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A NON-INVASIVE METHOD FOR EARLY SUDDEN CARDIAC DEATH DETECTION

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NANCY CRISTINA BETANCOURT MENDOZA

nancy.betancourt@epn.edu.ec

ADVISOR: CARLOS ALBERTO ALMEIDA RODRÍGUEZ

carlos.almeidar@epn.edu.ec

COADVISOR: MARCO JAVIER FLORES CALERO

mjflores@espe.edu.ec

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NANCY CRISTINA
BETANCOURT MENDOZA

Thesis supervised by

CARLOS ALBERTO ALMEIDA RODRÍGUEZ,

Professor at the Escuela Politécnica Nacional (Ecuador)

and co-supervised by

MARCO JAVIER FLORES CALERO,

Professor at the Universidad de las Fuerzas Armadas - ESPE
(Ecuador)

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Oral examination by the following committee:

Marco Eduardo Molina Bustamante, Ph.D.

Escuela Politécnica Nacional (EPN), Opponent Member

María Gabriela Pérez Hernández, Ph.D.

Escuela Politécnica Nacional (EPN), Coordinator

Miguel Alfonso Flores Sánchez, Ph.D.

Escuela Politécnica Nacional (EPN), Internal Member

Angel Domingo Sappa, Ph.D.

Escuela Superior Politécnica del Litoral (ESPOL), External Member

Esteban Pino Quiroga, Ph.D.

Universidad de Concepción, Chile, External Member

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STATEMENT

I, NANCY CRISTINA BETANCOURT MENDOZA, hereby declare under oath that the work here described is of my authorship and has not been previously submitted for any degree or professional qualification, and that I have consulted the bibliographical references that are included in this document.

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- N. C. Betancourt M., C. Almeida and M. Flores-Calero (2022). *Heart Rate Variability and T Wave Alternans as risk stratification indices for detecting Sudden Cardiac Death: A Review*, in IEEE Latin America Transactions, vol. 20, no. 9, pp. 2181-2188, Sept. 2022, doi: 10.1109/TLA.2022.9878174.

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I also declare that I have acknowledged the collaboration of third parties, and the contribution made by other published or unpublished material.

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NANCY CRISTINA BETANCOURT MENDOZA

CERTIFICATION

I certify that NANCY CRISTINA BETANCOURT MENDOZA has carried out his research under my supervision. To the best of my knowledge, the contributions of this work are novel.

PhD. CARLOS ALBERTO ALMEIDA RODRÍGUEZ

ADVISOR

PhD. MARCO JAVIER FLORES CALERO

CO ADVISOR

DEDICATED TO

Luis, who has supported me unconditionally throughout this new experience.

Cristian, Sebastián, and Nicolás. For being the forces behind my life.

God, for blessing me in every step and giving me the gift of life.

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RESUMEN

La muerte súbita cardíaca (MSC) es considerada una de las principales causas de mortalidad a nivel mundial. A menudo, las personas con antecedentes de cardiopatías muestran los síntomas. Sin embargo, una hora antes del evento fatal, los síntomas también pueden aparecer en individuos sanos. Comprender el origen de esta enfermedad cardíaca sigue siendo un desafío para la comunidad científica. Según el estado del arte, se han propuesto nuevos métodos para estratificar y predecir MSC. Se han implementado diferentes algoritmos y se han utilizado índices de estratificación de riesgos, como la variabilidad de la frecuencia cardíaca (VFC) y el análisis de la alternancia de la onda T (AOT).

AOT es el término utilizado para describir los cambios en la amplitud o forma de la onda T y ha sido considerada un importante indicador no invasivo para la detección de muerte súbita cardiaca, además este índice de estratificación ha sido incluido en equipos médicos modernos. VFC es un índice de estratificación del riesgo de muerte súbita que permite medir la variación de tiempo entre conjuntos consecutivos de latidos cardíacos.

Considerando estos índices y añadiendo técnicas de procesamiento digital de señales como el aprendizaje de diccionario se ha desarrollado un método híbrido.

El método propuesto identifica las principales características de la señal de ECG obteniendo una representación escasa que adapta una matriz (dicionario) con el fin de utilizarla para resaltar las características de la AOT y luego utilizar estas características para detectar MSC. Los resultados de los experimentos muestran una mejora del 32% comparado con el programa Physionet TWAnalyser usando señales sintéticas y de un 20% usando bases de datos públicas.

En esta investigación se presenta una estrategia innovadora para predecir la muerte cardíaca súbita utilizando el análisis TWA y diccionarios de aprendizaje. Para evaluar la metodología propuesta se utilizaron bases de datos públicas y se generaron señales sintéticas.

Palabras Claves - MSC, AOT, diccionarios de aprendizaje, ECG, detección

ABSTRACT

Sudden cardiac death (SCD) is considered one of the main causes of mortality worldwide. Frequently, people with a history of cardiopathies exhibit the symptoms. However, one hour prior to the fatal occurrence, the symptoms can also appear in healthy individuals. Understanding the origin of this heart disease continues to be a challenge for the scientific community. According to the state of the art, new methods to stratify and predict SCD have been proposed. Different algorithms have been implemented, and risk stratification indices have been used, such as heart rate variability (HRV) and T-wave alternans (TWA).

TWA is the term used to describe changes in the amplitude or shape of the T wave. TWA has been considered an important non-invasive indicator for detecting sudden cardiac death in addition to being included in modern medical equipment. HRV is a SCD risk stratification index that allows to measure time variation between consecutive heartbeat sets. Considering these indices and adding digital signal processing techniques as dictionary learning that can be found in the breakdown of signals on a specified basis, for instance, the Fourier transform, a hybrid method has been developed.

The proposed method identifies the main characteristics of ECG signal by obtaining a sparse representation that adapts a matrix (dictionary) in order to use it for highlighting the TWA characteristics and then use them for detecting SCD. Experimental results show an improvement of 32% compared to the Physionet TWAnalyser program by using synthetic data set and an improvement of 20% over public databases.

This research presents an innovative strategy for predicting sudden cardiac death using TWA analysis and dictionary learning. To evaluate the proposed methodology, public databases were used and synthetic signals were generated.

Keywords - SCD, TWA, Dictionary Learning, ECG, SCD detection.

