ECG Biometrics: New Algorithm and Multimodal Biometric System

by

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Abstract

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This thesis studies the challenges of applying the electrocardiogram signal (ECG) as a biometric. Unlike most biometric characteristics, ECG is time-dependent and naturally affected by the physical and psychological activity of the human body which is mainly neglected by the ECG biometric community. In this work we first presents the UofT ECG database (UofTDB) which offers a comprehensive analysis of the underlying interindividual variability under a number of conditions, such as body posture, physical activity, and time lapse. Then we propose a new biometric methodology and evaluate its performance using the UofTDB. The new method outperforms the state of the art ECG method AC/LDA and is robust to day-to-day ECG variations (3.12% EER). Finally we investigate the fusion of ECG and fingerprint and propose a fusion scheme to be robust to spoof attacks and achieves a very promising performance for real life applications (0.08% EER).

Dedication

To my loving husband,

Without whom none of my success would be possible.

Acknowledgements

Firstly, I offer my sincerest gratitude to my supervisor Prof. Dimitrios Hatzinakos, who has supported me throughout my thesis with his patience and knowledge. One simply could not wish for a better supervisor.

I would like to thank my thesis committee: Professor Leon-Garcia, Professor Aarabi and Professor Iravani for taking the time to provide useful insight.

Finally I would like to thank my family and friends for their constant encouragement during my studies.

Contents

Acronyms

AC Autocorrelation

AC/LDA Autocorrelation/Linear Discriminant Analysis

ANS Autonomic Nervous System

AV Atrio-Ventricular

DLDA Direct Linear Discriminant Analysis

DWT Discrete Wavelet Transform

ECG Electrocardiogram

EDB European ST-T Database

EEMD Ensemble Empirical Mode Decomposition

EER Equal Error Rate

FAR False Accept Rate

FRR False Reject Rate

IR Identification Rate

K-NN K-Nearest Neighbours

LDA Linear Discriminant Analysis

LLRT Log Likelihood Ratio Test

LTSTDB The Long-Term ST Database

MITDB MIT-BIH Arrhythmia Database

NSRDB The MIT-BIH Normal Sinus Rhythm Database

PAR Pulse Active Ratio

PCA Principal Component Analysis

PTBDB Physikalisch-Technische Bundesanstalt Database

ROC Receiver Operating Characteristic

SA Sino-Atrial

UofTDB University of Toronto ECG Database

WCCN Within-Class Covariance Normalization

WT Wavelet Transform

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Chapter 1

Introduction

1.1 Motivation for Biometrics

The word biometrics comes from the ancient Greek words: bios life and metros measure. It is well-known that humans use inputs such as face, voice or gait to recognize each other. Recognition of people based on their characteristics is important in many emerging technologies. These days, biometrics is used in a wide variety of applications that require the identification or verification schemes to confirm the identity of an individual. The term biometrics is described as an automatic personal recognition system based on physiological or behavioural characteristics. Biometrics use biological properties of a human, such as fingerprints, iris, voice, face, and hand geometry to identify individuals. Automatic and accurate identity validation is becoming increasingly critical in several aspects of our every day lives, such as in financial transactions, access control, traveling, healthcare and many others. Traditional strategies for automatic identity recognition include items such as PIN numbers, tokens, passwords and ID cards. Despite the wide deployment of such tactics, the means for authentication is either entity-based or knowledge-based which raises serious concerns with regard to the risk of identity theft. Biometric modalities are difficult to steal or counterfeit when compared to PIN numbers or passwords. In addition, the convenience of not having to carry a piece of ID or remember a password makes biometric systems more accessible and easy to use.

1.1.1 Biometric Systems

A biometric system is basically a pattern recognition system that can recognize a person based on specific physiological or behavioural features. A biometric system typically runs in three modes of operation

(Figure 1.1):

- Enrolment mode: During this mode of operation the biometric system collects the physiological or behavioural characteristics (ex. ECG, face and iris), performs some quality check, processes to extract discriminative features, and stores the result in the gallery set.
- Verification mode: In this mode the system validates a persons identity by comparing the captured biometric characteristic with the individuals biometric template, which is stored in the system database. The purpose of this operation is to answer the question: Is the user who he/she claims to be?
- Identification mode: In this mode the system recognizes an individual by searching the entire template database for a match. The system conducts a one-to-many comparison to establish an individuals identity. The purpose of this operation is to answer the question: What is the identity of this user?

However, each biometric system regardless of its operating mode (enrolment, verification or identification) contains the following parts:

- A sensor unit that represents the interface between the user and the machine. This is the point where the biometric trait is acquired.
- A processing unit where the acquired biometric is sampled segmented and features are being extracted. It also includes quality assurance to determine if the quality of the biometric is good enough to be used further in the process. If the quality of the acquired biometric is poor, the user may be asked to present the biometric again.
- A database unit where all the enrolled biometric templates are being stored and where the templates are being retrieved from in the authentication process.
- A matching unit that compares the newly acquired biometric template with the template stored in the database and based on decision rules determines either if the presented biometric is a genuine/impostor or if the user is identified or not.

Physiological biometrics are based on measurements and data derived from direct measurement of a part of human body. Here we list some example of those biometrics (Figure 1.2):

- DNA (Deoxyribonucleic acid): it is the one-dimensional ultimate unique code for one individual. DNA is currently used mostly in the forensic applications for person recognition. The main draw-

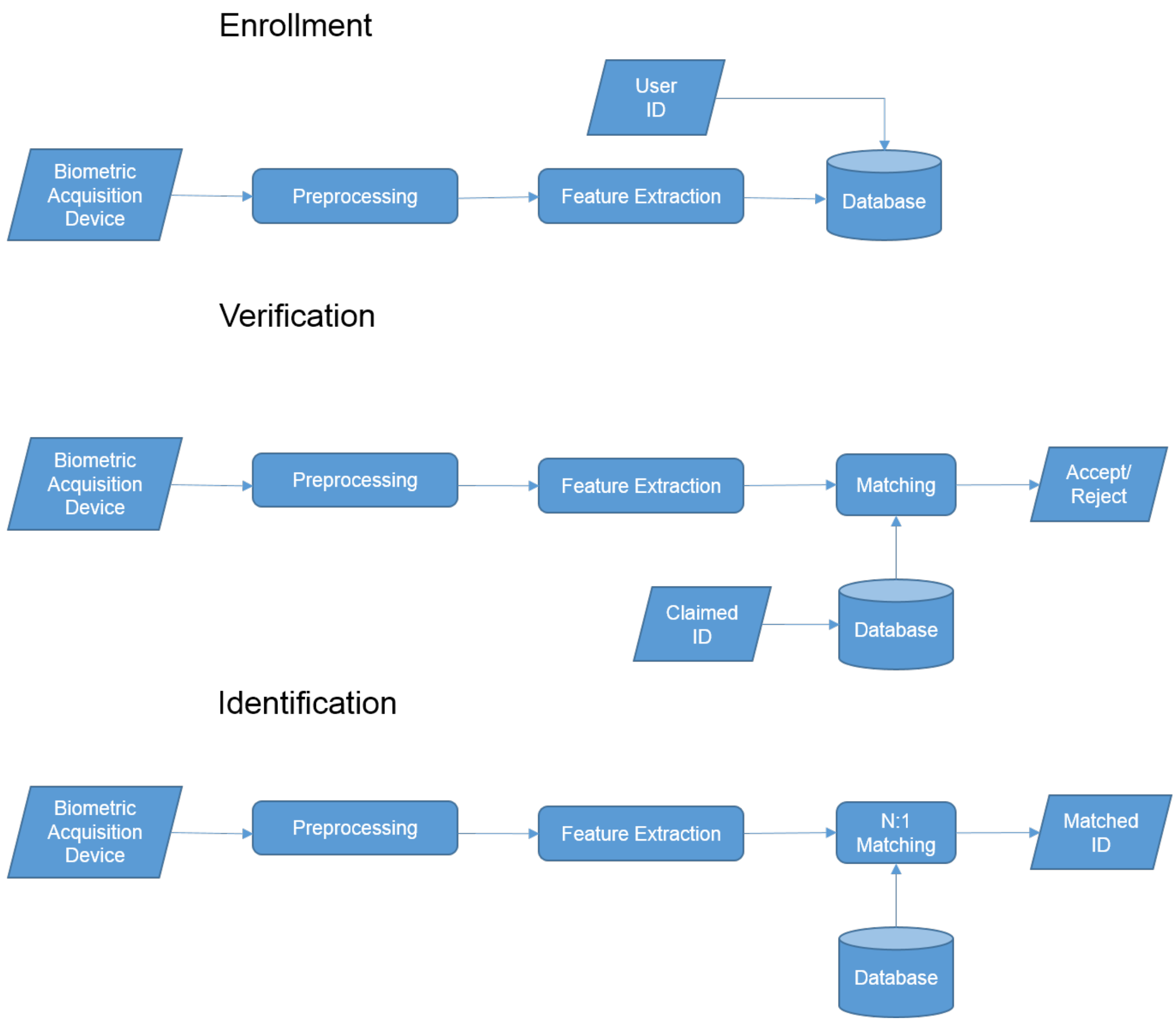

Figure 1.1: There are three modes of operation for a biometric system: 1) enrolment, 2) verification and 3) identification.

back with the application of DNA code in biometric systems is that it can be easily stolen from people since it can be acquired from any human trace.

- Face: A lot of attention has also been drawn to the application of face images for human. The benefit of analyzing facial images lies in the non intrusive process of the acquiring procedure and, depending on the algorithm, images are usually processed in a reasonable time. Examination of facial information can be performed either on localized features, such as the eyes and the nose, or on the global morphology of the face. However, environmental factors like illumination affect the performance of the respective systems. Furthermore, aging and sentimental expressions distort the recognition characteristics significantly, risking the accuracy of the applications [64].

- Fingerprint: This is one of the most commonly used features that have been used to identify humans. Prior to the advent of biometric tools, fingerprints (captured on paper using ink marks) have been used extensively in forensics for the identification and verification of criminals. Provided the advent of new technologies, fingerprints are now captured using optical, capacitive or ultrasonic sensors, that measure the ridges, valleys and islands in a fingerprint [43].

- Palmprint: The palms of human hands contain patterns of ridges and valleys much like the fingerprints. The area of the palm is much larger than the area of a finger and as a result, palmprints are expected to be even more distinctive than the fingerprints.

- Hand and finger geometry: Hand geometry recognition systems are based on a number of measurements taken from the human hand, including its shape, size of palm, and lengths and widths of the fingers. The geometry of a hand and fingers it is not very distinctive, and cannot be used for systems requiring identification of an individual from a large population [28].

- Iris recognition: The texture of the iris embeds highly distinctive characteristics in a population as well. The methodologies suggested so far, offer high recognition rates and propose time efficient applications, rendering identification via the iris rather promising. Iris traits employed by such systems are distinctive even between identical twins. The major drawback is that iris scanners are expensive and in most cases require subject's willingness to be subjected to identification.

Behavioural characteristics are based on an action taken by a person. On the other hand, behavioural biometrics are based on measurements and data derived from an action and indirectly measure characteristics of the human body. The following are the examples of biometric techniques based on behavioural characteristics (Figure 1.2):

- Gait: Gait is the way one walks and is a complex spatio-temporal biometric. However the main drawback of this biometric is that it can be easily mimicked [64]

- Signature recognition: The way a person signs his/her name is known to be a characteristic of that individual. Signatures change over a period of time and are influenced by physical and emotional conditions of the signatories [47].

- Voice recognition: Voice recognition systems use the characteristics of the voice in order to recognize a person. The behavioural part of the speech of a person changes over time due to age, medical conditions (such as common cold), emotional state, etc; therefore, voice is not very distinctive and may not be appropriate for large-scale identification [7].

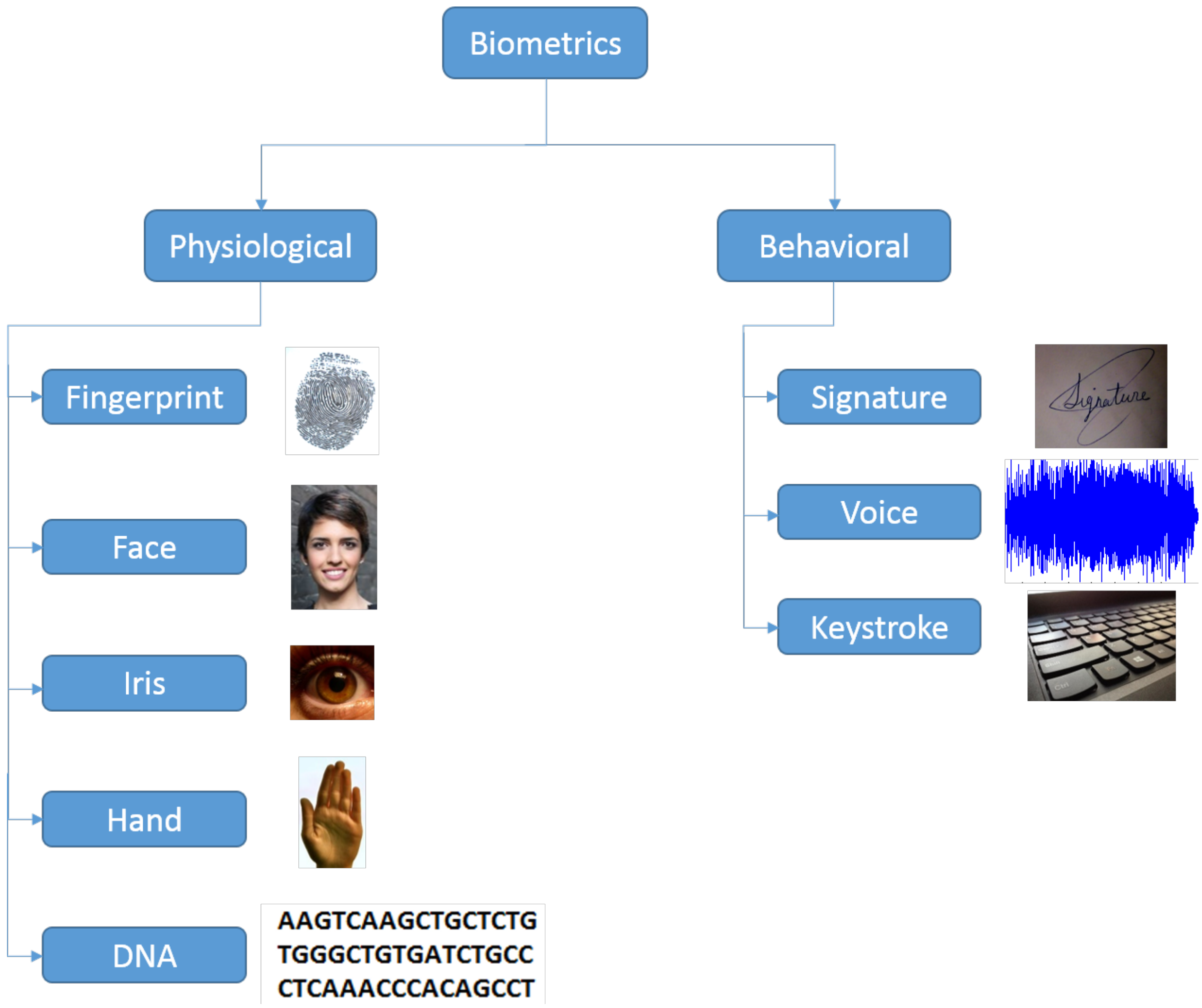

Figure 1.2: Examples of physiological and behavioural biometric modalities.

- Keystroke: It is hypothesized that each person types on a keyboard in a characteristic way. It is not unique to each individual but it offers sufficient discriminatory information to permit identity verification [45].

There are seven factors defined by Jain *et al.* [28] that determine the suitability of a physical or a behavioural trait to be used in a biometric application.

1. **Universality:** each person accessing the application should posses the trait.
2. **Uniqueness:** the given trait should be sufficiently different across individuals comprising the population.
3. **Permanence:** the characteristic should be sufficiently invariant with respect to the matching criterion over a period of time.
4. **Collectability:** the characteristic should be measured quantitatively.
5. **Performance:** the recognition accuracy and the resources required to achieve that accuracy should meet the constraints imposed by the application.
6. **Acceptability:** individuals in the target population that will utilize the application should be willing to present their biometric trait to the system.
7. **Circumvention:** this reflects how easily the system can be fooled using fraudulent methods.

1.2 Motivation for ECG Biometrics

The electrocardiogram signal (ECG) is one of the newer additions to the biometric community. The ECG reflects the electrical activity of the heart over time. There have been many studies on the use of this signal for identification and authentication. The ECG biometric has several advantages that will be discussed.

- **Universality** Among the primary strengths that encompass the practice of ECG signals as biometrics, is that the requirement for universality is satisfied. This criterion is met given that the electrocardiogram can be naturally monitored from every subject.
- **Permanence** The permanence requirement is also satisfied by ECGs, as the main structure of such signals is invariant over a large period of time. This statement does not imply necessarily that special characteristics of the signals do not get distorted. However, the diacritical waves

that compose a heart beat can be observed and recorded through someone's lifetime. In addition, human heart is very well protected in the body, thus environmental factors cannot have great impact on its activity, as opposed to other biometrics.

- **Circumvention** Another substantial advantage in the application of ECGs in biometric systems, is their robust nature against the application of falsified credentials. The electrocardiogram waveform is controlled by the autonomic nervous system, therefore by a combination of sympathetic and parasympathetic factors. This suggests that every time instance is relatively different, thus difficult to mimic or reproduce. Furthermore, compared to other biometrics such as fingerprint, if not impossible it is far more difficult to steal someone's ECG hence the systems are naturally more robust to spoof attacks.

- **Liveness Detection** ECG offers natural liveness detection, being only present in a living subject. With this modality the recognizer can trivially ensure sensor liveness. Other biometric modalities, such the iris or the fingerprint require additional processing to establish the liveness of the reading.

However, the disadvantages of employing the ECG for human identification need to be considered. Any biometric security system that is based on that trait has to be invariant to conditions such as physical activity, mental stress or exercise that affect the morphological properties of the ECG waveform.

1.3 Research Goals and Contributions

Since ECG is a physiological signal, it can change from day to day due to diet, mental wellness and etc., it can also change with posture changes, physical activity and other factors. Most researches in the ECG biometric community have ignored these intrinsic characteristics on the ECG signal which makes their results unreliable for real life applications. Therefore in this thesis we first study the effects of such factors on the ECG signal and collect an ECG database which has recordings under various conditions (different days, posture change and heart rate variability). Also most of the studies in ECG biometrics are based on small population sizes therefore their results do not reflect how the performance scales to a large population size. In order to look into the scalability issue of ECG biometrics our goal was to collect from a relative large population.

The second goal of this work is to propose a new ECG biometric algorithm that is robust to day to day ECG changes which is essential for deploying the system for real life applications. The performance of the method is analyzed with the collected database and compared with a state of the art method the AC/LDA[1]. Furthermore, since the ECG signal is a time series there is always the question of how long should the ECG be acquired. Considering that enrolment is done only once, users will agree to spend some time enrolling themselves into the system however for verification our goal is to minimize the authentication time for the users. Therefore in our study we evaluate the performance of the proposed method based on different number of heartbeats for verification. We will show how much the performance of the method will be compromised if less heartbeats are given to the system.

The third goal of this thesis is to explore the effectiveness of using the ECG signal in multimodal biometric systems. Since there is no "perfect" biometric and all biometrics have their own limitations and disadvantages, multimodal biometric systems deploy more than one biometric modalities for the sake of performance improvement, making the system robust to spoof attacks and etc. The challenge is that to choose appropriate biometrics such that the inherent weaknesses can be offset by overall system design. Therefore in order to further improve the ECG biometric system we propose a multimodal biometric system by fusing ECG and fingerprint. The combination of ECG and fingerprint is beneficial to both modalities. The fingerprint matcher offers high accuracy in terms of authentication however suffers from spoof attacks since a fingerprint trace can be easily taken from any surface that a finger has touched and can be placed on an artificial finger. On the other hand ECG naturally has liveness detection which ensure that a real finger is being used and makes the system robust to spoof attacks and further increases the performance of the system. Finally both modalities can be collected conveniently from users' fingertips which requires less cooperation from users unlike other systems. For instance fusion of face and fingerprint is less convenient since the user should provide their fingerprint and also pose to a camera for face recognition.

The research contributions of this thesis are the following:

1. In this work we collected the largest ECG biometric database called UofTDB from volunteers' fingertips in order to mimic practical deployment of ECG biometrics. The collected database has ECG recordings from 1020 subjects where a subset of them were recorded under different ECG variabilities that are very common in real life scenarios. The ECG variabilities are *across-session* variability as well as variabilities due to posture changes and heart rate fluctuations. *Across-session* variability is the result of overall day-to-day ECG changes therefore multiple session recordings were collected from subjects over a six month period. UofTDB also includes ECG recordings of subjects under different postures namely the supine, tripod, standing and sitting postures. Physical exercise results in sever increase of heart rate therefore post-exercise ECG recordings of subjects were recorded in order to capture ECG variability due to heart rate fluctuations.

2. Proposed a new ECG biometric algorithm. The novelties of the proposed method is in the feature

space and the classification method. The features are selected from the wavelet transform of the heartbeat and a new classification method based on Log Likelihood Ratio Test (LLRT) is proposed.

3. The performance of the proposed ECG method was evaluated by using recordings from UofTDB under different ECG variabilities. Furthermore the state of the art ECG biometric method called AC/LDA[1] was implemented and its performance was compared with the proposed method. Based on different set of simulations, the proposed method outperforms the AC/LDA[1]. On a relatively large population (1020 subjects) the proposed method reaches an Equal Error Rate (EER) of less than 2% and under *across-session* variabilities the average EER is 3.2%.

4. The effect of the number of heartbeats at verification is evaluated. As the number of heartbeats are increased the performance improves, with a minimum of two heartbeats the system has an EER of 7% under *across-session* variabilities however if the number of heartbeats is increased to 40 the system achieves an EER of 3.2%.

