ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΕΣΣΑΛΙΑΣ
ΣΧΟΛΗ ΘΕΤΙΚΩΝ ΕΠΙΣΤΗΜΩΝ
ΔΙΑΤΜΗΜΑΤΙΚΟ ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ
ΠΛΗΡΟΦΟΡΙΚΗ ΚΑΙ ΥΠΟΛΟΓΙΣΤΙΚΗ ΒΙΟΙΑΤΡΙΚΗ

Χρήση ηλεκτροκαρδιογραφήματος για τη βιομετρική αυθεντικοποίηση χρηστών

Αγγελική Ι.Κατσίκα

ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ
Επιβλέπων
Κωνσταντίνος Δελήμπασης

Λαμία, 2018

UNIVERCITY OF THESSALY

SCHOOL OF SCIENCE

INFORMATICS AND COMPUTATIONAL BIOMEDICINE

Using ECG biometric in human authentication

Aggeliki I.Katsika

Master thesis
Supervisor
Konstantinos Delimpasis

Lamia, 2018

ΠΑΝΕΠΙΣΤΗΜΙΟ ΘΕΣΣΑΛΙΑΣ
ΣΧΟΛΗ ΘΕΤΙΚΩΝ ΕΠΙΣΤΗΜΩΝ
ΔΙΑΤΜΗΜΑΤΙΚΟ ΜΕΤΑΠΤΥΧΙΑΚΟ ΠΡΟΓΡΑΜΜΑ
ΠΛΗΡΟΦΟΡΙΚΗ ΚΑΙ ΥΠΟΛΟΓΙΣΤΙΚΗ ΒΙΟΪΑΤΡΙΚΗ
ΚΑΤΕΥΘΥΝΣΗ
«ΥΠΟΛΟΓΙΣΤΙΚΗ ΙΑΤΡΙΚΗ ΚΑΙ ΒΙΟΛΟΓΙΑ»

Χρήση ηλεκτροκαρδιογραφήματος για τη βιομετρική αυθεντικοποίηση χρηστών

Αγγελική Ι.Κατσίκα

ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

Επιβλέπων
Κωνσταντίνος Δελήμπασης

Λαμία, 2018

«Υπεύθυνη Δήλωση μη λογοκλοπής και ανάληψης προσωπικής ευθύνης»

Με πλήρη επίγνωση των συνεπειών του νόμου περί πνευματικών δικαιωμάτων, και γνωρίζοντας τις συνέπειες της λογοκλοπής, δηλώνω υπεύθυνα και ενυπογράφως ότι η παρούσα εργασία με τίτλο [«τίτλος εργασίας»] αποτελεί προϊόν αυστηρά προσωπικής εργασίας και όλες οι πηγές από τις οποίες χρησιμοποίησα δεδομένα, ιδέες, φράσεις, προτάσεις ή λέξεις, είτε επακριβώς (όπως υπάρχουν στο πρωτότυπο ή μεταφρασμένες) είτε με παράφραση, έχουν δηλωθεί κατάλληλα και ευδιάκριτα στο κείμενο με την κατάλληλη παραπομπή και η σχετική αναφορά περιλαμβάνεται στο τμήμα των βιβλιογραφικών αναφορών με πλήρη περιγραφή. Αναλαμβάνω πλήρως, ατομικά και προσωπικά, όλες τις νομικές και διοικητικές συνέπειες που δύναται να προκύψουν στην περίπτωση κατά την οποία αποδειχθεί, διαχρονικά, ότι η εργασία αυτή ή τμήμα της δεν μου ανήκει διότι είναι προϊόν λογοκλοπής.

Η ΔΗΛΟΥΣΑ
Αγγελική Ι.Κατσίκα

07 / 02/ 2018

Υπογραφή

Χρήση ηλεκτροκαρδιογραφήματος για τη βιομετρική αυθεντικοποίηση χρηστών

Αγγελική Ι.Κατσίκα

Τριμελής Επιτροπή:

Κωνσταντίνος Δελήμπασης (επιβλέπων),
Επίκουρος Καθηγητής, Τμήμα Πληροφορικής με Εφαρμογές στη Βιοϊατρική,
Πανεπιστήμιο Θεσσαλίας.

Γεώργιος Σπαθούλας ,
Μέλος ΕΔΙΠ , Τμήμα Πληροφορικής με Εφαρμογές στη Βιοϊατρική,
Πανεπιστήμιο Θεσσαλίας.

Μαρία Αδάμ,
Αναπληρωτής Καθηγητής, Τμήμα Πληροφορικής με Εφαρμογές στη Βιοϊατρική,
Πανεπιστήμιο Θεσσαλίας.

Επιστημονικός Σύμβουλος:

Γεώργιος Σπαθούλας,
Μέλος ΕΔΙΠ , Τμήμα Πληροφορικής με Εφαρμογές στη Βιοϊατρική,
Πανεπιστήμιο Θεσσαλίας.

ABSTRACT

The present thesis that was developed within the framework of the Interdisciplinary Program of Postgraduate Studies titled: ”Informatics and Computational Biomedicine” (Biomedical Direction) discusses the usage of the electrocardiogram as a biometric feature for the authentication of users. Electrocardiography is an important diagnostic tool for the medical industry bearing large amount of information about heart function. In recent years, however, there has been increased interest in exploiting this information in order to identify users. Thus many researches have emerged about its processing and integration into biometric technology.

The search for the optimal and most reliable use of the electrocardiogram as a biometric data revealed the difficulty of comparing and assessing the proposed methods in the literature. Addressing this purpose, a draft comparison of the most prevalent methodologies was developed in this thesis. The main steps, as shown in most biometric systems, are the collection of biometric data, the extraction of the characteristics and the comparison of the set of characteristics of an individual over a previously registered model, mainly using classification techniques.

In particular, fifty electrocardiograms obtained from the Physikalisch-Technische Bundesanstalt (PTB) diagnostic ECG Database were preprocessed and used for feature extraction. The Fourier transform, Wavelet transform and Discrete Cosine transform were applied and for each of them, the twenty most significant coefficients were used as input in the classification process.

In terms of classification, the user’s identification from his electrocardiogram was defined as a two-class problem where the two possible classes for a sample are whether or not they belong to the user already identified in a previous step. Four classification techniques were used employing the Weka machine library: K-Nearest Neighbor Method (KNN), Multilayer Perceptron, RBFN, Random Forest. The results provide comparable information for combinations of techniques and their performance in the aforementioned authentication problem

SUBJECT AREA: ECG Biometrics
KEYWORDS: biometrics, electrocardiogram, feature selection, classification, authentication

ΠΕΡΙΛΗΨΗ

Στην παρούσα εργασία, που εκπονήθηκε στα πλαίσια του Διατμηματικού Προγράμματος Μεταπτυχιακών Σπουδών με τίτλο: «Πληροφορική και Υπολογιστική Βιοϊατρική» (κατεύθυνση Βιοϊατρικής) μελετήθηκε η χρήση του ηλεκτροκαρδιογραφήματος ως βιομετρικό χαρακτηριστικό για την αυθεντικοποίηση χρηστών. Το ηλεκτροκαρδιογράφημα αποτελεί σημαντικό διαγνωστικό εργαλείο για τον ιατρικό κλάδο φέροντας πληθώρα πληροφοριών για τη λειτουργία της καρδιάς. Τα τελευταία χρόνια, όμως, έχει αυξηθεί το ενδιαφέρον για την εκμετάλλευση αυτών των πληροφοριών με σκοπό την αναγνώριση χρηστών και έχουν προκύψει πολλές έρευνες σχετικά με την επεξεργασία και την ενσωμάτωσή του στη βιομετρική τεχνολογία.

Η αναζήτηση της βέλτιστης και πιο αξιόπιστης χρήσης του ηλεκτροκαρδιογραφήματος ως βιομετρικό δεδομένο αποκάλυψε τη δυσκολία σύγκρισης και εκτίμησης των προτεινόμενων μεθόδων στη βιβλιογραφία. Για αυτό το σκοπό στην παρούσα εργασία καταστρώθηκε ένα σχέδιο σύγκρισης των επικρατέστερων μεθοδολογιών. Τα κύρια βήματα, όπως εμφανίζονται στα περισσότερα βιομετρικά συστήματα είναι η συλλογή των βιομετρικών δεδομένων, η εξαγωγή των χαρακτηριστικών και η σύγκριση του συνόλου χαρακτηριστικών ενός ατόμου έναντι ενός προηγουμένως καταχωρημένου προτύπου, κυρίως με χρήση τεχνικών ταξινόμησης.

Συγκεκριμένα χρησιμοποιήθηκαν τα ηλεκτροκαρδιογραφήματα πενήντα ατόμων από τη διαγνωστική βάση δεδομένων Physikalisch-Technische Bundesanstalt (PTB) και μετά από κατάλληλη επεξεργασία για την εξαγωγή των χαρακτηριστικών εφαρμόστηκαν οι Μετασχηματισμοί Fourier, Wavelet και Διακριτού Συνημιτόνου. Για κάθε έναν από τους τρεις μετασχηματισμούς επιλέχθηκαν οι είκοσι πιο σημαντικές συνιστώσες οι οποίες αποτέλεσαν τους συντελεστές εισόδου της διαδικασίας ταξινόμησης.

Όσον αφορά στην ταξινόμηση, η αναγνώριση του χρήστη από το ηλεκτροκαρδιογράφημά του ορίστηκε ως ένα πρόβλημα δύο κλάσεων, όπου οι δύο πιθανές κλάσεις για ένα δείγμα είναι το αν ανήκει ή όχι στο χρήστη που έχει ήδη αναγνωριστεί σε ένα προηγούμενο βήμα. Με χρήση της βιβλιοθήκης εκμάθησης μηχανών Weka εφαρμόστηκαν τέσσερις τεχνικές ταξινόμησης: Μέθοδος K-Κοντινότερων Γειτόνων (KNN), πολυστρωματικό δίκτυο (Multilayer perceptron), δίκτυο ακτινικών συναρτήσεων βάσης (RBFN), τυχαίο δάσος (Random Forest) και τα αποτελέσματα παρέχουν συγκρίσιμες πληροφορίες για τους συνδυα-

σμούς των τεχνικών και την απόδοσή τους ατο παραπάνω πρόβλημα αυθεντικοποίησης.

ΘΕΜΑΤΙΚΗ ΠΕΡΙΟΧΗ: Βιομετρία ηλεκτροκαρδιογραφήματος
ΛΕΞΕΙΣ ΚΛΕΙΔΙΑ: βιομετρία, ηλεκτροκαρδιογράφημα, ελαχιστοποίηση μεταβλητών, ταξινόμηση, έλεγχος ταυτότητας

ACKNOWLEDGMENTS

I would first like to thank my thesis advisor George Spathoulas, member of the teaching staff of the Department of Computer Science and Biomedical Informatics at University of Thessaly, for the continuous support, his patience, motivation and knowledge. I could not have imagined having a better advisor for my thesis.

I am also thankful to Ilias Hamatidis, undergraduate student of the Department of Computer Science and Biomedical Informatics at University of Thessaly, for providing his programming skills and knowledge and his passionate participation, without which this thesis could not have been successfully conducted.

Besides my advisor, I would like to thank the rest of my thesis committee: Associate Professor Konstantinos Delimpasis and Associate Professor Maria Adam, for their knowledge and support throughout the postgraduate program.

Last but not least, I would like to thank my family for providing me with support and continuous encouragement throughout my years of study.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Introduction

The extensive use of computers and electronic communication devices along with the significant variety of network applications, such as e-government, e-banking, and e-commerce, require strict methodologies to identify authorized users in order to prevent malicious behavior, economic loss or fraud attempts. As traditional password-based authentication has long been proven inadequate, the use of biometrics has provided multiple solutions in the past years. Biometric features, providing unique and strictly associated data for each person. They are increasingly used for authentication and identification purposes in a broad variety of institutional and commercial systems, as the use of such data has been proven appropriate in order to achieve a higher level of security than that provided by traditional password protected systems. One of the most recent approaches to biometric authentication is using Electrocardiograms (ECG), as they are closely related to various unique characteristics of the heart of each person.

1.2 Biometrics

The term biometrics is defined as “automated recognition of individuals based on their behavioral and biological characteristics“ (Technical committee ISO/IEC JTC1 SC37). Biometric data consist of information extracted during a biometric procedure and provide distinctive and measurable features used to describe and label individuals in a unique way. Generally they are irrevocable, as most of biometric data cannot be changed during the human life and in most cases they are hard to forge. Biometric features are mainly categorized as physiological versus behavioral characteristics.

1.2.1 Physiological biometrics

Physiological characteristics are related to biological functions or the shape of the body and bear information that can be rooted to the uniqueness of DNA. Below the main types of physiological biometrics are listed :

- **DNA Matching:** The identification of a human using the analysis of DNA. Although

99,9 of human DNA sequences are the same in every person, it is possible to distinguish one individual from another, using repetitive sequences that are highly variable, in particular short tandem repeats (STRs), also known as microsatellites, and minisatellites.

