ROBUST SUBJECT RECOGNITION USING THE ELECTROCARDIOGRAM

by

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A thesis submitted in conformity with the requirements
for the degree of Master of Applied Science
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University of Toronto

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Abstract

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2008

This thesis studies the applicability of the electrocardiogram signal (ECG) as a biometric. There is strong evidence that heart’s electrical activity embeds highly distinctive characteristics, suitable for applications such as the recognition of human subjects. Such systems traditionally provide two modes of functionality, identification and authentication; frameworks for subject recognition are herein proposed and analyzed in both scenarios.

As in most pattern recognition problems, the probability of mis-classification error decreases as more learning information becomes available. Thus, a central consideration is the design and evaluation of algorithms which exploit the added information provided by the 12 lead standard ECG recording system. Feature and decision level fusion techniques described in thesis, offer enhanced security levels.

The main novelty of the proposed approach, lies in the design of an identification system robust to cardiac arrhythmias. Criteria concerning the power distribution and information theoretic complexity of electrocardiogram windows are defined to signify abnormal ECG recordings, not suitable for recognition. Experimental results indicate high recognition rates and highlight identification based on ECG signals as very promising.
Acknowledgements

First and foremost, I would like to sincerely thank my advisor Prof. Dimitrios Hatznakos. He gave me guidance and direction that was needed to produce this work. Without his generous help, this research would not have been possible. I would also like to thank the Department of Electrical and Computer Engineering for their financial support.

Thank you to my proposal and defence committees for taking the time to provide useful insight. I am also grateful to the Communications Group faculty members for teaching, offering technical advice and inspiration in the beginning of this thesis work. Financial support for this thesis was provided by the Natural Sciences and Engineering Research Council (NSERC) of Canada.

Last but not least, I would like to thank my family and friends for their constant encouragement during my studies.
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Chapter 1

Introduction

1.1 Security and Privacy Motivations

Automatic and accurate validation of human identity is required in numerous civilian applications. Criminal investigations, access control, financial transactions, airport check-in and homeland security are some examples which demonstrate the emerging need for reliable identity authentication.

Traditional strategies for identification rely on entities or textual and numerical modules. Object dependent mechanisms usually involve identity cards or tokens which can be easily stolen, manipulated or faked. In addition, passwords and PIN numbers that have gained wide acceptance are based on knowledge of secret codes which can be also stolen, forgotten or shared. Generally speaking, the dependence on items that a subject must remember or possess undermines security applications.

In 2006, a survey from the US Federal Trade Commission [5], concerning identity theft crimes, illustrated areas where ID fraud is usually encountered and their frequency of occurrence. According to [5], 25% of the reported identity theft or fraud complaints were related to credit card activities and 16% to bank frauds. The same annual survey documents the increasing incidents of identity falsification between 2004 and 2006. Fur-
thermore, another extensive analysis for the year of 2007 [6], demonstrated that only 11% of the total fraud activity is a true-name theft, compared to synthetic ID fraud which reached 88.3%. This clearly suggests that nowadays it is more likely for fraudsters to manufacture and use a fake identity, rather than steal the original one.

As technology for falsification and design of fake credentials advances, security concerns continue to grow. There is strong need for automatic and reliable techniques that will reassure privacy and safety in the e-world [7]. The resulting security gap is likely filled by the employment of characteristics that are physiognomy dependent for every individual, the biometrics.

Biometric traits are features highly correlated to a particular person. Instead of utilizing items or passwords to verify an identity, people’s inherent characteristics are employed for recognition. Biometrics have undoubtedly found their niche in the so bonded security and privacy world, because they offer airtight security [8].

1.2 Biometric Criteria and Solutions

Biometric characteristics can be roughly categorized as physiological or behavioral features associated with a specific individual. Behavioral traits often reveal personalized patterns which can be coupled with recognition systems. This class of biometric attributes has great potential in surveillance applications, as it is easy and non invasive to monitor someone’s gait, keystroke or signature. However, factors such as stress, drug usage, age and illness can lead to significant variability among multiple recordings of the same person [9]. In addition, behavioral-based identification methods are rather vulnerable to intrusion, as they can be easily mimicked. Figure 1.1 summarizes the types of biometric traits along with some examples of the corresponding characteristics.

The gait and keystroke are two behavioral biometric characteristics currently investigated for recognition applications. These biometrics have the advantage of being non
Chapter 1. Introduction

invasive to the subjects and can thus be employed for surveillance purposes. The main drawbacks are the variations among recordings of the same person and that they can easily mimicked [8, 10].

Physiological biometrics are attributes related mostly to a subject’s physical appearance and characteristics. This class of modalities involves applications which are already widely accepted by current security solutions, such as the fingerprint and the iris. Other examples of well known physiological features that serve for biometric use, are the face, hand geometry, DNA, ear, retina and palm print. Each of these characteristics has case dependent advantages and disadvantages, which most often is their defenseless nature against falsified credentials. It is important to get an overview of some examples of biometric applications, involving the aforementioned biometric modalities.

The DNA is an one dimensional code, which is well established for its uniqueness among human subjects. It can be easily but intrusively acquired from the human body, and it can serve forensic applications. The main drawback 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. Furthermore, biological samples need to be acquired, risking users’ acceptability and cooperation. In addition, the acquisition time for a subject to be identified precludes real-time recognition, because chemical processes need to take place.

The fingerprint, on the other hand, can be applied in real time identification systems since it can be acquired quickly, by scanning a subject’s finger, and processed digitally. Technologies that are based on minutiae points or non minutiae information have demonstrated that fingerprint traits are unique even between identical twins [8, 10]. The drawback of their application for recognition is their vulnerability to aging, environment and genetic factors. In addition, fingerprints can be easily falsified using latex and silicone gel.

A lot of attention has also been drawn to the application of face images for human
Identification. 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 [8, 10].

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. Furthermore, current high false rejection rates of such systems do not
make allowance for authentication applications \cite{8, 10}.

Even though any physiological or behavioral human attribute can be examined for its uniqueness among individuals, not all biological characteristics are qualified for biometric recognition systems. There are a few criteria that a biometric trait must meet. Roughly speaking, the requirements are mostly related to the ease and time span of the applications.

The first and most eminent criterion is the universality of the characteristic. This requirement is connected to the genuine and natural aspect of the attribute. Although, all suggested biometric traits are met in human subjects, their appearance is not catholic. For instance, physical disabilities will not allow for a portion of the population to be registered in a gait recognition system. Furthermore, there might be cases where the desired identification feature of a finger image is missing due to genetic reasons. When establishing a biometric recognition system, it is important to reassure that all enrollees possess the biological characteristic.

In addition, a strong biometric attribute should be distinctive in a population. Distinctiveness suggests that any subject’s characteristics should be personalized enough, to form an individual unique signature. There are doubts for some biometric traits analyzed today (odor for example) about whether their discriminative power is strong enough, to be appropriate for biometric use.

*Permanence* is another parameter criterion that qualifies biometric traits. This requirement dictates that employed characteristics should not change considerably over a period of time. This is not the case with the majority of the biometric features analyzed or already applied currently. For instance, face special attributes vary for any individual as years pass. This raises respectable worries about long term applications of the same face images in recognition systems.

The potential of collection for a biological characteristic is an additional factor that signifies appropriate for identification characteristics. *Measurability* means both the abil-
ity of a biological trait to be quantitatively measured, and the ease of the application. Digitizing biometric signals is central when aiming to detect patterns. Furthermore, in order to reassure user’s convenience, the acquisition process should be as less intrusive to the subject as possible [8, 10, 11, 12].

Given these criteria it is not easy to determine the best biometric characteristic [11]. All features have advantages and disadvantages. In addition, when designing recognition systems, the biological attribute employed is sensitive to the special properties of the application. It is therefore hard to compare the performance of these systems and the selection is left upon the deciding authority.

1.3 Motivation for Electrocardiogram

The idea of using medical attributes of the human body for identification purposes is relatively new. This thesis analyzes the cardiac electrical activity for biometric applications. Along with the electrocardiogram (ECG), there is on-going research in the application of the electroencephalogram, heart rate, blood pressure and pulse oximetry for identity configuration. There are plenty of benefits along with several restrictions surrounding the employment of medical traits in biometric systems.

Among the primary strengths that encompass the practice of ECG signals as biometrics, is that the requirements for universality and permanence are satisfied. These two criteria, are met given that the electrocardiogram can be naturally monitored from every subject.

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 heartbeat 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.

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, there is no falsification technology today that can steal and reproduce through muscles an electrocardiogram signal.

However, the disadvantages of employing the ECG for human identification need to be considered. First of all, any biometric security system that is based on that trait has to be invariant to conditions such as mental stress or exercise that affect the morphological properties of the ECG waveform. In addition, for the electrocardiogram to be recorded, electrodes have to be attached on the surface of the body (depending on the requirements of the system), rendering this biometric more invasive in terms of acquisition procedure.

The ECG signals embed information about the physiology of the subject, which also includes several medical conditions. This gives rise to privacy issues concerning information about the presence of diseases that can be used to discriminate a subject. Moreover, the appearance of heart diseases such as arrhythmias alter significantly the appearance of the waveform, depending on the severity of the symptoms.

1.3.1 Inter-individual Variability of ECG

Satisfying the requirements for universality and permanence, it is crucial to examine the uniqueness of electrocardiogram signals as well. When monitoring a population, different cardiac electrical signals conform to roughly the same repetitive pattern. However, further analysis of ECGs can reveal remarkably correlated trends among multiple recordings of a subject. Methodical demonstrations of ECG inter-individual distinctions can
Electrophysiological and geometrical variations of the heart are embedded in ECG signals. Model studies have shown that physiological factors such as the heart mass orientation, the conductivity of various areas of the cardiac muscle and the activation order of the heart, can introduce significant variability among subjects [18, 19].

Furthermore, geometrical attributes such as the exact position and orientation of the myocardium, and torso shape signify ECG signals with particularly distinct and personalized characteristics. Other attributes that determine electrocardiogram signals are the timing of depolarization and repolarization and lead placement. In addition, except for the anatomic idiosyncrasy of the heart, unique patterns are related to physical attributes such as the body habitus and gender [13, 17, 18, 19, 20]. The electrical map of the area surrounding the heart may also be affected by variations of other organs in the thorax [19].

Methodologies have additionally been suggested to eliminate the differences among electrocardiogram recordings of different individuals. The idea of clearing off inter-individual variability is standard when seeking to establish normal rates of the ECG morphology [14]. Automatic diagnosis of pathologies via the electrocardiogram is also more feasible when the level of variability among healthy people is lower [18]. In such algorithms, personalized parameters of every subject are treated as random variables and criteria are defined to quantify the degree of subjects’ similarities on a specific feature basis.

1.3.2 Liveness Indicator

A very commonly encountered practice is for intruders to try and trick an identification security system, presenting biometric traits that do not legally belong to them. This introduces a very high risk in biometric applications. Manipulating one’s biological attribute is not the only route of penetration. For example, a recorded voice can be submitted to
a system by an unauthorized person in order to grant access into a restricted area.

The question to be answered in such cases is *Is the individual offering the biometric, the real legitimate user?* A means of tracking the liveness of the ”entity” presenting the biometric is of prominent importance. Often, such problems are addressed by the physical presence of a security administrator, reassuring the validity of the delivered biometric trait. However, there is high need for automatic assistance for such matters.

The electrocardiogram signal is by definition human’s liveness indicator. Its presence alone ensures that the person presenting the biometric, is a legitimate user of the system. This is true with any medical biometric trait, that only seizes to exist after the subject passes away. Therefore, employing cardiac electrical potential as signatures in identification systems offers undoubtedly enhanced security.

### 1.4 Ethical Issues in Biometrics

Although biometric based systems serve purposes beneficial for security, their application has frequently encountered public fear and resistance. Especially during the initial stages of biometric practice, concerns about violation of human rights came to light. The possibility of linking biometric traits to personal data has strengthened the worries about the collection of biological information [7, 11].

Especially non intrusive biometric systems such as those identifying people through gait, face or keystroke, face strong distrust. Allowing a system to capture a biometric without a subject’s consent can break civil liberties. For instance, people who desire to remain anonymous at a specific time instance, will be deprived of their right. Intrusive biometrics can also be misused. Given the advances in the medical field, a fingerprint or iris measurements could be linked to private clinical information [8, 12].

Recently, research is being carried out on the employment of medical traits for biometric recognition, such as the electrocardiogram (ECG), heart rate, blood pressure, pulse
oximetry and the electroencephalogram (EEG). Traditionally, only physicians and qualified health care providers were allowed to access this medical information. In a restricted medical environment, patient privacy is subject to high standards of security. However, biometrics are envisioned to be more widespread, and this increases the implications for personal privacy.

A good biometric system should embed a mechanism to guarantee confidentiality. Encryption is one route of reassuring that no allowance for privacy violation will be made, even in cases of data theft. Another option is for the biometric databases to store as little information about the raw biometric feature as possible, so that biological data retrieval is rendered impossible.

1.5 Research Goals and Contributions

In this thesis, the analysis of a relatively new biometric feature: the electrocardiogram (ECG) is reported. ECG belongs to the general class of medical biometrics as it has been widely investigated for clinical diagnostic purposes. The primary objective of the current research work is to address the following issues:

1. Design of a non-fiducial based framework. Previously proposed approaches for the employment of cardiac signals in human recognition systems essentially depend on features extracted from single heart beats. However, in order to isolate and synchronize pulses, fiducial points i.e., points of special interest on ECG waveforms, need to be detected. Current fiducial points detectors do not offer adequate localization of waves’ boundaries, risking the recognition accuracy of certain approaches.

In this thesis, a non fiducial based methodology is described. The essence of the new approach is the use of the autocorrelation, which offers a wealth of discriminative information in a population. The autocorrelation operates on ECG windows, the samples of which would otherwise need to be subjected to detection of fiducial
2. **Propose recognition frameworks for all biometric operational modes.** Current approaches have mainly investigated the applicability of the electrocardiogram for identification purposes only. This thesis will address problems related to authentication functionalities as well. The reported techniques, will also be tested for subject identification and verification in intruder scenarios.

3. **Information fusion from 12 lead ECG signals.** Employing more learning information for every class often reduces the probability of missclassification error in pattern recognition problems. The standard system for ECG recording offers 12 cardiac signals picturing different aspects of heart’s activity. As opposed to most of the previously suggested methodologies, this thesis examines various levels of fusion for such information.

   A decision or feature based fusion of information, can be regarded as a multimodal biometric system, which increases the performance significantly while offering higher security levels. The current work will investigate a feature and a decision level fusion of 12 lead ECG signals.

4. **Propose system that is robust to commonly encountered cardiac diseases.** Although special experimentation has been carried out in previous works, to examine the effects of different factors on the recognition performance, issues related to cardiac arrhythmias have not yet been addressed. Among the central considerations of this thesis is to evaluate an identification framework which is robust to heart anomalies.

   Therefore the main novelty of the proposed methodology is the design of a recognition system which expands the applicability to arrhythmia settings as well. Malignant scenarios are taken into consideration and an arrhythmia screening algorithm is proposed to detect and discard abnormal electrocardiogram segments, which are not suitable for identity verification. This work is the first to address arrhythmia
related issues in security systems which operate on an ECG basis. Two criteria, related to the power distribution and the information theoretic complexity of autocorrelated ECG segments are defined to isolate arrhythmic ECG windows. This work has been partially presented in [21, 22] and submitted to [23, 24, 25, 26].

1.6 Thesis Outline

This thesis is organized as follows: Chapter 2 describes the operational modes of biometric systems as well as the requirements and error taxonomy. It also introduces some fundamental information about the electrocardiogram physiology, the acquisition procedure, noise artifacts and the effects of arrhythmia diseases in such signals. In addition, related works in this field are reported and analyzed in the same Chapter.

Chapter 3 introduces a new approach for identification and authentication. The analysis is carried out both for one lead signal and a fusion of signals from the 12-lead standard system. Different levels of information fusion are demonstrated, and the reasoning for the increased security levels is discussed.

Chapter 4 offers a literature review of the arrhythmia detection methodologies that have been suggested in the past, and which analyze either the autocorrelation or the complexity of finite series. The proposed framework for human identification in cardiac arrhythmia settings is introduced in the same Chapter.

Chapter 5 presents the simulation results of the described frameworks. First, the specifics of the electrocardiogram databases on which the methodologies have been tested are reported. The following sections describe the experimentation procedure and illustrate the recognition performance for each case. Finally, Chapter 6 presents comparisons of the current approach with other methodologies found in literature, and Chapter 7 concludes by presenting suggestions for future improvements of the techniques.
Chapter 2

The Electrocardiogram: A Medical Biometric

Electrocardiogram (ECG) signals reflect cardiac electrical activity over time. This chapter offers an introduction to ECG biometric systems, by analyzing three important aspects encountered in any recognition system: the requirements of the systems, different functionalities and the main taxonomy of errors. In addition, this chapter analyzes the previous works in the area while discussing the theoretical background for ECG signals processing.

2.1 ECG Biometric Systems

2.1.1 System Requirements

When evaluating recognition systems one should take specific parameters into consideration. The performance, vulnerability and acceptability are examples of issues which are present in biometric technologies. Performance is a dual factor that refers both to the recognition rates that the system can achieve, and to the speed of processing. Depending on the specifics of the investigated biometric characteristic, the identification
performance of a system can vary in terms of accuracy and time. For example, two dimensional feature spaces (i.e., fingerprint images) will most likely take longer to process compared to an one dimensional voice signal. Environmental parameters also play a great role on the accuracy of the applications. For example, if a voice recognizer operates in a noisy area, a drop in precision is expected. Storage requirements are also implied to affect the overall performance of the biometric system. This refers to the space needed for one compacted biometric template to be stored in the database, because it directly affects the search time.

