machine can learn in many more dimensions like even hundreds or thousands. That is why a machine can look at a lot of high dimensional data and determine patterns. One machine learns these pattern, they can make a prediction that human comes even close to.

2.4.2 Pattern Recognition Applications

With the development of computers and their application, pattern recognition has gained much attention. Furthermore, pattern recognition has crucial importance in several fields and areas. It used in the machine vision system that has the aim of analyzing a captured image and extracting descriptions for it. This system needs to locate and recognize different objects and classify them. Character recognition such as printed character recognition systems (i.e. machine reading of bank checks, automatic mail sorting by zip code, recognize whether an e-mail is a spam or not, automated check scanners at ATMs or handwriting recognition) where the system needs to identify letters or numbers is another field. It is based essentially on pattern recognition.

Pattern recognition was also applied in Computer-aided diagnosis domain. The medical data are not easily interpretable. The interpretation is changed from doctor to others depending on his skill. For this reason, computer-aided diagnoses work on interpreting this data using computer techniques to obtain a fast and uniform diagnosis. In many cases, pattern recognition systems were used as a second opinion in order to increase confidence in the diagnosis (Koutroumbas and THEODORIDIS, 2018). Recently, researchers develop various techniques and algorithms that allow using the obtained diagnosis as a first opinion.

It also used for remoting sensing, monitoring, camera & video recorder, Junk mail filtering, internet research, telephone directory assistance, forecasting crop yield, sequence analysis, searching for a meaningful pattern. Pattern recognition has gained many attentions in personal identification based on human biometric such as (face, iris, ear, voice, fingerprint, gait, ECG...). Others computationally demanding applications include:

- Bioinformatics: develop methods and techniques to understand biological data(e.g., DNA sequence analysis to detect genes related to particular diseases, analysis of RNA and protein sequences).
- Data mining: extracts significant and useful data from a large data set in order to solve different problems such as fraud detection, financial forecasting and credit scoring.
- Speech recognition: create intelligent machines in an attempt to recognize «spoken the information ». This type of machine is used in numerous potential applications such as helping handicapped patients to talk with machines to control them, improving efficiency in a manufacturing environment, communicating with computers and entering data to it using a microphone.
- Astronomy: develop systems that help on searching and recognizing the different celestial objects and phenomena that originate outside the Earth's atmosphere such as classifying galaxies based on their shapes, automated searches such as the Search for Extra-Terrestrial Intelligence (SETI) which aims to locate signals that might be artificial in origin by analyzing radio telescope data (Dougherty, 2012).

2.4.3 Pattern Recognition System Based Structure

The classic scheme of a pattern recognition process can be performed based on a set of steps. It must be noticed that some of the described steps may thus be obsolete or obscure in other types of pattern recognition systems (Cornelius, 1998). Figure 2.4.1 shows a diagram of a pattern recognition system that includes all steps that can be needed to.

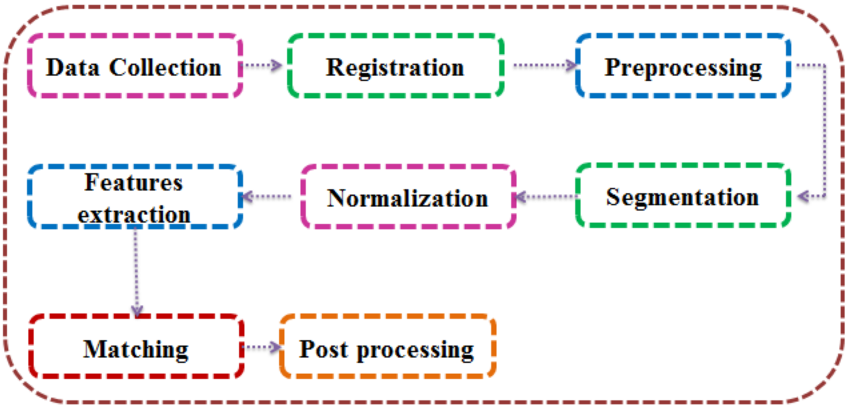

Figure 2.4.1: A diagram of a pattern recognition system (Cornelius, 1998).

2.4.3.1 Data Collection

Data collection is the first step of any pattern recognition system. This step consists of converting and digitizing the used measurements using an adequate sensor to a numerical form that allows the generation of pattern vector. Each type of data has its sensor (e.g. such equipment includes video cameras and scanners in case of image analysis or character recognition, electrodes in case of ECG, microphones in case of speech recognition . . . etc.). The quality of collected data has a big influence on the obtained results and the performance of the developed system which means that any noise will decrease the recognition rate. For these reasons, the acquired data should be recorded with the highest-fidelity available to build a robust system. Various types of sensors depending on the type of data in the case of biometric recognition system were shown in figure2.4.2.

Figure 2.4.2: Various types of sensors depending on the type of data.

2.4.3.2 Registration

The registration step attempts to fix the internal coordinates of the recognition system to the actual data acquired. This process is performed based on some of a priori knowledge about the world surrounding the system besides the conditions used during the collection of data. The external information will determine the answers of many questions such as the way of production of data, the time and the positioning of sensible input data interval.

2.4.3.3 Preprocessing

The preprocessing step has the aim of removing noises and improving the quality of registered data. Many techniques and filter methods can be applied in this stage in order to enhance this data. In the case of image recognition, the preprocessing step filters images to remove spurious point noise which might hamper the segmentation process. For signal recognition, it aimed at removing the base frequency and to enhance the higher frequencies.

2.4.3.4 Segmentation

Most of pattern recognition systems need the segmentation step that can be applied as an independent process or either interwoven with previous (preprocessing) or following (normalization) processes. This step consists of detecting some objects or important parts and splitting them which make meaningful entities for classification.

2.4.3.5 Normalization

The variance of the objects that will be recognized is one of the most challenges in pattern recognition systems. Therefore, it must define a method that can account for these variances. The normalization step works on reducing the dimensionality increase caused by noises.

2.4.3.6 Feature Extraction

Features extraction considered the main important step in most pattern recognition systems. It attempts to select the most relevant data and representative information that can be extracted from raw data which can be used in the next stage that is called classification. The applied techniques in this step must maximize the inter-class pattern variability and minimize the intra-class pattern variability simultaneously. The more the extracted characteristics are varied, the better the system is effective. In most cases, reduction methods can be applied to reduce the dimensionality of data in order to decrease the complexity of the system. Subsequently, it will allow savings the memory and the time consumptions besides improving its accuracy.

2.4.3.7 Classification

Another crucial step in pattern recognition is named classification. In this step, the quantitative input data will be transformed into qualitative output information that can be one of the predefined classes or likelihood values of the selected class. The achieved results and the success on this step depended on each of the previous steps as we precise formerly. Many algorithms were proposed to assign the extracted features to the correct output.

2.4.3.8 Post-processing

Post-processing step has quite the same target as the preprocessing step. It has the goal of helping systems to produce better results, understanding the environment of the system and its surrounding world and improving the overall classification accuracy (Cornelius, 1998). This step is applied to solve the problem of interdependencies between individual classifications.

2.4.4 Pattern Recognition Techniques

Different techniques and algorithms were proposed for pattern recognition. It can be divided into four groups namely statistical, structural, Syntactic and hybrid pattern recognition. Each group has its advantages and limitations and it possesses various ways in order to present patterns and classes besides different algorithms for learning and recognition.

2.4.4.1 Statistical Pattern Recognition

This category is a classical method of pattern recognition. It was found out during a long developing process and it has been commonly used in pattern recognition. It based on numerical descriptions of objects by generating feature vector distributing. This vector was getting from probability and statistical models which are defined by using a family of class-conditional probability density functions Pr(x|ci) (probability of feature vector x given class ci). The statistical decision focused on individual descriptions. This class ignores the relations between features so only features were used. A fully automated processing was used.

Various algorithms were developed to manipulate numerical values. The extraction of independent features for each object and the discard of the relation between them may lead to poor descriptions. It also makes this model unable to describe complex pattern structures and sub-pattern relations.

2.4.4.2 Structural Pattern Recognition

This class describes objects based on two types of description, namely numerical and symbolic description of objects. Unlike statistical pattern recognition system and besides to the extraction of independent features for each object, the structural pattern recognition gives also considerable importance to the relation between these objects. It also emphases on the way of the composition of one pattern based on sub-patterns which make it quite better to the statistical concept.

Algorithms based on manipulating numerical values cannot be used in this class because of the used complex structure (Graphs, Strings). It can distinguish two main methods in structural pattern recognition called syntax analysis and structure matching. While the former based on the theory of formal language, the latter based on some special technique of mathematics based on sub-patterns (Liu et al., 2006),(Tsai and Fu, 1980). To allow structural pattern recognition dealing with more complex problems of pattern recognition, statistic classification or neural networks were associated.

2.4.4.3 Syntactic Pattern Recognition

Syntactic pattern recognition is derived from structural pattern recognition. In other words, it is a special kind of structural pattern recognition. This category based on the rules of composition which can be used in the case of finishing the customization of a series of rules which describe the relationships among the parts of the object. Because of its suitability for dealing with recursion, syntactic pattern recognition gained many attentions (Liu et al., 2006). But it must be noticed that this pattern recognition type is weak in handling noisy patterns and numerical semantic information.

2.4.4.4 Hybrid Pattern Recognition

While each class has its strengths and weakness. The disadvantages of a class may be the advantage of another class. The hybrid class combines the strengths of each category which makes it more useful for real applications. Hybrid methods emphasis on enriching the set of combined methods by exploiting its strengths in order to build a robust structure that can deal with the addressed problems. Recently, this category is very used and many techniques were applied.

2.5 Conclusion

AI is the science of simulating human intelligence in a machine. It may outperform humans at whatever its specific task is. While AI aims at making an intelligent and independent machine that can reason, interact with a human, understand requests, observe and plan based on mimicking human abilities, machine learning is a specific subset of AI that trains a machine on how to learn data and make predictions.

In Information Technology (IT), pattern recognition is a subfield of machine learning. It can be defined as the identification of objects by extracting the representative information or features from these objects. The goal of pattern recognition is to classify unfamiliar objects very quickly even when partly hidden based on learning from data. Until now, AI which can outperform humans is designed to perform limited tasks. Many researchers work on developing AI for unlimited tasks and goals in futures in order to help civilization flourishing as long as keeping this technology beneficial.

In this chapter, we have introduced an overview for AI, ML and pattern recognition. A definition and application areas were presented.

CHAPTER 3

Ear BIOMETRIC

3.1 Introduction

In this chapter, we will present the ear as a biometric. The properties of the ear which make it acceptable for use in recognition will be detailed. Why do we use ear biometric, besides the different strengths and limitations will be presented. The anatomy of the ear will be also discussed. The third section includes relevant works in this field, starting with its first proposition until nowadays. Next section was reserved for ear detection techniques and some related researches. The different developed ear recognition approaches are presented in section five. Most ear databases are given in the next section. Finally, some multimodal systems, where the ear is one of the used modalities, will be cited in the last section.

3.2 Ear Biometric

Ear recognition was founded firstly by the FBI Academy and it was used for forensic domains during many years. Ear biometric has many advantages and strengths that make it a better choice for research in several cases to construct a robust and efficient biometric system. Ear biometric has received many attentions in various domains, especially in forensic science. Ear biometric has a stable structure with a little change with age and no change with the pose and facial expression over an acceptable period of human life.

Ear is larger than conventional modalities like iris or fingerprint providing more important information increasing efficiency (Jain et al., 2007). Therefore, it is more easily captured from a distance and doesn't require a high-quality camera (Woodward et al., 2001). Ear biometric is a non-invasive biometric technique because there is no need for the assistance of persons. It can easily capture his ear even without his knowledge. The uniformity of colour distribution on ear modality is more than other biometrics such as face or iris (Ibrahim et al., 2010). For all these reasons, many researchers prefer the use of ear recognition more than other biometric technologies.

Ear biometric has a definitive structure like the face. The shape of the outer ear consists of the helix or it can be called outer rim. Next valleys named antihelix or inner helix which runs roughly parallel to the outer helix but forks into two branches at the upper extremity. The little bump on the left of the intertragic notch exactly on lower of antihelix called antitragus. Continuing on the same curves, we find the intertragic-notch which can be exploited as a reference point for biometric purposes because of its very sharp bend at the bottom. At the opposite (right) side of helix and where the helix intersects with the lower branch of the antihelix can distinguish the crus of the helix. Alfered Iannerelli uses this point among the 12 measurement points on his biometric system. The point in the centre of ear shape called concha (Iannerelli, 1989). This point contains the ear hole. Figure 3.2.1 shows the external anatomy of the ear.

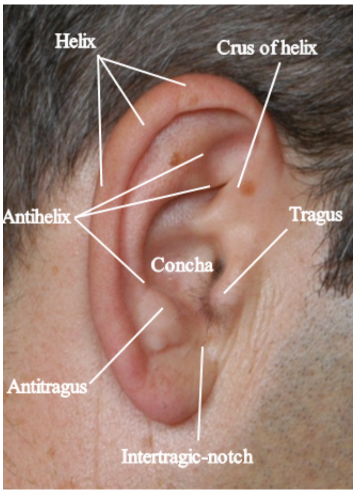

Figure 3.2.1: The anatomy of ear (Iannerelli, 1989).

3.3 Literature Reviews

The french criminologist Alfrid Iannerelli proved that the ear possesses the most stable and unique characteristics after fingerprints that can be used for identification purpose. Alfered Bertillon considers that the shape of the ear, its valleys and hills can be applied as the most significant factors point for recognition. Besides that, there are no two identical ears. Several studies have proved the uniqueness and the robustness of ear. Imhofer, in 1906, uses only 4 features to identify 500 ears. He could easily distinguish between ears on his studies which demonstrate the robustness and efficiency of the ear as a biometric modality for recognition (Ross and Byrd, 2011).

In California 1989, 10,000 ears captured from random persons.The achieved studies have proven that all the ears were distinguishable and no ears are the same. The anthropometric technique was developed by Iannarelli to identify ears. The "Iannarelli System" uses 12 measurements in his studies. A total of 12 measurements are illustrated in figure 3.3.1

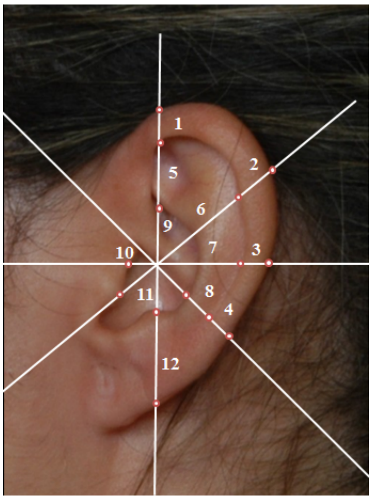

Figure 3.3.1: Iannarelli's manual ear measurement system (Ross and Byrd, 2011).

A medical report shows that ear has a stable structure and a noticeable variation can be viewed from four months to eight years old and over 70 years old which mean that ear has a fixed structure from eight years to 70 years. Because of the stability of ear and predictable change of its structure, it becomes one of the most used modalities for human identification. Due to the various strengths of this modality, many researchers have used ear as a biometric either alone or merged with other modalities on 2D and 3D domains.

Recently, different ear recognition systems have been developed in various areas. These systems aim to achieve a secure and robust system based on extracting a set of features. The extracted set of points represents the input ear using local approaches, global approaches, geometrical approaches or hybrid approaches. The methods of extraction are applied to 2D or 3D ear images.

Starting with 2D ear recognition system, here, the ear images are captured from different hardware such as commercial off-the-shelf cameras or surveillance systems cameras. In this system, the hardware detects a profile face as an input image. Next, an automated or manually segmentation is performed by the captured image. The segmented ear will be then normalized to account for potential variability in illumination. Next step is considered as the important phase in the whole system which named feature extraction step. Different techniques are proposed to extract the discriminant feature from the preprocessed ear. Finally, an adequate classifier was used in the matching step to identify the input ear image by comparing it with all templates which exist in the database.

A 2D ear recognition system was developed in (Boodoo-Jahangeer and Baichoo, 2013) that could be helpful in the medical domain. Especially, where the face of the patient injured and it's hard to recognize him. Local Binary Pattern was used to extract the discriminant features from 2D ear image. This method consists of dividing the image into cells of 3 × 3 pixel blocks. An LBP code was computed for each centre pixel $x_c$of each block based on a comparison with its neighbors P according to the following formula:

$$LBP = \sum_{K=1}^{P} sg(x_k - x_c).2^{k-1} \tag{3.3.1}$$

Where $x_k$is the kth neighbor. And sg represents the sign function and it is defined as:

$$sg(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \tag{3.3.2}$$

The next step consists of computing the histogram of the frequency of each occurring number . The achieved results have been compared with PCA. The proposed ear recognition system was performed on the Indian Institute of Technology (IIT-Delhi) ear image database which contains 125 subjects with 3 images for each one. A recognition rate of 93% was obtained which proves the power of LBP descriptor.

An automated personal identification system based on ear biometric was introduced by (Benzaoui et al., 2015). They have the objective of decreasing the recognition performance under unconstrained conditions like partial occlusion, illumination or pose variation. The proposed system was based on three steps. The first step is the normalization of ear image to a standard size and direction according to the long axis of outer ear contour. The long axis represents the max distance between two points of the ear contour. Then, the different detected max axes from all ear images were normalized to the same length and same direction.

The discriminant features were extracted in the next step to represent successfully the input ear image. LBP, LPQ and BSIF were applied on 2D ear image to extract the representing features. In order to solve the problem of sensitivity of LBP to blur, LPQ was applied. This method based on quantizing the Fourier Transform phase in local neighborhoods. An LPQ code is computed by quantizing the Fourier transform phase in local neighborhoods. It is represented by a convolution between the image intensity and a point spread function (PSF). A blur invariant LPQ code will be generated for each pixel. Then, a histogram was computed by collecting the occurrences of these LPQ codes.

In BSIF method and after convolving the image with a set of linear filters, each bit in the generated BSIF code was computed by binarizing the response of a linear filter with a threshold at zero. The number of filters used was determined based on the length of the bit string. Independent Component Analysis (ICA) was applied to learn the filters from statistics of natural images. A significant performance has achieved especially with BSIF.

ADWT-SIFT hybrid approach for ear features extraction was developed in (Ghoualmi et al., 2015). The proposed approach combines global approach named Wavelets with a local approach named SIFT. Different performance measures were calculated to evaluate their proposed method. Higher accuracy and less time consumption were achieved by the proposed authentication system better than each authentication system taken separately.

A recognition ear system was proposed based on Multi-scale Local Binary Pattern (MLBP) descriptor for the extraction step (Youbi et al., 2016). Instead of computing a single scale of the basic LBP, MLBP extracts features computed at different scales. Then, it combined the collected histograms which will be able to detect the dominant texture characteristics and solve the problems of image rotation and translation. The Kullback Leibler (KL) distance was used for the matching step.

Hassaballah et al develop a comparative study of ear recognition using local binary patterns variants. In this study, the authors aim to analyze and compare these extractors to determine its efficiency and robustness on ear biometric. Besides the traditional LBP variants, they develop a new modified LBP named Average Local Binary Patterns (ALBP). This comparative study is tested and validated based on five (5) databases called IIT Delhi (I), IIT Delhi(II), AMI, WPUT and AWE (Hassaballah et al., 2019). A CRR reaching up to 99% in case of constrained databases. But the performance of the system decreases in case of unconstrained databases which require more studies and improvements.

Researchers found that the use of 3D images instead of 2D images is useful in many cases to construct a recognition system. It can be a solution to many difficulties faced with biometric system that uses 2D images. The captured 2D ear image can be affected by noise because of the different condition of illumination or scale variation. Another challenge was the sensitivity towards pose. These limitations can be avoided using 3D images. Moreover, the cost of 3D scanners has been drastically reduced. All of these reasons motivate researchers to develop a robust biometric system based on 3D images.

The structure of ear possesses rich information. Its helix and valleys make them more significant for identification than other biometrics modality (Prakash and Gupta, 2015). 3D ear provides more textures and information thus improve performance and enhance the recognition of the developed system. Many researchers exploited the 3D technique either alone or concatenated with the 2D technique.

Yan et al introduced a powerful search and retrieval methods using ICP with PCA to find the relevant points in an ear shape volume (Yan and Bowyer, 2005). Four approaches are developed including PCA for 2D ear images with a recognition rate of 63.8%, PCA for 3D ear images with a lower recognition rate of 55.3%. The third approach consists of applying Hausdorff matching of edge images from range images, achieving 67.5%. The last and the best approach was ICP matching of the 3D data achieving 84.1%. 3D-ICP shows good robustness and scalability with the size of the dataset. The proposed techniques are validated and tested using UND database. The collected data are acquired from the University of Notre Dame (UND) from 2003 to 2004 assembling left ear images from 302 subjects.

Bhanu et al successfully use 3D data to represent significant features in ear images(Chen and Bhanu, 2007). New algorithms are presented for segmentation step, identification and verification modes. Firstly, a new technique is proposed to detect the shape of the ear using a single reference 3D ear shape mode. Then, a helix/antihelix representation is generated which will be used for ear identification and verification. Another representation consists of using a Local Surface Patch (LSP) which based on neighborhood information. These representations compare between a gallery-probe pair by computing the initial rigid transformation between them. A modified Iterative Closest Point ICP algorithm is employed for final probe and gallery image matching. University of California Riverside (UCR) database, which contains 902 images captured from 155 subjects, and UND database of 302 subjects are chosen for the validation step of the proposed ear recognition system. A recognition rate of 96.8%, 94.4 % are achieved with UND, UCR databases respectively.

Local and holistic features were used for multi-biometric 3D ear recognition (Zhou et al., 2011). In this study, after segmenting the 3D ear automatically, features are extracted from them based on two extraction methods. In the first extractor named local features, an extended descriptor called Surface Patch Histogram of Indexed Shapes (SPHIS) has been applied for surface patch representation and matching. Holistic features are used as a second extractor. In this technique, a robust representation is generated by voxelizing the ear surface. Score level fusion has performed. Then, a match score for the input ear image is generated. A recognition rate of 98.60% is obtained on the UND-G dataset, with an EER of 1.60%.

A new ear biometric system based on 3D ear images with co-registered 2D ear images was presented in (Prakash and Gupta, 2014). It is started with locating local 2D feature points from co-registered 2D ear images. Then, salient 3D data points were computed from 3D ear images which will be used in the next step for recognition purpose. Generalized Procrustes Analysis (GPA) and Iterative Closest Point (ICP) based matching techniques (GPA-ICP) are proposed for the matching step. To validate the implemented system and the proposed techniques, the

UND-Collection J2 (UND-J2) database has been exploited. UND-J2 database contains 1780 3D and co-registered 2D profile face images with scale and poses variations captured from 404 subjects. Each subject has at least two samples. A verification rate of 98.30% has been achieved with an EER of 1.8%.

A theoretical framework for a novel intelligent technique using 3d ear models was produced in (De Tré et al., 2016). This technique allows to forensic expert identifying precisely victims using their ears. Automated segmentation is proposed to extract the ear from the photographs. A normalization and enhancement of the detected ear are performed and an ear model will be generated using geometric and photometric corrections. Two features sets, Post Mortem (PM) and Ante Mortem (AM), which are extracted from ears models using shape fitting approach, are compared. Minkowski distance beside a new method named bipolar satisfaction degrees are proposed for matching.

Ganapathi et al implement a new technique based on both 2D and 3D ear images for human recognition (Pflug and Busch, 2012). The first step consists of applying curvilinear structures on 2D ear image in order to detect a salient features key-points. New techniques based on using curvilinear features to 3D were proposed. In the second step, the located features key-points are mapped onto the co-registered 3D ear image. Next step consists of extracting a feature descriptor vector for each mapped key-point computing rotational projection statistics (RoPS). RoPS technique adversely affects the performance of the system in the case of using highly similar objects like ear biometric. Iterative Closest Point (ICP) is coupled with RoPS to solve this limitation and improve the recognition of the proposed system. The developed work achieves a verification rate of 98.69% with an EER of 1.53%.

3.4 Ear Detection

The first proposition of using the shape of the ear for recognition was discovered by the French criminologist Bertillon. Then, Iannarelli developed the first ear recognition system (Pflug and Busch, 2012). Ear detection is considered one of the most important phases in the ear recognition system. Before the extraction step, it is necessary to locate the shape of the ear from the whole the input profile face image. This step requires a robust and optimal algorithm for segmentation. The detected ear will be used next to the extracted representatives features. The extracted features were matched with templates exist in the database. So, the detection of result has an influence on the whole next steps which will directly affect the performance of the recognition system.

In fact, the shape of the human ear is not elliptical for all individuals which make the ear detection stage more difficult (Prakash and Gupta, 2012). Figure 3.4.1 shows the different shapes that can be founded. Moreover, ear detection techniques can face other problems related to scale and pose variations. Ear detection remains a real challenging problem until now. For all these reasons, many researchers that focus on recognition use manually cropped ears technique and have not used automatic ear detection and segmentation. The use of manually cropped ears Ensures that the performance of the developed system is not affected by the detection phase. It also allows focusing more on the extraction technique and this is the case in our work. Many algorithms are developed to construct efficient automated ear detection from 2D or 3D profile face image.

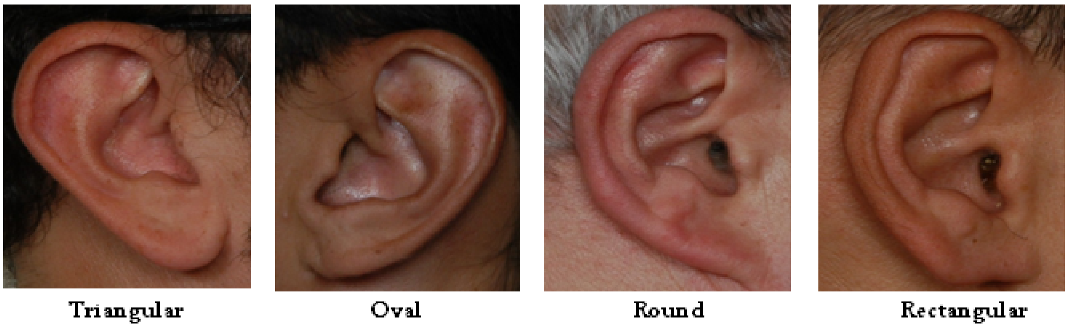

Figure 3.4.1: Ear shapes (Prakash and Gupta, 2012).

Burge and Burger in (Burge and Burger, 2000) capture profile grayscale images using CSD camera. The first step consists of locating the ear using a deformable contour on a Gaussian pyramid representation of the image gradient. Then, canny operator was applied to compute the edge of the located ears with specific thresholding.

An automatic detection system based on the shape of the ear was developed in (Abdel-Mottaleb and Zhou, 2006). The ear region was located from a colour profile face image following three steps. The first step named Skin-Tone Region Segmentation consists of generating a skin map image by applying Flek's method in order to locate the face region. The second step named Edge Detection on Skin Region applied canny edge detection on the located region. An edge size filter was used to improve the detection and remove noises. The next step consists of locating the ear region using a template matching. This technique was a part of an ear recognition system which recognized the ear after its detection.

Two main steps were presented by (Yuan and Zhang, 2009) to build robust ear detection from a video. The first step consists of following the profile face in the video frame sequences based on a modified Continuously Adaptive Mean Shift (CAMSHIFT) algorithm. Canny edge detection works on smoothing the image to eliminate noise and finds edge strength of the gradient and the edge direction. Ellipse fitting based on the least-squares method was applied to segment the ear due to the shape of the ear which is similar to the ellipse. The developed technique can be used in real-time under a practical situation.

Two approaches for human ear detection from side face range images were proposed in (Chen and Bhanu, 2007). The first approach includes template matching based ear detection method where the second based on the ear shape model. Principal curvatures compute an averaged histogram of shape index which represents the model template. Whereas, a set of discrete 3D vertices corresponding to ear helix and anti-helix parts were computed to represent the ear shape model. The proposed approaches are tested on 312 side face range images captured from 52 subjects. Each subject has six images. A detection rate of 92.6% and 92.4% and a detection time equal to 6.5 and 5.2 sec was achieved applying Ear shape model, template matching respectively.

In (Bhanu and Chen, 2008), they introduce a third approach based on the fusion of colour and range images and global-to-local registration based detection. In order to isolate the side face in an image, skin colour classifier is applied to generate a mixture of Gaussians. This latter allows modeling the skin colour and non-skin colour distributions. The fusion step consists of combining the edges from the 2D colour image with the step edges from the range image to locate regions-of-interest (ROIs) that may contain an ear. The proposed approaches are validated using UCR dataset and the UND dataset. The detection rate increase to 99.3% on the UCR dataset and 87.71% on UND by fusing colour and curvature information.

A robust ear detection method is proposed based on a bank of curved and stretched Gabor wavelets, known as banana wavelets (Ibrahim et al., 2010). The input image is convolved with eight filters. Then, response magnitudes are calculated to find the positions where this magnitude has local maxima. To test the proposed ear detection method, XM2VTS database with 252 profile images from 63 subjects was used and a detection rate of 100% is achieved. The developed method has succeeded in detecting the shape of the ear on all images in the database. A comparison between Gabor wavelet technique and the proposed Banana wavelet filters are performed using the same parameters. The obtained results proved that Banana wavelet filters can capture the curved structures better than Gabor wavelet filters.

The application of the Cascaded AdaBoost (Adaptive Boosting) approach to detect ear images from 2D profile face images was performed in (Islam et al., 2011). For training the cascade, the deferent stages were defined in order to help classifier to reject rapidly the false positives using a small number of features. So, AdaBoost is used to select good weak classifiers and then to combine them into strong classifiers. All the stages are used to construct in a cascaded manner the final ear detector. The proposed detector is scanned over an input image in different sizes and locations. If the test image is detected as positive (ear) by the classifier of the previous stage and accepted finally only when it passes through all of them, then, the classifier in the cascade can be used. The proposed work uses Collection F of the UND database to validate the results. A detection rate of 99.9% was obtained. AdaBoost approach demonstrates its efficiency and robustness even if ears have occluded with hair, ear-rings, or ear-phones.

In the purpose of solving some challenges encountered by ear detection and recognition such as rotation, scale and pose variations, a new technique was developed in (Prakash and Gupta, 2012). This technique exploits images in YCbCr space because it is more used in video compression standards. As an initial step, a conversion of RGB colour space to YCbCr colour space is applied. Based on information colour, a segmentation of skin and non-skin regions was performed, after separating luminance from it. A Gaussian model is applied to compute the likelihood of skin for each pixel which can be used to segment skin and non-skin regions. Skin segmentation is achieved by thresholding the skin likelihood image using appropriate thresholding generated by applying an adaptive thresholding process. Canny edge operator extracts all edges on skin segmented image. Each edge represents a sequence of pixels. To conserve only the important pixels exist in edge, line segments are fitted to it. The proposed technique is tested on IITK and UND databases with a detection rate of 95.61% and 96.63%, respectively.

A snake model was applied to detect the object in an image (Anwar et al., 2015). The initial position of the snake is selected manually by clicking on the image and selecting control points. The next step consists of specifying the different parameters of the model, the number of iterations. Then, in the purpose of removing noise, a median filter was used. After the binarization of the filtered image, the canny edge detector was applied to find edges. Finally, only strong edges and weak edges which they are connected to strong edges are collected. The proposed ear recognition system achieves 94% on the term of accuracy with IIT Delhi ear database.

3.5 Ear Recognition Approaches

In an ear recognition system, there are three main steps. The first step, namely the pre-processing step, includes segmentation of ear from the whole input image. Besides to different techniques of normalization which reduce noise and illumination, fixes the size and converts the colour level. . . etc. The second step considered as the important phase in the recognition system. In this step, the important traits were extracted applying an adequate extractor. The extracted features will be used in the last step, namely matching, to find its similar features in the database. Many techniques were proposed to build a robust and efficient feature extraction method as observed in Table 3.1. Depending on the used feature extraction method, 2D ear recognition approaches can be divided into four types: geometric, holistic, local and hybrid methods as shown in Figure 3.5.1.

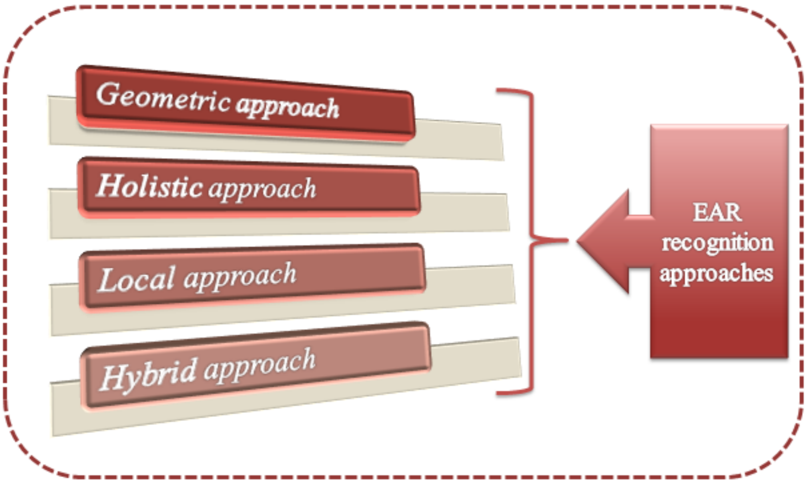

Figure 3.5.1: Ear recognition approaches (Emeršič et al., 2017b).

3.5.1 Geometric Approach

This technique, which introduced by Iannarelli in 1989, is based on the geometrical traits that can be extracted from the ear biometric such as the shape and its various edges and valleys, inner and outer of the helix, height line, the position of specific parts of the ear and the relation between these parts. The geometric approach is largely used due to the enormous discriminant information contained in the ear shapes and the stability of this information and the ability to use it in ear recognition system. Because of the large area of the ear, high features dimension can be obtained which decreases the performance of the recognition system and therefore increases the complexity. Moreover, geometric methods are sensitive to rotation and scale variations. Figure 3.5.2 illustrates the architecture of a geometric ear approach.

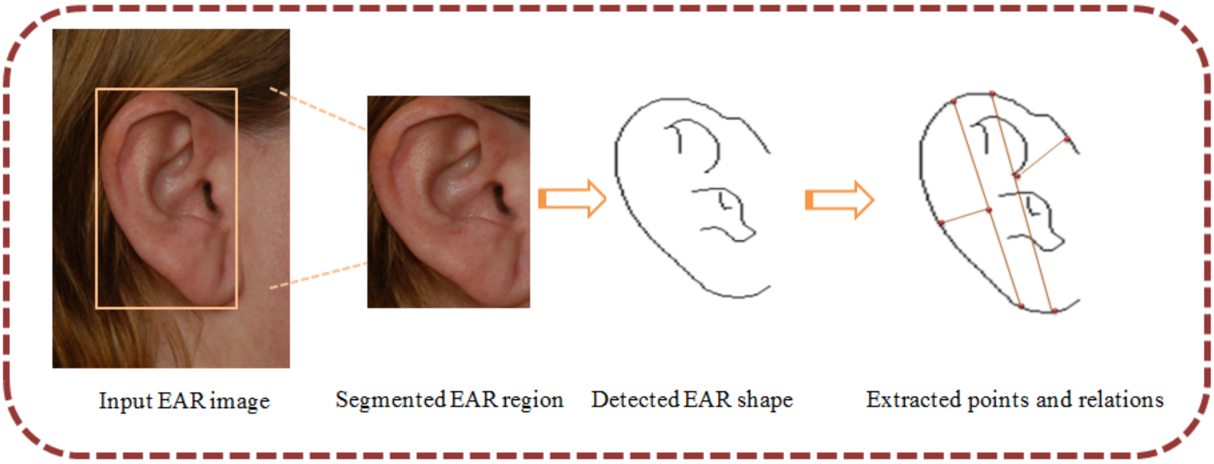

Figure 3.5.2: The architecture of geometric ear approach (Anwar et al., 2015).

A novel geometrical features extraction method was introduced for the extraction of specific geometrical points of ear biometric by (Islam et al., 2011). Image preprocessing was performed using a Gaussian filter. Then, Canny edge operator was applied to detect ear helix. The extracted geometrical features represented on the combination of maximal Ear Height Line (EHL) and minimum EHL. For maximal EHL, it can be determined by selecting the maximum distance between two edges points. Minimum EHL will be determined by selecting the shortest distance between the upper and the lower region. Other traits are added to these two features such as its summation and ratio where these features are invariant to scale changes. The proposed method is validated using USTB1 and IIT Delhi databases with an accuracy of 98% and 99% respectively

An efficient ear authentication system was developed by (Annapurani et al., 2015). In the presented work, an enhanced edge detection method was applied to extract tragus features from the ear biometric. For more robustness and efficiency, the shape of the ear is also extracted. Then the tragus and the shape of the ear are fused together at feature fusion level. IIT Delhi and AMI databases are used to test and validate the proposed system. An authentication rate of 100% was achieved from both AMI and IIT Delhi databases.