- **Eyes - Iris or Retina Recognition:** The use of the features found in the iris to identify an individual. Retinal scanning is an ocular-based biometric technology that uses the unique patterns on a person's retina blood vessels and is often confused with iris recognition. Iris recognition uses video camera technology with subtle near infrared illumination to acquire images of the detail-rich, intricate structures of the iris which are visible externally.

- **Face Recognition:** The analysis of facial features or patterns for the authentication or recognition of an individuals identity by extracting landmarks, or features, from an image of the subject's face. Most face recognition systems either use eigenfaces or local feature analysis.

- **Fingerprint Recognition:** The use of the ridges and valleys (minutiae) found on the surface tips of a human finger to identify an individual. The three basic patterns of fingerprint ridges are the ”arch” which enter from one side of the finger, rise in the center forming an arc, and then exit the other side of the finger, ”loop” ridges that enter from one side of a finger, form a curve, and then exit on that same side and ”whorl” ridges that form circularly around a central point on the finger. Those features are processed and classified using pattern algorithms.

- **Finger/Hand Geometry Recognition:** The use of 3D geometry of the finger to determine identity/usage of the geometric features of the hand such as the lengths of fingers and the width of the hand to identify an individual.

- **Ear Recognition:** The identification of an individual using the shape of the ear. It is based on the distinctive shape of each person's ears and the structure of the largely cartilaginous, projecting portion of the outer ear. Although ear biometrics appears to be promising, no commercial systems are available today.

- **ECG Recognition:** ECG is a biological signal created by the electrical currents that are generated by the activity of the heart. Therefore, shapes of the ECG waveforms depend on human heart and body anatomic features that can be used for human identification.

1.2.2 Behavioral biometrics

Behavioural characteristics are related to the pattern of an individual's behavior, including:

- **Keystroke dynamics:** The use of detailed timing information which describes exactly when each key was pressed or/and released as a person is typing at a computer keyboard, in order to approve access in a system.
- **Gait analysis:** The use of an individuals walking style or gait to determine identity. The parameters are grouped to spatial-temporal (step length, step width, walking speed, cycle time) and kinematic (joint rotation of the hip, knee and ankle, mean joint angles of the hip/knee/ankle, and thigh/trunk/foot angles) classes. Researchers have proven that there is a high correlation between step length and height of a person.
- **Voice/speaker recognition:** There is a difference between speaker recognition (recognizing who is speaking) and speech recognition (recognizing what is being said). These two terms are frequently confused, but regarding biometrics there are two major applications of speaker recognition, Voice - Speaker Verification which refers to the use of the voice as a method of determining the identity of a speaker for access control and Voice - Speaker Identification that determines an unknown speaker's identity.
- **Signature analysis:** The authentication of an individual by the analysis of handwriting style, particularly the signature. There are two key types of digital handwritten signature authentication, Static and Dynamic. Static is most often a visual comparison between one scanned signature and another scanned signature, or a scanned signature against an ink signature. Dynamic is becoming more popular as ceremony data is captured along with the X,Y,T and P Coordinates of the signor from the signing device.

1.3 Biometric System procedures

Biometric recognition refers to the automatic identification of a person based on one or more of the aforementioned characteristics. This method of identification offers several advantages over traditional methods, such as ID cards or passwords, as the person to be identified is required to be physically present and biometric techniques obviate the need to remember a password. In some applications, more than one biometric trait is used to attain higher security and to handle failure to enroll situations for some users. Such systems are called multimodal biometric systems.

A biometric system is essentially a pattern recognition system which recognizes a user by determining the authenticity of a specific anatomical or behavioral trait. Several important issues must be considered in designing a practical biometric system. Commonly, at first a user must be enrolled in the system so that his biometric template can be captured and stored in a central database. The template is used for comparing and matching when an individual needs to be identified in a later phase after initial enrollment. Depending on the context, a biometric system can operate either in a verification (authentication) or an identification mode.

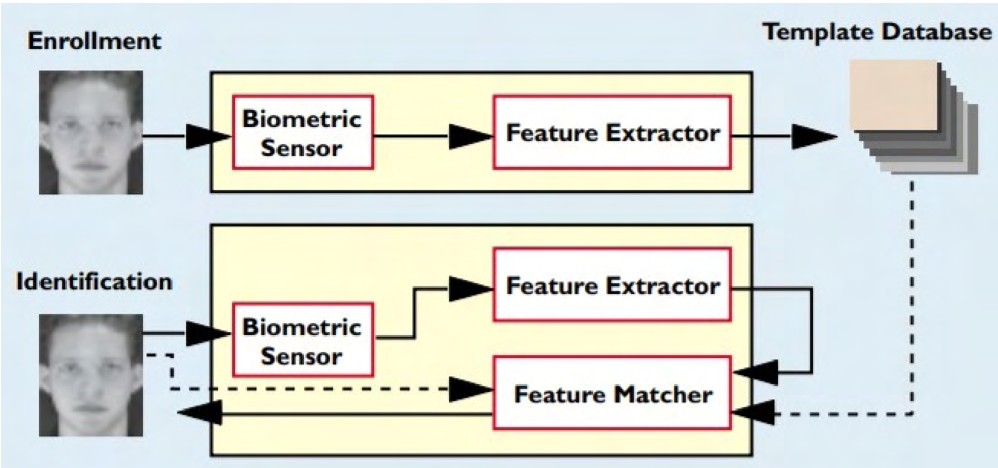

Figure 1.1: A generic biometric system.

1.3.1 Identity verification

In the context of identity verification, an identity is first announced by the subject, the signal is compared to stored signals (one-to-one comparison) and the decision consists in accepting or rejecting the claimed identity. This comparison lead to two possible scenarios.

The genuine case scenario, where two signals issued from the same subject are being compared or intra-subject case (the impostor case) scenario where two signals issued from two different subjects are being compared. The decision step relies on the use of a matching algorithm that decides if the subject is a genuine or an impostor, by comparing its score to a decision threshold. To evaluate a verification system, scores are computed between all the records of a database, leading to two types distribution, one for hypothesis H0 and one for hypothesis H1. The best case for the verification process is the scenario in which the distributions of H0 and H1 are well separated. In practice, false matching rate (FMR) and false non-matching rate (FNMR) may be computed for various threshold values, allowing to plot a Detection Error Tradeoff curve. Sometimes performances are given as a function of the Equal Error Rate (EER), where FMR and FNMR are equal. Figure 1.2 depicts the case where the distributions of the two hypothesis overlap [1].

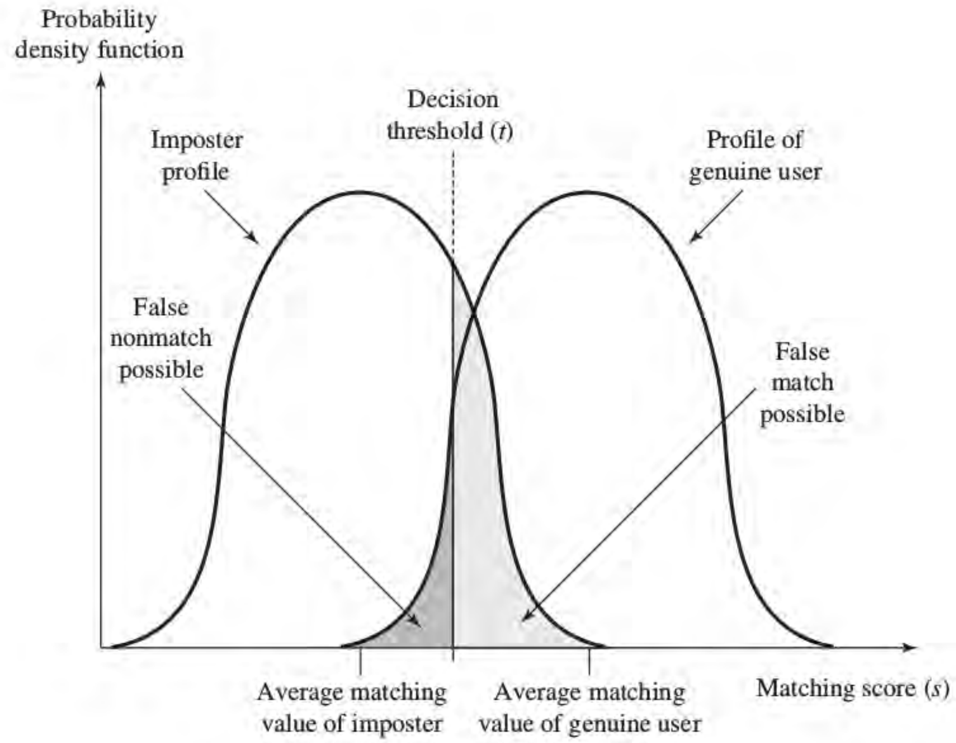

Figure 1.2: Probability distributions for hypothesis H0, H1

1.3.2 Human Identification

In the context of identification, the signal is compared to a biometric database (one-to many comparison). The decision step relies on the use of a ranking algorithm, providing the identity of the subject. To evaluate an identification system, for each record of the database, a score is computed between it and all the others. Performance may be evaluated by analyzing the nearest neighbors, and giving the rank necessary to find the same subject, or only considering the first rank (or first rank identity) which provides an identity of the subject (correct or not).

The overall performance of a biometric system is assessed in terms of its accuracy, speed, and storage combined with several other factors, like cost and ease-of-use. Biometric systems will sometimes mistakenly accept an impostor as a valid individual (a false match) or reject a valid individual (a false non-match). The probability of committing these two types of errors are termed false reject rate (FRR) and false accept rate (FAR). Figure shows the trade-off between a system's FRR and FAR at different operating points; The false reject rate (FRR): is the number of times the system does not recognize a sample as coming from the same individual who produced the reference.The false accept rate (FAR): is the number of times the system incorrectly matches a sample from one person to a reference from another. The definition of a recognition threshold establishes the boundary between acceptance and rejection of a request. Increasing the FAR due to lower thresholds makes the biometric system more tolerant to input variations and noise. However, raising the threshold, in order to make the system more secure, decreases the FAR.

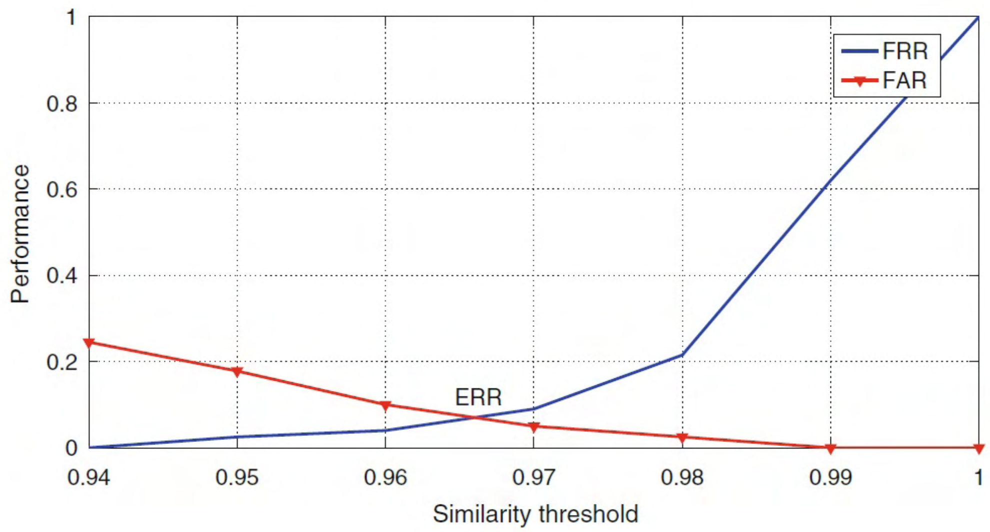

Figure 1.3: FAR and FRR carves define the recognition threshold

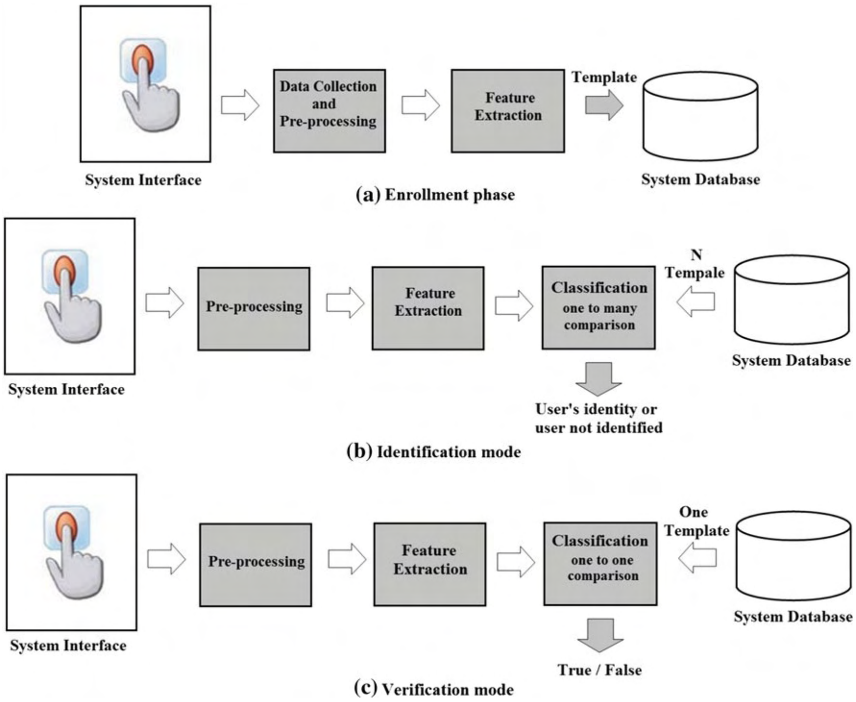

Figure 1.4: The enrollment and classification phases

1.3.3 Cancelable biometrics

Cancelable biometrics is aimed at enhancing the security and privacy of biometric authentication through the generation of intentionally distorted biometric data. Instead of using the originally obtained object (finger, face), the extracted feature is distorted in a repeatable manner, and this new altered feature is used, in the transformed domain. Designing a cancelable biometric scheme abides to the following main objectives:

- **Diversity:** No same cancelable features can be used across various applications, therefore a large number of protected templates from same biometric feature is required.