Vulnerability to fraud is a crucial issue with recognition systems. Fraud can take place either with the application of falsified credentials or through mimicking someone’s behavioral attributes. Depending on the utilized biometric trait, some systems are more robust to fraudulent methodologies than others. For instance, brain activity (electroencephalogram) offers strict security with respect to possible falsification, compared to the fingerprint for which one can easily manufacture falsified substitutes using for instance latex.

The acceptability of a recognition system is also a direction of current biometric related investigations. This property indicates the degree to which the public acknowledges and consents to the operation of such systems. This is highly related to the biological characteristic that the system employs, meaning that people feel more comfortable providing certain biometric traits [7, 8, 10, 12].

2.1.2 Modes of Operation

Many of the current access authorization systems encompass traditional identification measures along with a biometric feature. Combining recognition modules increases the potential level of security in any application. Usually, for a subject to be identified, an ID card is presented, to make a claim concerning the identity of the subject. As a second step, the subject offers his/her biometrical information. The biometric template of the
claimed identity is loaded from a gallery set and compared to the collected one. If the
two biometric traits make a good match, the system grants access to the subject.

This description is the basis for the introduction of two fundamental modes of op-
eration for biometric based security systems. The major differentiation is the state of
knowledge in which the system stands regarding the identity of a subject. During au-
thentication (or verification), the subject claims an identity and the system decides on
the validity of the claim. The procedure is depicted in Figure 2.1. Authentication is an
one to one process that configures the degree of similarity between the claimed identity
and the collected one. Usually, based on a threshold on the distance of the two feature
vectors, the system decides either to accept the user’s claim or not.

![Authentication mode diagram](image)

Figure 2.1: Authentication mode diagram

On the other hand, the identification mode is a one to many process, where the
system has no prior information about the identity of the subject i.e., there are no means
to make a claim. A flow chart of this mode is depicted in 2.2. For identification to take
place, all the compact biometric templates have to be compared to the input one, for
the best possible match to be brought to light. This is considered a time consuming
mode, since the computational effort to determine the most appropriate identity is high.
However, specific applications such as surveillance, can only operate on the identification
mode [8, 10, 11].

The identification mode encapsulates two diacritical operations: positive and negative
identification. During positive recognition the objective is to prove that the collected
biometric samples are known to the system. More specific, it is of greater importance
to validate the enrollment of subject, rather than defining the exact identity. This applica-
tion prevents people from using the same identity. Negative recognition answers
the exact opposite question. The purpose is to prove that a subject has not been regis-

Figure 2.2: Identification mode diagram
tered in the database before. This kind of applications is useful in cases where service for example, is required to be offered only once to every subject, and the biometric is acquired to indicate whether an individual has been registered before or not [11]. Figure 2.3 summarizes the functionality modes encountered in biometric systems.

2.1.3 Taxonomy of Errors

Matching two biometric feature samples is not a straight-forward problem having only a positive or negative answer. Even though the biometric instances originate from the same subject, several factors intervene to increase the variance among multiple measurements. Conditions affecting the accuracy of a decision are usually related to environmental or physiological factors. For instance, scars on faces obtained after the initial enrollment may affect future face recognition performance. Noisy measurements might also be obtained due to device imperfections.

It is expected in biometric system analyses, that such weaknesses have great impact on the identification performance. Following this observation, the output of a biometric system is often a match score, revealing the degree of resemblance for a given pair.
Therefore, instead of making strict decisions, the system expresses the degree of certainty (or uncertainty) about a user’s identity. Match score is allowed to take the form of a probability or similarity distance, and authentication is then carried out by setting a threshold empirically.

In order to distinguish the types of errors that a biometric system can make, it is important to enumerate the main states of such a system.

1. **Identify an individual correctly**, which is measured in identification rates.
2. **Misidentify an enrolled individual**, which is measured in mis-identification rates.
3. For more complex systems, **authentication of legitimate subjects** is referred to as **sensitivity** and measured in authentication (or verification) rates.
4. **Deny identity authentication to a legitimate subject**, measured in false rejection rates (FRR).
5. **Deny identity authentication to intruders**, is referred to as **specificity** of the system.
6. **Authenticate intruders**, is measured in false acceptance rates (FAR).

Each of these measurements are computed as fractions of the desired set divided by the probe set. Specifically, the false acceptance and rejection statistics are computed as:

\[
\text{FAR} = \frac{\text{Number of falsely authenticated subjects}}{\text{Total number of intruders}} \quad (2.1)
\]

\[
\text{FRR} = \frac{\text{Number of rejected legitimate subjects}}{\text{Total number of subjects}} \quad (2.2)
\]

The equal error rate (EER) is also defined as the point in the FAR and FRR curves, where false acceptance is equal to false rejection i.e., \( EER = FAR = FRR \). The lower the equal error rate, the better the authentication performance of the system.
Depending on the employed similarity measure, the appearance of the FAR and FRR distribution can vary. When distance is used to associate two records, suggesting that the higher the score the less the resemblance, FAR is expected to increase as the distance threshold increases. This way, for a higher selection of the threshold, intruder authentication is rendered more likely. Correspondingly, the false rejection percentage is expected to fall as the distance threshold increases, because more legitimate subjects will be rejected. Obviously, there is a trade-off between false acceptance and rejection cases, and even though ideally a biometric system would demand both of them to be low, it is usually left up to the designer to decide on the specifics of the application.

2.2 Fundamentals of ECG

With ECG being the central consideration of this chapter, it is important before proceeding to the related applications, to first examine this versatile and important class of cardiac signals.

2.2.1 Physiology of ECG

For the electrocardiogram to be recorded, electrodes have to be attached on the surface of the human body in multiple configurations allowing to emphasize typical aspects of the heart cycle. The first ECG recorder apparatus was developed by the physiologist William Einthoven in the 20th century. Up to now, the traits of heart’s electrical behavior have been under immense analysis for clinical applications.

ECG signals reflect the variations around the cardiac electrical potential over time. The diversity in voltage is due to the action potentials of cardiac cells. The sinoatrial node (SA) is the pacemaker of the heart, which suggests its responsibility for the heart rate. The electrical activity is initiated when the SA node depolarizes. The electrical impulse travels with rhythmicity through the conduction system for sequential contraction and
relaxation to take place. The final destination is the atrioventricular (AV) node, which is responsible for delaying the conduction rate, to properly pump blood from the atria into the ventricles.

The electrocardiogram is a non periodic but highly repetitive signal that is mainly composed of three waves, describing the sequential depolarization and repolarization of the heart. Figure 2.4 shows the most significant components of an ECG signal i.e., the $P$ wave, $QRS$ complex and the $T$ wave.

The $P$ wave has usually positive polarity and a duration of approximately 120 ms. A $P$ wave mainly reflects the depolarization of the right and left atria. However, its absence is an alarm for ventricular ectopic focus. The amplitude of the $P$ wave is relatively small, because the atria muscle mass is limited.

The $QRS$ complex corresponds to the largest wave, describing the depolarization of right and left ventricles. In normal sinus rhythms, its duration mostly lies in the 70-110 ms range. The anatomic characteristics of the $QRS$ complex are highly related to the origin of the heart beat. Finally, the $T$ wave reflects a depolarization of the ventricles and is usually observed about 300 ms after the $QRS$ complex. However, its position relies on the heart rate, appearing closer to the $QRS$ complex at rapid rhythms.

The spectral characteristics of ECG waves are central to the application of signal
processing algorithms. A healthy $P$ wave is considered to contribute to the low frequency components of about 10-15 Hz, though much higher frequencies can be observed when ensemble averaging techniques are applied. On the other hand, a $QRS$ complex has a spectrum of corporately high frequencies due to its steep slopes. The spectral content of this complex is usually found in the 10-40 Hz band. Similar to the $P$ wave, the $QRS$ complex can also include high frequency components when ensemble averaging is applied [27].

Typically, the heart rate of a normal sinus rhythm is 60-100 beats/min. Nevertheless, this is not a constant and it is significantly affected by emotions such as stress and anxiety, or exercise, shock, body chemistry and so on. When the rhythm is below 60 beats/min, the state is referred to as sinus bradycardia. On the other hand, when the rhythm is above 100 beats/min sinus tachycardia is observed. In ECG monitoring, sinus tachycardias are normal situations that express heart’s response to mental stress. Other than the rhythm changes, the morphology of the ECG is not affected, therefore every $P$ wave is yet observed upright, followed by a $QRS$ complex and the $RR$ interval (time between successive $R$ peaks) remains constant [28].

2.2.2 ECG Signal Acquisition and Noise Artifacts

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.

As explained in the previous section, the $P$ wave is a low-amplitude low-frequency wave, while the $QRS$ complex is observed with larger amplitude and higher frequency variations. In addition, the following sources of noise and artifacts are encountered in ECG monitoring. The baseline wander, is the most common type of noise artifact,
referring to a low frequency interference in the ECG, which may originate from cardiovascular 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. In addition, present in practical ECG recordings are electrode motion artifacts, due to skin stretching that distort the impedance around the electrode. The main issue with these kind of noise artifacts, is that their spectral content overlaps that of the desired signal components. Finally, inherent physiologically induced artifacts such as the respiration or chest movements lead to variations in the heart rate but also to modifications of the beat morphology. However, this class of artifacts is hard to control and eliminate.

There is more than one method for ECG recording, such as orthogonal and synthesized leads. However, the most widely applied system is the standard 12-lead ECG. This system is determined by three main sets of lead orientations. The bipolar limb leads are usually
denoted as I, II, and III and they track the electrical potential of the heart when three electrodes are attached at the right and left hand along with the left leg.

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, as depicted in Figure 2.5. Finally, in lead III configuration, the potential measured is between the left leg and hand.

Following the electrode position as pictured in Figure 2.5, the limb leads are measured in the following combinations:

\[
I = V_{LH} - V_{RH} \quad (2.3)
\]
\[
II = V_{LL} - V_{RH} \quad (2.4)
\]
\[
III = V_{LL} - V_{LH} \quad (2.5)
\]

which suggest that having recorded any two of the bipolar limb lead signals, the third
one can be directly derived.

The augmented unipolar limb leads fill the $60^\circ$ gaps in the directions of the bipolar limb leads. Using the same electrodes the augmented unipolar are measured as:

\[
\begin{align*}
aVR &= V_{RH} - \frac{V_{LH} + V_{LL}}{2} \quad (2.6) \\
aVL &= V_{LH} - \frac{V_{RH} + V_{LL}}{2} \quad (2.7) \\
aVF &= V_{LL} - \frac{V_{LH} + V_{RH}}{2} \quad (2.8)
\end{align*}
\]

The third category of lead orientation involved in the conventional 12-lead system are the precordial leads (V1, V2, V3, V4, V5, V6). These signals are recorded with 6 electrodes attached successively on the left side of the chest, thus capturing more detailed information in the electrocardiogram [27, 29]. All lead orientations of the standard 12 lead ECG system are depicted in Figure 2.6.

### 2.2.3 ECG in Medical Settings

The electrocardiogram is considered as a substantial source of medical information, with enormous importance in clinical diagnosis. As mentioned earlier, the sinoatrial node (SA) is the natural pacemaker of heart’s activity. However, depolarization can also be initiated by another group of pacemaker cells e.g., by the autonomic foci: the atrial, junctional and ventricular foci. In such cases the electrocardiogram is forced to deviate from its normal forms. Other conduction abnormalities are also capable of causing disorders. These pathological conditions, referred to as arrhythmias are usually observed as abnormal heart rhythms.

One can observe several types of arrhythmias in ECG monitoring. The most commonly encountered types however, are the premature heart beats. These beats are not generated by the SA node, but from other cells of the myocardium. Depending on their origin, the geometrical characteristics of the resulting heart beats may or may not be
altered. In addition, the presence of the $P$ wave is ambiguous. Two common types of premature beats are the *atrial premature contraction* (APC) and the *premature ventricular contraction*.

When multiple focal points within the atria are responsible for an impulse, atrial arrhythmias are observed. *Atrial tachycardia* and *atrial flutter* are some examples of these types of arrhythmias. For this kind of pathology, an abnormal or absent $P$ wave can be observed, revealing the location of the ectopic focus.

Arrhythmias that originate in the ventricles are a type of fatal rhythm disturbances that require immediate assistance since they lead to cardiac arrest. Examples of this type of arrhythmias are the *ventricular tachycardia*, *ventricular fibrillation* and *ventricular flutter*. In the worst case, the ventricles produce several electrical signals at a rapid rate which the rest of the heart’s mechanism cannot follow [27].

### 2.3 ECG as a Biometric: Literature Survey

Analysis of the electrocardiogram signal has been in the spotlight of study in the clinical field for the past two decades. Although extensive research has been conducted for medical applications, ECGs have only lately been studied for biometric applications. Current state-of-art methods can be roughly categorized as fiducial points or non-fiducial based feature extraction approaches. Fiducials are essentially points of interest on a heart beat. For example, pulse boundaries, the $P$, $QRS$, $T$ wave locations or other attributes of an ECG signal can serve for feature extraction.

Among the earliest works in the area is Biel *et al.*'s [2] proposal for a fiducial feature extraction algorithm, which demonstrated for the first time the feasibility of using ECG signals for human identification. The standard 12 lead system was used to record ECG signals from 20 subjects of varying ages. Special experimentation was carried out to test variations of lead placement in terms of the exact location and the operators who place
the electrodes. The rational was that variations in electrode placement can usually lead to different medical diagnoses.

For the experimental setup an Siemens ECG apparatus was used to record cardiovascular signals and at the same time to extract fiducial based features. The 30 characteristics extracted from the electrocardiogram are widely used by physicians for clinical diagnosis (\(P\) wave onset and duration, \(QRS\) onset and duration, \(QRS\) wave deflection, \(ST\) segment slope or amplitude and so on). Since all 12 leads were recorded and analyzed for feature retrieval, in total 360 (\(12 \times 30\)) personalized attributes were obtained for every subject.

The next step towards identification was to eliminate features that do not exhibit large inter-class separability. The correlation matrix was calculated for each feature. It was observed that given a measured characteristic, all 12-leads show strong correlation. To reduce the dimensionality of the feature space, first, only information from the chest
and limb leads was analyzed. The chest lead features were completely excluded from further analysis. The reasoning is first because limb and chest signals are assessed not to exhibit high differences, and second because limb leads are less invasive in terms of acquisition procedure. Another set of reductions was performed by inspection of the correlation matrix. Eventually, 12 features were retained for identification. Figure 2.7 summarizes some of these features.

A multivariate analysis was performed through the SIMCA model, for classification. First, the principal component analysis (PCA) was applied to picture the variance in the experimental dataset. PCA decomposed the features into principal components and score vectors were created to decide the direction of the components. A 100% human identification rate was achieved following this procedure for 20 subjects.

This work introduced the possibility of using the electrocardiogram for identification. However, the feature extraction stage was performed with a specific apparatus, rather than standard signal processing techniques. This restricts the application of the proposed system to involve only features usually desired from physicians to diagnose a disease. In addition, the suggested methodology lacks automatic feature selection, since the chosen characteristics were obtained through inspection of the correlation matrix.

A few years after Biel et al.’s proposal, a thorough analysis of ECG special discriminative characteristics for identification was reported by Israel et al. [3]. An ECG based recognition system was introduced analyzing pulses’ temporal features only. The methodology involved three clearly separated stages: filtering, feature extraction and classification. The applied filter was designed to retain signal information in the band 1.1-40 Hz and discard the rest of the spectral components which are attributed to noise. Targeting to keep discriminative information while applying a stable filter over the gallery set, different filtering techniques were examined to conclude to a local averaging, spectral differencing and Fourier band-pass filter.

The features utilized by this system, were fiducial based, thus before feature extrac-
tion, fiducial detection was required. Having isolated heart beats, the location of the exact \( P \), \( R \) and \( T \) complexes were estimated as the maximum values of the areas surrounding them. Since the base positions of the complexes were needed as well, they were estimated through the location of the minimum radius of the curvature.

Features extracted for classification, were temporal distances between fiducial points and the \( R \) peak which was used to synchronize the heart beats as shown in Figure 2.8. However, in electrocardiograms temporal distances between fiducial points vary with the heart rate and therefore normalization was performed to scale pulses to unit length. As explained by the authors, this was a rather heuristic than cardiologically based technique. The selected features are depicted in Figure 2.9, and normalization was applied for all except for the \( RQ \) and \( RS \) distances. The \( QRS \) complex is less sensitive to heart rate changes and therefore, normalization of the corresponding distances is not required.

The dimensionality of the composed feature space was reduced using Wilk’s lamda. The final feature space included 12 attributes for classification. The performance was evaluated in subject and heart beat recognition rates, suggesting that a subject is identified based on majority voting of the corresponding heart beats. The system achieved 100% subject and 81% heartbeat recognition rate for 29 subjects.
The essence of Israel et al.’s work lies in the variety of different experiments that were conducted to determine factors that affect the identification performance. A first series of experimentation focused on examining the effects of changes in the electrode placement. It was observed, that neck and chest leads had a lot of similarities, and therefore it was feasible to train the proposed system with neck data while classifying on chest originating heart beats, and vice versa.