3.5.2 Holistic Approach

This approach called also global technique. It is based on features taken from the whole ear image and attempt to correlate various features for biometric verification (Emeršič et al., 2017b). Unlike the geometric approach, holistic approach extracts information based on the global appearance of the ear. This approach is sensitive to pose and illumination variations. Hence the preprocessing step should be taken into account. Normalization techniques must be applied to solve these problems to allow extracting the correct features in the next step. A simple architecture of holistic ear approach is presented in figure 3.5.3.

Many algorithms are proposed in this field. Force Field transformation, PCA, LDA, Independent Component Analysis (ICA), all of these cited algorithms and others were exploited successfully for ear recognition. A PCA technique was used for face and ear recognition system separately with a recognition rate of 71.6 %, 70.5 respectively (Chang et al., 2003). Where a multimodal recognition system based on both ear and face increases the recognition rate to 90.9% using UND E database with 114 subjects.

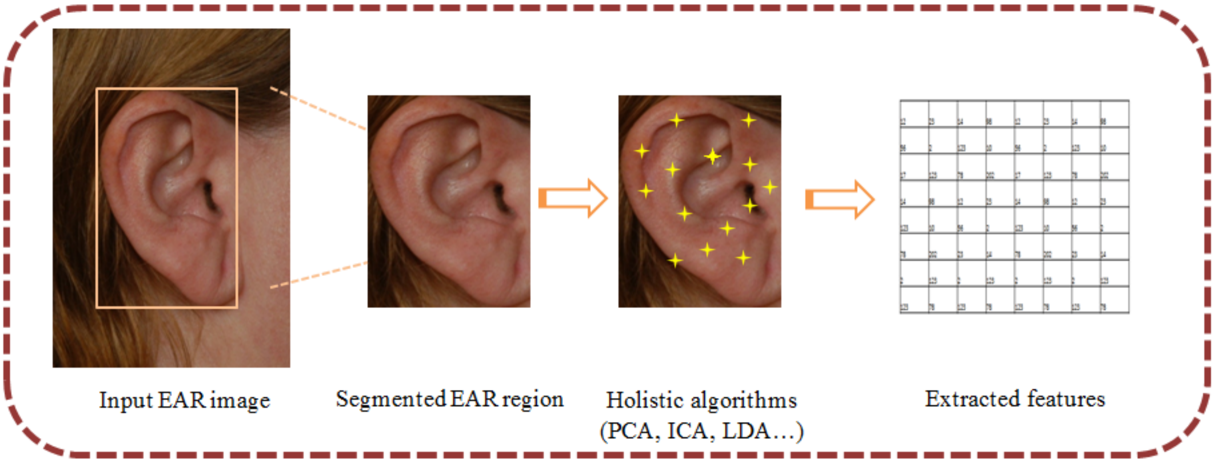

Figure 3.5.3: The architecture of holistic ear approach (Yuan and Mu, 2007).

ICA method was applied in (Dewi and Yahagi, 2006) on the processed ear images to extract a set of representative points which will be matched in the next step by applying Radial Basic Function (RBF) classifier. The experimental results are conducted on Carreira-Perpinan ear database and their own databases with 17 and 60 subjects, respectively. A performance rate of 94.1% was achieved with CP databases, where 88.3% was obtained with the second database. Another ear recognition system was developed based on Full-space Linear Discriminant Analysis (FSLDA) technique (Prakash and Gupta, 2013). FSLDA extracts the robust features set from the normalized ear image with different rotation variations. The experimental results carried out on USTB II ear image database which contains 77 subjects. A recognition rate of 90% was achieved.

A force field transform was applied to the detected ear region (Abdel-Mottaleb and Zhou, 2006). The detection step was explained previously in section 4. Features were extracted from the transformed image in order to obtain a set of point that can be used for representing ear in the next step. They use their own database by collecting profile face images from 103 subjects.

3.5.3 Local Approach

Local approach based ear recognition focuses on local areas of an image. Where geometric approach based on the localization of points and the relation between them, the local approach based on the description of a specific area in the image. In this approach, the shape of the ear, in general, had not the same importance in the geometric approach where each part has a meaningful description and location. The representative set of features can be founded in any area in the image. An example of a local ear approach architecture is shown in figure 3.5.4. Recently, the local approach is largely used due to its deferent advantages such as:

- Low computational complexity.
- Ease of implementing many techniques in this context.
- Insensitive in several cases to rotation and illumination variations.

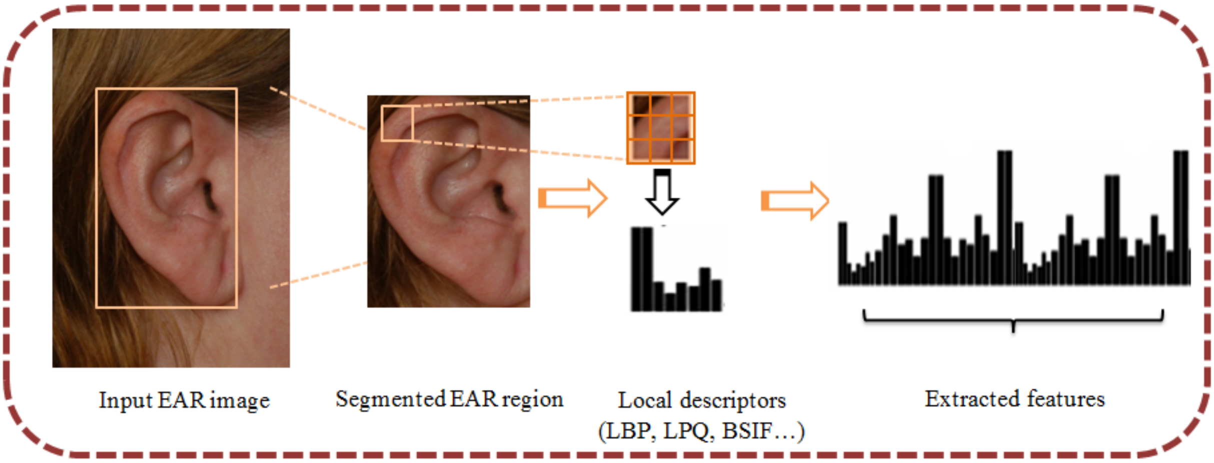

Figure 3.5.4: The architecture of local ear approach (Pflug et al., 2014).

Two types of techniques can be distinguished in this category. The first type consists of two sub-steps. Firstly, key-point locations must be detected in the image. Next, separate descriptors were computed for each detected key-point. Many techniques based on this group are presented in the literature. (Dewi and Yahagi, 2006) apply Scale Invariant Feature Transform (SIFT) to extract scale-invariant keypoints from ear image. The proposed ear recognition system outperforms PCA and forces field transform techniques.

Another technique, names Speeded Up Robust Features (SURF), was proposed in (Prakash and Gupta, 2013). The developed ear recognition system aims to work out on pose, poor contrast, change in illumination and lack of registration challenges faced by ear biometric.

SURF was applied to the enhanced ear images to obtain robust features. The experimental results have been evaluated on two public databases, namely IIT Kanpur ear database and the UND ear database (Collections E).

The second type does not detect key-points; it computes local descriptors in a dense manner from the whole image (Emeršič et al., 2017b). Different techniques have been proposed in this group such as Gabor filters, LBP, LPQ, BSIF and others. A Gabor Filters technique was used to extract the discriminant features from the training data of each subject (Benzaoui et al., 2014). The achieved results carried out on the UND collection G dataset with a rank-one recognition rate of 98.46%. LBP was applied to extract the important features from 2D ear images (Boodoo-Jahangeer and Baichoo, 2013). The obtained results were compared with other methods. LBP prove its efficiency against global illumination changes and low computational cost.

Three different texture descriptors: Histograms of Oriented Gradients (HOG), LBP and LPQ descriptors were applied to construct a robust ear recognition system (Nosrati et al., 2007). An automated unsupervised classification technique is applied in the matching step to compare the experimental results. Implement BSIF descriptor was developed to extract representative features that can be used to recognize the individual's ear (Ying et al., 2014). Two publicly available databases, which are IIT Delhi-1 and IIT Delhi-2 ,were used to validate and test the proposed ear recognition system.

3.5.4 Hybrid Approach

The combination of different techniques from the three previously discussed approaches creates the hybrid approach. The first proposition of this approach was introduced by (Nosrati et al., 2007) by fusing 2D Wavelet and PCA methods. The developed ear recognition system applies 2D wavelet on the normalized ear image. Then, the PCA technique was applied to the generated feature matrix in order to reduce features dimension. The introduced work carried out on USTB II and CP benchmark databases. A CRR of 90.5% and 95.05% was achieved with USTB II and CP, respectively.

Recently, the hybrid approach beside to local approach has gained many attentions in the fields of ear recognition and most competitive results have been achieved. A combination of Weighted Wavelet Transform and DCT techniques are performed to construct an improved ear recognition system (Sun and Liu, 2010). Two-dimensional Discrete Wavelet Transform (DWT) was applied to the human ear images as a first step. The next step consists of extracting DCT coefficients of the image using both blocks Discrete Cosine Transform (DCT) and weighted high-frequency components. In comparison with related works, they approve that the proposed hybrid approach outperforms ear recognition system based only on low-frequency components of the wavelet transform. A performance of 75 98.1 was obtained with their own database which contains 75 subjects.

Another proposition was introduced by (Morales et al., 2015). In this work, authors explore the discriminant properties and powers of local descriptors and global descriptors for earprint based automatic biometric recognition system. The implemented system extracts from the enhanced ear image the local and global features independently. SIFT technique was used in the purpose of extracting the local traits of the ear where the global traits were extracted based on matching binary or grey masks obtained from the whole earprint shape. A large database is used namely FEARID which contains 7364 prints obtained from 1229 donors collected from three different forensic laboratories.

A three-dimensional ear recognition system was developed by (Liu et al., 2016)based on a combination of local and global descriptors. Points, lines and area features represent the local features where the empty centres and angles were defined for the global features. A large dataset was collected using their own laser scanner designed for online 3D ear acquisition which contains 2,000 samples. An EER of 2.2% was achieved.

3.6 Ear Benchmark Databases

There are several benchmark databases that can be used to validate and analyze an ear recognition system. In case of adding an ear detection technique, it will be possible to use some face databases which contain a profile face images. Some of profile face databases which were used for ear recognition are introduced from Indian Institute of Technology Kanpur (IITK), UND, FERET, Pose Illumination Expression (PIE), West Virginia University (WVU) . . . etc. There is another type of ear database such as FEARID ear print database. This database does not contain ear images but it collects ear prints. Ear prints were collected using a specific scanning hardware.

We focus on our dissertation in constrained and unconstrained ear databases. Each constrained database captures ear images in specific conditions of lighting, rotation, resolution, illumination, left/right side, the distance between camera and subject, the quality and size of the collected ear images. Besides that, each ear database possesses a different set of subjects. In this section, we provide the most used ear databases chronologically sequenced.

3.6.1 CP Ear Database

The CARREIRA PERPIÑÁN (CP) database was collected in 1995. It is considered as the oldest ear database in order to build an automatic personal ear identification for a master's degree (Carreira-Perpinan, 1995). CP ear database captures images from 17 subjects. Each subject has six records which mean that there got 102 images in total. A high degree of uniformity presented by the images, due to the process of the collection followed. The same controlled conditions were performed for all captured images in the database. Some samples for CP constrained database were presented in figure 3.6.1

Figure 3.6.1: Samples from CP database (Carreira-Perpinan, 1995).

3.6.2 USTB Ear Database

Three ear databases were created by the University of Science and Technology in Beijing (USTB) (Zhichun Mu, 2004). The collected images were recorded from Students and teachers from the Department of Information Engineering, USTB.

For the first USTB I database in 2002, the right ear was captured with a digital camera. It contains 180 images from 60 subjects, three images of the right ear for each subject. The images collected through the databases were taken with different angle rotation and under different lighting condition. A few examples of images from this database are given in figure 3.6.2.

Figure 3.6.2: Samples from USTB I database (Zhichun Mu, 2004).

For the second database USTB II in 2004, 308 images were photographed from 77 subjects, four images of the right ear for each subject. Unlike USTB I which possesses a cropped ear images, USTB II provides profile images under illumination variations and angle variations. Figure 3.6.3 shows some examples for USTB II database.

Figure 3.6.3: Samples from USTB II database (Zhichun Mu, 2004).

USTB III database was created in 2004. While, in the two previous USTB I and USTB II databases, there is no need to ear detection techniques, USTB II was addressed especially for this purpose. Besides that, it will be helpful in face and ear multi-biometric recognition. All right profile face images were captured under specific angles and occlusions. USTB III contains 1600 images of 79 subjects. Figure 3.6.4 illustrates ear images for USTB III database.

Figure 3.6.4: Samples from USTBIII database (Zhichun Mu, 2004).

3.6.3 IIT Delhi Ear Database

Two ear databases were introduced by the Biometrics Research Laboratory at Indian Institute of Technology, Delhi (Kumar and Wu, 2012). The ear images were collected from the students and staff at IIT Delhi. For IIT Delhi I ear database, ear images were collected from 121 subjects. Each subject has at least 3 sample images with a resolution of 272*204 pixels for all images. While IIT Delhi II database collects ear images from 212 subjects with 754 ear images in total. The second version is automatically cropped and normalized. All images in IIT Delhi possess the same dimension, centred and mutually aligned and under different lighting conditions. Some ear images from both IIT Delhi I and IIT Delhi II were shown in figure 3.6.5.

Figure 3.6.5: Samples from IIT Delhi database (Kumar and Wu, 2012).

3.6.4 AMI Ear Database

Mathematical Analysis of Images (AMI) ear database was created by Esther Gonzalez in order to use it in his research to obtain Ph.D degree in Computer Science (Esther Gonzalez and Mazorra, 2008). 700 ear images are collected using a Nikon D100 camera from 100 subjects including students, teachers and staff of the Computer Science department at University of Las Palmas of Gran Canaria (ULPGC), Las Palmas, Spain. Each subject has seven profile images where six images were from the right ear and one for left ear. These images were acquired under the same lighting conditions with a resolution of 492 x 702 pixels. Some ear images examples of this database are shown in figure 3.6.6.

Figure 3.6.6: Samples from AMI database (Esther Gonzalez and Mazorra, 2008).

3.6.5 WPUT Ear Database

A large database was created by West Pomeranian University of Technology (WPUT), in 2010, aiming at reducing some challenges founded in the existed databases (Frejlichowski and Tyszkiewicz, 2010). WPUT took images from 501 subjects including 254 women and 247 men and achieving 2071 ear images in total. Each subject has at least two (profile and half-profile) ear images. In most cases, four ear images per individuals have been photographed. 166 individuals have possessed ear images occluded with hair. 147 individuals have ear images with earring. Others ear deformations have been also included in this database such as glasses, headdresses, noticeable dirt, dust, birth-marks, ear-pads ...etc. Ear images were taken under different indoor lighting conditions. WPUT was the first ear database that has 15,6% photos photographed outdoor and others were taken in the dark. Figure. 3.6.7 shows some examples of images from WPUT database.

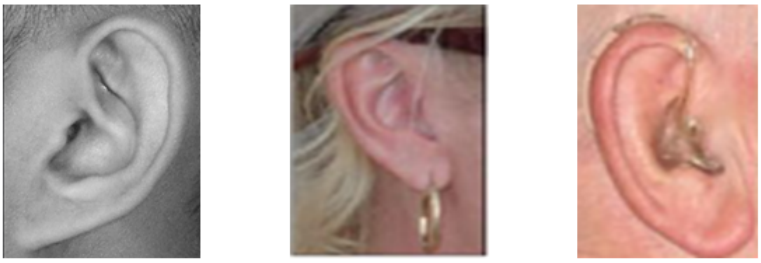

Figure 3.6.7: Samples from WPUT database (Frejlichowski and Tyszkiewicz, 2010).

3.6.6 AWE Ear Database

While the others discussed databases contain images captured in controlled laboratory condition with limited variability. Annotated Web Ears (AWE) database (Emeršič et al., 2017a) contains images taken from the web with different lighting condition and angle rotation, uncontrolled poses, different quality and sizes and uncontrolled environments. This unconstrained database introduced the notion of “images captured in the wild” and was created in 2016. The collected images were obtained from politicians, actors, musicians and other people who have various images on the web. AWE database contains 1000 ear images from 100 subjects. Each subject has 10 images for both left and right ear sides. Some ear images examples of this database are shown in figure 3.6.8.

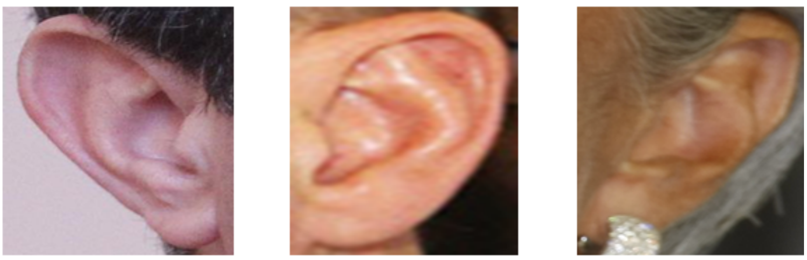

Figure 3.6.8: Samples from AWE databasev(Emeršič et al., 2017b).

3.7 Ear in Multimodal Systems

Ear was widely used for biometric recognition systems. Table 3.1 shows some of the existed works in this field. Extraction methods and approach type were mentioned. Benchmark ear databases which were discussed above have been used. Some studies use their own ear databases. A CRR varies from 70% to 99%. It can be noticed that geometric and holistic approaches have mostly used at the beginning of the development of the ear Biometrics. Recently, many studies focus on applying local approaches and also hybrid approaches.

Because of the successful results achieved using ear biometric in unimodal systems, researchers turned out to exploit ear in multimodal systems. Ear biometric was fused with various biometric modalities especially with face which seems more relevant to surveillance applications.

A multimodal biometric system was developed by (Chang et al., 2003). PCA standard algorithm was applied to extract features from both normalized ear and iris. Ear and face images were collected from 197 subjects from the university of South Florida. The captured images were taken under the same conditions at the same image acquisition session. Close results were obtained for ear and face unimodal system with recognition rate 70% and 71%, respectively, whereas a significant improvement was noticed after the fusion of ear-face data with recognition rate of 91%.

The fusion of ear and iris was proposed in (Nadheen and Poornima, 2013). An automated algorithm was introduced for ear modality. PCA technique is used to extract features from preprocessed ear and iris biometric data while ear and iris images are incompatible in nature, a min-max normalization scheme was employed. Then, the extracted sets of points were fused in feature level fusion. IIT Delhi ear database and CASIA-V1 for ear and iris respectively are used to validate the proposed system. An accuracy of 86% has been achieved for both ear and iris system separately, whilst an accuracy of 93% was obtained with the proposed ear- iris multimodal biometric system.

Human ear and palmprint were fused in a multimodal biometric system (Hezil and Boukrouche, 2017). Local texture descriptors namely LBP, weber local descriptor (WLD) and BSIF were applied to extract homogeneous features from the 2D ear and palmprint imaging. The Canonical Correlation Analysis (CCA) was applied in the purpose of finding the linear combinations between ear and iris features vectors which have a maximum correlation with each other. Serial feature fusion was utilized to generate a single features vector. The implemented system was carried out on IIT Delhi-2 and IIT Delhi databases for ear and palmprint respectively. A recognition rate of 98.19%, 80.53% and 100% was achieved applying LBP, WLD and BSIF respectively.

Table 3.1: A comparison of 2D ear recognition approaches.

Authors	Extraction method	Approach	Database	Subj	CRR
(Burge and Burger, 1996)	Adjacency Graphs of Voronoi Diagrams	Geometric	Own	#	#
(Chang et al., 2003)	PCA	Holistic	UND-E	114	71.6
(Yuan et al., 2006)	Non-Negative Matrix Factorization	Holistic	USTB II	77	91
(Nosrati et al., 2007)	Wavelet Transformation and PCA	Hybrid	USTB II	77	90.5
			Own	17	95
(Bustard and Nixon, 2010)	SIFT	Local	XM2VTS	63	96
(Zhou et al., 2011)	Global and Local Feature	Hybrid	UND-G	415	98.6
(Prakash and Gupta, 2013)	SURF	Geometric	IITK	168	97.35
			UND-E	114	96.75
(Pflug et al., 2014)	LPQ	Local	UND-J2 AMI, IITK,	555	93.1
(Ying et al., 2014)	Weighted Wavelet Transform and DCT	Hybrid	Own	75	98.1
(Yuan and Mu, 2014)	Gabor filter	Local	USTB	76	96.46
			UND-J2	150	94
(Benzaoui et al., 2015)	LBP,LPQ, BSIF	Local	IIT Delhi-1	125	96.68
			IIT Delhi-2	221	97.31
(Morales et al., 2015)	Global and Local Feature	Hybrid	FEARID	1200	98.5
(Anwar et al., 2015)	Geometric features	Geometric	IIT Delhi-1	50	98
(Liu et al., 2016)	Global and Local Feature	Hybrid	Own	500	#
(Ganapathi and Prakash, 2018)	Global and Local Feature	Hybrid	UND-J2	404	98.69
			Own	274	98.90
(Alqaralleh and Toygar, 2018)	LBP	Local	USTB I	60	98.3
			USTB II	77	88.31
			USTB III	79	96.6
(Ganapathi et al., 2018)	Curvilinear features	Local	UND-J2	404	98.69
(Sinha et al., 2019)	convolutional neural networks (CNNs)	Local	USTB II	77	97.9

3.8 Conclusion

More than other biometric modality such as face, fingerprint and hand-geometry, ear biometric has larger unique features and stable shape during human live. It considered as the future of biometric. Ear biometric is an excellent example for passive biometrics which does not need much cooperation from the subject. It also can be captured easily from a distance.

In this chapter, we have presented an introduction concerning the use of ear for recognition. The first section is a definition of ear biometric. Besides, it included ear properties. The last part of this section presented the anatomy of the ear and its measurements. Some of the existed works based ear recognition were discussed in the second section. The next section explained the detection of ear and presented the most used algorithms and proposed techniques. We have focused on section 4 on ear recognition approaches. We have detailed each presented approach giving a simple architecture to facilitate the annotation process. The most benchmark databases used to validate the developed ear biometric systems were cited with some samples examples for each database.

Based on the reviews and strengths of the existing techniques, we find that the geometrical approach faced some problems with edge detectors. This latter is very sensitive to variation lighting conditions or a small change of ear orientation during the capture images. The holistic approach has also some disadvantages related to changes in contrast or in brightness because it deals with the whole image. Unlike geometrical and global approaches, the local approach has proven to be more robust in real-world applications. It deals with small regions of the image which allows computing features efficiently. In particular, LBPs has gained many attentions and applied to numerous modalities. Its advantages and robustness in 2D and 3D biometric domains give successful results in a significant number of studies. Their invariance to monotonic grey level changes caused by illumination variations makes it a way out of many challenges. LBPs are also easy to implement with less computational. All of these powerful points motivated us to apply this technique in our proposed multimodal systems.

CHAPTER 4

ECG BIOMETRIC

4.1 Introduction

In this chapter, an ECG biometric will be presented. In the first section, the properties that make ECG acceptable for recognition will be described. Then, the anatomy of the human heart will be discussed. The different strengths and challenges are also explained in this section. A detailed section was reserved for the structure of ECG recognition system including all steps that can be used. Another section talks about the existed ECG recognition system mentioning its efficiency, its robustness...etc. As any biometric modality, ECG has some publicly available databases which will be discussed in the seventh section. The last section consists of presenting some existed multimodal systems that integrate ECG biometric.

4.2 ECG as Biometric

Biometric has largely used, in our day, due to its effectiveness and robustness to several types of spoofing in various fields. Face, fingerprint, Palm print, iris, Keystroke, Signature, Voice, Gait and others have been mostly used. The choice of a biometric modality depends on its strengths and weaknesses besides the application requirements (Regouid and Benouis, 2018). The exploitation of a selected biometric modality to identify individuals depends on a set of properties and conditions: universality, uniqueness, permanence, measurability, performance, acceptability and circumvention which are detailed in the first chapter.

The security plays a crucial role in most application, especially in the authentication phase. Biometric modalities such as fingerprint, face, iris, voice can be mimicked easily, especially in our day with the addiction to social media which provides photos and information everywhere and for everyone. The need for achieving more security obliged researchers to resort to a biometric trait that must be hard to spoof. One of the proposed biometric that solves this challenge is the Electrocardiogram (ECG).

Nowadays, ECG or in sometimes referred to EKG biometric has been gaining more attention from many research laboratories because of their strengths especially in the security domain, e-health medical, diseases prevention…etc. Analysis of electrocardiogram describes the electrical activity of the heart. The activity recorded by the ECG comes from extracellular currents related to the propagation of a depolarization front (atrial P wave, then ventricular QRS complex). Many studies have been developed to exploit the electrocardiogram (ECG) as a biometric modality that can be used for recognition. The first study was established by the physiologist Augustus (Waller, 1887). His main objective is to demonstrate that the electrical variation of the heart is physiological traits and not just mechanical alteration of contact between the electrodes. Next, ECG has been used widely in the medical field to solve and diagnose heart problems.

Researchers prove that ECG respects most of the discussed biometric properties which allow using it for recognition purpose. ECG analysis, or the heartbeat variability, has been studied in many fields such as medical science, psychology, robotics and Cardiovascular disease for decades(Biel et al., 2001; Shen et al., 2002; Belgacem et al., 2013). Recently, numerous research works have been published tackling the problem of ECG based recognition as the new key parameter to biometric identification. For example, in (Fratini et al., 2015; Coutinho et al., 2013) we can find a survey on this problem recapitulating some of the most popular approaches. Some of them use explicit morphological models of heartbeat variability (P-QRS-T), whereas others use either Spatio-temporal or frequency-domain features of the ECG signal.

4.3 ECG Anatomy

The ECG is known to contain characteristics originating from the geometrical features of the individual body and heart that might be utilized for biometrical applications (Wübbeler et al., 2007). ECG can be used as a liveness detector, universality, remote login process by ECG signal captured from a finger which improves security and privacy (Islam and Alajlan, 2017). Presenting liveness measurements to the system have the ability to protect it from spoof attacks and therefore more security will be achieved (Louis et al., 2014). Emotion, diet, physical exercises, diseases or position of the electrodes have the ability to change the human ECG signal.

An ECG signal is generated by a simple impulse of the heart that creates the heartbeat segments. The human heart contains four chambers: the right and left atrium and the right and left ventricle. The electrical impulse starts from a small node called the Sinoatrial node

(SA) located in the right atrium causing the P wave. SA node launches the contraction of the atrium causing the passage of blood into the ventricle, the electrical signal then propagates through the node artio-ventricular (AV). AV node stops the signal for short time duration to complete ventricular depolarization causing the QRS complex. Then, the electrical signal is then sent to the ventricles through the AV chamber causing T waves. Finally, the ventricular repolarization is completed by sending the signal out of the ventricles (Kalaskar, 2018). The whole process of generating an ECG signal is presented in figure 4.3.1.

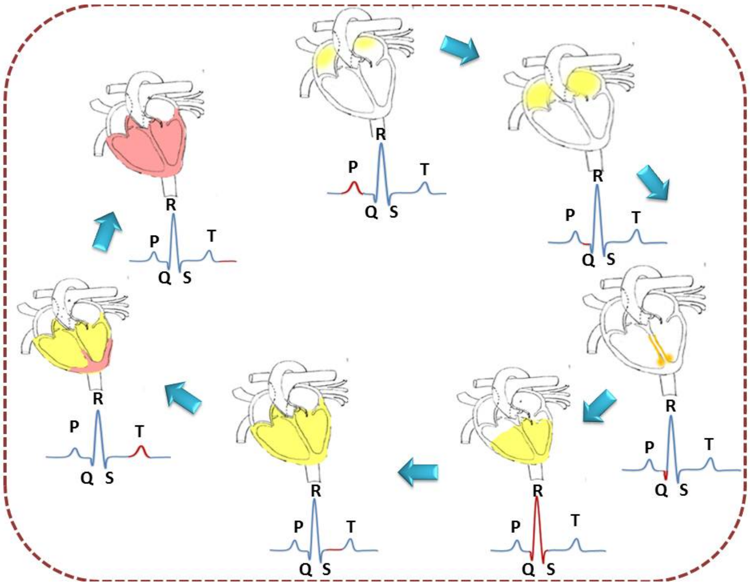

Figure 4.3.1: The electrical activity of the heart (Kalaskar, 2018).

4.4 ECG Strengths and Drawbacks

In fact, no biometric modality is reliable 100%. Each biometric modality has its own advantages and disadvantages. The selection of biometric modality depends on the application context. For the ECG modality, it has been used largely in hospitals to diagnose and detect various types of cardiac pathologies. So, they have an ECG signal for their patient. For this reason, the use of this ECG for identification of patient reduces the time and the cost of using other biometric modalities not collected yet. The liveness measurement of ECG makes it more universal. Moreover, The ECG recognition system is more robust and secure because it is very hard to spoof a life indicator. The use of ECG biometric helps people with different disabilities. Compared with other biometric modalities, ECG generates lower templates size and minimal computational requirements . It is easy to acquire it from any part of the body from fingers, hand or other places.

Like any biometric modality, ECG has some limitations which must be taken into consideration during the developing of the system. Started with ECG acquisition, different artifacts can affect the ECG signal in this step such as Electromyogram interference, Power-line interference, Baseline wander interference, Contact noise…etc. Compared with other biometric modalities, ECG takes more time on its acquisition which negatively affects the recognition rate of the system (Louis et al., 2014). Furthermore, the size of the ECG segment or the number of used ECG heartbeats segments must be reduced. The use of segmentation technique allows achieving an acceptable identification rate. Subsequently, it may have a significant influence on the cost. The nature of the ECG signal is also sensitive to diseases, diet, physical exercise, emotion and position of the electrodes.

4.5 ECG Biometric System Architecture

An ECG biometric recognition system can be divided into three main steps. Started with the preprocessing step, which aims to remove noises and the different artifacts that can face the ECG signal during the acquisition stage. Next step consists of extracting the representative set of points which can be used to identify users. After extracting the information from the input ECG signal, a matching with those signals exist in the database are performed in order to find the corresponding template. Figure 4.5.1 shows a global architecture for ECG recognition system.

4.5.1 Preprocessing Techniques for ECG Signals

In this step, the ECG signal obtained from different databases publicly available is frequency normalized using simple linear interpolation. The preprocessing step aims at reducing the noise from the ECG signal. Moreover, it removes various artifacts and improves the signal equality derived from muscular interference or more commonly from the power grid (50 Hz or 60 Hz). Various methods and filters can be exploited in the preprocessing step. These proposed methods work for the elimination of noises that can influence the acquisition of data.

There are different types of noises such as baseline wander which is appeared because of respiration. Electromyogram caused by muscles contractions. Other noises can affect the signal such as DC offset, power-line interference and high-frequency interference which has a relation with the country in which the ECG is collected. Contact noise which appeared because of electrode movements and baseline drift may impact the ECG signal (Louis et al., 2014). Many techniques, which they introduced to preprocess the ECG signals, were discussed in section 3.6. Figure 4.5.2 illustrates an example showing the difference between noised and preprocessed

ECG signal.

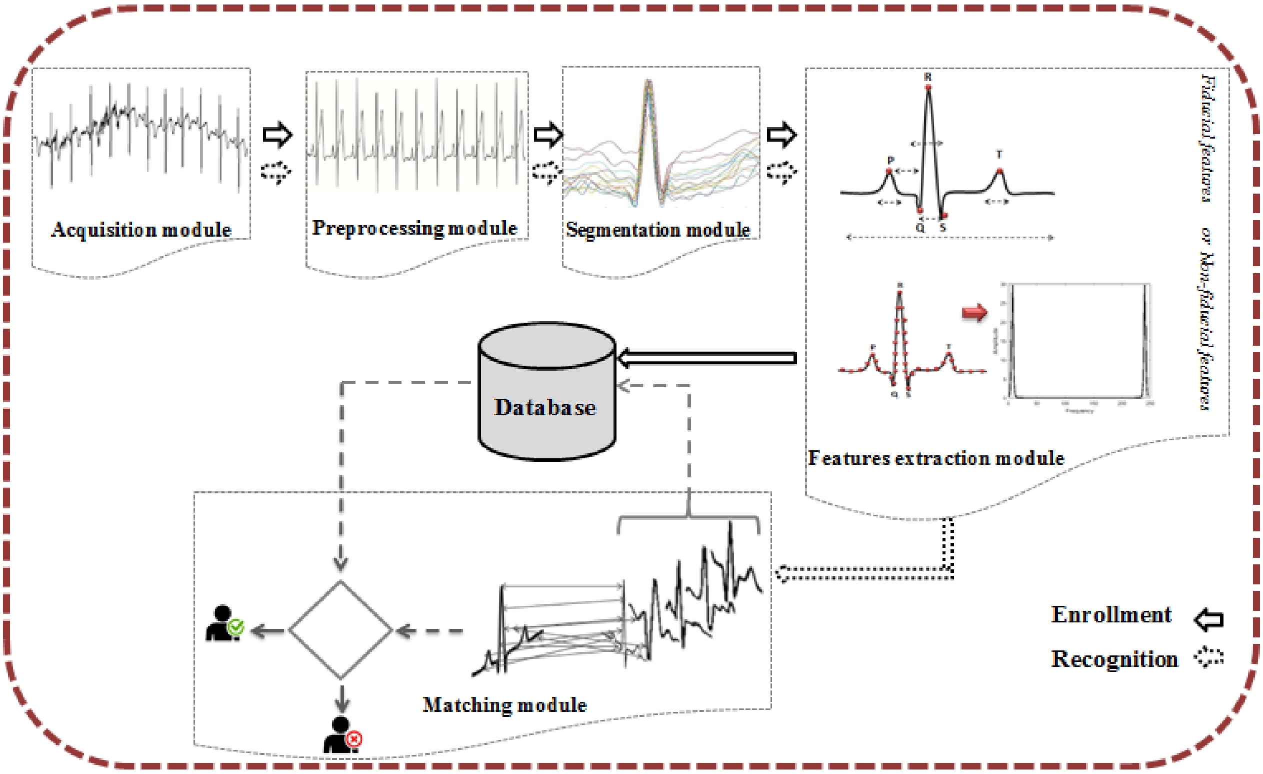

Figure 4.5.1: ECG recognition system based architecture (Lee and Kwak, 2019).

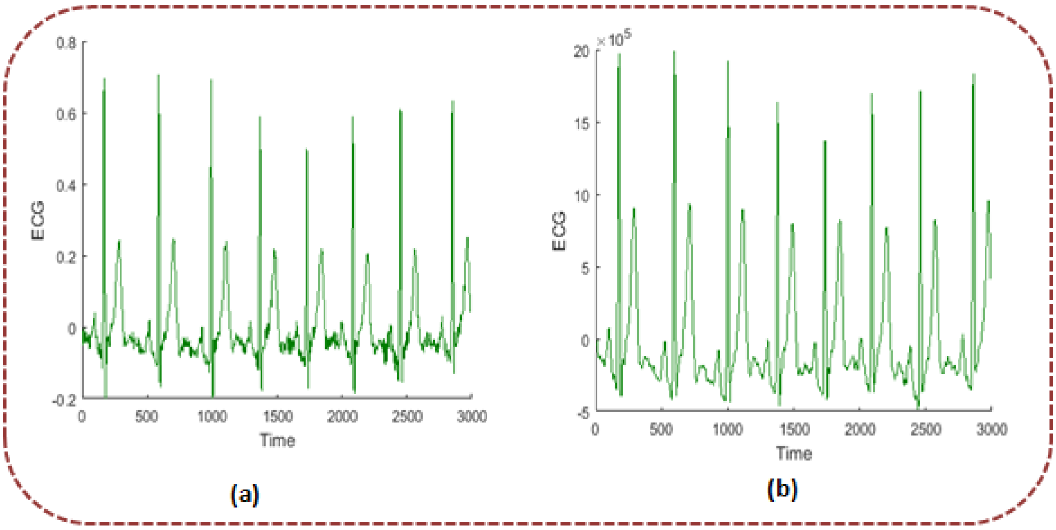

Figure 4.5.2: ECG signal before (a) and after preprocessing step (b).

4.5.2 Segmentation Module

The segmentation step is mostly used in the case of extracting non-fiducial features. Segmentation techniques based on extracting various fiducial points (QRS). Many algorithms were developed to detect QRS points. The most used technique is Pantompkin algorithm (Pan and Tompkins, 1985). These fiducial points were used to collect all heartbeats exist in the ECG signal. Based on the R peak which considered as the centre of the heartbeat, ECG heartbeat will be aligned by adding a set of samples for both left and right side of the R peak. Figure 4.5.3 shows the first sub-step of the segmentation technique which consists of detecting the R-peaks.

Segmentation step can be added to remove the noises that can affect the ECG signal due to the movement of electrodes as an example. Consequently, the use of heartbeats only improves the recognition rate. Some works didn't apply any segmentation techniques, they extract the features from the whole ECG signals (Biel et al., 2001; Bassiouni et al., 2018). On the other hand, some authors based segmenting the ECG signal and use all the detected heartbeats (Tseng et al., 2016) (Lee and Kwak, 2019)(Choi et al., 2019) whereas in other researches only a specific number of ECG heartbeats were used for recognition(Shen et al., 2002; Louis et al., 2014; Dar et al., 2015). The next figure 4.5.4 presents the alignment ECG heartbeat of a preprocessed ECG signal.