- **Reusability/Revocability:** Straightforward revocation and reissue in the event of compromise.

- **Non-invertibility:** Non-invertibility of template computation to prevent recovery of original biometric data.

1.4 ECG in biometrics

1.4.1 ECG Fundamentals

The electrocardiogram (ECG) is a biological signal widely used in healthcare that describes the electrical activity of the heart over time. Practically it corresponds to the sequential depolarization and repolarization of the different muscles that form the myocardium. It is recorded at the surface of the body, with electrodes attached in various configurations. The first recording device was developed by the physiologist Williem Einthoven, granting him the Nobel Prize in Medicine in 1924.

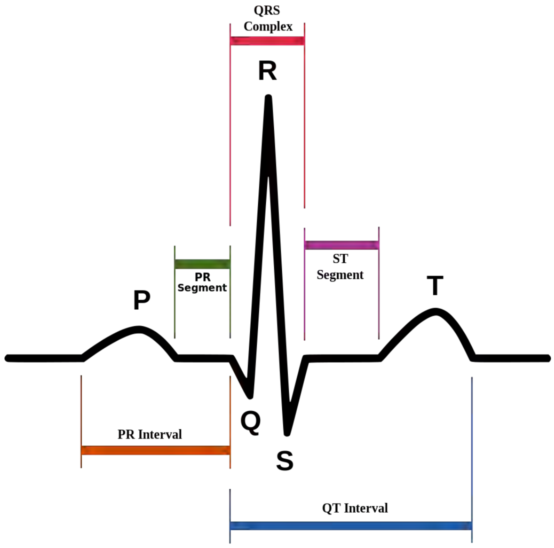

Figure 1.5: The primary components of an ECG signal: the P wave, the QRS complex and the T wave.

Anatomically, the heart consists of four chambers (left and right atrium, left and right ventricle), blood vessels, as well as four valves, which prevent backward flow within the heart. Another integral part of the heart is its electrical conduction system. The latter generates and conducts the electric stimulus for the muscle contraction. The whole ECG signal recording consists of several consecutive cardiac cycles. In the clinical practice ECG diagnosis is succeeded by its measurement in the time domain and interpreting the values between the beat intervals and amplitudes.

The track of the each heartbeat consists of three basic parameters: P, R and T waves. The P wave describes the depolarization of the right and left atria. The QRS complex reflects the depolarization of the right and left ventricles. The T wave corresponds to the ventricular repolarization and the QT interval is dependent on the heart rate. The amplitude of P wave is relatively small, because the atrial muscle mass is limited. The absence of a P wave typically indicates ventricular ectopic focus. This wave usually has a positive polarity, with a duration of approximately 120 ms, while its spectral content is limited to 10-15 Hz.

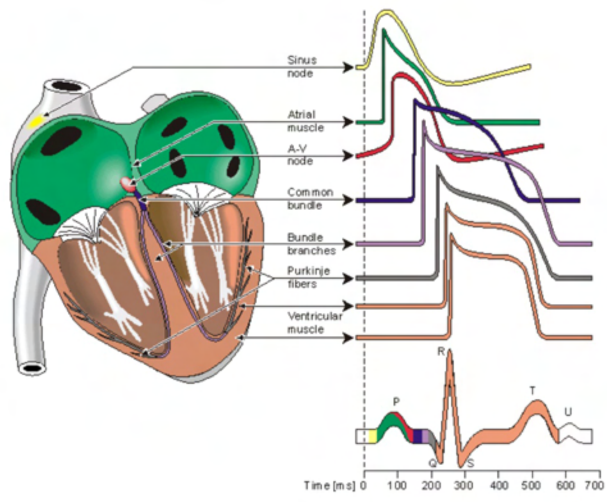

Figure 1.6: Analytical depiction of the sub-waves that forms a typical ECG signal .

The QRS complex corresponds to the largest wave, since it represents the depolarization of the right and left ventricles, being the heart chambers with substantial mass. The duration of this complex is approximately 70-110 ms in a normal heartbeat. The spectrum of a QRS wave is higher compared to that of other ECG waves, and is mostly concentrated in the interval of 10-40 Hz. Finally, the T wave depicts the ventricular repolarization. It has a smaller amplitude, compared to the QRS complex, and is usually observed 300 ms after this larger complex. However, its precise position depends on the heart rate appearing closer to the QRS waves at rapid heart rates.

Classical recording of the electrical heart activity is based on the recording of a 12-lead: ECG and contains 12 channels, denoted by: three bipolar leads: I, II, III, three augmented unipolar leads: avR, avL, avF, and six precordial electrodes: V1 to V6. The bipolar leads are the electrical potentials between the right and left arm (lead I), the right arm and left foot (lead II) and between the left arm and left foot (lead III).The monopolar leads represent four different artificial that are the average of the signals seen at two or more electrodes. Using these reference points the potentials appearing on the left arm (aVL), the right arm (aVR), the left foot (aVF) and on the six chest electrodes (V1 V6) are measured. The right foot is normally used for grounding purposes only. The orientation

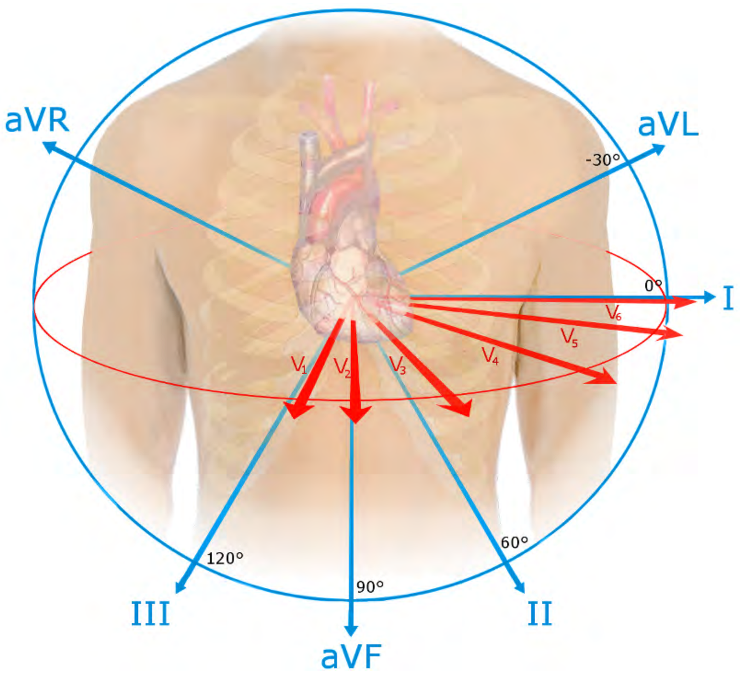

Figure 1.7: 12-leed points orientation and placement

for the placement of the 12-leed points is depicted in Figure 1.7.

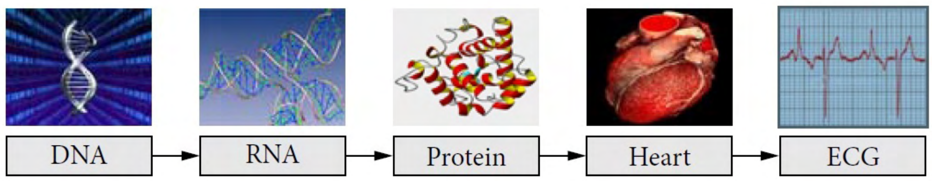

Figure 1.8: Inheritance Model of ECG biometric from DNA biometric

The ECG is a promising biometric trait that satisfies the requirements for biometric characteristics such as universality (it can be detected in all living humans), measurability (it can be easily acquired using suitable devices), uniqueness (no identity on two individuals with the characteristics) and permanence (no change in the characteristic over time). Furthermore, ECG signals provide intrinsic aliveness detection and are continuously available, which are also highly desirable properties in biometrics. State-of-the-art work has shown the potential of ECG as a biometric trait, both for identification and authentication.

1.5 Research Problem

State of the art literature is quite extensive regarding the use of ECG biometrics either for authentication or identification problems. The ECG signal although is fully apprehended for biomedical purpose remains vague as a biometric trait. This is due to the plethora of proposed approaches that acquire, process and implement the ECG in copious ways.

The most commonly used preprocessing tools of the ECG signal are bandpass filter that have been proven suitable for biometric purpose as well as medical. With regard to feature extraction transformation such as Fourier Transform, Discrete Cosine Transform and Wavelet Transform are usually performed achieving promising results. In the matter of classification simple but robust approaches such as kNN classifier, MLP classifier, RBFN classifier and Random Forest Classifier are frequently encountered in literature.

The diversity of ECG sources, in addition to the complexity of the biometric process, make the comparison of the accomplished results even harder to assess. Most of the researchers use medical databases or capture the signal using different devices.

The purpose of this thesis is to highlight the diversity of current ECG biometric procedures and propose a basic testbed for evaluating their results. In the following chapters the current methods are analyzed and categorized (Chapter 2), a common testbed for testing each approach is built (Chapter 3), the obtained results of the comparison are discussed (Chapter 4) and finally the basis for future research work on the field is set (Chapter 5).

2. BACKGROUND AND RELATED WORK

2.1 Basic steps

ECG biometric recognition systems consist of a set basic steps that includes data acquisition, preprocessing, feature extraction, feature reduction and classification. Firstly the signal is being acquired by sensors located in multiple areas of the human body and is stored in database, where it can be further used for matching purposes.

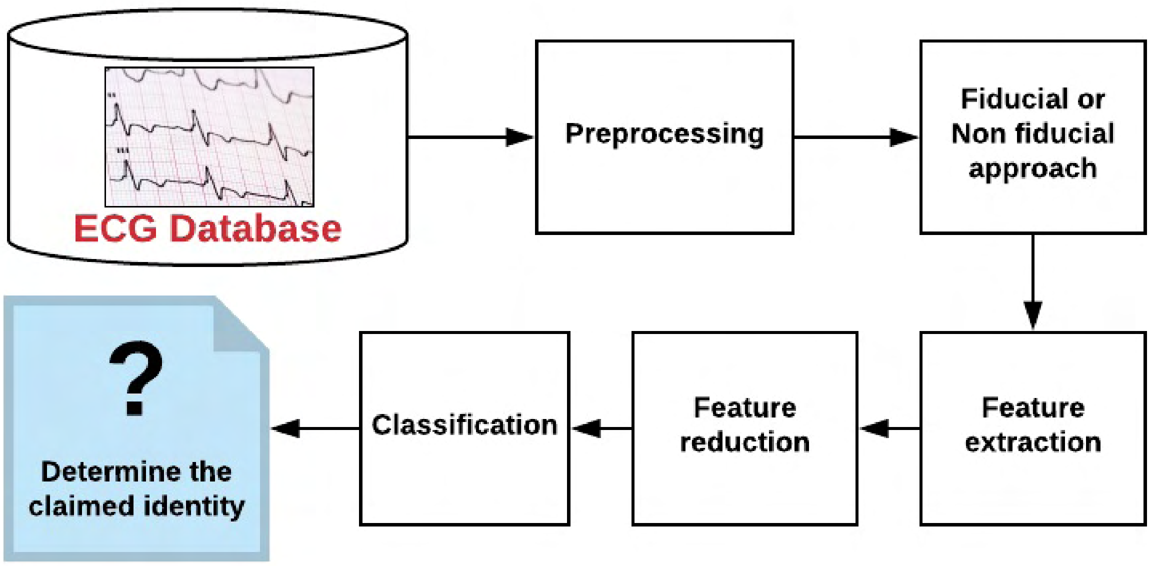

Figure 2.1: Basic stages of ECG biometric system

2.1.1 ECG acquisition

Acquiring the ECG signal is the first step to ECG biometrics applications and a challenging procedure regarding the elimination of extra noise that could corrupt its unique characteristics and make it unsuitable for authentication purpose.