5. Discussed different types of fusion and their applicability to the fusion of ECG and fingerprint. We further discussed the advantages and disadvantages of each scheme and proposed a sequential fusion scheme for fusing ECG and fingerprint.

6. For analyzing the fusion of fingerprint and ECG we collected a multimodal database where from each subject fingerprint images from ten fingers and ECG recordings from fingertips were collected. The data was collected from 61 subjects. Most of the studies in multimodal biometric systems assume that different biometrics are statistically independent so that they can combine different unimodal biometric databases for their evaluations. Since ECG and fingerprints are both from fingertips, we studied their linear dependencies (correlation) by using the collected multimodal database.

7. Finally the proposed fusion scheme was evaluated by using the collected databases and its performance was compared with different commonly used score-level fusion techniques. The best performance that the fusion scheme provides is an EER of 0.084% under *across-session* variabilities.

1.4 Taxonomy of Errors

Performance analysis of any biometrics algorithm is highly dependent on the error criteria that is used. In this section we define a few basic error types and describe the metrics that will be used for performance evaluation throughout this thesis. In this thesis, only the verification scenario has been assumed and analyzed for the different methods and signals. Hence, we define the different errors present in such a scenario. They are:

- Authentication leads to a denial of access to a legitimate user, measured in false rejection rates (FRR).
- Authentication leads to a acceptance of access to an intruder i.e., an illegitimate user, measured in false acceptance rates (FAR).

These error rates are computed as ratios of the corresponding error's set divided by the complete trial set. i.e.,

$$FAR = \frac{\text{Number of falsely authenticated intruders}}{\text{Total number of intruders}} \tag{1.1}$$

$$FRR = \frac{\text{Number of rejected legitimate users}}{\text{Total number of users}} \tag{1.2}$$

Furthermore, the equal error rate (EER) is defined as the error value when the false acceptance is equal to false rejection i.e., EER = FAR = FRR. Lower equal error rate translates as better authentication performance of the system that is being evaluated.

1.5 Related Publications

- [58] S. Pouryayevali, S. Wahabi, S. Hari, and D. Hatzinakos. On establishing evaluation standards for ECG biometrics. In *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3774-3778, 2014.
- [79] S. Wahabi, S. Pouryayevali, S. Hari, and D. Hatzinakos. On evaluating ECG biometric systems: Session-dependence and body posture. *IEEE Transactions on Information Forensics and Security*, 9(11): 2002-2013, 2014.
- [80] S. Wahabi, S. Pouryayevali, and D. Hatzinakos. Posture-invariant ECG recognition with posture detection. In *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2015.

1.6 Outline of Thesis

This thesis is organized as follows:

Chapter 2 introduces the fundamental information about the electrocardiogram physiology, the acquisition procedure, sources of variability and noise artifacts. In addition, related works in this field are reported in the same Chapter.

Chapter 3 gives an overview of existing databases and introduces the newly collected database and sets a benchmark for ECG biometric databases.

Chapter 4 introduces a new approach for ECG biometric authentication. The analysis is carried using the collected database and the performance of the proposed method is evaluated under various ECG variability conditions. Furthermore the performance of the proposed method is compared with the state of art and the effect of different number of heartbeats at verification is evaluated.

Chapter 5 offers a review of multimodal biometrics along with different types of fusion methods. In addition the fusion of ECG and fingerprint is discussed and a new framework is proposed that takes advantage of the liveness detection property of ECG and the high performance of the fingerprint biometric to construct a compact finger-based system.

Chapter 6 first gives a review on the performance of unimodal fingerprint biometric systems. Then the collected fingerprint and ECG database is presented, the performance of the described framework is tested on the collected database. The performance of the fusion is then compared to the performance of the individual unimodal system and the improvement to their performances is reported. Furthermore a study is done on the correlation of fingerprint and ECG since both are acquired from the fingertips. Finally, Chapter 6 presents comparisons of the current approach with other methodologies found in literature.

Chapter 7 summarizes the main results of this work and presents suggestions for future improvements.

Chapter 2

ECG as a Biometric

2.1 Introduction

In this chapter we first describe what the electrocardiogram signal represents and introduce it's different components. We then demonstrate how the ECG signal can be recorded and explain the different lead configurations. We furthermore discuss in detail the variations in the ECG signal and the factors that cause these variations both within a single person and between different people. We also present the different sources that may cause noise in the recorded signal and the filtering methods that are used to mitigate the effect of the noise. Later in the chapter we review the literature on ECG biometrics from the pioneering work to the state of the art research.

2.2 ECG Signal

The electrocardiogram signal reflects the electric activity of the heart over time (Figure 2.1). The heart has a natural pacemaker that regulates the pace of the heart. It sits in the upper portion of the right atrium and is a collection of specialized electrical cells known as the sino-atrial (SA) node. Like the spark-plug of an automobile it generates a number of "sparks" per minute. Each "spark" travels across a specialized electrical pathway and stimulates the muscle wall of the four chambers of the heart to contract (and thus empty) in a certain sequence or pattern. The upper chambers or atria are first stimulated. This is followed by a slight delay to allow the two atria to empty. Finally, the two ventricles are electrically stimulated.

As the SA node fires, each electrical impulse travels through the right and left atrium. This electrical activity causes the two upper chambers of the heart to contract. This electrical activity is known as the

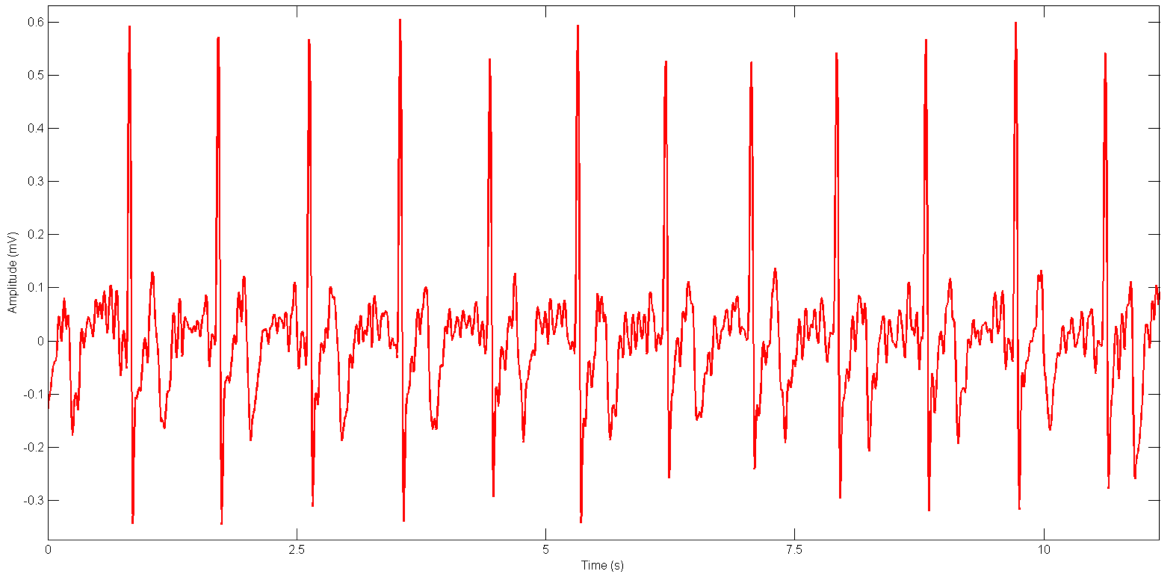

Figure 2.1: Sample Electrocardiogram (ECG) recording of a subject.

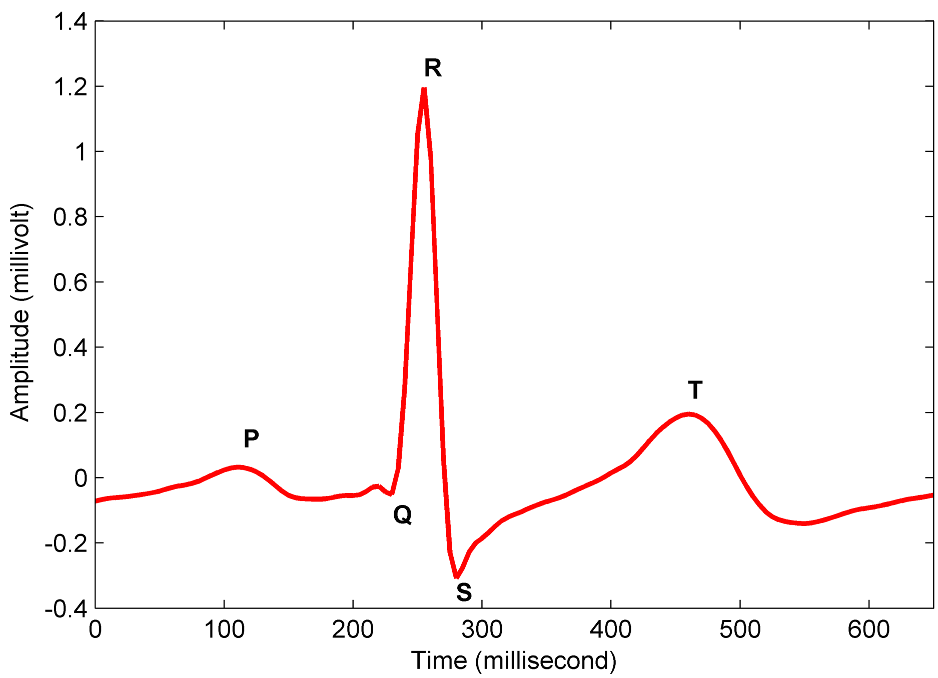

Figure 2.2: A heartbeat is composed of three main components: P-wave, QRS-complex and T-wave.

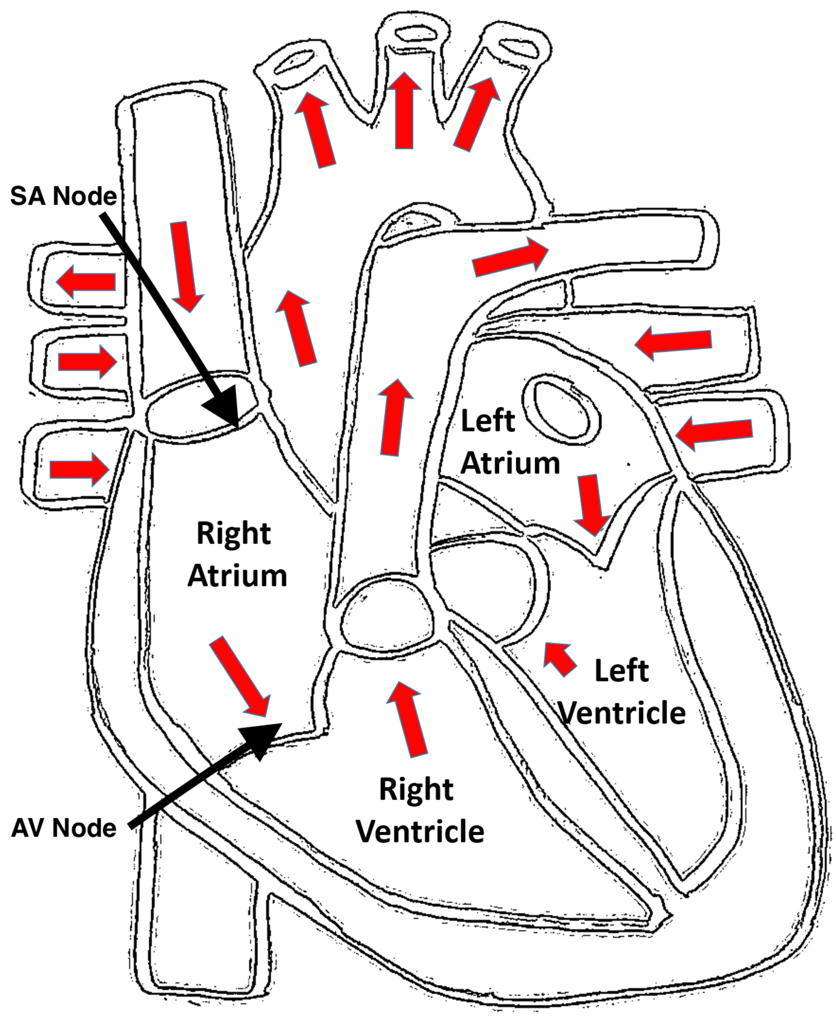

Figure 2.3: The heart and its pacemakers: the sino-atrial (SA) and atrio-ventricular (AV) nodes.

”P” wave” of the ECG (Figure 2.2). The electrical impulse then moves to an area known as the AV (atrio-ventricular) node. This node sits just above the ventricles. Here, the electrical impulse is held up for a brief period to allow the right and left atrium to continue emptying it’s blood contents into the two ventricles. This delay is recorded as a ”PR interval”. Following the delay, the electrical impulse travels through both ventricles. The electrically stimulated ventricles contract and blood is pumped into the pulmonary artery and aorta. This electrical activity is recorded from the surface of the body as a ”QRS complex”. The ventricles then recover from this electrical stimulation and generates an ”ST segment” and T wave on the ECG [75]. As discussed the ECG signal is composed of three waves; the P wave, QRS complex and the T wave. More specific, the frequency spectral components of the P wave is in the range of 10 Hz-15 Hz with a duration of approximately 120 ms, the QRS consists of higher frequency

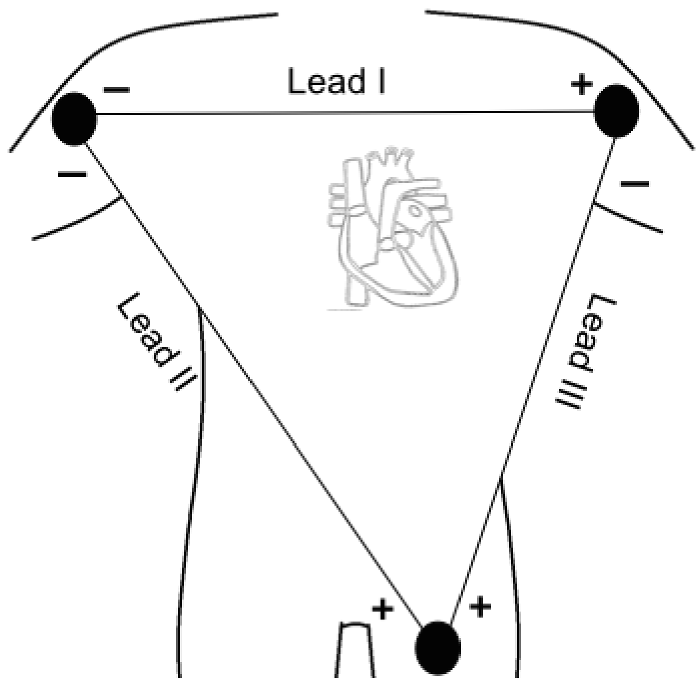

Figure 2.4: Three different lead configurations: Lead I, Lead II and Lead III.

components, 10 Hz - 40Hz and in normal sinus rhythms, its duration mostly lies in the 70-110 ms range. The T wave represents is usually observed about 300 ms after the QRS complex. However, its position is dependent on the heart rate of the person; closer to the QRS complex when the heart rate is higher. Typically the normal resting adult human heart rate ranges from 60-100 beats/minute. Bradycardia is a slow heart rate, defined as below 60 beats/minute and Tachycardia is a fast heart rate, defined as above 100 beats/minute at rest.

2.3 ECG signal acquisition

The ECG signal is usually acquired with a multiple-lead configuration, the most widely applied system is the standard 12-lead ECG. This system is determined by three main sets of lead orientations namely, lead I, II, and III (Figure 2.4). By convention, lead I measures the potential difference between the two arms. In lead II, one electrode is attached on the left leg and the another one on the right hand. Finally, in lead III configuration, the potential measured is between the left leg and hand. Nevertheless, the ECG can be easily captured with sensor contact of any two points across the heart. As such, the hands and the fingers present a practical solution for real-world applications [19, 20, 21, 22, 23, 24].

2.4 Sources of Variability in ECG

In order to further interpret ECG signals we must also have knowledge about the factors that cause variability in normal ECGs. This variability can be divided into two categories, namely, inter-subject variability and intra-subject variability. Intra-subject variability is between different ECGs from the same person, or variability within one ECG which is also known as day-today variability or beat-to-beat variability. On the other hand, inter-subject variability is the variability between ECGs from different people. The two categories of variability will be discussed further in the following sections.

2.4.1 Inter-subject ECG variability

Physiological and geometrical variations of the heart are embedded in the ECG signal. Physiological difference include the heart mass orientation, the conductivity of various areas of the cardiac muscle and the activation order of the heart. On the other hand geometrical difference are due the heart position and orientation relative to the ribs which causes a lot of variance among different people [24]. In other words we can justify these variations with this logic that each person can be identified by a unique code i.e. DNA. In nature the genetic information flows from DNA to RNA (ribonucleic acid) to protein. Eventually protein is responsible for the uniqueness provided by other biometric data (finger print, iris, face, retina, etc.). Therefore, it can be inferred that the uniqueness provided by the ECG signal is inherited from the uniqueness of DNA [77]. Furthermore, other physical factors such as gender, race, and age contribute to the variations of different ECGs [39]. For example, the amplitude of the QRS complex increases from birth to adolescence and the begins to decrease thereafter. It has also been shown that the PR interval increases slightly with increasing age. Sex differences in the ECG signal are more apparent in young adulthood and tend to decrease their effect in other stages. It has been seen that the S wave amplitudes are lower in women than in men between the ages of 18-40 [39].

2.4.2 Intra-subject ECG variability

There are many sources of variability for an individual's ECG, such as smoking, food, posture, exercise, respiration, anxiety and so on. As it can be seen in figure 2.5 an individual's ECG changes in different sessions possibly due to the factors mentioned above and other unknown factors.

- Smoking: has been shown to increase the heart rate and decrease the amplitude of the T wave significantly and in some cases cause inversion of the T wave [22].

- Food: affects the ECG signal by increasing the heart rate and the amplitude of the QRS complex.

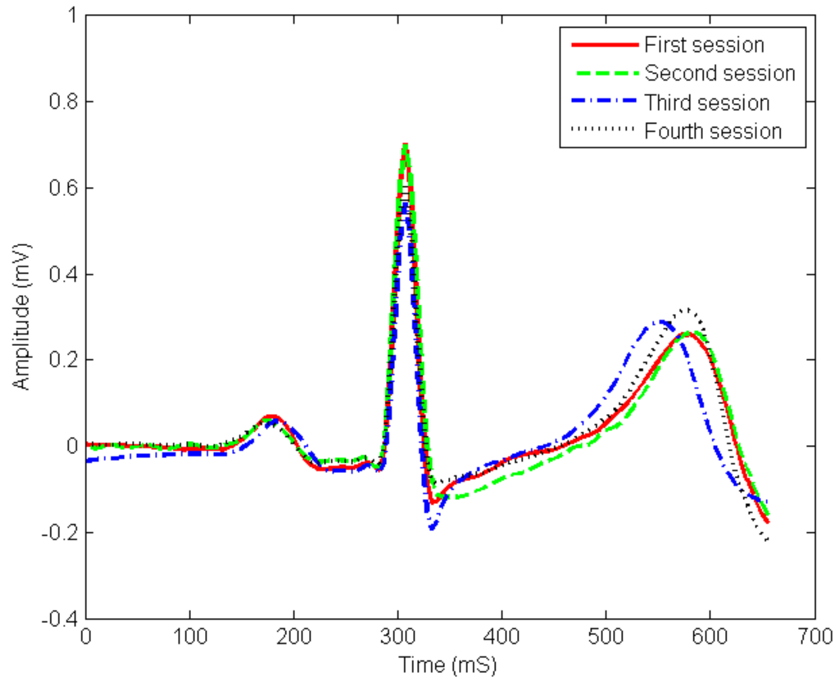

Figure 2.5: Heartbeats of a subject from different recording sessions. Data is from the UofT ECG biometric Database.

Exercise on the other hand, will cause the amplitude of the QRS complex to decrease and the RS-T segment and T wave demonstrate changes immediately after exercise. More specifically the amplitude of the T wave decreases and the RS-T segment shifts to the left slightly [61].

- Posture changes: for example changing from supine to sitting position, also produce changes to the QRS and T wave. The QRS changes are presumably due to change in the heart position [61] (Figure 2.6).

- Anxiety: causes similar effects such as the depression of RS-T segment and the decrease of the T wave amplitude [40].

- Drinking iced water: the effect of ingestion of iced water was shown to be maximized in the first five minutes of ingestion, and the major change was in the amplitude of the T wave which was decreased or in some cases inverted [18].

- Exercise: affects increases the heart rate. Variations in the heart rate are more noticeable on the relative position of the T-wave rather than the P-wave or the QRS-complex which are more stable. When comparing a resting and an active state it is observed that the T-wave moves closer to the QRS-complex (Figure2.7).

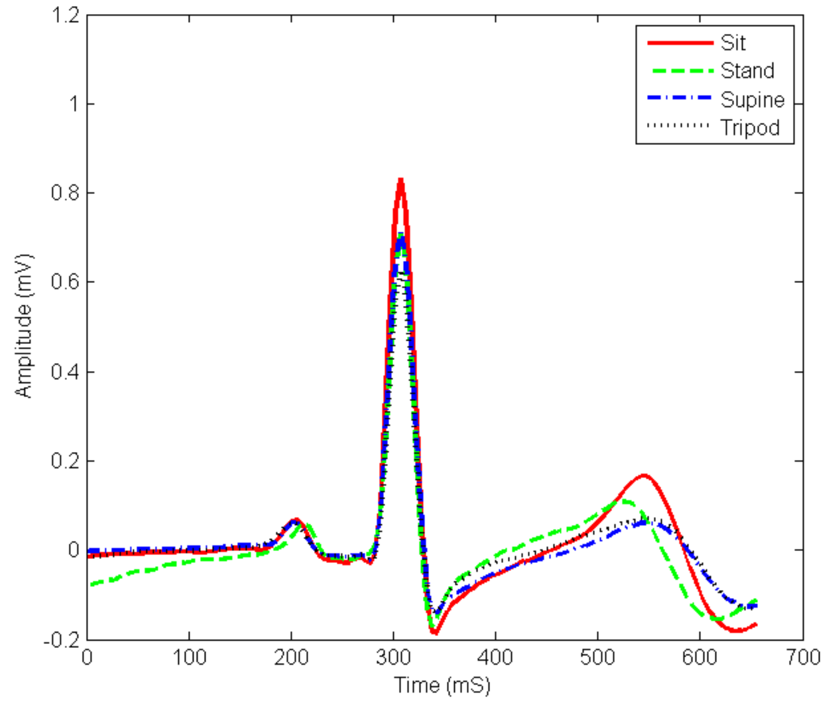

Figure 2.6: Heartbeats of a subject recorded under different postures. Data is from the UofT ECG biometric Database.