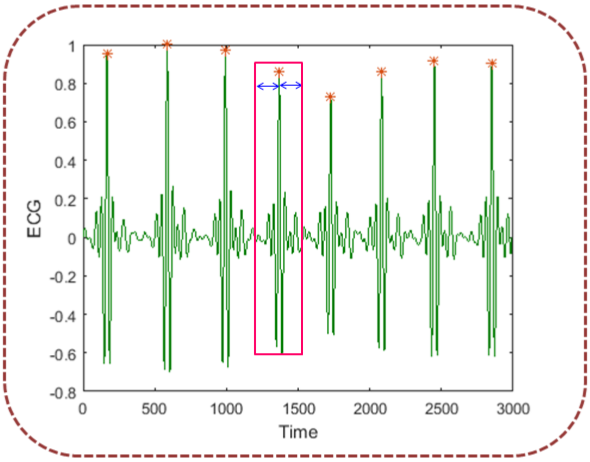

Figure 4.5.3: The detection of R-peaks using Pantompkin technique.

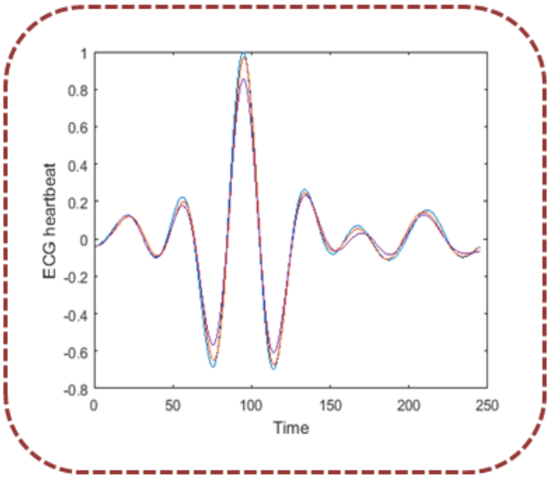

Figure 4.5.4: Alignment of the segmented ECG heartbeats based on the detected R-peaks.

4.5.3 Features Extraction from ECG Signals

Feature extraction step is considered the main important operation in the biometric recognition system. The extractor method depends on the biometric modality and the requirements of the system. In ECG recognition, we can extract 2 kinds of features which are fiducial points and non-fiducial points. Fiducial points referred to P-Q-R-S-T waves which are shown in figure 4.3.1. Based on these points, a set of features can be generated by computing the distance between these points. Various intervals will be produced such as RR interval, angles, amplitudes, durations, indexes . . . etc. Figure 4.5.5 shows the localization of the fiducial points on an ECG heartbeat segment.

Fiducial approach is the most used in the literature (Biel et al., 2001; Shen et al., 2002; Israel et al., 2005). Detecting the R peaks from ECG signal was the first step in localizing fiducial features. The ECG heartbeats can be easily aligned based on R peaks. Two methods could be applied to localize the remaining fiducial points either finding the maximum in the surrounding area (P and T) or with the radius of curvature. After the localization of these points, temporal distances between them can be computed.

The non-fiducial based approach extracts features from the whole ECG signal or ECG heartbeats segment in place of using some interest points. Many techniques can be applied to extract non-fiducial features (Louis et al., 2014; Chakraborty et al., 2016). In other works, holistic approaches based on the combination of fiducial and non-fiducial points were introduced (Dar et al., 2015).

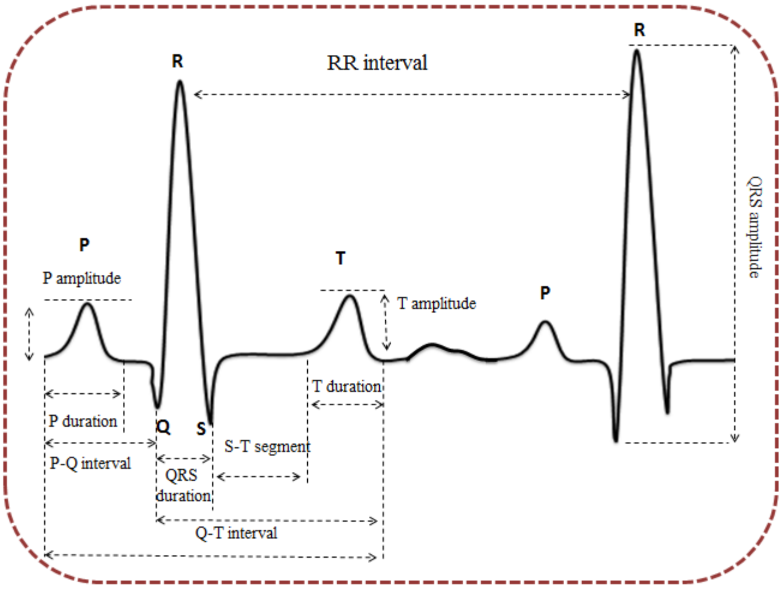

Figure 4.5.5: Fiducial features in ECG signal (Biel et al., 2001).

4.5.4 Matching

The matching step consists of classifying the input ECG signal with templates stored in the database. Many techniques can be applied in this step. The extracted points will be matched against those exist in the database and similarity values will be computed. The decision of whether the input ECG segment is a client or imposter was performed based on the computed similarity.

4.6 Literature Reviews

In recent years, ECG has gained much attention in the biometric recognition domain due to its different advantages discussed in section 3.4. A new approach was proposed in (Biel et al., 2001). They have proposed a new approach by using 12- electrocardiogram leads (six limb leads and six chest leads) recorded for human identification where it was carried out on ECG-ID database. ECG measurements were collected from 20 subjects including both men and women in the experiments. Each individual has four to ten records. Fiducial features mainly capture the holistic patterns from the ECG waveform signal and may be represented as the distances, amplitudes and angle deviation and so on.

In this works, 30 temporal features were extracted from the analyzed ECG including PQRST wave onset, amplitude, wave duration, wave deflection, wave morphology, wave area . . . etc. Each subject has 30 features for each lead. So, 360 features (30*12) will be achieved per subject for identification. Authors propose the use of one lead in order to reduce data. The experiments have been shown that there is no difference between using limb leads or chest leads. While the variation in positioning of the chest electrodes has a negative influence on the collected ECG records, the limp electrodes have been used. Moreover, the limp electrodes are easier to attach them compared to the chest leads. Applying this reduction decreases the size of features to 180. To obtain more optimal results, the correlation matrix is computed again in order to reduce and remove features have a high correlation with other features. Finally, a number of 12 features were achieved. For matching, Soft Independent Modeling of Class Analogy (SIMCA) was applied. The experimental results demonstrate the possibility of identifying a person using features extracted from only one lead achieving a recognition rate of 98%.

An ECG biometric verification and identification system was developed by Wübbeler et al (Wübbeler et al., 2007) based on fiducial features. The developed work aims at studying the long-term stability of the individual ECGs. In the preprocessing step, a moving median of 1 s width was applied on the three ECG recorded with a length of 10s for each one. Another preprocessed technique was applied. It consists of using a low-pass filter with a cut-off frequency of 75 Hz. Next step consists of heartbeat segmentation based on the localization of R-peaks. A low-pass filtered based on threshold procedure was applied for each ECG signal in order to determine the R-peaks. The identification and verification were performed based on ECG characteristics by computing the distance measure between the ECGs. This is based on the evolution of the corresponding heart vectors during the QRS interval. ECG-ID database was used for testing and validating the proposed approaches. An EER of 2.8% was achieved for verification mode and a recognition rate of 98% was achieved for identification mode.

An ECG based human identification system using random forests was introduced (Belgacem et al., 2013). Adaptive Filters were applied to remove the different kinds of noises and artifacts faced during the acquisition of ECG signal beside to select its heartbeats. The averaged of the first 100 segmented heartbeats from each ECG signal has been computed. Then, DWT technique was applied on these ECG heartbeats to extract the coefficients which will be considered as features in the next step. Random Forest was proposed in this work for the matching step and as a measure of identification. The developed system was carried out on four benchmarks databases named MIT-BIH, ST-T, NSR and PTB. Beside these benchmark databases, authors validate their achieved results with their own database. The introduced ECG database was collected from 40 students and staff at Paris Est University.

1D-MR-LBP technique was proposed for the purpose of extracting regular ECG waveforms (Louis et al., 2014). In the preprocessing step, working on reducing baseline wander, higher frequencies of power line interferences and edge effects by applying the fourth-order band-pass Butterworth filter with cutoff frequencies of 1-40Hz and a low order filter. The segmentation step consists of the detection of QRS waves. Then, ECG heartbeats are aligned with their R peaks. Each heartbeat was centred with the detected R peak with length duration of 1 second. For features extraction, a novel method named 1D-MR-LBP was introduced. The main objective of using this method is to detect the regular and irregular ECG heartbeats which represent healthy and non-healthy ECG heartbeats, respectively.

The experimental results prove the efficiency of 1D-MR-LBP on tolerating noise, discovering local and global features and preserving the morphology of ECG heartbeats. For matching, SVM and Bootstrap Aggregating (bagging) with a decision tree are applied. The extracted regular ECG waveforms are passed through to a biometric system and the irregular ECG waveforms are filtered out. The proposed approach is validated using PTB benchmark database. An EER and accuracy of 0.09% and 91% respectively were obtained which demonstrates the ability of 1D-MR-LBP technique of extracting high discriminants features which allow distinguishing between regular and irregular ECG heartbeat correctly.

DWT of the cardiac cycle and Heart Rate Variability (HRV) based features were proposed for the purpose of developing an ECG recognition system (Dar et al., 2015). Curve fitting was applied with 6th order polynomial to preprocess the ECG signals and make the detection of R-peaks easier. ECG signal was detruded in order to remove DC baseline wandering followed by normalization. Kubios HRV analysis software technique was applied to remove HRV artifacts. A simple technique based on local maxima and thresholding was used to detect R-peaks. Then, based on localized R-peaks, ECG heartbeats were segmented. Only 25 heartbeats were extracted for each subject.

Another technique named Interquartile Ranges (IQR) was applied to remove extreme values. Next step consists of extracting discriminating features from each beat based on DWT algorithm. A technique of reduction called Greedy Best First Search (BFS) is introduced to select features which are highly correlated and belong to the same class and in the same time having a less inter-class correlation. The developed system was validated using publicly available databases like MIT-BIH/Arrhythmia, MIT-BIH/Normal Sinus Rhythm (NSR) and ECG-ID database including all subjects. Random Forests technique was applied for the classification stage achieving an accuracy of 100% using MIT-BIH/NSR database and 83.88% for a challenging ECG-ID database.

A single pulse ECG was used for authentication assuming that there is no access to other ECG signals (Chun, 2016). For the enrollment phase, a guided filter (GF) method was applied to reduce the noise of a single ECG pulse. In the preprocessing step, while ECG can be suffered from several types of noise, different preprocessed techniques were adopted. Wavelet drift correction was applied for baseline wander, adaptive band-stop filter for power-line interference and low-pass filter and smoothing for high-frequency noise. The R-peaks were detected based on both Pan-Tompkin algorithm and matched filter. Two simple similarity measures, Euclidean distance and DWT, between the enrolled ECG and the input signal were computed that they may be applicable to both small scale and large scale authentication systems. A comparison with PCA based authentication system was performed achieving an EER of 2.4%. GF with Euclidean distance and DTW demonstrate that it is a robust ECG denoising method for improving the performance of an authentication system.

Another work was presented by (Bassiouni et al., 2018) for the purpose of developing an ECG biometric identification system. Wavelet decomposition (DWT) was applied to the preprocessing step in order to correct the base-line drift noise. High-frequency noise was removed by using a low-pass Butterworth filter. The last sub-step consists of smoothing the ECG signal. For the features extraction step, three approaches have been exploited. The first non-fiducial approach is applied the Auto-Correlation/Discrete Cosine Transform (AC/DCT) on the preprocessed ECG signal. The purpose of using DCT is to reduce the dimensionality of the produced features.

The second approach was based on fiducial features involving duration, amplitude differences, along with angles between (PQRST...). Thus, fiducial points (QRS, P-QRS, QRS-T and P-QRS-T) were detected. A final sub-step in the second approach consists of selecting discriminant fragments, based on a set of conditions, which provide robust and representative information that can be used for recognition. The third approach fused both the P-QRS-T fragments and ECG features decomposed by the wavelet transform as a unique feature. Three different types of classifiers SVM, ANN and KNN were used to generate the much score used for identification. Data were acquired from ECG-ID and MIT-BIH Arrhythmia databases. Reported total classification accuracy of 98% and 100% was achieved for ECG-ID and MIT-BIH databases, respectively.

4.7 ECG Databases

Some databases are available for ECG analysis. While ECG has used largely for medical domain, especially for diagnostic and detection of cardiac pathologies, the most available database may not be useful for biometric. In the case of biometric ECG databases, the need for multiple acquisitions in different timestamps for each subject was required. This allows evaluating and testing the developed ECG recognition system. A large number of users that make the experimental results more reliable are needed. Furthermore, the morphology of the ECG signal can be affected by emotion (happiness, angry, scare...etc), Exercises and physical stress, diet and others. For these reasons, ECG signals must be collected in different environments (Louis et al., 2014). Many researchers have used their own ECG databases. In our day, because the

ECG has been used successfully in the biometric domain, some databases are available and can be exploited for biometric.

4.7.1 PTB Database

The Physikalisch Technische Bundesanstalt (PTB) database collects ECG data from 290 healthy and non-healthy subjects for medical diagnosis. It is a publicly available database. A total of 549 records were acquired from 209 men and 81 women (Bousseljot et al., 1995). The ages range from 17 to 87 years. Each subject has at least one to five records maximum. PTB database uses 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) besides to 3 Frank lead ECGs. The collected ECG signals were sampled at 1KH with Resolution of 16 bit with 0.5 µV/LSB and duration between 2 to 3 minutes. This database includes header files contained detailed information for 268 subjects such as gender, age, diagnosis, data on medical history and other information. PTB database has 52 healthy persons and 216 non-healthy. The most cardiac pathology that non-healthy persons suffered from it was Myocardial infarction. Some signals of the database are shown in Figure 4.7.1.

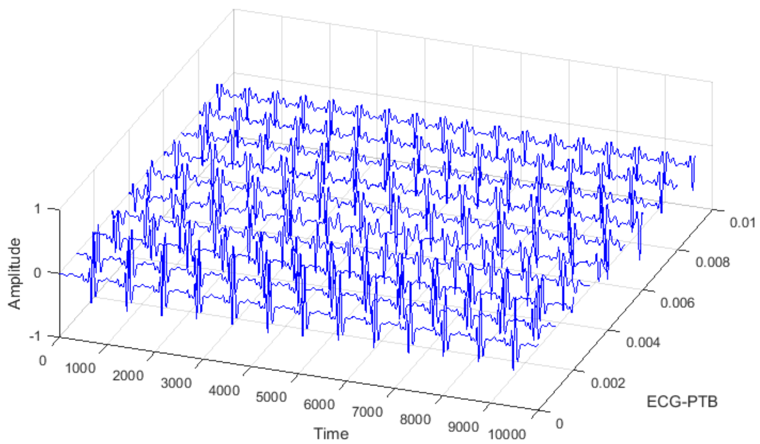

Figure 4.7.1: Signals samples from PTB database (Bousseljot et al., 1995).

4.7.2 MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database (MIT-BIH-A) was created from laboratories at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Centre) and at MIT (Moody and Mark, 2001). MIT-BIH-A was used firstly for the purpose of evaluating the arrhythmia detectors and for basic research into cardiac dynamics. It contains 47 subjects. Each record was digitized at 360 samples per second per channel. The resolution is 11-bit over a 10 mV range. A detailed file was created by two or more cardiologists which offer various information attached to each record including date of registration, age, gender and prescribed medications. Some signals of the database are shown in Figure 4.7.2.

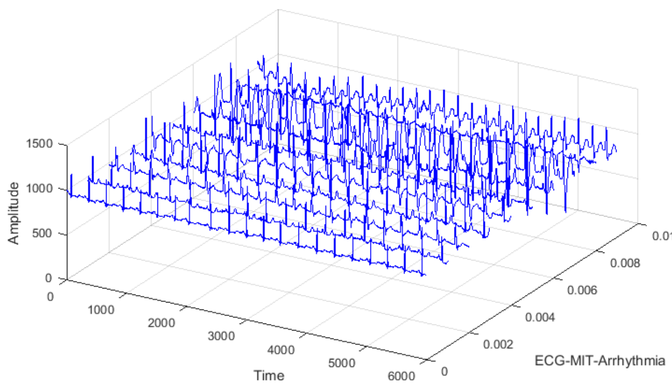

Figure 4.7.2: Signals example from MIT-BIH-A (Moody and Mark, 2001).

4.7.3 INCART Database

This database collects ECG data from patients undergoing tests for coronary artery disease. INCART public database created by the St-Petersburg Institute of Cardiological Technics (INCART) and it is available online (Goldberger et al., 2000). This database contains 75 annotated recordings extracted from 32 Holter records. 12 standard leads were attached. Each record was digitized and sampled at 257 Hz with duration of 30 minutes. The ages range from 18 to 80 years including 17 men and 15 women with a mean age of 58.

Different cardiac ECG problems have been included focusing on individuals who have ECGs with ischemia, coronary artery disease, conduction abnormalities and arrhythmias. Header files have been included. It contains the patient's age, sex, diagnoses, a summary of features of the ECG and a patient number (1–32) that identifie the source recording. Some signals of the database are shown in Figure 4.7.3.

4.7.4 Normal Sinus Rhythm Database

MIT-BIH Normal Sinus Rhythm Database (NSR) contains different long-term ECG recordings from 18 subjects (Goldberger et al., 2000). This dataset has been used in many studies focusing on different problems. One record for each of 18 healthy persons was required for about 20 hours referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital. The included subjects have a regular rhythm at a rate of 60-100 bpm, no diagnosed cardiac abnormalities, with beat annotations. Some signals of the database are shown in Figure 4.7.4.

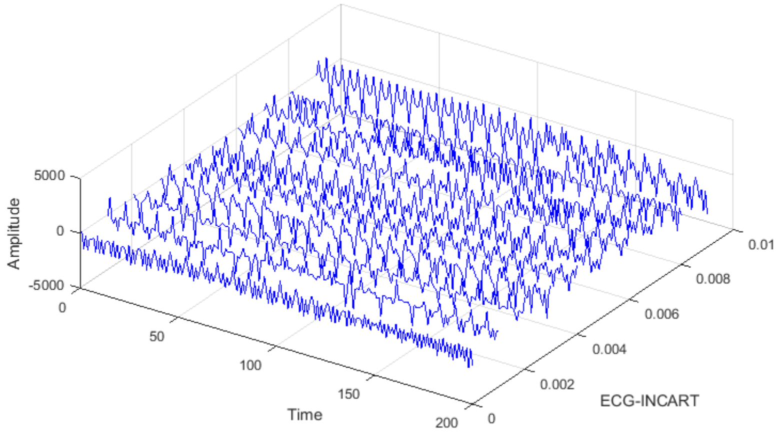

Figure 4.7.3: Some signals from INCART database (Goldberger et al., 2000).

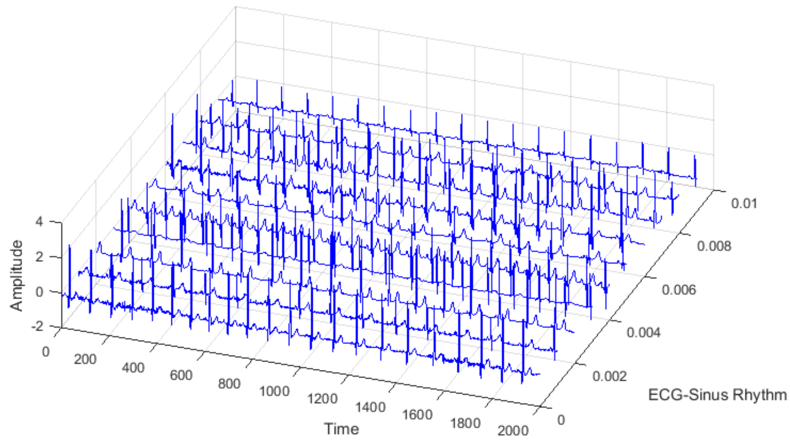

Figure 4.7.4: Some signals samples from NSR database (Goldberger et al., 2000).

4.7.5 ECG-ID Database

ECG-ID database contains different ECG signals from 90 subjects. This database contains 310 ECG recordings where each subject has at least two records and at most 20 records (Lugovaya, 2005). ECG data were collected from students, colleagues and friends of the author. The ages range from 13 to 75 years from 44 men and 46 women. ECG-ID database uses ECG lead I, recorded for 20 seconds. The resolution is 12-bit over a nominal ±10 mV range. ECG recordings were digitized at 500 Hz. ECG recordings includ both noisy and filtered ECG signals. Header files were added to the database containing age, gender and recording date. Some signals of the database are shown in Figure 4.7.5.

4.7.6 QT Database

QT database contains more than 105 two-leads ECG recordings. Each ECG record has duration of 15 minutes (Zhang et al., 2005). The most used recordings are excerpted from other databases. This database includes onset, peak and end markers for P, QRS, T and U waves from 30 to 50 selected beats in each recording. Each record was presented by a header file, a signal file and up to 9 annotation files. Figure 4.7.6 shows some signal obtained from QT database.

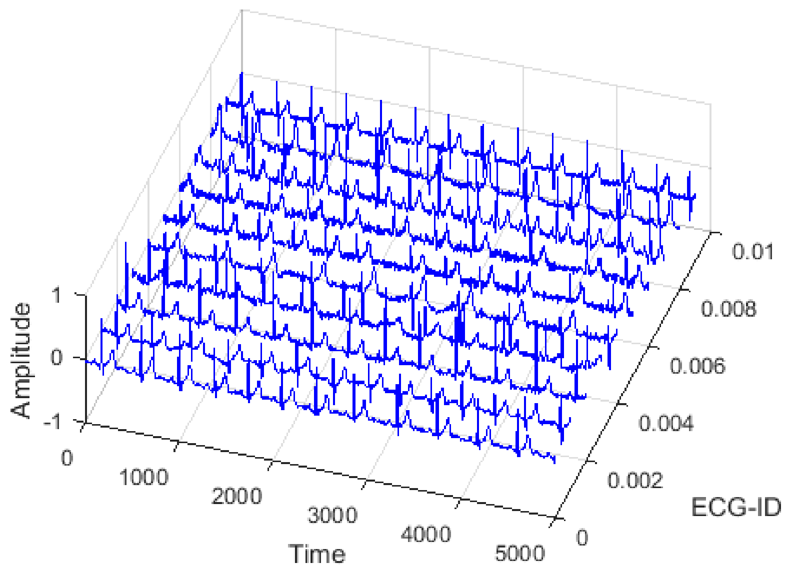

Figure 4.7.5: Some signals obtained from ECG-ID database (Lugovaya, 2005).

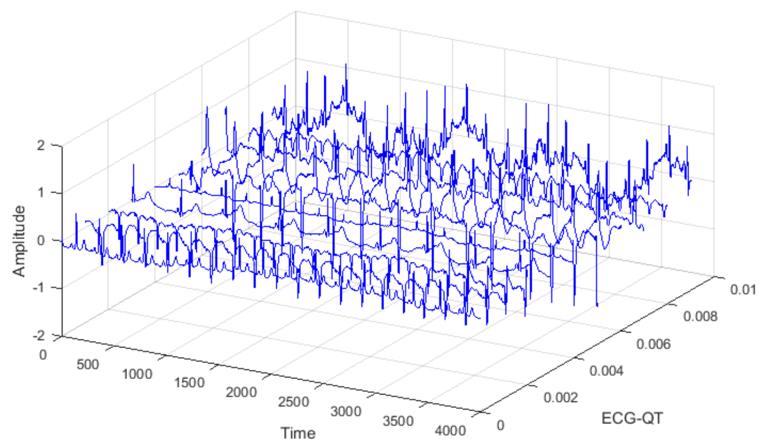

Figure 4.7.6: Example signals from QT database (Zhang et al., 2005).

4.8 ECG in Multimodal Systems

In recent years, ECG has gained many attentions. Fiducial and non-fiducial features have been extracted. Table 4.1 presents some important studies in this field. In can be seen that in the first proposed ECG recognition systems, only fiducial points were used for identification. Lately, researchers turn out to non-fiducial points. They proved its efficiency and robustness. Hybrid approaches were also introduced which combine both fiducial and non-fiducial features. Because the ECG databases are limited, most studies use their own database for test and validation. The accuracy of the developed ECG systems have reached to 100%.

The various strengths of ECG biometric motivated researchers to combine these advantages with other biometric modalities. Implementation of a multimodal system by (Al-Hamdani et al., 2013) is proposed combining three modalities at score level fusion. this system aims to reach a higher security level. Fusion of speech, ECG and phonocardiography (PCG) with sum score fusion is performed.

Fusion of fiducial features (peaks) from the first lead (I) of the electrocardiogram (ECG) with spectrum features from six different bands of the electroencephalogram (EEG) was introduced. This fusion has a goal of constructing a robust and secure multimodal biometric recognition system (Barra et al., 2017). The extracted fiducial points from ECG signal will be combined with spectrum features of the EEG. Based on simple peak detection method, the local minima and local maxima from a given signal were selected. The fusion step was performed based on sum, product and weighted sum operators. Then, Euclidean Norm Distance was applied to match the fused features. An ERR of 0.93 was achieved .

Face and ECG are incorporated for based authentication system. The same process was followed for both biometric modalities (Chakraborty et al., 2016). As regards the ECG, three consecutive R peak as extracted from the normalized ECG signal by the square derivative-based method. Then, ECG shape was computed from shape response function. For the side of face, many techniques are applied based on edge detector. Next, face shape was calculated from shape response function in order to extract the representative features that can be used for authentication. On Feature level fusion, the extracted features from both preprocessed face and ECG have been concatenated into a new signature template. The last step consists of matching the fused template with templates existed in the database using the mean square deviation algorithm. An accuracy of 97.5% was obtained.

Table 4.1: A comparison of some of the existed ECG recognition systems.

Authors	Extraction method	Database	Subj	CRR
(Biel et al., 2001)	Fiducial features	Own	20	98
(Shen et al., 2002)	Fiducial features + DBNN	MIT-BIH-A	20	100
(Lee et al., 2005)	Fiducial features	Own	10	#
(Israel et al., 2005)	Fiducial features	Own	29	98
(Plataniotis et al., 2006)	Non fiducial features (AC + DCT)	PTB	14	100
(Wübbeler et al., 2007)	Fiducial features	PTB	74	98.1
(Wang et al., 2007)	AC+DCT	PTB	13	94.47
		MIT-BIH-A	13	97.8
(Singh and Gupta, 2008)	Fiducial features	QT	25	99
(Chan et al., 2008)	Non-fiducial features (Signal Averaged (SAECG))	Own	50	90.8
(Coutinho et al., 2010)	Non-fiducial features (Ziv-Merhav Cross Parsing (ZMCP))	Own	19	100
(Safie et al., 2011)	Non-fiducial features (Pulse Active Ratio (PAR))	PTB	112	#
(Chen and Yu, 2012)	Non-fiducial features (Nonlinear Correlation-Based filters using Symmetrical Uncertainty (NCBFSUs))	MIT-BIH-A	15	97
(Yen et al., 2013)	Non-fiducial features (DWT + fiducial features)	MIT-BIH-A	15	98.34
(Louis et al., 2014)	Non-fiducial features (1D-MR-LBP)	PTB	290	91
(Dar et al., 2015)	Non-fiducial features (DWT + HRV)	ECG-ID	90	83.88
		MIT-BIH-A	47	95.85
		MIT-BIH-NSR	18	100
(Tseng et al., 2016)	Hybrid (Fiducial +non fiducial features using Local Statistical Feature)	PTB	38	97.6
		MIT-BIH-NSR	18	100
(Dalila et al., 2017)	Non-fiducial features (AC/DCT)	ST-T	32	100
		MIT-BIH-A	47	75
(Bassiouni et al., 2018)	Non-fiducial features (AC/DCT) + fiducial features	ECG-ID	90	99
		MIT-BIH-A	47	100
(Choi et al., 2019)	Non-fiducial features (2D Resized Spectrograms)	Own	100	93
(Lee and Kwak, 2019)	Non-fiducial features (robust PCA network (RPCANet))	PTB	290	99
		CU-ECG	100	98.25

Another multimodal authentication system was developed in (Derawi and Voitenko, 2014) based ECG and gait biometric at score level fusion. A wireless ECG sensor was used to collect ECG signals based on two led ECG signals attached on the breast. The same techniques were applied for both modalities with some modification. A linear time interpolation algorithm was applied to obtain a linear observation. Then, the average cycle length is computed. The next step applied a Dynamic Time Warping (DTW) to remove cycles that are very different from the others. Before the fusion data, score normalization technique was used to map the achieved scores of ECG and gait biometric into one common domain. Simple Sum, Minimum Score and User Weighting fusion techniques were applied. An EER of 1.26% was achieved based on Simple Sum fusion technique.

To enhance the advantages for ECG and fingerprints biometric, hence minimizing their weakness, a multimodal authentication system fusing both modalities was proposed in (Arteaga-Falconi et al., 2018). For ECG signal, they extract eight fiducial features from segmented ECG heartbeat. The extracted features represent the distance in time between peaks and valleys and amplitudes distances. The SVM classifier was applied for matching. MINDTCT algorithm was used to extract the minutiae of the normalized fingerprint. Then, a score value was generated applying BOZORTH algorithm. Fusion at the decision level was performed. An EER of 0.46% was achieved.

4.9 Conclusion

With the great security requirement that the system needs nowadays, the search for ideal biometric traits that prevent imposter from accessing the system is still in progress. ECG is now one of the most biometric modalities that researchers are trying through to find radical solutions to this kind of problems. The uniqueness and the liveness measurement of the ECG signal make it hard to spoof.

In this chapter, we have been explained carefully the effectiveness of ECG biometric that can make it a robust biometric trait based on discussing the different ECG strengths and drawbacks. The architecture of ECG recognition system was presented explaining each module separately. The main important module is the extraction of representative traits from the preprocessed ECG signal. It can be distinguished two approaches namely fiducial and non-fiducial features. Whilst the former based on the local trait of the heartbeat, the latter based on the overall morphology of ECG trace. In the first proposed systems, the fiducial approach was widely used. Fiducial points can be easily affected by noise and artifacts, inverted or abnormal waves or signal slopes. For these reasons, recently researchers focus on the second approach. Many techniques have been proposed and applied to extract non-fiducial points of a preprocessed ECG signal.

We have also referred to some of the existent ECG-based recognition systems. Based on the achieved results that have been obtained with ECG biometric, it had been also combined with other modalities developing multimodal biometric recognition systems. Depending on all these strengths, we have chosen ECG as the main biometric modality in our proposed recognition systems.

CHAPTER 5

Iris BIOMETRIC

5.1 Introduction

With the uniqueness and robustness that can be found in the iris in the purpose of identifying or verifying human identities, iris recognition expected to become a fundamental component of modern society. In this chapter, we will present an introduction to iris recognition. In the first section, a definition of iris will be introduced including a brief history. Then, the anatomy of the human eye will be explained. The different strengths besides the encountered challenges of an iris-based biometric system will be detailed in section 4. Section 5 consists of listing some of the existed iris applications. The whole architecture of an iris-based recognition system will be presented and detailed in the next section. After that, we will discuss some of the related works. The most used iris benchmark databases will be explained in section 8. We conclude the chapter by presenting some of the multimodal biometric systems which combine iris with other biometric modalities.

5.2 Iris as Biometric

Biometric is largely used in recognition systems for the purpose of authentication or identification. Nowadays, the developed countries use biometric for recognition in their authentication systems, in many domains such as banks, airport, hospital and forensic.They have the goal of ensuring more security and robustness. Besides that, there is no biometric reliable at 100%, a lot of modalities were proposed and tested aiming at exploiting the different advantages and solving the existed challenges for each modality.

Iris of the eye is one of the firstly proposed modalities; it received great interest from researchers. Furthermore, Iris has been used in several critical applications. In 1936, the ophthalmologist Frank Burch proposes the use of iris in recognition system. A year later, John Daugman was the pioneer in this field. He developed the first iris-based identification method called Iriscode (Benaliouche, 2018). Iris presents an important texture, significant information, variability, stability and uniqueness. So, many researches were introduced where most of these works based on Daugman's method. Daugman algorithm has been tested under numerous studies with a failure rate of 0% in the most cases. Its experimental results demonstrate the reliability of iris authentication system. Typical iris recognition system consists mainly on image acquisition, localization, preprocessing, features extraction and matching stages which they will be detailed clearly in section 6.

5.3 Iris Anatomy

Iris defined as an annular part located between the pupil and the sclera region. Iris takes its final form before a few months from the birth of a person. The different parts exist in the coloured circle that surrounds the pupil of each eye generate random patterns which are unique for each individual. Ophthalmologists propose the use of iris for identification or authentication based on its clinical reports and experiences. They prove that iris has a highly detailed and discriminant traits. These unique textures are stable and still unchanged in clinical photographs which spanning decades (Daugman, 1993). Besides that, the phenotypic expression of two irises has uncorrelated textures even if they had the same genetic genotype or in the case of iris of the same subject.

Many idiosyncratic features could be distinguished from a captured eye image. The main important components that could be noted are eyelashes, eyelid, sclera, iris and pupil. Iris component differentiates between pupil and sclera. A set of patterns can be detected and used as robust features for recognition such as freckles, furrows, ridges, corona, serpentine vasculature, fibers, rings, rifts. Figure 5.3.1 shows the important parts of the eye image.

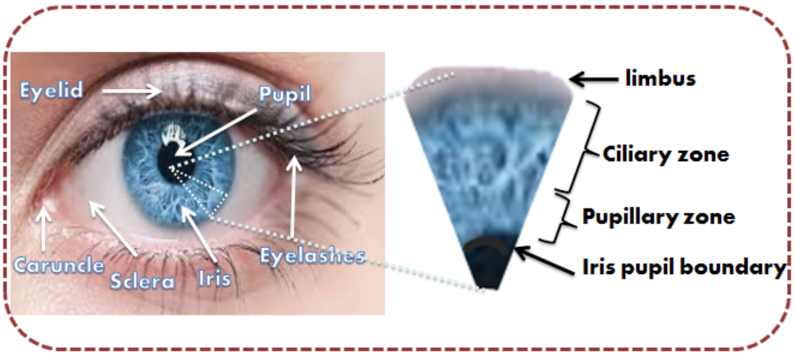

Figure 5.3.1: Anatomy of iris (Jain et al., 2011).

5.4 Advantages and Challenges

Iris is one of the first biometric modalities that were used for recognition. It has unique stable traits according to the lifetime of a person. Iris as biometric was demonstrating its efficiency by producing rich and distinctive information. It possesses a robust and stable structure which make it hard to mimic. Furthermore, iris rarely suffers from damage. Since the report introduced by Daugman, many researchers were highly exploited the uniqueness of human iris in various domains based on Daugman's algorithm (Bowyer and Burge, 2016). Its research consists of using 632 500 different iris images, spanning 152 nationalities. The Daugman algorithm can achieve a false match rate of less than 1 in 200 billion. Like other biometric modalities, Iris suffers from some problems.

- One such research problem is the use of contact lenses and their effects on iris recognition accuracy. Daugman proposes an algorithm which allows verifying whether or not a person is wearing a cosmetic contact lens that obscures the natural iris texture. This problem could decrease the accuracy of the iris recognition system. Iris images [1] with contact lenses were illustrated in figure 5.4.1.

Figure 5.4.1: Example iris images exhibiting texture from a cosmetic contact lens.

- Another problem can be faced caused by accidents which could be able to damage the shape of the whole eye especially the iris region. From figure 5.4.2, it can be noticed that the shape of iris doesn't take a circular shape which provokes a failure of segmentation of iris from the eye image [2].

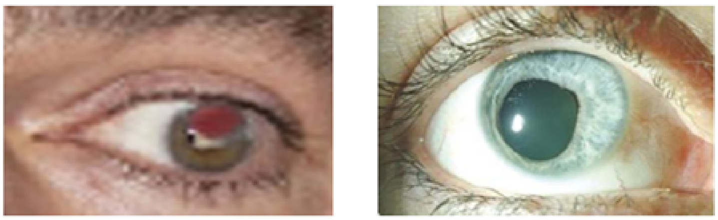

Figure 5.4.2: Example iris images showing accidental damage that destroys its shape.

[1] https://en.wikiquote.org/wiki/I_Origins
[2] https://www.wjgnet.com/2218-6239/full/v4/i1/WJO-4-1-g001.htm

There are several eye conditions that obstruct the iris identification or authentication system and in particular, the segmentation step which considered a crucial operation in iris recognition system (Bowyer and Burge, 2016). A set of eye conditions examples with its influence on the developed system are listed below:

- In rare cases, the remains of a fetal membrane can still appear in the eye. This type of condition, called persistent pupillary membrane, has no effect on the person's sight. But, it can make the segmentation step more difficult. Figure 5.4.3 presents an example of two irises having this kind of condition [3].