It has been proven that ECG signal can provide trustworthy initial data for biometric procedures but the majority of proposed schemes are tested on biosignals obtained from biomedical databases, that have been recorded using the standard 12 lead system.

Nevertheless, using ECG for user authentication requires the dynamic recording of the signal in a convenient, prompt and affordable way using as less sensory equipment as possible. As in recent years, wearable technology has make an impact in modern life, it is commonly accepted and even fashionable to bear a recording device in public.

Nymi Band is a commercial example of ECG authenticator, as it verifies its wearer and communicates the confirmed identity to any device with Bluetooth and NFC capabilities. Its simple design focuses in recording the user's ECG via two electrodes. The top electrode, which is where the user places her finger, is located in the upper surface of the wristband and the bottom sits against the wrist to complete the circuit.

2.1.2 Preprocessing

ECG signal is a noisy signal and due to presence of noise the feature extraction and classification become less accurate. Thus it is essential to be preprocessed in order to remove baseline wander, DC shift, power-line noise, high frequency interference. Most of these noises are removed using low pass filters, band pass filters and high pass filters. The main sources of noise can be the powerline interference due to abnormalities of the sensors, physiological interference that comes from muscle noise or motion artifact. In addition normalization can be used to prevent parasitic influence of variation of the input signal, which can lead to misclassification.

2.1.3 Feature Extraction

After collecting the database and pre-processing the most important process is the feature extraction and feature reduction process, as it generates the input of the classification algorithm.

ECG biometrics can be categorized in two main approaches considering the feature extraction. The fiducial approach requires the detection of fiducial points from heartbeat that represent the temporal and amplitude distances between fiducial points along with angle features. Therefore, fiducial based approaches rely on local features of the heart beats.

On the other hand, non-fiducial approaches usually operate in the frequency domain, treating the ECG signal holistically, and extract features based on the overall morphology of the waveform. Holistic approaches have the advantage of reducing the detection process as they focus only on the R peak, which is the sharpest and easiest to detect point. On the other hand they carry a large amount of information that needs to be reduced; whilst fiducial methods risk to miss the bigger picture hidden behind the overall morphology of the signal. The efficiency of the fiducial approach significantly relies on the accuracy of the fiducial detection process, which is a big challenge by itself. Such methods are susceptible to error and there is no universally acknowledged rule for defining exactly where the wave boundaries lie.

The goal of the feature extraction phase is to find the smallest set of features that enables acceptable classification rates to be achieved. The performance of a set of features cannot be estimated without training and testing the classification system. Therefore, a feature selection is an iterative process that involves training different feature sets until acceptable classification performance is achieved. Some commonly used methods are listed below:

1. **Fourier Transformation (FT)** : The Fourier transform is called the frequency domain representation of the original signal. The original signal is transformed in the frequency domain where the most dominant frequencies are selected as features.

2. **Wavelet Transformation (WT)** :The wavelet transform is similar to the Fourier transform but uses functions that are localized in both the real and Fourier space. Both discrete wavelet transformation and continuous wavelet transformation can be used for feature extraction.

3. **Principal Component Analysis (PCA)**: A technique used to transform a high-dimensional dataset into smaller-dimensional subspace before inserting it in a machine learning algorithm. PCA is a classical statistical method based on eigenvalues and eigenvectors. The eigenvector with the largest eigenvalue will have the direction of the largest variance of the data, and therefor the most information will be found in that direction.

4. **Linear Discriminant Analysis (LDA)**: A method used in pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects. The resulting combination may be used as a linear classifier or more commonly, for dimensionality reduction before later classification.

2.1.4 Classification Techniques

The features, which represent the classification information contained in the signals, are used as inputs to a classifier model during classification phase. The goal of classification is to identify a subject or to verify an identity claim, by using the sensors' observations. The extracted features are compared against the stored templates to generate match scores. In a heart-based biometric system, the number of matching data between the input and the template feature sets is determined and a match score is reported.

There are various classification algorithms designed for this reason, namely Radial Basis Function (RBF), K Nearest Neighbor (kNN), Bayes Network (BN), Multilayer Perceptron (MLP), Vector Quantization, Gaussian Mixture Mode (GMM) [2], Support Vector Machine (SVM), Artificial Neural Network (ANN), Radial Bias Function Neural Network (RBFNN), Euclidean Distance (ED) and Hidden Markov Models(HMM).[3] [4]

1. **K-nearest neighbors classifiers** include the nearest (k=1) neighbor classifier (NNC) as a special case, is the most frequently used classifier type in the ECG recognition literature. It involves comparing a feature vector to a collection of feature vectors, and selecting the top vectors that produce the best match.

2. **Nearest Center Classifiers**: A nearest center classifier can be seen as a special kind of nearest neighbor classifier, where a representative training feature vector is created during training, as opposed to using the entire training feature vector set.

3. **LDA Classifiers**: Classification based on linear discriminant analysis, a special case of generative model classifiers (GMCs), has been used by several studies in the ECG biometrics literature.

4. **Neural Network Classifiers**: Neural network classifiers have been used extensively for classification, because of their ability to learn complex relationships between the feature vectors in the training set. The most commonly used neural network for ECG biometric recognition is the multilayer feedforward (perceptron) neural network. Other neural networks that have been used in the literature include decision-based neural network (DBNN) and radial basis function neural network (RBFNN).

5. **Generative Model Classifiers**: Generative model classifiers depend on modeling the distribution of the feature vectors. The estimated models are later used for clas-

sification. These classifiers include the log-likelihood ratio (LLR), Bayes' classifier, SIMCA.

6. **SVM Classifiers**: Support vector machines have also been used in a few studies to find the linear boundaries between classes, after projecting the feature vectors in the training set to a high (possibly infinite) dimensional space. Ye et al. used an SVM based on a Gaussian radial basis kernel. Also, Li and Narayanan used SVMs based on a linear kernel for classification.

7. **Match Score Classifiers**: This category of algorithms include those that cannot be strictly put into any of the six groups above. Most of the algorithms in this category depend on the computation of match scores based on the similarity (cross correlation, spatial correlation) or the dissimilarity (MNPD) between a feature vector and a stored template/model.

2.2 In literature

Although ECG biometrics is a rather new subject, it has aroused the interest of many researchers and there is an extensive literature on the subject. The proposed ECG based authentication schemes diverge a lot regarding the extracted data, the processing tools and the classification techniques, thus it is rather difficult to compare and assess their results.

In the following paragraphs, the research work that has been examined for the purpose of this thesis, will be briefly presented in an attempt to reveal the diversity of the proposed approaches.

Biel et al. [5] in "*ECG analysis a new approach in human identification*" defines features using the fiducial points from a standard 12-lead ECG and implements (SIMCA-Soft Independent Modeling of Class Analogy) method for classification achieving high accuracy for identifying a person in a predetermined group. The SIMCA classifier is trained using a subset of measurements for each subject and creates a statistical model for each one of the subjects which will be compared against the input in the enrollment stage. The output of the classifier is the person providing the best match. The test set consists of 50 samples whereas the number of samples per person vary depending on the number of measurements. The system achieved 100% identification rate tested on a database of 20 persons bearing on the other hand a major drawback due to the employment of specific equipment for feature extraction (Siemens Megacart).

Israel et al.[6] in "*A Sequential Procedure for Individual Identity Verification Using ECG*" uses linear discriminant analysis (LDA) for classification. By using a method based on a sequential procedure for statistical hypothesis testing, the number of heartbeats needed for the system to make a decision is minimized. The data was segmented into two non-overlapping groups that respectively served as the training data to generate statistics for each enrolled individual and the test data, which contain heartbeats from the sensor. The output is either a confirmation of the individual's identity or a rejection that indicates an impostor. The extracted features are the distances between fiducial points, normalized by the length of the heartbeat in an attempt to insure that the verification procedure is tolerant to changes due to variations of physical, mental and emotional state. In later work Israel et al. [7] proposed a more extensive set of descriptors using 15 fiducial features, which are time duration between detected fiducial points from each heartbeat. Wilks' Lambda method is applied for feature selection and linear discriminant analysis

LDA for classification. This system was tested on a database of 29 subjects achieving 100% human identification rate and around 81% heartbeat recognition rate.

Wang et al. [8] in ”*Analysis of Human Electrocardiogram for Biometric Recognition*” follows a similar approach and extends the analysis based on a discrete cosine transform (DCT) of the auto-correlation function. The fiducial framework incorporates appearance attributes requiring the detection of only one fiducial point. The proposed approach suggests the estimation and comparison of the most significant coefficients that are extracted upon applying the discrete cosine transformb(DCT) on the autocorrelated heartbeat signals. Authors used ECG data from two public databases, PTB and MIT-BIH.

Gahi et al. in [9] ”*Biometric Identification System Based on Electrocardiogram Data*” present an identification system based on the extraction of 24 temporal and amplitude features from an ECG. Experimental results indicate that the system can achieve a 100% identification rate when the set of features is reduced to nine most relevant features. Mahalanobis distance-based classifier is used to identify the individuals in a typical identification procedure. For each heartbeat, the Mahalanobis distance between it and the stored templates is computed. The template resulting in the smallest distance is considered to be a match. This scheme was tested by using ECG collected from 16 participants.

Saechia [10] in ”*Human Identification System Based ECG Signal*” uses Fourier coefficients to examine the effectiveness of segmenting ECG heartbeat using three subsequences, each respectively representing P, QRS, and T waves. In order to compare the performance of classification, the significant Fourier coefficients obtained from whole sequence and subsequences cases are separately trained by neural network. The results prove that the performance of the subsequences are superior to those of whole signal.

Plataniotis [11] in ”*ECG biometric recognition without fiducial detection*” first introduced an ECG biometric recognition method that does not require any waveform detection. It analyzes the auto-correlation of ECGs and applies DCT to achieve dimensionality reduction offering significant computational advantages and performance compared to previously existing methods. An advantage of this approach that contributes to the appealing computational simplicity is that neither the heartbeat synchronization is necessary nor the exact heart rate detection. Agrafioti [12] as well,in ”*ECG based recognition using second order statistics*” performed a template matching introducing an auto-correlation template using DCT and LDA.

Fatemian [13] in ”*A new ECG feature extractor for biometric recognition*” uses less templates per subject, to speed up computation and reduce memory requirements and designed a personalized heartbeat template using Discrete Wavelet Transform Coefficients. The proposed method achieved substantial reduction of storage requirements as personalized heartbeat template consists of only one heartbeart per subject. Experimental results for identification over PTB and MIT ECG databases presented identification rate of 99.61% using only 2 heartbeats in average for each individual.

Shen et al. [14] in ”*One-lead ECG for identity verification*” applied two techniques, template matching and a decision-based neural network (DBNN). DBNN is a supervised learning method that uses both reinforced and anti-reinforced learning rules. This means that the system adjusts the weight vector either in the direction of the gradient of the discriminant function (i.e., reinforced learning) or opposite to that direction (i.e., anti-reinforced learning). 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, whereas the combination of the two methods achieved a 100% correct rate.

Wubbeler et al. [15] in ”*Verification of humans using the electrocardiogram*” employed template matching approaches to classify QRS complex related characteristics. A test set of 234 ECG recordings from 74 subjects was compiled by using short measurements, of ten seconds, to emulate a realistic approach to the practical implementation of ECG biometrics.

Singh et al.[16] in ”*ECG to Individual Identification*” proposed a single lead identification system where techniques for P and T wave delineation are based on time derivative and adaptive thresholding. From each heartbeat, 19 stable features related to interval, amplitude and angle are computed. The proposed identification system achieved an accuracy of up to 99% when tested with recordings of 25 individuals from the Physionet ECG database.

Chan et al. [17] in ”*Wavelet Distance Measure for Person Identification Using Electrocardiograms*” presented a method of biometric authentication, based on electrocardiogram (ECG) waveforms by using a distance measure calculated after wavelet transform has been applied. The one-lead ECG signals were collected from 50 subjects, and the wavelet distance measure presented a classification accuracy of 89%.

Irvine et al. [18] in ”*Heart rate variability: A new biometric for human identification*” introduced a system to exploit heart rate variability as a biometric and used principal component analysis (PCA) to extract features.

Tawfik et al. [19] defines non-fiducial features, using DCT on the QRS complex, and uses neural networks for classification. The system is tested using a test set of 550 lead I ECG traces recorded from 22 healthy people at different times.

In recent studies neural networks and learning techniques have provided useful and efficient tools in biometric and researchers have incorporated those methods for improving the classification performance.