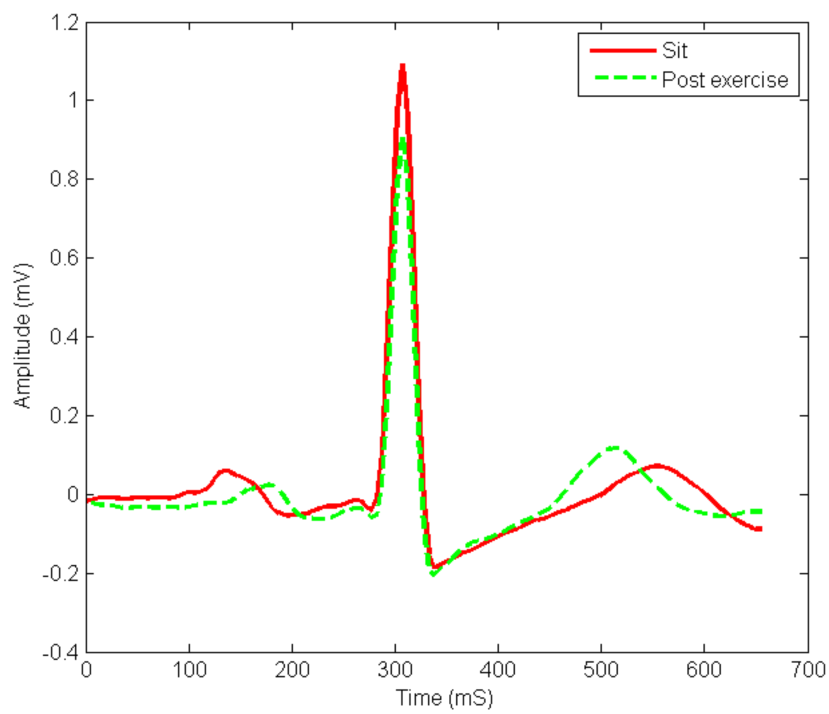

Figure 2.7: Heartbeats of a subject under heart rate fluctuations due to exercise. Data is from the UofT ECG biometric Database.

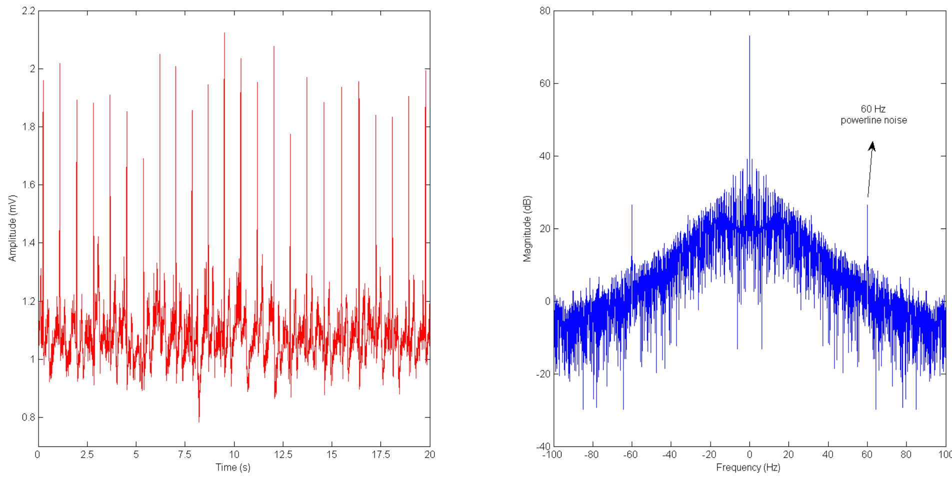

Figure 2.8: Noise in raw ECG data: Baseline wander and 60Hz powerline noise.

2.5 Sources of Noise

One of the main issues in biometric signal processing is the high degree of noise and variations. In many cases, a reliable acquisition is only possible with sufficient knowledge of the spectral content and the dynamic range of the desired signal components. This is so that the appropriate filters and quantizers can be constructed to extract the needed signals, and reject the noise effects. The three most common types of noise are; the baseline wander, the power line interference and the disturbance caused by muscle movement. Muscle noise present in the ECG can be reduced with techniques that benefit from the fact that the ECG is a recurrent signal. For example, by averaging time-aligned heartbeats the effect of muscle noise can be minimized. The baseline wander, is the most common type of noise artifact, referring to a low frequency interference in the ECG, which may originate from cardio- vascular activities. The amplitude change due to baseline wander can potentially exceed the respective QRS amplitude by several times. The signal is forced to deviate from the iso-electric line, causing a spectral component usually below 1 Hz. Another source of error is the powerline interference. This type of noise effect contributes to the spectrum frequencies in the range 50-60 Hz. The source of powerline interference is usually the insufficient grounding or interference with nearby devices (Figure 2.8). Several techniques have been presented for this purpose, ranging from straightforward linear, bandstop filtering to more advanced techniques that handle variations in powerline frequency.

2.6 ECG Biometric Systems Literature Survey

A biometric system is essentially a pattern recognition system that acquires biometric data from an individual, designs a biometric signature, and compares this signature against other templates in the database. In the ECG biometrics literature, data acquisition typically refers to single channel recordings. Although the use of the complete medical (12-lead ECG system) setup has been shown to increase the overall biometric accuracy [5, 2, 84, 88, 20], Biel *et al.* [5] showed that a single channel ECG has sufficient information for biometric purposes and is far more convenient for the user than the 12-lead configuration. Similar to Biel *et al.*'s work are Chan *et al.*'s [11] proposal for ECG recording from the thumbs, Shen *et al.*'s [69] proposal from the palms and Odinaka *et al.*'s [51] from the lower rib cage.

The process of designing the biometric signature from the ECG signal typically encompasses three steps: 1) Pre-processing, 2) Feature Extraction and 3) Feature Selection. The preprocessing step generally consists of filtering the raw ECG signal to eliminate noise caused by body movement, misplacement of electrodes and any interference by nearby devices. Thanks to the advancements in ECG signal processing for medical applications a powerful set of algorithms and processes are available to clean and enhance the quality of the ECG signals. A survey on ECG signal denoising techniques can be found in [31].

Feature extraction techniques aim to detect attributes of the ECG signal that are unique and permanent for each subject which can divided in two categories; fiducial and non fiducial. Fiducial techniques consider features such as the amplitudes and angles of the waves, on the other hand non-fiducial methods extract features without having to localize fiducial points, making feature extraction in the frequency domain, or even using the values of a global pattern from several heartbeat waves as features. We will briefly explain the feature extraction techniques of several methods from the early work to the present and report the performance achieved by them in the following section.

- Biel *et al.* [5] proposed a fiducial based method using ECG recordings from 20 subjects. The extracted features are the local characteristics of the QRS complex, T wave and P wave. The best performance that was achieved by combining 10 different features was reported an identification rate of 100%.

- Kyoso *et al.* [34] proposed a fiducial method using four features i.e. the P wave duration, PQ interval, QRS and QT durations. The highest performance reported was an identification rate of 94% using the QRS and QT intervals of nine subjects.

- Shen *et al.* [68] proposed an ECG based recognition method with seven fiducial based features that relate to the QRS complex. This research applied two techniques, template matching and a decision-based neural network (DBNN), to implement the identity verification. Using each of the two methods separate on a predetermined group of 20 subjects. The experimental results showed that the rate of correct identity verification was 95% for template matching and 80% for the DBNN. Combining the two methods produced a 100% recognition rate.

- Israel *et al.* [27] presented the three clear stages of ECG biometric recognition i.e., preprocessing, feature extraction and classification.The proposed system employed 15 temporal features. The highest achieved performance was reported to be an identification rate of 100% tested on 29 individuals.

- Palaniappan *et al.* [53] also proposed a similar approach. In addition to commonly used features within the QRS complex, a form factor, which is a measure of signal complexity, was proposed and tested as input to a neural network classifier. An identification rate of 97.6% was achieved over recordings of 10 individuals, by training a Multilayer Perceptron - Backpropagation (MLP-BP) with 30 hidden units.

- Kim *et al.* [32] proposed a fiducial method based on the characteristic points on the ECG waveform, P, QRS, T were extracted in terms of its time location and the ECG data is reconstructed in beat-by-beat basis by Fourier synthesis. R-T interval, Q-T interval, and QRS interval on the reconstructed ECG sequence in rest and in physical active mode were computed. They tested their method on 10 individuals.

- Saechia *et al.* [65] proposed a method by normalizing the heart rates of the ECG signals to a standard heart rate and then dividing the normalized ECG signals into three sub-sequences: P wave, QRS complex and T wave. The Fourier transform was applied on a heart beat itself and all three sub-sequences. The spectrums were then passed to a neural network for classification. It was shown that false rate was significantly lower (17.14% to 2.85%) by using the three sub-sequences instead of the original heart beat.

- Plataniotis *et al.* [57] are one of the first to propose a non fiducial based method. They take the autocorrelation of the windowed ECG signals and then performed the Discrete Cosine Transform for dimensionality reduction. With the objective of capturing the repetitive pattern of ECG, the authors suggested the AC of an ECG segment as a way to avoid fiducial points detection. The method was tested on 14 subjects and achieved an identification rate of 100%.

- Wubbeler *et al.* [84] also proposed a non fiducial method by analyzing the distance between two ECGs which was determined utilizing one single heart beat of the two-dimensional time- dependent heart vector which is known as a characteristic of the ECG. The method was tested on 74 subjects and achieved a 2.8% EER.

- Irvine *et al.* [26] propose a non fiducial method by using the extracted heartbeats of the ECG signal and normalizing them to have a dynamic range between zero and one. Furthermore apply Principle Component Analysis for feature extraction. Then an euclidean distance measure along with majority voting is used to make the final decision. They achieve an identification rate of more than 80% based on 43 subjects.

- Chan *et al.* [11] also propose a non fiducial method which utilizes the detail coefficients of the discrete wavelet transform of PQRST complexes for the feature space and a proposed wavelet distance measure for classification. The ECG data were collected from 50 subjects during three data-recording sessions on different days. Data from session 1 were used to establish an enrolled database, and data from the remaining two sessions were used as test cases. Classification was performed using three different quantitative measures: percent residual difference, correlation coefficient, and a novel distance measure based on wavelet transform. The highest performance reported was 89% using the wavelet distance measure.

- Chiu *et al.* [12]proposed the use of the Discrete Wavelet Transform (DWT) on extracted heartbeats. More precisely, every heart beat was determined on the ECG signal, as 43 samples backward and 84 samples forward from the R peaks. The DWT was used for feature extraction and the Euclidean distance as the similarity measure. When the proposed method was applied to a database of 35 healthy subjects, a 100% verification rate was reported.

- Agrafioti *et al.* [1] method using the autocorrelation as a source of discriminative information in a population, to eliminate the need for fiducial points detection. On top of the autocorrelated ECG signals, discrete cosine transform or linear discriminant analysis are applied for dimensionality reduction. The best performance reported is an EER of less than 1% tested on 27 subjects.

- Singh *et al.* [71]proposed a way to delineate the P and T waveforms for accurate feature extraction. Once the exact positions of the QRS complex, T wave and P wave are known, 19 fiducials are extracted from each heartbeat as the feature vector. The accuracy of this system was reported as 99%, tested over 25 subjects.

- Odinaka *et al.* [51] proposes the time-frequency content of the heartbeats as the feature space and proposes a feature selection method for dimensionality reduction and performance enhancement. They test their method on a database containing recordings from 269 subjects and report an EER of 5.58%.

- Safie *et al.* [66]proposes a new fiducial based method that uses the pulse active ratio (PAR) algorithm for feature extracation instead of conventional temporal and amplitude features. First the individual heartbeats are detected and then the PAR feature vector is computed. Their evaluations were performed on 112 individuals and reported an EER of 9.89% on healthy subjects.

- Zhao *et al.* [93] proposed a non fiducial method based on ensemble empirical mode decomposition (EEMD). They first eliminate the noise of the ECG signal using wavelet decomposition and then they extract the individual heart beats. Furthermore heartbeat normalization and quality measurement is performed to eliminate the effects heart rate variability. Then the ECG heartbeats are decomposed into a number of intrinsic mode functions (IMFs). Principal component analysis is used reduce the dimensionality of the feature space, and the K-nearest neighbors (K-NN) method is applied as the classifier tool. The system achieved an identification accuracy of 95% for 90 subjects.

- Li *et al.* [36] also propose a non fiducial technique for both healthy and cardiac irregular conditions using the heartbeat level and segment level information fusion. They first extract and normalize the individual heartbeats, then apply principal component analysis and also apply linear discriminant analysis (LDA) and within-class covariance normalization (WCCN) for beat variability compensation followed by cosine similarity and Snorm as scoring. At the segment level, they use the hierarchical Dirichlet process auto-regressive hidden Markov model (HDP-AR-HMM) in the Bayesian non-parametric framework for unsupervised joint segmentation and clustering without any peak detection. They fuse the two subsystems together and achieve an EER of 14.5% on 290 individuals among which 52 subjects are healthy and the rest 238 subjects suffer from a variety of cardiac disorders.

2.7 Chapter Summary

As a physiological signal, ECG is affected by many factors which we discussed in this chapter. Different factors affect the ECG signal in different ways. However, most of the variations were introduced on the T-wave and as the studies suggest, the QRS complex is the most robust feature to variations. We then looked into the various features of the ECG signal used in the literature and give a brief summary of the methods proposed to the present. However the majority of prior works did not examine the evolution of the ECG signal with time, effect of posture change and exercise. To some extent, the sources of intra-subject variability of the ECG signal have been ignored. We advocate that the factors that affect the ECG waveform must be taken into consideration since they may render the biometric template less accurate which is very important for real life deployment of this technology.

Chapter 3

ECG Database

3.1 Introduction

In this chapter we give an overview on the existing ECG databases that are used for evaluation of ECG biometric systems. As discussed in the previous section unlike most biometric characteristics, ECG is time-dependent and naturally affected by the physical and psychological activity of the human body. This indeed presents a challenge for ECG biometric deployment and measures have to be taken to ensure that ECG-enabled biometric systems are robust to such variations. However these variations have been mostly ignored by the ECG biometric community. In this chapter we introduce a new ECG Biometric database that has recordings under those factors.

3.2 Existing ECG databases

To date the investigation of the above-mentioned factors for the ECG, in a biometric recognition context, is very limited. This is primarily due to the lack of availability of a signal database that encompasses all this information simultaneously. It is important to note that the majority of the existing work in this area has focused on ECG biometric evaluation using signal readings that were acquired within the same experimental session or within the same day. Additionally, most of the early ECG databases have a small population size (couple of hundreds of subjects at most). Therefore, while earlier works demonstrated a proof of concept for ECG biometric systems, feasibility studies for large-scale deployments has, so far, been limited. Table 3.1 shows a summary of existing databases used in the literature.

Table 3.1: Public and Private ECG Databases

Database/Researc Name	Public/ Private	N	# of Sessions	Sensor Positions	Conditions or Disorders	Performance (%)
UofTDB	private	1020	up to 5	fingers	sit, stand, exercise, supine and tripod	-
Zhang and Wei [91]	private	520	-	limbs & chest	-	97.4 (IR)
PTBDB [21]	public	290	up to 5	limbs & chest	healthy and cardiac disorders	-
Odinaka *et al.* [51]	private	269	3	lower rib cage	healthy and heart-related disorders	0.37% (AR), 99 (IR)
Shen *et al.* [69]	private	168	-	palms	sit	95.3 (IR)
QTDB [21]	public	105	-	chest	exercise and variety of cardiac disorders	-
LTSTDB [21]	public	80	-	chest	-	-
EDB [21]	public	79	-	chest	myocardial ischemia	-
Wübbeler *et al.* [84]	private	74	2-20	limbs	resting in supine position	2.8(AR), 98.1 (IR)
Jang *et al.* [30]	private	65	6	-	different stress levels	>96.92 (IR)
Chan *et al.* [11]	private	50	3	thumbs	-	>89 (IR)
Agrafioti & Hatzinakos [3]	private	52	up to 2	limbs & chest	-	>10 (AR), 92.3 (IR)
MITDB [21]	public	47	-	chest	Arrhythmia	-
Irvine *et al.* [26]	private	43	-	neck & chest	different stress levels	100 (IR)
Silva *et al.* [70] & Coutinho *et al.* [14]	private	26	-	chest	cognitive task	100 (IR)
Yao and Wan [87]	private	20	up to 4	limbs	-	>80 (IR)
Biel *et al.* [5]	private	20	4-10	limbs & chest	resting	100 (IR)
NSRDB [21]	public	18	1	-	no significant arrhythmias	-
Lourenco *et al.* [38]	private	16	1	fingers	-	13 (AR), 94.3 (IR)
Homer *et al.* [25]	private	12	12 or 18	-	-	85.2 (IR)
Kim *et al.* [32]	private	10	-	arms	resting and exercise	-

N = number of subjects, AR = Authentication Rate, IR = Identification Rate

3.3 Benchmarking an ECG biometric database: UofT Database

3.3.1 The Database

To address the above-mentioned shortcomings, this work presents a new biometric database for evaluation of ECG biometric systems. The UofT database (*UofTDB*) is an ECG database captured from subjects' fingers, thereby mimicking real world application settings [1]. Emphasis has been given to the collection of ECGs from a large number of individuals under several conditions and in uncontrolled environments. The database can be divided into two portions, one is the single session and the other is the follow-up sessions.

The single session recordings took place at multiple public locations in the University of Toronto; Sandford Fleming Building, Bahen Centre for Information Technology, Gerstein Science Information

[1]The UofT database will be made available to researchers and institutions upon request.

Table 3.2: Properties of UofT ECG Database

	Number of Recording Sessions						Conditions				
	single	two	three	four	five	six	supine	tripod	exercise	sit	stand
Number of subjects	1020	72	65	54	47	43	63	63	71	1020	81
	Age Range: 18 - 52, Gender: 61% Female, 39% Male, ***Total number of subjects = 1020***										

Centre in the Sigmund Samuel Library Building, J. M. Kelly Library and the Athletic Centre. In order to explain our intention for this experiment and increase participation, a set of promotional banners was created and placed close to the workbench and a member of our signal collecting team was in charge of motivating potential candidates. The principal members of our collecting team were Saeid Wahabi, Shahrzad Pouryayevali and Foteini Agrafioti. The experimental procedure was disclosed to the volunteers in the beginning of the experiment, who also signed consent forms. None of the participants were asked about any health problems therefore the database can have a mixture of healthy and non healthy subjects. As a reward for participating in the experiments, a gift card was given to the participants. The single session data collection process was spanned over three months, and in the end data had been collected for an overall total of 1020 participants, the majority of which were students.

The follow-up session recordings took place at the Biometrics Security Laboratory of the University of Toronto. Data recollection from the set of volunteers previously enrolled in the experiment was done with the purpose of studying the changes in the ECG morphology over time and the effect of posture change and heart rate variability. Overall 100 volunteers participated in these experiments. Five recording sessions took place several weeks apart, however not all the 100 subjects participated in the five follow-up sessions only 43 subjects were recorded at all five sessions. Similarly the experimental procedure was disclosed to the volunteers in the beginning of the experiment, who also signed consent forms.

Overall, the age range of the participants was between 18 and 52 and 61% were female and 39% were male. The whole signal collection process took 6 months and ended in the Fall of 2013. More specific, the characteristics of the UofTDB are as follows (See Table 3.2):

- **Database size:** The UofTDB has ECG records from 1020 subjects. The length of the recordings varies between 2-5 minutes.
- **Number of sessions:** 100 subjects, randomly selected , participated in follow-up recordings. The follow-up study consists of five sessions of recordings spanned over a period of six months.
- **Testing conditions:** During each follow-up session, the subjects were recorded under five different conditions (Refer to Figure 3.1):

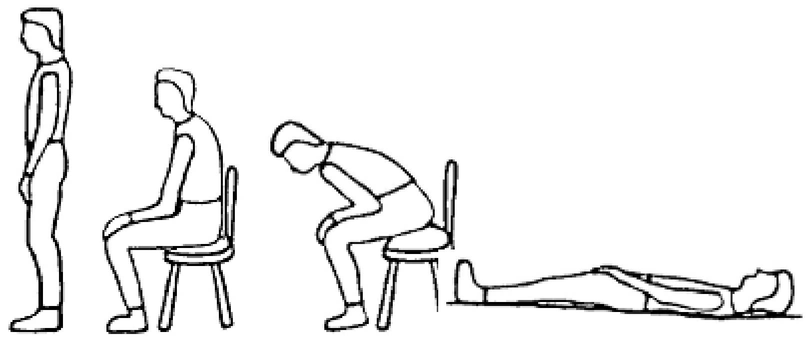

Figure 3.1: (a) Standing (b) Sitting (c) Tripod and (d) Supine

Interface Sampling Rate	200Hz
Interface Resolution	12 bits / sample
Sensor Offset	1.00 V($\pm$0.3 V)
Sensor Gain	1 mV body potential / 1 V sensor output
Sensor Roll-off Frequency	250Hz

Table 3.3: Vernier EKG sensor and USB interface specifications.