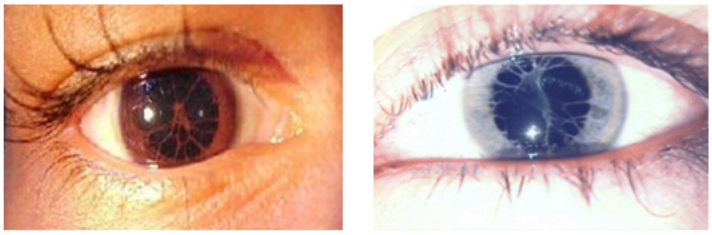

Figure 5.4.3: Example iris image illustrating effects of persistent pupillary membrane.

- There are other problems for eye conditions that strongly decrease the efficiency of iris segmentation algorithms. One of them was illustrated in figure 5.4.4 which showing a dense cataract in the pupil region causing a catastrophic segmentation failure [4].

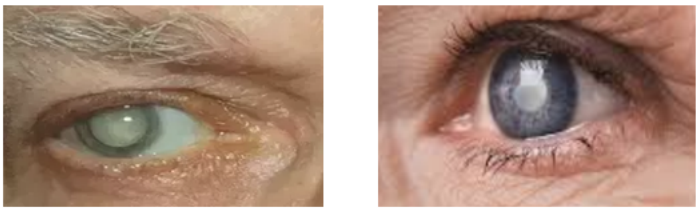

Figure 5.4.4: Example iris image having a dense cataract in the pupil region.

- Another eye condition could make the iris segmentation impossible referred to corneal disease impacting the pupil region. Figure 5.4.5 shows this type of eye condition [5].

[3] https://www.studyblue.com/notes/note/n/pathology-eye-terms/deck/6428079

[4] https://www.slideshare.net/sunnymumu/cataract-easy-ppt-for-nursing-students

[5] https://www.researchgate.net/publication/7214271_Toxic_anterior_segment_syndrome/figures?lo=1

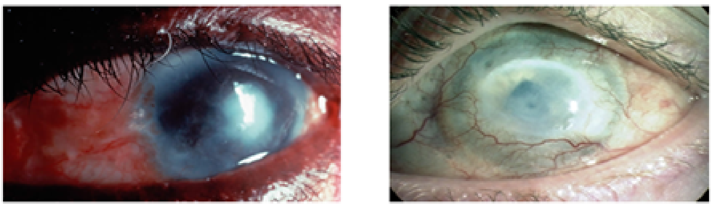

Figure 5.4.5: Example iris image having a dense cataract in the pupil region.

5.5 Iris Applications

The achieved results of many reports were encouraging iris to become an indispensable tool for many high-security applications (Manasa et al., 2014). Patterns extracted from human iris have an abundance of invariance. Moreover, iris biometric presents reliable and unique information compared with DNA. These strengths made from iris a good choice for an authentication system in a corporate or enterprise environment. It also exploited in several public applications in various fields especially in the e-commerce, the core of banking, government and forensics.

The United Arab Emirates (UAE) launches Homeland Security Border Control system. This system includes over 330,000 persons. All foreign nationals who need a visit visa to enter the UAE are enrolled (Daugman, 2006). The government of India develops an iris-based identification system named AADHAAR, which means 'foundation' in Hindi, has adopted iris recognition. This system includes 1.2 billion individuals with a rate of around 99% of the adult population are enrolled (Manasa et al., 2014). Another iris-based recognition system was exploited by Hashemite Kingdom of Jordan. This government introduced the first ATM on the world based on iris biometric. Individuals don't provide a bank card or pin. They must just present their eye to the iris recognition camera on the ATM.

In our day, the human iris was largely used and exploited in many countries such as Mobile Offender Recognition and Information System for police forces across America, Restricted Area Identity Card (RAIC) program in Canada, an "Iris on the Move" system for U.S. Government clients. Recently, Microsoft produces two Lumia phones using iris-based authentication (Wikipedia contributors, 2018). World Food Program (WFP) started to deploy iris recognition in its food distribution system for the first time in Uganda.

5.6 Iris based Recognition System

The various strengths of iris biometric make it an attractive modality in several fields. A height recognition rate was achieved in most developed researches. In general, the iris recognition system can be divided into four main modules: image acquisition, preprocessing including segmentation and normalization, features extraction and matching stages. Figure 5.6.1 shows a simple architecture of iris-based recognition system.

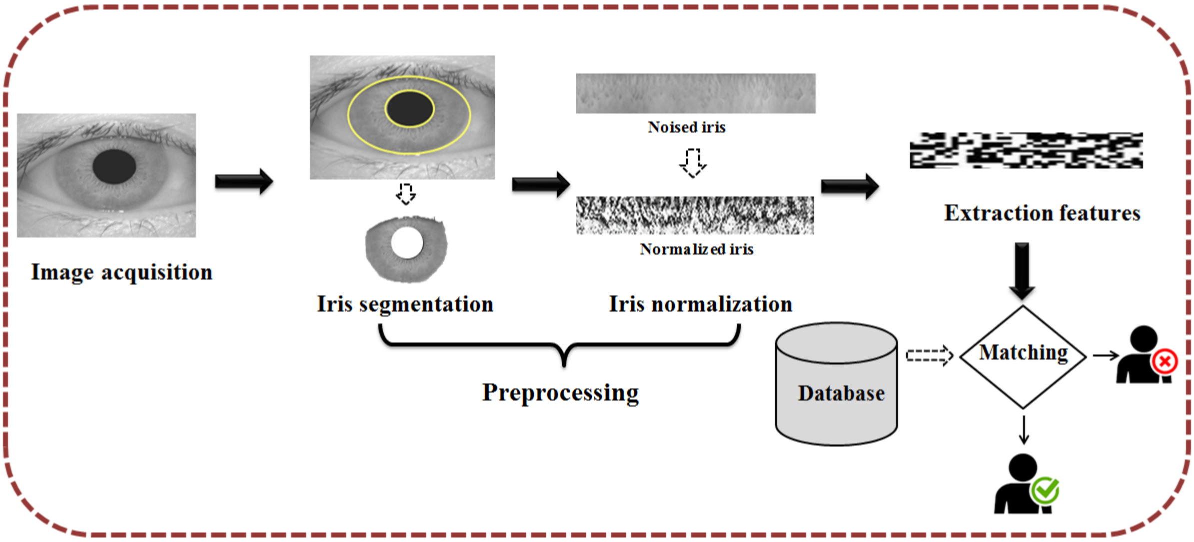

Figure 5.6.1: The architecture of iris based recognition system (Barpanda et al., 2018).

5.6.1 Preprocessing Step

5.6.1.1 Segmentation

In this step, the detection of the iris was performed by locating two circles on the eye image. One consists of isolating the iris from the sclera. The second circle, which is located within the first circle, corresponds to separate the pupil region. There are many artifacts making iris segmentation more difficult and can decrease the robustness and the efficiency of the proposed segmentation algorithm. Besides the differences challenges detailed in section 4 related to contact lenses and eye conditions, specular reflections can also occur within the iris region corrupting the iris pattern. Furthermore, the eyelids and eyelashes can, in many cases, occlude some parts of the iris region. The quality of the acquired eye images has also an influence on the applied segmentation technique.

The segmentation step is a crucial and critical phase on the CRR of the developed iris-based recognition system. Some of the techniques mostly used for iris segmentation and have been achieved a successful result, there are Integro-differential Operator, Hough Transform, Active Contour Models and Eyelash and Noise Detection (Masek et al., 2003).(Daugman, 1993) developed an Integro-differential Operator algorithm which allows the location of the circular iris, pupil regions and the arcs of the upper and lower eyelids. (Ritter et al., 1999) propose Active Contour Models which allows the location of the pupil region.

(Wildes et al., 1994; Masek et al., 2003)and others employ Circular Hough Transform (CHT) technique for an automated segmentation algorithm in order to detect the iris and pupil boundaries.

5.6.1.2 Normalization

The human eye can face variations of illumination during the acquisition phase. These variations have a relation with the rotation of the camera, head tilt, rotation of the eye within the eye socket and also the imaging distance which causes a pupil dilation of the eye. Consequently, the segmented iris images will have different sizes and dimensions. The normalization step consists of solving this problem by fixing all segmented iris regions on the same size in order to allow comparisons. In other words, the circular segmented iris was transformed from cartesian coordinates into a fixed rectangular image size which means using a polar representation. This step aims at minimizing the difference between two iris images of the same subject and maximizing the similarity between them even if they are captured under different conditions.

Many techniques were proposed in the literature. The first algorithm was proposed by Daugman named Daugman's Rubber Sheet Model (Daugman, 1993) which based on remapping each point within the iris region to a pair of polar coordinates. This model takes into consideration the problem of pupil dilation and non-concentric pupil displacement. Another method called Image Registration was introduced by (Wildes et al., 1994). This technique is based on aligning the input iris image with a selected template from the database. (Boles, 1998) developed a normalization technique, called Virtual Circles, where scaling is at match time and is relative to the comparing iris region.

5.6.2 Features Extraction

Iris biometric possesses rich and unique information that can be used to identify persons. In an iris-based recognition system and after the preprocessing step where the iris was segmented and normalized. The next step consists of extracting the discriminant textures that can be used for identification or verification. Several studies have proposed on this stage such as Gabor Filters which was introduced firstly by Daugman, different Wavelet techniques, LBP and SIFT (Manasa et al., 2014; He et al., 2011; Hamouchene and Aouat, 2016).

5.6.3 Matching

The matching step consists of comparing the extracted features of the segmented input iris with the templates exist in the database. In other words; it computes the similarity between the input iris with all templates in the database in the case of the identification mode. In the verification or the authentication mode, it will be compared with one template. The largely used methods are KNN, NN (like RBF, GRNN, MLP), SVM. . . etc. Recently, Deep learning has also exploited.

5.7 Related works

Daugman was the pioneer in this field. Its proposed techniques are used in most iris recognition systems till the current day. The first idea of using iris for biometric recognition was introduced by the ophthalmologist Frank Burch. Next, many reports were studied from two other ophthalmologists dr.Leonard Flom and Aran Safir. They demonstrate that each iris has its unique textures, two different subjects can't have the same iris features. In their last studies, they propose iris biometric for human identification.

After these analyses, Daugman in 1993 proposed a complete iris system based on a mathematical model. He developed the first iris-based recognition system. While the outer and the inner boundaries of the iris have not a circular shape, Daugman in his works, proposes applying a homogeneous rubber sheet model for the segmentation and the normalization step. In this model, pair of dimensionless real coordinates were assigned to each pixel in the iris. This pseudo polar coordinate system is not concentric according to the assumption that the pupil and the iris have not the same centre in most cases. For the extraction step, the two-dimensional (2-D) Gabor wavelets technique was exploited to encode iris patterns. The used 2D-filters were introduced by Daugman (Daugman, 1993). To match two IrisCodes, Hamming distances has computed across a population of unrelated IrisCodes. The proposed method, called Iriscode, was applied later on many researches (Benaliouche, 2018).

Recently, various researches were introduced to exploit the different strengths and advantages of iris biometric in order to construct a robust iris-based recognition system. The work presented in (Birje and Krishnan, 2011) presents an iris-based recognition system based on Daugman's methods. Because iris recognition systems are widely used in various domains, the need for large iris databases is growing. In this work, Authors introduce compression techniques in order to reduce the storage space, cost and time. In the segmentation step, the circular iris regions and the pupil were located by applying the CHT method which computes the radius and centre coordinates of both circles.

Daugman's Rubber Sheet Model was exploited to normalize the segmented iris aiming at achieving a constant radius. The IrisCodes were generated by convolving the normalized iris pattern with 1D Log-Gabor (LG) wavelets. The discriminant features were encoded into binary templates and stored in the database to be used in the matching step applying the Hamming distance algorithm. Two images compression techniques were applied named SPIHT and JPEG2000. The proposed system was validated using CASIA iris image database. The obtained results demonstrate that JPEG2000 provides better results than SPIHT.

A new segmentation technique was proposed for robust and efficient online iris recognition system in (Tan and Kumar, 2013). The proposed approach consists of exploiting a random walker algorithm to efficiently estimate coarsely segmented iris images. Because iris segmentation is a crucial stage in the iris recognition system, authors applied some normalization operations including Retinex algorithm and Gaussian filter to eliminate the noise and enhance the quality of images to make the segmentation more accurate. Binary iris mask was generated by applying the random walker (RW) algorithm. Circular model was used to localize limbic and pupillary boundaries by applying a canny edge detector. The localized limbic coordinates (centre and radius) were exploited to detect the upper and lower eyelid regions using adaptive eyelid model. The implemented iris segmentation and recognition system was carried out on three publicly available databases: UBIRIS.v2, FRGC and CASIA.v4-distance databases.

In the work presented in (Tan and Kumar, 2014) for the same authors, an iris recognition system was proposed using unconstrained iris images which are captured under different conditions and at a distance. Authors develop a new approach by extracting the geometrical information from local region pixels. For iris segmentation and normalization, the automatic segmentation presented in (Tan and Kumar, 2013) was used. For the extraction step, a new approach, named GeoKey encoding scheme, which based on localizing geometrical information from the local region iris pixels was presented. Then, simple transformation operations, which can't be applied on iris image, will be applied on the encoded GeoKey. Log-Gabor was applied to extract the global iris features. A fusion of both localized and global iris texture was performed at matching scores by using weighted sum method in the purpose of achieving better accuracy. UBIRIS.v2, FRGC and CASIA.v4 databases were exploited to test and validate the proposed approach. An EER of 0.16% was achieved with UBIRIS database, 0.19% with FRGC database and 0.03% for CASIA database.

Multiple feature descriptors were extracted from segmented iris captured at distance in (Ali et al., 2016). The proposed iris recognition system uses random walk algorithm to localize the iris from distantly acquired facial images. Daugmans rubber sheet model was applied to normalize the segmented iris image. The presented work focuses on the extraction step applying multiple extractors which are LG, Contourlet Transform (CT), Gradient Local Auto-Correlation (GLAC) and CNN descriptors. The selected extractors were applied on the normalized iris and on the contextual eye image. KNN, SVM and Kernel Extreme Learning Machine (KELM) were used for the matching step. The best recognition rate was obtained by CNN extractor with 92.00% , which is computed with KELM classifier.

Near-infrared (NIR) images and visible wavelength (VW) images were considered as a major problem that may occur in iris recognition systems during the acquisition step. Many techniques were proposed to handle these challenging issues. An iris recognition system was developed based on two segmentation techniques in order to solve both NIR and VW challenges (Umer et al., 2019). The first technique, which is in the case of NIR images, consists of detecting inner boundary using the CHT followed by outer boundary using inversion transform followed by CHT. For VW images contrary to the first case, the introduced approach based on detecting the outer boundary followed by the inner boundary.

CHT was used after a set of operations and thresholding to mark the outer border. The inner was localized by extracting boundary points from the grey-level histogram information's and morphological boundary extraction algorithm. Then, the centre and radius coordinates were computed using CHT. Daugman's rubber sheet model was applied to normalize the segmented iris. The textons with the bag-of-words model were used to extract the discriminant features. The experimental results have been demonstrated using ten benchmark iris databases, namely MMU1, UPOL, IITD, UBIRIS.v1, CASIA-Interval-v3, CASIA-Iris-Twins, CASIA-Iris-Thousand, CASIA-Iris-Distance, CASIA-Iris-Syn and UBIRIS.v2. An accuracy ranging from 93% to 100% and an EER from 0.01% to 0% were achieved.

5.8 Iris Databases

At the large scale of using iris as a biometric modality that can be exploited successfully in recognition system, many benchmarks publicly databases are presented. Some of the most used databases are mentioned the following:

5.8.1 CASIA Database

Institute of Automation, Chinese Academy of Sciences (CASIA) developed many versions of iris images since 2002 to the present day. Each version has its own characteristics and environmental conditions. Beside different devices were used to collect data. Until now, CASIA professors and teams develop fourth versions of iris databases. Recently, they include the first version of iris mobile database and iris subject ageing database. These databases and the following figures ,which present some samples as examples, are available in (Tan, 2010).

5.8.1.1 CASIA-Iris V1

The first version of iris image database (CASIA-Iris V1) includes images from 108 eyes. Each eye has seven images with 756 in total. Iris images were collected into two sessions at different times. Three images exist in the first folder and four in the second one. The resolution of CASIA-Iris V1 images is 320x280 with their self-developed device CASIA close-up iris camera. All images are saved as BMP format. Iris images in this database are faintly covered with eyelids and eyelashes. Also, they are preprocessed by applying an automatic algorithm to detect the pupil regions of all iris images with a circular region of constant intensity. This database is one of the most used iris databases. Samples images of the database are shown in Figure 5.8.1.

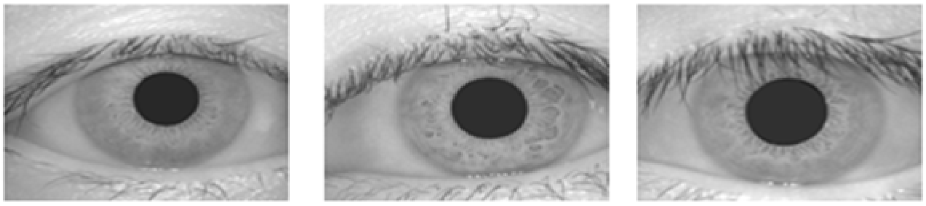

Figure 5.8.1: Samples images from CASIA v1 database (Tan, 2010).

5.8.1.2 CASIA-Iris V2

The second database version CASIA-Iris V2 was used firstly in a conference on biometrics recognition in 2004. CASIA-Iris V2 uses two different devices to collect iris images. The first subgroup includes iris captured with OKI camera where the second uses their self-developed device CASIA-IrisCamV2. Each subgroup contains 1200 images collected from 60 classes. A total of 2,400 iris images were obtained from both subgroups with a resolution of 640x480. Figure 5.8.2 shows some samples images of the database.

Figure 5.8.2: Samples of iris images obtained from CASIA-Iris V2 database (Tan, 2010).

5.8.1.3 CASIA-Iris V3

For more progress on iris recognition and in order to support researchers to hold out the occurred issues, a third version named CASIA-IrisV3 was presented. Three subgroups were included named CASIA-Iris-Interval, CASIA-Iris-Lamp and CASIA-Iris-Twins. More than 700 subjects are participating in the collection of this database with a total of 22,034 grey-level iris images. All iris images are stored with JPEG format. The collected data are captured under NIR illumination. For the first subgroup CASIA-Iris-Interval, data were captured using CASIA close-up iris camera. This database includes 2639 iris images obtained from 249 individuals. The resolution is 320x280. CASIA-Iris-Lamp database contains the largest number of individuals compared with the two other data sets which include 411 subjects with 16,212 iris images. Besides a resolution of 640x480 was used. Two hundred individuals participated in the last subgroup (CASIA-Iris -Twins) presenting 3,183 iris images captured outdoor. The same resolution of CASIA-Iris-Lamp database was used. It is considered as the first publicly available iris image dataset for twins. Figure 5.8.3 shows iris samples images for each subgroup CASIA-Iris-Interval, CASIA-Iris-Lamp and CASIA-Iris-Twins, respectively.

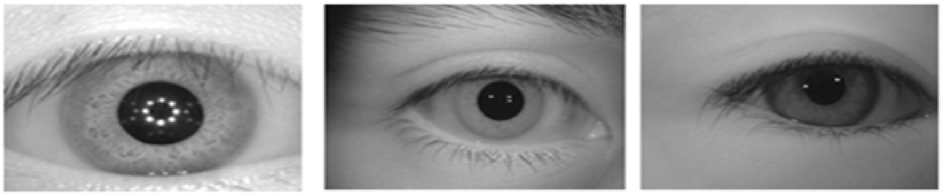

Figure 5.8.3: Samples eye images from CASIA-Iris V3 database for CASIA-Iris-Interval, CASIA-Iris-Lamp and CASIA-Iris-Twins, respectively (Tan, 2010).

5.8.1.4 CASIA-Iris V4

In the fourth version of CASIA is a combination of the three subsets of CASIA-Iris V3 (CASIA-Iris-Interval, CASIA-Iris-Lamp and CASIA-Iris-Twins) and three new subsets namely CASIA-Iris-Distance, CASIA-Iris-Thousand and CASIA-Iris-Syn. CASIA-Iris V4 database includes 54,601 iris images which were acquired from more than 1,800 genuine subjects and 1,000 virtual subjects under near infrared illumination. All the captured iris images are gray level and saved on JPEG format. Because the three subsets of CASIA-Iris V3 (CASIA-Iris-Interval, CASIA-Iris-Lamp and CASIA-Iris-Twins) were illustrated in figure 5.8.3, figure 5.8.4 shows iris samples images for the new added subgroups.

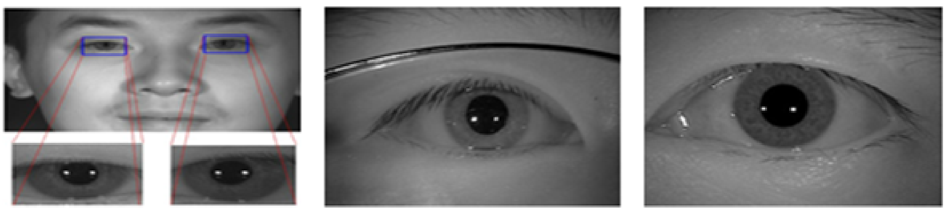

Figure 5.8.4: Example eye images from CASIA-Iris V4 database for CASIA-Iris-Distance, CASIA-Iris-Thousand and CASIA-Iris-Syn, respectively (Tan, 2010).

5.8.2 UPOL

UPOL (University of Palackeho and Olomouc) database contains 384 iris images captured from 64 subjects. Each subject presents 3 left iris images and 3 right iris images (Dobeš et al., 2006). All iris images are on PNG format with a resolution of 576x768. TOPCON TRC50IA optical device connected with SONY DXC-950P 3CCD camera was used to scan irises. The images were taken at near distance with human subject cooperation as shown in figure 5.8.5.

Figure 5.8.5: Samples eye images from UPOL iris database (Dobeš et al., 2006).

5.8.3 BATH

NIR iris images were collected from the university of Bath using a limited smart sensor. A total of 32,000 iris images for both left and right eye with high quality were captured from over 800 subjects. The resolution is 1280×960 (Monro, 2008). Some samples are shown in Figure 5.8.6.

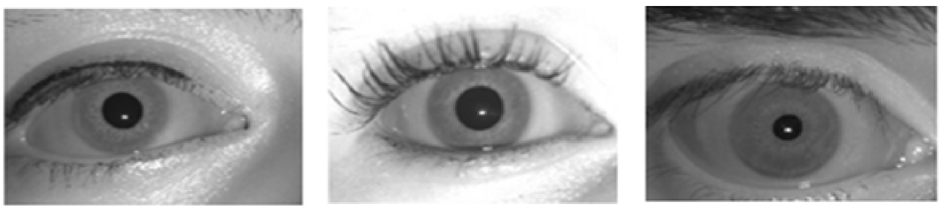

Figure 5.8.6: Samples eye images from BATH iris database (Monro, 2008).

5.8.4 UBIRIS

In this database, noisy images were collected in the purpose of validating and testing the robustness of iris algorithm under unconstrained environments (Proença and Alexandre, 2005). It is considered as one of the noisiest iris databases. UBIRIS database was created by the university of Beira. It has two distinct versions. The first version includes 241 individuals with total iris images of 1877 collected on two sessions with a two weeks' interval. Images were taken using Nikon E5700v1.0 camera. More than 11000 images were captured in the second version. These images were collected at-a-distance and on-the-move providing more realistic noise factors. Figure 5.8.7 illustrates two examples of iris samples for the first and the second version, respectively.

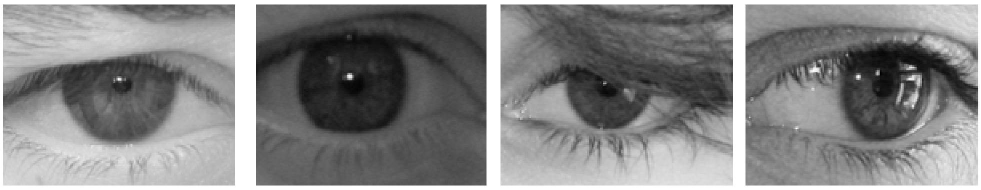

Figure 5.8.7: Some eye images from UBIRIS database (Proença and Alexandre, 2005).

5.9 Iris in Multimodal Systems

The robustness and the efficiency of iris modality have proved in a significant number of unimodal biometric recognition systems. Table 5.1 represents a comparison between some iris unimodal systems. The segmentation and features extraction techniques were mentioned. The accuracy ranges from 89% to 100%. The achieved results made iris a good resource for identification. These advantages stimulate many researchers to fuse iris with other modalities developing multimodal biometric recognition.

Face and iris biometrics are combined together in many researches to benefit from the strengths of each modality and construct a robust, secure and efficient recognition system. The work introduced in (Eskandari and Toygar, 2014), LBP was applied to extract the local features from face biometric. The global features were extracted from iris biometric using LDA. A normalization method was applied to generate a match score for each modality separately. Then, Weighted Sum Rule fuses the computed scores. Another work based on using two fusion levels. Feature fusion level was employed to fuse features extracted from iris biometric applying PCA, subspace LDA, sub-pattern-based PCA, modular PCA and LBP. For face biometric, LBP was applied. Weighted Sum Rule was used to fusing the normalized face and iris scores.

Iris and fingerprint are also fused in many studies such as in (Vishi and Yayilgan, 2013), (Benaliouche and Touahria, 2014) and (Khoo et al., 2018). The proposed multimodal biometric authentication system in (Vishi and Yayilgan, 2013) fuses iris and fingerprint at score level. The presented system consists of combining the obtained scores from both modalities using a three score normalization techniques (Min-Max, Z-Score, Hyperbolic Tangent) and four score fusion approaches (Minimum Score, Maximum Score Simple Sum and User Weighting).

Table 5.1: A comparison of some of the existed iris recognition systems.

Authors	Segmentation	Extraction method	Database	Subj	CRR
(Daugman, 1993)	Integrodifferential operator (Rubber Sheet Model)	2D Gabor Wavelets	Own	323	99.9
(Wildes et al., 1994)	CHT	#	Own	40	#
(Ma et al., 2004)	Hough Tansform	Key Local Variations	CASIA	213	100
(Sun et al., 2006)	#	LBP	UPOL	64	#
			CASIA	213	#
(Nabti and Bouridane, 2008)	Multiscale Edge Detection	Gabor filters and Wavelet Maxima Components	CASIA v1	108	99.5
(Kekre et al., 2010)	Not used	DCT and Kekre's Fast Codebook Generation Algorithm (KFCG)	UPOL	64	89.1
(Birje and Krishnan, 2011)	CHT	1D LG Wavelets	CASIA v1	100	#
(Da Costa and Gonzaga, 2012)	Sobel Edge Detector and CHT	Dynamic Features	Own	111	99.1
(Singh and Kaur, 2014)	CHT	LBP	CASIA	108	91
(Bellaaj et al., 2015)	Multiscale Edge Detection Nabti and Bouridane (2008)	Gabor filters and Wavelet Maxima Components + Possibilistic Modeling	CASI v4	200	99
(Li et al., 2015)	Improved three-point location	Average Local Binary Pattern (ALBP)	CASI v4	218	99.9
			UBIRIS	241	95.6
(Shekar and Bhat, 2016)	Daugman's Rubber Sheet	Partial Sum of second order Taylor Series Expansion	IITD	100	98.6
			MMU v-2	99	#
			CASIA v4	70	#
(Hamouchene and Aouat, 2016)	CHT	2D Gabor filter Daugman (1993)	CASIA v1	100	99.9
(Czajka et al., 2017)	Rubber Sheet Model Daugman (1993)	Feature Engineering and Feature Learning	Own	135	99
(Menon and Mukherjee, 2018)	Not mentioned	CNN	UBIRIS	241	95.4
			IITD	224	99.8
(Barpanda et al., 2019)	CHT	Wavelet Cepstrum Feature	CASIA v3	700	89.9
			UBIRIS	241	88.9
			IITD	224	89.8

While in (Benaliouche and Touahria, 2014), the developed multimodal biometric system fuses iris and fingerprint at the matching score and the decision levels. Besides the sum rule and the weighted sum rule matching algorithms, a new matching technique was proposed. Itconsists of applying a fuzzy logic method for the matching scores combinations at the decision level. The achieved results demonstrate the robustness of the proposed technique. It outperforms the classical fusion techniques with FAR of 0%. The developed multimodal biometric system introduced in (Khoo et al., 2018) presents a new approach for the feature fusion level based on Indexing-First-One (IFO) hashing and integer value mapping strategy. In the work presented in (Gandhe and Jawale, 2016), authors develop a multibiometric system including iris, signature and gait. Global features, Local features and Transition features were extracted and matched.

5.10 Conclusion

The iris was used since the first exploitation of biometric for recognition. Many techniques were developed with the aim of constructing a robust and secure iris-based recognition system. Until our day, the iris is still considered one of the most powerful biometric that can be used to identify individuals. It presents rich information which is hard to falsify. In some cases, iris may suffer from damages that distort its shape and consequentially influence negatively the extracted biometric traits used for recognition and reduce the accuracy of the system.

In this chapter, we have presented a state of the art on iris biometric. Starting with a definition of iris, beside a brief history about the use of iris in recognition purpose was presented. We have discussed in the next section about the anatomy of iris and its important parts that could be used for the identification of persons. Iris strengths and drawbacks were also detailed. Then, the iris based system architecture was presented. The iris segmentation step is considered a critical phase in the development of the iris recognition system. Many techniques such as Integro-differential Operator, Hough Transform and Active Contour Models were proposed. Daugman was the pioneer in this filed. His techniques are used in several kinds of research. In our work, we decide to use the circular Hough transform technique for the iris and pupil boundaries detection. Some of the developed iris based recognition systems were explained.

Because of the encouraging results achieved by proposed unimodal iris-based recognition systems, combining iris with other biometric traits has the ability to improve the recognition rate. Moreover, this combination develops secure and robust multimodal recognition systems. We conclude this chapter by referring to some existed iris-based multimodal recognition systems.

Part II

PROPOSED MULTIMODAL BIOMETRIC SYSTEMS

CHAPTER 6

Ear-ECG BASED MULTIMODAL SYSTEM

6.1 Introduction

With the evolution of technology, the implementation of secure personal identification protocols has been increased. In our day, biometric can be considered as the optimal solution for this purpose. For this reason, many biometric systems were developed with the intention of achieving a high level of security using suitable and acceptable biometric modalities from users.

Each biometric trait has some limitations which make it not able to accomplish all system requirements. Accordingly, the use of a single hardware modality for recognition makes systems sufferer from many problems such as noisy data, intra-class variations, non-universality, spoof attacks and distinctiveness. Most of these challenges can be addressed by deploying multimodal biometric systems. This latter merges more than one biometric trait in a single scan. The use of multiple biometric modalities works on exploiting the strengths of the combined modalities to improve the performance of the multimodal system and increase the security level.

The main characteristic that made ECG very recommended is its universality. The heartbeat is a necessary sign of life. Moreover, different hardware are available to record the ECG signal with minimum inconvenience to the individual. For these reasons, there is an increasing interest in using the ECG in biometric identification.

There's real power in using the appearance of an ear for computer recognition. Ear shape has played a significant role in forensic science and it was used by law enforcement agencies for many years. Many studies for ear photographs of thousands of people have been performed for decades. These researches have the purpose of checking the possibility of use ear for recognition and how much is suitable. It is found that the ear has a unique shape even in the case of twins. It has also a stable structure which does not change radically over time.

This chapter subdivided into three parts. Firstly, we will present local descriptors methods used in our contributions so as to extract the representative features of our used modalities. In the second part, we will explain our proposed ECG unimodal system based on shifted 1D-LBP for the cause of analyzing and testing the power of using ECG in recognition. Finally, our proposed multimodal biometric system based on combining ECG and ear using 1D-MR-LBP methods will be also explained. A discussion of the experimental results will be performed.

6.2 Local Descriptors

Features extraction is the main phase of the biometric recognition system. Numerous methods have been developed such as local descriptors. The latter is widely applied on various 2D and 3D biometric modalities like face (He et al., 2009), fingerprint (Nikam and Agarwal, 2008), iris (Singh and Kaur, 2014). These algorithms based on finding specific key points in the image. Then, the characteristics are extracted around these specific points. Local features have proved its efficiency and robustness under unconstrained environments. During the last few years, Local Binary Patterns (LBP) has proven its efficiency and robustness in image processing and computer vision. LBP is a non-parametric method which is applied to the 2D image. It was originally proposed for texture analysis in order to describe local structures.

In our contribution, we fuse ear and ECG in a multimodal biometric system. As the dimensionality of these modalities is large, their fusion by concatenation is difficult, inefficient and lacks of robustness. It is well known in the literature that if the feature space has very high dimensionality, it is susceptible to the curse of dimensionality. This problem can be solved by feature extraction and dimensionality reduction phases. Local texture descriptors, namely 1D-LBP (One-Dimensional Local Binary Patterns), Shifted-1D-LBP (Shifted One-Dimensional Local Binary Patterns) and 1D-MR-LBP (One-Dimensional Multi-Resolution Local Binary Patterns) are used in this study for features extraction purpose from 1D signals and 2D images after projecting these images into 1D space.

6.2.1 Basic LBP

The local binary pattern, proposed by (Ojala et al., 1996), is considered one of the famous approaches used for the feature extraction task. Therefore, it has been successfully applied in several fields of machine vision. The original version of the local binary pattern operator is applied on a 3×3 pixel block of an image which means 8 neighborhoods. The neighborhoods of each block are threshold by its centre pixel value to generate an LBP-code for the centre pixel (Pietikäinen et al., 2011). The formulation of LBP for a centre pixel $\mathtt{x_c}$ is given as:

$$LBP(x_c) = \sum_{p=0}^{7} S(x_p - x_c).2^p \tag{6.2.1}$$

Where the S() indicates the sign function and is defined as:

$$S(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \tag{6.2.2}$$

A value of 1 was assigned to the S() function if the input parameter are grater or equal to 0. Otherwise, a value of 0 was assigned. Figure 6.2.1 illustrates the basic LBP operator.

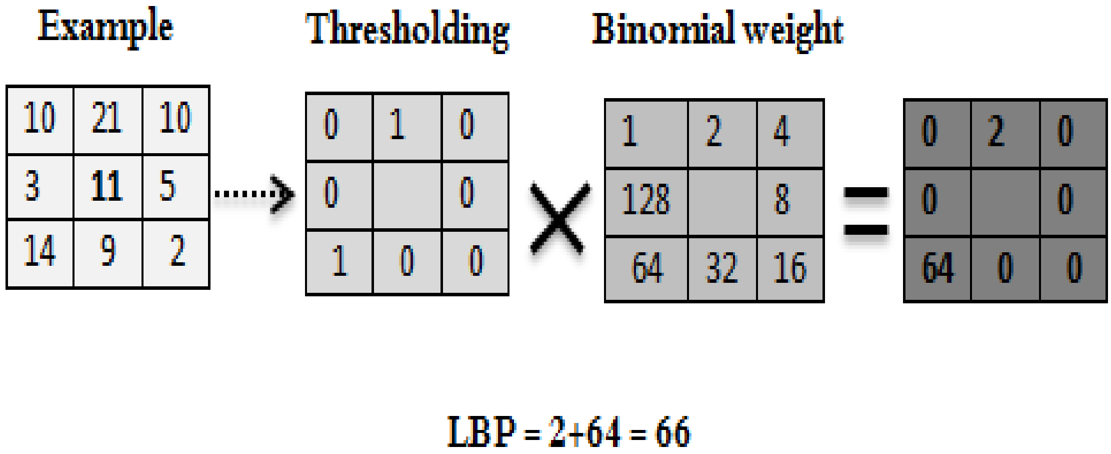

Figure 6.2.1: An example of the basic LBP operator.

6.2.2 1D-LBP

LBP method has gained great popularity since its first proposal by (Ojala et al., 1996) due to its efficiency of extracting important textures that exist in the processed image using its local neighborhood (Pietikäinen et al., 2011). LBP generates a binary code by thresholding each value of neighborhood with the value of the centre pixel of an image based on the assumption that texture has locally two complementary aspects, a pattern and its strength.

While LBP method was used to process pixels of a 2D image, 1D-LBP was used to process samples data for the 1D signal. The first proposition of 1D-LBP method was introduced by (Chatlani and Soraghan, 2010) for the purpose of extracting features from a speech signal and identifies the voiced and the unvoiced components. 1D-LBP generates a binary code, which named 1D-LBP code, by thresholding each value of neighborhood with the value of each centre samples from a signal. The formulation of 1D-LBP on the $\mathtt{i}^{\mathtt{th}}$ sample of processed signal x[i] is given as:

$$1DLBP(x[i]) = \sum_{j=0}^{\frac{p}{2}-1} \left\{ S\left[x\left[i+j-p/2\right]-x\left[i\right]\right].2^{j} + S\left[x\left[i+j+1\right]-x\left[i\right]\right].2^{j+\frac{p}{2}} \right\} \tag{6.2.3}$$

Where the S() indicates the sign function as mentioned in equation (6.2.2). P is the number of neighboring samples. The input parameter of S() is the result of the difference between each neighboring sample and the centre sample. Its output parameter is a thresholding binary number which will be converted to an LBP code by applying a binomial weight. i represents the i^{th} sample where i=[(P/2)+1:N-P/2], N is the length of processed signal x. An example of the 1-D LBP operator is given in figure 6.2.2 where P = 8 and the centre sample PC is mentioned.