Shen [20] proposed a four stage algorithm to select the dominant features by using the Quartile Discriminant Measurement (QDM) and a correlation matrix. The correlation matrix of the selected features is used to separate the features into groups, so each group contains highly correlated features. A score is assigned to each feature by the QDM measure and the low ranked features are removed from groups containing more than one feature.

In Shen's [21] work the Piecewise Linear Representation (PLR) is deployed to decrease the template dimension and the Dynamic Time Warping (DTW) method is used as a similarity measure between two signals, while the performance evaluation was carried out on three ECG databases, MIT-BIH Database, PTB Database and a self-Collected Database.

Fang and Chan [22] present a different approach as they use the whole ECG signal quantified in a multi-dimensional phase space. In this way the reconstructed portrait is directly used as a discreet feature and implements the topological characteristics of the ECG. The dataset was derived from 100 subjects, while only R-peak detection was performed for feature extraction.

Tantawi et al. [23] proposes a discrete wavelet feature extraction method for an electrocardiogram (ECG)-based biometric system. In this method, the RR intervals are extracted and decomposed, using discrete bi-orthogonal wavelet, in wavelet coefficient structures. The DCT coefficients are derived from the AC of ECG segments and then processed into the RBF network for classification.

Sidek et al.[24] addresses the problem of ECG recognition in different physiological conditions. They use Cross correlation to measure the similarity between different activities and apply a Multilayer Perceptron classifier to evaluate the distinctiveness of subjects achieving a classification accuracy of 96.1%, when using the proposed normalized method.

Tang and Shu [25] use rough sets and quantum neural networks (QNN) and claim superior results in comparison to BP and RBF networks, successfully reducing the dimension of feature space.

Gutta and Cheng [26] combine feature selection and classifier design into a single learning problem, by using probabilistic nonlinear kernel classifiers for binary classification.

2.3 Comparison

Searching up to date literature reveals that the majority of the techniques achieve high accuracy using either small databases or arbitrary subjects, ECG segments from different lead recordings and various ECG segmenting approaches, making the generalization of the obtained results implausible.

The number of subjects range from 10 to 100, usually derived from most commonly databases such as PTB Database or MIT/BIH database. In many cases the dataset compilation is self-collected with controvertible means as it cannot be easily repeated or thoroughly controlled as a procedure. Feature extraction utilize various techniques such as Fourier Transform, Discrete Cosine Transform (DCT) and Wavelet Transform (WT) and in the classification stage various techniques have been applied making it even harder to establish a general reliable scheme. It is apparent

The main characteristics of the aforementioned research work are depicted in the following tables in an attempt to present the diversity of the existing research. The datasets used range from 9 to 100 individuals raising question for the highly successful results. Additionally many of the proposed schemes fail to describe the training and testing settings for the classification stage which can affect gravely the achieved accuracy.

Paper	No of subjects	Samples / segmentation	Data Acquisition
[5]	20	30 recordings	SIEMENS ECG apparatus
[14]	20	20 heartbeat	MIT/BIH
[27]	10	200 beat	MIT/BIH
[28]	90	310 recordings	ECG - ID
[6]	29	-	-
[10]	35	-	-
[11]	14	10 sec windowing	PTB
[29]	10	200 R-R segments	-
[8]	13,13	2, 1 recordings	PTB , MIT-BIH
[17]	50	90 sec sequence	self recorded
[16]	25	125 recordings	Physionet
[9]	16	-	-
[30]	29,75	-	-
[22]	100	-	Nicolet EEG machine
[13]	14,13	1 heartbeat template	PTB , MIT-BIH
[31]	9	-	industry-standard ECG hardware
[32]	-	85945 heartbeats	-
[33]	50	-	-
[34]	13,14,15	-	PTB , MIT-BIH, self recorded
[35]	30	-	Revitus ECG module
[23]	13,25,50,75, 90	-	PTB
[36]	13	-	PTB , MIT-BIH
[37]	40	-	MIT-BIH
[38]	63	2 recordings	-

Table 2.1: Synoptic table of studied papers regarding the number of subjects and data acquisition

paper	approach	feature selection	feature extraction/processing
[5]	fiducial	7 features - QRST points	-
[14]	fiducial	6 features = QRS + RR + Form Factor	-
[27]	non-fiducial	(N=250) QRS wave, P wave, T wave	(PCA) & (WT)
[28]	fiducial	15 (distances) - kept 12	-
[6]	non-fiducial	normalized 1 period heart beat	FT
[10]	non-fiducial	autocorrelation	AC, DCT
[11]	fiducial	R-R segment	-
[29]	fiducial	15 & heartbeat recognition	-
[8]	non-fiducial	PQRST complexes	Correlation Coefficients
[17]	fiducial	19 features from each beat	-
[16]	fiducial	24 feature - thresholding	-
[9]	non-fiducial	9 features	R-R interval
[30]	non-fiducial	-	-
[22]	non-fiducial	QRS - delineation of T& P wave	PCA, LDA
[13]	non-fiducial	HMM – SGM based segmentation	(PCA)
[31]	non-fiducial	morphological feature & R-R interval	(WT) & (ICA)
[33]	fiducial	13 features	-
[34]	non-fiducial	-	(PLR)
[35]	non-fiducial	QRS complex (Normalized)	normalized QRS
[23]	fiducial	fiducial approach- intervals	reduced WT &(AC / DCT)
[36]	non-fiducial	AR parameters	QRS detection
[37]	non-fiducial	Rough sets	WT - reduction
[38]	non-fiducial	RR heartbeats	-

Table 2.2: Synoptic table of studied papers regarding the feature selection and extraction

paper	classification technique	training / testing	accuracy
[5]	SIMCA	85 training / 50 test	98%
[14]	correlation &DBNN	20 training / 1 test	80% - 100%
[27]	MLP-BP & SFA	1000 beats	96,17 % - 93,61 %
[28]	NM Classifier, LDA, MVC	195 training / 115 test	96 %
[6]	LDA	-	78% - 98%
[10]	MLP, BP	-	FR=0%
[11]	Euclidean & Gaussian Distance	-	-
[29]	ED, Nearest Neighbor	1 rec./ subject, 1 rec.	100%
[8]	-	-	-
[17]	PRD, CCORR, WDIST	-	70%, 80%, 89%
[16]	Template Matching	-	99%
[9]	Mahalanobis distance-based	-	100%
[30]	-	-	-
[22]	Spatial correlation- nearest point distance	-	99%
[13]	AC	-	99,6%
[31]	RBFNN, LDA	-	94%
[33]	SVM- using LIBSVM	-	99,25%
[34]	DTW	-	100%
[35]	MLP	-	Normalized QRS=96.1%
[23]	RBFN	-	RR=100% QT=100%
[36]	KNN	-	98.89%
[37]	RS QNN	-	average - 91.7%
[38]	KNN- Euclidean distance	-	95.2%

Table 2.3: The classification techniques and achieved accuracy of the studied papers

3. PROPOSED FRAMEWORK

The proposed testbed for comparing the techniques used in ECG biometrics, requires the clear definition of the followed steps. Firstly, the signal is preprocessed for noise elimination and segmented. Then, feature extraction algorithms produce the information that will serve as input in the classification stage. For each subject Fourier, Discrete Cosine and Wavelet Transform are applied and the twenty most important coefficients, that correspond to each transform, are selected.

The authentication procedure is addressed as a classification problem with two classes, i.e. the enrolled ECG can either belong to the identity, already declared in previous stage, or not.

The training and testing phases of the classifier are described in 3.1. 60% of the feature set of the subject is used for training the classifier along with the same amount of features from the rest subjects, whereas 40% of the features are inserted for testing.

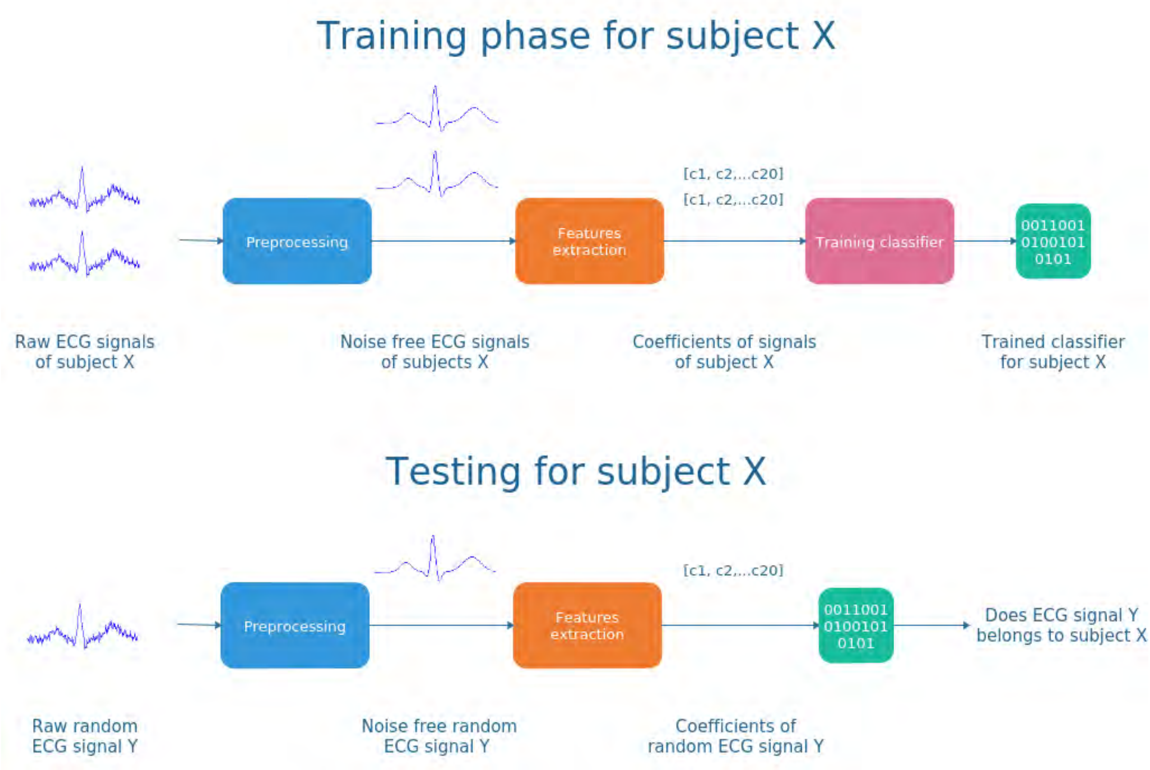

Figure 3.1: A schematic presentation of the proposed scheme

3.1 Filtering/Preprocessing

The importance of pre-process filtering has been thoroughly discussed as it is essential to obtain accurate features from the ECG signal. High frequency noise, powerline interference and baseline wandering are usual among ECG data. They are mainly caused by subject movements, abnormalities in contacts between subjects skin and electrodes, electromyographic (EMG) noise and equipment interference. All these factors create unwanted distortion that haws to be eliminated, in order for the comparison of different signals to be feasible.

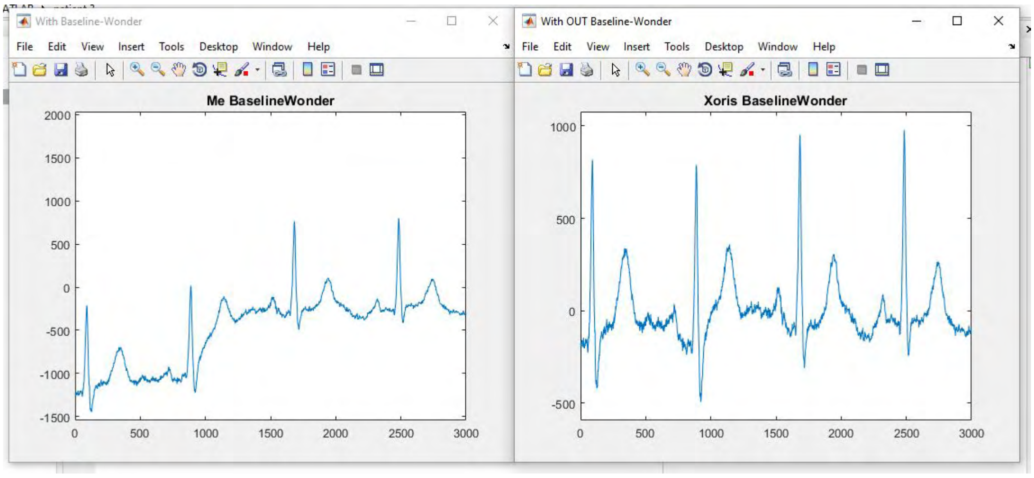

Figure 3.2: The removal of baseline wonder from raw ECG signal

Every signal is filtered using an 8th order Butterworth filter between 0.5Hz and 40 Hz. This is a commonly used preprocessing step (among other approaches), which provides stable and usable signals to commit the rest of the procedure on.

3.1.1 Butterworth filter

The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the passband. It is also referred to as a maximally flat magnitude filter. The higher the Butterworth filter order, the closer the filter becomes to the ideal "brick wall" response as depicted in Figure 3.3.