1. Sitting: The subject's ECG was recorded while sitting comfortable on a chair.
2. Standing: The subject was asked to stand still during the recording.
3. Supine: In this position, the subject was asked to lay back and relax
4. Tripod: The subject completely leaned forward while sitting on a chair.
5. Exercise: The subject performed basic structural workouts such as jumping jacks and push-ups for 3-5 minutes depending on their physical status. After exercise, the heart rate raised on average to 132 beats per minute.

3.3.2 Acquisition Protocol

The ECG signals recorded from the subjects were anonymized in order to protect their personal information in accordance with the University of Toronto Research ethics policy.

The acquisition device: The Vernier EKG Sensor and the Vernier Go!Link interface[2] were used for recording. The device resolution is 12 bit per sample and the sampling frequency was set at 200 Hz. Table 3.3 summarizes the specifications of the acquisition device.

Placement of electrodes: three dry AgCl electrodes were used to capture the ECG from the subjects' fingertips similar to a lead I configuration. The left thumb was positioned on the positive

[2]www.vernier.com

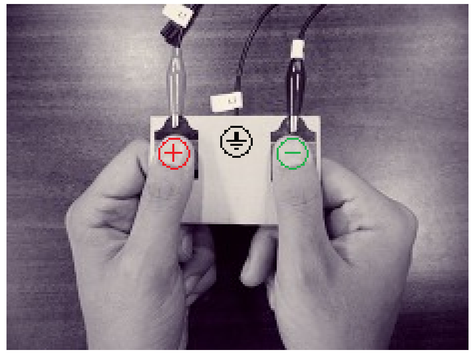

Figure 3.2: Placement of electrodes according to lead I configuration

electrode, the right thumb on the negative and a reference electrode was in contact with the right index finger. All the three electrodes were attached to a pad so that the subject could rest their fingers on the electrodes by holding the pad as shown in Figure 3.2.

Signal quality: during each recording session, an operator verified that the acquired signal is a valid ECG. The operator instructed the volunteer to position their fingers according to the experimental protocol. High frequency noise was observed in the recordings of certain volunteers, however the current analysis did not discard any such records. Low quality signals are a direct consequence of the uncontrolled environment and the subjects' natural movements. The inclusion of such signals in the database simulates the challenge that all ECG biometric systems encounter in real-world scenarios.

3.4 Chapter Summary

In conclusion, most of the existing databases do not have recordings in the different sessions, different conditions or their population is small. Therefore these databases are not suitable for evaluating ECG biometric techniques that will be used for real-world applications. In order to have reliable results ECG biometric techniques must be evaluated on databases that have these factors. We propose a new ECG database that has several advantages compared to existing databases. The UofTDB was acquired from fingertips, it has recordings in different sessions, different postures and in exercise condition and furthermore it has a relatively large population.

Chapter 4

ECG Recognition Based on Wavelet Transform

4.1 Introduction

In this section we propose a new ECG biometric method based on the Wavelet Transform of heartbeats. Our proposed method is non fiducial and the features are extracted from the individual heartbeats of an ECG signal. We explain in detail the steps of our system; preprocessing, feature extraction and classification. We then compare our method with the state of the art ECG biometric technique and furthermore evaluate our system under various conditions such as, across different sessions, posture change and in exercise condition. Additionally we explore the effect of different number of heartbeats used for verification.

4.2 Methodology

4.2.1 Preprocessing

The raw ECG signal is first filtered by using a fourth order bandpass Butterworth filter with cut-off frequencies at 0.5Hz and 40Hz (Figure 4.1). Under 0.5Hz the signal is corrupted by baseline wander, and over 40 Hz there is distortion due to muscle movement, power-line interference and etc. [76].

The proposed ECG method extracts features from each heartbeat. By using Pan and Tompkins [54] QRS detection algorithm, the heartbeats were extracted and aligned at the R peaks (Figure 4.2). Furthermore in order to reduce the effect of heart rate variability on the performance of the system, the

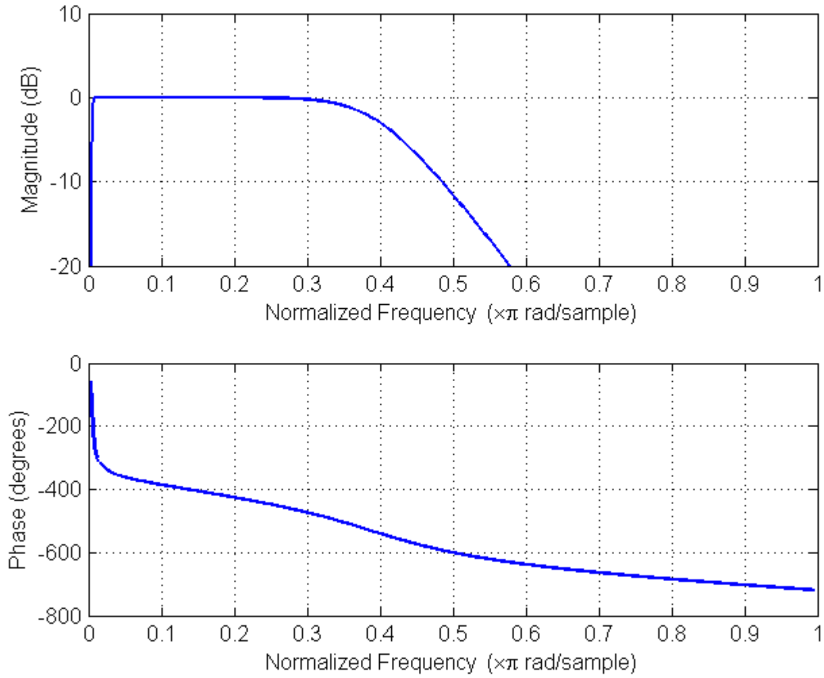

Figure 4.1: Magnitude and phase response of the fourth order Butterworth bandpass filter. The cut-off frequencies are at 0.5Hz and 40Hz.

heartbeats were windowed to mainly contain the QRS complex. The QRS complex is less affected by heart rate variability than the other waves [46] and we empirically chose a window length of 350 msec with 150 msec before the R peak. The outlier heartbeats were discarded by calculating their Euclidean distance from the subject's median heartbeat.

The heartbeats were then normalized to have a dynamic range of one using the following formula:

$$hb_{norm} = \frac{hb - \min(hb)}{\max(hb) - \min(hb)}$$

Finally, every two consecutive heartbeats were time averaged to further reduce the amount of high frequency noise in the heartbeats.

4.2.2 Time-Frequency Representation and LDA-Based Dimensionality Reduction

The features are extracted from the time-frequency representation of the heartbeats by using Wavelet transform. Unlike Short Time Fourier Transform (STFT), Wavelet transform has a multi-resolution approach to time-frequency representation which tiles the time-frequency plane more naturally. A low frequency needs to be observed for a relatively long time to be estimated whereas the high frequency

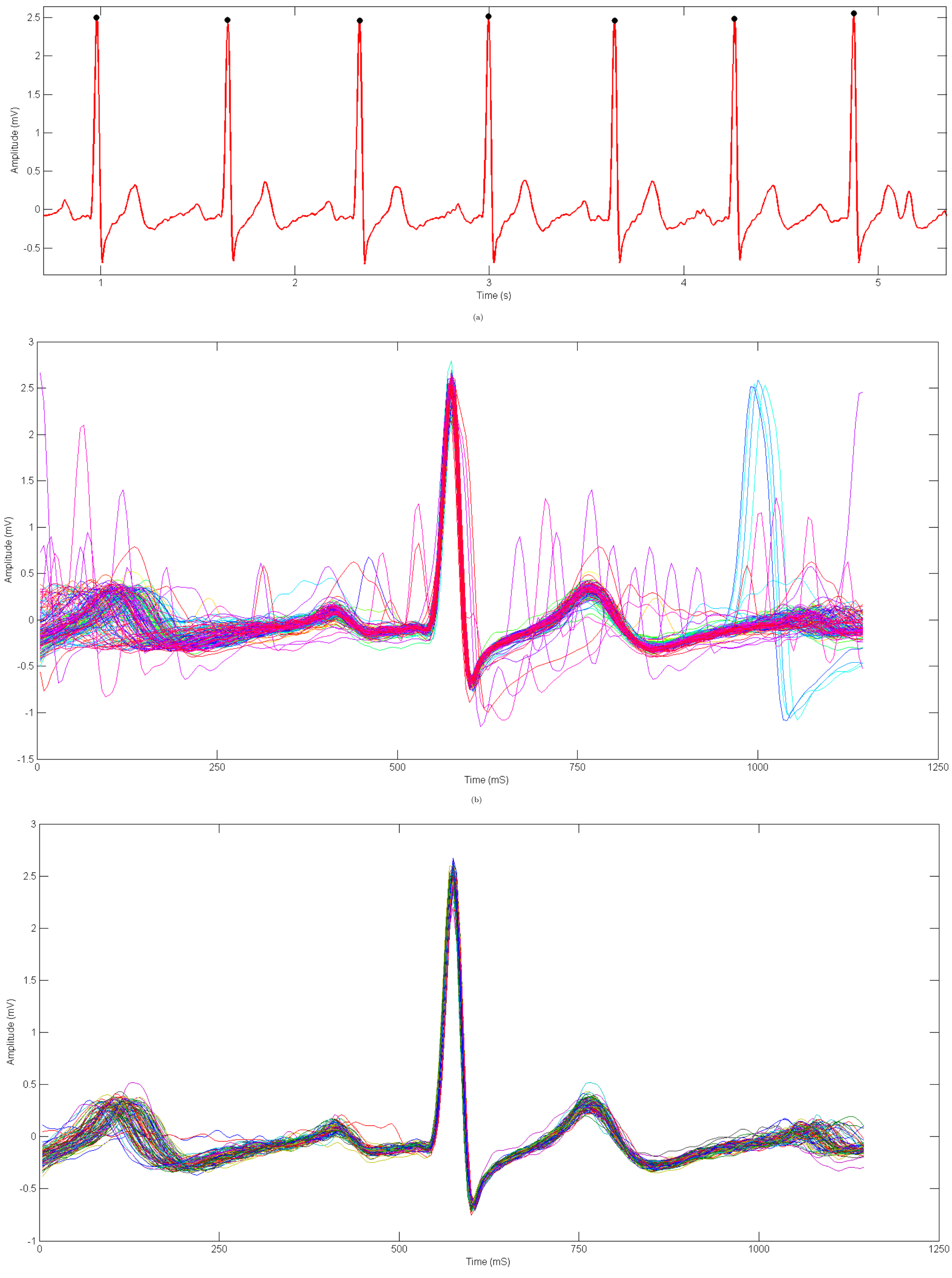

Figure 4.2: (a) R peak detection of an ECG recording using Pan and Tompkins [54] algorithm, (b) extracted heartbeats, and (c) heartbeats after outlier removal.

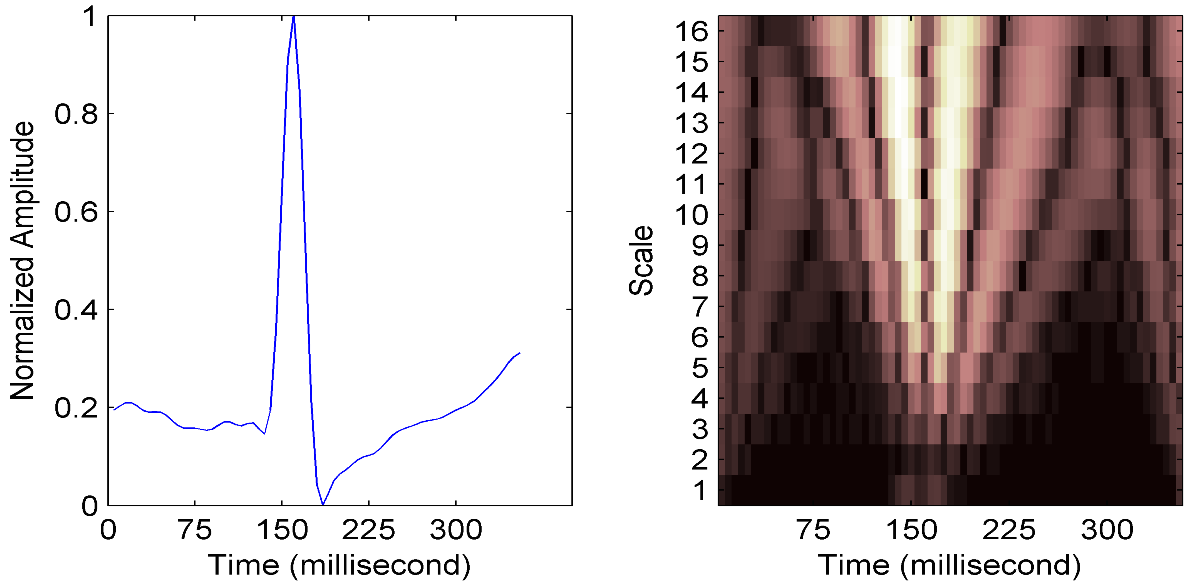

Figure 4.3: A heartbeat (left) and its continuous wavelet transform (right) .

content can rapidly change at any time hence they require smaller observation window.

Let $\Psi(t)$ be the mother wavelet function for scale parameter $a > 0$, and dilatation τ. The Wavelet Transform (WT) of a heartbeat $x(t)$ is:

$$WT(a,\tau) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\Psi^*(\frac{t-\tau}{a})dt \tag{4.1}$$

where $*$ denotes the complex conjugate. In STFT, the analyzing functions are windowed complex exponentials ($w(t)e^{j\omega t}$) and resulting coefficients, $F(\omega, \tau)$, represent the correlation between the signal and a sinusoid with angular frequency ω in an interval of a specified length by $w(t)$ centered at τ. In the wavelet analysis, the analyzing function is a mother wavelet function, Ψ, where the signal is correlated with the shifted (dilated) and scaled versions of the wavelet ,Ψ. When the scale is small, the wavelet function is contracted in time-domain which provides a detailed view of the signal. On the other hand, when the scale increases, the wavelet spreads out in time-domain and the wavelet transform takes into account the long term behaviour of the signal. The choice of the wavelet function remains as an "engineering problem" and is dependent on the application. In this work we used Daubechies scalar wavelet (Db5) at all integer scales from 1 to 16 which empirically found to yield optimal results (Figure 4.3).

Let M be the total number of scales and N be number of time samples, then the WT of each heartbeat can be represented as a point in $\mathbb{R}^{MN}$ by vectorizing its time-frequency components. After transforming the heartbeats, we use Linear Discriminant Analysis (LDA) to select a subset of features from $\mathbb{R}^{MN}$ that maximizes the inter-subject separability and at the same time minimizes the intra-subject separability. LDA is a dimensionality reduction technique that selects the linear subspace transformation matrix W that maximizes the ratio:

$$maximize \;\; trace\Big(\frac{W^T S_b W}{W^T S_w W}\Big) \tag{4.2}$$

where

$$S_b = \sum_{i=1}^{C} P_i(\boldsymbol{\mu_i} - \boldsymbol{\mu})(\boldsymbol{\mu_i} - \boldsymbol{\mu})^T$$

is the *between-class* scatter matrix, and

$$S_w = \sum_{i=1}^{C} \sum_{\mathbf{x} \in \mathbf{X_i}} (\mathbf{x} - \boldsymbol{\mu_i})(\mathbf{x} - \boldsymbol{\mu_i})^T$$

is the *within-class* scatter matrix. Let each class represent a subject, then C is the total number of subjects, P_i denotes the number of observations (WT of heartbeats) per subject i and $\mathbf{x}$ is the input WT of a heartbeat.

In order to reduce the input dimension from $\mathbb{R}^{MN}$ to $\mathbb{R}^K$, one can show that the linear subspace, $W \in \mathbb{R}^{MN \times K}$, is formed by the eigenvectors of $S_w^{-1} S_b$ that corresponds to its top K eigenvalues. Therefore the projected input vector can be found by

$$\mathbf{y} = W^T \mathbf{x}$$

In practice S_w is usually singular which can be due to the fact that the number of training heartbeats are smaller than the dimensionality of the sample space, known as *Small Sample Problem (SSS)*. for instance after Wavelet Transform the input dimension is $71(timesample) \times 16(scale) = 1136$ and there are $20(\frac{heartbeat}{subject}) \times 45(subject) = 900$ total training heartbeats. Although there are several approaches to overcome this problem [78], we used a variation of LDA called *Direct-LDA* (DLDA) [89].

In DLDA [89] it is assumed that the null space of S_b does not include useful discriminative information. The idea is to ignore the null space of S_b and at the same time keep the important null space of S_w. To perform DLDA [89], first S_b is diagonalized and then its null space is discarded. Second S_w is projected onto this new space. Finally, the eigenvectors corresponding to the largest eigenvalues of the projected within-class scatter matrix are selected as the final transformation matrix.

4.2.3 Classification

Let the projected WT of the heartbeats, $\{Z_p\}$ for $p = 1 \ldots P$, serve as the feature vectors of a subject. For simplicity, we assume that the feature vectors $\{Z_p\}$ are independent and have a multivariate Gaussian distribution. In the enrolment step, the mean vector $(\underline{\mu}_i)$ and covariance matrix (C_i) of a subject i is estimated using the maximum likelihood estimation: $\hat{\theta}_i = (\underline{\mu}_i, C_i)$.

In the verification step, we develop a statistical hypothesis testing for making the final decision of the system. The unknown ECG signal undergoes the same steps described above to obtain the projected WT of the heartbeats $\{Z_t\}$ for $t = 1 \ldots T$. In this approach we treat identity verification as a test of hypothesis. The two hypothesis are:

$$H0 : \text{subject is who (s)he says}$$

$$H1 : \text{The subject is not who (s)he says}$$

If a person claims to be subject i, then $\hat{\theta}_i$ is drawn from the statistical distribution corresponding to subject i. Therefore the statistical hypothesis testing problem becomes:

$$H0 : Z_t \sim \mathcal{N}(\underline{\mu}_i, C_i)$$

$$H1 : Z_t \sim \mathcal{N}(\underline{\mu}_j, C_j) \text{ where i} \neq \text{j}$$

In this hypothesis formulation the subject $j \neq i$ is chosen to be the "closest" enrolled subject to the test data. Subject j is selected such that

$$j^* = \underset{j}{\operatorname{argmin}} \|\overline{Z} - \underline{\mu}_j\|$$

where $\|.\|$ is the Euclidean norm operator and $\overline{Z}$ denotes the mean feature vector of the unknown subject. Assuming that the heartbeats are statistically independent, the score of the T test heartbeats claiming the i-th subject identity is given by the log-likelihood ratio (LLR):

$$\sum_{t=1}^{T} \log \left[\frac{p(Z_t|\hat{\theta}_i)}{p(Z_t|\hat{\theta_{j^*}})} \right] \underset{H1}{\overset{H0}{\gtrless}} \alpha$$

where α is a constant that determines which hypothesis to accept.

4.3 State of the Art ECG Biometric Method

Based on the evaluation of the state of the art ECG biometric methods using the UofTDB, AC/LDA method proposed by Agrafioti *et al.* [1] outperformed the other methods based on 1020 subjects. Therefore in this section we use this method as a benchmark for comparison with the state of the art.

In AC/LDA method [1], features are extracted from the normalized autocorrelation of the ECG signal. The filtered ECG signal is blindly segmented into overlapping windows of 6 seconds length with 50% overlap. The normalized autocorrelation coefficients, AC, of each window were then estimated using:

$$\hat{R_{xx}}[m] = \frac{\sum_{i=0}^{N-|m|-1} x[i]x[i+m]}{\hat{R}_{xx}[0]}$$

where $x[i]$ represents the windowed ECG and $x[i+m]$ is the delayed version of ECG window with a time lag of $m = 0, 1, \ldots M-1$ and $M << N$. Empirically we chose 50 lags for each window.

The Linear Discriminant Analysis (LDA) method is applied as a second step, to project the AC windows into a lower dimensional subspace while improving the separability for different subjects. Since the number of training AC windows available for each subject is smaller than the dimensionality of the sample space, the LDA suffers from the *small sample sized* problem [59]. To overcome this problem we used DLDA [89] method which was described in this section. Henceforth, we refer to this method as AC/LDA. The projected AC windows, AC_{proj}, serve as templates for each subject and the main task of verification is to match the templates of the unknown subject to the ones of the claimed subject. The template matching is done by estimating the Euclidean distance and regulating it using a threshold τ.

4.4 Empirical Performance Evaluation of Methods

In this section we evaluate the performance of the proposed method and compare it with AC/LDA [1]. The ECG recordings from the UofTDB will be used for enrolment and testing the algorithms. The methods are tested in verification mode of operation where the user makes an identity claim and the system should either accept or reject the claim.