PROLOGUE

In the following pages, we look at a critical topic in the field of health: Sudden Cardiac Death (SCD). This condition, which has claimed countless lives worldwide, remains a mystery to the scientific community. Although it frequently affects those with a history of heart disease, it can also strike otherwise healthy people, sometimes with as little as an hour's notice. This makes it even more alarming. This thesis represents an attempt to understand the origins of SCD and to address one of the most pressing challenges in modern cardiology: risk prediction and stratification. Through these pages, we will explore a novel approach that combines key elements such as heart rate variability (HRV), T-wave alternans analysis (TWA), and digital signal processing techniques, including dictionary learning. TWA, a tool of great importance in the detection of SCD, is one of the central pillars of this research. We will discover how this technique has become a crucial non-invasive indicator and has been incorporated into cutting-edge medical equipment. Another important component of our work will be heart rate variability (HRV). We shall explore how HRV has been used to categorise of SCD-related risks. HRV allows us to assess the time variation between heartbeats. However, the most exciting part is the combination of these elements in a hybrid method. This innovative method seeks to identify the key features of ECG signals, using dictionary learning techniques to highlight the characteristics of the TWA, and then using these features to detect the SCD. The results of our experiments promise substantial improvements in the detection and prediction of this fatal disease. Through these pages, we will share the findings and results of our research. We will show how our hybrid method has demonstrated a significant increase in accuracy compared to previous approaches, both in synthetic signals and in public ECG databases. We hope that this research will be a further step towards effective prevention and treatment of sudden cardiac death and will inspire others to continue exploring the limits of scientific knowledge for the benefit of humanity.

Chapter 1

INTRODUCTION

Contents

Due to current lifestyle habits, sudden cardiac death is one of the leading causes of mortality in developed countries, and there is no effective method to identify patients at high risk of suffering from it [1]. Contrarily, the phenomenon known as basal T-wave alternans has emerged as a very promising non-invasive marker for stratifying certain risks, particularly in individuals who have had cardiopathies in the past [2], [3]. This demonstrates the necessity for the development of automatic systems for the detection of this phenomena, as present methods for estimating the likelihood of developing ventricular fibrillations resulting from heart collapse are still ineffective and frequently give false positive results. On the other hand, it is customary to perform the risk assessment alongside the patient in the hospital units for those who have experienced myocardial infarction. It is impossible to select the patient group that has to be closely observed in the hospital and administer the appropriate therapy to them because there are no reliable techniques for automatically detecting this kind of phenomenon. Therefore, the high prevalence of false positives contributes to the health system's saturation. Nevertheless, because of the high incidence of false positives,

the health system frequently decides not to maintain hospitalized patients who have been labeled as at risk. By avoiding hospital saturation, expenditures are increased, but a glaring deficit in the help process is typically created. The creation of systems for the early, non-invasive detection of T-wave alternances is the main goal of this thesis. By facilitating risk categorization and bringing about significant improvements in the assistance process, these systems will help to achieve the overall goal of this thesis. To process the ECG signal digitally, a number of effective and practical technologies will be created.

The organization of this chapter is as follows: We begin by outlining the issue that will be dealt with in this assignment. The goals of this research are then presented. We describe the research methodology used. We then go over our primary contributions to this effort. The subsequent chapters' structure is then presented.

1.1. Problem Statement

A risk factor for the emergence of malignant ventricular arrhythmias and, subsequently, sudden cardiac death is the alternation in the microvoltage of the T-wave (TWA) on the surface ECG. It entails a continual fluctuation in the T-wave's shape, amplitude, or duration every two beats. TWA is also linked to ventricular fibrillation vulnerability, as demonstrated by a wealth of experimental and clinical data [2], [4].

The surgical installation of an automated defibrillator is a successful method for treating sudden cardiac death, although it is risky and expensive. As a result, only patients identified as high-risk are eligible for defibrillator installation. The electrophysiology study (EEF) is a useful tool for selecting the risk group and assessing the likelihood of malignant arrhythmias. However, this surgical test has the drawbacks of being expensive, intrusive, and risky. Finding non-invasive indicators of the risk of arrhythmic death is crucial.

The present goal is to create non-invasive ways to find these patients before they have serious arrhythmia episodes. TWA is a key topic of this study. The main constraint on its scope is the rarity of apparent TWA episodes; nevertheless, the digital signal processing is enabling the identification of non-visual alternans (of the order of microvolts) that are the most common.

Different approaches have been proposed for automatic TWA analysis, like: Spectral Methods (SM), Modified Moving Average methods (MMA), Complex Demodulation methods (CD) and Statistical Test methods (ST) [2].

The most popular method for TWA detection is the spectral method, which is based

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on the calculation of the periodogram of the temporary series created by aligning the ST-T complex of succeeding beats. The procedure should be applied to a large set of data, ideally 128 beats, and calls for the ECG to behave in a quasi-stationary manner. Additionally, increased heart frequencies show signs of TWA existence. Ergometry, or stress testing, is the standard approach used to achieve the aforementioned requirements. Although it is not an invasive test, it has some drawbacks, including a significant proportion of patients who are unable to exercise at the appropriate frequencies, leading to a high percentage of indeterminate results. Therefore, this approach is not recommended.

Designing reliable processes that work with ongoing clinical monitoring and laboratory experimental studies is the direction that is now being pursued. In general, the approach should be able to deliver findings that can be understood without requiring the heart rate to be under control and should be able to deal with noise and artifacts. On long-term outpatient records or Holter records, the TWA study could be carried out in this manner. This would suggest an inherent improvement in data collection, as patients could go about their regular lives while the data was being collected. This would also help to facilitate access to healthcare at reduced prices, thereby enhancing the aid process.

Despite the methods for detecting TWA, the scenario described in the previous paragraph is one that is still up for discussion. This is because there is currently no "gold standard" for methodologically validating the suggested approaches [2]. As was previously stated, TWA occurrences are not visible to the unaided eye, which has prevented the availability of registered databases up until this point. The technique that is used and authorized the most commonly is working with simulated signals [5], [6]. This disadvantage is a fundamental reason to continue to investigate new techniques.

1.2. Objectives

The proposed methods for TWA detection are significantly improved by using alternative techniques, such as learning dictionaries. This is quite new, since in the literature that has been consulted, no prior work with this strategy has been found.

1.2.1. General Objective

The fundamental objective of this thesis is to develop a new methodology for early and non-invasive detection of sudden cardiac death by using TWA and digital signal processing

techniques.

1.2.2. Specific Objectives

- In order to have a deeper understanding of the pertinent factors that should be taken into account when developing the methodology, review and assess the literature that is linked to sudden cardiac death.

- Integration of processing methods based on dictionary learning to enhance ECG signal processing methods.

- Develop innovative processing methods to produce options for the detection of T-wave alternans.

- Methodological evaluation of the obtained results.

1.3. Research Methodology

Design science [7], a type of research technique frequently used to create design artifacts like methods, process models, and algorithms, served as inspiration for the development of our methodology. With the stated goal of enhancing the artifact's functional performance, design science study focuses on the creation and operation of artifacts. The following are the six stages that comprise the design study and that allowed us to direct the research.