The generalised equation representing a "nth" Order Butterworth filter is given as:

$$H_{(}j) = \frac{1}{\sqrt{1 + \frac{j\omega}{j\omega_p}^{2n}}}$$

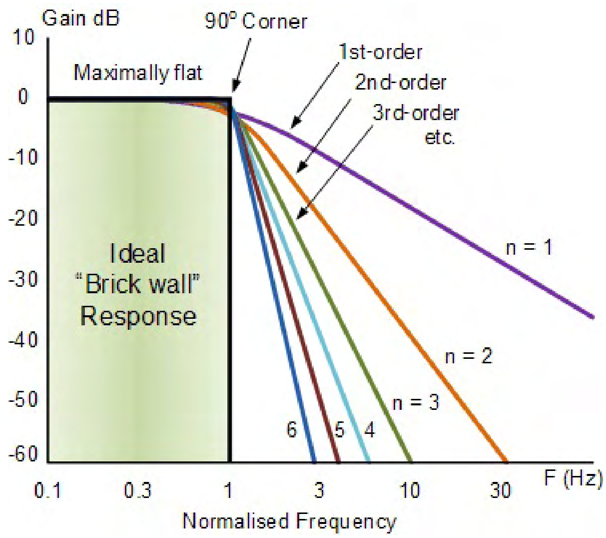

Figure 3.3: Frequency Response for a Butterworth Filter

3.2 Feature Extraction

Feature extraction is one of the most important steps in the data analysis process as it affects the success of any subsequent statistics or machine learning procedure. The raw ECG signal bears many information and feature extraction is a vital step for reducing data and minimizing computational requirements.

3.2.1 Fourier Transform

Discrete Fourier Transform is a common and basic feature extraction method in non fiducial ECG authentication. It transforms a signal from the time domain to frequency domain. The values of the resulting coefficients represent the amount in which a specific frequency is present in the original signal.

The following equation describes the Fourier transform commonly used in signal processing, where f(t) is the incoming signal, and S(f) is the signal in frequency domain.

$$S(f) = \int_{-\infty}^{\infty} s(t)e^{-2\pi ft}dt$$

Discrete Fourier Transform can also be applied to a sequence of N complex num-

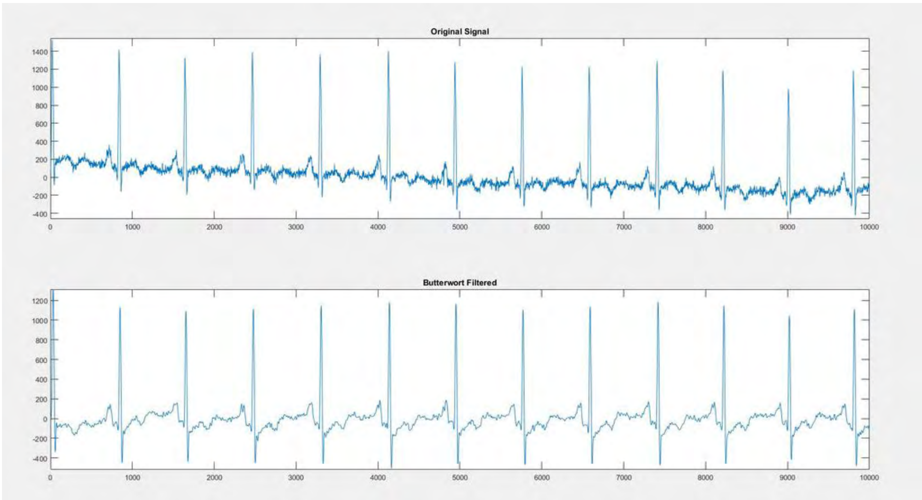

Figure 3.4: The ECG signal after using a Butterworth Filter

bers as defined in the following equation. S_n is the value of the signal at a discrete time offset n and S_k is the complex number that represents the amplitude and phase of a sinusoidal component in S_n at a frequency $\frac{k}{N}$.

$$S_N = \frac{1}{NT} \sum_{N} s_N[n] e^{-i2\pi n \frac{k}{N}}$$

$$S_k = \sum_{n=0}^{N-1} s_N[n] e^{-2\pi i n \frac{k}{N}}$$

3.2.2 Discrete Cosine Transform

Discrete Cosine Transform bears similarity to FT. It expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. It is mainly used for compression. It uses only real numbers to depict the information from the time domain to the frequency domain. The DCT boundary conditions are responsible for the ”energy compression” resulting from the properties of DCT and make the transform suitable for image and sound compression applications.

DCT-II

$$y(k) = \sum_{n=0}^{N-1} x(n) \cos(\frac{\pi}{2N}(2n+1)k)$$ για k=0,1,...,N-1

where:

3.2.3 Discrete Wavelet Transform

Wavelet transform (WT) is an ideal tool to analyze signals containing different structures. It decomposes signals into different scale components and provides a method for space-frequency localization. When it comes to focusing on very high frequency signals, such as a QRS complex, WT is more efficient than the short Fourier transform or the local cosine basis. It must also be considered that the wavelet coefficients produced in a wavelet analysis provide explicit information on the location and type of signal singularities. Particularly the QRS complex can be considered as a singularity of the ECG, since it corresponds to sharp changes in the signal, and can be detected using wavelet functions.

The wavelet transform is similar to the Fourier transform with different merit function. While Fourier transform decomposes the signal into sines and cosines, the wavelet transform uses functions that are localized in both the real and Fourier space.

The Wavelet transform is an infinite set of various transforms, depending on the merit function used for its computation. This is the main reason it is applied in various applications and can be categorized in various types respectfully. Based on the wavelet orthogonality the transform is categorized in discrete wavelet transform and continuous wavelet transform. The discrete wavelet transform for discrete signals:

$$S_{m,n} = \int_{-\infty}^{\infty} \overline{\psi}_{m,n} s(t) dt$$

$$\psi_{m,n}(t) = a_0^{-m/2} \psi(\frac{t - nb_0}{a_0^m})$$

$a = a_0^m$ and $b = nb_0$

where m,n are integers .

3.3 Classification

A classification problem belongs to the category of pattern recognition problems and is the problem of sorting a new input to a category. Supervised learning is used, as the classification algorithm i.e classifier, is trained with a set of data that already is categorized. Every new input will be identified to one of the categories. According to proposed methodologies, four classification techniques were selected and applied:

3.3.1 KNN classifier

The KNN algorithm is a rather simple Instance-based learning classifier that is used in a variety of applications such as economic forecasting, data compression and genetics and even as a benchmark for more complex classifiers such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM).

The K-nearest neighbor classifier algorithm predicts the target's class by finding the dominant class through the nearest neighbors. The similarity metric used is a distance measure such as the Euclidean distance. The neighbors are taken from a set of objects for which the class is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. Specifically it searches through the entire training set for the K most similar samples (the neighbors) and decides the result of the classification by the most common class value, between these K neighbors.

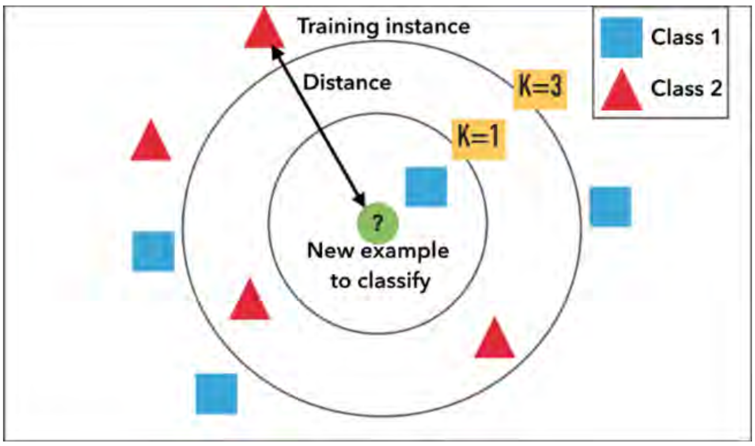

Figure 3.5: An example of knn algorithm with two classes

The most frequently used distance forms are given below:

Euclidean Distance :

$$d = \sqrt{\sum_{i=1}^{N}(x_i - y_i)^2}$$

Manhattan Distance:

$$d = \sum_{i=1}^{N}(|x_i - y_i|)$$

In some cases, examples of a more frequent class tend to dominate the prediction of the new example, because they tend to be common among the k nearest neighbors due to their large number. To overcome this problem is to weight the classification, taking into account the distance from the test point to each of its k nearest neighbors. The class (or value, in regression problems) of each of the k nearest points is multiplied by a weight proportional to the inverse of the distance from that point to the test point.

3.3.2 MLP classifier

Multilayer perceptron is the classical neural network model. The classifier used has a twenty nodes input layer, one hidden layer and a two nodes output layer to predict the two classes. Back-propagation has been used for training the model. The algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small leading to the conclusion that the network has learned a certain target function.

MLP is a typical feed-forward neural network so the information moves from the input nodes, through the hidden nodes and to the output nodes without any cycles or loops. Neural networks have been proven very successful in multiple applications, thus MLP is a good option for setting a baseline performance for a classification problem.

3.3.3 RBFN classifier

A Radial basis function network resembles to a neural network and has many uses, namely function approximation, time series prediction, classification, and system control. It consist of two layers: a hidden radial basis layer and an output linear layer. In the hidden layer,

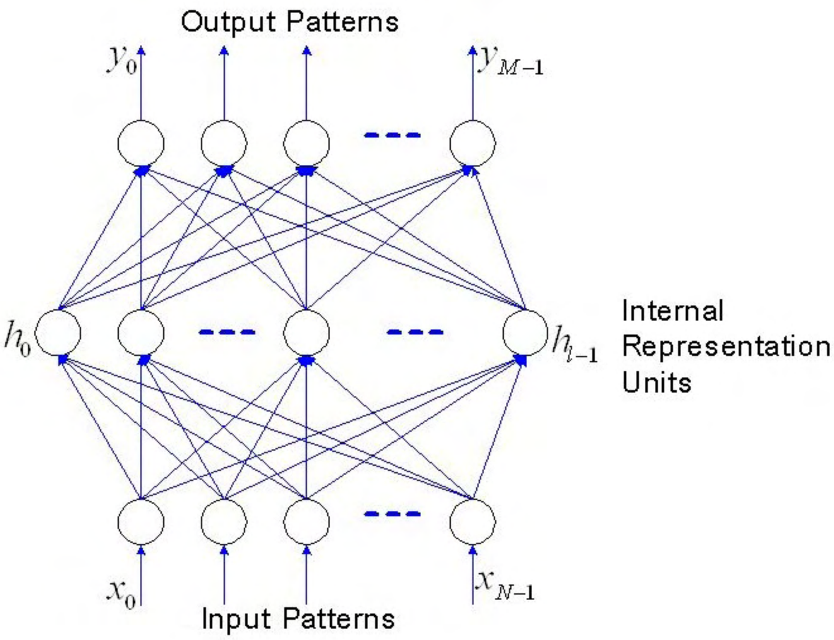

Figure 3.6: Typical diagram of MLP Classifier

the input vector is transformed by a radial basis activation function (Gaussian function). Each node measures the inputs similarity to samples from the training set. Each input is classified according to the class of the training samples it mostly resembles to.

The hidden units are known as radial centers and represented by the vectors c1, c2, · · · , ch as they provide a set of functions that constitute an arbitrary basis for the input patterns.

The radial basis functions in the hidden layer produces a significant non-zero response only when the input falls within a small localized region of the input space. It has a single hidden layer It has multiple hidden layers. RBFN as oppose to MLP has only one hidden layer and has a linear output even though the hidden layer is nonlinear.

3.3.4 Random Forest classifier

Random forest classification method constructs multiple random trees. Each tree depends on the values of a random vector, sampled independently and with the same distribution for all trees in the forest. The classification result produced from the random forest is the most common result between the classifications made by the random trees. In practice

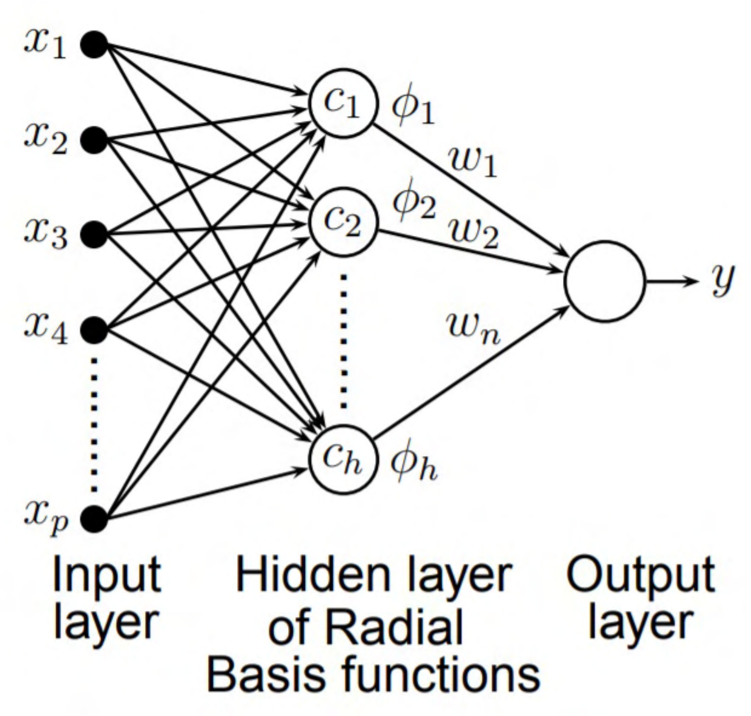

Figure 3.7: Architecture of RBFN Classifier

the errors that may be induced to the classification result by a specific tree are canceled out from the results produced by the rest of the trees.