A second series of experiments was conducted to test the hypothesis that human recognition via the electrocardiogram is possible under any stress conditions. Seven tasks were designed to simulate possible psychological states of subjects (meditative, VR driving, reading and so on). Systematic analysis was then performed to compare the identification performance of systems trained with low stress exhibiting ECGs and tested on high stress pulses, and vice versa. In addition, experimentation among classes of the same level of stress was carried out. The subject identification rate achieved under any case was close to 100% which generally suggested that ECG based identification can achieve good performance in any anxiety conditions.
Israel et al.’s work is very important in terms of the variety of experiments conducted and hypotheses tested. Issues like anxiety and stress effects on the electrocardiogram were primarily addressed in [3]. Although the methodology offered automatic identification, the accuracy of the system is low due to insufficient representation of the feature extraction methods. Problems related to the fiducial points detection were not covered by the description for fiducial localization. In ECG monitoring, healthy heart beats with high degree of anomalies are common, not allowing accurate fiducial point localization, meaning that useful information might be thrown away.

In a later work by Israel et al. [30], worries about the effectiveness of a single biometric modality were expressed, to suggest a multi-modal biometric security system. The proposed framework integrated face and ECG information for human identification to address problems of spoofing and defeating security applications.

For the experimentation setup, ECG traces were obtained from 35 subjects. The signals were first filtered with a band-pass filter to eliminate noise effects in order to isolate and synchronize individual heart beats on an $R$ wave basis. The same normalization and feature extraction procedure described in [3] was applied on the recordings. In addition, the corresponding to [3] attributes were used for identification.

During the enrollment process, after recording electrocardiogram signals, images were taken from the subjects participating in the experimentation. The facial expressions and lightning conditions were not controlled. Facial data was then transformed via principal component analysis [31], and the selected eigen-vectors were associated to the gallery set using a Euclidean distance measure. The face recognition system was first trained on 500 images from the FERET database and then tested on facial traits from the 35 participating subjects.

When the two biometric characteristics were fused at the raw data level, 99% of the subjects were positively recognized. However, a decision based fusion resulted in 94% subject identification rate, and a voting fusion to 60%.
Figure 2.10: Fiducial based features used for classification in [4].

In 2002, Shen et al. [4] reported an ECG based recognition methodology which utilized seven fiducial based features mostly related to the QRS complex. The underlying idea was that this wave is less affected by varying heart rates, thus is appropriate for the design of a robust to stress conditions framework. The chosen for identification features are depicted in Figure 2.10.

The proposed methodology encapsulated two basic schemes. During a first step, template matching was used to compute the correlation coefficient among QRS complexes to find possible candidates. A decision based neural network (DBNN) was then used to strengthen the validation of the identity resulting from the first step.

For template matching, isolated QRS complexes were associated using a correlation coefficient measure. A threshold on that metric defined a good or a bad match. A value of 0.85 was chosen empirically, since in most cases, QRS waves belonging to the same subject exhibited substantial similarities in shape.

After the pre-screening process, heart beats were subjected to feature extraction (Figure 2.10) and the acquired attributes served as inputs to a decision based neural network. This well established machine learning method performed supervised learning and even-
tually classification among a selection of possible candidates highlighted by template matching. The DBNN was trained to encourage correct identification and punish mistakes.

When each of the techniques was tested independently on heart beats recorded from 20 subjects, a 95% and 80% subject recognition rate were achieved for the template matching and DBNN respectively. However, when the two modules were combined in one framework, the reported performance was 100%.

The combination of the two modules in [4] offers a strong recognizer in terms of subject identification rates. However, the interest was limited to only a few fiducial points, surrounding the $QRS$ complex, risking the discarding of useful discriminative information. In addition, the detection of $QRS$ waves automatically is rather difficult because healthy artifacts may distort heart beats in a way that two high magnitude peaks instead of one appear close to the complex. This fiducial based methodology would consider the pulse an outlier, which is not always the case.

In a later work by Shen et al. [32], the relationship between the electrocardiogram and the body mass index (BMI) was investigated. Lead I ECG signals of 168 healthy subjects were analyzed in this work. During pre-processing a band pass filter centered at 1-50 Hz was applied to eliminate baseline wander, dc shift and high frequency power line noise. The feature extraction procedure targeted to acquire temporal and amplitude attributes from isolated heart beats. The number of selected features was extended from [4] to include more characteristics outside the $QRS$ wave area. For example, $RP$ and $RT$ amplitudes were also included. After feature extraction, in order to analyze the effects of age, gender, height, weight and BMI, the records were first divided into groups for the two genders respectively, and correlation as well as linear regression analysis were carried out using SPSS 12.

It was reported that the selected characteristics describe 25.3% of variance with respect to the body mass index and only 6.5% of the age variability. Given that BMI has
a much greater impact on the ECG biometric traits, it was used for further analysis, to demonstrate that male subjects have larger ECG variability because of BMI than women.

Wubbeler et al. [33], have recently reported an ECG based human recognizer by extracting biometric features from a combination of Leads I, II and III i.e., a two dimensional heart vector also known as the characteristic of the electrocardiogram. The ECG signals were first pre-processed to remove noise artifacts. Low frequency baseline wander was addressed by subtracting a moving median, and powerline interferences with a low pass filter at 75 Hz.

To locate and extract pulses a thresholding procedure was applied. For classification, the distance between two heart vectors as well as their first and second temporal derivatives was calculated. A verification functionality was also designed by setting a threshold on the distances. Authenticated pairs were considered those which were adequately related, while in any other case, input signals were rejected.

The suggested false acceptance and rejection rates were 0.2% and 2.5% corresponding to a 2.8% equal error rate (EER). The subject recognition rate of the system when tested for human identification was 99 % for 74 subjects. Although high recognition rates were achieved during both the identification and authentication processes, the problem of pulse localization and synchroization was not addressed. Features were heart beat vectors, and not just distances among fiducial points. However, determining pulses’ boundaries is not a very accurate process because of different and unexpected changes in the heart rate.

Wang et al. [34], investigated the use of analytic and appearance based features of heart beats in ECG based identification. The three clearly separated steps of the framework involved pre-processing, feature extraction and classification, to obtain the desired identity. During pre-processing, signals from 13 subjects were filtered using a Butterworth bandpass filter centered at 1 - 40 Hz. The filtered signals where then subjected to fiducial detection using the QRS detector ECGPUWAVE. Outliers were removed through a thresholding procedure, and the heart beats were aligned by the R peak position.
The feature extraction scheme, suggested both analytic and appearance based attributes for identification. The analytic feature extraction procedure is similar to [3]. In total, 15 time distance measures were acquired as in [3], and 6 amplitude differences of fiducial points: the $PL'$, $RS$, $PQ$, $TS$, $RQ$ and $TT'$ distances. For appearance based feature extraction, the principal component analysis technique was evaluated on ECG heart beats, to capture the principal features of the waveforms while reducing the dimensionality of the space. Like [3], further feature selection was carried out based on Wilk's lambda, in SPSS. Classification consisted the final stage of the application, where the feature vectors were compared via the Euclidean distance and clustering was performed based on nearest neighbor and nearest centre techniques.

Using analytic features only, a 74.45% heart beat recognition rate was achieved. However, when the appearance originating features were integrated with the analytic ones for classification, the heart beat recognition rate reached 92.4%. Another set of experiments was conducted, to compare the application of linear discriminant and principal component analyses for dimensionality reduction of the feature space. The two techniques were employed for appearance feature analysis only. It was shown that appearance based features, are a better tool for human identification. The corresponding heart beat recognition rates were 95.55% and 93.01% for PCA and LDA respectively. In addition, PCA and LDA were combined in two mixing schemes: simple integration of the feature vectors and hierarchical integration, which offered the benefit of cutting down the possible identities for a test heart beat. The latter integration reported 98.90% and 100% heart beat and subject identification performance respectively.

Although in this work the interest was confined in individual heart beat information, a major contribution was the comparison the identification performance of systems which depend on fiducial features only as opposed to employing appearance information. A substantial difference in the recognition rates was illustrated using analytic features compared to appearance based attributes. However, the localization of heart beats, by ac-
accurate boundaries detection was still an open problem, that could affect the performance when applied on an ECG database with larger variations in waveform anomalies.

In 2004, Palaniappan et al. [35], analyzed lead I electrocardiogram recordings from 10 subjects of the MIT-BIH database for biometric use. A filter was used to remove low frequency noise and the 60 Hz interference, and an algorithm was then applied to detect \( QRS \) complexes. The features employed in classification were mostly related to that wave: \( R-R \) interval, \( R \) amplitude, \( QRS \) interval, \( QR \), \( RS \) amplitudes and a factor picturing the complexity of the \( QRS \) wave.

The six features served as inputs for two neural network architectures. A multilayer perceptron using backpropagation (MLP-BP) was chosen because of its ability to produce accurate results and to generalize. This network was designed to have only one hidden layer, and binary outputs for every class. The simplified fuzzy ARTMAP (SFA) was also used for classification because of its incremental abilities combined with high speed learning time. Input characteristics of the SFA were assigned to specific category nodes which were linked to a class-identity.

Several architectures for the neural nets were tested for their identification performance. Varying factors were the number of hidden nodes and the vigilance parameter. On average, the MLP-BP network achieved 96.17\% recognition rate and the SFA 83.61\%. When designing identification systems for real time applications it is prominent to take into consideration the computational effort for an individual to be recognized. Although, neural networks offer high accuracy in classification problems, updates of the gallery set (in case of new registrations) might last for an inconvenient amount of time, depending on the system. Furthermore, in [35] features were chosen to embed \( QRS \) wave information only, risking once more to discard important discriminative information.

Another work on ECG analysis for human identification was reported by Kyoso et al. [36]. The purpose of the investigation discussed in [36] was to determine fiducial based attributes of individual heart beats that primarily affect the recognition performance.
The features under examination were: the $P$ wave and $PQ$, $QRS$, $QT$ intervals duration. To detect the desired attributes, the second order derivative of the signals was used to emphasize the location of the fiducials.

Mahalanobis distance was applied as a similarity measure between feature vectors. Aiming to find the feature combination that offers the highest recognition performance, the effectiveness of the method was evaluated for a combination of two attributes at a time. When analysis was carried out on electrocardiograms from 9 subjects, it was demonstrated that the $P$ wave has poor discriminatory ability compared to the rest of the features. However, in this work, a limited number of subjects was analyzed and the examined characteristics were restricted to the basic time durations of ECG’s inherent waves.

In a later work by Kyoso [37], the examined features described in [36], were extended to include heart beat amplitude attributes from 21 subjects. To address false acceptance problems that limited the accuracy of the method, a threshold on the Mahalanobis distance was selected to define good or poor matches. The threshold value was chosen based on the mean and standard deviation of the calculated distances.

From the description in [37], false acceptance is a critical problem for systems working in the identification mode, since there is no means to reassure that a matched heart beat is indeed registered in the gallery set. Using thresholds on the similarity measure, reduces the acceptance of unregistered subjects. There is however a trade-off with legitimate subjects which are not identified. In [37], the false rejection rate achieved was not reported so as to allow fair comparisons.

Ogawa et al. [38] proposed a system for ECG based identification applied in home health monitoring. The data used in this study was obtained from a bathtub while the subject was taking a bath. A wavelet transform was applied on the ECG waveforms to retain only two levels of the wavelet coefficients. The reduced ECG traces served as inputs to a neural network. Back propagation was used for training and each output
was assigned to a class. The 6 level coefficients were demonstrated to perform higher recognition rates than the 7 level ones. The corresponding identification rate for level 6 was 91.6% and for level 7 coefficients 63.2%. In a later work by Ogawa et al. [39], the same approach was described using a three layer neural network for classification of wavelet coefficients. The later methodology was suggested for long-term experiments, to offer a non invasive data acquisition technique that would identify the person from the collected data.

Chan et al. [40], analyzed electrocardiogram traces recorded from 50 subjects during three sessions. Feature extraction was carried out on a PQRST wave basis. A backward differences algorithm was employed to isolate such waveforms from raw ECG signals. Data acquired from the first session were used to build a gallery set, and the next sessions’ recordings were employed for testing purposes.

The features used for classification in [41] are essentially two appearance based attributes i.e., the correlation coefficient between two pulses and the wavelet distance measure. To make a decision, the identity that offered the highest numerical value for the correlation coefficient and the lowest for the wavelet distance was chosen as the best match, given an input heart beat. The identification rates achieved with these two features was 90.08%.

The detection of fiducial points increases the complexity of ECG based identifiers. In addition, there are no definite rules or techniques for localizing wave boundaries, especially in varying heart rates or ECG traces that exhibit anomalies. Motivated by these difficulties, methodologies have been suggested for non fiducial based feature extraction. Generally, the employment of windowing techniques, as a precursor to the feature extraction, has been found to overcome important problems related to pulse localization and synchronization in fiducial points based methodologies.

Plataniotis et al. [1], are among the earliest to report a non-fiducial based technique for ECG identification. The essence of the proposed methodology, was that ECG windows
were used for feature extraction instead of individual heart beats. The autocorrelation of ECG segments was computed for its ability to capture essential attributes of the heart beats, eliminating the need for fiducial points detection.

It was demonstrated in [1] that the autocorrelation of windowed ECG signals, embeds highly discriminative information in a population. However, depending on the original sampling frequency of the signal, the dimensionality of a segment from the autocorrelation, was considerably high for cost efficient applications. To reduce the dimensionality and retain only useful for recognition characteristics, the discrete cosine transform (DCT) was applied.

Thanks to the energy compaction property of DCT, the autocorrelation samples were translated into power coefficients. Near zero DCT coefficients were discarded and classification was carried out on the remaining frequency information. In this method, the similarity measures used to associate records from different subjects, were the normalized Euclidean and Gaussian log-likelihood distances. The method was tested on 14 subjects, for which multiple ECG recordings were available, acquired a few years apart. The identification performance, was 100% for window and subject based recognition.

Wang et al. [21], demonstrated a systematic analysis of ECG signals for methodologies with and without fiducial points detection. A fiducial based framework that combined analytic and appearance attributes as in [34], was illustrated and compared to a window based approach for feature extraction. The proposed techniques were tested on two public electrocardiogram databases. It was demonstrated that the non-fiducial points method can achieve high recognition accuracy, compared to the fiducial one.

2.4 System application

The practical application of the systems that are described in this thesis, are relevant to the corresponding biometric operational mode. An identification based system, that
<table>
<thead>
<tr>
<th>Method</th>
<th>Principle</th>
<th>Subject Recognition Rate</th>
<th>Window / Heart beat Recognition Rate</th>
<th>Number of Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biel et. al [2]</td>
<td>Use a SIEMENS ECG apparatus to record medical diagnostic features for classification</td>
<td>100%</td>
<td>Not reported</td>
<td>20</td>
</tr>
<tr>
<td>Israel et. al [3]</td>
<td>Analyze fiducial based temporal features under various stress conditions</td>
<td>100%</td>
<td>82%</td>
<td>29</td>
</tr>
<tr>
<td>Israel et. al [30]</td>
<td>Fuse ECG and face information in the same biometric system</td>
<td>94%</td>
<td>No reported</td>
<td>35</td>
</tr>
<tr>
<td>Shen et. al [4]</td>
<td>Use template matching and neural networks to classify QRS complex related characteristics</td>
<td>100%</td>
<td>Not reported</td>
<td>20</td>
</tr>
<tr>
<td>Shen et. al [32]</td>
<td>Apply correlation analysis and linear regression to investigate the relationship between BMI and ECG features</td>
<td>95.3%</td>
<td>Not reported</td>
<td>168</td>
</tr>
<tr>
<td>Wubbeler et. al [33]</td>
<td>Utilize the characteristic vector of the electrocardiogram for fiducial based feature extraction out of the QRS complex</td>
<td>99%</td>
<td>Not reported</td>
<td>74</td>
</tr>
<tr>
<td>Wang et. al [34]</td>
<td>Merge and compose analytic and appearance based features for classification</td>
<td>100%</td>
<td>98.9%</td>
<td>13</td>
</tr>
<tr>
<td>Palaniappan et al. [35]</td>
<td>Use two different neural network architectures for classification of six QRS wave related features</td>
<td>96.17%</td>
<td>Not reported</td>
<td>10</td>
</tr>
<tr>
<td>Kyoso et. al [36]</td>
<td>Analyzed four fiducial based features from heart beats, to determine those with greater impact on the identification performance</td>
<td>99.6%</td>
<td>Not reported</td>
<td>9</td>
</tr>
<tr>
<td>Kyoso [37]</td>
<td>Address false acceptance problems using distance thresholds</td>
<td>100%</td>
<td>Not reported</td>
<td>21</td>
</tr>
<tr>
<td>Ogawa et. al [38]</td>
<td>Acquire ECG data from a bathtub and analyze them using wavelets</td>
<td>91.6%</td>
<td>Not reported</td>
<td>13</td>
</tr>
<tr>
<td>Chan et. al [40]</td>
<td>Use the correlation coefficient and a wavelet distance measure as a feature vector</td>
<td>90.08%</td>
<td>Not reported</td>
<td>50</td>
</tr>
<tr>
<td>Plataniotis et. al [1]</td>
<td>Analyze the autocorrelation of ECGs for feature extraction and apply DCT for dimensionality reduction</td>
<td>100%</td>
<td>100%</td>
<td>14</td>
</tr>
<tr>
<td>Wang et. al [21]</td>
<td>Compare fiducial based and non fiducial methodologies for ECG identification</td>
<td>100%</td>
<td>99.43%</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 2.1: Summary of related to ECG based recognition works
aims to find a match between the collected biometric and the corresponding ones that are stored in a gallery set, can be applied for computer authorization or criminal investigation. The electrocardiogram in such a case can be quickly acquired through the fists of the subject (Lead I signal), this way not being invasive to the users.

Authentication operations target to find if the collected biometric and one which corresponds to the identity claimed by the subject, make an acceptable match or not. Such system can be easily applied in access or border control, where the identity claim can be made through a biometric trait stored in a magnetic card or passport.