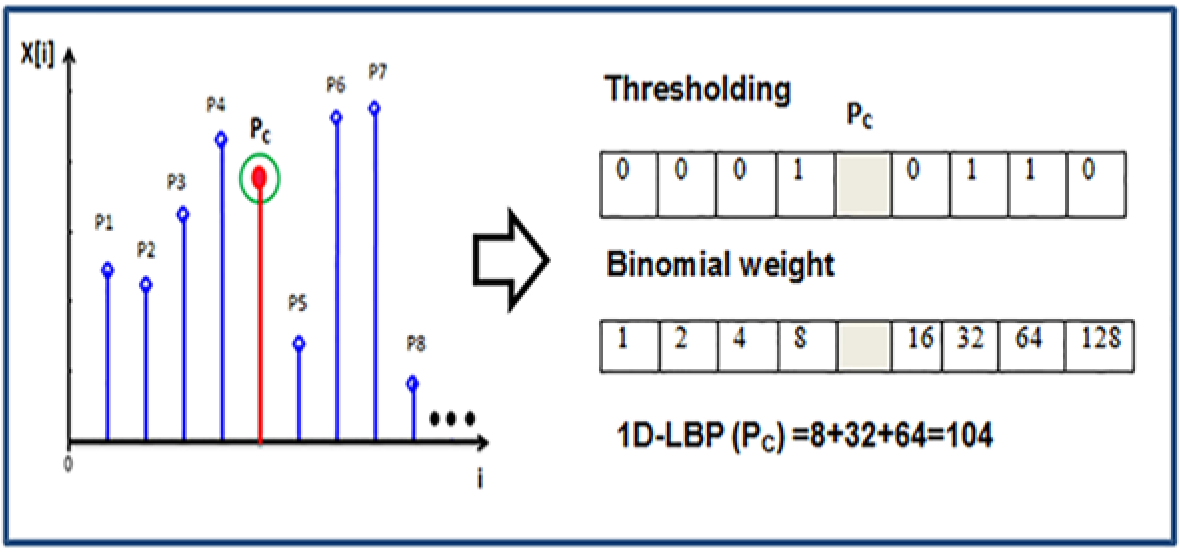

Figure 6.2.2: An example of 1-D LBP operator.

6.2.3 Shifted 1D-LBP

Shifted 1D-LBP method was adapted from a 1D-LBP method which was introduced by (Chatlani and Soraghan, 2010). Both methods are applied to sensor signals for the purpose of extracting features or segmentation. They are inspired by the 2D-LBP method proposed by (Ojala et al., 1996). The same process will be applied using 1D-LBP or Shifted 1D-LBP methods at each sample of signal. While 1D-LBP method uses constant left and right neighbors of the central sample and obtained a limited macros patterns. Shifted 1D-LBP method use shifted left (PL) and right (PR) neighbors of the central sample Pc (Ertuğrul et al., 2016). After the selection of neighborhoods, Shifted 1D-LBP generates a binary code, which named a Shifted

1D-LBP code, by thresholding each value of left and right neighborhood with the value of each centre samples from a signal x[i]. The formulation of Shifted 1D-LBP of centre sample Pc of the processed signal x[i] is given as:

$$Shifted1DLBP(P_c) = \sum_{j=1}^{p} S(P_j - P_c).2^{j-1} \tag{6.2.4}$$

Where the S() indicates the sign function as mentioned in equation (6.2.2). Pc and Pj represent the centre sample and number of neighbors, respectively. An example of Shifted-1D-LBP operator is given in figure 6.2.3 where PL = 5 and PR=3, the centre sample Pc is mentioned.

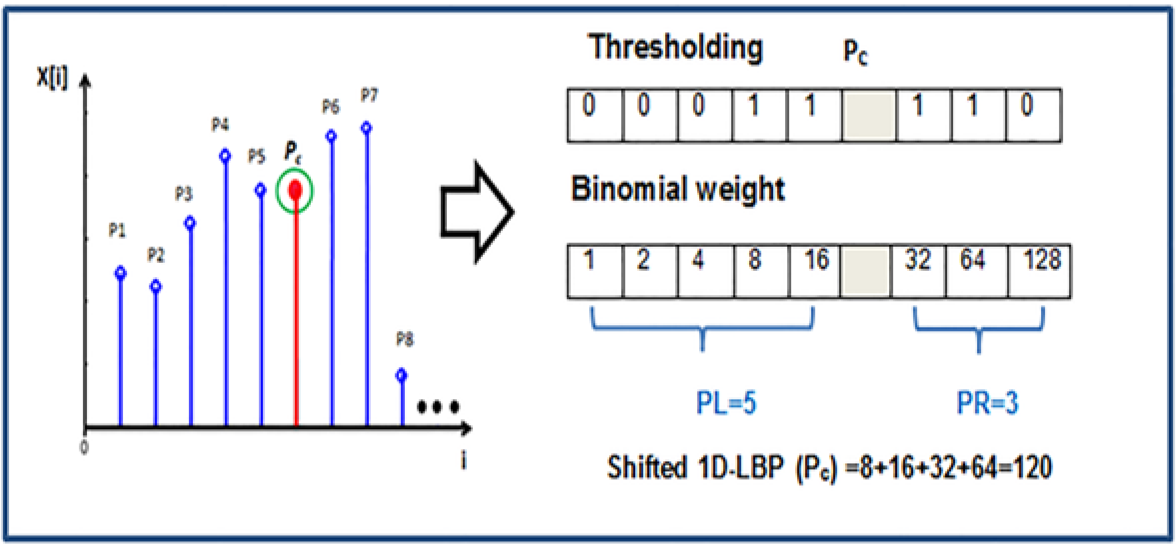

Figure 6.2.3: An example of Shifted-1D-LBP operator.

6.2.4 1D-MR-LBP

1D-MR-LBP methods, which is applied on a 1D signal, was proposed by(Louis et al., 2014)to solve the problem of passing irregular signals to the biometric system and of an unknown amplitude of a signal and achieve better performance.1D-MR-LBP methods were inspired by the 2-dimensional Local Binary Patterns. While 1D-LBP and Shifted 1D-LBP based on just the selection of neighbors on both left and right side for extraction, 1D-MR-LBP based on two variables p and d. Where the first paramater represents the number of selected samples that are used for 1D-MR-LBP feature extraction from both sides, which considered by neighbors on 1D-LBP method. The second one represents the distance between the centre sample x_c and the last/first selected sample pi used for 1D-MR-LBP feature extraction from left/right side.

The formulation of 1D-MR-LBP on the i^{th} sample of processed signal x[i] is given as:

$$1DMRLBP(x[i]) = \sum_{j=1}^{p} S(x(i+j-p-d)-x(i)).2^{j-1} + S(x(i+j+d-1)-x(i)).2^{j+p-1} \quad (6.2.5)$$

Where the S() indicates the sign function by adding epsilon (ε) as a new parameter which makes ECG signals less influenced by noises beside to take on consideration the quantization error (Louis et al., 2014). The S() function defined as:

$$S(x) = \begin{cases} 1 & if \quad x+\varepsilon \geq 0 \\ 0 & if \quad x+\varepsilon < 0 \end{cases} \quad (6.2.6)$$

And where p and d are defined above. The input parameter of S() is the result of the difference between each sample pj where j=[1,2,..,p] and the centre sample. Its output parameter is a thresholding binary number which will be converted to an LBP code by applying a binomial weight. i represents the i^{th} sample where i=[p+d:N-p-d+1], N is the length of the processed signal x. An example of a 1-D-MR-LBP operator is given in figure 6.2.4 where P = 3 and d=3 and the centre sample PC is mentioned.

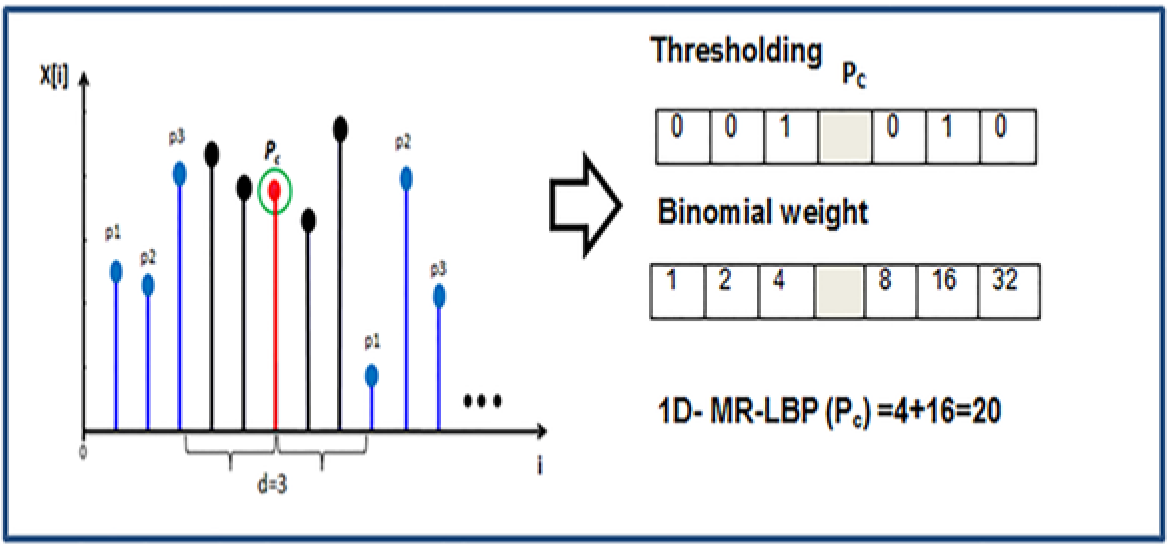

Figure 6.2.4: An example of 1D-MR- LBP operator.

6.3 Motivation and Goals

With the development of technology, the need for security has increased to control the access to systems. The biometric systems were a real alternative to passwords, signatures and other identifiers. It defined as the quantitative study of biological, behavioral or morphological characteristics of the human. Face, fingerprint, hand geometry and other modalities have been applied. While each modality has its limitations and weaknesses, the search for new modalities and combinations is the aim of researchers in our day.

The human heartbeat (ECG) is considered as a new biometric technology characterized by his liveliness measurement , which makes it hard to spoof. Human ear is also a promising biometric modality. It presents a rich and stable structure which may be considered as a perfect source of information for identification or verification purpose. Ear recognition is a new biometric technology that largely used in recent years. Combining these two biometric modalities in a multimodal biometric system is an effective strategy for recognition purpose. Our main objectives discussed in this chapter are:

- Identify the extent of the impact of the preprocessing stage on the whole ECG biometric system.
- Examining the robustness of ECG biometric traits by developing a new ECG based biometric system.
- Developing a multimodal system by combining the developed ECG unimodal system with ear based system based on local descriptors for the sake of avoiding the unimodal biometric systems limitations.

6.4 Related Works

Multimodal biometric recognition systems have attracted recently significant research attention, as they offer a method of solving the different drawbacks of unimodal systems. (HONG et al., 2008)developed a prototype biometric authentication system using faces and fingerprints at decision fusion's level. (Ross and Jain, 2004) proposed a multimodal biometrics system which includes face, fingerprint and hand geometry, using a matching score fusion's level. Subsequently, many modalities have been fused to fulfil various application requirements. Ear, ECG or iris biometric modalities have been introduced in different combinations and fusion strategies, using various levels of fusion by these researchers.

A multimodal biometric system (Monwar and Gavrilova, 2013), has been constructed which integrates face, iris and ear data. Fisher image technique wa applied to face and ear recognition and Hough transform and Hamming distance techniques to iris recognition. A novel method based on Markov chain was then used for rank fusion's level. In order to improve on the accuracy and reliability of other rank fusion methods, they also suggested a new Markov chain approach for fusing rank information in a multimodal biometric system.

Different rules (min rule, max rule, product rule and sum rule) were applied in decision fusion's level for ECG-face multimodal biometric system (Boumbarov et al., 2011). ECG features were extracted via KPCA (Kernel Principal Component Analysis). PCA was used to extract features from face modality. Spectral Regression (SR) algorithms are applied to combine ECG and face features. It has as aim to treat the problem of combining different biometric modalities in intelligent video surveillance systems.

An implementation of a multimodal system by (Al-Hamdani et al., 2013) combining three modalities using score fusion's level to reach a higher security level. The fusion of speech, ECG and PCG with sum score fusion was performed. SIFT (Scale Invariant Feature Transform) technique was exploited in order to extract features from both ear and iris data. The fusion at the feature level was applied. A FAR of 0% was achieved (Ghoualmi et al., 2014).

The fusion of fiducial features (peaks) from the first lead (I) of the ECG, with spectrum features from six different bands of the EEG was developed in (Barra et al., 2017). They aim to construct a robust and secure multimodal biometric recognition system. Sum, product and weighted sum operators were used. Then, the Euclidean norm distance was applied to match the fused features. An ERR of 0.93% was achieved.

In (Tahmasebi and Pourghassem, 2017), game theory was used to combine ear, palm-print and signature features. Gabor filter was applied for the extraction step to obtain optimal logistic regression weights for rank-level fusion. Face and ECG were also incorporated for an authentication system (Chakraborty et al., 2016). Both modalities were also fused together for person identification in (Israel et al., 2003), at feature fusion's level.

6.5 Proposed ECG based Unimodal System

ECG analysis has been investigated as promising biometric in many fields especially in medical science and cardiovascular disease for the last decades. It aims to exploit the discriminative capability provided by these liveness measures developing a robust ECG based recognition system. In this section, an ECG biometric recognition system was proposed based on shifted 1D-LBP. Shifted 1D-LBP operator was applied to extract the representative non-fiducial features from preprocessed ECG heartbeats. The current section is an extension of our paper published in (Regouid and Benouis, 2018). The proposed approach consists of three stages namely preprocessing, features extraction and matching. Figure 6.5.1 shows the architecture of the proposed system.

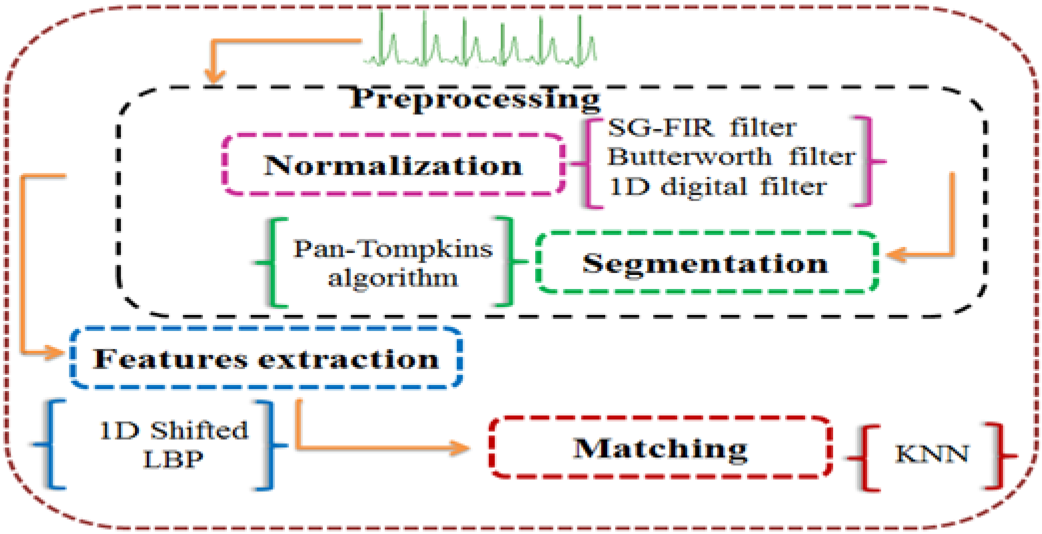

Figure 6.5.1: The architecture of ECG unimodal biometric system.

6.5.1 Preprocessing

The preprocessing step is subdivided into two sub-steps: Normalization and segmentation.

6.5.1.1 Normalization

In the normalization step, we have applied three techniques to reduce the noise from the ECG signal and remove various artifacts and improve equality of the signal. We will compare the effectiveness of each algorithm so as to apply the good technique on the proposed ECG biometric recognition system.

The first algorithm is SG-FIR which proposed by Savitzky and Golay. SG-FIR smoothing filter is based on local least-squares polynomial approximation. It works on reducing noise while maintaining the shape and height of waveform peaks. This method is more attractive and useful in ECG processing where the peak shape preservation property is very important (Savitzky and Golay, 1964). Subfigure 6.5.2 (a) and subfigure 6.5.2 (b) show about 10 seconds from the original and the normalized ECG signal using SG-FIR filter for signal obtained from ECG-ID database. The normalized ECG signal for NSR database is shown in subfigure 6.5.3 (b)

The second technique consists of applying a fifth-order bandpass Butterworth filter combined with a zero-phase filter which is a special case of a linear-phase filter. Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the passband. It can be also called a maximally flat magnitude filter. This filter has the ability to achieve successively closer approximations with increasing numbers of filter elements of the right values. Subfigure 6.5.2 (a) and subfigures 6.5.2 (c) show about 10 seconds from the original and the normalized ECG signal using SG-FIR filter for ECG-ID respectively. Whilst for NSR database, the normalized ECG signal is shown in subfigure 6.5.3 (c).

The third technique based on applying a 1D digital filter. This technique has the aim of filtering the input signal using a rational transfer function. Subfigure 6.5.2 (a) and subfigure 6.5.2 (d) show about 10 seconds from the original and the normalized ECG signal using a 1D digital filter for ECG-ID respectively. For NSR database, the normalized ECG signal is shown in subfigure 6.5.3 (d).

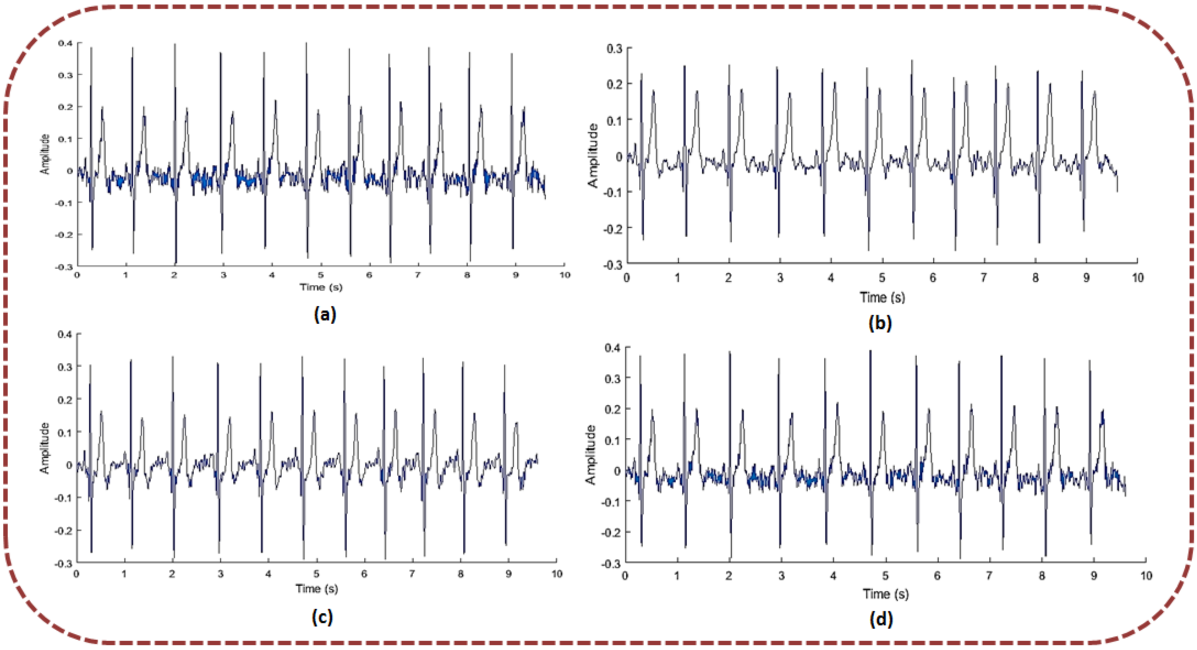

Figure 6.5.2: The original (a) and the normalized ECG signal using SG-FIR filter (b), Butterworth filter (c) and 1D digital filter (d) from ECG-ID database.

6.5.1.2 Segmentation

The second step consists of segmenting the normalized ECG signal. This step can be performed by locating the fiducial points "QRS" adopting Pan-Tompkins algorithm (Pan and Tompkins, 1985). It aims to isolate the fiducial points (P, Q, R) for each beat segment. Each detected R-peak determines the centre of the QRS complex.

Then, to isolate the heartbeat, we take 94 samples before the R-peak and 150 samples after the R-peak. This means that each ECG heartbeat has 245 samples with 490 ms segment duration for ECG-ID database. Whereas, we take 50 samples before and after the R-peak obtaining 101 samples for NSR database.

An alignment of segmented heartbeats for the same subject from both used ECG databases is illustrated in figure 6.5.4 and figure 6.5.6. Figure 6.5.5 and 6.5.7 shows segmented heartbeats for different subjects aligned with the R peak from both ECG-ID and NSR databases.

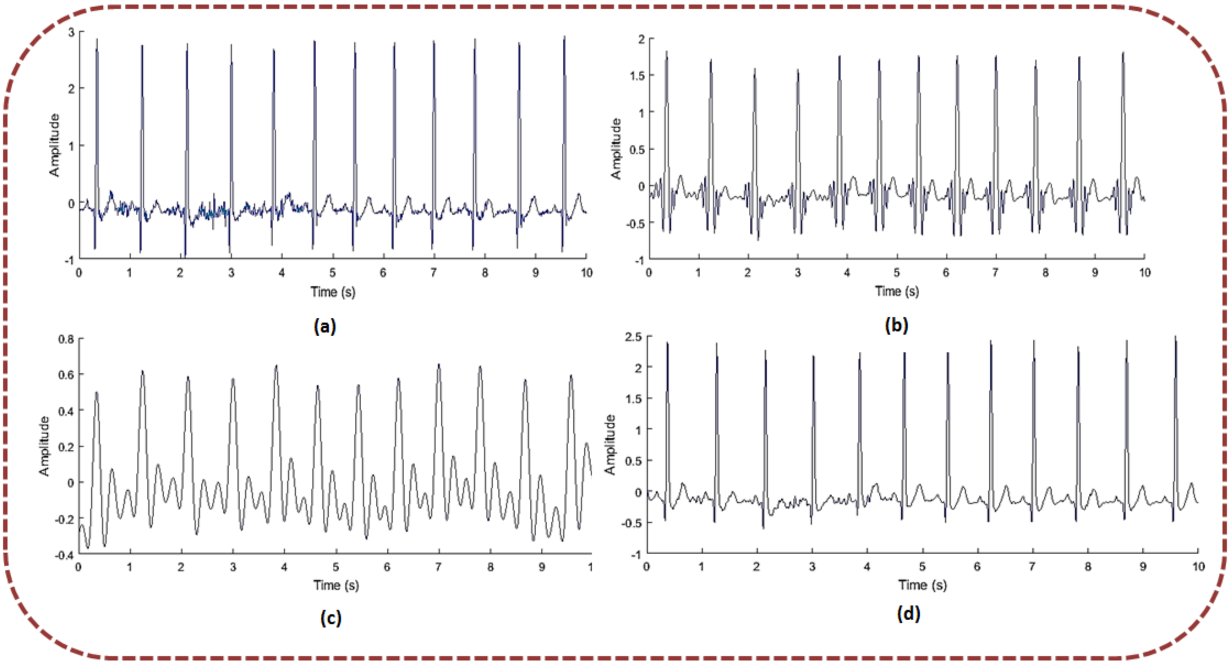

Figure 6.5.3: The original (a) and the normalized ECG signal using SG-FIR filter (b), Butterworth filter (c) and 1D digital filter (d) from NSR database.

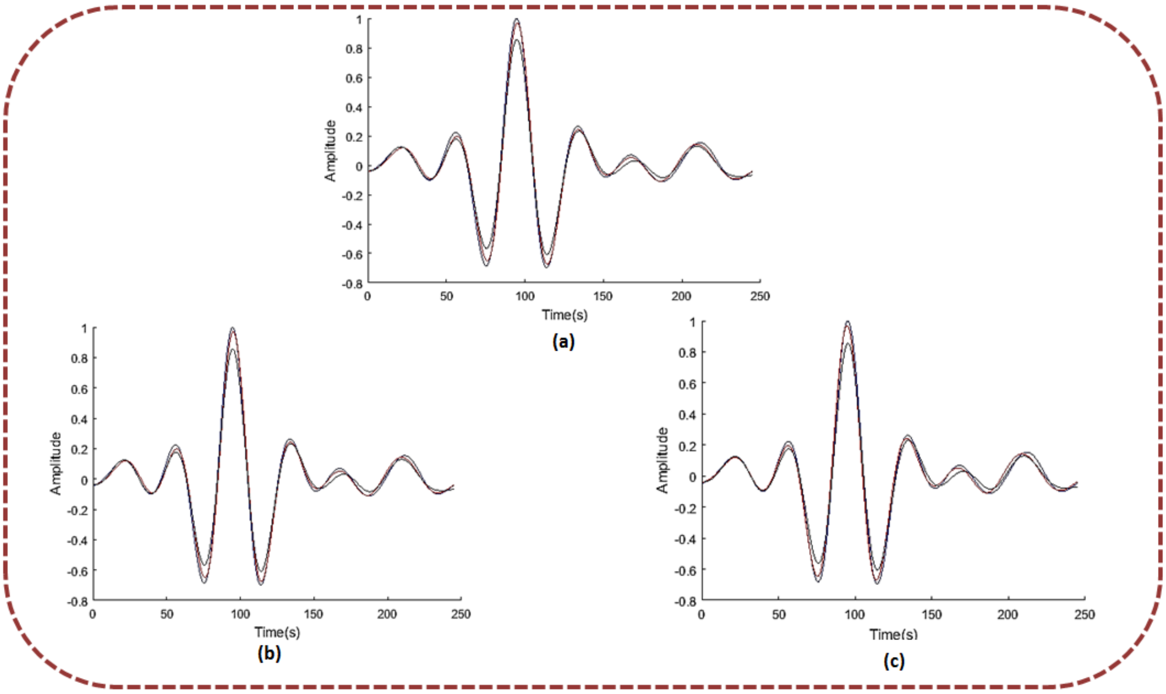

Figure 6.5.4: Segmented heartbeats for the same subjects aligned with the R peak using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from ID database.

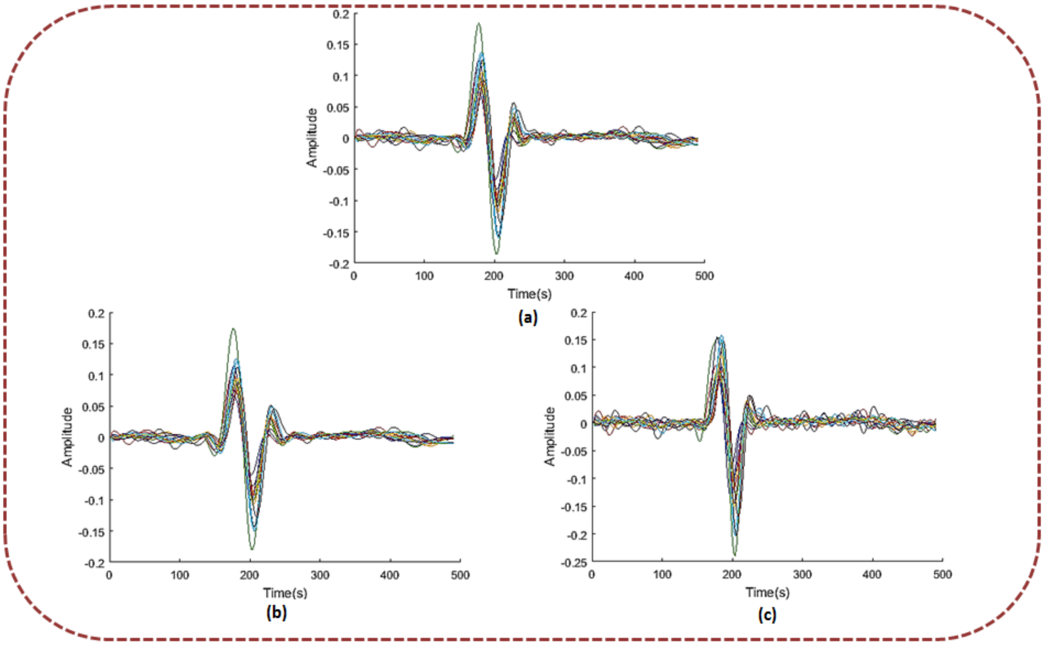

Figure 6.5.5: Segmented heartbeats for different subjects aligned with the R peak using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from ID database.

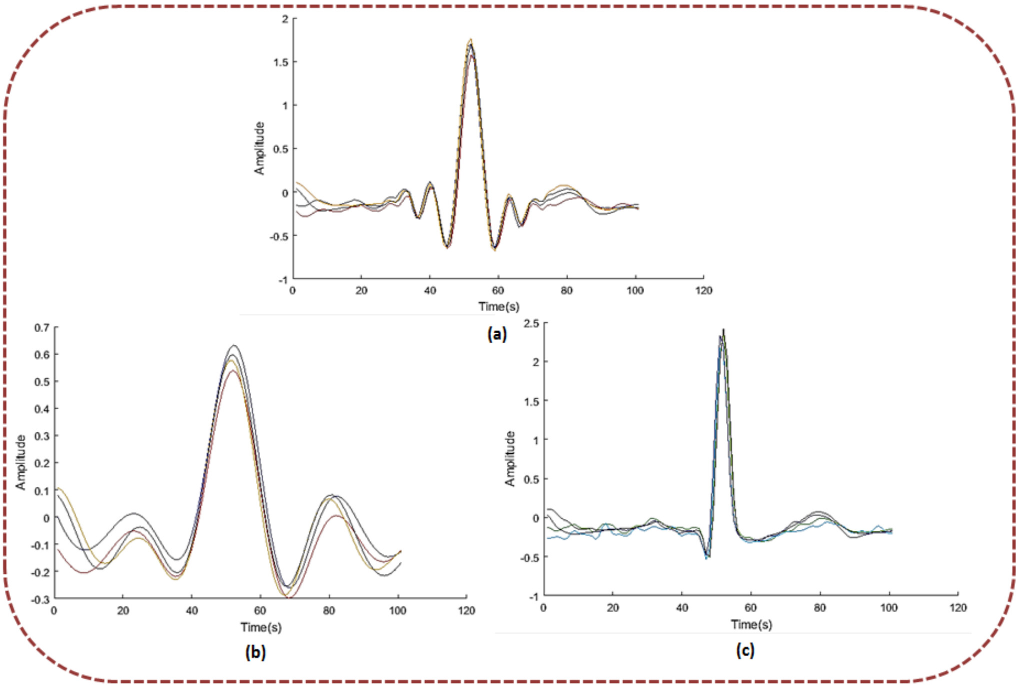

Figure 6.5.6: Segmented heartbeats for the same subjects aligned with the R peak using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from NSR database.

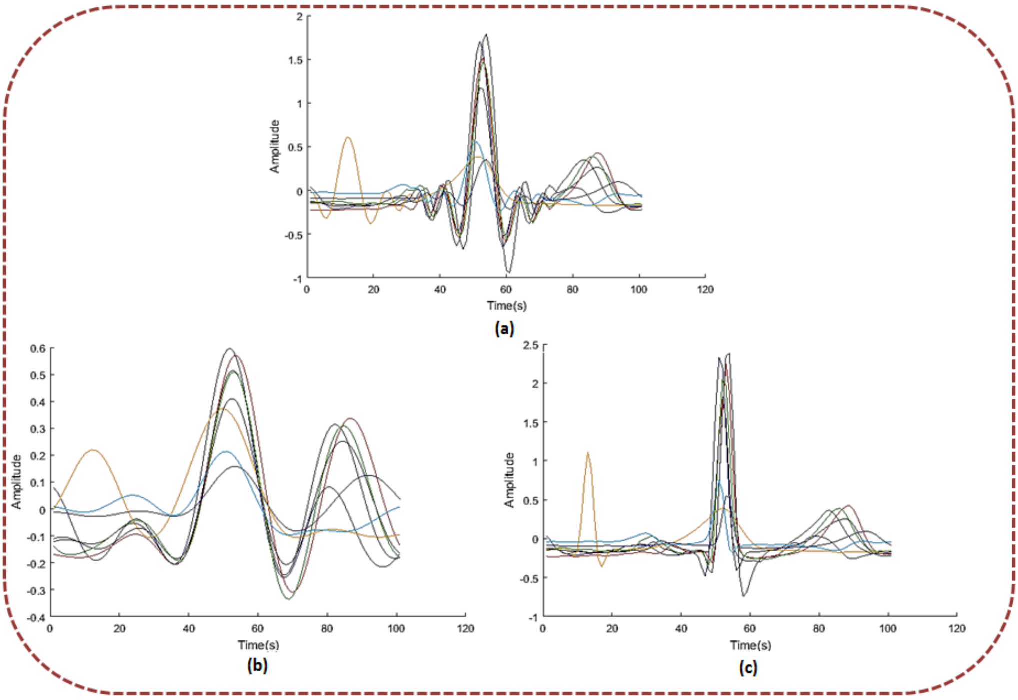

Figure 6.5.7: Segmented heartbeats for different subjects aligned with the R peak using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from NSR database.

6.5.2 Features Extraction

For features extraction step, Shifted 1d-LBP was applied to extract the non-fiducial features from the ECG heartbeats. After many experiences to select the best combination of parameters, a number of 5 neighbors from the left side and 3 neighbors from the right side (PL=5, PR=3). To visualize the difference between the extracted features using different techniques of normalization which is explained above, diagrams were generated. This is illustrated in figure 6.5.8 and figure 6.5.9 for ECG-ID and NSR databases, respectively.

6.5.3 Matching

In the matching step, we have assessed the performance of our proposed approach by using KNN classifier. The performances of the classifiers were evaluated in terms of accuracy presented in equation (1.6.3).

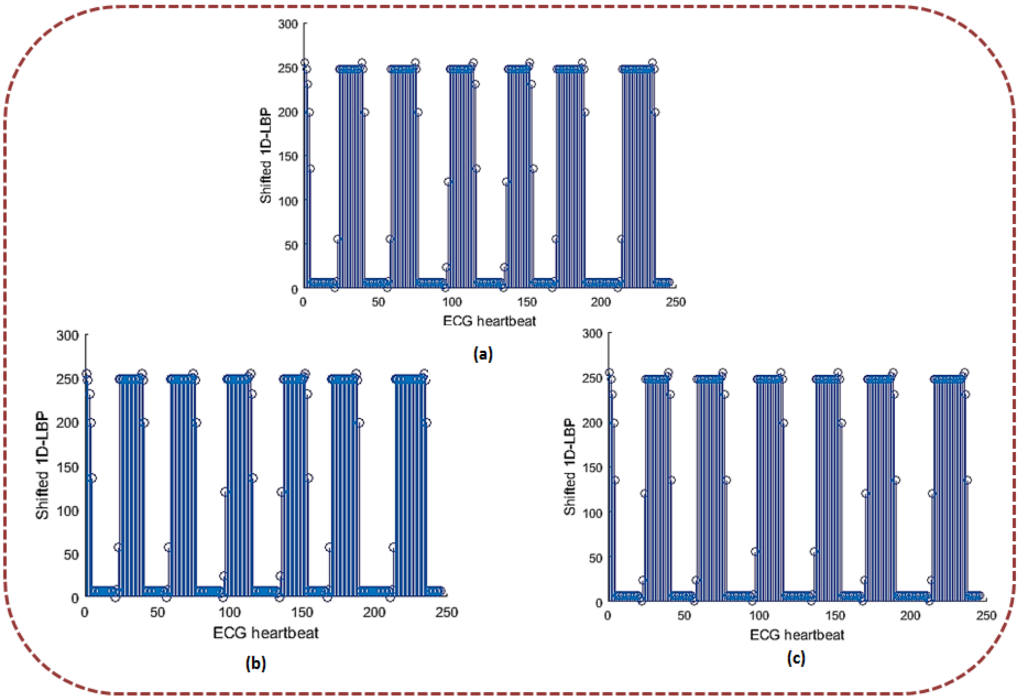

Figure 6.5.8: Shifted 1D-LBP features extraction diagram of an ECG heartbeat using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from ID-ECG database.