4.4.1 Single Session Analysis

In the first experiment the methods were tested based on the ECG recordings from the single session portion of the UofTDB. There are a total of 1020 subjects in sitting posture. For both methods, the first half of the signal was used for enrolment and the second half was used for testing. Figure 4.4 is the ROC

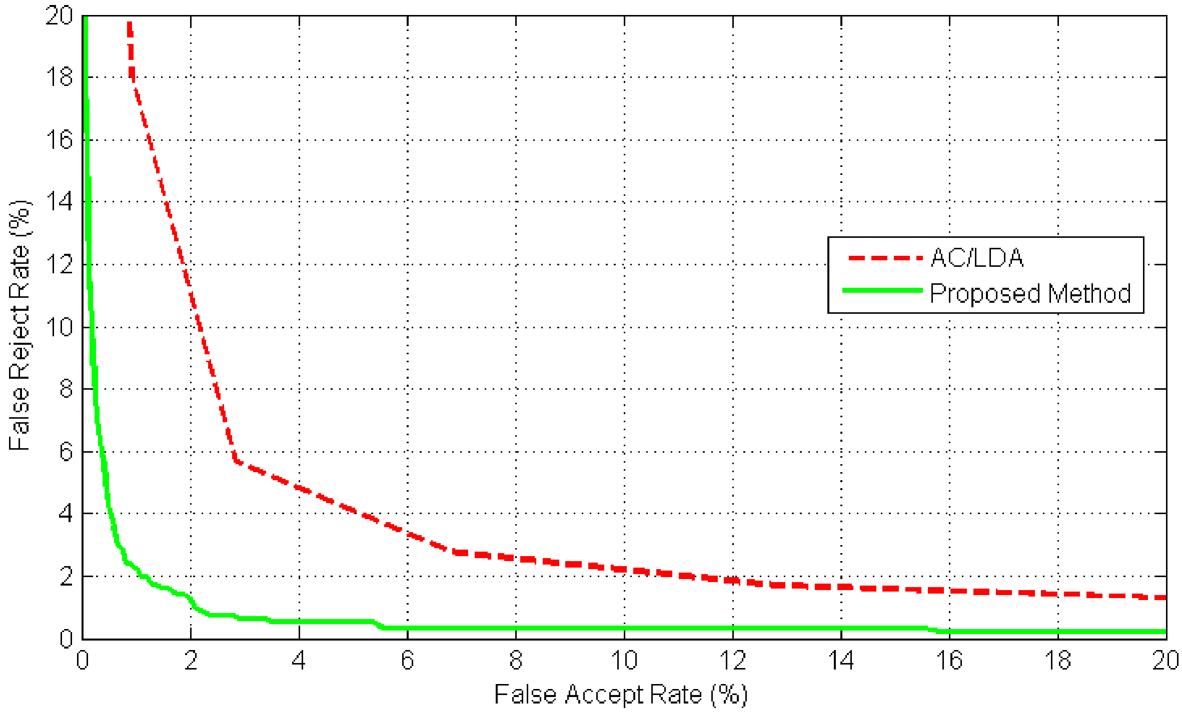

Figure 4.4: Receiver Operating Characteristic (ROC) curve of AC/LDA [1] method and the proposed method based on 1020 subjects.

curves of the two methods which clearly shows that the proposed method outperforms the AC/LDA [1] at all points. The proposed method achieves an EER of 1.6% whereas the AC/LDA [1] EER is 4.5%. Agrafioti *et al.* AC/LDA [1] method was reported to have an EER of less than 1% based on a relatively small population size (27 subjects). This gap in performance can be due to increased population size as well as noise that is present in UofTDB.

4.4.2 Across Session Analysis

In this experiment we evaluated the effect of template degradation over time. For each method the enrolment data was from session two and the testing data was from the subsequent sessions (session three, four and six). For this evaluation data from 45 subjects spread over a six month period in sitting posture were used. Session 5 recordings were excluded since all the recordings are in supine and tripod posture. The results are shown in Figure 4.5. From this Figure, it is clear that there are factors that affect the biometric accuracy over time. Except for test session 4, the performance of AC/LDA [1] is very close to its single session analysis (4.5%). However the proposed method outperforms AC/LDA[3] in all testing sessions with an average EER of 3.21%.

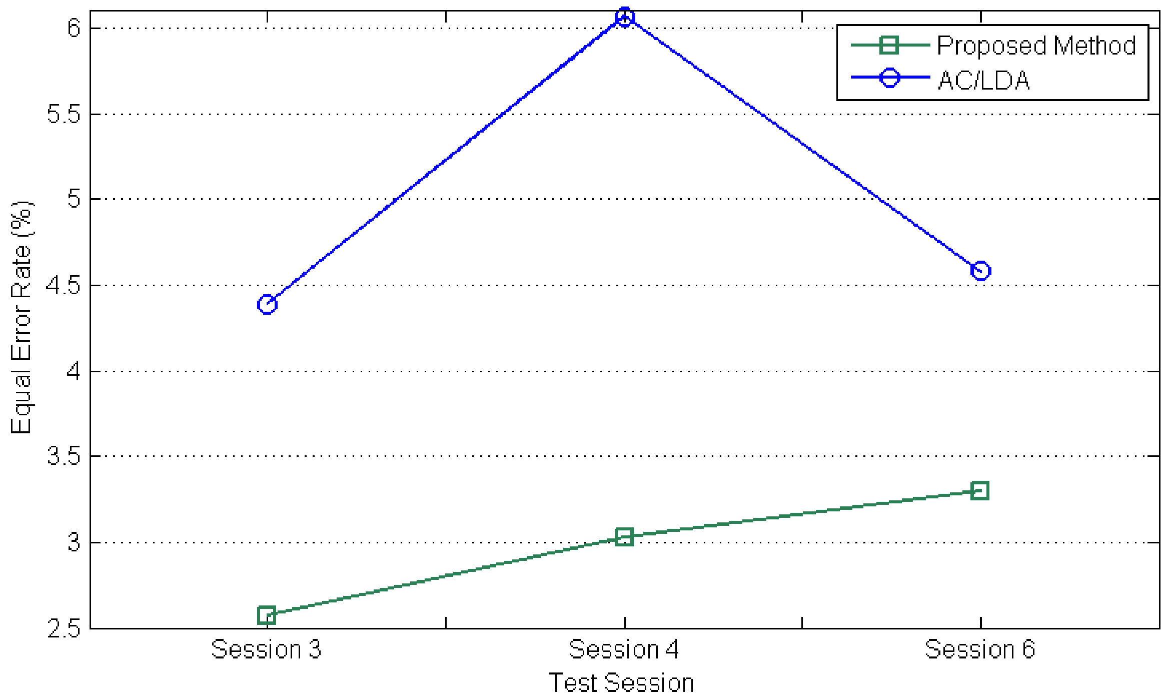

Figure 4.5: Performance of AC/LDA [1] method and the proposed method in *across-session* analysis. Enrol data is from session two whereas test data are from session three, four and six.

4.4.3 Effect of Posture and Exercise

The effect of body posture on ECG biometric accuracy was further investigated. The enrolment and testing data for each method was from four different body postures and exercise condition within the same sessions. The results of the four methods are summarized in Table 4.1. There are 69 subjects on overage in each simulation. The performance of the two methods degrade when the train and testing data are not from the same body posture or condition. The performance of the two methods are fairly close expect for the case when enrol data is from tripod posture and test data from supine.

Exercise condition which results in severe heart rate fluctuation has the greatest impact on the accuracy of both methods. However, the proposed method outperforms the AC/LDA [1] method by around 6%.

4.4.4 Effect of Authentication Time

In many real life applications the authentication latency is an important factor. In this context, authentication latency refers to the amount of time that the user needs to be recorded in order for the system to make a decision. Therefore the effect of number of heartbeats used for authentication is investigated in this section. Figure 4.6 shows the average EER of the proposed method when different number of

(a) Agrafioti *et al.* [1]

Enrol \ Test	Sit	Stand	Supine	Tripod	Exercise
Sit	2.57%	8.16%	-	-	24.10%
Stand	8.16%	4.09%	-	-	-
Supine	-	-	1.44%	6.24%	-
Tripod	-	-	5.61%	1.73%	-
Exercise	20.08%	-	-	-	6.73%

(b) Proposed method

Enrol \ Test	Sit	Stand	Supine	Tripod	Exercise
Sit	0.11%	7.24%	-	-	15.38%
Stand	8.7%	0.69%	-	-	-
Supine	-	-	0%	2.49%	-
Tripod	-	-	6.50%	0.05%	-
Exercise	16.92%	-	-	-	3.12%

Table 4.1: Equal Error Rate for the two methodologies tested in different body postures and exercise condition.

heartbeats were used for authentication. Since the algorithm is based on time-average of every two heartbeats, the minimum number of heartbeats that can be used is two. In all the simulations we can see that as the number of heartbeats increase, the performance of the system improves. However the major improvements (50% improvement) happen within the first four heartbeats.

4.5 Chapter Summary

In this chapter we proposed a new ECG biometric method which is based on the Wavelet Transform of subjects' heartbeats and LDA dimensionality reduction technique. The performance of the method was evaluated by using the UofT ECG database (UofTDB) and was compared with the well-known state of the art ECG biometric method called AC/LDA[1]. Based on recordings from 1020 subjects from the single-session portion of UofTDB an EER of 1.6%. The AC/LDA [1] method resulted in 4.5% EER.

Then we evaluated the performance of the system when the enrol and test recordings are from different sessions which is the case for almost all practical applications. The average achieved EER for the proposed method was 3.12% which shows a drop in performance from the single-session analysis and the average EER for the AC/LDA [1] method was 5.01%.

Further we considered the case when the enrol and test data are from different body positions.

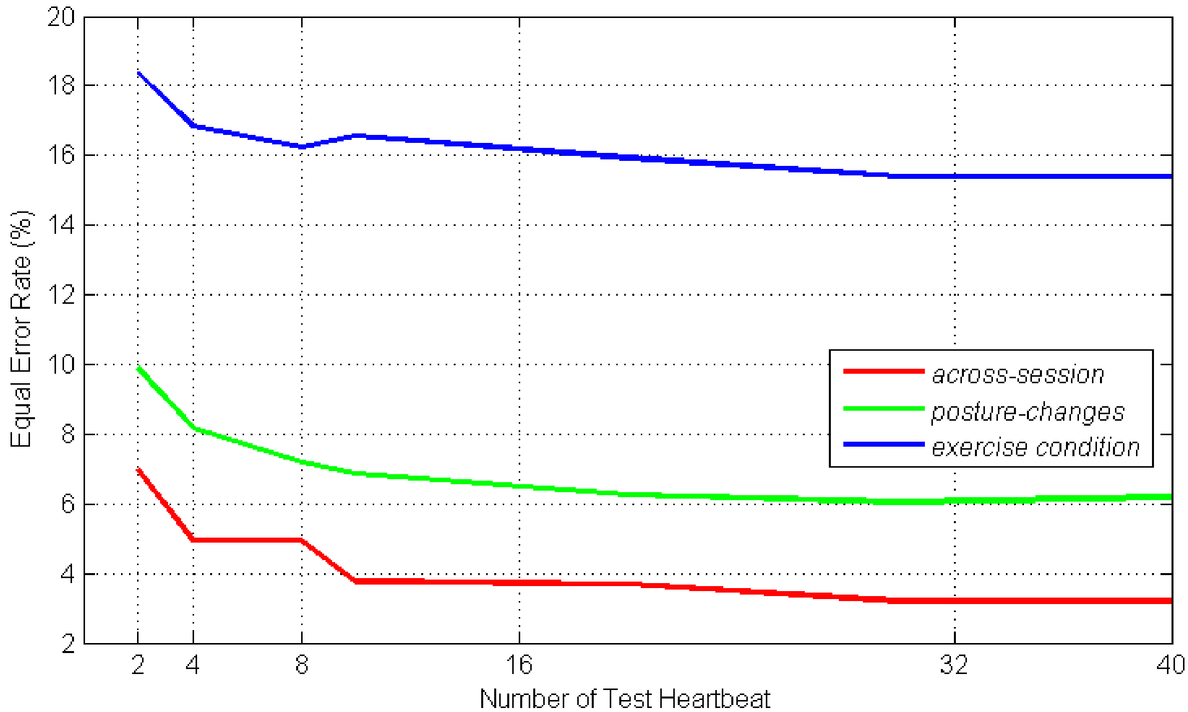

Figure 4.6: The effect of number of test heartbeats on the performance of the proposed method.

Posture changes have a greater effect on the performance of the both methods which increases the EER of the system to almost 9% in some cases. Severe heart-rate fluctuations due to exercise can severely impact the performance of the systems where the EER drops to 16% on average for the proposed method and 22% for AC/LDA [1].

Finally the performance of the proposed method was tested when different number of heartbeats are used for authentications. We showed that in all testing conditions, as the number of testing heartbeats increases the performance of the system improves which is a challenge for real-time applications.

In summary the proposed method outperforms the state of the art in large scale evaluation (1020 subjects) by 2.9%, in *across-session* analysis by 2.11%, in exercise condition by 6% and in body posture changes by 0.8%.

Chapter 5

Multimodal Biometric Systems: Fusion of ECG and Fingerprint

5.1 Introduction

Multimodal biometrics combine information from different sources as opposed to unimodal biometric systems which perform person recognition based on a single source of biometric information. Unimodal biometrics often cannot meet all the system requirements, therefore combining multiple biometrics can overcome the limitations of unimodal biometrics and also improve the performance of the overall system. In this section we will discuss the advantages of fusion and explore the different types of fusion in multimodal biometric systems. As it was shown in the previous section, the performance of the ECG biometric system is very sensitive to different factors which is a challenge for practical applications. Although the proposed method outperforms the state of the art, still it is not accurate for many applications. We will specifically discuss the fusion of ECG with fingerprint and propose a new sequential fusion system. The fusion of the two biometrics is beneficial to both of them; the combined system provides liveness detection and performance improvement for both the unimodal systems.

5.2 Advantages of Multimodal biometric Systems

Multimodal biometrics have many advantages which come from the fact that they use multiple sources of information. The prominent implications of this are increased recognition performance and enhanced security and fewer enrolment problems [63]. The improvements are described below in detail:

- Noise can be present during biometric data acquisition due to various reasons such as defective equipment, improper sensors or environmental factors. However when multiple biometrics are available they are able to provide additional information to reliably determine the identity of the user. For example, in a face and voice based multimodal biometric system, if the individuals voice is corrupted due to noise present in the environment, the facial characteristics can be used for identification.

- Universality is one the main characteristics of a biometric identifier, however not all biometrics are truly universal. The National Institute of Standards and Technology has reported that approximately 2% of the population may not easily be fingerprinted because they do not have detectable of repeatable friction ridge patterns (due to disabilities, cuts and bruises on their fingerprint) [60]

- Features extracted from biometric characteristics of different individuals can sometimes be quite similar for example the gaits (pattern of movements of the limbs) of two persons of the same family or the facial characteristics of identical twins can be similar. In these scenarios, the unimodal biometric systems may result in false recognitions, however by increasing the number of biometric traits additional information is provided to the system which will increase the reliability of the system.

- The biometric data acquired during verification may not be identical to the data used for enrolling the user in the system. This variation may be caused by incorrect sensor placement (for example changes due to pressure or rotation of the finger in fingerprint recognition) or environmental conditions (for example illumination changes in face recognition) or physical changes (for example the appearance of wrinkles in face recognition or scars on fingertips in fingerprint recognition). However if multiple modalities are present even if one of the biometric traits is affected by the mentioned variations the other traits can offer additional evidence about the authenticity of the identity claim.

- Although biometrics are very hard to be stolen, it is still possible to circumvent a biometric system using spoofed traits. Studies have shown that it is possible to fool fingerprint system using gummy fingers that have fingerprint impressions [44]. Furthermore behavioural biometrics such as signature are more susceptible to such attacks than physiological traits. By having more biometric traits the risk of such attacks can be decreased simply because it will be much more difficult for the attacker to imitate multiple biometric traits.

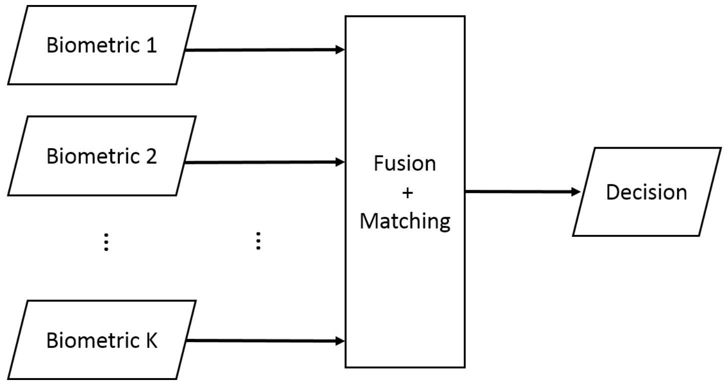

Figure 5.1: Block diagram of parallel fusion scheme.

Multimodal biometrics consequently provide an improved performance over unimodal biometrics in their ability to authenticate a user in presence of various limiting factors discussed above. In addition, multimodal biometric systems also provide improved security.

5.3 Fusion in Multimodal Biometrics

Information of multiple biometrics are fused in various ways. Fusion methods can be classified based on the following parameters: scheme, sources of information and levels of fusion. The design of different multimodal biometrics depends on the application scenario. In the following subsections the different techniques are described based on the above three parameters.

5.3.1 Scheme

Fusion methods can be divided into two categories: sequential and parallel fusion. In parallel fusion techniques multiple biometric traits are used simultaneously while in sequential fusion depending on the design of the system, subjects are first given to a particular biometric trait and then passed on to the next biometric trait. Verification in parallel fusion requires the user to present all the biometric traits which will cause more inconvenience for the users (Figure 5.1), however sequential fusion tries to reduce the total number of biometric traits needed to identify each user by accepting a portion of the subjects in each stage using a single biometric trait, once the subject is accepted in a particular stage they will no longer have to proceed to the next stage and can bypass the rest (Figure 5.1). Therefore sequential fusion will improve the efficiency by decreasing the user time and effort [90, 49]. On the other hand biometric systems in parallel mode generally have higher accuracy since it utilizes more information about the user for recognition. The choice of each scheme depends on the application requirements, for example

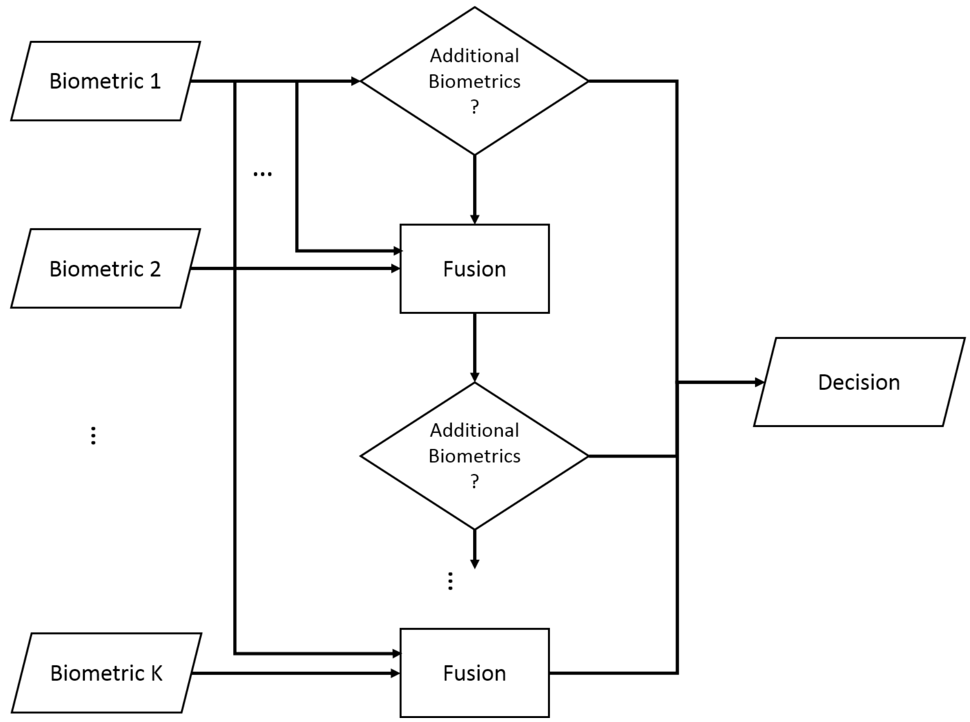

Figure 5.2: Block diagram of sequential fusion scheme.

for highly secure facilities (e.g. access to military facilities) parallel schemes are more suited however for less security critical applications serial schemes are prefered as they can be more user-friendly and convenient.

5.3.2 Sources of Information

As discussed before unimodal biometrics are combined to create multimodal systems. The information can be combined through [48]:

- Multiple Sensors, in this system different sensors are used for capturing a single biometric trait. For example face images of an individual can be captured using thermal cameras and visible cameras .
- Multiple Traits, in these systems information from different biometric traits are combined to authenticate a user. For example a biometric system may use the face and fingerprint of a user for authentication.
- Multiple Instances, these systems use multiple instances of a single biometric trait, such as the image of the left and right eye of a user for a retina recognition system.
- Multiple Algorithm, these system use one biometric trait but use different matching algorithms.

The main advantage of this system is that it does not require additional hardware or sensors therefore is cost-effective.

- Multiple Sample, in this system a single sensor is used to capture multiple samples of a single biometric characteristic of a user, for example frontal, left and right profiles used in face recognition.

Using multiple sensors may address the problem of noisy sensor data, however all the other limitations of unimodal biometric systems still remain. Also with multiple instances, samples and matching algorithms for the same biometric may enhance the performance of the system but still suffer from many of the problems faced by the unimodal systems. Therefore, a multimodal biometric system based on different biometric traits is expected to be more robust to noise, address the problem of non-universality, improve the matching accuracy, and provide reasonable protection against spoof attacks.

5.3.3 Different levels of fusion

In multimodal biometric systems fusion can be done in different levels, such as the feature level, decision level and the score level. Each method of fusion is briefly explained below:

- Feature Level: Fusion at this level is done by combining more than one feature set extracted from multiple data sources that create a new feature set to represent the individual as shown in Figure 5.3. If the features extracted from one biometric indicator are (somewhat) independent of those extracted from the other, it is reasonable to concatenate the two vectors into a single new vector, provided the features from different biometric indicators are in the same type of measurement scale.

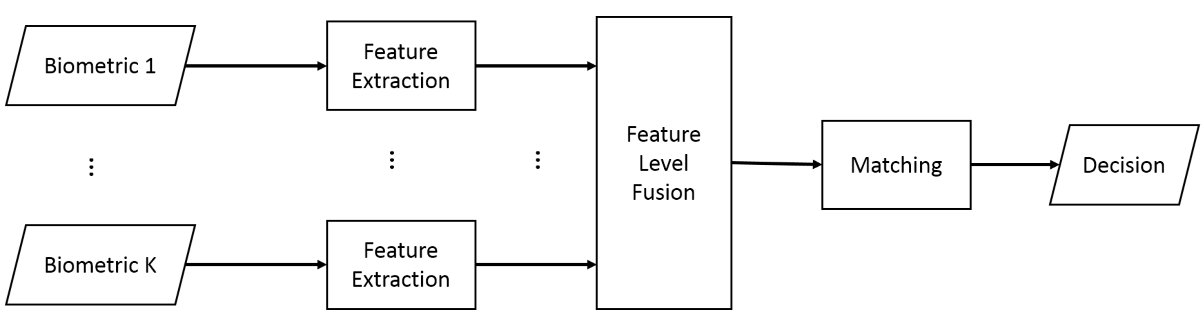

Figure 5.3: Block diagram of feature level fusion.