Possible factors affecting the recording quality are most often an unexpected body movement, which introduces noise to the recorded signals. ECG is envisioned for automated applications where the presence of trained personnel is not required. Body movement and respiration cause baseline wander artifacts on the signals. This kind of noise is usually observed below 1 Hz and can be filtered. However, in the extreme case of spectral overlap with information contributed by the $P$ wave, special assistance is required.

Biometric applications often involve an extra stage, referred to as quality check, the purpose of which is to clarify whether the recorded biometric template is employable for the recognition application or not.
Chapter 3

ECG Analysis for Identification and Authentication

As mentioned before, biometric based security systems can operate in essentially two modes: Identification and Authentication (or verification). This chapter introduces two novel techniques for human recognition via the electrocardiogram without fiducial points detection. The target is to either identify an individual among a set of subjects, or to validate an individual’s claim about his/her identity.

3.1 Identifying Individuals

The standard 12-lead ECG system offers a wealth of information about the electrical activity of an individual’s heart. Merging features from 12 electrocardiogram traits has the substantial benefit of higher accuracy degree, since more distinctive characteristics are involved in the analysis. However, there is a prominent restriction in the application of such a system. Attaching more electrodes on the body, increases the invasiveness of the application. This section presents two ECG identification techniques, based on either one or 12 lead signals.
3.1.1 One lead ECG Identification

Human identification is essentially a pattern recognition problem involving three principal steps: preprocessing, feature extraction and classification. Preprocessing can be regarded as a noise and artifact removal step. Feature extraction is performed directly on the autocorrelation of ECG windows to form distinctive personalized signatures for every subject. Following any other pattern recognition problem, classification among a gallery set constitutes the last step of the identification process.

**Pre-processing.** The ECG data in raw format contains a lot of noise which has to be eliminated. As discussed earlier, the most commonly met types of noise in ECGs are the baseline wander and the powerline interference. Baseline wander is caused by low frequency components that force the signal to extend away from the isoelectric line. The source of this kind of artifacts is respiration, body movement or inadequate electrode attachment. Furthermore, powerline interference is generated by poor grounding or conflicts with nearby devices.

![Figure 3.1: A) Zoomed Fourier frequency view of a raw ECG signal. B) Same view of the signal after filtering](image-url)
Figure 3.2: A) Raw ECG signal from the PTB database digitized at 128 Hz. B) Fourier frequency domain of the same signal

Figure 3.3: A) Filtered ECG from the PTB database. B) Fourier frequency domain of the same signal

Filters with linear and non-linear structures have been designed to remove noise artifacts from ECG signals. However, noise due to muscle activity is very hard to eliminate because of its spectral overlap with the desired wave information. Ensemble averaging techniques have been used for muscle noise reduction on synchronized heart beats [27].
Even though the evaluation ECG filtering techniques is not the main focus of this thesis, without filtering, the feature extraction procedure is not feasible and the identification precision is low. To reduce noise effects, a Butterworth band pass filter of order 4 is applied in the current experimentation. The cutoff frequencies of the filter are 1 Hz - 40 Hz based on empirical results.

The rational behind the selection of the filter is that it offers a sharp edge at the low frequency area as observed in Figure 3.1.A. This allows for significant information after the cutoff of 1 Hz to be retained. Figure 3.1.B illustrates a zoomed aspect of the spectrum after filtering. Most of the low frequency noisy area is discarded while information right after the 1 Hz cutoff point is partially attenuated.

Figures 3.2.A and 3.2.B are time and frequency domain plots of an ECG signal from the PTB database along with the frequency response of the applied filter. In addition, Figures 3.3.A and 3.3.B picture the time and frequency representation of the same ECG recording after noise removal. It can be seen that after the 40 Hz frequency point most of the noise is eliminated. Figure 3.4 pictures an ECG signal from the PTB database (with a sampling frequency at 128 Hz) before and after filtering. It can be clearly observed that the low frequency baseline wander is reduced and the filtered signals extends on the isoelectric line.

Additionally, windowing is performed on the filtered ECG signals with no overlapping. A window is allowed to blindly cut the electrocardiogram even in the middle of a pulse. The only restriction concerning the length of the window is that it has to be larger than the average heart rate so that multiple heart beats are included.

**Feature Extraction.** In the bibliography, the most commonly met type of features for human identification, are morphological characteristics of single heart beats. It has been suggested [2, 3, 30, 4, 32, 34, 33] that amplitude and normalized time distances between successive fiducial points constitute unique patterns for different individuals. However,
in these applications it is implied that fiducial points can be successfully detected. The algorithms which perform such a task are built solely for medical applications, where the exact wave boundaries are not needed to diagnose abnormalities. This is not the case for human recognition and authentication systems, where accuracy is demanded in order to further analyze patterns. Furthermore, there is no universally acknowledged rule about the exact location of wave boundaries, which could constitute the basis of fiducial detectors [42]. Other than that, in ECG monitoring, several kinds of anomalies are met, some of which affect the morphology of the signal a lot, making the boundaries of the waves hard to localize.

To address this problem, non fiducial points methods can be adopted for feature extraction. The autocorrelation (AC) has been reported [1, 21], to embed significant variances among subjects. Autocorrelation, in general, captures the repetitive property of the electrocardiogram, and its shape is primarily dependent on the $P$, $QRS$ and $T$ waves. Analyzing AC, non random patterns associated with distinctive characteristics of a person’s ECG can be brought to light.
Figure 3.5: Normalized autocorrelation of ECG windows from six subjects of the PTB database. Two records are available for every subject, recorded at different times. Sequences from the same record are shown in the same shade.

The syllogism behind autocorrelation with respect to fiducial points detection, is that it blends into a sequence of sums of products, electrocardiogram samples that would otherwise need to be subjected to fiducial detection. In addition, AC allows a shift invariant representation of similarity features over multiple cycles. The normalized autocorrelation can be evaluated as:

$$\hat{R}_{xx}[m] = \frac{\sum_{i=0}^{N-|m|-1} x[i]x[i + m]}{\hat{R}_{xx}[0]}$$  (3.1)

where $x[i]$ is the windowed ECG for $i = 0, 1, \ldots (N - |m|1)$, and $x[i + m]$ is the time shifted version of the windowed ECG with a time lag of $m = 0, 1, \ldots (M - 1)$; $M \ll N$. Even though the major contributors to the AC are the three characteristic waves, normalization is required because large variations in amplitudes appear, even among the windows of the same subject.

The expectations for the autocorrelation to embed distinctive characteristics for every
subject, and to capture similarities between signals recorded at different times, are confirmed by the AC plots of Figure 3.5. An AC vector can be used directly for classification. However, depending on the sampling frequency of the ECGs, the dimensionality of an autocorrelation window, can be considerably high. For this reason, Linear Discriminant Analysis (LDA) is recruited for dimensionality reduction before the classification scheme. We refer to this method as AC/LDA.

LDA is a well-known statistical method for feature extraction. Supervised learning is performed in a transform domain so that eventually feature’s dimensionality is reduced and the classes are better distinguished [43]. The methodology description follows the above mentioned definitions:

- Let $U$ be the number of classes i.e., the number of subjects registered in the system.
- Let $U_i$ be the number of autocorrelation windows for a subject (class) $i$, where $i = 1...U$.
- We define as $z_{ij}$ an AC window $j$, where $i = 1...U_i$ and $i = 1...U$.
- Let $Z_i$ be the set of AC windows for a subject (class) $i$, defined as $Z_i = \{z_{ij}\}_{j=1}^{U_i}$.
- Let $Z$ be a training set consisting of all AC windows of all subjects i.e., $Z = \{Z_i\}_{i=1}^U$.

Given these definitions, a set of $K$ feature basis vectors $\{\psi_m\}_{m=1}^K$ can be estimated by maximizing Fisher’s ratio. Maximizing this ratio is equivalent to solving the following eigenvalue problem:

$$
\psi = \arg \max_\psi \frac{|\psi^T S_b \psi|}{|\psi^T S_w \psi|}
$$

where $\psi = [\psi_1, ..., \psi_K]$, and $S_b$ and $S_w$ are the between and within class scatter matrices respectively, which can be computed as follows:

$$
S_b = \frac{1}{N} \sum_{i=1}^U U_i (z_i - \bar{z})(z_i - \bar{z})^T
$$
Chapter 3. ECG Analysis for Identification and Authentication

\[ S_w = \frac{1}{N} \sum_{i=1}^{U_i} \sum_{j=1}^{U_i} (z_{ij} - \bar{z}_i)(z_{ij} - \bar{z}_i)^T \]  (3.4)

where \( \bar{z}_i = \frac{1}{U_i} \sum_{j=1}^{U_i} z_{ij} \) is the mean of class \( Z_i \) and \( N \) is the total number of windows and 
\( N = \sum_{i=1}^{U} U_i \).

Maximizing Fisher’s ratio is equivalent to forcing large separation between projected windows of different subjects, and small variance between windows of the same subject. Linear discriminant analysis finds \( \psi \) as the \( K \) most significant eigenvectors of \((S_w)^{-1}S_b\) which correspond to the first \( K \) largest eigenvalues. A test input window \( z \) is subjected to the linear projection \( y = \psi^T z \), prior to classification [43].

The dimensionality reduction can be regarded as:

1. Originally, the dimensionality of an autocorrelation vector \( z_{ij} \) belonging to subject \( i \), is \((M \times 1)\).

2. The size of the between and within subject scatter matrices, \( S_b \) and \( S_w \) is \((M \times M)\)

3. When calculating \( \psi \), only \( K < M \) eigenvectors of the \((S_w)^{-1}S_b\) are retained.

4. The size of \( \psi \) is then \((M \times K)\)

5. With the final projection: \( y = \psi^T z \), the new AC test vector \( z \) of dimensionality \((M \times 1)\) is linearly transformed into \( y \) of dimensionality \((K \times 1)\).

Template Matching and Classification. A central consideration in our development of a computationally efficient classification scheme is to transform a large-class number problem into a small-class number problem. The motivation behind Template Matching (TM) is that it reduces significantly the possible number of classes and eventually classification is carried out in a smaller scope. The efficiency of the system is subsequently improved due to pruning of the search space. In other words, for any given input \( z \),
classification is performed among $N_2$ groups that are certified to be possible subjects instead of the total number of subjects in the gallery set $N_1$ ($N_2 < N_1$).

Template Matching with the correlation coefficient (CC) is performed on the auto-correlated ECG signals, before dimensionality reduction. The correlation coefficient is a statistical criterion, showing the degree of similarity of any two signals. It takes values in $[-1, 1]$ with 1 demonstrating a prefect match, 0 non related signals and -1 an inverse relationship. However, this measure is not sufficient to perform identification and it is thus employed as a pre-classification scheme which reduces significantly the number of candidate classes among which classification is then performed.

The process of Template Matching with the correlation coefficient serves also as an intruder detector. Unwelcome visitors appear often in current security systems claiming a fake identity which does not exist in the database. An efficient and secure biometric based identification system has to be able to detect an illegal entrance.

Setting a threshold for the correlation coefficient experimentally and not allowing classification of individuals that are below this threshold, reduces the possibility of an individual to illegally penetrate the system substantially. The hierarchical method that we propose is graphically depicted in Figure 3.6. Experimental results on human identification based on this framework demonstrate very accurate recognition. In addition, experimentation on intruder scenarios exhibit high effectiveness in detecting them.

For clustering, a similarity measure based on the normalized Euclidean distance, and the nearest neighbor (NN) are recruited. The normalized Euclidean distance between two feature vectors $z_1$ and $z_2$ is defined as:
\begin{equation}
D(z_1, z_2) = \frac{1}{V} \sqrt{(z_1 - z_2)^T(z_1 - z_2)}
\end{equation}

where $V$ is the dimensionality of the feature vectors. For a $U$ class problem, LDA can reduce the dimensionality of the feature space to $U-1$ due to the fact that the rank of the between class scatter matrix cannot go beyond $U-1$. Factor $V$ is there to assure fair comparisons for different dimensions that $z$ might have.

### 3.1.2 12 lead ECG Identification

Information fusion is widely applied in multi-modal biometric systems, i.e., systems which take advantage of more than one biometric trait. For instance, [30] suggests that face characteristics can be combined with the electrocardiogram to increase the security levels of current approaches. When data is combined in the right framework, the precision of biometric based systems can be augmented.

We will demonstrate in this section different levels of fusion of ECG information obtained from different leads. The motivation behind this implementation is that ECG windows which are recorded at the exact same time from different electrode orientations, can be combined to increase the distinctive information for every subject.

Fusion can be performed in three different levels: the raw-data level, the feature level and the decision level. Combining raw information means direct fusion of different sources of the same trait. In the electrocardiogram case for example, one could average the ECG signals from different leads. However there is no practical reason why such a process would offer more substantial information for our application.

Fusion at the feature extraction level can be performed in two ways. Data collected from different biometric traits or different aspects of the same trait can be concatenated in one feature vector with a higher dimensionality, provided that these features are in the same type of measurement scale [8]. Furthermore, feature level fusion also includes combination of scores that are produced from different classifiers, each tested on a feature
vector from different sensor. In other words, every classifier is trained on inputs from specific sensors, offering a distance (or score) measure when tested. Classifier fusion in that case means that scores are combined to make a final decision.

The third type of fusion is decision based. Different classifiers make decisions about specific feature vectors and the final decision is a result of a structured synthesis (such as majority voting). An extensive description of methods for combining the outcomes of different classifiers can be found in [44].

Features obtained when the AC/LDA method is applied on ECG segments from different leads, are combined at the decision level, based on variants of the voting principle. Specifically for our problem, 12 classifiers are trained, each with signals recorded from the corresponding lead. We denote that classifier \( k \) is tested on a input \( x \) as \( cl(x)^k \). The final decision where all classifiers are fused is noted as \( CL(x) \). If the system has \( N \) registered subjects which can be identified, then every classifier makes a decision from the set \( \Omega = 1, 2, \ldots N \). The following characteristic function is introduced to simplify the description on the fusion methodology:

\[
\Phi_k(x \in C_i) = \begin{cases} 
1, & \text{if } i \in \Omega \text{ and } cl(x)^k = i \\
0, & \text{otherwise}
\end{cases}
\]  

(3.6)

We introduce here four rules that guide the decision fusion of different classifiers.

- **Case 1:**
  
  This rule is used to make conservative decisions. Voting takes place, but the system rejects \( (R) \) the input unless all classifiers agree on the same cluster. The final decision \( CL(x) \) is given from:

\[
CL(x) = \begin{cases} 
 j, & \text{if } j \in \Omega \text{ and } \sum_{k=1}^{12} \Phi_k(x \in C_j) = 12 \\
 R, & \text{otherwise}
\end{cases}
\]  

(3.7)

- **Case 2:**
  
  A less conservative rule for decision synthesis can be given from:
Chapter 3. ECG Analysis for Identification and Authentication

\[ CL(x) = \begin{cases} 
  j, & \text{if } \Psi(x, j) = \max_i \Psi(x, i) > 6 \\
  & \text{and } j, i \in \Omega \\
  R, & \text{otherwise} 
\end{cases} \quad (3.8) \]

where \( \Psi(x, j) = \sum_{k=1}^{12} \Phi_k(x \in C_j) \). Here an input \( x \) is identified as subject \( j \) if more than half of the classifiers agree on that (majority voting).

- **Case 3**:

  This case is a generalization of case 2, to accommodate less or more conservative decision fusions, based on the parameter \( \alpha \) which takes values in \((0,1]\). The final estimation for the subject is given from:

\[ CL(x) = \begin{cases} 
  j, & \text{if } \Psi(x, j) = \max_i \Psi(x, i) > \alpha \cdot 12 \\
  & \text{and } j, i \in \Omega \\
  R, & \text{otherwise} 
\end{cases} \quad (3.9) \]

For \( \alpha=0.5 \) cases 2 and 3 are equivalent, so this rule can be regarded as a generalization of majority voting.

- **Case 4**:

  To assist situations of equal votes for two or more classes, or cases where the final class is chosen with votes which are not considerably higher than the second maximal, the final decision can be made through:

\[ CL(x) = \begin{cases} 
  j, & \text{if } \Psi(x, j) = \max_1 \\
  & \text{and } \max_1 - \max_2 \geq \alpha \cdot 12 \\
  R, & \text{otherwise} 
\end{cases} \quad (3.10) \]
where

\[ \max_1 = \max_i \Psi(x, i) \] (3.11)

\[ \max_2 = \max_{i \neq j} \Psi(x, i) \] (3.12)

When \( \alpha \) is big, this rule becomes very conservative, since in order to assign an input to a class, it must be supported by many classifiers and not to have opponents [44].

### 3.2 Authenticating Individuals

Identity authentication is a very critical process performed by biometric systems other than identification. The major difference between identification and verification is the presence or absence of an a-priori claim regarding an individual’s identity. During the identification mode the purpose is to find the best match between the subject’s biometric characteristics and all individuals stored in the gallery set. However, during the validation procedure the person to be verified claims an identity and the system decides on the validity of the claim.

In the present work, authentication is accomplished by setting a threshold with respect to the distance between the enrollees and an input subject. When applying linear discriminant analysis the similarity measure employed is the Euclidean distance, and a threshold is selected for that metric. In cases where the resemblance of a pair is unacceptable (higher in distance than allowed) the system denies the validation of the so claimed identity. On the other hand, an individual is positively authenticated when there is an adequately small distance between the paired match.

Linear discriminant analysis offers feature compaction and higher class separability. However, applying supervised techniques during the authentication mode increases the computational effort and validation time of the system. Authenticating is a one to one process, and class-dependent methodologies would force the system to stay out of
operation for some time, while updates would take place for a new enrollee. On the other
hand, unsupervised learning makes allowance for new registrations to happen without
affecting the on-going authentication procedure.