1. *Problem identification and motivation*: The precise research issue was now identified, and the benefit of a solution was established.

2. *Define the objectives for a solution*: Using the problem definition and your understanding of what is feasible and possible, we infer the objectives of a solution.

3. *Design and development*: Build the artifact. Constructs, models, procedures, or instantiations are some examples of such artifacts. In our work a new methodology have been developed.

4. *Demonstration*: Using an experiment we show that the artifact can be used to solve the problem.

5. *Evaluation*: Assess the artifact's ability to aid in finding a solution to the issue.

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6. *Communication*: Inform researchers and other pertinent audiences, such as practicing professionals, about the problem and its significance, the artifact, its utility and novelty, the rigor of its design, and its effectiveness. In this sense, we published our work and results in journals and conferences.

1.4.   Research Contributions

The main contributions of this thesis are:

- N. C. Betancourt M., C. Almeida and M. Flores-Calero (2022). *Heart Rate Variability and T Wave Alternans as risk stratification indices for detecting Sudden Cardiac Death: A Review*, in IEEE Latin America Transactions, vol. 20, no. 9, pp. 2181-2188, Sept. 2022, doi: 10.1109/TLA.2022.9878174.

- Betancourt, N., Flores-Calero, M., Almeida, C. (2021). *A Non-invasive Method for Premature Sudden Cardiac Death Detection: A Proposal Framework.* In: Guarda, T., Portela, F., Santos, M.F. (eds) Advanced Research in Technologies, Information, Innovation and Sustainability. Communications in Computer and Information Science, vol 1485. Springer, Cham. https://doi.org/10.1007/978-3-030-90241-4_5.

- Betancourt, N., Flores-Calero, M., Almeida, C. (2021). *An Algorithm for Automatic QRS Delineation Based on ECG-gradient Signal.* In: Guarda, T., Portela, F., Santos, M.F. (eds) Advanced Research in Technologies, Information, Innovation and Sustainability. Communications in Computer and Information Science, vol 1485. Springer, Cham. https://doi.org/10.1007/978-3-030-90241-4_10.

- Betancourt, N., Almeida, C., Flores-Calero, M. (2019). *T Wave Alternans Analysis in ECG Signal: A Survey of the Principal Approaches*. In: Rocha, Á., Ferrás, C., Paredes, M. (eds) Information Technology and Systems. Advances in Intelligent Systems and Computing, vol 918. Springer, Cham. https://doi.org/10.1007/978-3-030-11890-7_41.

- Nancy Betancourt, Marco Flores-Calero, and Carlos Almeida. (2019). *ECG Denoising by using FIR and IIR Filtering Techniques: An Experimental Study*. In Proceedings of the 2019 11th International Conference on Bioinformatics and Biomedical Technology (ICBBT'19). Association for Computing Machinery, New York, NY, USA, 111–117. https://doi.org/10.1145/3340074.3340088

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1.5. Thesis Contributions

The main contributions of this work are:

1. A hybrid methodology using TWA and dictionary learning has been developed. The framework proposed shows 4 stage: preprocessing, feature extraction, dictionary learning and classification.

2. A new algorithm for detecting QRS complex was implemented, and high performance was obtained.

3. For segmenting the ST-T intervals an algorithm is presented. In this stage, different values of threshold have been used, according the RR interval analyzed.

4. A dictionary learning has been building for highlighting the TWA characteristics and to detect SCD.

5. An algorithm to create ECG synthetic signals.

1.6. Thesis Structure

The structure of this thesis is as follows: Chapter two describes the general concepts used in this work and related works are presented. Chapter three explains the proposal's research methodology. Chapter four shows the experimental results and comparative discussion. Finally, the conclusions and future works are presented in the last chapter.

Chapter 2

BACKGROUND

Contents

Sudden cardiac death (SCD) is a natural death caused by heart failure. Heart electrical failure, which results in cardiac arrest, is the primary cause of SCD. The heart stops pumping blood to the rest of the body because this failure prevents a beat from happening. Without cerebral blood flow, there is a deficiency in brain oxygen, which causes sudden loss of consciousness and eventual death [8]–[11]. SCD is one of the causes of cardiovascular mortality [1], [12] producing millions of deaths worldwide [13]. In Ecuador, there are no official records for SCD, but there are data associated with deaths of heart origin. According the National Institute of Statistics and Census (INEC) , heart ischemic diseases mortality is about 13.5% of the total deaths recorded in year 2020. Non-communicable diseases, such as

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cardiovascular disease, cancer, diabetes, and chronic respiratory diseases, are the primary causes of premature death in the Region of the Americas, and heart disease accounted for 20% of these fatalities in 2019, according to the Pan-American Health Organization [14]. SCD is a multifactorial issue; it has various underlying causes that change with age and may continue to rise in the years to come as a result of the rise in coronary heart disease (tabac, obesity, diabetes mellitus, arterial hypertension, and increased cholesterol), which makes it a significant challenge. The early identification of SCD risk factors is an unresolved problem in bio-engineering and clinical cardiology [10]. In this sense the urgency of developing new methods to estimate and predict SCD increases, which leads to more effective prevention.

For analyzing the different cardiac anomalies, there are non-invasive tools such as the electrocardiogram (ECG), magnetic resonance imaging, or computed tomography [9], [11], [15].

The ECG is considered by experts as an important tool that allows for the observation of cardiac failures [3]. The waves inside the ECG are known as the P wave, Q, R, and S (QRS complex), and the T wave. The study of ECG morphology, intervals, waves, amplitude, and other features allows for the proposal of new approaches [6], [16].

The T-wave represents ventricular repolarization. The normal T wave is positive and asymmetric in most leads. Then, when an alteration or change in the shape or amplitude of the T wave is detected, it is known as a T-wave alternans (TWA) [2], [3]. The magnitude of the alternans is on the order of microvolts, so it is difficult to detect it. TWA is a heart rate-dependent magnitude that has proven to be a non-invasive indicator to stratify cardiac risks [16], [17].

On the other hand, dictionary learning is a technique that has been used in digital signal processing, allowing the signal to be analyzed in the time-frequency domain [18]. The dictionary captures the information required to recognize the particular features of the signals. This technique has demonstrated high performance in classification tasks [19].

2.1. Definitions

2.1.1. Sudden Cardiac Death

Sudden cardiac death is defined as natural death caused by heart problems. In most cases this condition occurs in people with pre-existing heart disease, for example: ventricular fibrillation and ventricular tachycardia [9], [20]. In addition, SCD has been reported to appear

in healthy people one hour before the patient dies [6], [8]–[10].