Random Forest classifier is known to performing efficiently on large data bases as it can handle thousands of input variables without variable deletion. Additionally it generates an internal unbiased estimate of the generalization error as the forest building progresses. It provide an effective method for estimating missing data and maintains accuracy when a large proportion of the data are missing. Finally it can be used in clustering, locating outliers, or (by scaling) give interesting views of the data.

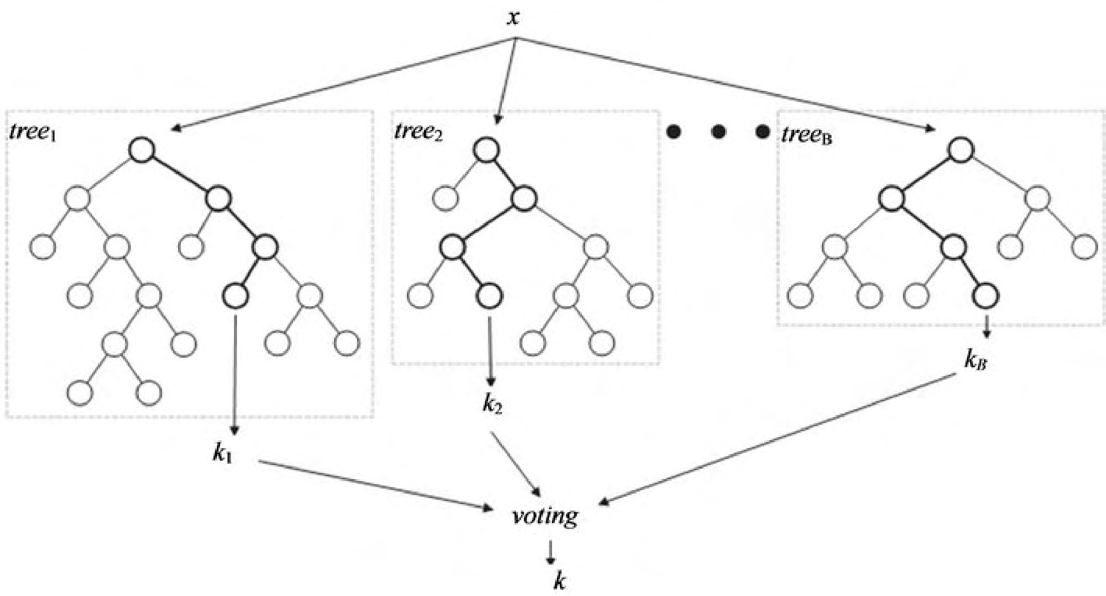

Figure 3.8: Architecture of Random Forest Classifier

4. EXPERIMENTS AND RESULTS

4.1 Data-set

A typical form of the ECG signals in the database is shown in Figure 4.1.The subjects were selected from the Physikalisch-Technische Bundesanstalt (PTB) Diagnostic ECG Database as it contains 549 records from 290 subjects regardless gender or age variations. Five records are given for each subject that include fifteen simultaneously measured signals: the twelve conventional ones along with the three Frank lead ECGs. Each signal is digitized at 1000 samples per second.

The signal used in the following steps is the one recorded through lead V1, one of the chest electrodes, positioned in the right side of sternum.

Figure 4.1: typical form of the ECG

Specifically, the ECGs in this database were obtained using a non-commercial, PTB prototype recorder with the following specifications:

- 16 input channels, (14 for ECGs, 1 for respiration, 1 for line voltage)
- Input voltage: ±16 mV, compensated offset voltage up to ± 300 mV
- Input resistance: 100 Ω (DC)
- Resolution: 16 bit with 0.5 μV/LSB (2000 A/D units per mV)
- Bandwidth: 0 - 1 kHz (synchronous sampling of all channels)
- Noise voltage: max. 10 μV (pp), respectively 3 μV (RMS) with input short circuit
- Online recording of skin resistance
- Noise level recording during signal collection

In the first step, every ECG record was segmented into non-overlapping windows of duration of 5 seconds, a time window that contains multiple heart beats and diminish the risk from abnormal heartbeats. Additionally this time segmentation provides more samples as the duration of the window is much smaller than the duration of each signal in the database which is around 90 seconds.

A main objective of this segmentation is to incorporate a larger number of subjects with multiple recordings and to this scope, the database was under-sampled and a subset of 50 subjects (the ones with 4 recordings each) was selected ending up using 3600 samples in total, owned evenly by 50 subjects.

4.2 Metrics

In order to evaluate the performance of the classification stage the usage of Receiver operating characteristics (ROC) graphs is the dominant visualizing tool. According to T.Fawcett in [39], considering a classification problem that utilizes only two classes the ROC graph has proven a richer measure of classification performance than scalar measures such as accuracy, error rate or error cost.

The basis of most common metrics regarding a given classifier and an instance, is the confusion matrix (or contingency table) that depicts the four possible outcomes, 4.4 If the hypothesis for the instance is positive and it is classified as positive, it is reckoned as a true positive; if it is classified as negative, it is counted as a false negative.Respectively, if the hypothesis is negative and it is classified as negative, it is counted as a true negative; if it is classified as positive, it is counted as a false positive.

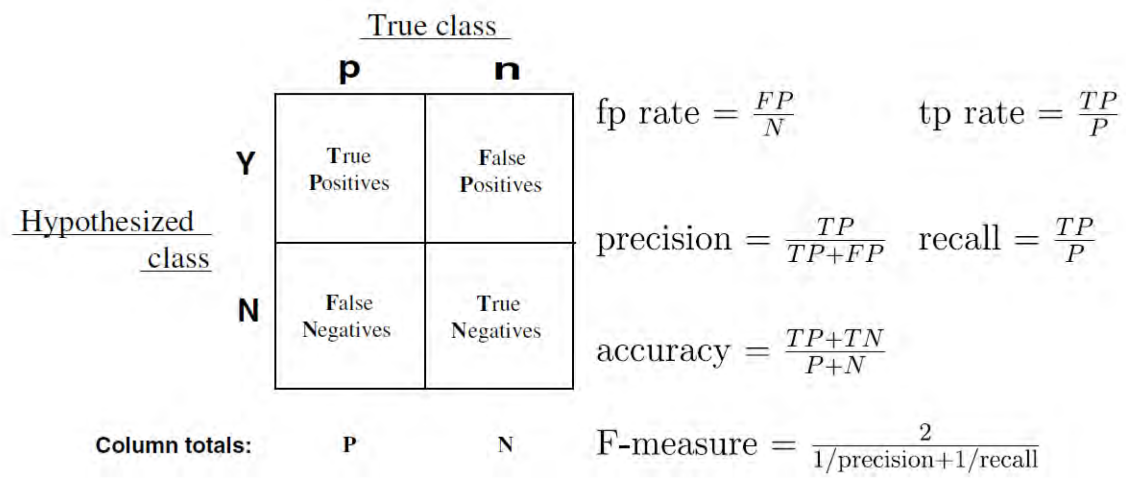

Figure 4.2: The confusion matrix and common performance metrics

4.3 Results

Aiming at designing a plain and robust procedure that could provide a reliable comparison of the proposed methods the three transformations have been conducted by using Matlab (2016a, The MathWorks), while the four classifiers have been tested by using the Weka machine learning library.

In the present work, the authentication procedure was strictly defined as a classification problem with two classes. The subject, who has already declare her identity in previous enrollment stage, provides her ECG that can be either accepted or declined. So in order to evaluate each approach, for each one the selected subjects, after preprocessing, the aforementioned classifiers were trained and applied for every set of feature respectively.

The ECG signal was segmented into 5” pieces $\mathbf{S}_{i,j}$ in order to enlarge the dataset while maintaining large enough duration to include multiple heartbeats.

The segmented ECG signals were transformed using Discrete Fourier, Discrete Cosine and Wavelet Transform:

Classification	Correct %	TP rate	FP rate	Precision	Recall	F-Measure	ROC Area
KNN	81.616	0.832	0.199	0.801	0.832	0.814	0.817
MLP	81.409	0.86	0.233	0.787	0.864	0.817	0.871
RBFN	80.233	0.912	0.301	0.747	0.912	0.628	0.855
RandForest	83.993	0.881	0.199	0.813	0.881	0.843	0.903

Table 4.1: Results of different classifiers for Cosine transformation

Classification	Correct %	TP rate	FP rate	Precision	Recall	F-Measure	ROC Area
KNN	82.53	0.867	0.214	0.796	0.867	0.828	0.827
MLP	82.601	0.87	0.215	0.8	0.87	0.826	0.886
RBFN	81.076	0.911	0.284	0.758	0.911	0.824	0.871
RandForest	85.204	0.89	0.183	0.825	0.89	0.854	0.914

Table 4.2: Results of different classifiers for Fourier transformation

$$y_{1,i} = \mathcal{F}\{\mathbf{F}_{i,j}\}$$
$$y_{2,i} = \mathcal{C}\{\mathbf{F}_{i,j}\}$$
$$y_{3,i} = \mathcal{W}\{\mathbf{F}_{i,j}\}$$

For each transformation, the twenty most significant coefficients were selected, excluding the DC component.

$$coef_{1,i} = sort\{y_1[1:20]\}$$
$$coef_{2,i} = sort\{y_2[1:20]\}$$
$$coef_{3,i} = sort\{y_{3,level3}[1:20]\}$$

The feature sets for each subject were separated into two sets in order to be used for training $train_i$ and testing $test_i$ of the classifiers. 60% of the features are used for training and 40% for testing. Both training and testing sets include equal amount of features from the rest of the subjects.

The average results of the fifty subjects are depicted in Tables 4.1,4.2 and 4.3 obtained by using the traditional approaches, proposed in literature.

In a classification task, the precision for a class is the number of true positives (in this case the ECG sample is correctly assigned to a subject) divided by the total number of elements labeled as belonging to the positive class. Recall in this context is defined as the number of true positives divided by the total number of elements that actually belong to the positive class.

Classification	Correct %	TP rate	FP rate	Precision	Recall	F-Measure	ROC Area
KNN	86.974	0.908	0.166	0.841	0.908	0.871	0.871
MLP	85.753	0.887	0.17	0.837	0.887	0.857	0.918
RBFN	85.873	0.919	0.198	0.82	0.919	0.864	0.909
RandForest	88.447	0.917	0.146	0.859	0.917	0.885	0.952

Table 4.3: Results of different classifiers for Wavelet transformation

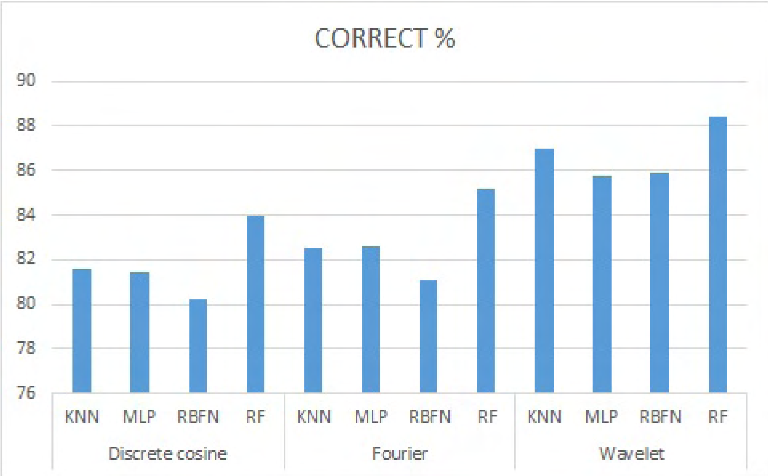

Figure 4.3: The average Correct% for each classification algorithm and transformation

It is apparent that the most efficient feature extraction technique is Wavelet Transform. Specifically the accuracy obtained by using Wavelet is on average 5 percentage units higher than that obtained by using Cosine, irrespectively of the the classifier choice. In comparison to the accuracy obtained by using the Fourier transformations, Wavelet approach produces on average 3 percentage units higher accuracy ratios.