A well known unsupervised technique to provide optimal projection in lower dimen-
sions, is the Principal Component Analysis (PCA). PCA does not engage class informa-
tion, but manages to retain useful data (principal components) and eliminate redundan-
cies.

PCA is an unsupervised learning technique that provides an optimal representation
of an input in a lower dimensional space, in terms of the least mean square. Following
the description for the LDA, given a training set \( Z = \{\mathcal{Z}_i\}_{i=1}^U \), containing \( U \) classes
with each class \( U_i = \{z_{ij}\}_{j=1}^{U_i} \) consisting of \( U_i \) autocorrelated ECG windows \( z_{ij} \), a total
of \( N = \sum_{i=1}^U U_i \) AC windows, the PCA is applied to the training set \( Z \) to find the \( L \)
eigenvectors of the covariance matrix:

\[
S_{\text{cov}} = \frac{1}{N} \sum_{i=1}^U \sum_{j=1}^{U_i} (z_{ij} - \bar{z})(z_{ij} - \bar{z})^T
\]

(3.13)

where \( \bar{z} = \frac{1}{N} \sum_{i=1}^C \sum_{j=1}^{U_i} z_{ij} \) is the average of the ensemble. The \( L \) eigenvectors are the
first \( L (\leq N) \) eigenvectors corresponding to the largest eigenvalues, denoted as \( \Psi \). The
original heartbeat is transformed to the \( L \)-dimension subspace by a linear mapping:

\[
y_{ij} = \Psi^T(z_{ij} - \bar{z})
\]

(3.14)

where the basis vectors \( \Psi \) are orthonormal. The subsequent classification of autocorre-
lation patterns can then be performed in the transformed space [43].

When PCA is applied for authentication, the cosine distance is used to associate input
ECG windows and those belonging to the target identity. The Euclidean distance can be
used instead, but test simulations showed that a similarity measure associating the angles
between different subjects performs better (see Chapter 5). However, experimentation
results for authentication with Euclidean distance will be also presented.
The cosine distance can be estimated as:

\[ D(z_1, z_2) = 1 - \frac{z_1 \cdot z_2}{\|z_1\| \|z_2\|} \quad (3.15) \]

A threshold on this measure will lead to validation or rejection decisions. It is expected for LDA to outperform PCA, because class information is not embedded in the principal component calculations. However, the waiting time saved with PCA is important for real time applications. This is because, LDA needs more than one electrocardiogram recordings to enroll a new subject and update the system, which is not the case with PCA.

### 3.3 Chapter Summary

In this chapter, the proposed methodologies for healthy subject recognition via ECG were described. Two applications have been reported, to accommodate different types of biometric systems’ operational modes i.e., identification and authentication. Human identification using one lead information can be performed on windows of the electrocardiogram to avoid fiducial points detection. The autocorrelation of ECG segments embeds highly discriminative information in a population. The dimensionality of the AC feature vector was advised to be reduced using a linear discriminant analysis, which does not only allow representation into lower dimensions, but also makes classes more separable.

In addition, this chapter suggested different fusion schemes for 12 lead ECG signal integration. During feature based fusion, feature vectors for every subject were concatenated. A decision based fusion has also been demonstrated, in order to raise current security levels. This multi-modal system is designed to make decisions based on a more or less conservative rule.

When the biometric identification system operates in the authentication mode, the proposed framework adopts a technique that validates an identity claim. Based once
more on the autocorrelation of signals, the principal component analysis was proposed to be applied for dimensionality reduction.
Chapter 4

Robust Identification in Cardiac Arrhythmia Settings

A drawback regarding the application of electrocardiogram signals for identification is their vulnerability to rhythm distortions i.e., cardiac arrhythmias. Arrhythmias are anomalies of the cardiac function, expressed in ECG signals as distortions of a general healthy appearance. Depending on the severity of the symptoms, ECGs can be affected to a great degree, rendering identification impossible. It is however a prerequisite that biometric security systems based on electrocardiograms to be invariant to such malignancies, especially for the isolated ones.

4.1 Arrhythmia Detection: Literature Review

ECG analysis for medical applications is a very active area of research. To date, numerous methodologies have been proposed for cardiac arrhythmia classification. The correlation coefficient [45], autoregressive modeling [46], linear predictive filters [47], wavelets [48] and bispectrum [49] are some examples of the applied techniques for arrhythmia configuration. This section offers a brief introduction to the arrhythmia detection methodologies that operate on the same basis as the framework that will be introduced in the next section.
Chapter 4. Robust Identification in Cardiac Arrhythmia Settings

Among the earliest approaches for arrhythmia detection was proposed by Chen et al. [50]. The short term autocorrelation function of electrocardiogram signals was observed to contain significant information with respect to its periodicity, that could dictate arrhythmias. The autocorrelation of ECG signals with a standard rhythm (healthy, tachycardia or bradycardia) exhibits regular peaks that diminish almost linearly with time. An example of that observation is illustrated in Figure 4.1 for an ECG record of the MIT-BIH normal sinus rhythm database.

The proposed method essentially consisted of two steps. The short term autocorrelation was computed for every ECG window, for its simplicity in representing properties of periodic signals. The autocorrelation peaks were then detected and sorted with respect to their magnitude for labels to be assigned i.e., the peak with the highest magnitude was recorded as $P_0$ and the second higher as $P_1$ and so on. In general, peak localization was performed by finding the next maximum magnitude in the AC waveform.

Having acquired the time of occurrence and magnitude for each AC peak, a standard linear regression test was applied. The null hypothesis was that peaks of the autocorrelation, when ECG is characterized ventricular fibrillation arrhythmias, would not fit to a linear distribution.
A variance ratio was applied as a test statistic. This statistic was compared to an $F$-test value for a specific level, to accept or reject the hypothesis. Rejecting the hypothesis, would suggest a ventricular fibrillation detection.

Lead II ECG signals from 31 subjects were used for the experimental setup. The signals were carefully selected to contain characteristic and distinctive arrhythmia anomalies. The diagnosis for every subject was performed based on either one, two or three of the corresponding windows. The classification performance was 74%, 90% and 100% for the respective test record numbers.

Analysis of the dynamical properties of ECG waveforms introduced another class of methodologies for arrhythmia detection. This kind of techniques is characterized by measures revealing the complexity of ECG waveforms. Among the earliest applications to examine the degree of disarrangement of arrhythmias was Zhang et al.’s [51] work on the application of the complexity measure, originally proposed by Lempel and Ziv [52].

Targeting to classify among normal sinus rhythms, ventricular fibrillation (VF) and ventricular tachycardia (VT), the complexity measure was evaluated directly on 204 electrocardiogram signals (34 normal, 85 VT and 85 VF). As a first step, the signal was transformed into a finite binary sequence, using a threshold dynamically defined for each record, with respect to the magnitude and number of maximum and minimum peaks. The normalized complexity measure was employed to reassure independency from signal’s length.

Computing the complexity measure for several different window lengths of ECGs, thresholds dictating sinus, or VF rhythms were defined. The obtained complexity values for every class were analyzed so that every class was characterized by the maximum and minimum observed value, along with the mean and standard deviation. Following this analysis, a probability density function was defined for each class. It was observed that a 5 second ECG window is capable to distinguish between VF and VT signals, while a 7 second window could discriminate between healthy and VT waveforms. The sinus rhythm
and VF complexities never interfered. Therefore, the 7 sec window length was further analyzed to decide on thresholds. It was illustrated that there is a tradeoff between the detection performance and the window length. For a 7 sec window the accuracy of the system in detecting both VT and VF was reported to be 100%, however, it dropped significantly for shorter windows. Furthermore, one limitation of the described approach is that it was not tested on a different dataset other than the training one.

A later work by Ayesta et al. [53], a second measure that can distinguish between healthy and arrhythmic ECG segments was presented, to be combined with the complexity measure. This novel metric was referred to as Sample Percentage in the Dynamic Range (SPDR). The central concept of SPDR was based on the observation that the percentage of ECG samples that are in the interval \([PPV-10\%PPV]\) (where PPV is the Peak Positive value), is distinctive between healthy and abnormal ECGs.

A threshold value was selected to pre-classify records between normal sinus rhythms and arrhythmic (involving both VT and VF). For those records that were clustered as arrhythmic, the complexity measure was employed for further analysis. According to [53], using this measure to classify between VT and VF was more accurate than separating healthy and diseased records. The system was tested on several ECG window lengths, and even though sinus rhythms were always positively detected, the discrimination between VT and VF did not offer high performance (on average 67.8% window classification for VT and 94.1% for VF).

A fusion of the complexity measure analysis with a sequential hypothesis testing (SHT), has been reported lately by Chen [41]. Aiming to address the open problem regarding the robustness of the complexity measure when applied on only one window for a diagnosis, an alternative was proposed to combine in a feature vector complexity values obtained from several overlapping ECG segments. Studying a 10 sec electrocardiogram recording, an overlapping window of 5 sec length and a step of 1 sec was used to acquire 6 ECG segments. The selection of the window length (5 sec) was performed based on
Chapter 4. Robust Identification in Cardiac Arrhythmia Settings

Having acquired the complexity values for the two classes i.e., VT and VF, the means and standard deviations were quantified to be applied in SHT. Roughly, the hypotheses formed were that a VT and VF could actually be characterized by the computed means and standard deviations. To test the hypotheses, a likelihood ratio test was constructed. The likelihood was compared to two predefined thresholds and if the decision was ambiguous, the next complexity measure value of the feature vector was tested. The proposed technique was evaluated on 30 ECG recordings (10 VF and 20 VT), and a 97% correct classification rate was achieved.

4.2 Identification in Arrhythmia Scenarios

The analysis of ECG of cardiac arrhythmia scenarios is mainly similar with the one described in the previous chapter, for healthy ECGs. The framework consists of three main steps i.e., preprocessing, feature extraction and classification. The last two stages are adopted from the description of the methodology for healthy ECG based identification. Autocorrelation characteristics are used, both to acquire highly personalized signatures and to avoid fiducial points detection, which in arrhythmias is even more difficult. The linear discriminant analysis is applied to reduce the dimensionality of the feature space, while rendering classes more separable. Classification is performed with a nearest neighbor technique, utilizing the Euclidean distance as a similarity measure.

The difference between recognizing patterns in healthy and distorted ECGs lies in the preprocessing stage. The autocorrelation of arrhythmic ECG windows deviates from a healthy appearance significantly, even when comparing healthy and arrhythmic ECG segments of the same subject. To assure accuracy of the decided identity, the system should be able to detect and discard those segments that correspond to distorted electrocardiogram windows. This is not the case for all kinds of arrhythmias, as some of them
deform the signal in total and to such a degree, that the repetitive property is lost, and identification becomes impossible.

The methodology described here, is capable of addressing identification scenarios where two kinds of arrhythmias are present, i.e., *premature ventricular contraction* (PVC) and *atrial premature contraction* (APC). These arrhythmias are not lethal. It is important to make a brief introduction to these two kinds of anomalies, before continuing with the description of the identification process.

The sinoatrial node (SA) is the pacemaker of the heart suggesting that it is responsible for the heart rate. Therefore, the activity of the heart is initiated when the SA node depolarizes. The electrical impulse which is generated, travels with rhythmicity through the conduction system, so that sequential contraction and relaxation take place. When depolarization starts from another group of pacemaker cells rather than the SA node, or when the conduction of the impulses is altered, the rhythm of the heart beats becomes abnormal and arrhythmia is introduced [27].

An ectopic heart beat, is a premature beat which can either be categorized as supraventricular or a ventricular premature contraction, depending on the origin of the beat. A premature ventricular contraction originates in the ventricles where contraction takes place before accepting atria’s electrical signal. PVCs result in beats whose appearance deviates completely from the sinus ones. They usually inhibit the following normal sinus heart beat and force a pause of almost twice the length of a cycle. The rate of appearance of such beats may vary. When a ventricular ectopic beat is observed after every sinus beat, the condition is called *bigeminy*, and correspondingly when one PVC appears every two normal heart beats, it is called *trigeminy*. This kind of arrhythmic beats force the autocorrelation to deviate from that of a repetitive signal as demonstrated in Figure 4.2 [27].

However, not only ventricles can cause cardiac arrhythmias. There might be the case where rhythm disturbances originate from multiple ectopic foci in the atria. Although the
ventricles are in position to respond to this electrical impulse, the heart rhythm is affected without monitoring any abnormal morphologies. Therefore, the repetitive property of the ECG signal is not distorted. An APC results in heart beats that are physiologically healthy just earlier in time than expected. In such cases, the autocorrelation is not affected and the ECG segment is considered suitable for identification.

The arrhythmia screening algorithm described here, attempts to find and discard those ECG segments that are not suitable for human recognition, from an autocorrelation point of view. Thus, the framework is tolerant to APC rhythm variations, but not to ventricular premature heart beats. In the remainder of this chapter ECG windows with PVCs (and not APCs) are referred to as arrhythmic and a methodology is evaluated to uncover them, so that identification can proceed without accuracy losses.

Figure 4.3 pictures the main steps of the described methodology. For the arrhythmia screening step, two criteria are used to decide whether an ECG segment is arrhythmic or
not. The first one is a power criterion that is placed on the power spectrum of the ECG windows. The second criterion is autocorrelation morphology dependent, showing high complexity for PVCs.

PVC is a localized event and its presence in a recording does not infer that the subject is not recognizable. Depending on the symptoms, often a few seconds after a PVC is observed, a healthy recording can be acquired so that identification can proceed. The arrhythmia screening step is aiming to reassure that the propagated to the identification stage ECG windows are healthy. In other words, it is of greater importance not to misclassify arrhythmia recordings as healthy, rather than vice versa. This justifies the reason why the proposed arrhythmia detection scheme is appropriate for biometric applications. On the other hand, such framework should be critically applied in medical systems.
4.2.1 Power criterion

When exposing an ECG window to a premature ventricular heart beat, the morphology of the autocorrelation is distorted as graphically illustrated in Figure 4.2. The regularity of the AC peaks is strongly affected, and the spectrum of the signal is penetrated by smaller frequencies. The discrete cosine transform (DCT) is utilized at this point, to define a criterion for the power distribution, because of its energy compaction property.

Fourier transform can also be applied to distinguish between arrhythmia and healthy power distributions. However, the criterion for the concentration of power that will be demonstrated here applies better to DCT. Fourier transform results along with a comparison to DCT is illustrated in Appendix A.

The frequency coefficients of the AC waveform with the discrete cosine transform are estimated as follows:

\[ Z[u] = G[u] \sum_{i=0}^{N-1} z[i] \cos \left( \frac{(2i + 1)u\pi}{2N} \right) \]  

where \( N \) is the length of the signal \( z[i] \) for \( i = 0, 1, \ldots, (N - |m| - 1) \). For the arrhythmia screening algorithm \( z[i] \) is the autocorrelated ECG. \( G[u] \) is given by:

\[
G(k) = \begin{cases} 
\sqrt{\frac{1}{N}}, & k = 0 \\
\sqrt{\frac{2}{N}}, & 1 \leq k \leq N - 1 
\end{cases}
\]  

Figure 4.4a demonstrates the normalized autocorrelations of 24 healthy and arrhythmic ECG subjects while Figure 4.4b shows the corresponding frequency distribution with DCT.

To distinguish between healthy and arrhythmia DCT waveforms, the criterion determined concerns the concentration of power. It has been observed that the AC of arrhythmic ECG segments has half of its total power centralized in the frequency interval 0.5 Hz - 7.2 Hz. Examples of this are presented in Appendix A. For any power distribution, the number of DCT coefficient where half of the total power is reached can
Figure 4.4: a) Normalized autocorrelation (zoomed) of healthy and arrhythmic ECG windows. b) Frequency spectrum of healthy and arrhythmia ECG windows with the discrete cosine transform. Arrhythmia recordings are plotted in dashed lines.

Figure 4.5: A) Arrhythmia ECG segment B) Corresponding autocorrelation C) Zoomed normalized AC D) DCT coefficients
be computed as:

$$k = \min \left( \left| \sum_{i=1}^{k} Z(i) - \sum_{i=k}^{N} Z(i) \right| \right) \quad (4.3)$$

where $Z(i)$ are the coefficients of the discrete cosine transform. Figure 4.5 summarizes the route of power analysis for a healthy and an arrhythmic ECG window.

### 4.2.2 Complexity Measure

The complexity measure (CM) of finite sequences has been proposed by Lempel and Ziv [52]. In addition, a few works have been reported about its applicability in analyzing ECG signals [51, 53, 41]. For the current framework, CM is associated to the autocorrelation of ECG segments since it is computationally efficient.

A complexity measure reveals the number of patterns that are hidden in a finite sequence, to picture the rate of disarrangement. Here, CM is quantified to capture essential morphological structures of the autocorrelated ECG. More specifically, acknowledging that the autocorrelation of quasiperiodic or repetitive signals has peaks recurring periodically, CM is expected to reveal their frequency of appearance.

Prior methodologies utilize the complexity measure to detect ventricular fibrillation (VF) and tachycardia (VT) arrhythmias [51, 53, 41]. In this class of arrhythmias, not only does the rhythm change rapidly, but also the ECG waveform itself deviates from a healthy one physiologically.

On the other hand, premature atrial and ventricular contractions result in isolated abnormal heart beats, while healthy pulses also appear. The complexity measure can not be used to detect localized differences between healthy and PVC or APC, but it is suitable for the detection of VT and VF. Aiming to detect PVCs, the complexity of the autocorrelation sequence is quantified instead of that of raw ECG signals.