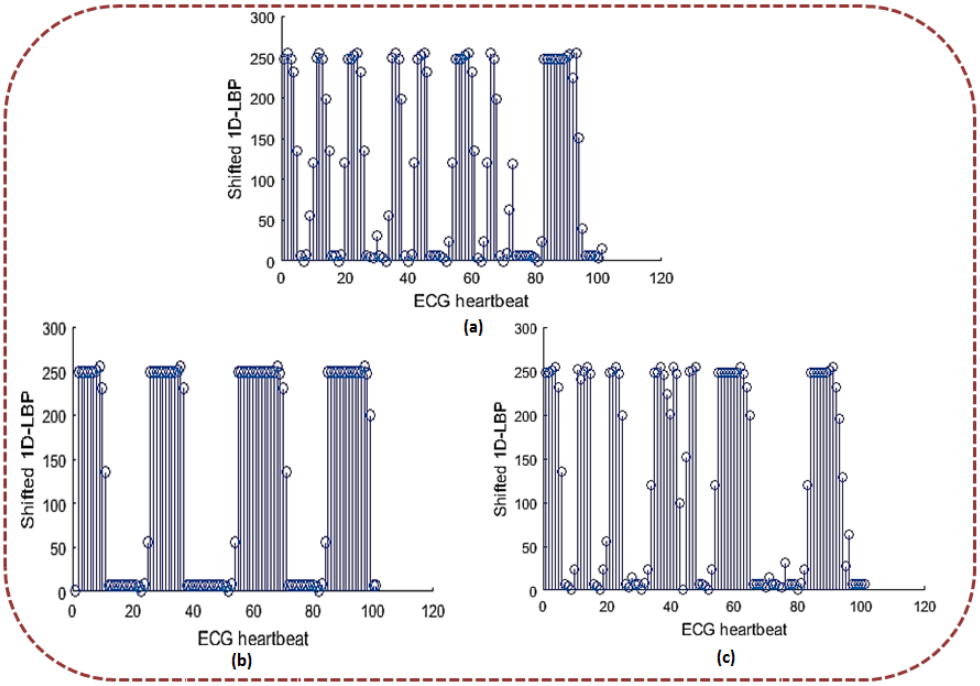

Figure 6.5.9: Shifted 1D-LBP features extraction diagram of an ECG heartbeat using SG-FIR filter (a), Butterworth filter (b) and 1D digital filter (c) from NSR database.

6.6 Results and Discussion

Our proposed ECG biometric system was carried out two benchmark databases namely ECG-ID and NSR databases with regard to test and validate our work. ECG-ID database contains different signals from 90 subjects. In our experiments, two records were used per subjects, one for the training set and the second as a testing set. MIT-BIH NSR Database contains different long-term ECG recordings from 18 subjects. In our experiments, each ECG signal was divided into two sub-signals, about 20 seconds were used from the first sub-signal for the training set and 20 seconds were used from the second sub-signal for testing set. More details were presented in chapter 4 section7 for both ECG databases.

In our approach, the studied ECG signal was firstly preprocessed in order to get an enhanced ECG signal. In this step, three techniques which are widely applied in literature have been used called SG-FIR filter, Butterworth filter and 1D digital filter algorithms. To more distinguish between these methods, we have applied and illustrated each step using each of the three filters. From the obtained results, it can be observed that this step has a significant impact on even the segmentation or the features extraction step as shown in figures 6.5.4 to figure 6.5.9 and subsequently on the CRR of the system.

For the extraction step, our proposed ECG recognition system extracts the non-fiducial features from the segmented ECG heartbeats applying Shifted 1D-LBP.

From Table 6.1, the achieved results are subdivided based on the used ECG database and the applied normalized techniques. Our purpose is analyzing and visualizing the influence of normalized technique on the final performance results of the proposed system. The obtained results are exanimated using the following performance measures of CRR, EER, FAR and FRR which they explained in chapter 1_section 7.

As it can be seen from Table 6.1, for ECG-ID database, we have achieved a CRR of 96.67 when applying SG-FIR filter beside to 2.68%, 2.02%, 2.22% for EER, FAR and FRR, respectively. These results are decreased when applying Butterworth algorithm with all used performance measures where the CRR had become 94.44% and 3.66%, 2.8%, 4.4% for EER, FAR, FRR, respectively. Contrarily to the results applying a Butterworth filter, when we normalized the ECG signal using a 1D digital filter, the CRR is increased to 95.56%. The results had been decreased with remaining performance measures.

For NSR database, as we can observe from Table 6.1, the CRR and FRR were not affected by the used normalized algorithms where we obtain a rate of 100% for CRR and FRR of 5.6. An EER of 2.61% and a FAR of 0% with both SG-FIR and 1D digital filter were attained. These metrics have changed with a Butterworth filter to 3.1%, 0.6% for EER and FAR, respectively. Figure 6.6.1 and figure 6.6.2 show the ROC curve for the proposed approach using ECG-ID and NSR databases which allow us to visualize easier the accuracy of our results.

Table 6.1: Comparison of the performance evaluation of the proposed approach to the other existing systems

Authors	**Extraction method**	**Database**	**CRR**	**EER**	**FAR**	**FRR**
(Biel et al., 2001)	Fiducial features	ECG-ID	98	—	—	—
(Shen et al., 2002)	Fiducial features	NSR	100	—	—	—
(Nemirko et al., 2005)	Fiducial features	ECG-ID	96	—	—	—
(Wübbeler et al., 2007)	Fiducial features	ECG-ID	98	2.8	—	—
(Louis et al., 2014)	1D-MR-LBP	PTB	91	0.09	0.09	0.09
(Dar et al., 2015)	DWT and HRV	ECG-ID	83.8	—	16.1	0.3
		NSR	100	—	0	0
(Barra et al., 2017)	Simple Peak Detection	PTB	96.1	1.33	—	—
(Bassiouni et al., 2018)	Fiducial features +DWT	ECG-ID	98	—	—	—
Our proposed ECG biometric system	Shifted 1D-LBP + SG-FIR filter	ECG-ID	96.67	2.68	2.02	2.22
		NSR	100	2.61	0	5.6
	Shifted 1D-LBP + Butterworth filter	ECG-ID	94.44	3.66	2.8	4.4
		NSR	100	3.1	0.6	5.6
	Shifted 1D-LBP + 1D digital filter	ECG-ID	95.56	3.92	3.4	4.4
		NSR	100	2.61	0	5.6

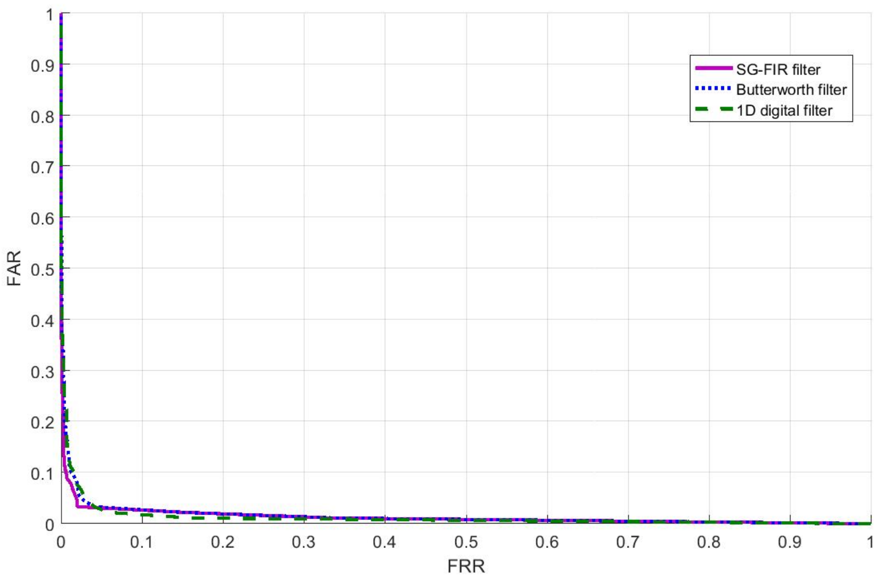

Figure 6.6.1: ROC curve for the proposed approach using ID-ECG databases applying three different normalization techniques.

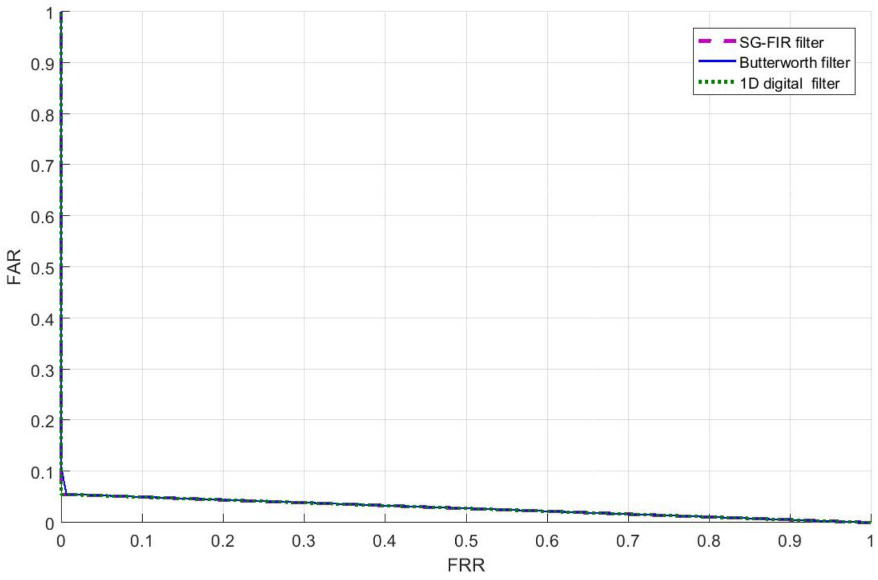

Figure 6.6.2: ROC curve for the proposed approach using NSR database applying three different normalization techniques.

6.7 Proposed Ear – ECG Multimodal Biometric System

Ear biometric is considered as new biometric technology as well as compared to the conventional biometric (iris, face. . . etc.). Indeed, Ear modality has fixed anatomy. It provides important information that increases efficiency and robust texture that can be used for identification or verification system. Alfred Iannarelli (1989) was the pioneer in this field; his work is considered the most reported work in the ear biometrics. His results have shown that the ear has the most unique external design. Also, he demonstrates that ear constitutes important characteristic features and peculiarities that can be used for identification purpose (Iannerelli, 1989). Moreover, many works have been proposed to further improve the confidence of this biometric technology (Anwar et al., 2015; Benzaoui et al., 2014; Ying et al., 2014; Bustard and Nixon, 2010; Kumar et al., 2003).

In order to get better results and increase the performance of our system and overcome the weakness of the unimodal system, we propose a new multimodal system that combines our proposed ECG unimodal system which was explained in the previous section with ear modality. This section is an extension of our work presented in (Regouid Meryem, 2018).

6.7.1 Motivation and Goals

Benefiting from the encouraging results obtained from our proposed ecg biometric system by fusing this modality with ear biometric.

- Exploiting the robustness of local descriptors on 1D domain.
- Increasing the CRR which leads to offering better security.
- Accomplishing better compromise between the (FRR) and the (FAR) and minimizing EER simultaneously.

6.7.2 Architecture of Ear – ECG based Multimodal System

We propose to combine ECG and ear biometric modality in a multimodal system in furtherance of the obtained ECG biometric results and to see the extent of multimodal systems power. The architecture of the proposed approach is detailed as below and depicted in figure 6.7.1.

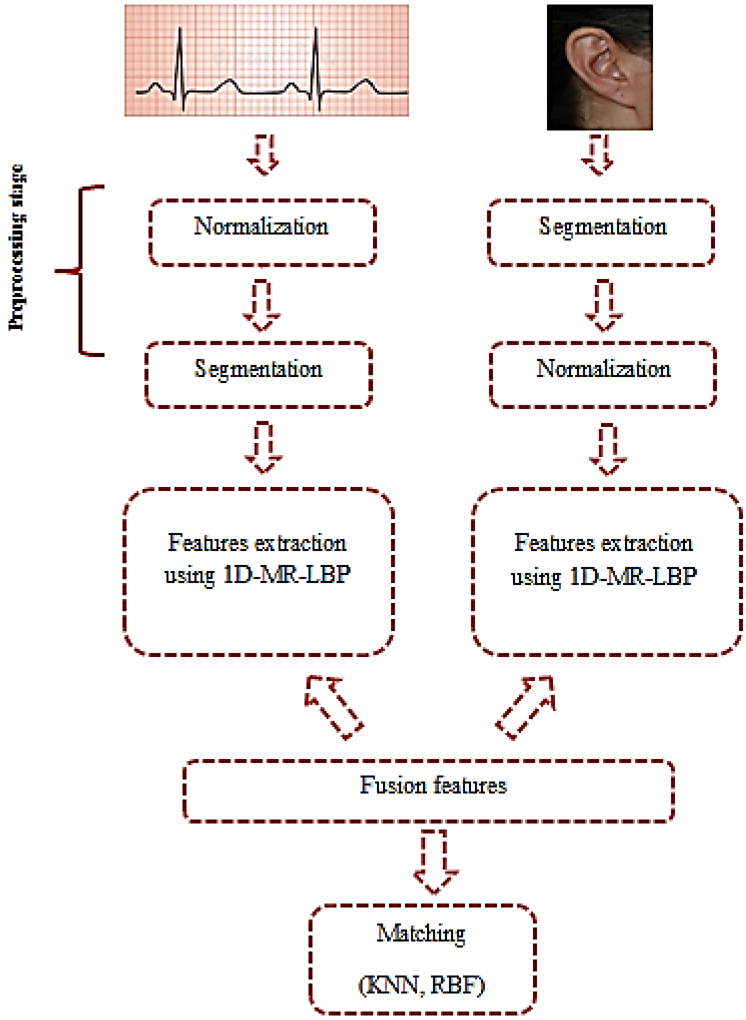

Figure 6.7.1: The proposed Ear – ECG based recognition system.

6.7.2.1 Preprocessing Stage

This stage includes two sub-steps for each biometric modality which consists of normalization and segmentation for both ECG signal and ear image.

With regard to ECG, we maintained the same process for the preprocessing step. SG-FIR filter was applied. it proves its efficiency and power of reducing noises and preserving the ECG signal structure depending on the obtained results on terms of CRR, EER, FAR and FRR from both ECG-ID and NSR databases.

For ear preprocessing, the ear is manually cropped from different artifacts that reduce the accuracy and maximize the EER such as hair and skin areas. Next step consists of converting the different cropped ear images size to a fixed size of 50 x 50 pixels. The resized images were converted then to grayscale images. The preprocessed ear image can be shown in figure 6.7.2.

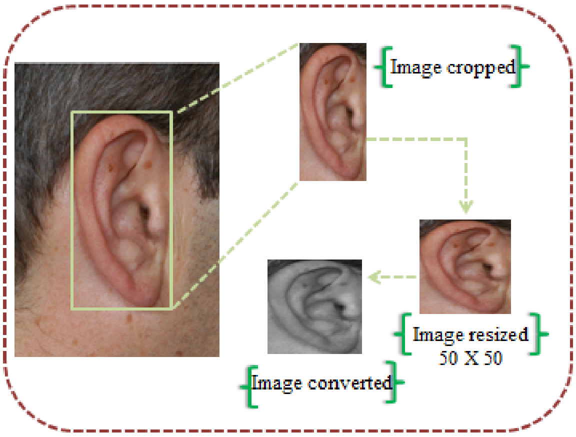

Figure 6.7.2: The ear preprocessing process.

6.7.2.2 Extraction Features

We have applied 1D-MR-LBP method on each of the preprocessed modalities, ECG signal and ear images. The ear image must be converted to 1D data as well as to extract from them the significant features. We have done many experiences to select the best combination of parameters p (p=5) and d (d=4) for ECG and ear biometric. Figure 6.7.3 and figure 6.7.4 show the features results of the 1D-MR-LBP method for ear image and ECG signal, respectively.

Figure 6.7.3: Ear images after applying 1D-MR-LBP.

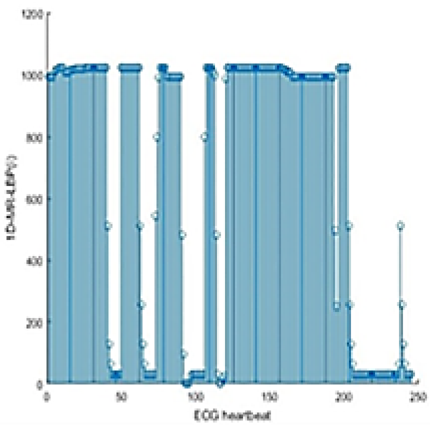

Figure 6.7.4: Features extraction diagram from an ECG heartbeats using 1D-MR-LBP

6.7.2.3 Fusion Features

Once the features data for each modality are successfully generated. We have used a simple rule to fuse both features of modalities as new signature data into a new vector as shown in figure 6.7.5. The generated vector is simply computed as follows:

$$V(_{New\,data}) = V_{EAR}, V_{ECG} \tag{6.7.1}$$

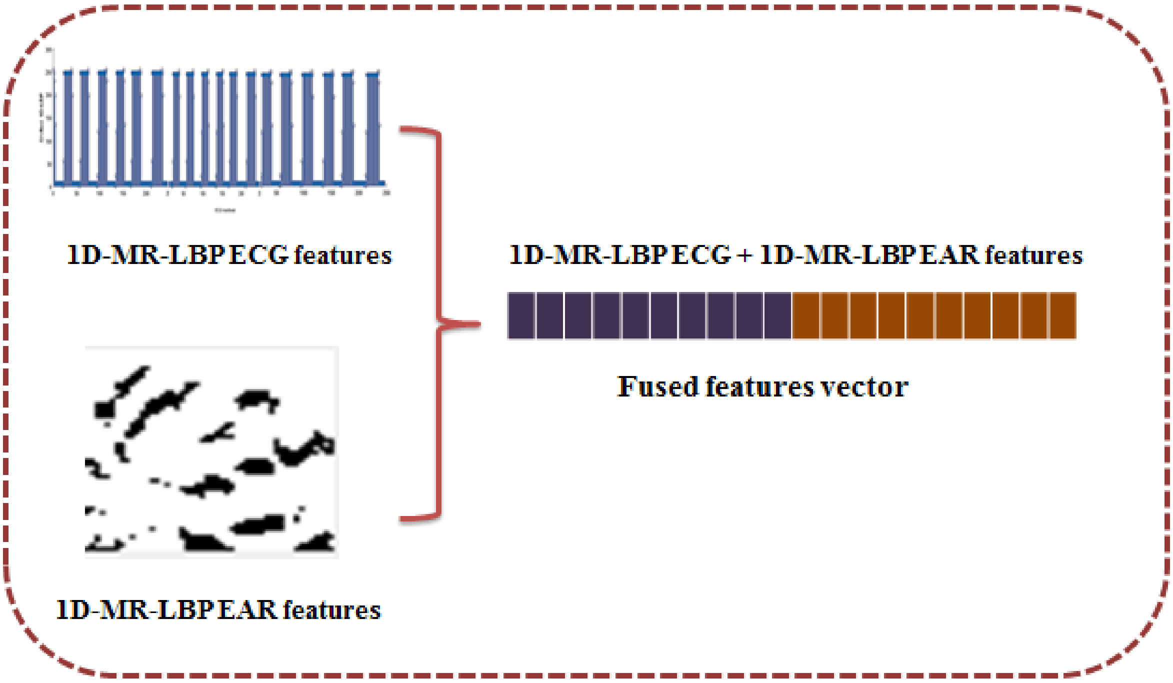

Figure 6.7.5: The fusion of ECG-EAR features process.

6.7.2.4 Classification

In this step, we have assessed the performance of our proposed approach by using two classifier KNN and RBF (Radius Basis Function) network (Haykin et al., 2009). The performances of the classifiers were evaluated in terms of accuracy by equation (1.6.3).

6.7.3 Experimental Results

AMI and ECG-ID public databases are used to validate and test our proposed work. The used AMI and ECG-ID databases are described in detail in chapter3_section 6 and chapter 4_section 7, respectively. In our experiments, for ECG biometric, two records were used per subject, one for the training set and the second as a testing set. Whereas, AMI database was divided into six images per subject as a training set and one image as testing set for ear biometric.

Our discussions will be based on the same performance measures that were used in the first approach. We carry out a comparison between the results achieved from the proposed multimodal system and the results attained from each unimodal system separately.

Table 6.2: Performance evaluation of the proposed EAR-ECG approach.

Modalities	**CRR**	**EER**	**FAR**	**FRR**
ECG-based recognition system (Chun, 2016)	99	2.4	—	—
ECG-based recognition system (Bassiouni et al., 2018)	98	—	—	—
EAR-based recognition system (Ghoualmi et al., 2015)	97.15	—	0.85	4.84
EAR-based recognition system (Benzaoui et al., 2017)	90.26	—	—	—
Our ECG-based recognition system	98	3.10	1	6
Our ear-based recognition system	100	4.01	0.24	6,67
The proposed fusion approach	100	1.51	0.7	3.33

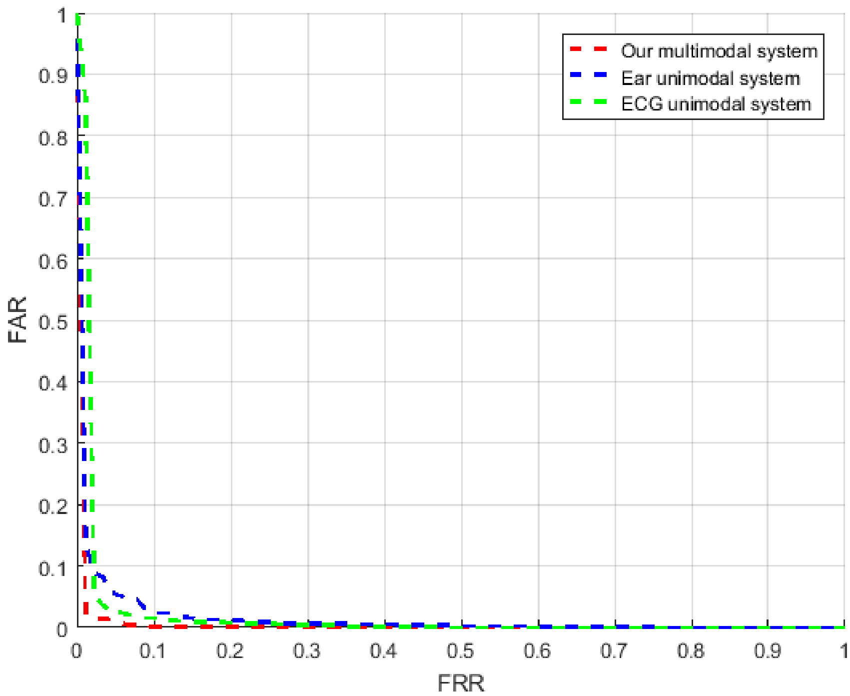

Figure 6.7.6: Roc curve for multimodal system and ECG-EAR unimodal system separately.

From Table 6.2, our ECG unimodal system gets a CRR of 98% where a CRR of 96.67% has been achieved with shifted 1D-LBP. This is demonstrating that 1D-MR-LBP outperforms 1D-shifted-LBP descriptor in terms of CRR and FAR. Unfortunately, it did not maintain its superiority regarding the EER which is increased to 3.1%. For ear unimodal system, a CRR of 100% was achieved beside to a FAR of 0.24%. Whilst a rate of 4.01%, 6.67% was obtained for EER, FRR, respectively. On the other hand, the proposed EAR-ECG multimodal system demonstrates its efficiency by achieving a CRR of 100%. The EER rate was decreased from 4% in the unimodal system to 1.51% in the proposed multimodal system. The FAR was decreased from 1% to 0.7% and FRR from 6% to 3%.

These statistical comparison results showed that our multimodal system can effectively outperform the ECG an ear unimodal system separately in term of CRR, ERR, FAR and FRR. Figure 6.7.6 shows the ROC curve for the proposed approach besides the two ECG and ear unimodal system to more visualize and compare the accuracy of our results.

6.8 Conclusion

We propose in this chapter a novel ECG unimodal biometric system based on Shifted 1D-LBP. We have taken en consideration the importance of each step of the proposed system and analyze its influences on the obtained performance. Three preprocessed technique namely SG-FIR filter, Butterworth filter and 1D digital filter were applied separately on the ECG signal to allow us choosing the best technique in the next proposed multimodal system. Shifted 1D-LBP was applied to extract the non-fiducial features from the segmented heartbeats. The obtained results demonstrate that SG-FIR algorithm outperforms the other applied techniques.

The second proposed approach combines the developed ECG biometric system with ear biometric. 1D-MR-LBP was used to extract the representative patterns from the preprocessed ECG signal and ear image after converting this latter to 1D space. Comparison of the results between ear and ECG multimodal biometric system against each unimodal system separately shows the robustness and the efficiency of 1D-MR-LBP in the extraction of discriminant features.

Based on the observation and results obtained besides the performed analysis, the next chapter will present our contribution of a multimodal biometric system based on ear, ECG and iris biometric. Local descriptors were applied with the purpose of constructing a robust multimodal system with a high-security level. Moreover, it is used to exploit the benefit of local descriptors in the 1D domain.

CHAPTER 7

ECIREA MULTIMODAL BIOMETRIC SYSTEM

7.1 Introduction

Multimodal biometric systems have gained many attentions at a recent time and become an emerging trend. These systems can be defined as the fusion of more than one physiological or behavioral characteristic for verification or identification purpose. Some of the most important reasons to combine multiple biometric traits are to increase security and improve the recognition rate. As security is a vital importance in several domains, many multimodal biometric systems have been proposed.

In recent years, newly emerging biometric technologies have been used extensively for both human identification and security tasks. The use of multiple biometric traits from the same person at the same time minimize the chance of spoofing because it is very hard for a hacker to mimic multiple types of biometric traits at once. Consequently, the security level will be increased. Another power point is the universality of multimodal systems. When a user is unable to provide a form of biometric due to disability or illness, the system can take other forms of biometric for authentication.

In a multimodal biometric system, single or various sensors can be employed to capture the input data depending on the nature of the used modalities. It must be mentioned that the use of multiple devices to take biometric data will increase the cost of the system. Take advantage of all the discussed benefits and decrease the cost of the developed systems depends on many factors. The main factor is the choice of the fused biometric modalities.

Implementing a multimodal biometric system overcomes the weaknesses of unimodal systems and offers these additional benefits:

- The use of various types of data increases significantly the accuracy of identification. It is rare that all measurements will be affected at once by the aforementioned conditions in which they have been captured.

- Sufficient population coverage will be ensured by capturing multiple biometric traits. Therefore, this can address the problem of non-universality.
- Spoof various biometric traits of an enrolled or legitimate user simultaneously is very difficult for an intruder.

Each modality has considerable strengths and weaknesses. The combination of suitable modalities depends on the requirements of the environment. For this reason, there is no one-size-fits-all solution. The choice of appropriate modalities, extraction methods, fusion level, matching techniques and other factors are crucial steps during the development of the multi-modal system. Many multimodal biometric systems have introduced. Various techniques have proposed taking into consideration the factors above to ensure the success of these systems for human identification.

Iris is considered one of the oldest used biometric. Its advantages such as the uncorrelated nature of the iris codes for unrelated persons and its uniqueness lead the system to achieve a high level of security. Analysis of electrocardiogram is considered a new biometrics measure for human identity recognition. Nowadays, ECG biometric has been gaining more attention of many research laboratories because of its strengths especially in the security domain, e-health medical and diseases prevention. Another emerged biometric trait is ear. This last feature is simpler and more accepted by people. Also, it may be easier to acquire data using a simple camera. In this chapter, we will propose a new multimodal biometric system, named ECIREA, based on combining three biometric traits, which are ear, ECG and iris using local descriptors.

7.2 Motivation and Goals

Biometric systems demonstrate its effectiveness and robustness to various types of malicious attacks in various areas in modern society and organizations. The fingerprint is one of the oldest biometric that was used and applied for identification for decades. Recently, many biometric modalities such as face, iris or geometry of hand have been introduced, tested and validated.

This chapter presents our new contribution that fuse ear, ECG and iris in a multimodal biometric system based on local descriptors. We named our system as ECIREA. Monomodal systems based on single biometric traits suffer from some limitations as well as problems concerning missing data and unreliable identification problems. Some of the challenges commonly encountered by the use of each biometric characteristic separately are that this latter can be easily affected by ambient conditions changes. The quality of the used sensor has an influence on the quality of the acquired data, poorly illuminated or variations poses for some modalities.

Because the main objective on authentication system is achieving high security level, hackers find it easier to sneak into a monomodal biometric system. Moreover, some biometric traits are publicly used which makes its spoofing easier. In some cases, the enrolled data can differ from the data during the recognition (identification or verification) which is the problem of intra-class variations besides to interclass similarities also. Another challenge consists of the non-universality where some users may do not have the applied biometric modality. All of these limitations will influence negatively on the developed monomodal biometric system and leads to a limited accuracy. Subsequently, the performance will be decreased.

7.2.1 Motivation

Overcome the pitfalls of unimodal biometric systems by proposing a new multimodal biometric system fusing ear, ECG and iris modalities. The developed system as we have named it ECIREA biometric recognition system aims to get better and robust results.

7.2.2 Goals

- Combining the advantage of each proposed unimodal system.
- Increase the system security level using three biometric modalities. Moreover, fusing biological (ECG) and morphological (ear, iris) biometric traits make it hard to spoof.
- Decreasing EER and maximizing CRR simultaneously.
- Exploiting the benefits of local descriptors (LBPs) on our proposed modalities in 1D space where this method is on 2D in nature with the intention of reducing the complexity weaknesses of a multimodal system.
- Reviewing the results obtained from each proposed 1D-LBPs and the impact of given 1D-LBPs parameters on the achieved results to determine the suitably used parameters.

7.3 Proposed ECIREA Multimodal Biometric System

In this contribution, a new fusion approach of three modalities, namely ECG, ear and iris, was proposed in an attempt to develop a secure and robust multimodal biometric recognition system. The proposed modalities used in the proposed approach were fused with other biometric modalities in many researches (Lumini and Nanni, 2007; Ghoualmi et al., 2014; Tahmasebi and Pourghassem, 2017; Monwar and Gavrilova, 2013; Boumbarov et al., 2011; Al-Hamdani et al., 2013). Until now, there is no system fuses the three biometric modalities together. This section is an extension from our work published in (Regouid et al., 2019).

1D-LBP, Shifted 1D-LBP and 1D-MR-LBP are applied with the aim of getting high-frequency information of ECG signal and ear and iris images. Furthermore, we attempt to enhance the recognition accuracy rate and reduce the EER. Since the nature of biometrics modalities, local texture features impose its existence in several approaches (He et al., 2009; Chatlani and Soraghan, 2010; Louis et al., 2014; Ertuğrul et al., 2016). In our study, 1D-MR-LBP will be applied for the first time on ear and iris biometrics after projecting each image into a 1D signal. We seek to demonstrate its efficiency compared with 1D-LBP and shifting 1D-LBP methods. The proposed recognition process is divided into four phases as described in figure 7.3.1.

7.3.1 Preprocessing Step

7.3.1.1 ECG Preprocessing

The ECG signal can be recorded using a set of electrodes placed on specific places in the human body like chest, neck, arms and legs. The number of attached electrodes has a significant influence on the system. More electrodes improve the accuracy of the developed system but sequentially, more expensive. Therefore, the correct positions of the attached electrodes and its movement during the acquisition have also an impact on the performance of the system.

Generally, there is no fixed number of electrodes; it is depending on the acquisition method. The most largely used acquisition method is the standard 12-lead ECG system placing three electrodes on the surface body (Sörnmo and Laguna, 2005). But there are ECG recognition systems which use only one or two electrodes (Shen et al., 2002). Nowadays, attaching sensor contact on any two points across the heart, ECG can be easily acquired. For real-world and remote login access, hands or fingers can be used to present the ECG of users(Chun, 2016; Coutinho et al., 2010; Zhao et al., 2012; Lourenço et al., 2011; Da Silva et al., 2013).

In the first step, the ECG signal obtained from different databases publicly available is frequency normalized using simple linear interpolation. The preprocessing step aims at removing the noise from the ECG signal and improving the signal equality, derived from muscular interference or more commonly from the power grid (50 Hz or 60 Hz). SG-FIR recursive digital has shown a powerful role in the achieved results.

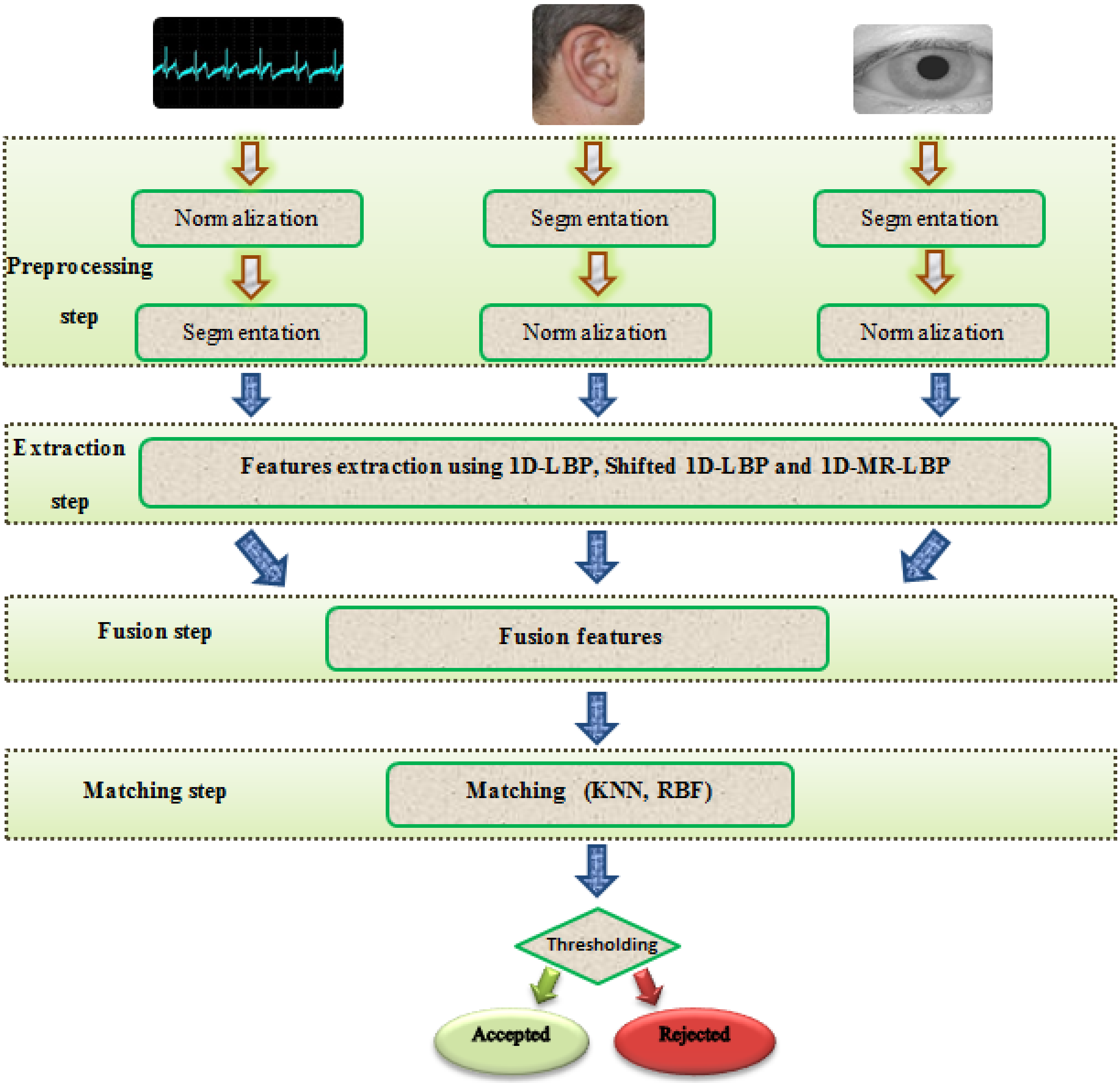

Figure 7.3.1: The proposed recognition process.

In the first step, the ECG signal obtained from different databases publicly available is frequency normalized using simple linear interpolation. The preprocessing step aims at removing the noise from the ECG signal. The second purpose is to improve the signal equality derived from muscular interference or more commonly from the power grid (50 Hz or 60 Hz). SG-FIR technique has shown a powerful role in the achieved results.

The ECG waveforms contain a lot of information. They were located by either on fiducial or non-fiducial techniques. The QRS complex was considered one of the most important fiducial features that might be used to learn the local and global variation of the ECG signal. Therefore, it used to facilitate the heartbeat segmentation task. In this fact, in our paper, we have used

Pan-Tompkins algorithm (Pan and Tompkins, 1985) to isolate the fiducial point (P, Q, R, S and T) for each beat segment. Due to the non-stationary and aperiodic nature of ECG signal, beat lengths for all of the ECG records are not equalized. Each signal has different numbers of waveforms. The same process applied to our proposed ECG unimodal system described in the previous chapter (chapter 6_ section5) is used for our ECIREA system.