According to the World Health Organization, SCD is a major factor in cardiovascular mortality, accounting for nine million deaths worldwide in 2019 [1], [12], [13]. SCD causes an estimated 400,000 deaths per year in the United States [17], [21]. The majority of individuals are not found until they have developed significant heart conditions such ischemia, infarction, or aberrant ventricular conduction. 2–3 percent of all SCD casualties are represented by these patients [1], [21]–[23]. Understanding the origin of this disease continues to be a challenge for the medical and scientific community.

The two main methods of treatment for SCD are the implantation of an Implantable Cardioverter-Defibrillators (ICD) and the prescription of antiarrhythmic medications [2], [15]. ICD is an effective technique to prevent SCD. However, it is an invasive and costly method. Hence, it is important to develop new non-invasive methods to estimate and predict this pathology.

2.1.2. Electrocardiogram

Electrocardiogram (ECG) is a non-invasive test that captures the electrical activity of the heart. It is the most common test used to research and diagnose cardiac disorders due to its ease of use, low cost, and high utility. The heart, which has four hollow chambers, is a muscle. It is a twin pump, with the left side operating at a higher pressure than the right side. The cardiac conduction system elements consist in the following components: sinus node (SA), atrioventricular node (AV node), bundle of His, right bundle branch, left bundle branch, and Purkinje network (Purkinje fibers) [24] (see Figure 2.1).
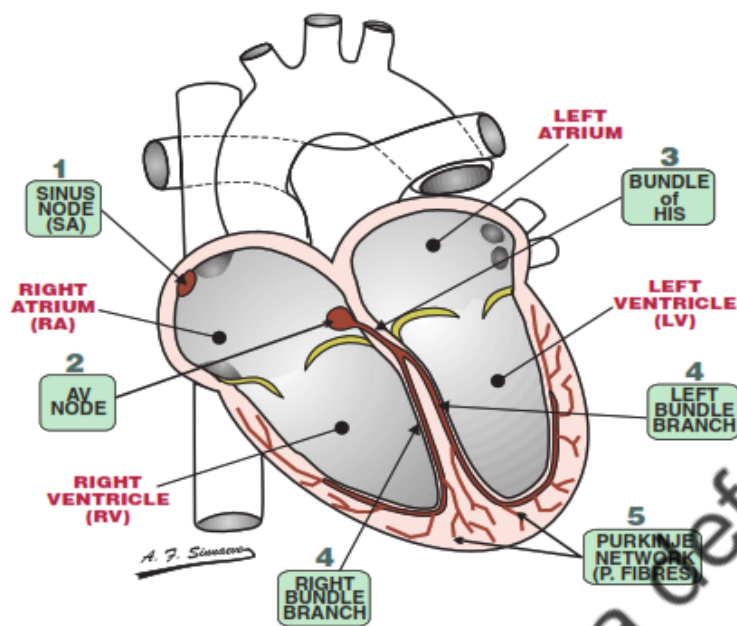
Figure 2.1. `Cardiac conduction system.  Reproduced from [24]`

The conduction system of the heart performs the following stages: The sinus node, which is made up of unique pacemaker cells, is where the excitement begins. The left and right atria both experienced the electrical impulses. The AV node slows down the impulses as they pass through it on their way to the bundle of His. The impulses are quickly conducted to the Bundle Branches by the Bundle of His, which is located at the distal end of the AV junction. The fast-conducting branches of the right and left bundles split into progressively smaller branches, the smallest of which join the Purkinje fibers. Under the endocardium, the Purkinje fibers are dispersed throughout the ventricles and speed up the delivery of electrical impulses to the myocardial cells [2], [24], [25].

For recording the ECG signals, a set of electrodes is placed on the chest of the patient. Typically 10 electrodes are used to record the signal to obtain 12 leads, which can be split into two groups based on orientation [24]. The orientation of one group is in the horizontal plane formed by six precordial derivations named V_1, V_2, V_3, V_4, V_5 and V_6. The other group is in the frontal plane of the body and is formed by three standard derivations and three augmented derivations. The standard derivations were proposed by Einthoven, and they are known as bipolar derivations I, II, and III. The three augmented derivations were proposed by Goldberger and they are named aVR, aVL, and aVF [2], [24], [25]. Figure 2.2 shows the typical derivation system's electrode placement for frontal (on the left) and precordial (on the right) derivations. To reduce noise and make placement easier, the electrodes that make up the Einthoven triangle (LA, RA, LL) are positioned on the extremities. The corresponding

points on the torso are probed by the extremities.
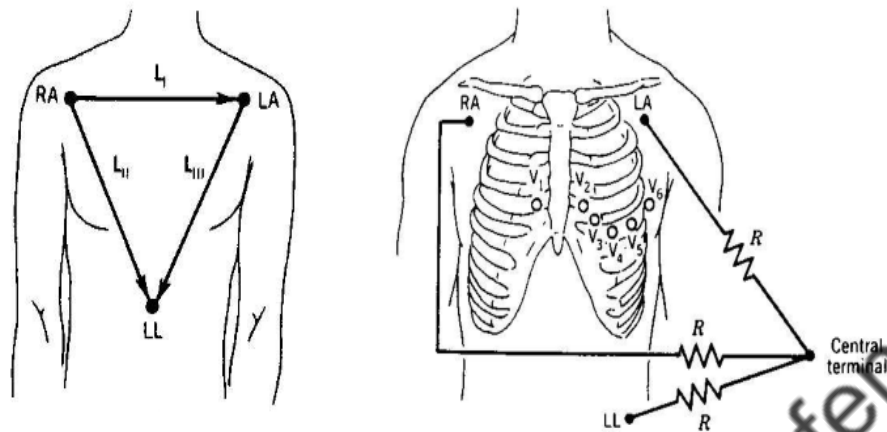
Figure 2.2. System of derivations. Reproduced from [2].

A typical ECG is showed in Fig. 2.3. ECG is composed of waves, intervals, segments, and one complex. An electrical event is indicated by a wave, which is a positive or negative displacement from the baseline (isoelectric line). There are different wave types that can be seen on an ECG: P, Q, R, S, and T waves. The interval is the space of time between two particular ECG events. The PR, QRS, QT, and RR intervals are among the intervals that are frequently monitored on an ECG. A complex is the result of numerous waves coming together in one location. The only significant complex on an ECG is the QRS complex [3], [12].
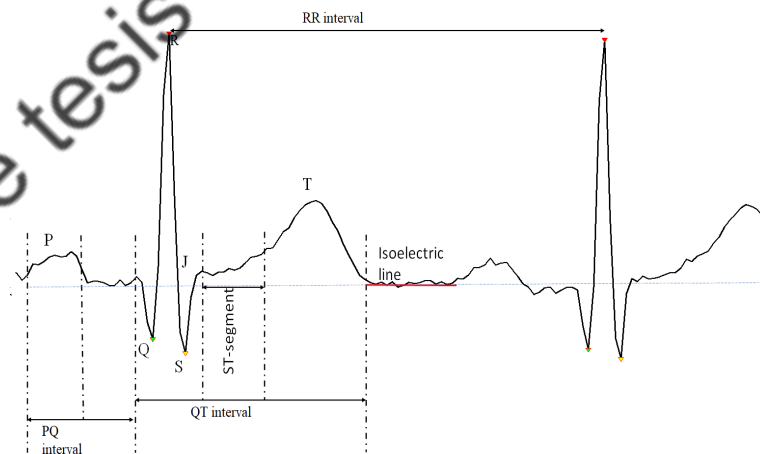
Figure 2.3. A heartbeat and its morphology. Source the author.