Examining the performance of the classifiers Random forest outperforms the other three. The accuracy succeeded by Random forest is on average 2.5 percentage units higher than that of KNN and MLP and 3.5 percentage units higher than that of RBFN.

Conclusively, the combination of the Wavelet transformation and the Random Forest classifier grants the best results achieving an 88.45% accuracy ratio and a 0.95 ROC area.

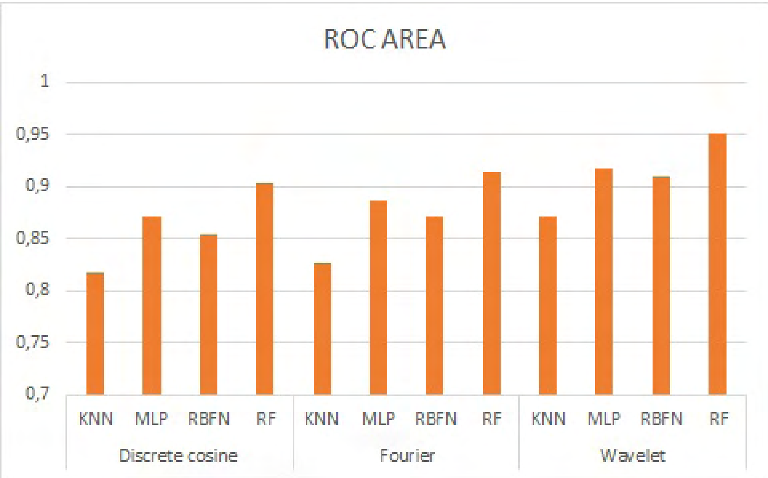

Figure 4.4: The average ROC Area for each classification algorithm and transformation

5. CONCLUSIONS

This thesis describes a framework for comparing human biometric authentication procedures based on ECG signals. ECG signal has been proven to provide a viable trait for multi-biometric or standalone biometrics as it can be easily and real-time acquired ensuring the liveliness of the user.

Initially, the state of the art literature was presented in order to delineate the proposed ECG biometrics systems, regarding the feature selection tools and classification approaches, and to underline their diversity.

The primary goal was to provide a generic scheme for evaluating the numerous methodologies proposed in literature. For this purpose, the raw ECG signal of fifty subjects have been taken into account and the necessary preprocessing that ensures noise and baseline wander elimination has been applied. Then the signals were processed for feature extraction using Fourier Transform, Discrete Cosine Transform and Wavelet Transform. For each subject the twenty most significant coefficients of each transform were forwarded to the classification stage. Four classification algorithms were applied using the Weka machine library, namely K-Nearest Neighbor Method (KNN), Multilayer Perceptron, RBFN, Random Forest.

The authentication problem was defined as a two-classes problem, as each incoming ECG can either belong to the proclaimed user or not. The results represent the average performance for fifty subjects, taken from the Physikalisch-Technische Bundesanstalt (PTB) Diagnostic ECG Database. The higher accuracy is achieved by combining the Wavelet transformation and the Random Forest classifier presenting 88.45% accuracy ratio and 0.95 ROC area.

Future work will focus on extending the proposed framework and experimenting with alternative feature analysis and classification methods, such as deep learning neural networks that have been proven to outperform traditional classification schemes in many use cases. Deep learning is capable of processing numerous input features, a grave advantage against traditional machine learning for solving complex problems. Additionally other signal processing approaches, such as PCA analysis or fiducial features extraction are going to be evaluated.

Finally the proposed methods are going to be re-designed according to the cancelable biometrics scheme [40]. Biometric templates are very sensitive private data and relative privacy violations should not be allowed. Cancelable biometrics demands that the templates stored for each subject should be distorted with one way procedures in such a way that they can be used for comparison but they can also be canceled if they are leaked. ECG based biometrics work-flow described herein is going to be adapted according to this approach.

ABBREVIATIONS - ACRONYMS

ECG	Electrocardiogram
FAR	False Acceptance Rate
FRR	False Rejection Rate
FT	Fourier Transform
WT	Wavelet Transform
PCA	Principal Component Analysis
LDA	Linear Discriminant Analysis
kNN	K Nearest Neighbor
RBF	Radial Basis Function
BN	Bayes Network
MLP	Multilayer Perceptron
VQ	Vector Quantization
GMM	Gaussian Mixture Mode
SVM	Support Vector Machine
ANN	Artificial Neural Network
RBFNN	Radial Bias Function Neural Network
HMM	Hidden Marchov Models
SVM	Support Vector Machine
DCT	Discrete Cosine Transform
AC	Autocorrelation
SIMCA	Soft Independent Modeling of Class Analogy

REFERENCES

[1] William Stallings, Lawrie Brown, Michael D Bauer, and Arup Kumar Bhattacharjee. *Computer security: principles and practice*. Pearson Education, 2012.

[2] M. Abo-Zahhad, Sabah M. Ahmed, and S. N. Abbas. Biometric authentication based on pcg and ecg signals: present status and future directions. *Signal, Image and Video Processing*, 8(4):739–751, May 2014.

[3] Gaganpreet Kaur, Dheerendra Singh, and Simranjeet Kaur. Electrocardiogram (ecg) as a biometric characteristic: A review. 2015.

[4] Amit Kaul, Ajat Arora, and Sushil Chauhan. Ecg based human authentication using synthetic ecg template. 03 2012.

[5] Lena Biel, Ola Pettersson, Lennart Philipson, and Peter Wide. Ecg analysis: a new approach in human identification. *IEEE Transactions on Instrumentation and Measurement*, 50(3):808–812, 2001.

[6] Steven A Israel, John M Irvine, Andrew Cheng, Mark D Wiederhold, and Brenda K Wiederhold. Ecg to identify individuals. *Pattern recognition*, 38(1):133–142, 2005.

[7] Steven A Israel, John M Irvine, Brenda K Wiederhold, and Mark D Wiederhold. *The heartbeat: the living biometric*. Wiley-IEEE Press, New York, NY, USA, 2009.

[8] Yongjin Wang, Foteini Agrafioti, Dimitrios Hatzinakos, and Konstantinos N Plataniotis. Analysis of human electrocardiogram for biometric recognition. *EURASIP journal on Advances in Signal Processing*, 2008:19, 2008.

[9] Y. Gahi, M. Lamrani, A. Zoglat, M. Guennoun, B. Kapralos, and K. El-Khatib. Biometric identification system based on electrocardiogram data. In *2008 New Technologies, Mobility and Security*, pages 1–5, Nov 2008.

[10] Sukkharak Saechia, Jeerasuda Koseeyaporn, and Paramote Wardkein. Human identification system based ecg signal. In *TENCON 2005 2005 IEEE Region 10*, pages 1–4. IEEE, 2005.

[11] Konstantinos N Plataniotis, Dimitrios Hatzinakos, and Jimmy KM Lee. Ecg biometric recognition without fiducial detection. In *Biometric Consortium Conference, 2006 Biometrics Symposium: Special Session on Research at the*, pages 1–6. IEEE, 2006.

[12] Foteini Agrafioti and Dimitrios Hatzinakos. Ecg based recognition using second order statistics. In *Communication Networks and Services Research Conference, 2008. CNSR 2008. 6th Annual*, pages 82–87. IEEE, 2008.

[13] S Zahra Fatemian and Dimitrios Hatzinakos. A new ecg feature extractor for biometric recognition. In *Digital Signal Processing, 2009 16th International Conference on*, pages 1–6. IEEE, 2009.

[14] Tsu-Wang Shen, WJ Tompkins, and YH Hu. One-lead ecg for identity verification. In *Engineering in medicine and biology, 2002. 24th annual conference and the annual fall meeting of the biomedical engineering society embs/bmes conference, 2002. proceedings of the second joint*, volume 1, pages 62–63. IEEE, 2002.

[15] Gerd Wübbeler, Manuel Stavridis, Dieter Kreiseler, Ralf-Dieter Bousseljot, and Clemens Elster. Verification of humans using the electrocardiogram. *Pattern Recognition Letters*, 28(10):1172–1175, 2007.

[16] Y. N. Singh and P. Gupta. Ecg to individual identification. In *2008 IEEE Second International Conference on Biometrics: Theory, Applications and Systems*, pages 1–8, Sept 2008.

[17] A. D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee. Wavelet distance measure for person identification using electrocardiograms. *IEEE Transactions on Instrumentation and Measurement*, 57(2):248–253, Feb 2008.

[18] JM Irvine, BK Wiederhold, LW Gavshon, SA Israel, SB McGehee, R Meyer, and MD Wiederhold. Heart rate variability: a new biometric for human identification. In *Proceedings of the International Conference on Artificial Intelligence (IC-AI'01)*, pages 1106–1111, 2001.

[19] Mohamed M Tawfik and Hany Selim Tarek Kamal. Human identification using qt signal and qrs complex of the ecg. *Online J Electron Electr Eng (OJEEE)*, 3:1–5, 2011.

[20] Jun Shen, Shu-Di Bao, Li-Cai Yang, and Ye Li. The plr-dtw method for ecg based biometric identification. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 5248–5251. IEEE, 2011.

[21] J. Shen, S. D. Bao, L. C. Yang, and Y. Li. The plr-dtw method for ecg based biometric identification. In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 5248–5251, Aug 2011.

[22] Shih-Chin Fang and Hsiao-Lung Chan. Human identification by quantifying similarity and dissimilarity in electrocardiogram phase space. *Pattern Recognition*, 42(9):1824 – 1831, 2009.

[23] Manal M Tantawi, Kenneth Revett, Abdel-Badeeh Salem, and Mohamed F Tolba. A wavelet feature extraction method for electrocardiogram (ecg)-based biometric recognition. *Signal, Image and Video Processing*, 6(9):1271–1280, 2015.

[24] Khairul Azami Sidek, Ibrahim Khalil, and Magdalena Smolen. Ecg biometric recognition in different physiological conditions using robust normalized qrs complexes. In *Computing in Cardiology (CinC), 2012*, pages 97–100. IEEE, 2012.

[25] X Tang and L Shu. Classification of electrocardiogram signals with rs and quantum neural networks. *International Journal of Multimedia and Ubiquitous Engineering*, 9(2):363–372, 2014.

[26] Sandeep Gutta and Qi Cheng. Joint feature extraction and classifier design for ecg-based biometric recognition. *IEEE journal of biomedical and health informatics*, 20(2):460–468, 2016.

[27] Ramaswamy Palaniappan and Shankar M Krishnan. Identifying individuals using ecg beats. In *Signal Processing and Communications, 2004. SPCOM'04. 2004 International Conference on*, pages 569–572. IEEE, 2004.

[28] T. Lugovaya. Biometric human identification based on ecg the ecg-id database. *physionet.org*, p, 2011.

[29] G. G. Molina, F. Bruekers, C. Presura, M. Damstra, and M. van der Veen. Morphological synthesis of ecg signals for person authentication. In *2007 15th European Signal Processing Conference*, pages 738–742, Sept 2007.

[30] John M. Irvine and Steven A. Israel. A sequential procedure for individual identity verification using ecg. *EURASIP Journal on Advances in Signal Processing*, 2009(1):243215, May 2009.

[31] O. Boumbarov, Y. Velchev, and S. Sokolov. Ecg personal identification in subspaces using radial basis neural networks. In *2009 IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications*, pages 446–451, Sept 2009.

[32] C. Ye, M. T. Coimbra, and B. V. K. Vijaya Kumar. Arrhythmia detection and classification using morphological and dynamic features of ecg signals. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pages 1918–1921, 2010.

[33] Y. Singh and S. Singh. Evaluation of electrocardiogram for biometric authentication. *Journal of Information Security*, 3(1):39–48, 2012.

[34] J. Shen, S. D. Bao, L. C. Yang, and Y. Li. The plr-dtw method for ecg based biometric identification. In *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 5248–5251, Aug 2011.

[35] K. A. Sidek, I. Khalil, and M. Smolen. Ecg biometric recognition in different physiological conditions using robust normalized qrs complexes. In *2012 Computing in Cardiology*, pages 97–100, Sept 2012.

[36] Branislav Vuksanovic. Analysis of human electrocardiogram for biometric recognition using analytic and ar modeling extracted parameters. 4, 01 2014.

[37] X Tang and L Shu. Classification of electrocardiogram signals with rs and quantum networks neural. 9:363–372, 02 2014.

[38] Tiago Araújo, Neuza Nunes, Hugo Gamboa, and Ana Fred. Generic biometry algorithm based on signal morphology information: Application in the electrocardiogram signal. In Ana Fred and Maria De Marsico, editors, *Pattern Recognition Applications and Methods*, pages 301–310, Cham, 2015. Springer International Publishing.

[39] Tom Fawcett. An introduction to roc analysis. *Pattern Recognition Letters*, 27(8):861 – 874, 2006. ROC Analysis in Pattern Recognition.

[40] V. M. Patel, N. K. Ratha, and R. Chellappa. Cancelable biometrics: A review. *IEEE Signal Processing Magazine*, 32(5):54–65, Sept 2015.