To apply the complexity measure with the mathematical definitions provided by Lempel and Ziv [52] the autocorrelation needs to be translated into a binary sequence. In this
Figure 4.6: (a-b) A healthy and an arrhythmic ECG window (c-d) The corresponding normalized autocorrelations after filtering (e-f) Binary sequences showing the peaks of the autocorrelated ECGs.

binary projection, local maxima are represented by ones while all the remaining samples by zeros. For peak detection, AC waveforms are passed through a lowpass filter with cutoff frequency at 5 Hz for small peaks of less interest to be eliminated. Our expectations for the complexity of arrhythmic AC to be higher than that of healthy records are strengthened by the results of Figure 4.6 which demonstrates the computational route of CM for a healthy and an arrhythmic record.

According to [52], the algorithm for the computation of the complexity measure proceeds as demonstrated in Figure 4.7, with the following definitions:

- $x$ is the binary autocorrelation sequence of length $l(x)$.
- $S$ and $Q$ are two binary strings.
- $SQ$ is the concatenation of $S$ and $Q$ of length $l(SQ)$.
- $SQ\pi$ is $SQ$ where the last character is deleted.
\( \nu(SQ_\pi) \) is the vocabulary of \( SQ_\pi \), i.e., different substrings that \( SQ_\pi \) embeds.

The following algorithm summarizes the steps for the computation of the complexity measure:

- **Step 1:**
  
  \( (\text{Initialization}) \)
  
  \( Cm=1 \)
  
  \( S=x_1 \)
  
  \( Q=x_2 \)

- **Step 2:**
  
  \( (\text{In the midst of computations}) \)
  
  \( S=x_1x_2...x_i \)
  
  \( Q=x_{i+1}x_{i+2}...x_{i+k} \)
  
  \( SQ_\pi=x_1x_2...x_ix_{i+1}x_{i+2}...x_{i+k-1} \)

  \text{if } Q \in \nu(SQ_\pi) \)

  1. \( S \) remains the same
2. \( C_m \) remains the same

3. \( Q = x_{i+1}x_{i+2}...x_{i+k}x_{i+k+1} \)

else

1. \( C_m = C_m + 1 \)

2. \( S = x_1x_2...x_ix_{i+1}...x_{i+k} \)

3. \( Q = x_{i+k+1} \)

- Step 3:
  
  if \( l(SQ) = l(x) \)

  Return \( C_m \)

  else

  Go to Step 2

When the algorithm begins, the complexity measure \( (C_m) \) is tuned to one. \( S \) is set to be the first character of sequence \( x \), and \( Q \) the second character. In the midst of the computations, if \( Q \) is an existing word in the \( v(SQ\pi) \) vocabulary, then \( Q \) is appended with the next symbol of \( x \), while \( C_m \) and \( S \) remain the same. However, if \( Q \) does not exist in \( v(SQ\pi) \), \( C_m \) is augmented by one, \( SQ \) is assigned to \( S \), and \( Q \) becomes the next character of the \( x \) sequence. This process stops when all sequence \( x \) is scanned.

Lempel and Ziv [52] also showed the upper limit of \( C_m \) for a binary sequence \( x \) of length \( l(x) = n \) to be:

\[
\lim_{n \to \infty} C_m(n) = b(n) \equiv \frac{n}{\log_2(n)} \tag{4.4}
\]

Following the above descriptions, CM is highly related to the length of the sequence, and in order to eliminate this effect a normalized complexity measure \( C \) is utilized instead:
\[ C = \frac{C_m(n)}{b(n)} = C_m(n) \frac{\log_2(n)}{n} \] (4.5)

Therefore, \(0 \leq C \leq 1\) with values closer to one showing higher complexity.

### 4.3 Chapter Summary

This Chapter introduced a novel framework for human identification through electrocardiogram traits, in arrhythmia scenarios. The described system is invariant to atria premature heart beats while an arrhythmia screening step was introduced to locate and discard premature ventricular contraction segments, not employable for identification.

The arrhythmia screening algorithm consists of two main steps, which make a decision and might not allow an ECG trace to be propagated to the final identification stage. Comparing healthy and PVC ECG windows, it was observed that frequency representation of the corresponding autocorrelations was penetrated by lower frequencies whenever a PVC window was monitored. To distinguish between healthy and arrhythmic windows, a criterion was proposed about the distribution of power. The discrete cosine transform was employed to acquire the spectrum of autocorrelated ECG windows.

In addition, a criterion concerning the complexity of the autocorrelation waveform was described in this chapter. The complexity measure has been used before for detection of severe arrhythmia diseases. Seeking for isolated arrhythmia events, in this thesis, this measure was applied directly on the autocorrelation instead of the raw electrocardiogram signals. It is expected that the AC of PVC inhibited signals will have a higher complexity value, mainly because ECG’s repetitive property is lost. A threshold on the complexity measure is expected to correctly classify between healthy and arrhythmic signals.
Chapter 5

Performance Evaluation

This chapter presents the experimental results of the proposed method for ECG based human identification. The evaluation of the AC/LDA method was primarily performed on two public datasets i.e., the PTB [55] and MIT-BIH normal sinus rhythm [56] databases. For the experimental setup of the integration of the recognition system with the arrhythmia screening framework, the aforementioned healthy ECG recordings were fused with the MIT-BIH arrhythmia [54] database.

5.1 Electrocardiogram Data

The MIT-BIH Arrhythmia database contains 48 ECG signals that were recorded between 1975 and 1979 at the Beth Israel Hospital Arrhythmia Laboratory. Each of the records is around 30 minutes long, and they show various kinds of arrhythmias. The sampling frequency of this database is 360 Hz. For our experimental setup, 30 subjects were selected to form a subset of the MIT-BIH arrhythmia database. This selection was performed in a way that the subset consisted of ECGs which show mostly premature ventricular and atrial contractions. Since the database offers only one recording for every subject, we partitioned the electrocardiogram signals into two halves, one for the gallery set and one for testing.
The MIT-BIH Normal Sinus Rhythm database contains 18 electrocardiogram recordings from subjects that did not exhibit significant arrhythmias. The recordings were collected at Boston’s Beth Israel Hospital and the sampling frequency is 128 Hz. For our experimental setup, a subset of the database containing 13 subjects was composed. The selection of the subjects for our experiments was based on the length of the recordings. The waveforms of the remaining recordings had many artifacts that reduced the valid heart beat information and for this reason they were not used in our experiments. Once again, the signals were partitioned into two halves, one to build the gallery set, along with the arrhythmia records, and one to test the system. In order to provide comparative results between the two databases, the records of the MIT-BIH Normal Sinus Rhythm Database were re-sampled to 360 Hz.

The PTB database is offered from the National Metrology Institute of Germany and it contains 549 ECG recordings from 294 subjects. Every record includes the conventional 12-leads and 3 Frank leads ECG. The sampling frequency of these recordings is 1 kHz but it was resampled to 360 Hz for our experiments. In addition, for every subject in the PTB database, at least two recordings are available which were collected a few years apart. A subset of 14 healthy subjects was formed from the PTB database for our experiments. The criteria for the selection of the records were, to demonstrate healthy ECG waveforms and to have at least two recordings for every subject. The older recording of every subject was used to build the gallery set and the newer one to test the performance of the method.

5.2 One-lead ECG Identification of Healthy Subjects

When a subject arrives to the system to be identified, 5 sec of his/her ECG is collected and subjected to preprocessing, to eliminate the effects of noise. Having prepared the signals for further analysis, the normalized autocorrelation is computed, and several window lengths of the AC are tested for dimensionality reduction and classification, so
that the optimal one is identified. The optimal window can be found in terms of subject and window recognition rates.

The difference between calculating window and subject recognition rates is that in the first case, a subject is recognized based on only one of his/her corresponding electrocardiogram recordings. In the second case a subject is recognized following a majority voting scheme of multiple ECG recordings.

Even though it is possible that windows of AC which correspond to the length of a heart beat from the ECG, offer high performance, it is important to note that not all waves of a heart beat are invariant to stress conditions, risking the identification performance in anxiety situations. However, there is evidence that the $QRS$ complex, is less affected by emotional conditions [57, 30] compared to the rest of the waves, thus the corresponding AC window length is suggested to be more appropriate for feature extraction.

Using an autocorrelation window of 30 samples, which is approximately equal to the $QRS$ length, the AC/LDA method achieves its highest performance. All subjects are identified correctly (100%) and the corresponding window recognition percentage is 95.8%. More detailed results about the AC/LDA performance of different AC windows will be presented in Chapter 6.

Template matching with the correlation coefficient measure is used to reduce the search space and improve the computational time of the classification process. This measure cannot be used directly to identify a subject, since high morphological similarities exist between the AC of different subjects’ ECGs if feature extraction is not performed. However, setting a threshold for the correlation coefficient value, allows the system to find only those subjects from the gallery set that consist possible identities for an input. For every newcomer classification is carried out only among selected candidates. Figure 5.1 shows the percentage of possible identities found in the gallery set for every test subject with template matching. Integrating the AC/LDA method with template matching all subjects are identified correctly and the window recognition rate increases to 96.6%.
It is however important to note that if TM is used for intruder detection as well, then a careful selection of a threshold value should be performed. The higher the threshold, the more likely it is to detect illegal attempts but it is less probable for the real identity to be included in the reduced subset of possible identities. This is attributed to the fact that correlation coefficient alone is not adequate to recognize a person. Figure 5.2 depicts the performance of the method in finding subject matches for both legal subjects and intruders. It is shown in that Figure that every probe subject makes an acceptable match with approximately 20% of the gallery set. Using template matching, a pruning of the search space takes place to improve the computational effort required for classification. Aiming to find the threshold which offers low intruder rate and high legal subject rate, intrusion tests have been simulated by averaging the performance of the system with a leave-one-out methodology. In this type of analysis a subject is left out of the simulations to be then tested as an intruder.
Figure 5.2: Match performance for different correlation coefficient thresholds using one lead information. a) Subject match rate of legal subjects and intruders. b) Corresponding window match rates.

5.3 12-lead Identification of Healthy Subjects

In this section, we present the results of the AC/LDA method for feature extraction from 12 lead ECG signals. The framework starts with filtering of the electrocardiogram recordings for each lead. The normalized autocorrelation is computed on a 5 sec ECG segment, and the linear discriminant analysis is applied for dimensionality reduction of an equal to a QRS length segment from the AC.

The performance is measured in terms of subject and window recognition rates as well. A subject is identified based on majority voting of the corresponding windows. As a first step towards 12-lead ECG fusion, it is crucial to investigate the recognition power of all 12 leads separately.

Individual results for every lead are shown in Table 5.1, which suggests that all lead signals have discriminative power and that integration of this information in the right
<table>
<thead>
<tr>
<th>Lead</th>
<th>Subject Recognition Rate</th>
<th>Window Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>100%</td>
<td>97.2%</td>
</tr>
<tr>
<td>II</td>
<td>100%</td>
<td>97.9%</td>
</tr>
<tr>
<td>III</td>
<td>100%</td>
<td>97.58%</td>
</tr>
<tr>
<td>αVR</td>
<td>100%</td>
<td>97.58%</td>
</tr>
<tr>
<td>αVL</td>
<td>100%</td>
<td>97.88%</td>
</tr>
<tr>
<td>αVF</td>
<td>100%</td>
<td>97.88%</td>
</tr>
<tr>
<td>V1</td>
<td>85.71%</td>
<td>82.47%</td>
</tr>
<tr>
<td>V2</td>
<td>100%</td>
<td>97.88%</td>
</tr>
<tr>
<td>V3</td>
<td>92.85%</td>
<td>92.74%</td>
</tr>
<tr>
<td>V4</td>
<td>85.71%</td>
<td>84.29%</td>
</tr>
<tr>
<td>V5</td>
<td>100%</td>
<td>98.48%</td>
</tr>
<tr>
<td>V6</td>
<td>100%</td>
<td>99.39%</td>
</tr>
</tbody>
</table>

Table 5.1: Experimental results from classification of the PTB data of different leads

The framework will enhance the performance of the identification procedure. In addition, Figures 5.4.A and 5.4.B present the contingency matrices of two separate leads.

5.3.1 Feature Level Fusion

By recording the electrocardiogram signal simultaneously from every lead, different aspects of the instantaneous potential of the heart are captured. Depending on the electrode configuration, numerous details are pictured in each of the 12 lead signals. The purpose of information fusion is to utilize this source of distinctive characteristics as much as possible.

To apply a feature-level fusion of the data, a segment from the autocorrelated ECG
Figure 5.3: Contingency matrix after feature-level fusion of leads

Figure 5.4: A) Identification rates with the AC/LDA method on lead 7. B) Identification based on lead 10. C) Decision based fusion of 12 leads

windows of every lead is subjected to dimensionality reduction with the LDA. Having obtained an optimum feature set, the vectors are concatenated since they are of the same measurement scale. This procedure is performed for all the 12 instances of every 5 sec ECG that is recorded from a subject. The Euclidean distance between every con-
catenated vector in the test and gallery set is computed, and classification is performed with nearest neighbor. The contingency matrix in Figure 5.3 demonstrates the window identification rates for each subject in the test set. In a perfect system, it is expected that the diagonal would show 100% window recognition rate. However, even though the subject identification rate is 100%, the window rate is 95.16%. This implies that concatenation of the feature vectors leads to loss of discriminative information (less powerful leads overrule the results) and a decision based fusion will be more appropriate.

5.3.2 Decision Level Fusion

In order to combine the 12 leads at a decision level, 12 classifiers are trained, each on the corresponding lead ECG signals. The feature space is once again obtained from the normalized autocorrelation of ECG windows and the dimensionality is reduced with discriminant analysis. The output of every classifier can be regarded as binary for every class, given an input $x$. The four cases described earlier introduce rules which guide the fusion of the 12 decisions.

However, this kind of fusion brings up rejection ($R$) cases. Rejection takes place when the system does not make a decision because either it is too conservative, or the class of the input data is ambiguous. Rejection might be unacceptable for biometric identification systems, since the subject will need to be recognized with a different module. On the other hand, it reduces significantly the possibility of illegal penetration. When the system is not absolutely confident about a person’s identity, it sets off the alarm rather than assigns someone to a false identity. However, it is useful to find a fusion framework, which would be conservative enough to detect intruders, and at the same time have as low rejection rate as possible.

The window and subject identification results of our experiments are obtained among those subjects which are not rejected for every specific case. The first case is conservative enough, since a window is identified only if all classifiers agree. As expected, this rule
leads to very high window and subject rejection rates, as reported in Table 5.2. A subject is rejected if all the corresponding windows are rejected. For the first case, classification among the remaining subjects provides 100% subject and window recognition rates.

The second rule is less conservative than the first one, since it is based on majority voting. This kind of fusion rule is expected to have lower rejection losses. Table 5.2 shows that the window rejection rate is reduced to 0.9% while still being able to identify correctly all the subjects. The percentage of rejected windows in this case, is distributed among all subjects, and therefore no subject is excluded from the system. Figure 5.4.C pictures the contingency matrix when fusion is performed using majority voting as the decision rule.

Cases three and four introduce window and subject rejection rates as well. In these cases, the degree of rejection is controlled by the parameter $\alpha$. This measure mainly expresses the order of confidence about the decision which is made. However, there is a tradeoff between highly confident decisions and rejection rates. The greater the number of the classifiers that participate in the voting process, the bigger the probability of successful identification, especially for large datasets. Given that $\alpha$ lies in the interval $(0,1]$, several values have been tested, offering 100% subject and window recognition rates. Figure 5.5 depicts the rejection rates for different values of $\alpha$. Both cases result in window rejection rates which are greater than 30% at the extreme cases of being conservative. However, a moderate selection for parameter $\alpha$ offers less rejection cases (less than 1%) while at the same time allows the system to make accurate decisions (100% identification performance).

### 5.4 Authentication of Healthy Subjects

Both the linear discriminant and principal component analyses have been tested for identity authentication purposes. The selection of a threshold on the Euclidean and
### Table 5.2: Rejection and identification rates with case 1 and 2 decision level fusion

<table>
<thead>
<tr>
<th>Case</th>
<th>Window Rejection Rate</th>
<th>Subject Recognition rate</th>
<th>Window Recognition rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>32.32%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>2</td>
<td>0.9%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Figure 5.5: Rejection rates when the 12 leads are combined in a decision level

cosine distances respectively, is performed empirically by inspection of the experimental results. Figure 5.6.A shows the validation performance of the system i.e., the rate at which legitimate subjects are verified when reducing dimensionality via discriminant analysis. Correspondingly, Figure 5.7.A demonstrates the verification rates with PCA at the feature extraction stage. The validation rates achieved support the perspective of application in larger ECG databases.

However, such a validation step has undesired effects, such as false rejections and acceptances. A false rejection takes place when the system denies the claimed identity of a legal user. False acceptance refers to the case where the system verifies the identity of a
subject which is to be misidentified. The false acceptance and false rejection rates (FAR and FRR) are plotted against different distance thresholds in Figures 5.6.B and 5.7.B for LDA and PCA features respectively. It is usually left up to the designer’s will to choose
the optimum distance threshold for the system. For instance, if a given application has a means to reassure that no intruders will claim an identity, a larger selection of the threshold would be preferable. Examples of low false acceptance and false rejection rates achieved are summarized in Table 5.3. The Equal Error Rate (EER) i.e., the performance when the FAR and FRR are equal is also presented in this Table.