The P wave, which is the first wave in the ECG, denotes the activation (depolarization) of the atria. Following the P wave, the QRS complex signals the ventricles' activity. The repolarization of the ventricles is represented by the ST-T complex, which is constituted of the

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ST segment and the T wave. The area that is got no electrical activity is the area between two complexes: after the T wave and before the P wave. So, the baseline or isoelectric line should be the TP segment. The set of waves (P,Q,R,S,T) corresponds to a heart beat.

Table 2.1 and Table 2.2 show the amplitude and duration of the intervals in a typical ECG.

Table 2.1. Wave amplitudes of the ECG [26].

Wave	Amplitude
P	0.25 mV
Q	25% R wave
R	1.60 mV
T	0.1 - 0.5 mV

Table 2.2. Intervals and segments duration's of the ECG [26].

Intervals - Segments	Duration
PR interval	0.12 - 0.20 s
QT interval	0.35 - 0.44 s
ST segment	0.05 - 0.15 s
P wave	0.11 s
QRS complex	0.06 - 0.1 s
RR interval	0.6 - 1.0 s

The study of ECG morphology, intervals (RR, QT, PQ), segments (ST, ST-T), waves, amplitude and other characteristics, allow to investigate and develop new methods focused on detecting cardiac anomalies such as: heart rhythm irregularities, diseases in the coronary arteries, arrhythmia and SCD [3], [27], [28]. In particular, the normal T wave is positive and asymmetric in most leads. However, when an alteration or change in its shape or amplitude is detected, it is known as TWA [2], [3], [6].

2.1.3. Segmentation and Alignment

The goal of segmentation is to split a signal into many components with similar statistical properties, such as amplitude and frequency. The analysis of specific segments of the ECG is a common non-invasive technique for the diagnosis of cardiovascular diseases. In this

sense, the accurate identification of specific points in the ECG could help to improve results in a clinical application such as heart arrhythmia. The ECG segmentation process can be performed manually and may offer reliable results when it is done by expert clinicians. However, this method is tedious and time consuming. So, many researchers have been interested in automatic ECG segmentation [1], [3], [29].

Phase alignment is a concept used in system optimization to ensure a smooth transition between two or more signal sources. It involves aligning the timing or phase of these sources to create the most transparent transition between them. The alignment procedure requires comparing each of the ECG signal's extracted periods to a reference, which is the median sample value calculated from each R peak value found [3].

2.1.4. ECG Noise and Artifacts

ECG is a non-stationary signal which is interfered by different types of noises. Common noises in ECG can be considered as technical origin and physiological origin [30].

Noise of technical origin

- **Baseline wander (BW)** Noise with a low frequency is baseline wander. According to [31], the frequency range is often less than 1.0 Hz. This type of noise is brought on by variations in electrode-to-skin polarization voltages brought on by breathing and movement of the body.

- **Power line interference (PLI)** The most prevalent type of noise in the 50–60 Hz band is PLI [32]. Power lines' electromagnetic interference is the main source of the interference. Improper grounding of the patient or the ECG machine; Electrical equipment such as air conditioners, elevators, and X-ray units, which draw heavy power line current, are other causes of interference [33].

- **Electrode contact noise (ECN)** ECN is caused by the loss of contact between the electrode and the skin, which effectively disconnects the measurement system from the subject [32]. They occur mainly in the range from 1 to 10 Hz.

- **Electrosurgical noise** This noise is generated by other medical equipment present in the patient care environment at frequencies between 100 KHz and 1 MHz [32].

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Noise of physiological origin

- **Electromyogram (EMG) noise** EMG is the electrical activity of the muscles. This noise occurs at the time of muscle activity during an ECG recording. 10% of the ECG amplitude is affected by this kind of noise [32].

- **Motion artifacts (MA)** Abrupt movements such as coughing while ECG is being recorded results in MA in ECGs which appear as sudden changes the in electric potentials [33].

2.1.5. Convolution

Convolution is a mathematical process that takes two functions (f and g) and creates a third function (f*g) that expresses how the shape of one is changed by the other. It can be characterized as the integral of the product of the two functions after one of them has been moved and reflected on the y-axis. The decision of which function is reflected and shifted in front of the integral has no effect on the outcome of the integral [34].

Discrete convolution

Let x, y be the discrete functions defined on the set Z of integers. The convolution of two functions (signals) x and y, in discrete-time, is defined as equation (2.1) [34].

$$G[n] = (x * y)[n] = \sum_{k=-\infty}^{\infty} x(k)y(n-k) = \sum_{k=-\infty}^{\infty} y(k)x(n-k) \tag{2.1}$$

2.1.6. k-Nearest Neighbors Classification (K-NN)

In the Nearest Neighbor rule. It gives a set of n pairs $(x_1, \theta_1), (x_2, \theta_2), ..., (x-n, \theta_n)$, where x_i takes values from a metric space X over which a metric d is defined, and the values of θ_i are in the set $\{1, 2, ..., M\}$. Each θ_i is considered to be the index of the category to which the $i-$th individual belongs, and each x_i is the result of the set of measurements performed on that individual. A new pair (x, θ) is given , and θ is expected to be estimated using the information contained in the correctly classified set of points. If $min \quad d(x_i, x) = d(x'_n, x), \quad i = 1, 2, ..., n$, then we refer to $x'_n \in \{x_1, x_2, ..., x_n\}$ as x's nearest neighbor [35].