7.3.1.2 Ear Preprocessing

For the preprocessing step, the ear image was manually cropped. We apply the same step proposed in the ear-ECG multimodal system that has been detailed in the previous chapter (chapter 6 _ section 7). Figure 7.3.2 shows the original and the preprocessed ear image.

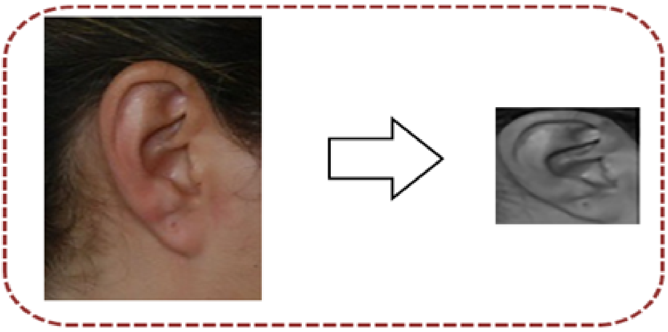

Figure 7.3.2: The original and the preprocessed ear image.

7.3.1.3 Iris Preprocessing

Two sub steps can be distinguished in this stage: segmentation and normalization.

For iris Segmentation step, several algorithms were proposed in the literature for segmentation procedure. (Daugman, 1993) developed an Integro-differential Operator algorithm which allows the location of the circular iris, pupil regions and the arcs of the upper and lower eyelids. (Ritter et al., 1999)proposed Active Contour Models which allows the location of the pupil region. (Wildes et al., 1994), (Masek et al., 2003) and others employed a Circular Hough Transform technique for an automated segmentation algorithm in order to detect the iris and pupil boundaries. We decide to use a Circular Hough Transform technique for the iris and pupil boundaries detection (Masek et al., 2003). As shown in figure 7.3.3, this can be realized in the following phases:

1. Detection of centre coordinates and radius of the detected iris/pupil boundaries using Canny edge detection and Hough Transform.

2. The use of linear Hough Transform to isolate Eyelids by fitting a line to the upper and lower eyelid.

3. The use of thresholding technique to isolate eyelashes .

The next step consists of the normalization process of the segmented image. The main objective of this step is to solve the different problems that can face iris during the acquisition phase such as pupil dilation caused by varying levels of illumination or camera rotation. The normalized image will have the same constant by unwrapping the circular region into rectangular block dimensions. A technique based on Daugman's rubber sheet model was applied. In figure 7.3.4, the difference between noised and normalized iris images were illustrated.

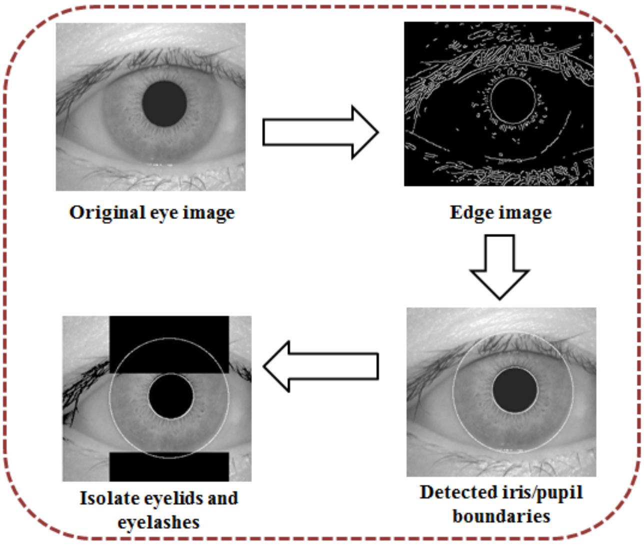

Figure 7.3.3: The iris segmentation steps.

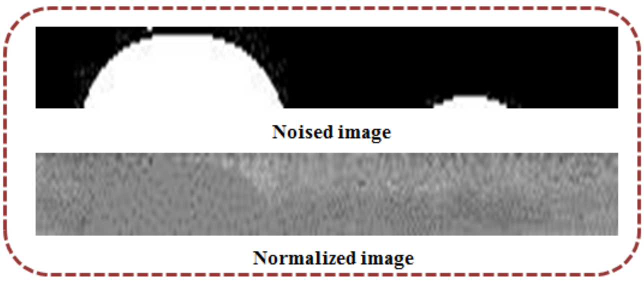

Figure 7.3.4: Example of noised and normalized iris image.

7.3.2 Features Extraction

Local texture descriptors have proven their efficiency in biometric domains which have been applied in a 3D shape, 2D image and also recently 1D signal. Researchers demonstrate the robustness of local texture descriptors in multimodal biometric systems especially in real-world applications as well as easy data acquisition. LBP method has gained great popularity since its first proposal by (Ojala et al., 1996) due to its efficiency of extracting important textures that exist in the processed image using its local neighborhood. LBP generates a binary code by thresholding each value of neighborhood with the value of the centre pixel of an image. It based on the assumption that texture has locally two complementary aspects, a pattern and its strength. While LBP method was used to process pixels of a 2D image, 1D-LBP was used to process samples data for the 1D signal. The first proposition of 1D-LBP method was introduced by (Chatlani and Soraghan, 2010)for the purpose of extracting features from a speech signal and identifies the voiced and the unvoiced components.

The two major steps involved in the biometric system are feature extraction and classification step. In this work, we have more investigated the first step. Feature extraction step aims to reduce the data and select the significant features which must be invariant against multiple issues that may be appeared in the biometric task. Furthermore, feature extraction is one of the crucial step of the biometric system. As well as, it is related to dimensionality reduction and abstraction data (i.e., image, signal, etc.) to get features that will be useful in decision and identification of subjects. Although, many studies on handcraft features have appeared in recent years, LBP remains an interesting feature extraction technique. It keeps attracting researchers particularly after its performance's results on biometric applications such as face, iris and ear. In this purpose, three local texture descriptors, namely 1D-LBP, Shifted 1D-LBP and 1D-MR-LBP, have been implemented and detailed in this dissertation in an attempt to evaluate our multimodal biometric system.

We have implemented 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP methods. Next, we applied these methods on each preprocessed modality (ECG signal and preprocessed ear and iris images) to extract the local features. We must mention that we have firstly converted ear and iris images to 1D space. Many experiences have been performed to determine the suitable parameters for each proposed method and for each modality. Table 7.2 presents some of the tested cases in the aim of choosing the optimal parameters for ECG signal.

We have set the number of neighbors p to 6 in ear and iris features extraction and to 5 in ECG features extraction for 1D-LBP operator. Regarding the number of the obtained bins, which they are related to the choice of neighbors (p), will be equal to 2^{2xp}. In our case, we have 4096 bins for ear and iris converted signals and 1024 for ECG signal. Subfigure 7.3.5 (a) and subfigure 7.3.6 (b) show ear, iris images and ECG features extraction diagram applying 1d-LBP method. The following algorithm 7.1 summarizes the process of 1D-LBP descriptor.

Algorithme 7.1 1D-LBP descriptor

```
Inputs:
        Img, P;
Output:
        1D_LBP_feat;
Begin
    Iv ← Img(:); (Convert the matrix Img to a vector Iv)
    Pc←(P/2)+1;
    Insert P/2 zeros value for left /right side of the vector Iv;
    For i from (P/2)+1 to (size( Iv)+P/2), do
        H ← Iv (i-P/2 to i+P/2 );
        Pc ←H(Pc);
        Feat = 0;
        for k= from 1 to size(H), do
            if ( k not equal to Pc ) then
                if ((H(k)-Pc) >= 0 ) then
                    Sing(k) = 1;
                else
                    Sing(k) = 0;
                endif;
                Feat = Feat + (Sing(k) * 2^(k-1));
            endif;
        Endfor;
        LBP_feat (i-P/2) ←Feat;
    Endfor;
end;
```

On Shifted-1D-LBP operator, we have set the number of left PL and right PR neighbors to 6 and 2, respectively for both ear and iris converted signals. A number of 5 and 3 were assigned to left PL and right PR neighbors respectively for ECG signal. The number of the obtained bins is equal to2^{PL+PR}, therefore, in our case, we have 256 for ear, iris and ECG signals. Subfigure 7.3.5 (a) and subfigure 7.3.6 (b) show ear, iris images and ECG features extraction diagram applying Shifted-1d-LBP method. Algorithm 7.2 explains the mechanism of Shifted 1D-LBP descriptor.

Algorithme 7.2 Shifted-1d-LBP descriptor

```
Inputs:
        Img, PL,PR;
Output:
        Shifted_1D_LBP_feat;
Begin
    Iv ← Img(:); (Convert the matrix Img to a vector Iv)
    Pc= PL+1;
    Insert PL/ PR zeros value for left /right side of the vector Iv;
    For i from PL+1 to (size( Iv)+PL), do
        H ←Iv(i-PL to i+PR);
        Pc ←H(Pc);
        Feat = 0;
        for k from 1 to size(H), do
            if (k not equal to Pc) then
                if ((H(k)-Pc) >= 0) then
                    Sing(k) = 1;
                else
                    Sing(k) = 0;
                endif;
                Feat = Feat + (Sing(k) * 2^(k-1));
            endif;
        Endfor;
        Shifted _LBP_feat (i-PL) ← Feat;
    Endfor;
end;
```

On 1D-MR-LBP operator, the two variables p and d are assigned to 5 and 4 respectively for the three preprocessed ECG, ear and iris signals. Like 1D-LBP, the number of bins obtained was 1024. Subfigure 7.3.5 (c) and subfigure 7.3.6 (c) show ear, iris images and ECG features extraction diagram applying 1D-MR-LBP method. This latter is more detailed in Algorithm 7.3.

Algorithme 7.3 1D-MR-LBP descriptor.

```
Inputs:
        Img, P,d;
Output:
        1D_MR_LBP_feat;
Begin
    Iv ← Img(:); (Convert the matrix Img to a vector Iv)
    Insert P+d zeros value for left /right side of the vector Iv;
    New_sz ← the size of updated Iv;
    k=New_sz;
    ε=0.01;
    For t from P+d to ( New_sz – (P+d) + 1), do
        Feat = 0;
        i = 0;
        Bln = false;
        do
            if ( ( (t+i+d) > k ) OR ( (t+i) < (p+d) ) ) then
                Feat = 0;
                Bln = true;
            Else
                if ( ( ( Iv(t+i–p–d+1 ) – Iv (t) ) + ε) >= 0) then
                    Sing(k) = 1;
                else
                    Sing(k) = 0;
                endif;
                Feat = Feat + (Sing(k) * 2^i);
                if (( ( Iv(t+i+d ) – Iv (t) ) + ε) >= 0) then
                    Sing(k) = 1;
                else
                    Sing(k) = 0;
                endif;
                Feat = Feat + (Sing(k) * 2^(i+p));
            endif
            i = i+1;
        While ( ( i < P ) AND (Bln = false) ) ;
        1D_MR_LBP_feat (t-(P+d) +1) ←Feat;
    Endfor;
end;
```

For the ECG signal, the extracted non-fiducial features for each heartbeat, applying the three methods described above, were post-processed. This phase consists of dividing the extracted features on the addition of heartbeat length and its maximum value. Each constructed features vector was stored for the matching process. The proposed normalization features vector is given as:

$$F(i) = \frac{F(i)}{N + max(F)} \tag{7.3.1}$$

Where F represents the ECG features vector. N is the length of ECG heartbeat.

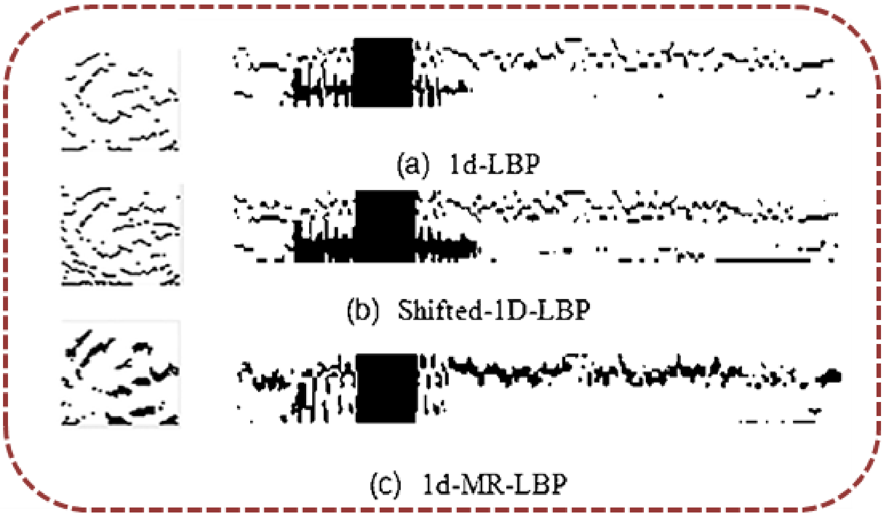

Figure 7.3.5: Ear and iris images after applying (a) 1d-LBP (b) Shifted-1D-LBP (c) 1d-MR-LBP , respectively.

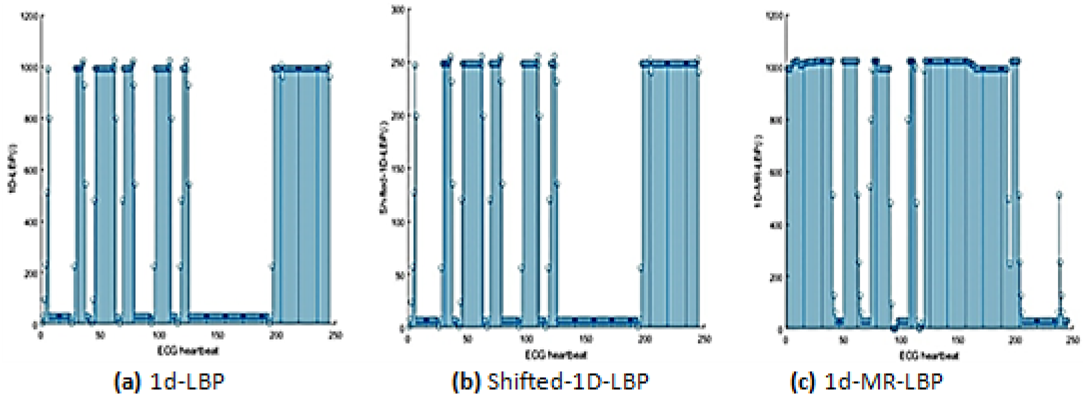

Figure 7.3.6: Features extraction diagrams from ECG heartbeats using (a) 1d-LBP with parameters p=6. (b) Shifted -1d-LBP with parameters pl=6 and pr=2. (c) 1d-MR-LBP with parameters d=4 and p=5.

7.3.3 Features Fusion

Numerous identification systems based on different modalities have been proposed. The combination of these modalities can be performed at different levels. It can be fused at five scenarios i.e. sensor level, feature-extraction level, matching-score level, rank level and decision level. Fusion at the match score, rank and decision levels have been extensively studied in the literature as shown in Table 7.1.

The ease of these levels made them widely used in various multimodal systems, whereas the fusion at the feature level can face some difficulties. The integration of features that are extracted from multiple information sources may not feasible in some cases. Richer information can be found in the features' set compared with the match score or decision. Thus, better results are expected to be achieved. Many sets reduction, normalization and transformation techniques are applied during the concatenation of features sets in order to generate the fused vector.

In practice, the following pitfalls make feature fusion level difficult to achieve:

- Non-homogeneous feature, this is caused by two cases. Either by using multiple modalities where the nature of fused data may be incompatible for example, hand geometry and face. Or by applying different techniques of extraction on the same data.
- In certain situations, it may be not possible to know the relationship between the feature spaces of different biometric systems.
- Another problem, called the curse of dimensionality, can be appeared during the concatenation of multiple features set. In other words, the new fused vector may have a large dimensionality.
- To classify the generated features vectors, a robust and more complex matcher might be required.

In feature extraction level fusion, a new feature vector is formed by the concatenation of different feature sets extracted from multiple biometric sensors. Sometimes, Feature level fusion employs some feature selection and normalization technique to perform feature selection on the concatenated feature vector.

The selected technique has the purpose of deleting useless information that lead to misclassification. Except, the important and representative characteristics must be selected. Although, the features normalization has the aim of change the location and scale parameters of individual feature values. This modification allows the transformation of the value into a common domain. Several types of normalization schemes can be applied like Z-score, tanh or min-max (Ross and Govindarajan, 2005).

Table 7.1: Various fusion levels for multimodal biometric systems discussed in literature.

Authors	**Fused modalities**	**Fusion level**
(Frischholz and Dieckmann, 2000)	Face, Voice, Lip	Match score
(Ross and Jain, 2003)	Face, Hand, Finger	Match score
(Chang et al., 2003)	Face, Ear	Feature
(Kumar et al., 2003)	Palm, Hand	Match score, Feature
(Ross and Govindarajan, 2005)	Hand, Face	Feature
(Kryszczuk et al., 2007)	Face, Voice	Decision level
(HONG et al., 2008)	Palm print, Face	Decision level
(Boodoo and Subramanian, 2009)	Ear , Face	Decision level
(Razzak et al., 2010)	Fingerprint ,Face	Score level
(Gawande et al., 2012)	Iris, Fingerprint	Feature level
(Bokade and Sapkal, 2012)	Face, Palm print	Feature level
(Dhameliya and Chaudhari, 2013)	Palm print, Fingerprint	Score level
(Abdolahi et al., 2013)	Iris, Fingerprint	Decision level
(Bharadi et al., 2014)	Iris, Fingerprint	Decision level
(Benaliouche and Touahria, 2014)	Fingerprint, Iris	Score and decision levels
(Arteaga-Falconi et al., 2018)	ECG, Fingerprint	Decision level
(Khoo et al., 2018)	Fingerprint, Iris	Feature level

In our contribution, the extracted features templates from the three modalities ECG, ear and iris for each subject are concatenated together into a new fused feature vector. We aim that the generated vector will contain more important information which allows us identify the person.

Results of Ross research's have proved that feature level fusion outperforms matching score fusion. Besides that, the merged vector represents richer information at an earlier stage of processing (Kumar et al., 2003). A popular technique for data fusion in feature level which is used in the proposed work is a concatenation by a union. A simple normalization technique was applied for ear and iris features vectors where the number of templates is greater than 1 template in order to reduce the size of fused features. Our objective is to fuse the three data in new feature vector Z.

The first step consists of normalizing and converting the ear and iris matrixes to 1D space by applying the followed function:

$$Y = \frac{\sum_{i=1}^{n} V((i-1)*m+1, i*m)}{m-1} \tag{7.3.2}$$

Where V is the computed features matrixes (in our case, it can be either ear features matrix or iris features matrix), n represents the number of subjects and i = 1...n. m is the number of used templates for each subject.

After applying this techniques, let F = {f1, f2, f3....fk}, H = {h1, h2, h3...hs} and T = {t1, t2, t3...tj} denote features vectors representing the information extracted via ear, ECG and iris biometric sources. We propose to employs a simple concatenation method to fuse these data defined as:

$$Z = f1, f2, f3....fk, h1, h2, h3...hs, t1, t2, t3...tj \tag{7.3.3}$$

This process is well illustrated in figure 7.3.7.

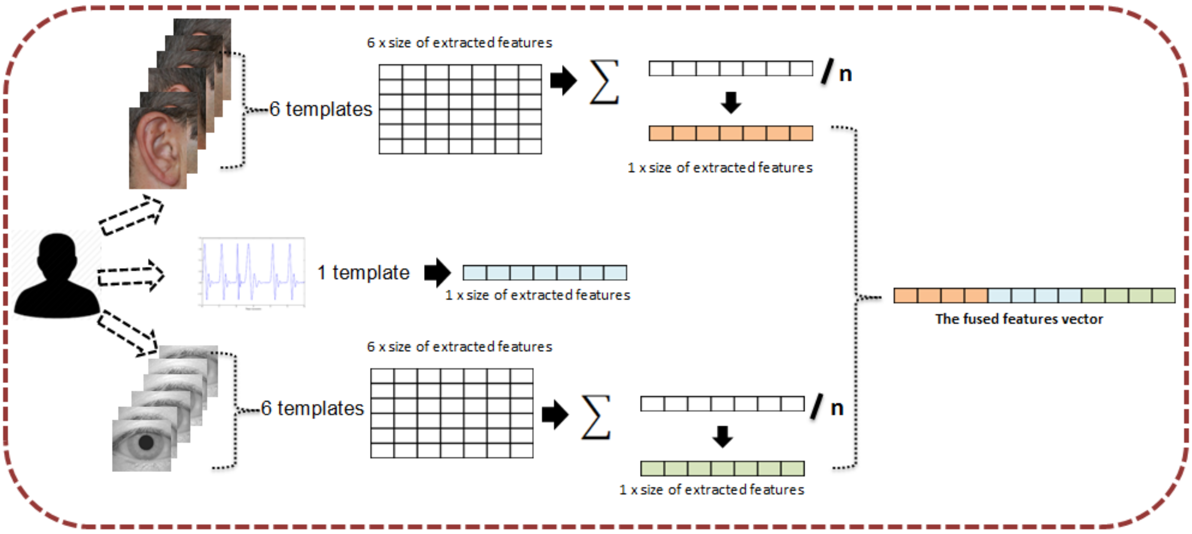

Figure 7.3.7: The proposed fusion scheme.

7.3.4 Matching

In the matching step, the features extracted from the three input data (ECG, ear and iris) were fused in a new vector which will be compared with the templates collected during the enrollment phase. KNN and RBF classifiers are used to match the input template with the registered templates (Haykin et al., 2009).

Our neural network training algorithm did not require many parameters compared to other neural networks (MLP, LVQ), which usually use the smoothing parameter σ to control the fitting of training of the network. Obviously, to get a higher recognition rate, we have made a series of experiments to choose the best smoothing parameter σ used in RBF.

7.4 Experimental Results

7.4.1 Databases

Our proposed approach is validated by applying different public databases. We have used AMI, USTB1 and USTB2 database for ear biometric, ECG-ID database for ECG biometric and CASIA database for iris biometric. More details on the employed ear, ECG and iris benchmarks databases has offered in chapter 3, 4, 5, respectively.

In our experiments, two records were used per subjects for ECG database, one as a training set and the other as a testing set. We have taken 2 images per subject as training set and one image as testing set from USTB 1 database and 3 images per subject as training set and one image as testing set from USTB 2 database. Concerning the division of data from AMI database on train/test set, we have divided it into six images per subject as a training set and one image as testing set. Regarding CASIA Iris V1 database, six images were taken as a training set and one as testing set.

In our ECIREA multimodal system, an equal number of subjects must be performed. Since three databases (AMI, USTB1 and USTB2) for ear were done, three cases were considered. In the case of validating our proposed experiments using AMI databases, 90 subjects are chosen from ECG-ID, CASIA and AMI database. In the second case using USTB1 databases, 60 subjects are chosen from ECG-ID, CASIA and USTB1 database. The last case using USTB2, 77 subjects are chosen from the three databases.

7.4.2 Performance Measures

To validate any biometric recognition system, FRR (False Rejection Rate), FAR (False Acceptance Rate), ERR (Equal Error Rate), ROC (Receiver Operator Characteristic) and accuracy must be calculated which indicate the performance measures. Accuracy can be calculated by:

$$CorrecteRecognitionRate = 100 - \frac{(FRR + FAR)}{2} \tag{7.4.1}$$

Where: FRR indicates that genuine person was considered as an imposter and FAR indicate that imposter was considered as a genuine person. EER indicates the point where: FRR-FAR=0. We also generate ROC curves which allow evaluating and comparing our algorithms with others and visualizing their performances.

7.4.3 Results

In this section, to assess the performance of the effectiveness of the methods that have been stated in this work, three experiences have been implemented and analyzed in this study. This study is looking ahead to distinguish the different strengths and weaknesses of these proposed methods in each unimodal system on the one hand and their effects in the multimodal system. A comparison of our results against relevant literature, on the other hand, was performed. MATLAB framework 2016b was used to implement the proposed multimodal biometric system and plot the desired figures.

Figure 7.3.1 shows the architecture of the proposed multimodal biometric system. As described above in section 4, each unimodal biometric system has three stages. The preprocessed stage has normalization and segmentation sub-stages including the conversion of preprocessed ear and iris images to 1D space as shown in figure 7.3.2 to figure 7.3.4. Then, the textures descriptors namely 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP were extracted from the preprocessed signals, figure 7.3.5 and figure 7.3.6 illustrate the different extracted features from the three biometric modalities. Finally, KNN and RBF were adopted for the matching step. The results are tabulated in Table 7.3, Table 7.4 and Table 7.5 for each unimodal biometric system. Table 7.6 summarizes the results of ECIREA multimodal systems based on local descriptor textures.

Many experiences have been performed to select the parameters' values for the three experiments. Table 7.2 presents CRR for sixteen different parameters value's for each descriptor for ECG processing in order to choose the optimal cases. For 1D-LBP method, it can be seen that the best result was obtained by assigning P to 5. These results are degraded when P takes high values such as 15 and 16 neighbors. For Shifted D-LBP, the first best CRR is achieved by assigning PL to 5 and PR to 3. Because 1D-LBP gives good results with P=5, we keep the same value for 1D-MR-LBP. The parameter d is changed from 1 to 16 to visualize its influence on the obtained results. It can be noticed from Table 7.2 that the first high CRR is given by setting d to 4. It must be mentioned that the CRR decreases when we maximize the distance parameter d. The same process was followed for both ear and iris biometric for assigning the parameters' values. In addition, we plotted boxplot to visualise the CRR for the three experiments based on different parameters' values., results are shown in figure 7.4.1.

Table 7.2: The three descriptors applying different parameters' values.

1D-LBP	**P**	1	2	3	4	5	6	7	8
	CRR	94.44	95.55	95.55	95.55	**96.66**	96.66	94.44	94.44
	P	9	10	11	12	13	14	15	16
	CRR	94.44	93.33	95.56	95.56	95.56	93.33	92.22	92.22
Shifted 1D-LBP	**PL**	2	3	3	4	5	3	7	4
	PR	3	2	4	3	3	5	4	7
	CRR	94.44	95.55	95.66	95.66	**96.66**	96.66	94.44	96.66
	PL	6	5	2	5	8	3	9	2
	PR	5	6	5	2	3	8	2	9
	CRR	96.66	96.66	95.55	96.66	94.44	96.66	94.44	95.55
1D-MR-LBP	**d**	1	2	3	4	5	6	7	8
	CRR	92.22	88.88	96.66	**97.77**	97.77	96.66	95.55	95.55
	d	9	10	11	12	13	14	15	16
	CRR	96.66	94.44	94.44	94.44	92.22	92.22	92.22	92.22

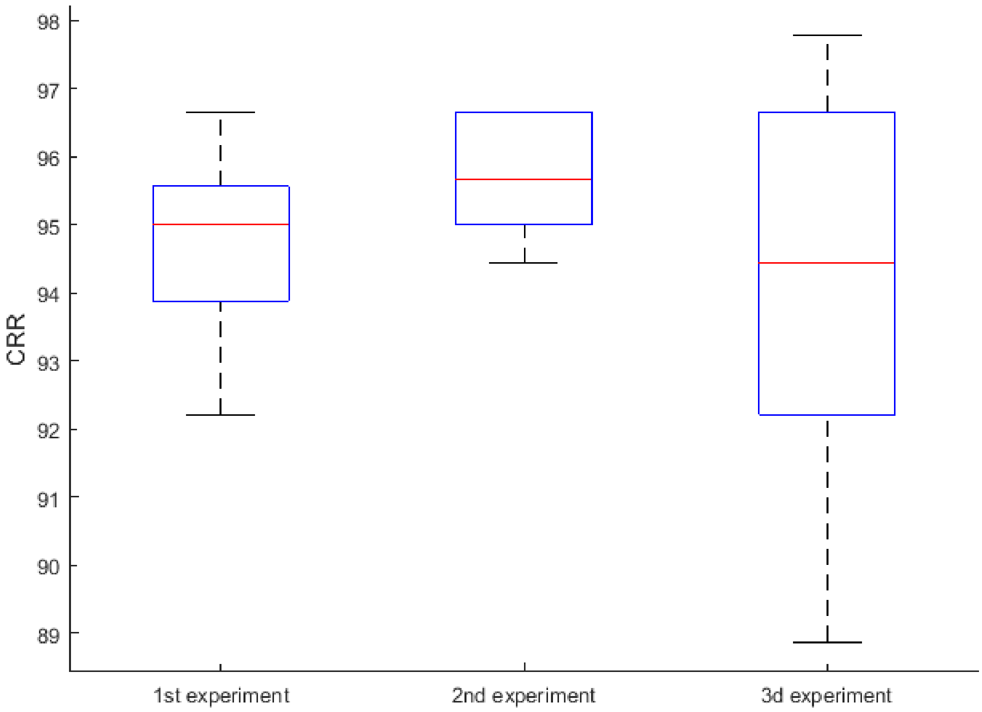

Figure 7.4.1: Boxplot for the distribution of CRR for the three experiments based on different parameters' values.

In Table 7.3, the proposed unimodal ECG biometric was tested over the three experiments. Different measures have been calculated to evaluate the performance of our unimodal system. Locale descriptors textures, 1D-LBP, Shifted-1D-LBP and 1D-MR-LBP, extract rich and complex non-fiducial information from the segmented heartbeats. For classification, we can see that 1D-MR-LBP has achieved a CRR of 98%. The same result was obtained using the two classifiers (KNN and RBF) whereas less CRR of 97% has obtained by 1D-LBP and Shifted-1D-LBP. To envisage better the difference between the applied descriptors on ECG data, a ROC curve was generated and illustrated in figure 7.4.2.

Table 7.3: Comparison of performance measures for our proposed unimodal ECG systems with related systems.

Authors	**Extraction method**	**Database**	**CRR**	**EER**	**FAR**	**FRR**
(Biel et al., 2001)	Fiducial features	ID-ECG	98	—	—	—
(Nemirko and Lugovaya, 2005)	Fiducial features	ID-ECG	96	—	—	—
(Boumbarov et al., 2011)	PCA and LDA	Own	95.7	—	—	—
(Al-Hamdani et al., 2013)	Mel-Frequency Cestrum Coefficients	Own	98.5	4.5	—	—
(Louis et al., 2014)	1D-MR-LBP	PTB	91	0.09	0.09	0.09
(Dar et al., 2015)	(DWT)and (HRV)	ID-ECG	83.88	—	16.1	0.3
(Chakraborty et al., 2016)	histogram based method	Own	95	—	—	—
(Chun, 2016)	Guided filter + distance measurements	ID-ECG	99	2.4	—	—
(Barra et al., 2017)	simple peak detection	PTB	96.15	1.33	—	—
(Bassiouni et al., 2018)	Fiducial features +DWT	ID-ECG	98	—	—	—
Our 1^{st}experiment	1D-LBP	ID-ECG	96.67	2.16	0. 71	5.56
Our 2^{nd} experiment	shifted 1D-LBP		96.67	2.16	0. 71	5.56
Our 3^{rd} experiment	1D-MR-LBP		98	3.10	1	6

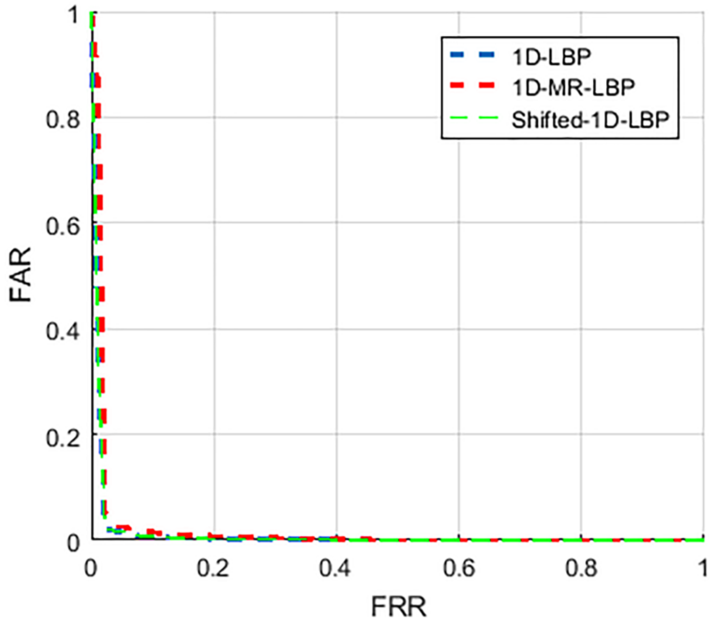

Figure 7.4.2: ROC curve for unimodal ECG systems by the three experiments.

In Table 7.4, evaluation of the proposed unimodal ear biometric was performed over the three experiments using USTB1, USTB2 and AMI database. After the enhancement of 2D ear image, the conversion on 1D space was accomplished to allow the proposed descriptors extracting features. The same results were obtained with KNN and RBF classifiers. With USTB1 database, we got a CRR of 100% using the three methods, whilst, a lower CRR has been acquired from USTB2. The ROC curves are shown in figure 7.4.3, figure 7.4.4 and figure 7.4.5 for USTB1, USTB2 and AMI databases, respectively. It allows us to visualize easily our results mentioned in Table 7.4 for 1D- LBP (where p=6), Shifted-1D-LBP (where PL=6 and PR=2) and 1D-MR-LBP (where p=5 and d=4).

Table 7.4: Comparison of performance measures for our proposed unimodal ear systems with related systems.

<table>
<tr><th>Authors</th><th>Extraction method</th><th>Database</th><th>CRR</th><th>EER</th><th>FAR</th><th>FRR</th></tr>
<tr><td>(Ghoualmi et al., 2014)</td><td>SIFT</td><td>USTB2</td><td>91.36</td><td>—</td><td>0.65</td><td>7.74</td></tr>
<tr><td>(Ghoualmi et al., 2015)</td><td>SIFT</td><td>USTB1</td><td>97.15</td><td>—</td><td>0.85</td><td>4.84</td></tr>
<tr><td rowspan="2">(Hezil and Boukrouche, 2017)</td><td>LBP</td><td rowspan="2">IIT Delhi-2</td><td>95.02</td><td>—</td><td>—</td><td>—</td></tr>
<tr><td>BSIF</td><td>98.9</td><td>—</td><td>—</td><td>—</td></tr>
<tr><td>(Tahmasebi and Pourghassem, 2017)</td><td>Gabor filter</td><td>UND</td><td>—</td><td>—</td><td>18</td><td>10</td></tr>
<tr><td rowspan="3">Our 1^{st} experiment</td><td rowspan="3">1D-LBP</td><td>USTB1</td><td>100</td><td>1.05</td><td>1.33</td><td>1.60</td></tr>
<tr><td>USTB2</td><td>98.70</td><td>6.54</td><td>1</td><td>11</td></tr>
<tr><td>AMI</td><td>98</td><td>0. 77</td><td>1.09</td><td>4.9</td></tr>
<tr><td rowspan="3">Our 2^{nd} experiment</td><td rowspan="3">shifted 1D-LBP</td><td>USTB1</td><td>100</td><td>1.05</td><td>1.22</td><td>1.6</td></tr>
<tr><td>USTB2</td><td>97.40</td><td>6</td><td>1</td><td>13.5</td></tr>
<tr><td>AMI</td><td>98</td><td>0. 70</td><td>1</td><td>4.5</td></tr>
<tr><td rowspan="3">Our 3^{rd} experiment</td><td rowspan="3">1D-MR-LBP</td><td>USTB1</td><td>100</td><td>2.03</td><td>1.05</td><td>3.33</td></tr>
<tr><td>USTB2</td><td>97.40</td><td>6.22</td><td>1</td><td>14</td></tr>
<tr><td>AMI</td><td>100</td><td>2.07</td><td>0.24</td><td>6,67</td></tr>
</table>

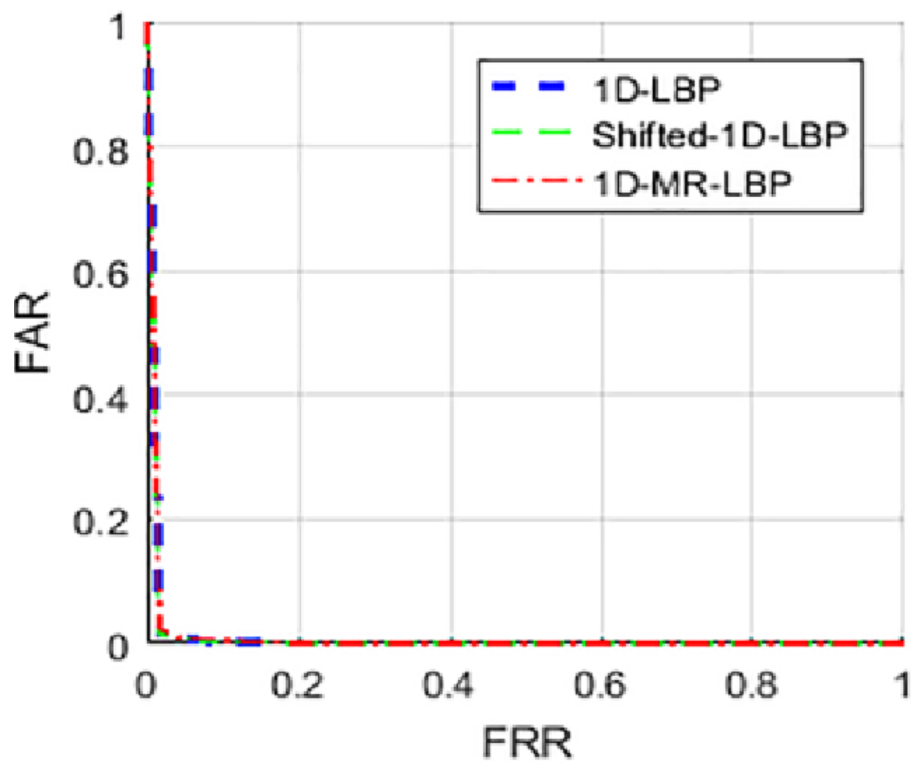

Figure 7.4.3: ROC curves for unimodal ear systems using USTB1 database.