- Decision Level: In this level, each biometric trait makes a decision independent of the other biometric traits and then the decisions are combined into one single decision (Figure 5.4). There

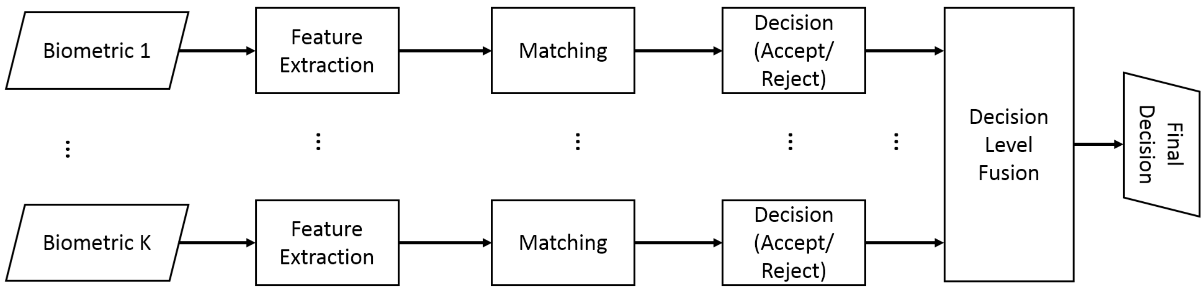

Figure 5.4: Block diagram of decision level fusion.

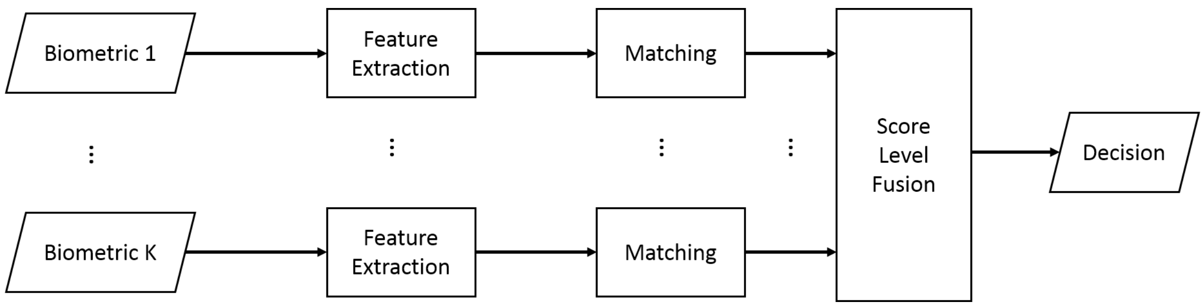

Figure 5.5: Block diagram of score level fusion.

are many methods proposed for decision level fusion such as, AND and OR rules, majority voting and weighted majority voting [64].

- Score Level: Score level fusion is done by combining the match scores generated by different biometric systems, where match score is a measure of similarity between the input and template biometric feature vectors (Figure 5.5). This fusion is also known as fusion at the measurement level or confidence level. This level of fusion is the most commonly used approach in multimodal biometrics due to the fact that it is relatively easy to generate and combine the match scores of different biometric matchers.

5.4 Score Level Fusion Approaches

Score fusion techniques can be divided into three categories. The first approach is referred as density-based score fusion, which is based on the likelihood ratio test and requires estimation of the genuine and impostor match score densities. The second technique is known as transformation-based score fusion. It consists of transforming the match scores obtained from the different matchers into a common domain in order to make them comparable. This transformation is known as score normalization and the normalized scores do not have any probabilistic interpretation. Consequently, in the transformed domain, the sum, max and min classifier combination rules can be directly applied. The third approach is classifier-based score fusion in which the the scores from multiple matchers are treated as a feature vector and a classifier is designed to discriminate genuine and impostor scores. Each of these three approaches has its own advantages and limitations. Each one requires estimation of some parameters using the training data and presents different levels of sensitivity to problems like lack of sufficient training data and noisy training samples. Therefore, none of these three methods is guaranteed to provide optimum performance.

5.4.1 Density-based Score Fusion

The density functions of the match score, given that the scores come from the corresponding classes, are known as the class conditional densities. These densities are usually not known and have to be estimated from a set of training scores of the classes. Density estimation can be done either by parametric or non-parametric methods [19]. If the form of the density function is assumed to be known, only the parameters of the density are estimated from the training data using the parametric density estimation techniques. Otherwise, non-parametric techniques are used because they do not assume any standard form for the density function and are essentially data driven. One the most commonly used approaches is based on the likelihood ratio test. For each user all the genuine and impostor scores are combined separately and probability density functions (pdfs) of genuine and impostor match scores are estimated. Using the likelihood ratio hypothesis testing [35], an unknown subject is either decided as genuine or impostor as follows:

$$LR(\underline{X}) = \frac{P(\underline{X}|\mathcal{H} = genuine)}{P(\underline{X}|\mathcal{H} = impostor)} \quad \underset{impostor}{\overset{genuine}{\gtrless}} \quad \tau \tag{5.1}$$

where $\underline{X}$ is a vector of n match scores $\underline{X} = [X_1, X_2, ..., X_n]$ and $P(\underline{X}|\mathcal{H} = genuine)$ and $P(\underline{X}|\mathcal{H} = impostor)$ are the estimated conditional pdfs.

5.4.2 Combination-based Score Fusion

In practice, due to the limited availability of training data, accurate estimation of the joint conditional densities for all classes is not always possible. In such situations, a more appropriate fusion method is to directly combine the match scores provided by different matchers without converting them into a posteriori probabilities. However, the combination of match sores is meaningful only when the scores of the individual matchers are comparable. Hence, a score normalization transformation is applied to transform the match scores obtained from the different matchers into a common domain. Such normalized match scores do not have any probabilistic interpretation; consequently, the sum, max and min classifier combination rules can be applied to obtain the fused match scores.

5.4.2.1 Normalization Techniques

In the following section we present several commonly used normalization techniques, the raw matching scores are represented by $\{X_k\}$ and the normalized matching scores are represented by $\{X_k^{'}\}$.

1. Min-Max Normalization: This is simple normalization, where it is best to be used when the maximum and minimum values are known, however they can be estimated from the training set even if the matching scores are not bounded. This normalization keeps the original distribution and transform all score to a common range of $[0, 1]$. Th normalization is given by the following formula:
$$X_k^{'} = \frac{X_k - min}{max - min} \tag{5.2}$$

2. Decimal Scaling Normalization: This is normalization is mostly used when the matcher scores are on a logarithmic scale, for example when one matcher generate scores in the range of $[0, 1]$ and another generate scores in the range of $[0, 100]$. The normalization is given by the following formula:
$$X_k^{'} = \frac{X_k}{10^n} \tag{5.3}$$
where $n = log_{10} max(X_i)$.

3. Median Normalization: For this normalization the median and median absolute deviation (MAD) are calculated, the advantage of this normalization is that it disregards the outliers. The normalization is as the following:
$$X_k^{'} = \frac{X_k - median}{MAD} \tag{5.4}$$
where $MAD = median(|X_k - median|)$.

4. Tanh Normalization: This normalization is given by:
$$X_k^{'} = \frac{1}{2}\Big(tanh\Big(0.01\Big(\frac{X_k - \mu_{GH}}{\tau_{GH}}\Big)\Big) + 1\Big) \tag{5.5}$$
where μ_{GH} and τ_{GH} are the mean and the standard deviation estimates, respectively, of the genuine score distribution as given by Hampel estimators [23].

5. Z-Score Normalization: This normalization is one of the most commonly used normalizations. It is computed using the arithmetic mean and standard deviation of the given data. For this

normalization it is best to know the distribution of the scores beforehand, otherwise the mean and standard deviation must be estimated using a set of matching scores. The normalization is done using the following formula:

$$X_k^{'} = \frac{X_k - \mu}{\tau} \tag{5.6}$$

where μ is the mean and τ is the standard deviation of the given data.

6. Double Sigmoid Normalization: This normalization scheme provides a linear transformation of the scores in a specific region, while the scores outside this region are transformed non-linearly. The normalized scores are computed using the following formula:

$$X^{'} = \begin{cases} \frac{1}{1+exp(-2(\frac{(x_k-1)}{r_2}))} & \text{if } X_k < t \\ \frac{1}{1+exp(-2(\frac{(x_k-1)}{r_2}))} & \text{otherwise} \end{cases} \tag{5.7}$$

where t is the reference operating point and r_1 and r_2 denote the left and right edges of the region in which the function is linear. These parameters must be tuned carefully to achieve a good performance. Generally, t is chosen to be some value that is in the region of overlap between the genuine and impostor score distribution and r_1 and r_2 are chosen to represent the extent of the overlap between the two distributions toward the left and right of t, respectively [9].

5.4.2.2 Fusion Techniques

After normalization the match scores can be combined using the combination rules, each user will then have one final score.

1. Sum Rule: combines the scores as a linear transformation:

$$X = w_1X_1 + w_2X_2 + ...w_nX_n \tag{5.8}$$

where X_i are the match scores of a user computed by matcher i and w_i is the corresponding weight of the matcher. In the literature the weights have been computed in many different ways, some have used equal weight, EER based weights and user specific weights.

2. Product Rule: Computes the final score by multiplying all of them:

$$X = X_1 * X_2 * .... * X_n \tag{5.9}$$

3. Max Rule: The final score of each user is the maximum score from different matchers:

$$X = max(X_1, X_2, ..., X_n) \tag{5.10}$$

4. Min Rule: The final score of each user is the minimum score from different matchers:

$$X = min(X_1, X_2, ..., X_n) \tag{5.11}$$

5.4.3 Classifier-based Score Fusion

In classifier-based score fusion the vector of match scores is treated as a feature vector which is then classified into one of the two classes, namely, genuine and impostor. Based on the training set of match scores from classes, the classifier learns a decision boundary between the classes. In general, the decision boundary can be quite complex depending on the nature of the classifier. However, the classifier is capable of obtaining the decision boundary irrespective of how the feature vectors are generated. Hence, the output scores of the different matchers can be non-homogeneous such as: distance or similarity metric, different numerical ranges, etc. Also, no processing is required prior to designing the classifier. These approaches use the well-known statistical and others classifiers, such as the k-NN classifier, classical k means clustering, fuzzy clustering, neural network based classifier, support vector machine (SVM) and the Bayesian classifier.

5.5 Fusion of ECG and fingerprint

As discussed in the previous sections biometrics are physiological or behavioural characteristics of individuals which makes them very convenient, however the major flaw in most biometrics is that they are not robust against falsification. Which means they can easily be spoofed by artificial signals, for example a photo can be used instead of a live face, a fake finger with fingerprint patterns can be used [44], contact lenses can be used to fool iris biometric systems [6] or for voice recognition a signal which contains the speaker's vocal characteristics can be generated to obfuscate the system [4]. Combining more than one appropriate biometrics into a composite system can offer improvement in performance of the overall system while also providing greater robustness to attacks by making it more difficult for an impostor to spoof multiple traits [62, 81]. However one of the key issues of designing a multimodal biometric system is having a convenient interface with the system to ensure the efficient acquisition of biometric information [64]. As stated in Oviatt [52]: "An appropriately designed interface can ensure that multiple pieces of evidence pertaining to an individual's identity are reliably acquired whilst causing minimum inconvenience to the user". For example, in a face, ear and fingerprint based multimodal biometric system, if a user needs to present his/her three biometric identifiers separately, that would be very inconvenient. Instead, if in designing multimodal biometrics we would take into account the aspect of human-computer interaction with the biometric system and designed systems that acquire physically related biometric traits simultaneously we could improve the user experience.

Some combinations of biometrics require less cooperation from the user and are more convenient, for example in a combined face and iris multimodal biometric system the user should only pose in front of a camera [13], however with a fingerprint and face multimodal biometric system the user must place his/her finger on a fingerprint scanner and also pose for a camera in order to capture his/her face features.

In the literature there have been studies that combine different characteristics of the finger such as the fusion of fingerprint and finger vein [67, 37, 86, 33] and different combinations of multiple characteristics (finger geometry and finger knuckle print) [56, 55]. However in this work we combine two characteristics from the fingers that are very different in nature, one is physical (fingerprint) and the other is vital (Electrocardiogram) which also offers the advantage of liveness detection to the system.

The ECG signal can easily be acquired from fingers which naturally make sense to be fused with another biometric that can also be recorded from the fingers. Therefore ECG sensors and fingerprint readers can be implemented on devices for a compact multi-biometric system. In an ECG and fingerprint bimodal biometric system, the ECG can be used for anti-spoofing and also for improving the performance of the system. Trying to replicate the ECG signal is far more difficult than replicating a finger. It can not be taken away from a body as other biometrics can be, an impostor would face a great challenge to be able to replicate and reproduce the signal.

Zhao *et al.* [92] suggested a multimodal biometric system with the finger-based ECG signal and fingerprint recordings but did not evaluate such a system. Singh *et al.* [73] also reported such a multimodal biometric system but the ECG they were using was captured from the chest which disregards one of the main advantages of a compact finger-based system.

5.5.1 Background on Fusion of ECG and Fingerprint

Zhao *et al.* [92] evaluate the feasibility of authenticating individuals using fingertip-ECG. Three different acquisition configurations were tested, in which three electrodes were used and also the signals were collected two weeks apart . In each session all three configurations were collected and in each configuration one electrode placed on one of the the left hand fingers and one electrode on one of the right hand fingers and a third electrode was placed on either the right hand wrist or the right hand middle finger. Different scenarios were tested where enrolment was from the first session and verification was from the second session and the signals were acquired using different configurations in order to evaluate the effect of different configurations. The performance of the system was evaluated using 22 subjects, based on the previously proposed AC/LDA method and achieved an Equal Error Rate (EER) of 9.23% on average.

On the other hand, Singh *et al.* [73] explore the several multimodal biometrics, namely, ECG and Face, ECG and Fingerprint and all three together. The performance of the proposed fused systems are evaluated using a parallel score level fusion method. For the ECG identification system they use the previously proposed method in [72] which is a fiducial based method. The feature extraction includes detecting the dominant fiducials of the ECG waves which consists of interval features, amplitude features and angle features. The score measure for a user against another is calculated by averaging the euclidean distance between the attributes of feature vectors of the two templates. Furthermore the the distance scores are converted to similarity scores by subtracting from the maximum score of the score set. For the fingerprint identifier they used the match scores generated by the NIST-BSSR1 and normalized the score using the min-max rule. Then, the similarity scores were calculated subtracting them from one.

Two different fusion techniques were explored using the weighted sum rule. In the first method the weights assigned to each modality are inversely proportional to their equal error rates(EER). Let e_k be the EER of the biometric matcher k, then the weight (w_k) assigned to matcher k is computed by:

$$w_k = \Big(\sum_{k=1}^{t} \frac{1}{e_k}\Big)^{-1} * \frac{1}{e_k} \tag{5.12}$$

where $0 \leq w_k \leq 1$ and $\sum\limits_{k=1}^{t} w_k = 1$.

In the second fusion technique the weights are computed based on the separation between the impostor and genuine match score distributions proposed by Daugman *et al.* [16] . The mean (μ) and standard deviation (τ) for the genuine and impostors score distributions are calculated, then the distance between the genuine and impostors scores distribution is measured for each biometric matcher as the following:

$$d_k = \frac{|\mu_{G_k} - \mu_{I_k}|}{\sqrt{(\tau_{G_k})^2 + (\tau_{I_k})^2}} \tag{5.13}$$

where μ_{G_k} and μ_{I_k} are the mean of the genuine and impostor score distributions of matcher k respectively. Furthermore, τ_{G_k} and τ_{I_k} are the standard deviations. If d_k is small it indicates that the overall between the two distributions is more, conversely if d_k is large then the overall between the two distributions is less. Therefore the weights are assigned as the following

$$w_k = \Big(\sum_{k=1}^{t} d_k\Big)^{-1} * d_k \tag{5.14}$$

where $0 \leq w_k \leq 1$ and $\sum_{k=1}^{t} w_k = 1$.

The final score for each individual is computed by summing the weighted scores of the different matchers. The performance of multiple configurations was evaluated using 78 virtual subjects, each having a ECG signal and fingerprint and face information but from independent databases. Based on the assumption that the ECG signal and face and fingerprint information are statistically independent they constructed a chimeric database. For the fusion of ECG and fingerprint they achieved an EER of 1.52% based on the first fusion method (EER wieghting) and achieved an EER of 1.82% based on the second fusion method (match score distance). Furthermore they showed that the performance can be improved further by adding an additional biometric, therefore the performance of the multimodal biometric system composed of ECG, fingerprint and face was increase and the lowest EER was 0.22% based on the EER weighting technique.

5.5.2 Parallel and Sequential Fusion of ECG and Fingerprint

In this section we will explore the different schemes of fusion and discuss the advantages and disadvantages of each scheme for the ECG and fingerprint multimodal biometric system. Due to ease in accessing and combining of matching scores, fusion at matching score level is the most commonly adopted approach in the literature, therefore we will also be considering score level fusion. Our criteria for the comparison of the different schemes will be liveness detection, authentication latency and performance.

- Liveness Detection: A biometric with vitality assurance will require that the person to be authenticated is physically present. Consequently the ECG signal as a physiological signal inherently has the vitality feature, therefore if ECG biometric system is able to authenticate the person that means that a valid ECG was present and therefore vital signs are present, on the contrary if the person is not authenticated we will assume that the ECG signal was not valid and vital signs were not present. In other words, the effectiveness of the liveness detection will be dependent on the ECG biometric performance.

- Authentication Latency: This is defined as the wait time for a user to be authenticated. For the ECG biometric system at least a few heartbeats of the ECG signal is required for authentication whereas the fingerprint image can be captured in the orders of milliseconds.

- Performance Enhancement: This criteria will be met no matter which scheme is used because all the different schemes will at the end benefit from the main advantage of multimodal biometric systems which is improvement in performance. However one needs to empirically evaluate each scheme to determine which scheme improves the performance the most.

5.5.2.1 Parallel Fusion

In parallel fusion mode, all biometrics for all users are required to perform authentication. In a verification setting, each user presents his ECG and fingerprint to the respective sensors, and claims his identity. Each matcher then separately compares the presented trait with the corresponding template of the claimed identity, and produces an ECG and a fingerprint matching score, S_{ECG} and $S_{fingerprint}$, respectively. Finally, these matching scores are fused through a fusion rule $f(S_{ECG}, S_{fingerprint})$. If the fused score S is equal or greater than a predefined threshold τ, then user is accepted as genuine, otherwise it is rejected as an impostor.

From the liveness detection point of view, it depends on how the fusion rule will assign a weight to the ECG biometric system. For example if a fake finger is used and the fingerprint system fails to detect the impostor and the ECG biometric system detects that a vital signal was not provided and assigns a small match score, the final score will depend on how much the ECG biometric system contributes to the final decision. If the contribution is low and the user manages to be accepted then the liveness detection has failed, on the other hand if the contribution is high and the user is rejected. In conclusion in this scheme there is no guarantee that there is liveness detection which is a major flaw for this system. Furthermore, because all the biometrics are required for authentication thus the verification time depends on the slowest system therefore (ECG biometric system).

5.5.2.2 Sequential Fusion

In the sequential mode, first the user provides a particular biometric trait, then that biometric matcher will decide whether the user must proceed to the next step or make the final decision itself and terminate the process. In an ECG and fingerprint multimodal biometric system, the system must begin with the ECG matcher in order to guarantee liveness detection since we have associated liveness detection with the authentication of the ECG matcher. Based on figure 5.6 we observe that the ECG matcher has low false reject rates and reaches FRR of zero at approximately FAR of 15% on the other hand, the fingerprint matcher has very low false acceptance rates and reaches FAR of zero at approximately FRR of 10%. In other words, the ECG matcher is better at rejecting impostors and the fingerprint matcher is better at accepting genuine users.

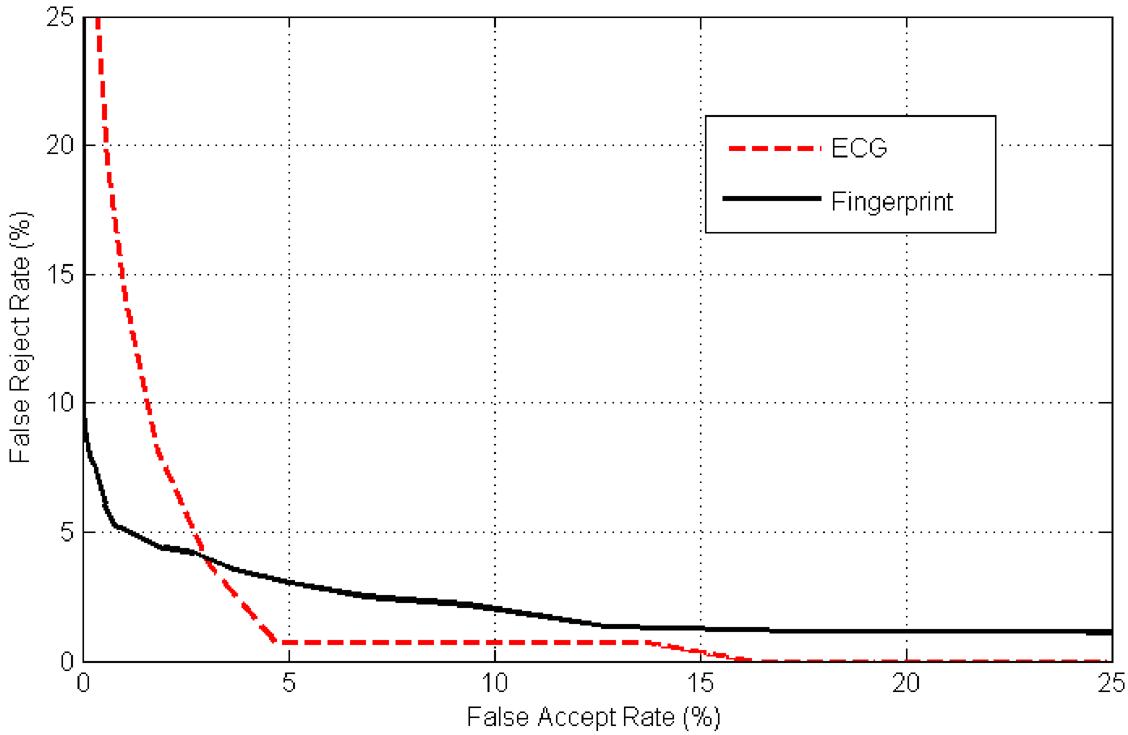

Figure 5.6: ROC of ECG and Fingerprint matchers using data from UofTDB and collected finger database. ECG ROC is based on average *across-session* analysis (40 heartbeats per subject for authentication).