2.1.7. T-wave Alternans

TWA is characterized as a change in the T wave's shape, amplitude, or duration [2], [3]. Knowing as re-polarization alternans, TWA is regarded as a measure for risk stratification in SCD patients [6], [20], [36]. Figure 2.4 shows a periodic alternation that occurs continuously every two beats (even and odd beat).
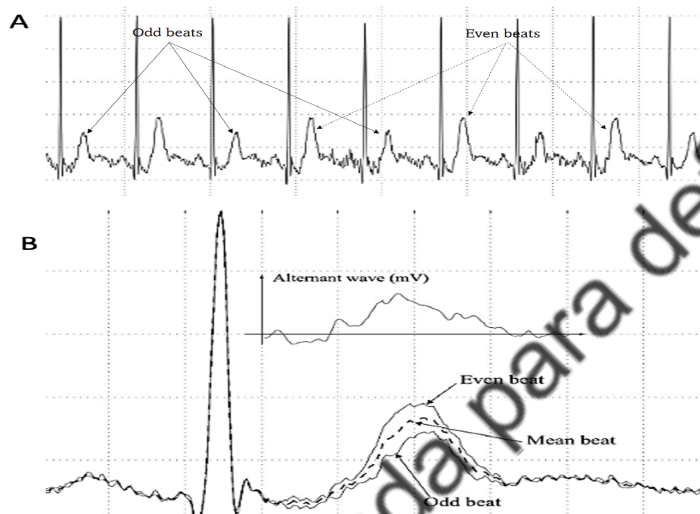
Figure 2.4.   (A) Every two beats, the ECG signal displays a periodic alternation pattern. (B) As the difference between the even-beat average and the odd-beat average, TWA is visually interpreted. Reproduced from [6].

Any wave section of the ECG, including the QRS complex, ST segment, and T wave, might exhibit alternans. However, T-wave alternans is regarded as a trustworthy index for determining sudden cardiac risk [22], [36].

The most popular techniques for examining alternans in the T wave are:

• Method of Modified Moving Averages (MMA): The TWA magnitude is calculated by averaging the absolute maximum difference between the pair and impair beat series of the T waves or of the ST-T segments [28], [36], [37]. Figure 2.5, shows the MMA method for calculating TWA.
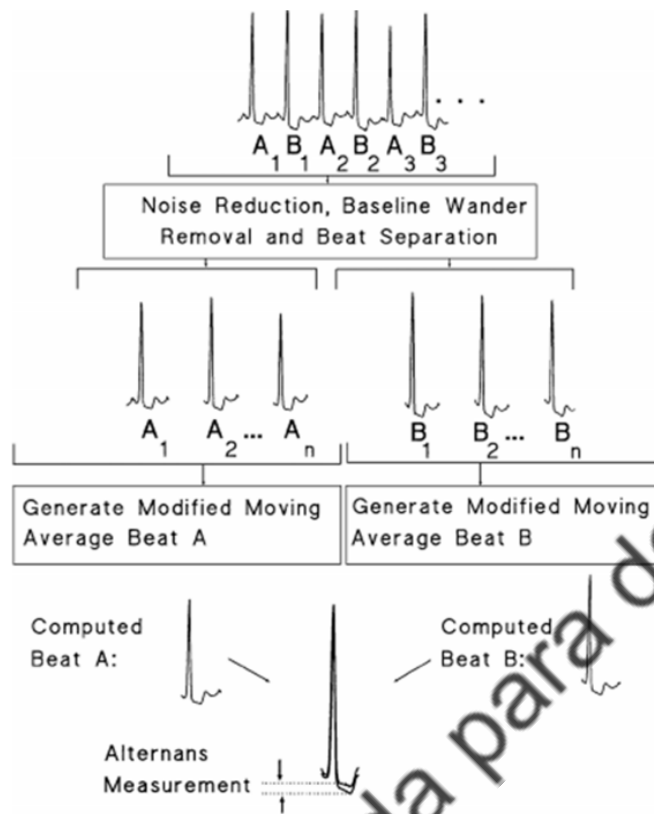
Figure 2.5. MMA Method. Reproduced from [38].

- Spectral method (SM): To determine whether or not TWA is present, the alternans is calculated by comparing the power spectrum at 0.5 cpb with the noise level spectrum. Figure 2.6 shows the method proposed by J.M. Smith [39]. In (A) is observed the selection of 128 ST-T complexes in 128 ECG beats. (B) is the variation of amplitude along the 128 beats (128 periodograms). In (C) The spectrum is calculated by the Fourier transform. (D) is the calculation of the composite spectrum. (D) The corresponding TWA amplitude is the square root of the alternating power.
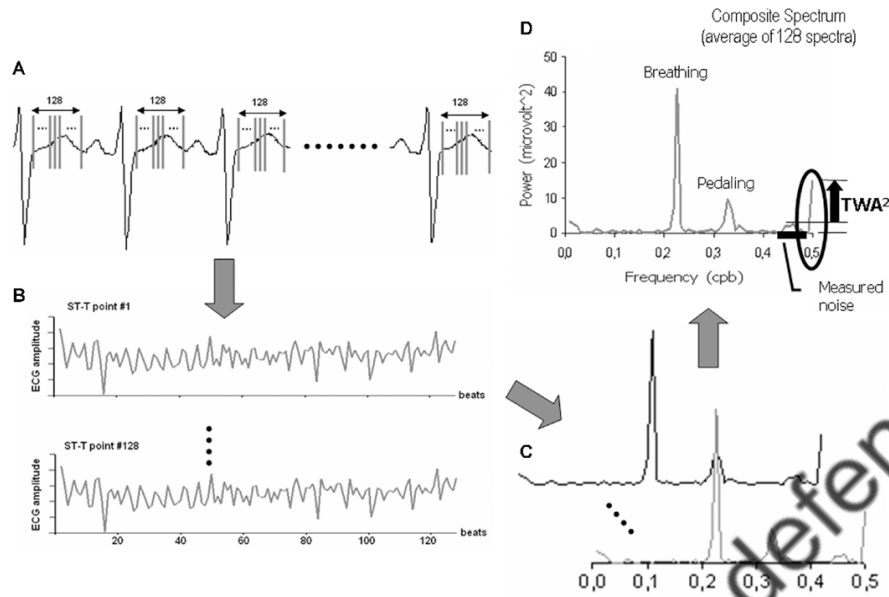
Figure 2.6. `Spectral Method.  Reproduced from [40].`

Figure 2.7 presents the process to analyse TWA [2]. The system takes an ECG signal as an input. It can be seen from the output H_0 that the signal contains a T-wave alternan. The absence of the alternans is represented by H_1, on the other hand.
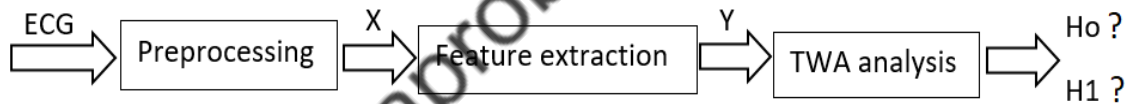
Figure 2.7. `Procedure for analysing TWA.`

2.1.8.   SCD by TWA

TWA is a magnitude that depends on heart rate and has been proven to be a non-invasive measure for determining SCD risk [6], [27], [28], [41]–[43]. Techniques in the time and frequency domains, including spectral methods (SM), modified moving average methods (MMA), complex demodulation methods (CD), empirical mode decomposition (EMD), and statistical methods (ST), have been developed for the analysis of TWA [2].