Table 5.3: FAR, FRR examples and EER for authentication based on PCA or LDA feature selection

<table>
<thead>
<tr>
<th></th>
<th>Lower FAR</th>
<th>Lower FRR</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>0.13%</td>
<td>0.19%</td>
<td>10.76%</td>
</tr>
<tr>
<td>LDA</td>
<td>0.084%</td>
<td>0.13%</td>
<td>3.8%</td>
</tr>
</tbody>
</table>

As mentioned earlier in the description for the PCA based authentication methodology, the Euclidean distance can be used as a similarity measure between feature vectors of different individuals. Applying however this similarity measure the performance of the validation framework is lower than that when cosine distance is utilized. Figure 5.8 shows the identity validation performance and the corresponding FAR and FRR for different distance thresholds.

To provide a fair comparison between the two similarity measures, Table 5.4 presents the equal error rates achieved with both measures along with examples for the false acceptance and rejection rates. Choosing a specific performance rate for the FAR and comparing the corresponding FRR at the same threshold, the lowest FRR reveals the most appropriate distance measure selection. The same syllogism is applied for a standard FAR value. Inspecting Table 5.4, cosine distance outperforms the Euclidean one.
Table 5.4: Cosine and Euclidean distance comparative results for PCA based authentication

<table>
<thead>
<tr>
<th></th>
<th>EER</th>
<th>FRR (FAR=10%)</th>
<th>FAR (FRR=10%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cosine Distance</strong></td>
<td>10.76%</td>
<td>11.39%</td>
<td>11.75%</td>
</tr>
<tr>
<td><strong>Euclidean Distance</strong></td>
<td>11.8%</td>
<td>14.5%</td>
<td>13.5%</td>
</tr>
</tbody>
</table>

Figure 5.8: Principal component analysis A) Window verification performance for different Euclidean distance thresholds. B) Corresponding false acceptance and rejection rates.

5.5 Experimental Results with Arrhythmia Screening

The AC/LDA method can be applied for ECG based identification in cardiac arrhythmia scenarios as well. The difference is that a pre-screening step is introduced in preprocessing, which is targeting to locate and discard malignant ECG segments that are not appropriate for subject recognition.
The framework is tested on a fusion of the three datasets i.e., the PTB, MIT-BIH healthy and MIT-BIH arrhythmia databases. In order to get comparable ECG signals, all recordings from the PTB and MIT-BIH healthy datasets were re-sampled to 360Hz.

The power criterion concerns the distribution of the ECG power spectrum, when computed with DCT on autocorrelated ECG segments. Adjusting a threshold criterion for clustering at 5 Hz, and categorizing a subject as arrhythmic if at least one of his/her windows meets the arrhythmia standards, an 80% correct classification rate was achieved for both healthy and arrhythmia clustering. Figure 5.9 illustrates the classification performance for healthy and arrhythmia subjects separately and for different power distribution thresholds.

![Figure 5.9: Arrhythmia detection rates with the power criterion](image)

Complexity measure is the second option for detection of arrhythmic ECG segments. As analyzed earlier, ECG windows that exhibit ventricular premature beats result in autocorrelation morphologies that correspond to high complexity since the repetitive property of the signals is lost. Several thresholds for the complexity measure are tested for
their efficiency in detecting malignant recordings as shown in Figure 5.10 for arrhythmia and healthy records separately.

A threshold of 0.048 for the complexity measure that signifies arrhythmic and healthy records was distinguished for its classification performance. Following the definition for the power criterion, a subject is considered to be arrhythmic if at least one of the corresponding ECG windows have autocorrelation complexity higher than the optimal threshold. Employing the complexity measure, 78% of the subjects are correctly classified as arrhythmic or healthy.

![Complexity Measure Threshold](image)

**Figure 5.10: Arrhythmia detection rates with the complexity measure criterion**

Each of the criteria can be used separately for arrhythmia screening before identification. However, the misclassified windows at that step, introduce an error which is propagated to the identification stage, limiting the accuracy of the decision. Figures 5.11.A and 5.11.B demonstrate the recognition performance of the system when arrhythmia screening is performed either with the power or the complexity criterion.
Figure 5.11: A) Window and subject recognition rates when arrhythmia screening involves CM alone. B) Corresponding rates using a power criterion for arrhythmia detection

For the optimal threshold values, using the power criterion alone before identification a 94.7% window recognition rate is achieved. On the other hand, for the optimal threshold, using the complexity measure alone, a 92.5% window recognition rate is accomplished. The corresponding subject recognition rates are higher as depicted in Figure 5.11 for any threshold.

Integrating the two principles enhances the precision of system. Roughly speaking, two criteria in stead of one reassure that the propagated for identification ECG segments exhibit indeed healthy autocorrelation structures. Applying strict thresholds for both of them, a more accurate assessment for ECG windows is obtained.

Out of the windowing process, along with discarding windows categorized as arrhythmic, a testing set of 2905 windows is formed. Euclidean distance is the similarity measure chosen to handle classification. The window recognition rate accomplished is 96.2% which indicates that a finer selection took place in the arrhythmia screening step,
when integrating two criteria. Finally, subject recognition rate is estimated according to majority voting of the corresponding windows, offering an identification performance of 96.5%.

The overall performance of the described framework is presented in Figure 5.12. In this Figure, the classification percentages between every subject in the gallery set and the rest of the subjects including himself is demonstrated in terms of window recognition rates. Cases of misclassified ECG windows appear mostly among arrhythmic subjects.

The arrhythmia detection algorithm currently introduced, is highly efficient in detecting and discarding inappropriate windows for identification. However, the misclassification error at that step is propagated to the identification phase, affecting the performance of the system.

Nevertheless, the experimental results demonstrate that an ECG based human identification in arrhythmia scenarios is feasible. The superiority of the normalized autocorrelation in embedding distinctive characteristics between healthy and arrhythmic ECGs is crucial for future investigation. In addition, the designed autocorrelation based technique eliminates the dominant need for fiducial detection, increasing the efficacy of the system.

5.6 Chapter Summary

This chapter reported the experimental results of the proposed methodologies for biometric recognition. The experimental setup made use of three public databases i.e., the PTB, MIT-BIH normal sinus rhythm and MIT-BIH arrhythmia. First, the evaluation performance of the identification procedure using only lead II signals was presented. It was shown that the AC/LDA method is accurate in extracting discriminative features from the electrocardiogram. The subject and window recognition rates achieved, were 100% and 95.8% respectively (100% and 96.6% when integrated with template matching).
Figure 5.12: Classification percentages of every subject against all subjects in the gallery set. A) Identification performance when only the power criterion is applied during arrhythmia screening. B) Performance on the complexity measure for screening. C) Identification performance when criteria are combined. Although it is expected that in a perfect system the diagonal (i.e. correct identification) would show 100% recognition rates, arrhythmias lead to identification errors.

Before evaluating the suggested fusion techniques for 12 lead signals, the AC/LDA method was applied to examine the discriminative power of each lead signal independently. It was observed that no matter the electrode configuration, the acquired signals have great potential in distinguishing subjects. The feature level fusion of the 12 leads for identification did not increase the performance of the system, as specific leads with comparatively lower recognition ability overruled the rest (95.16% window recognition rate). The decision level fusion lead to rejection cases either because an input was ambiguous or the rule too conservative. However, decision based fusion of 12 signals achieved 100% window recognition rates.

To test the proposed authentication methodology classification was carried out based
on either the Euclidean or cosine distance. Cosine distance offered more accurate results in terms of false acceptance and rejection rates. The equal error rate achieved by the framework was 12% when PCA was used for feature selection, and 3.8% for LDA. Although the LDA authentication performance was better, PCA is an unsupervised learning technique offering significant benefits such as assisting better situations of new enrollments where the system needs to be updated, thus retrained, and if LDA was used instead more than one ECG recordings of a subjects would be demanded before training could begin. This would increase the waiting time of the application significantly.

The arrhythmia screening algorithm was tested on the combination of the three public databases. It was shown to be highly effective in detecting PVC electrocardiogram segments. The power criterion classified correctly 80% of the subjects as arrhythmic or healthy, and the complexity measure 78%. When the arrhythmia screening step was fused with the identification stage (AC/LDA), the subject and window recognition rates achieved were 96.5% and 96.2% respectively.
Chapter 6

Comparison with other Schemes

This chapter presents a comparison of the AC/LDA method, with the AC/DCT method that has been reported in [1] and a fiducial points based technique analyzed in [3]. The experimentation procedure described, has been reproduced from [3, 1] on the PTB and MIT-BIH sinus rhythm databases.

6.1 The AC/DCT Methodology

The AC/DCT method, reported by Plataniotis et al. [1], is among the earliest works for ECG based human identification without fiducial points detection. Issues concerning the inadequate performance in detecting fiducial points, that can risk the identification performance of a biometric system, were brought to light in [1].

Windowing was applied as an alternative to analyzing isolated heart beats. The proposed method for feature extraction without fiducial detection was based on a combination of autocorrelation (AC) and discrete cosine transform (DCT). The AC/DCT method involved four stages: 1) Windowing, where the preprocessed ECG traces are segmented into non-overlapping windows, 2) Estimation of the normalized autocorrelation for each window 3) Discrete cosine transform over $M$ lags of the autocorrelated signal; and 4) Classification based on significant coefficients of DCT. A graphical demonstration
Chapter 6. Comparison with other Schemes

Figure 6.1: Block diagram of the AC/DCT method.

of different stages is presented in Figure 6.1.

As explained in the description for the AC/LDA methodology, autocorrelation of ECG segments embeds information about representative characteristics of the signal. In addition, when AC is applied on ECG samples, fiducial points detection can be avoided. However, the dimensionality of autocorrelation features was considerably high (for example $M=100, 200, 300$ depending on the original sampling frequency of the ECG signal).

In [1], the discrete cosine transform was applied to the autocorrelation coefficients for dimensionality reduction. The energy compaction property of DCT allowed representation in lower dimensions. This way, near zero components of the spectrum could be discarded, and the number of important coefficients was eventually reduced substantially. Assuming we take an $M$-point DCT of the autocorrelated signal, only $C \approx M$ non-zero DCT coefficients contain significant information for identification.

Ideally, from a frequency domain perspective, the $C$ most significant coefficients will correspond to the frequencies between the bounds of the bandpass filter that was used in preprocessing. This is because after the AC operation, the bandwidth of the signal was retained.

The discrete cosine transform is not a standard machine learning methodology for dimensionality reduction. However, it performs that task, in the sense that low amplitude coefficients do not contribute any discriminative information for each class and can be discarded. Compared to the linear discriminant analysis, it is expected that LDA will outperform DCT for identification purposes.

LDA does not only project the feature space to lower dimensions, but also renders the classes more separable. This is because projection is performed on the basis of
maximizing the ratio of the between-class to the within-class scatter matrices. DCT does not offer any such guarantee for class separability, without inferring that it grows the between-class variances. Generally, when classes are more distinctive, any similarity measure offers higher and more accurate recognition rates.

The size of the reduced feature space is another basis on which LDA and DCT can be compared. The LDA can offer dimensionality reduction up to $U-1$, where $U$ is the number of classes i.e., subjects enrolled in the system. On the other hand, there is no database related rule which could guide the dimensionality reduction via DCT. Roughly, close to zero DCT coefficients will appear after the frequency edge of the band-pass filter applied in pre-processing. The dimensionality of the DCT feature vector will then depend on the sampling frequency of the signal, without being able to determine its exact length. DCT feature vector plots can be found in Appendix B.

### 6.1.1 Performance Evaluation

The AC/DCT technique described by Plataniotis et. al [1], has been reproduced here to compare with the AC/LDA method for ECG based identification. The experimentation was carried out on the combination of the PTB [55] and MIT-BIH normal sinus rhythm [56] databases. For this reason, the PTB database was resampled to 128 Hz.

Table 6.1, shows the window and subject recognition rates when the system is tested on different autocorrelation window lengths $M$ (more analytic results are available in Appendix B). The number of DCT coefficients used for identification is denoted by $C$, while the corresponding number of LDA features after dimensionality reduction depends on the size of the dataset.

Splitting the available ECGs into segments of 5 sec each, a test set of 506 windows from 27 subjects is generated. Both the AC/DCT and AC/LDA achieve their highest performance for an AC window length that corresponds approximately to the QRS complex of the electrocardiograms. However, only the LDA achieves 100% subject iden-
Figure 6.2: (a and b) 5 seconds window of ECG from two subjects of the PTB data set, subject A and B. (c and d) The normalized autocorrelation sequence of A and B. (e and f) Zoom in to 300 AC coefficients from the maximum form different windows of subject A and B. (g and h) DCT of the 300 AC coefficients from all ECG windows of subject A and B, including the windows on top. Notice that the same subject has similar AC and DCT shape.

tification rate and 95.8% window recognition rate. The subject and window recognition rates when the AC/DCT method is tested are 96.3% and 86.3% respectively.

The LDA method for dimensionality reduction outperforms DCT for every AC window tested. This is expected because, discriminant analysis, embeds class information when projecting to lower dimensions, therefore targeting at the same time to make clusters more separable. This is not the case for DCT where the frequency analysis is
Figure 6.3: A) Contingency matrix of the AC/DCT method applied on the combined datasets of MIT and PTB. B) Corresponding AC/LDA contingency matrix. Although it is expected the diagonal to show 100% window recognition rates, there are few miss-classified windows.

performed individually. Fig. 6.3.A and 6.3.B picture the contingency matrices for both frameworks.

### 6.2 Fiducial Points Based Scheme

Among the earliest works in the application of the electrocardiogram for identification purposes, was reported by Israel et. al [3]. A fiducial points dependent methodology was suggested for feature extraction from heart beats. This section attempts to reproduce the proposed experimental procedure, on the available ECG databases.

In [3], filtered ECG signals, were subjected to fiducial points detection. The desired
Table 6.1: Classification performance of the AC/DCT and AC/LDA method on the PTB database

<table>
<thead>
<tr>
<th>M</th>
<th>C (DCT only)</th>
<th>Subject Rate DCT</th>
<th>Window Rate DCT</th>
<th>Subject Rate LDA</th>
<th>Window Rate LDA</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>7</td>
<td>25/27</td>
<td>401/506</td>
<td>26/27</td>
<td>464/506</td>
</tr>
<tr>
<td>20</td>
<td>13</td>
<td>25/27</td>
<td>416/506</td>
<td>26/27</td>
<td>461/506</td>
</tr>
<tr>
<td>30</td>
<td>19</td>
<td>26/27</td>
<td>437/506</td>
<td>27/27</td>
<td>485/506</td>
</tr>
<tr>
<td>50</td>
<td>32</td>
<td>25/27</td>
<td>426/506</td>
<td>25/27</td>
<td>441/506</td>
</tr>
<tr>
<td>70</td>
<td>44</td>
<td>25/27</td>
<td>421/506</td>
<td>24/27</td>
<td>434/506</td>
</tr>
<tr>
<td>100</td>
<td>63</td>
<td>23/27</td>
<td>377/506</td>
<td>24/27</td>
<td>433/506</td>
</tr>
<tr>
<td>150</td>
<td>94</td>
<td>25/27</td>
<td>347/506</td>
<td>23/27</td>
<td>412/506</td>
</tr>
<tr>
<td>200</td>
<td>125</td>
<td>23/27</td>
<td>337/506</td>
<td>24/27</td>
<td>400/506</td>
</tr>
</tbody>
</table>

points are shown in Figure 6.4.A. The first step towards fiducial localization is to detect the $R$ peaks and to synchronize the pulses as depicted in Figure 6.4.B. Since the heart beats were aligned at the $R$ position, it was suggested for the temporal features to be computed from that peak.

The remaining fiducial points were localized either by finding the maximum in the surrounding area ($P$ and $T$), or with the radius of a curvature (for $L', P', S', T'$) (Figure 6.4.C). Having acquired the approximate location of fiducial points, temporal distances between them were computed, to obtain the 15 selected attributes for identification.

However, employing temporal distances only, risks the system’s applicability in varying heart rates, since the time difference between successive points of heart beats originating from the same subject can vary a lot. Following [3], normalization is required, to reassure robustness in anxiety conditions. All features except for the $RQ$ and $RS$ distances, were divided by $L'T'$ and eventually, every heart beat was considered to have
The specifics of the feature extraction and dimensionality reduction methodologies, are not described in [3] in detail, therefore in this reproduction we use the linear discriminant analysis. The main consideration of this section is to evaluate the selected for identification features.

Deviations from the originally reported experimental procedure, mainly have to do with the different electrocardiogram datasets on which the described technique was tested. Other than the difference in the size of the recordings, in [3], special experiments were reported on different sensor location (neck and chest ECG signals) and anxiety conditions. A database with varying sensor configurations and stress conditions is not available, and therefore no such experiments can be reproduced.
Figure 6.5: Examples of isolated and aligned heart beats belonging to different subjects of the PTB database.

6.2.1 Performance Evaluation

For the reproduction of Israel et al.’s experiments, electrocardiogram records from the PTB database [55] were down sampled to 128 Hz, to be fused with recordings from the MIT-BIH normal sinus rhythm database [56]. The earliest records were used to form a training set, consisting of 1948 heart beats in total, and the later ones to create a probe set of 1893 heart beats.

Fiducial points were localized with the methodology described in [3], and the heart beats were synchronized using their $R$ peaks. Figure 6.5 demonstrates some examples of aligned pulses, where it is clear that for some subjects, heart beats can not be synchronized completely, risking the precision of the feature extraction process.

The reader can find some fiducial points detection examples in Appendix B. After acquiring and normalizing the selected features, linear discriminant analysis is applied
Figure 6.6: Contingency matrix for the reproduction of [3] on the combination of the MIT-BIH healthy and PTB datasets.

for dimensionality reduction. Classification of the projected feature space is carried out as the last step towards identification. The overall performance of the reproduced methodology is illustrated in Figure 6.6. This plot is essentially a contingency matrix visualization, where the heart beat recognition rates between subjects in the test and gallery set are pictured as bars.