We set our first threshold at $FAR = 16\%$ and $FRR = 0\%$ and assign the ECG matcher to be in charge of rejecting impostors, since the FRR is zero the ECG matcher will not reject any genuine user. Then in the next step if we assign the fingerprint matcher to be in charge of accepting users and we set our threshold at $FAR = 0\%$ and $FRR = 10\%$, since the FAR is zero the fingerprint matcher will not accept any impostor. After the system has confidently rejected the impostors and accepted the genuine users, the remaining subjects will be authenticated using both their ECG information and fingerprint information (Figure 5.7). Although our system satisfies our liveness detection however one limitation of our work is that the authentication latency will at least be as long as the authentication time of the ECG matcher.

5.5.2.3 A User-Weighting Score Fusion Based on Second Closest

Based on the previous discussion our multimodal fingerprint and ECG system is designed as the following: 1) ECG biometric 2) Fingerprint biometric 3) Fused biometrics (ECG and Fingerprint), as shown in figure 5.7. For authentication the system will primarily try to authenticate the user using its ECG signal, if the user is rejected then that is the final decision of the overall system, however the accepted users will

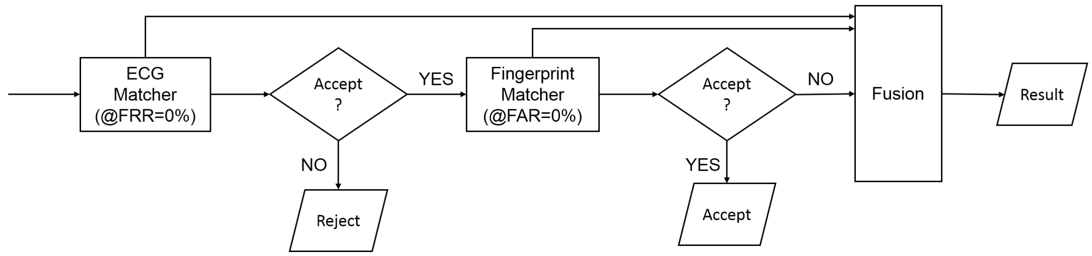

Figure 5.7: Block diagram of ECG and fingerprint fusion.

be given to the fingerprint matcher. If the user is accepted in this stage then that is the final decision for that user. The remaining rejected users will be given to the combination of the ECG and Fingerprint multimodal biometric system which fuses the two at score level to make the final decision.

ECG and fingerprint biometrics generate scores in different ranges. In order to fuse the score we will normalize them to have a dynamic range of one. For the fingerprint scores we use a linear function and for ECG scores a piecewise linear function which are found empirically to be optimal.

$$f' = \frac{f - min(F)}{max(F) - min(F)} \quad e' = \begin{cases} 1, & \text{if } e > \gamma \\ \frac{e+\gamma}{2\gamma}, & \text{if } -\gamma \leq e \leq \gamma \\ 0, & \text{if } e \leq -\gamma \end{cases}$$

where f and e denote the score generated by the fingerprint and ECG biometrics respectively and F represents the set of all scores generated by the fingerprint matcher. γ is the cut-off threshold and is chosen empirically to be 50.

After normalizing the scores each score is weighted and the sum of the two weighted scores is the final score. Our score fusion method is based on the User Weighting fusion technique where it assigns weights to individual matchers that are generally different for distinct users. Let $\omega_{i,m}$ represent the weights for the biometric matcher m of subject i, $n_{i,m}$ be the respective matching score claiming subject i, then the final score S_i is:

$$S_i = \sum_{m=1}^{M} \omega_{i,m} n_{i,m}$$

where M is the total number of biometric matchers, in our case $M = 2$. The main question that remains is how to find the weights for each user. Jain and Ross [29] exhaustively searched a coarse sampling of the weight space where the weights are multiples of 0.1 in the range of $[0, 1]$. This approach may not find the optimal weights and the search can be quiet costly when the number of matchers increase. However Snelick *et al.* [74] used the concept of *wolf-lamb* introduced by Doddington *et al.* [17] for finding the weights. A *wolf* is a subject who can imitate another subject (*lamb*) in a space of matcher m. The idea is to use low weights for matcher m of user i if user i is a *lamb*. They used the d-prime metric as a measure of the separation between the genuine and impostor score distributions of each user in every matcher in order to determine the weights.

In our method, the weights are calculated as the reciprocal of the maximum score it has with all the users except the claimed user i:

$$\omega_{i,m} = \frac{1}{max\{n_{j,m}\}_{\substack{j \neq i \\ j=1,\dots,N}}}$$

where N is the total numbers of subjects in the database. If the claimed identity i is genuine and there exists a subject j that is "close" to i in the matcher space m, then $\omega_{i,m}$ will be small. On the other hand if subject i is well-separated from the other subjects then $max\{n_{j,m}\}$ is small and $\omega_{i,m}$ is large. Also if the unknown subject is an impostor, then generally $max\{n_{j,m}\}$ is large and consequently $\omega_{i,m}$ becomes small.

The proposed weighting scheme is very simple and does not require prior knowledge of the genuine and impostor distributions for each user as in [74]. Also the weights are calculated dynamically at verification which does not require weight updating due to the time varying characteristics of the subjects biometrics. However it should be noted that for N subjects and M biometric matchers, every verification requires calculating $M \times N$ matching scores which can be costly for large M and/or N.

5.6 Chapter Summary

In this chapter we presented an overview of how information fusion is done in multimodal biometrics. There is no guarantee that which method will give the best result, depending on the application a particular scheme may be preferable than others. All methods have there own limitations and advantages, however score level fusion has been the focus of many research work in multimodal biometrics specifically transformation based fusion. Later in the chapter we specifically looked into the previous work done on the fusion of ECG and fingerprint. Then, we examined the different possible schemes of fusion and discussed their advantages and disadvantages. For our sequential scheme, in order to satisfy our criteria of liveliness detection the ECG matcher must be in the beginning and those who have been authenticated by the ECG matcher (passed liveliness detection) will be asked for their fingerprint. Since the fingerprint matcher is shown to be better at accepted genuine users and the ECG matcher is better at rejecting impostors, in the first stage the ECG matcher will be in charge of rejecting impostors and in the next stage the fingerprint will accept the genuine users and the remaining will be authenticated based on the combination of the two matchers.

Chapter 6

Performance Evaluation of ECG and Fingerprint Multimodal Biometric System

6.1 Introduction

This chapter aims to provide a comprehensive study on the performance of the proposed ECG and fingerprint multimodal biometric system. We first give an overview of the performance of unimodal fingerprint based biometric systems reported in the literature. We then review the NIST Biometric Scores Set (BSSR1) [50] which is the commonly used score database for evaluating multimodal biometric systems. Most multimodal biometric studies assume different biometrics are independent therefore multiple biometric databases are combined in order to create virtual subjects instead of actually collecting multiple biometrics from each subject. However since in our work the ECG signals and fingerprint recordings are both collected from fingertips we will study the statistical dependency of ECG and fingerprint using a multibiometric database that we collected from 61 subjects. Furthermore we evaluate our proposed sequential ECG and fingerprint biometric system (introduced in previous section) using our collected databases and in addition we evaluate the effectiveness of fusing the two biometric modalities under different ECG variabilities such as *across-session*, posture changes and heartrate variabilities. Finally the performance of the proposed system is compared with different commonly used score level fusion techniques namely the Weighted Sum Rule, SVM-based, Likelihood Ratio based.

6.2 Fingerprint Biometric Systems

The development of new algorithms for fingerprint recognition has constantly grown in recent years however many of the performance results are reported based on self-collected databases and ad hoc testing protocols, thus leading to incomparable and often meaningless results. Therefore the fingerprint community has been organizing Fingerprint Verification Competition in order to establish a common basis to better understand the state-of-the-art and what can be expected from the fingerprint technology in the future. Several of these competitions have been organized namely, the FVC2000 [41], FVC2002 [42], FVC2004 [10] and FVC2006 [8]. The goal of this technology evaluation is to compare algorithms from a single technology. Testing of all algorithms is done on a standardized database collected by a "universal" sensor. Nonetheless, performance against this database will depend upon both the environment and the population in which it was collected. Consequently, the "three bears" rule might be applied, attempting to create a database that is neither too difficult nor too easy for the algorithms to be tested. Although sample or example data may be distributed for developmental or tuning prior to the test, the actual testing must be done on data which has not been previously seen by algorithm developers. Testing is done "off-line" processing of the data . Because the database is fixed, results of the technology tests are repeatable [41]. In the latest competition, the FVC2006, four databases were provided to used, each database is from 150 fingers and has 12 sample per finger (1800 fingerprint images). The last 10 fingers of each database was given to the participants in order to tune the parameters of their algorithms. Each database was collected using different sensors and the image size and resolution also vary depending on the database. In this competition 70 algorithms were tested and the best algorithm achieved an average EER of 2.155% over all four databases. Also The Fingerprint Vendor Technology Evaluation (FpTVE) 2003 [83] was conducted on behalf of the Justice Department by The National Institute of Standards and Technology (NIST) to recent evaluate commercial fingerprint matching, identification and verification. The NIST study examined 34 commercially available systems used to match fingerprints and was the most extensive test of the technology ever conducted by a government agency. 48,105 sets of fingerprints from 25,309 people, with a total of 393,370 distinct fingerprint images, were used to enable thorough testing, however for security reasons these data are not publicly available. The most accurate system was capable of identifying more than 98% of the mates in every subtest, with a false accept rate of 0.01%.

Furthermore, the NIST has released a Biometric Scores Set (BSSR1) [50] which contains face and fingerprint matching scores from two face and one fingerprint matcher. The BSSR1 dataset has the advantage of being publicly available, unlike the other datasets. BSSR1 includes scores from one fingerprint matcher: the NIST VTB Bozorth matcher, in the FpTVE [83] evaluations, the performance of the VTB was shown to be about average in comparison to the performance of the commercially available matchers that participated in those evaluations. BSSR1 includes 3 datasets:

- Set 1 is based on face and fingerprint data from 517 subjects, with scores from two face matchers and one fingerprint matcher.
- Set 2 is based on fingerprint data from 6000 subjects.
- Set 3 (Face data from 3000 subjects) was not used in this study.

These databases are widely used for evaluating score fusion techniques in multimodal biometric systems. The second set is one of the common sets used for the fusion of fingerprint systems and other biometrics.

6.3 A Multimodal ECG/Fingerprint Database

This section describes the collected multimodal database which has ECG recordings and fingerprint images for each subject. The recordings took place at the Biometrics Security Laboratory of the University of Toronto (Ethics protocol # 31357). Similar to the collection of the UofTDB we explained our intentions for this experiment and increased participation by posting promotional banners close to our workbench and a member of our signal collecting team was in charge of motivating potential candidates. The members of our collecting team were Shahrzad Pouryayevali and Saeid Wahabi. The experimental procedure was disclosed to the volunteers in the beginning of the experiment, who also signed consent forms. As a reward for participating in the experiments, a gift card was given to the participants.

Our data collection was done for the purpose of studying the dependence of ECG signals collected from fingertips and fingerprint images.The data collection was done in one full day, and in the end data had been collected for an overall total of 61 participants, the majority of which were students. The ECG signals and fingerprint images recorded from the subjects were anonymized in order to protect their personal information in accordance with the University of Toronto Research ethics policy.

Each recording session started with ECG recording followed by fingerprint acquisition:

- **ECG:** At the beginning of each recording session, each subject was recorded for at least 2 minutes in a sitting posture. The Vernier EKG Sensor and the Vernier Go!Link interface[1] were used for recording. The device resolution is 12 bit per sample and the sampling frequency was set at 200 Hz. The electrode placements were similar to the collection of UofTDB: three dry AgCl electrodes were

[1] www.vernier.com

Figure 6.1: Ten fingerprints collected from a subject by using Futronic's FS80H Fingerprint Scanner. LLF=Left Little Finger, RLF=Right Little Finger, LFF=Left Fourth Finger, RFF=Right Fourth Finger, LMF=Left Middle Finger, RMF=Right Middle Finger, LIF=Left Index Finger, RIF=Right Index Finger, LT=Left Thumb and RT=Right Thumb.

used to capture the ECG from the subjects' fingertips similar to a lead I configuration. The left thumb was positioned on the positive electrode, the right thumb on the negative and a reference electrode was was in contact with the right index finger. All the three electrodes were attached to a pad so that the subject could rest their fingers on the electrodes by holding the pad.

- **Fingerprint:** Then we recorded the fingerprints of each subject where we captured recordings from all ten fingers. Figure 6.1 shows ten finger recordings of a subject. For every finger we captured two scans. After the first scan the subject was asked to remove their finger from the sensor and place it again on the sensor. Futronic's FS80H fingerprint sensor was used for recording fingerprints. It is a optical type of sensor with a standard 500DPI resolution. It has a scanning window size of 16x24mm. Table 6.1 summarizes the specifications of the acquisition device.

Table 6.1: Futronic's FS80H Fingerprint Scanner Specifications

Scanning Window Size	**Image Resolution**	**Image File Format**	**Image Format**	**Scanner Type**
16x24mm	320x480 pixel, 500 DPI	WSQ	8 bit 256 grayscale	Optical

6.3.1 NIST Biometric Image Software

In order to generate match scores for the fingerprint images we used the fingerprint classifier from the NIST Biometric Image Software (NBIS 5.0.0)[2]. NBIS consists of a minutiae detector called MINDTCT and a finger print matching algorithm known as BOZORTH3.

- **MINDTCT** is the feature extractor module that automatically locates the ridge endings and bifurcation (the minutiae) in a fingerprint image and assigns to each minutia point its location, orientation, type, and quality. For low contrast images, it has the option to improve the image contrast by evaluating the histogram of the input image.

  MINDTCT takes the following steps for feature extraction where each step corresponds to a module:

  1. Generation of image quality map
  2. Image binarization
  3. Detection of minutiae
  4. False minutiae removal
  5. Counting ridges between a minutia point and its nearest neighbours
  6. Minutiae quality assessment

  User's Guide to NIST Biometric Image Software (NBIS) [82] provides a comprehensive description of the MINDTCT module.

- **Bozorth3** module computes a match score between the pairs of minutiae from any two fingerprints. The algorithm is based on the location and orientation of the minutiae points where only the 150 highest-quality minutiae are used for score calculation. Bozorth3 algorithm is designed to be rotation and translation invariant

6.4 Correlation of Fingerprint and ECG from fingertips

Most of the studies in multimodal biometrics use chimeric databases for evaluation. Chimeras are composites of data representing virtual "subjects" that combine biometrics from multiple individuals. Chimeras are often used in evaluations that lack sufficient real data. For example, an evaluation that has fingerprint data from one set of subjects and ECG data from another set of subjects may choose to

[2]www.nist.gov/itl/iad/ig/nbis.cfm

treat the data as if the ECGs and fingerprints came from the same individuals. The assumption behind the use of chimeras is that ECG and fingerprint data are fully independent. In this study we explore the correlation between these two biometrics.

For all the subjects in the collected multimodal biometric database, the cross-match scores of the ECG signal was calculated by using the ECG method described in chapter 4 and the fingerprint BIST algorithms. Based on ten fingers, the correlation coefficient of impostor scores yielded an average value of -0.0570±0.0420 and -0.0068±0.0420 for genuine scores, as the correlation varies from -1 to 1. Although the correlation value is not zero, the actual mean correlation of -0.0570 is fairly small.

As a basis for comparison the correlation of randomly generated vectors was investigated. Based on MATLAB Normally distributed pseudorandom number generator (randn), 3660 pairs of independent normal variables were generated and their correlation was calculated. This process was repeated for 100 times which resulted in a correlation coefficient of 0.0028±0.0175.Note that the average correlation value is smaller than the collected database coefficients, they are not zero which can be due to limited sample size and/or the limitations of MATLAB random number generator.

Based on the above observations, we are assuming that using a chimeric database will not affect the results dramatically and for the rest of the chapter we randomly assigned each of the individuals in the UofT ECG database (UofTDB) to an individual in the collected fingerprint database. We also assume that ECG variabilities caused by day-to-day variations, exercise and posture changes will not affect the fingerprints.

6.5 Empirical Performance Evaluation of ECG and Fingerprint Fusion

Since the performance of the ECG matcher can be very optimistic when enrolment and verification are from the same session and the same condition we will only use the ECG recordings of subjects in the UofTDB who have recordings from different sessions and conditions. Therefore we omit the *same-session* analysis from this evaluation and we investigate the system performance under ECG variabilities over time, posture changes and exercise. For the fingerprint matcher we used the images of our collected database and generated the match scores by using NIST Fingerprint Image Software Packages as described in section 6.3.1.

6.5.1 Pre-fusion Performance of ECG

For the *across-session* analysis, 45 subjects in UofTDB for whom we have recordings in four different sessions in sitting posture were used. Three sets of simulations were performed where in the first set each subject was enrolled using the data from session two and verified using the data from session three. The two other sets have the same enrolment data but the verification data is from session four and six respectively. Therefore the reported results are based on the average ROC curve and average EER. In each simulation we used 40 heartbeats per subject for enrolment and two heartbeats for verification. As shown in chapter 4, the performance of the ECG method improves when more heartbeats are used for verification. However to decrease the authentication latency we only consider the minimum number of heartbeats required by the ECG matcher which is two heartbeats.

For posture changes and exercise conditions we used recordings from 61 subjects since there are only 61 subjects in the fingerprint dataset. There are four sets of simulations for posture changes and two simulation sets for exercise condition. For posture variability simulations, enrolment data are from one posture and the verification data from a different posture. The postures are from sit, stand, supine and tripod positions where sit and stand postures are from session two, supine and tripod postures are from session five. In order to eliminate the effect of *across-session* ECG variability we only considered the posture combinations that are from the same session hence four sets of simulation (enrolment-verification = sit-stand, stand-sit, supine-tripod and tripod-supine). For exercise condition we take into account the effect of heart-rate fluctuations on the performance of the system. The enrolment data are from session three sitting posture and the verification data from session three post-exercise ECG and vice versa. Similarly we used 40 heartbeats per subject for enrolment and two heartbeats verification in each simulation.

Figure 6.2 summarizes the performance of the ECG matcher under different ECG variabilities. In terms of average EER, the performance of the ECG matcher is 6.97%, 9.90% and 18.66% under *across-session* analysis, posture-changes and heart-rate variability.

6.5.2 Pre-fusion Performance of Fingerprint

In this section we generate fingerprint scores based on MINDTCT feature extractor and Bozorth3 matching algorithm using the collected fingerprint database. The generated scores will be used in the following sections for ECG and fingerprint fusion simulations.

Figure 6.3 shows the EER per finger with the lowest EER of 0.28% for left thumb and an average EER of 3.62% across all fingers. The Little fingers have the highest EER rates which can be due to the

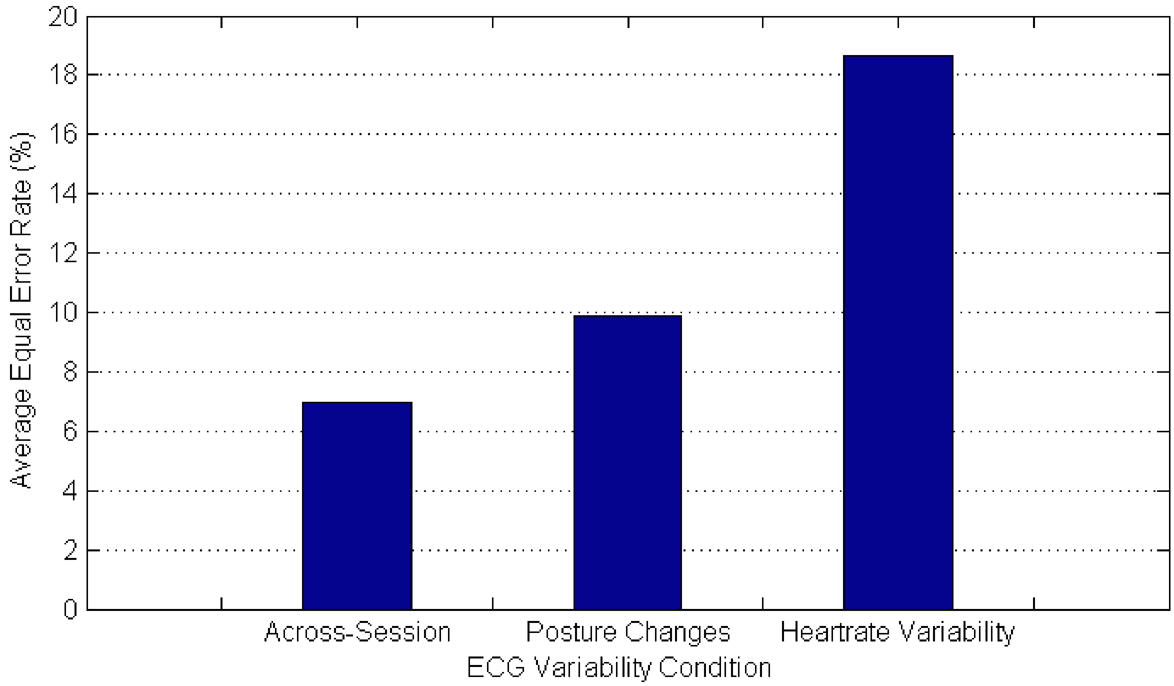

Figure 6.2: Summary of ECG biometric performance under different ECG variabilities.

fact that they have smaller surface area relative to the other fingers. It was also observed that subjects generally tend to put more pressure on the sensor with their thumb, index and middle fingers rather than the little finger and the fourth finger which can be related to the human anatomical capabilities. In fingerprint literature it is shown that when the subjects put higher pressure on the sensor, the quality of the image becomes better, more finger area is covered and consequently the performance of the system improves [85]. Furthermore there is no evidence to explain the variance in the left and the right thumb performance which could be due to the small size of the database.