The alternations along the T waves are marked by techniques in the frequency domain, such SM, by examining the power spectrum of the sample points. The article [3] describes a three-step TWA detection and estimate approach that includes segmenting the ST-T wave in accordance with the ECG phase, filtering the ECG signal with a Kalman filter (KF) variant, and identifying and calculating the value of TWA using the spectral method. Based on

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a dynamical model that is not directly amplitude-dependent, the research [44] offers an Extended Kalman Smoother (EKS) for TWA detection. Within this framework, the authors take into consideration independent states for PQRS and an amplitude-free state model for T-wave. In [45], new statistical and spectral detectors, the modified matched pairs t test, the extended spectral method and the modified spectral method are proposed for T-wave alternans (TWA) detection. In paper [46], a novel machine learning-based method for TWA detection is put forward. The K closest neighbor, decision trees, random forests, support vector machines, and multi-layer perceptrons are among the machine learning algorithms that use the spectral method (SM), modified moving average technique (MMA), and temporal domain method (TM) to gather input data. In Paper [47], a brand-new approach based on tensor decomposition techniques is suggested for automatically detecting TWA. Canonical polyadic decomposition and the more generalized version PARAFAC2, which permits the T waves to shift in time, are two alternative tensor decomposition techniques that are compared and contrasted. A novel EMD-based least squares T-wave alternans estimation scheme is presented in [48] that outperforms estimation in 10–40 dB Gaussian noise.

2.1.9.   Dictionary Learning

A dictionary is a collection of atoms that can be used for signal decomposition. An atom d_i is an elementary signal that represent part of the energy or features of a specific type of signals for which the dictionary was adapted [19].

A real column vector **x** of finite length $n \times 1$ is used to represent the original signal. If the majority of the entries in a vector **x** are zero, or if the set of values $F(\mathbf{x}) = \{1 \leq i \leq n | \mathbf{x[i]} \neq 0\}$ has cardinality $k \ll n$, then the vector is said to be sparse. So, a signal that has exactly k samples with a non-zero value is said to be $k-$sparse [19].

Modeling the signal **x** as the linear combination of m elementary wave forms (atoms) will result in

$$\mathbf{x} \approx D\alpha = \sum_{i=1}^{m} \alpha[i] d_i \tag{2.2}$$

where α is a column vector of size $m \times 1$ that contains the representative coefficients of x in a matrix dictionary $D = [d_1, d_2, ..., d_m]$, of size $n \times m$, and d_i is a vector of size $n \times 1$, it represents the atom of the dictionary. The setting $\mathbf{x} \approx D\alpha$, which means that the signal x is reconstructed using sparse representation, is used when the dictionary contains more columns than rows $m > n$, which is referred to as being over-complete or redundant.

A Dictionary learning (DL) is created by using Gabor functions over a set of samples of signals. This dictionary captures the particular characteristics of each wave enhancing the signal, and representing these characteristics into a matrix (set of atoms). These dictionaries have demonstrated high performance in classification task [49], [50]. After the dictionary is defined, the sparse representation of the signal could be obtained.

2.2.   Review of State of the Art

TWA is an important phenomenon not only within the clinical field but also within the scientific and technological fields. It has been considered an important, non-invasive, and very promising indicator to stratify the risk of sudden cardiac death. Due to its microvolt amplitude and background noise, sophisticated signal processing techniques are required for its detection and estimation. In this chapter, we present a survey of the state of the art focusing on the detection of sudden cardiac death by analyzing the T wave on long-term ECG signals.

2.2.1.   Methodology Used for Developing the Literature Review

To carry out the research, a Literature Review (LR) was undertaken based on the guidelines proposed by Kitchenham [51]. The LR is divided in three phases:

1. **Planning review:** In this stage, research questions, keywords and scientific databases for the review are defined. Table 2.3 shows the information used in this stage.

Table 2.3. Planning Review

Research questions	Keywords	Scientific databases
Is it possible to detect SCD by analyzing the ECG? Are there methods to stratify SCD risk?	SCD stratification indices	IEEE Xplorer Springer Web of Science

2. **Review development:** In this stage, articles related to the detection of sudden cardiac death were selected. In Table 2.4 you see the search chains and related terms that were used to conduct a comprehensive review, improving the selection of articles in the selected scientific bases.

Table 2.4. Boolean Search Chains

Search chains	Related terms	Boolean chains
Sudden Cardiac Death (SCD)	ECG	ALL("sudden cardiac death" AND "ECG") OR ("SCD" AND "ECG")
	Preprocessing	ALL("sudden cardiac death" AND "preprocessing") OR ("SCD" AND "preprocessing")
	Feature extraction	ALL("sudden cardiac death" AND "feature extraction") OR ("SCD" AND "feature extractions")
	Detection	ALL("sudden cardiac death" AND "detection") OR ("SCD" AND " detection")
Heart Rate Variability (HRV)	ECG	ALL("heart rate variability" AND "ECG") OR ("HRV" AND "ECG")
	Preprocessing	ALL("heart rate variability" AND "preprocessing") OR ("HRV" AND "preprocessing")
	Feature extraction	ALL("heart rate variability" AND "feature extraction") OR ("HRV" AND "feature extractions")
	Detection	ALL("heart rate variability" AND "detection") OR ("HRV" AND "detection")
T wave alternans (TWA)	ECG	ALL("T wave alternans" AND "ECG") OR ALL("TWA" AND "ECG")
	Preprocessing	ALL("T wave alternans" AND "preprocessing") OR ALL("TWA" AND "preprocessing")
	Feature extraction	ALL("T wave alternans" AND "feature extraction") OR ALL("TWA" AND "feature extraction")
	Detection	ALL("T wave alternans" AND "detection") OR ALL("TWA" AND "detection")

In total, 60 articles related to the research topic were obtained. Then 14 repeated jobs have been removed. In the next step, the inclusion and exclusion criteria of Table 2.5 were used. Subsequently, 11 items that used invasive techniques such as the IDC were removed, leaving 35 items left, of which 20 used the ECG as a tool for sampling. So we have 20 articles for review, of which 6 deal with HRV as a stratification index, 7 deal with TWA, and 5 use other indices; these latter were discarded. Of the 7 TWA works, 2 were removed by using methods such as complex demodulation. Finally, in this review, we have 11 relevant works to analyze SCD risk stratification indices.