Following the description in [3], a subject is identified based on majority voting of his/her heart beats. In total, the subject recognition rate is 88.46% and the corresponding heart beat recognition rate is 54.7%. This is a lot different from the reported recognition rates. Although the number of subjects in the experimentation procedure is approximately the same, in this reproduction, ECG signals from lead II were used in stead of neck or chest recordings, and this might be the cause of variations.

Non fiducial based methodologies offer significant advantages, when it comes to the
accuracy of the employed feature space. Inadequacies at the estimation of the desired
feature vectors are no longer met, as localized heart beat abnormalities do not affect
windowing processes. In addition, confining the interest to only a few characteristics
of the ECG waveform (temporal distances in Israel et al.’s case), risks the selection of
discriminative features, since personalized information might be thrown away.

6.3 Summary of Current Approaches

This section presents an overall comparison of the methodologies proposed in this thesis
with other currently suggested approaches. A qualitative comparison can be performed in
six levels (see Table 6.2) i.e., the feature extraction procedure, selection of characteristics,
classification algorithms, electrode configuration, special issues addressed and the final
performance.

- Compared to the techniques suggested in [3, 2, 4, 34], this thesis described a method
  for feature extraction which is not based on fiducial points. A windowing technique
  made allowance for employment of characteristics which are not limited into single
  heart beats, thus addressing issues related to inaccuracies in fiducial points detec-
  tion. The autocorrelation has been applied for feature extraction as opposed to
temporal only features selected in [3], temporal, amplitude and slope traces used in
[2], temporal and amplitude features in [4] and a combination of time, amplitude
distances with appearance characteristics selected in [34].

- The selection of features varies for every methodology as well. In the current
  approach, the linear discriminant and principal component analyses are employed
  for dimensionality reduction. The same procedure was used in [34], while a test
  statistic called Wilk’s lamda and simple inspection of the correlation matrix were
  performed in [3] and [2] respectively. It is important to notice, that feature selection
### Table 6.2: Comparison milestones between the current approach and other methodologies in the field

<table>
<thead>
<tr>
<th>Feature Extraction</th>
<th>Israel et. al</th>
<th>Biel et. al</th>
<th>Shen et. al</th>
<th>Wang et. al</th>
<th>Proposed method</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Feature</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fiducial Detection</strong></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td><strong>Feature Origin</strong></td>
<td>Heart Beats</td>
<td>Heart Beats</td>
<td>Heart Beats</td>
<td>Heart Beats</td>
<td>ECG windows</td>
</tr>
<tr>
<td><strong>Feature Specifics</strong></td>
<td>Temporal</td>
<td>Temporal + Amplitude + Slopes</td>
<td>Temporal + Amplitude</td>
<td>Temporal + Appearance</td>
<td>Auto-correlation</td>
</tr>
<tr>
<td><strong>Extraction method</strong></td>
<td>Automatic</td>
<td>Machine based</td>
<td>Automatic</td>
<td>Automatic</td>
<td>Automatic</td>
</tr>
<tr>
<td><strong>Feature Selection</strong></td>
<td>Wilks' Lambda</td>
<td>Inspection of the correlation matrix</td>
<td>-</td>
<td>PCA or LDA</td>
<td>LDA</td>
</tr>
<tr>
<td><strong>Classification</strong></td>
<td>LDA and Majority voting</td>
<td>SIMCA model based on PCA</td>
<td>Prescreening and Distance classification</td>
<td>Nearest Centres, Nearest Neighbor, LDA</td>
<td>Nearest Neighbor on Euclidean Distance</td>
</tr>
<tr>
<td><strong>Electrode Orientation</strong></td>
<td>Neck, Chest</td>
<td>Limb leads (I, II, III)</td>
<td>Lead I</td>
<td>Lead II</td>
<td>Lead II</td>
</tr>
<tr>
<td><strong>Special experiments</strong></td>
<td>1) Electrode configurations</td>
<td>Different operators</td>
<td>Analysis of the effects of age, gender weight, height and BMI</td>
<td>Integration of analytic and appearance features</td>
<td>1) Arrhythmia scenarios</td>
</tr>
<tr>
<td><strong>Assumptions</strong></td>
<td>Normal ECG morphology *</td>
<td>Normal ECG morphology *</td>
<td>Normal ECG morphology *</td>
<td>Normal ECG morphology *</td>
<td>-</td>
</tr>
<tr>
<td><strong>Performance</strong></td>
<td>100%</td>
<td>100%</td>
<td>95.30%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Heart beat / Window rates</td>
<td>92%</td>
<td>-</td>
<td>98.90%</td>
<td>96.6%</td>
<td>96.6%</td>
</tr>
<tr>
<td>Number of Subjects</td>
<td>29</td>
<td>20</td>
<td>168</td>
<td>13</td>
<td>27 (506 windows)</td>
</tr>
</tbody>
</table>

* Normal ECG morphology refers to:
1) Clear and apparent P, QRS and T waves, for fiducial detection to be feasible.
2) Healthy ECG traits only.
needs to be carried out automatically, and manual techniques [2] suffer from that weakness.

- There is a variety of classification algorithms utilized to assign feature vectors into clusters. Usually, the chosen algorithm depends on the appearance and concentration of the classes. In this thesis, clustering was carried out by a nearest neighbor technique, using the Euclidean or cosine distance as similarity measures. Other classification algorithms that are met in the related literature are the nearest centre, LDA, SIMCA model or simple majority voting.

- In terms of electrode configuration, there is a variety of different analyses performed. In Israel et al.’s [3] approach, electrodes were attached at the neck and chest and a hypothesis about their similarities was tested. In Biel et al.’s [2] work, signals obtained from lead I, II and III orientations of the standard 12 lead system were used, while in [34] lead II signals were analyzed. In the current methodology, signals from all 12 lead standard system were employed to evaluate their discriminative ability and propose ways of fusion.

- In each work, special experiments were performed, to address issues about the application of electrocardiogram signals in identification. In [3], variances in the electrode configurations and anxiety conditions were tested, while Biel et al. [2], reported experiments on different operators who attached the electrodes on subjects. In addition, Shen et al. [4], examined the effects of age, gender, weight, height and body mass index on the identification performance. In [34], a combination of appearance and analytic features was evaluated to demonstrate that the later do not offer high recognition performance. In this thesis, authentication experiments were carried out instead of identification only, to demonstrate that identity verification via ECGs is feasible. Furthermore, experiments on arrhythmia settings were carried out on an arrhythmia screening basis methodology, that extended the range
of applications significantly. Table 6.2 summarizes the comparison of the proposed approach to related works.

- Every suggested methodology has been tested on ECG datasets from each research group. The performance presented in Table 6.2 corresponds to the reported baseline framework i.e., without any analysis of special parameters. For instance, the window and subject identification rates enumerated for the current approach are based on experimentation on healthy subjects and without fusion of 12-lead signals. In any case, when assessing the accuracy of each approach it is important to take into consideration the number of subjects involved in the experiments.
Chapter 7

Conclusions and Future Improvements

7.1 Research Summary

In this thesis, an identity recognition system based on electrocardiogram signals is reported and evaluated. It is demonstrated that human identification via the electrocardiogram is feasible and highly effective. ECG’s robust nature against falsification renders its engagement to security systems rather promising, as it offers airtight security in all situations.

The motivation behind this work is primarily the fact that most of the up to date methodologies, utilize fiducial points based techniques to extract features for identification. However, biometric analysis requires exact localization of waves boundaries, because pulses have to be synchronized before subjected to further analysis. Subsequently, waveform anomalies force the applications to discard useful for identification information.

To completely eliminate the need for fiducial points detection, the autocorrelation of ECG segments is utilized as a source of distinctive signatures among subjects. Discriminant analysis operates on AC coefficients to project the features into a lower dimensional
space while preserving significant information, and augmenting the separability of the clusters. Since this method is performed on ECG windows, no pulse synchronization is needed, keeping this way the accuracy and computational effort of the system in low levels.

An ECG based authentication method is also suggested in the current work, to validate individual’s claim for their identities. The principal component analysis is utilized for dimensionality reduction and feature extraction. Since authentication is an one to one problem, supervised learning techniques (such as LDA) are not required even though they could be applied.

Furthermore, most of the current approaches study the applicability of this biometric trait using only one lead signal. The employment of all the 12 leads is proposed for ECG based biometric identification, as this increases the security level significantly while capturing possible illegal penetration. It was demonstrated that all signals of the conventional 12 lead system embed discriminative power.

Two approaches are suggested for fusion of this information. When the features are associated on a feature based level, the identification performance is not as high as expected. This suggests that specific lead information with poor performance, when tested independently, overrules highly discriminative information offered by other leads. When combining the outcome of different classifiers at a decision based level, the subject and window recognition performance increases while there is a tradeoff between the identification and rejection rates.

The major novelty of the current work lies in addressing issues related to cardiac arrhythmias which is a commonly observed heart disease that would otherwise lead the identity authentication systems to misjudge an individual. Current approaches have not addressed such problems. Fiducial points detection is rendered even more risky when PVC and APC segments invade the electrocardiograms. Furthermore, previously suggested features for identification do no longer apply for malignant recordings.
The methodology discussed in this thesis, is invariant to the presence of atrial premature heart beats, while an arrhythmia screening algorithm is proposed to discard windows which involve ventricular originated heart beats. It is demonstrated that a power and a complexity measure criterion can constitute a strong combination in isolating pathological ECG segments.

The effectiveness of the method was evaluated on healthy and arrhythmia suffering subjects. Intruder detector methodologies have also been analyzed and tested on a combination of three public datasets. The authentication and identification performance is considerably high and it is expected that the electrocardiogram will soon find its own niche in the biometric world.

However, one should notice that the described system is a potential application which is still under research as ECG based recognition is new area of study. Comparisons with performance reported for other traditional biometrics (fingerprint, iris and so on) is not yet fair, however, the ECG still offers significant advantages mostly related to its robustness to identity fraud.

7.2 Future Directions

There are two major topics that could extend the methodologies described in this thesis. A first direction is the design and evaluation of techniques that could possibly increase the recognition performance of the system. Another extension can be performed at a system level, to address issues mostly related to the application of the electrocardiogram for biometric recognition.

7.2.1 Automatic Parameter Configuration

Automatic selection of the autocorrelation window, where the AC/LDA or AC/PCA methods operate is very important for real applications. As analyzed in the methodology
description, we suggest the employment of an AC segment of equal to a QRS length, in order to avoid effects of stress conditions. However, the length of this wave was pre-specified for our simulations. It is important for future implementations to encompass a methodology for automatic QRS duration determination.

In addition, the current approach was tested on three public databases, which did not exhibit any significant heart rate variations. Although the QRS wave is considered to exhibit the less variability under different heart rates [57], compared to other ECG inherent waves, it is useful to test this assumption on the appropriate data.

For any biometric based recognition system, environmental factors often have great impact on the recognition accuracy. A careful selection of the autocorrelation coefficients that are used for feature extraction is suggested in this thesis. A composition of a new database consisting of recordings under various anxiety conditions will allow experimentation on the robustness of the presented framework.

### 7.2.2 Feature Level Fusion

The fusion of the 12 lead ECG signals described in this thesis was carried out on two levels. The decision based level mixture, offered considerably high recognition performance. However, the corresponding feature level integration of the 12 signals did not exhibit the same degree of discriminative power.

Concatenating the feature vectors obtained by the linear discriminant analysis of autocorrelation coefficients assumes that all lead ECG signals have the same recognition power. A straight fusion in one feature vector treats the signals equally. The evaluation of a weighting procedure is suggested to affect directly the impact that each of the signals has in the final feature vector.

There can be found many ways to quantify clustering weights in literature. One possible way to determine weights, is by examining the discriminative power of each the leads separately. This can be done either by the identification performance when the
signals were tested independently, or by analyzing the corresponding Euclidean distances of each test ECG lead with the respective ones of the gallery set. Autocorrelated lead signals that have higher resemblance with the corresponding ones stored in the database, can be weighted higher.

7.2.3 Multi-modal Biometric Systems

Using multiple modalities for identification or authentication purposes is strongly believed to increase the security levels. Roughly, integrating more than one biometric characteristics in a system increases the accuracy of the final decision and makes the application harder to defeat. Furthermore, there are inherent limitations for any single-modality biometric system. For instance, a perfect face recognizer will have an upper bound of identification performance based on the number of identical twins [10].

Therefore, employing more than one biometric characteristics has the prominent benefit of making allowance for more people to enroll, while reducing the possibility of applying falsified credentials. The electrocardiogram can be combined with any other biometric characteristic into a multi-modal framework. However, there are limitations that need to be examined such as the level of invasiveness of the acquiring procedure.

The electrocardiogram, can be well fused into a system involving other related medical biometrics. Blood pressure makes a good example of a biological characteristic that is associated to ECG signals. The inherent waves observed in blood pressure signals are linked to the activity of the heart and thus can be related to the electrocardiogram. In addition, the AC/LDA methodology for identification described in this thesis, is invariant to the specific structure of ECG pulses. The blood flow is also a repetitive signal where the AC/LDA could be applied for feature extraction.
Chapter 7. Conclusions and Future Improvements

7.2.4 Privacy Issues

When dealing with sensitive personal information it is important to take into consideration the degree of acceptability that the designed systems will have in a population. Given the technological advances, any biometric characteristic could be linked to someone’s private information such as name or race.

The electrocardiogram belongs to the general class of medical biometrics. This raises even more concerns about the distribution of information that could be directly related to people’s medical record. A great risk appears when intruders illegally penetrate into a system and steal the stored biometric templates.

The dichotomy line between privacy and security is not clear. However, there should be ways of protecting the acquired biometric characteristics. Biometric encryption is a roughly new area of research that addresses this problem. The main idea is that a feature template can be encrypted by a key generated by the same signal.

Future works can concentrate in the design of an self-encryption identification system, based on the autocorrelation of ECG signals. If the autocorrelation feature vectors are quantized and an error correction code is applied, classification could be carried out based on the encrypted template.
Appendix A

Arrhythmia Screening: DCT and DFT Comparison

The power criterion described in Chapter 4, for arrhythmia screening, has been evaluated on the discrete cosine transform of an autocorrelation window. The discrete Fourier transform (DFT) can be utilized instead. However, the performance of the arrhythmia detection algorithm will not be the same.

In this section, the power criterion is applied on the DFT of autocorrelated ECGs to be compared to DCT. As demonstrated in Chapter 4, when premature ventricular heartbeats invade electrocardiogram signals, the spectrum of the corresponding autocorrelation is dominated by smaller frequencies. The power metric discussed can be estimated as:

\[ k = \min\left(\left| \sum_{i=1}^{k} Z(i) - \sum_{i=k}^{N} Z(i) \right| \right) \quad (A.1) \]

where \( k \) is the coefficient at which the autocorrelated signal reaches approximately half of its total power. Using this measure, and selecting the right threshold, it is essential to be able to distinguish between healthy and abnormal power distributions. Figure A.1 illustrates examples of healthy and arrhythmia power waveforms when DCT operates on the autocorrelation. The same Figure shows the coefficients at which half of the
Figure A.1: Examples of healthy and malignant DCT distributions

Figure A.2: Examples of healthy and malignant DFT distributions
Appendix A. Arrhythmia Screening: DCT and DFT Comparison

Figure A.3: Histograms of distances between healthy and arrhythmia power measures

power is reached, estimated using Equation 4.3. In addition, Figure A.2 pictures power distributions of the same healthy and arrhythmia ECG signals, acquired with the Fourier transform.

The idea behind the selection of DCT for further analysis in ECG arrhythmia screening lies in its comparative performance to DFT. There is a need to rely on a metric that allows high separation between healthy and arrhythmia waveforms. Subsequently, it is required for the distance between separation points of the two clusters (healthy and arrhythmic) to be as high as possible. There is no optimal threshold that will allow to perfectly distinguish the clusters, therefore the selection between DCT and DFT depends on their comparative ability to distinguish them.

It is expected that the power criterion will apply better to the cosine transform, because of its energy compaction property. To test this hypothesis, a test set of 21 healthy and 18 arrhythmia ECG windows from the MIT-BIH healthy [56] and MIT-BIH arrhythmia [54] databases was composed.

The point at which half of the total power is observed is estimated for every record-
Figure A.4: Percentage of opponent pairs under distance thresholds. Higher separability offers the methodology that allows greater percentage of opponent pairs to have large distance between them.

Figure A.3 illustrates a histogram of the distances when applying DCT and DFT. Ideally, pairs from opponent clusters would have high distances, but this is not the case neither with DCT nor with DFT. However, comparing the two histograms, there is a higher trend for DCT to offer greater separability (more pairs with high distances) between the clusters.

Figure A.4 demonstrates the performance of DCT and DFT in terms of the percentage of opponent pairs (a healthy with an arrhythmic one) observed below selected distances. This plot suggests that for a threshold selection $D = 3$ for example, 42% of the records will be misclassified with DFT, but only 27% with DCT. The percentage of pairs that are below any specified power measure distance, is greater for DFT. Therefore, the discrete cosine transform offers higher separability between healthy and arrhythmia clusters.
Appendix B

Chapter 6 Plots

Figure B.1: DCT feature vector plots used in [1]. Difference in shade reveals different recording periods
Figure B.2: DCT feature vector plots used in [1]. Difference in shade reveals different recording periods.
Table B.1: Extended comparison results with the AC/DCT methodology described in [1]

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Figure B.3: Fiducial points detection results as described in [3]
Figure B.4: Examples of pulse synchronization for the reproduction of [3]
Bibliography