Figure 6.4 compares the average ROC curve of the collected database with the NIST score set. For the NIST score set, 61 subjects with right index finger images were selected randomly and the ROC curve was generated. This process was repeated 100 times and the average ROC curve is presented in Figure 6.4. The acquired average EER was 4.71% where minimum and maximum EERs were 0% and 10.6% respectively. The ROC curve for the collected database is based on the average ROC of all ten fingers where an average EER of 3.6% is reported.

In the following sections we use scores generated from the right thumb for two reasons:1) ECG data were also collected from subjects' thumbs and 2) the EER of 3.39% is close enough to the NIST performance and also gives us enough room for fusion improvements.

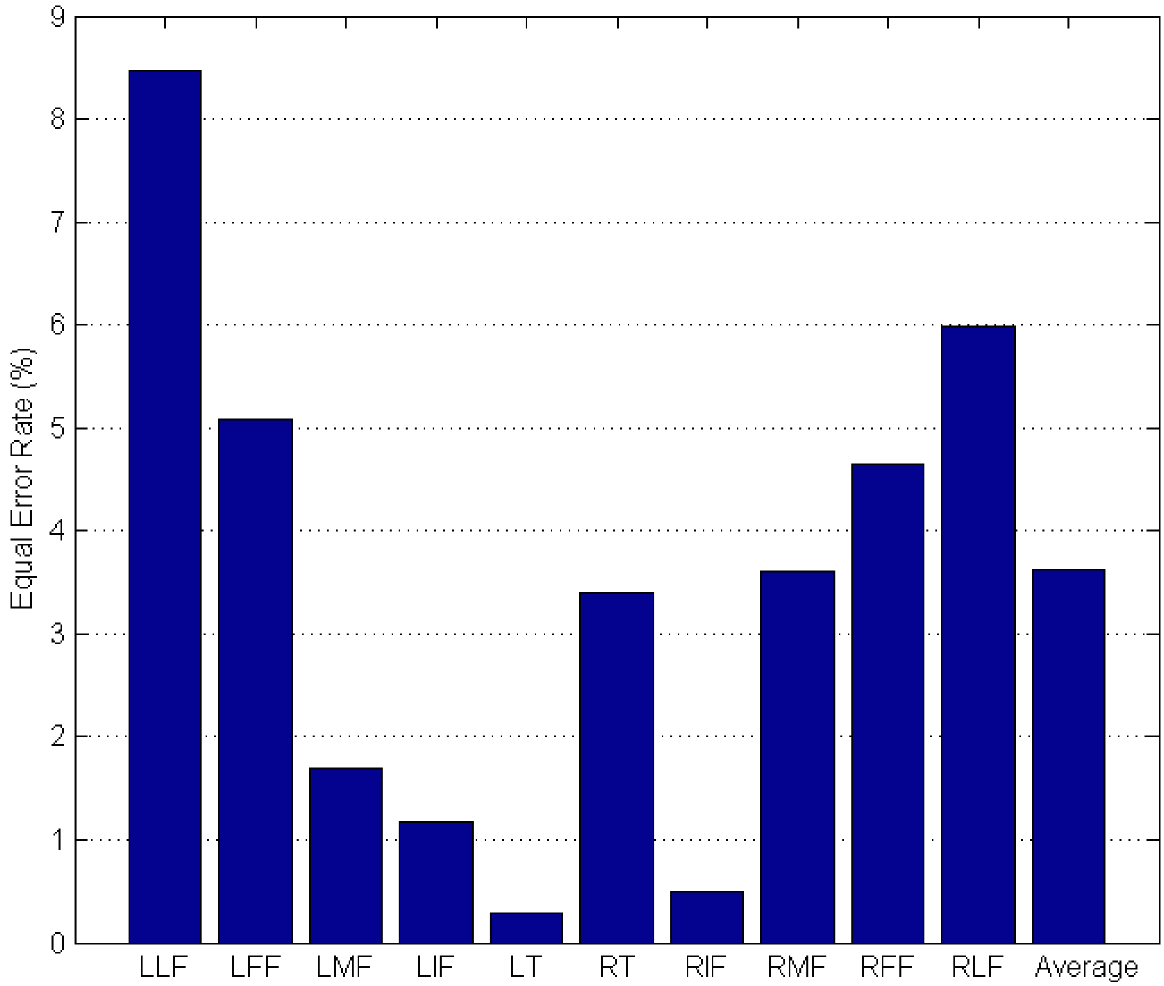

Figure 6.3: EER of fingerprint biometric for each fingers. LLF=Left Little Finger, RLF=Right Little Finger, LFF=Left Fourth Finger, RFF=Right Fourth Finger, LMF=Left Middle Finger, RMF=Right Middle Finger, LIF=Left Index Finger, RIF=Right Index Finger, LT=Left Thumb and RT=Right Thumb.

6.5.3 Sequential Fusion of ECG and Fingerprint

The performance of the sequential fusion scheme explained in chapter 5 is evaluated in this section. The thresholds of the ECG and fingerprint matchers were set at FRR = 0 and FAR = 0 respectively. Figure 6.5 displays the average ROC curve of the fusion scheme along with the user-weighting score fusion technique and the average ROC of the ECG biometric and ROC of fingerprint biometric matchers. As explained previously, the ECG results are based on 45 subjects from the *across-session* portion of UofTDB. Each individual in the UofTDB was randomly assigned to an individual in the collected fingerprint database to create a ”virtual” subject. The fused system achieves an EER of 1% when the EER of the ECG matcher is 6.97% and the EER of the fingerprint matcher is 2.22%.

Furthermore we used the sequential fusion scheme to compare the proposed user-weighting score

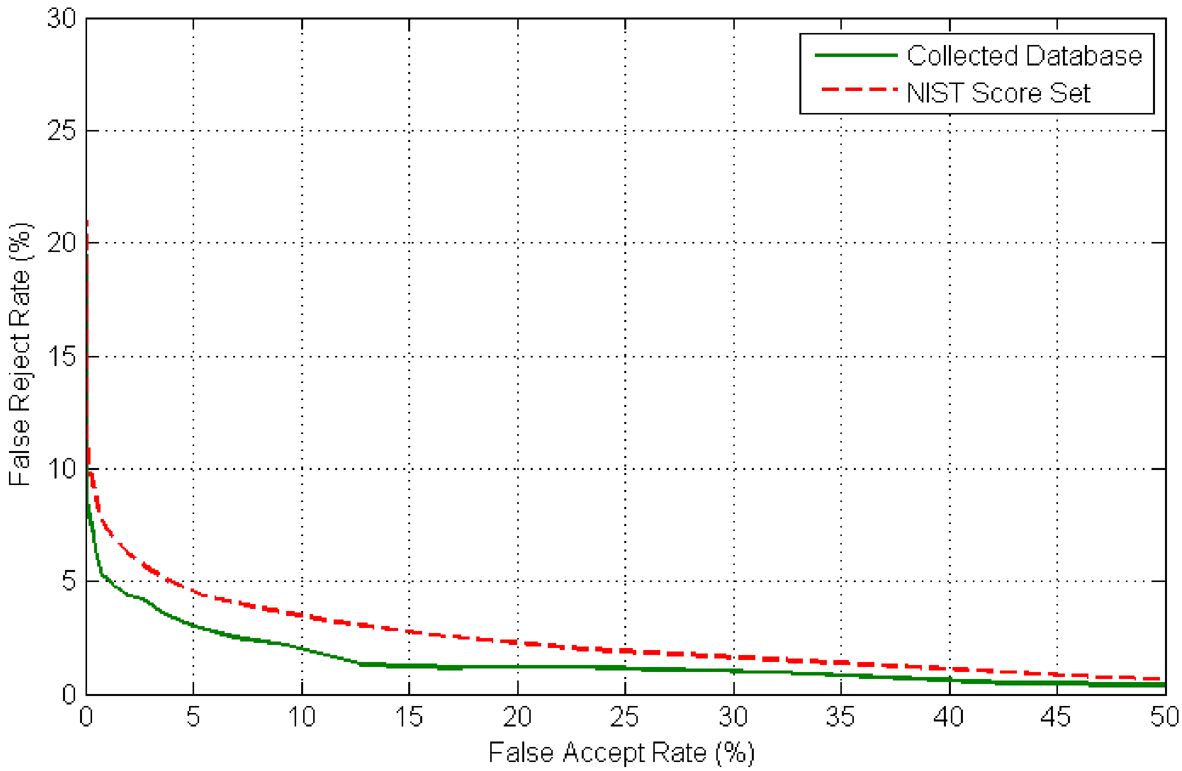

Figure 6.4: ROC curve of fingerprint biometric based on NIST score dataset and the collected dataset.

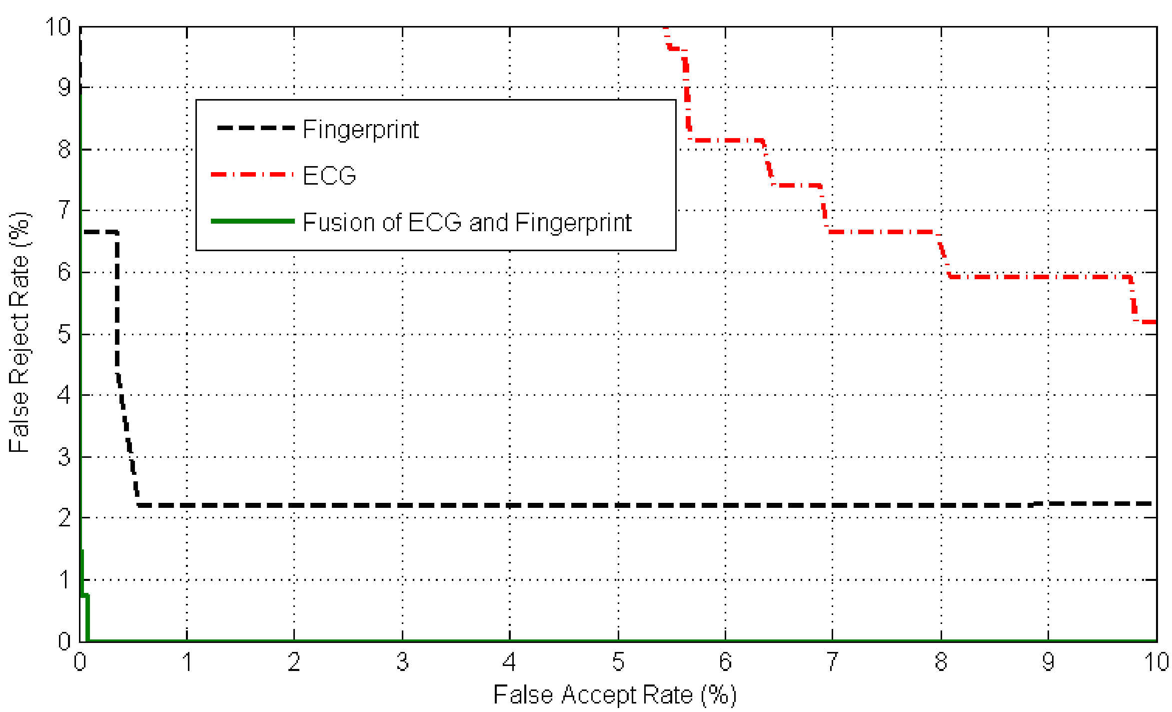

Figure 6.5: ROC curve of ECG and fingerprint and fusion biometrics.

fusion method with other popular methods in the state of the art namely the SVM, Weighted Sum Rule and Likelihood Ratio based methods:

- **LR (Likelihood Ratio):** LR is a density-based score fusion method that relies on the estimated probability density functions (pdfs) of genuine and impostor match scores. Using the likelihood ratio hypothesis testing [35], an unknown subject is either decided as genuine or impostor as follows

$$LR(\underline{x}) = \frac{f(\underline{x}|\mathcal{H} = genuine)}{f(\underline{x}|\mathcal{H} = impostor)} \underset{impostor}{\overset{genuine}{\gtrless}} \tau$$

where $\underline{x}$ is a vector of two match scores

$$\underline{x} = [\bar{x}_{ECG}, \bar{x}_{fingerprint}]$$

$f(x|\mathcal{H} = genuine)$ and $f(x|\mathcal{H} = impostor)$ are the estimated conditional pdfs.

- **SVM (Support Vector Machine):** In this fusion method scores from multiple matchers are treated as a feature vector and the SVM method is used to discriminate genuine and impostor scores. SVM is a supervised learning model that constructs hyperplanes with the largest margins between two classes [15]. It is used for classes that can not be divided linearly by mapping the data to a higher dimension, using a kernel, where they can be separated linearly. In this paper we are using the linear kernel function.

- **WSR (Weighted Sum Rule):** In this case the sum of individual biometric scores is obtained based on the weights w_1 and w_2:

$$WSR(\bar{x}_{ECG}, \bar{x}_{fingerprint}) =$$
$$(w_1 \times \bar{x}_{ECG}) + (w_2 \times \bar{x}_{fingerprint})$$

We considered three sets of weights, one is equal weights and in the other we assign weights to each biometric score based on the error occurred during matching. The weights are inversely proportional to their equal error rates (EER). Let E_1 and E_2 be the two EERs of the systems then the weights w_1 and w_2 are computed as follows [74]:

$$w_1 = (\frac{1}{E_1} + \frac{1}{E_2})^{-1} \times \frac{1}{E_1}$$

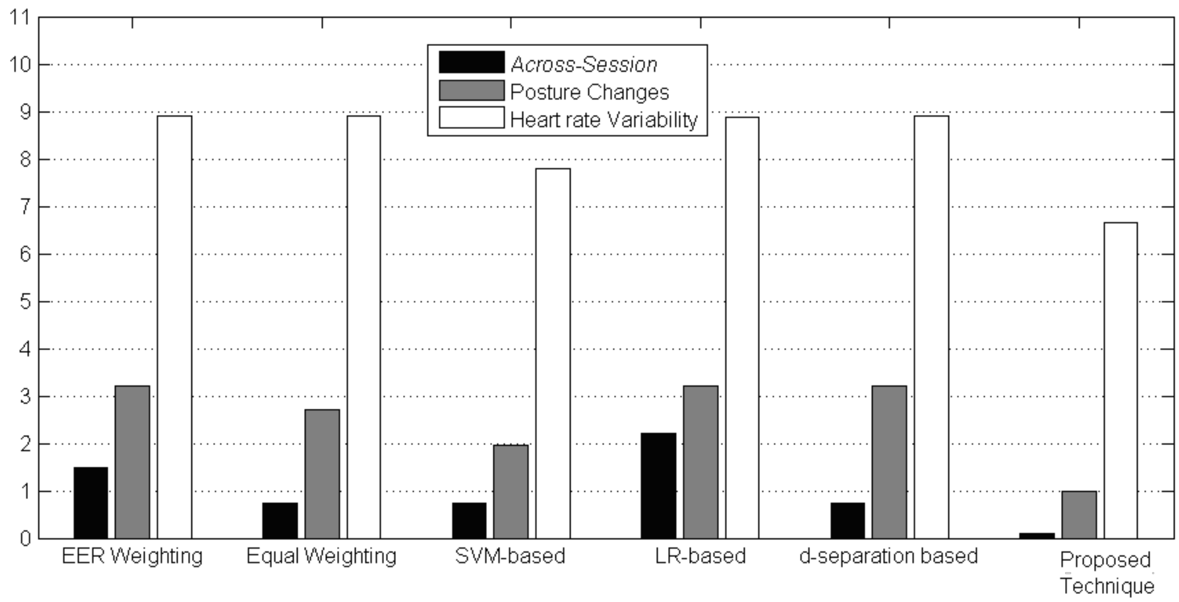

Figure 6.6: Performance Comparison of different score fusion methods.

$$w_2 = (\frac{1}{E_1} + \frac{1}{E_2})^{-1} \times \frac{1}{E_2}$$

In the third set the weights are assigned based the distance between the distributions of genuine and impostor as explained in section 5.5.1 of chapter 5 which we will refer to as the d-distance method.

For SVM and density-based score fusion methods, we used the data for each testing to model the distributions or train the SVM classifier. For example, in *across-session* analysis, we used all the data from all the sessions to train the SVM classifier. Radial Basis Functions (RBF)kernels were empirically chosen for SVM classifier and for simplicity we used multivariate Gaussian distributions for density-based fusion. For EER weighting, an EER of 2.22% for fingerprint and for ECG the average EERs of each test case was used used (Figure 6.2).

A summary of the results are reported in Figure 6.6 where the ECG data are from *across-session* analysis, posture changes and heart rate variability as explained previously. We can observe that the proposed score fusion technique outperforms the other score fusion techniques in all the testing cases. All the score fusion techniques seem to improve the performance of the ECG method however only the SVM-based and the proposed technique improved for both biometrics in all cases except for heart rate variability. The best performance that was achieved by the proposed method is and EER of 0.084%. It is not possible to compare the results with the work of Singh *et al.* [73] since the fusion scheme and the ECG methods are different, however the best performance they achieved was an EER of 1.52% based on the EER weighting score fusion technique.

Another factor that affects the accuracy of the ECG biometric method is the number of heartbeats used for verification. As shown in section 4 as the number of heartbeats used for authentication increases the EER of the system drops. However we used only two heartbeats for authentication which is the minimum amount of required time by the proposed ECG biometric matcher. The average EER reduces to 0.067% when four heartbeats are used and eventually reaches an EER of 0.033% when 40 heartbeats are used.

6.6 Chapter Summary

In this chapter we evaluated the effectiveness of fusing ECG and fingerprint. As it can be seen from the results the fusion of ECG and fingerprint provide improvement to both of the unimodal biometric matchers. In addition to the performance improvement this fusion scheme provides liveliness detection which can be used to avoid spoof attacks to the fingerprint system. Although we discussed in the previous section that the authentication latency may be compromised because of the ECG matcher, we saw in this chapter that with a minimum of two heartbeats (approximately 2 seconds) we achieve promising results. Furthermore under different ECG variabilities (posture changes and exercise conditions) the fused system improved the performance of the overall system where an average EER of less than 2% was achieved.

Chapter 7

Conclusion and Future Improvements

7.1 Research Summary

This thesis studies the challenges of applying the electrocardiogram signal (ECG) as a biometric. While the use of the ECG in biometric recognition is relatively new, the same signal has been extensively studied for medical diagnostics. However unlike most biometric characteristics, ECG is time-dependent and naturally affected by the physical and psychological activity of the human body. This indeed presents a challenge for ECG biometric deployment and measures have to be taken to ensure that ECG-enabled biometric systems are robust to such variations. Still these variations have not been sufficiently addressed by the ECG biometric community. In this work we first look into several factors that can affect the ECG signal and consequently the performance of the ECG biometric systems. Then we introduce a new ECG Biometric database (from 1020 subjects) that has recordings from multiple sessions, multiple postures and in exercise condition. In addition the database is collected from fingertips thereby mimicking real-world application settings. Then we propose a new ECG biometric methodology to improve the performance of ECG biometric systems in various settings and with the new database we systematically compare its performance with the state of the art method namely the AC/LDA [1]. The proposed method achieves an EER of less than 2% on 1020 subjects and 3.12% under *across-session* analysis.

Furthermore we propose a multimodal biometric system which integrates ECG from fingertips and fingerprints. This system overcomes the limitations of both single systems, offers performance improvement and also makes the system robust to spoof attacks. Compared to most of the multimodal systems, the combination of ECG and fingerprint improves the user experience since both biometrics can be conveniently acquired from the same body part. We propose a sequential fusion method using the proposed ECG biometric method and a user weighting score fusion technique. In order to be able to evaluate the potential of such a system we also collected a multibiometric database consisting of fingerprint and ECG recordings from 61 individuals. We first study the dependency of the two biometric since they are recording from the same body part and then evaluated performance of the proposed system using our collected databases. We compare the results of our proposed score fusion method with multiple fusion methods and evaluate its performance under various ECG variability conditions. The best performance that our proposed fusion scheme achieves is and equal error rate (EER) of 0.084% which improves the ECG system by about 7% and the fingerprint system by more than 2%.

In summary the main novelties of the this thesis is identifying the factors that cause variability in the ECG signal and collecting a new database for ECG biometric evaluation which takes these factors into consideration and in addition proposing a new ECG biometric method which outperforms the state of the art under various ECG variability conditions. Furthermore, in order to further improve the performance of the ECG biometric system we propose a multimodal biometric system by fusing ECG and fingerprint which not only improves the performance of the individual unimodal systems but also provides liveness detection and improves the user experience since both can be easily acquired from fingertips.

7.2 Future Directions

Based on the research findings in this thesis the following are possible future directions that needs to be studied:

- Increasing the *across-session* population size of UofTDB and also recording subjects over longer period of time possibly over a few years. This can help study the ECG variability over a long period of time and reliably analyze the performance of ECG biometric systems.

- Optimizing ECG biometric methods for posture changes and heart rate fluctuations. In most of the real life scenarios the posture and heart rate of a user is unpredictable at the time of verification. Therefore the final systems need to be able to reliably authenticate the users under those conditions.

- Investigating the effectiveness of fusing ECG with other modalities. Although the combination of ECG and fingerprint is very beneficial, the fusion of ECG with other modalities that originate from fingers (finger vein images for instance) can further improve the performance of the system as well as its robustness to spoof attacks.

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