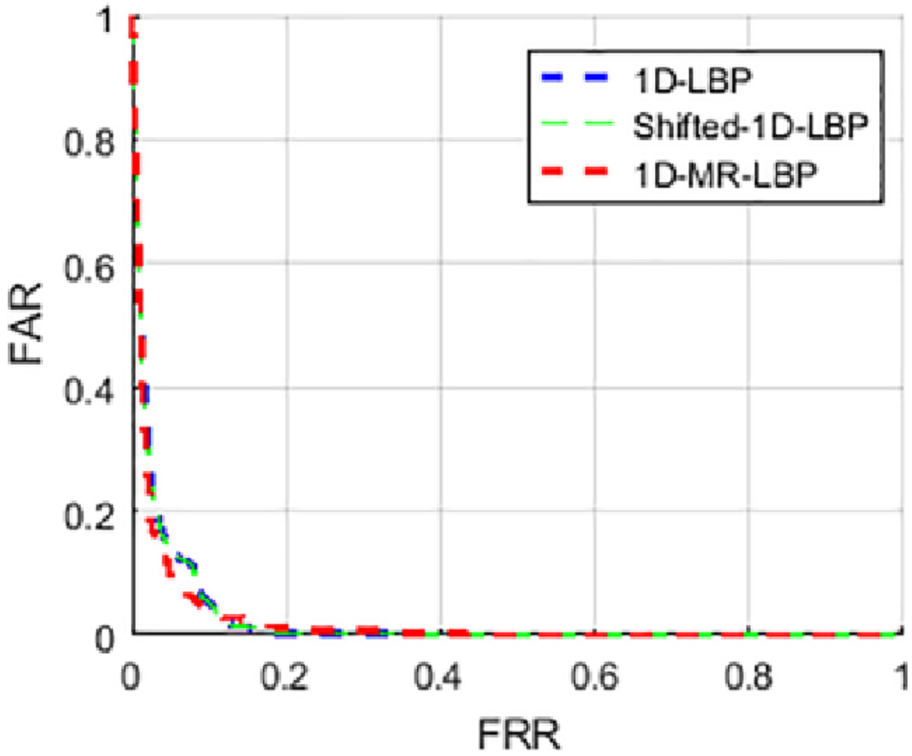

Figure 7.4.4: ROC curve for unimodal ear systems using USTB2 database.

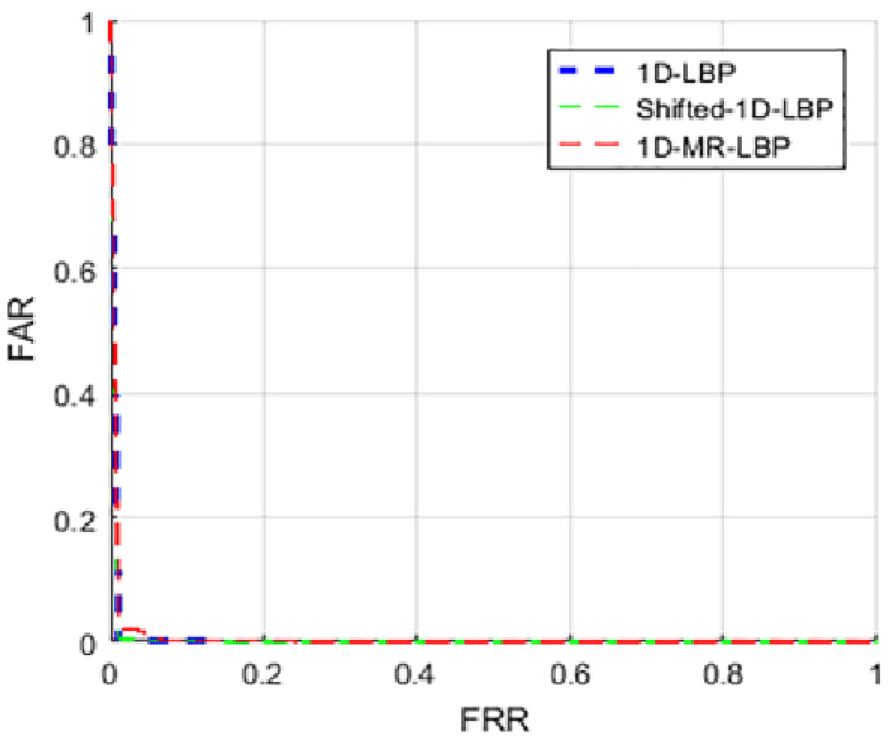

Figure 7.4.5: ROC curve for unimodal ear systems using AMI database.

In Table 7.5, we have tested the performance of our unimodal iris system over the proposed 3 experiments. CASIA database was used to validate our proposed approaches. It can be seen that 1D-MR-LBP has proved its efficiency in terms of CRR, EER, FAR and FRR with 100%, 1.19%, 0.16% and 2.22% respectively. From Table 7.5, it can be noticed that 1D-MR-LBP achieves better results than 1D-LBP and Shifted-1D-LBP. Figure 7.4.6 presents the ROC curve for unimodal iris system.

Table 7.5: Comparison of performance measures for our proposed unimodal iris systems with related systems.

Authors	**Extraction method**	**Database**	**CRR**	**EER**	**FAR**	**FRR**
(Daugman, 1993)	1D- Gabor filters	Own	99.61	0.32	—	—
(Ghoualmi et al., 2014)	SIFT	CASIA v1	95.80	—	0.65	7.74
(Marciniak et al., 2014)	LG filters	CASIA v1	97	—	3.25	3.03
(Barpanda et al., 2018)	tunable filter bank	CASIA v3	91.65	8.35	8.45	8.25
Our1st experiment	1D-LBP	CASIA v1	98.89	1.90	0.27	3.33
Our2ndexperiment	shifted 1D-LBP		98.89	1.88	0.21	3.22
Our3rd experiment	1D-MR-LBP		100	1.19	0.16	2.22

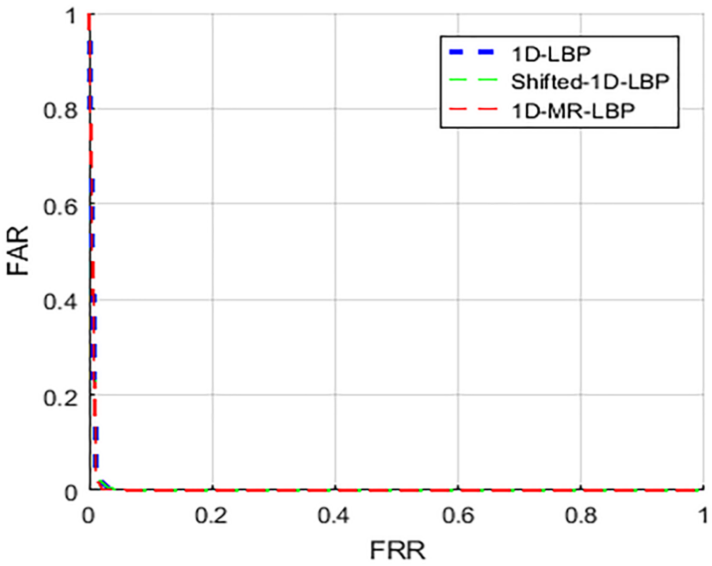

Figure 7.4.6: ROC curve for unimodal iris systems by the three experiments.

In Table 7.6, three multimodal systems were evaluated, tested and compared with literature works. The difference between these systems is centred in the features extraction method where the first system use 1D-LBP, the second use Shifted-1D-LBP, while the third system extract features using 1D-MR-LBP. Because we have used 3 databases for ear biometric, 3 cases in each multimodal system will be studied: the first case consists of fusing the ID-ECG, USTB1 and CASIA v1 databases, the second case consists of fusing the ID-ECG, USTB2 and CASIA v1 databases. The last case consists of fusing the ID-ECG, AMI and CASIA v1 databases. ROC curves for multimodal systems for the three experiments using USTB1 database are illustrated in figure 7.4.7, figure 7.4.8 and figure 7.4.9.

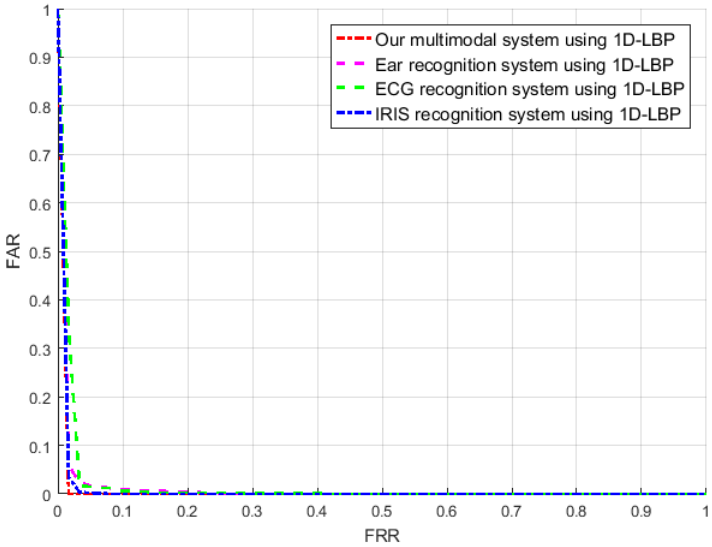

Figure 7.4.7: ROC curve for multimodal systems for the first experiment using USTB1 database.

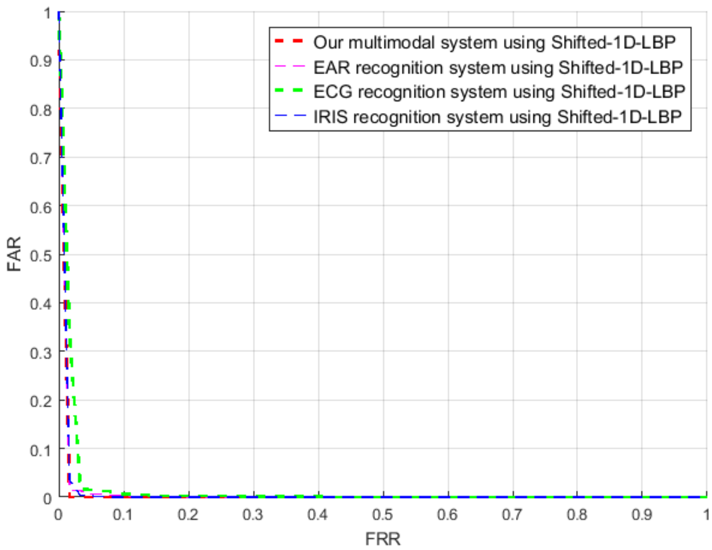

Figure 7.4.8: ROC curve for multimodal systems for the second experiment using USTB1 database.

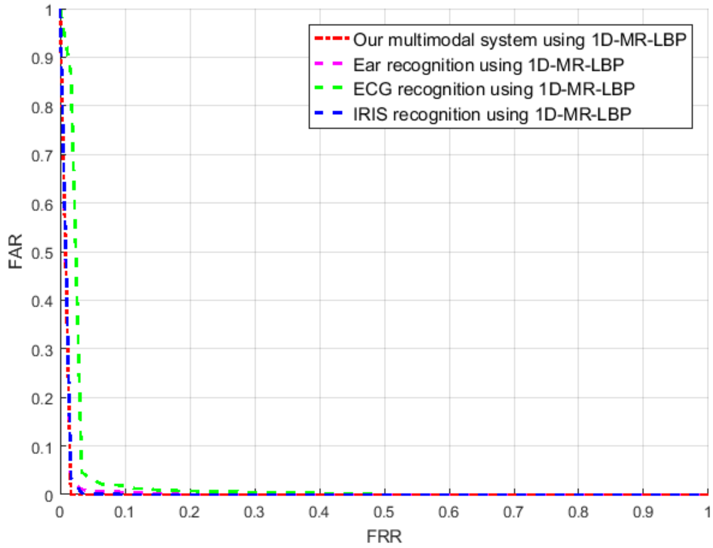

Figure 7.4.9: ROC curve for multimodal systems for the third experiment using USTB1 database.

Table 7.6: Comparison of performance measures for our ECIREA system with related systems.

Authors		**Modalities**	**Fusin level**	**CRR**	**EER**	**FAR**	**FRR**
(Boumbarov et al., 2011)		ECG and face	Decision	99.5	—	—	—
(Nadheen and Poornima, 2013)		Ear and Iris	Features	93	—	0.05	0.1
(Al-Hamdani et al., 2013)		ECG and speech	Score	—	0.7	—	—
(Monwar and Gavrilova, 2013)		Ear, Iris and face	Rank	98.29	—	—	—
(Ghoualmi et al., 2014)		Ear and Iris	Features	99.67	—	0	0.64
(Chakraborty et al., 2016)		ECG and Face	feature	97.5	—	—	—
(Hezil and Boukrouche, 2017)		Ear and palmprint	Features	100	—	—	—
(Tahmasebi and Pourghassem, 2017)		Ear, Palmprint and signature	Rank	99.63	0.37	0.17	0.37
(Barra et al., 2017)		ECG and EEG	Score	96.85	0.94	—	—
Our 1^{st}experiment	1^{st} case	ECG, ear and Iris	Feature	100	0.82	0	1.57
	2^{nd} case			99	2.08	1.28	2.60
	3^{rd} case			100	**0.54**	**0**	**1.110**
Our 2^{nd} experiment	1^{st} case			100	0.81	0	1.64
	2^{nd} case			99	2.07	1.28	2.60
	3^{rd} case			100	0.56	0	1.111
Our 3^{rd} experiment	1^{st} case			100	0.82	0	1.42
	2^{nd} case			99	0.73	0.09	1.30
	3^{rd} case			99	0.57	0	2.022

In each experiment, as previously stated, the 1D-LBP, Shifted-1D-LBP and MR-LBP were applied on each preprocessed ECG, ear and iris biometric. The extracted features were fused together at the feature level to obtain a single vector. The main advantage of fusion, at this level, is that our homogeneous data don't require any normalization which reduces the complexity that shortens the time. For the classification step, we got the same results applying KNN and RBF classifiers. It can be observed, from Table 7.6, that the 3^{rd} case achieves better results than the other two cases in all experiments in terms of EER with 0.5% where the CRR varies from 99% to 100% in the 3 experiments. From the obtained results, we can affirm that our multimodal systems perform better than different unimodal systems. Minimum EER was obtained with the 1st experiment using 1D-LBP descriptor in the 3^{rd} case using ID-ECG, AMI and CASIA v1 databases. Figure 7.4.10 to figure 7.4.15 show ROC curves for our experiments for the two cases (USTB2 and AMI) which allow us to conjure up the obtained results clearly.

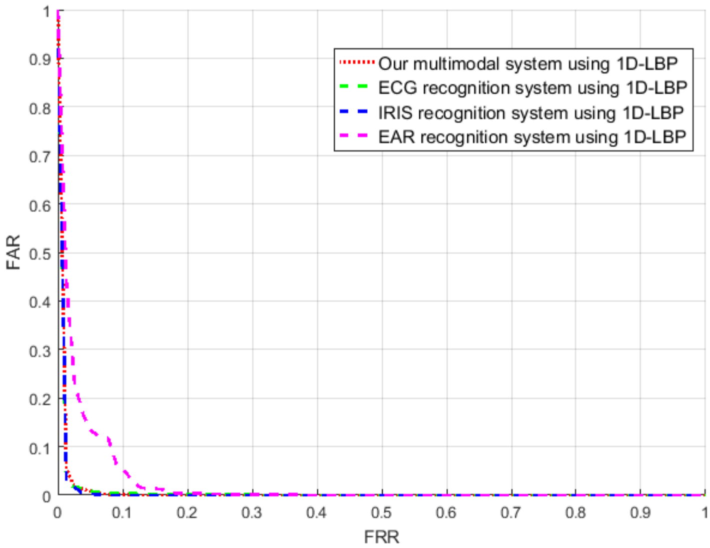

Figure 7.4.10: ROC curve for multimodal systems for the first experiment using USTB2 database.

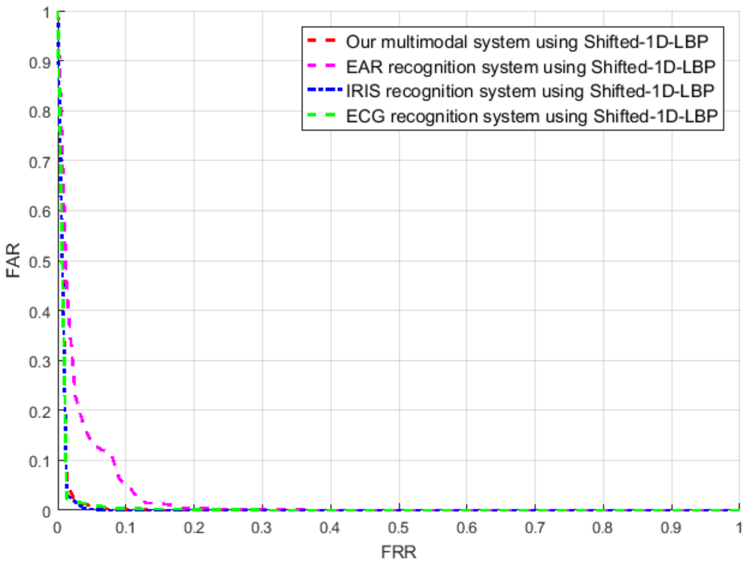

Figure 7.4.11: ROC curve for multimodal systems for the second experiment using USTB2 database.

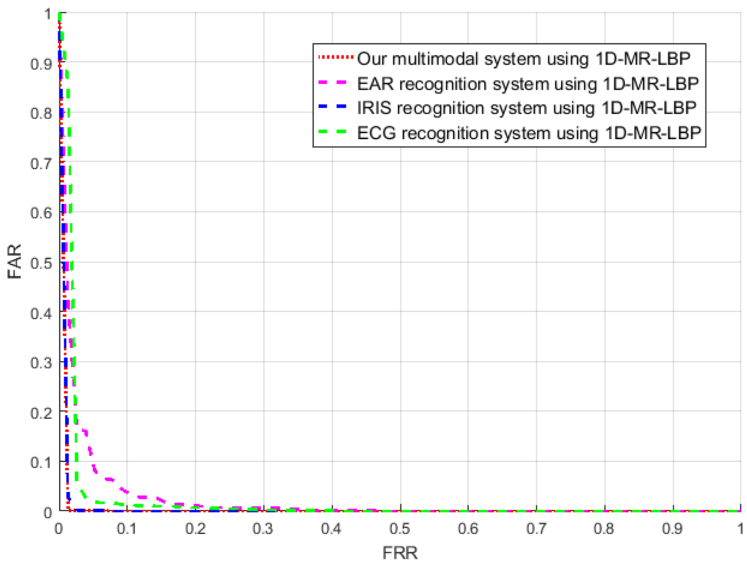

Figure 7.4.12: ROC curve for multimodal systems for the third experiment using USTB2 database.

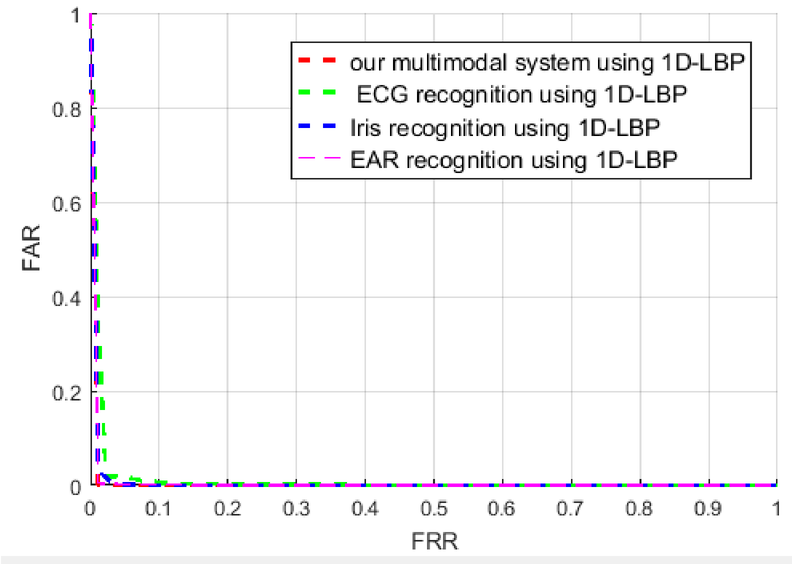

Figure 7.4.13: ROC curve for multimodal systems for the first experiment using AMI database.

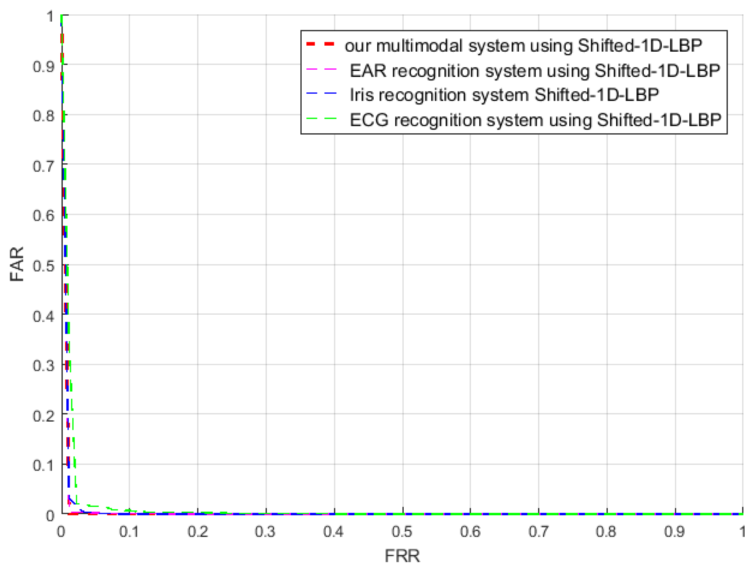

Figure 7.4.14: ROC curve for multimodal systems for the second experiment using AMI database.

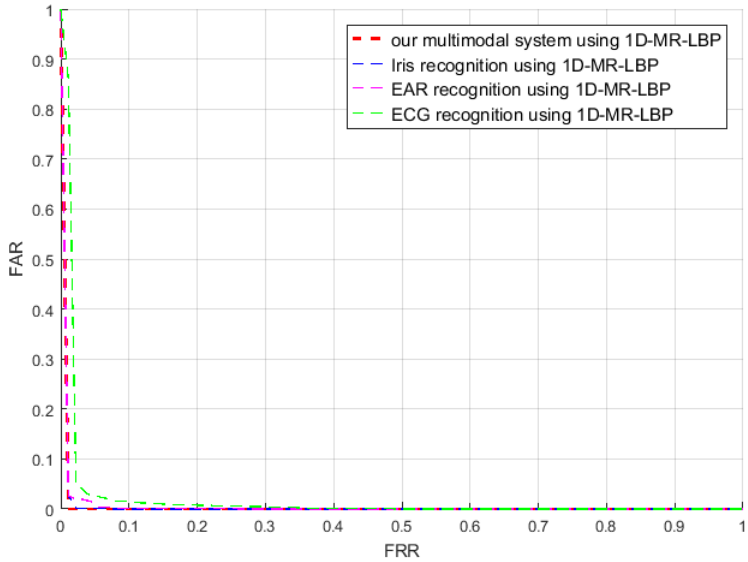

Figure 7.4.15: ROC curve for multimodal systems for the third experiment using AMI database.

7.5 Discussion

In this chapter, we presented a novel multimodal biometric system named ECIREA. The proposed system was accomplished following four steps. Firstly, ECG, ear and iris were preprocessed following two phases, named normalization and segmentation. Ear and iris images will be converted to 1D space. After preprocessing each modality separately, three local descriptors 1D-LBP, shifted 1D-LBP and 1D-MR-LBP have been applied to extract the discriminant features. These features will be fused in the next step to generate a sole vector. We aim that the new vector gains more robust representative characteristics that have the ability to improve the performance of the proposed multimodal system and increase the security level. Two learners (KNN and RBF) were applied to much the input fused vector with the stored database templates.

Because there is no study that combines our proposed modalities in the same system, we will discuss obtained results from each (ear, ECG or iris) unimodal biometric system separately and compare it with our ECIREA multimodal biometric system. We can also take a look at the related works that combine one or even two of the three used modalities.

To validate and test ECIREA multimodal system and find out the efficiency of local descriptors, benchmark databases were used. We are used three databases for ear biometric which they differ in the number of included subjects. For this reason, we must validate our ECIREA system on three cases depended on the used ear database.

Starting with ECG unimodal system, statistical comparison results showed that the proposed 1D local descriptors can effectively recognize the majority of subjects. A CRR of 97% for the first experiments was achieved. The second experiment obtained a CRR of 97%. The last one has got 98%. The best result was achieved with 1D-MR-LBP. This latter recovers more signal characteristics based on capturing multiple resolutions for the same pattern. Contrariwise, it can be noticed that the same results were obtained from 1D-LBP and Shifted-1D-LBP. These results were better than the 1D-MR-LBP method on terms of EER, FAR and FRR with a value of 2.16%, 0.71% and 5.56% respectively. Comparing the obtained results with state-of-the-art works, we can see that the three experiments have shown its efficiency, robustness and capability of extracting discriminative features from ECG signal.

Secondly, the proposed 1D-LBPs are carried out on three ear databases which generate three cases (USTB1, USTB2 and AMI). For the first case, the three experiments have achieved a CRR of 100%. A range from 1.5% to 3.3% was found with other terms. Approximately, the same results were obtained from all cases with all experiments. AMI database which considered as the third cases has got a better CRR of 100% with the third experiment i.e. applying 1D-MR-LBP. Shifted-1D-LBP got a good result on term of EER by having 0.7%. 1D-MR-LBP outperform the two experiments in most cases.Comparing our results with existing researches, local descriptors have proved its capability of extracting the important information for ear recognition purpose.

The last unimodal system based on iris biometric was carried out CASIA-v1 database. Good results were obtained applying the three experiments with a range vary from 98% to 100% in term of CRR. The achieved results in terms of EER, FAR and FRR were pretty close. 1D LBPs have shown significant power in extracting the discriminant features from the converted iris.

Our second contribution named ECIREA multimodal system combines these three modalities in a single system. Feature fusion level was used to fuse ECG, ear and iris LBPs features in a new vector. Comparing the obtained results from each unimodal system separately, we find that these results were greatly improved with the ECIREA system. A CRR of 100% and 99% were achieved for the first and the second cases, respectively with all experiments. The third case has got 100% in term of CRR with the two first experiments, whereas 99% was achieved with the last experiment. An EER of 0.5% was obtained with all experiments.

From the acquired results, we find that our ECIREA multimodal biometric system has the ability to recognize almost all enrolled users. Comparing our experiments against the existing works, it can be noticed that our ECIREA system achieved better results in terms of CRR and FAR and partly in term of EER.

Since there is no system fulfills all the requirements or conditions, it is worth to note that our contribution has some limitations that must be taken into consideration:

- We have a problem with the dataset, for example, the samples used in ECG are smaller than ear and iris. As a solution, we have reduced these sizes according to the size of ECG data set .
- 1D-LBPs techniques seem very straightforward and its parameters can't deal with the data challenges that often appear in real-time applications. Until now we have considered the proposed works as a handcart feature approach which still needs further preprocessing tasks that consequently increase the performance of the multimodal system under realistic environment.
- The generated feature vector combined from the three features vectors is fairly large. Moreover, some of these features may be duplicated and noisy. This limitation will lead to the curse of dimensionality problem. One attempt to overcome this issue is to introduce a reduction method that will be able to select a minimal feature set that improves the accuracy of the system.

7.6 Conclusion

In this chapter, we present a novel multimodal biometric approach. The proposed system investigates the power and strengths of ear, ECG and iris biometrics. Besides fingerprint, iris is the oldest used biometric. It has widely used and fused in numerous multimodal biometric systems. whilst ear and ECG are considered as an emerged biometric. Recently, these biometric traits have been combined with many other biometric modalities. Three local descriptors (1D-LBP, shifted 1D-LBP and 1D-MR-LBP) were applied in the objective of extracting discriminant and definiteness features from the preprocessed modalities. A feature fusion level was accomplished in the aim of exploiting the robustness of each modality beside to the efficiency of 1D-LBPs to create representative vector features.

By making comparison of results of this work, our multimodal biometric system demonstrates its robustness and outperforms each unimodal system separately. Moreover, 1D-LBPs descriptors, in particular case 1D-MR-LBP have shown its power of extracting the desired characteristic that can be used for recognition. Subsequently, the performance of the system is increased and a high-security level can be realized which is already proved recording to the obtained results.

Conclusion and Perspectives

Biometric can be defined as the quantitative study of physiological or behavioral characteristics of the human. These traits are unique for each person even for twins. It can be used as a great alternative to traditional methods like passwords and tokens. There are a set of properties that biometric traits must respect it to be used for recognition. Biometric system has the ability to solve a significant number of problems affecting the authentication system based on traditional methods.

With the evolution of technology, systems need more security and require efficient authentication protocols. For these reasons, challenges for developing robust identification or verification biometric system have been increased. Achieving a high level of security besides to improving accuracy are the most important concerns for all global technology markets. Biometric modalities such as fingerprint, face and iris are already used. The search for new biometric traits that can be used for recognition stills going on.

The biometric recognition system can execute depending on two modes. The first mode named identification that aims to recognize the owner of the concerned biometric traits. The answer to this question will be checked by comparing the input data with all templates existing in the database. The second mode called verification which has the purpose of checking if the claimed is the same person as in the database or no. In such situations, the response was given by comparing the input data with one template of the database. While each modality has specific strengths and weaknesses, the researches for optimal solutions still the goal of most laboratories and scientists.

Biometric modality has not the ability to meet all system requirements, for this reason, the unimodal biometric system suffers from various problems such as:

1. Different conditions may affect the system environment during authentication.

2. The poor quality of sensors can noise the captured data.

3. Illumination variations obstruct the acquiring of good data which decreases the performance of the system.

4. Intra-class and inter-class variations which mean that the matcher was misclassified the input biometric data either by rejecting an enrolled user or by accepting an imposter.

5. Some people have lost the required biometric traits and hence the system becomes non-universal.

6. Hackers find it easy to spoof a single modality especially if the used biometric traits are visible or can be founded in public.

In order to exploit the strengths of each biometric modality and eliminate most of its weakness, a combination of more than one biometric trait will be performed. This fusion is named a multimodal biometric system. The latter has the goal of overcoming most of challenges faced by unimodal biometric systems.

It can distinguish the following levels: sensor fusion, features fusion, score fusion, rank fusion or decision fusion. It is not possible to use any fusion level on any multimodal system. The choice of a suitable level depends on the nature of fused biometric data. When designing a multimodal biometric system, a set of requirements must be clearly defined which they interlinked with each other.

Iris, since its first proposition by (Daugman, 1993), was one of the first proposed modalities used for recognition. This is depicted by the increasing number of published works for decades. His algorithms were widely adopted in several studies. The iris of the eye is considered as the most suitable biometric modality for a large number of applications. A highly transparent and sensitive membrane protects the internal organ against damage which offers a robust structure.

ECG is a recording of the electrical activity generated by the human heart. It was used for decades for the purpose of cardiac diagnostics. ECG signal is usually acquired by attaching records (called also sensors) to the body. Studies demonstrate that each person has a unique cardiac rhythm. From this point, it can be concluded that ECG is a powerful metric that can be used to recognize individuals.

A new class of biometrics-based upon ear features is introduced for using it in the development of biometric systems in numerous recent studies. Ear biometric is shown its power and efficiency in both unimodal and multimodal biometric systems. Its unique and measurable features beside to its stable structure over the time make from ear a good choice in many developed works.

In this dissertation, we performed a review of considerable unimodal and multimodal biometric recognition systems. Based on this analysis, we have proposed two contributions. The first approach consists of developing two biometric systems. In the first system, shifted 1D-LBP extracted method was applied to ECG biometric. The proposed unimodal ECG biometric system has been accomplished following three steps (preprocessing “normalization + segmentation”, features extraction and matching). With a view to finding out how important the preprocessing stage is for the system and its effect on the performance, we have applied three different algorithms: SG-FIR, Butterworth and 1D digital filters. Better results were obtained with SG-FIR so as to use it in the next approaches.

Based on the discussed results, we have proved that:

1. The normalization technique has a significant impact on the extracted features and subsequently on the accuracy of the system.

2. Shifted 1D-LBP has successfully extracted the desired traits from the preprocessed ECG signal.

The second proposed system combines ECG and ear biometric in a multimodal system based on 1D-MR-LBP. We kept the same process for ECG biometric. The SG-FIR algorithm is applied for denoising the ECG signal. For the ear biometric, manual segmentation was performed. Then, the normalization of the cropped ear was applied. 1D-MR-LBP descriptor extracts the discriminant features from both ECG and ear data. The two ECG-ear features vectors were concatenated in a new vector. Compared the achieved results with the proposed ECG unimodal system, we find that :

1. 1D-MR-LBP outperforms Shifted 1D-LBP techniques in terms of CRR and FAR achieved by ECG unimodal system. Whereas, Shifted 1D-LBP gives better results in terms of EER and FRR.

2. ECG-ear multimodal system overcomes the weakness of ECG and ear unimodal systems.

3. The proposed multimodal system increases accuracy. Besides to decreases the EER, FAR and also the FRR .

The second contribution is based on fusing ear, ECG and iris in a novel multimodal system named ECIREA based on three 1D local descriptors. Ear and iris preprocessed images have been converted in 1D space to allow the 1D-LBPs descriptors extracting the desired features. A single augmented features vector was generated by combining the extracted features from the three modalities. The choice of this level is based on the assumption that the used data sources must be homogeneous, which is the case of our proposed system besides the robustness of this level. Furthermore, compared with match score or decision fusion level, the extracted characteristics possess richer information that allows better identification of an individual. KNN and RBF classifiers were applied for matching. ECIREA system was carried out different ECG, ear and iris benchmark databases to more analyzing and processes various kinds of data that were collected in different conditions environment.

According to the presented results, we have successfully developed a multimodal system that is able to:

- Overcome the weakness of the unimodal system.
- Increase the accuracy of the unimodal system (from 96.67% with the proposed ECG unimodal system to 100% with the proposed multimodal system).
- Minimize EER (from 2.68% to 0.5%).
- Solve the problem of inter class similarity (FAR from 2.02% to 0%), thus the most secure system is accomplished.
- Minimize the challenges of intra class variation (FRR from 2.22% to 1.6%).
- Identify all enrolled users in most cases (CRR=100%).
- Decrease the computational complexity which leads to reasonable execution time.
- Guarantee high security by fusing three modalities at the same time besides the liveness measurements properties of ECG which make it almost impossible to spoof from an imposter.

In spite of the success of our multimodal biometric system, many limitations and issues still banding which must be taken on consideration and constitute a significant research topic in the field of multimodal biometric system. Some of the problems that we have faced are:

- A limited dataset as in the case of ECG data which is rather restricted compared with other biometric sources.
- Our proposed ECIREA based multimodal system still needs more improvement efforts for the objective of increasing the performance of the multimodal system for a real application.
- Because of the simplicity of 1D-LBPs, it may have not the ability to solve the difficulties faced by the data challenges that appeared in a realistic environment.
- The homogeny of data sources used in this dissertation gives as the opportunity of using the feature fusion level approach and exploiting its strengths such as preserving the biometric information and merging it in an augmented vector. But unfortunately, this

generated vector may have mostly a high dimensionality and less important features that can decrease the performance of the system. Applying reduction techniques that have the ability to select only the important features set will be a solution for this challenge and consequently increase the performance.

For many purposes detailed in this dissertation, security in particular, biometric was the path of a tremendous amount of research. Extracting more robustness, representative and discriminative features, improving the accuracy, achieve high-security levels were the main objectives in biometric recognition. For our ECIREA multimodal biometric system, multiple perspectives works are to be considered:

- Giving space to detect the different claimed emotions using bio-signal ECG will improve security system and allows predict the psychological state of intruders (fear, anxiety, confusion...etc.).
- Testing our work on large datasets in order to further confirm the performance of our proposed multibiometric framework.
- Investigating our contribution to mobile and healthcare applications.
- Exploiting the deep learning framework, given its success in other domains.
- Computer science has recently started to think about quantum computing rather than conventional computing (binary), so we suggest integrating the quantum computing into the convention algorithms.

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