Table 2.5. Criteria of inclusion and exclusion

Inclusion criteria	Exclusion criteria
Non-invasive techniques	invasive techniques
Applied to ECG analysis	Not applied to ECG analysis
Applicable to SCD	Not applicable to SCD
Using Artificial Intelligence	Clinical Approach

3. Finally, in the results analysis stage, three domains were defined that allow grouping the results and discussion: i) Sudden cardiac death ii) Heart Rate Variability, and iii) T wave alternans.

2.2.2. Related Works

Several methods have been developed in recent years to detect and quantify TWA. Some of the most widely employed methods in clinical practice follows:

1. **Modified moving average method (MMA):** In the article presented by [37], the authors showed a new approach to detect and estimate alternans in the T-wave. The magnitude of TWA is obtained by means of the maximum absolute difference of averages of series of even and odd beats calculated in T-waves or ST-T complexes.

Different approaches have been presented based on MMA for example: In their paper [36] proposes a new method called template matched-filter based scheme for detection and estimation of T-wave alternans (TMFD), in this work a preprocessing stage for the MMA method to ensure an optimal alignment of the computed averages is presented. In the work of [28], the authors propose an Enhanced modified moving average (EnMMA)

the accuracy of the method was improved with a better aligned prior to distance calculation. In order to achieve the improvement, the authors added a preprocessing stage based on continuous dynamic time warping (DTW).

2. **Spectral methods (SM):** SM was proposed by [39] in this method digitized ECG beats are aligned, and periodogram based power spectral evaluations are calculated for every sample in the segment of interest. The value of an added spectrum at 0.5 cpb is compared with the spectral noise level to decide if TWA is present. Different versions of the SM have been presented. Paper [17] presents an improved spectral method that contains three component: enhanced spectral method (EnSM); spectral analysis of T-Slope variations (TSV); and singular value decomposition (SVD). Another version of SM is presented by [21] named non-negative matrix factorization (NMF)-Adaptive SM, the Adaptive SM have the advantages of both SM and Modified moving average. In [3] the paper presents a three step TWA detection and estimation strategy which consists of filtering the ECG signal using a variant of Kalman filter (KF), segmenting the ST-T wave based on ECG phase and applying the spectral method to detect TWA and estimate its value.

3. **Complex demodulation method (CD):** In this method, the beats are aligned, and TWA is showed in each series as a sinusoidal signal of frequency and variable amplitude and phase. TWA amplitude in each beat-to-beat series is projected by demodulation of the 0.5-cpb component and low-pass filtered to obtain a continuous beat-to-beat alternans measurement [52].

4. **Correlation method:** A single cross correlation coefficient is computed for every ST-T complex against a representative for a heartbeat series. The single beat-to-beat series of coefficients is evaluated by a time-domain zero-crossing counter. If the correlation index alternates for some consecutive beats, a TWA episode is detected [4] [53].

5. **Karhunen-Loève transform (KLT):** The KLT transform has been used for its ability to achieve the maximum compaction of energy in a few coefficients[54]. Two proposals have made use of this transform: The first proposals, each ST-T complex is represented by the first four coefficients of its KLT transform. Then each beat-to-beat series of KL coefficients is analyzed spectrally using a periodogram [2].

6. **Capon filtering method (CF):** In this method, the low-pass filter is replaced by the

filter cap. It is the filter system that preserves the alternating component, minimizes the power of the signal at its output. The filter is based on the data and is obtained from the auto correlation function of the input signal [55].

7. **Statistical test method (ST):** This method is based on statistical tests: Student's t tests for independent and paired samples, applied to study if there are differences between the characteristics of the T wave between the odd and even beats and the Rayleigh periodicity test [56]. Recent methods have been developed, [57] presents a non parametric adaptive surrogate test to assist in accurate detection of TWA, independent of the particular estimation algorithm being used. In their paper, [58] presents a new class of algorithms, based on the Monte Carlo method, for the detection and quantitative measurement of alternans.

8. **Laplacian likelihood ratio method (LLRM):** The LLRM method calculates the maximum likelihood estimation of the TWAs by assuming a Laplacian noise distribution, and applies the generalized likelihood ratio test to decide whether the TWAs are present or not in the ECG [59]. In [12], they propose the use of a multilead TWA analysis scheme that combines LLRM method and periodic component analysis (πCA), an eigenvalue decomposition technique whose aim is to extract the most periodic sources of the signal.

9. **Poincaré mapping method (PMM):** PMM are formed by plotting T-wave magnitude of alternate beat. Semi periodic signal such as TWA, appear as close clusters. TWA magnitude is the intercluster distance [60].

10. **Singular Value decomposition (SVD):** This method is used for signal processing and analysis of statistical data. SVD has two important steps, first the coarse TWA detection and second fine TWA detection [61].

We inform the reader that all the methods presented in the above section are considered important; however, in this chapter we will focus on the analysis of the results of the methods (SM and MMA) by the following reasons: According to the literature SM and MMA are the most used methods. These methods have been included in medical equipment such as CH2000 and Heartwave (Cambridge Heart Inc, Bedford, MA) [62].

Databases

The papers that was presented in the state of the art, used databases that allowed to perform the experiments and validate the methods. Table 2.6 summarize these databases.

Table 2.6. Databases of ECG signals used in the state of the art for TWA

Article	Database	Method
[12]	Physionet TWA Database	LLR
[36]	MIT-BIH Arrhythmia Database, from MIT Physionet	TMFD
[28]	Simulated ECG signals: European ST–T database (0123, e0103, and e0105)	EnMMA
[53]	MIT-BIH Arrhythmia Database, from MIT Physionet	CM
[63]	Simulated ECG signals	SM
[17]	MIT/BIH Sudden Cardiac Death Holter Database (seventeen records with T waves presented)	SM
[3]	Simulated ECG signals	SM
[57]	NSRDB, CHFDB and SCDDB)	ST
[58]	NS	ST
[37]	7-French USCI quadripolar catheter	MMA

Preprocessing and feature extraction

The paper [36] presents TMFD approach. The QRS and T-wave peak detection is performed using the waveform locator available at Physionet. The comparative evaluation is carried out with three most common classical techniques in the case of stationary as well as non-stationary TWA (SM, MMA and CM). In the preprocessing stage, [28] presents an enhanced MMA method using Dynamic Time Warping (DTW) curve alignment. DTW is described as a method that can eliminate shift-related artifacts from measurements by correcting a sample vector of length J towards a reference of length I. This method performs well for different levels of TWA, noise, and phase shifts, but it is sensitive to the alignment of the T-waves.

The method proposed by [17] Enhanced modified moving average (EMMA), digital filters were used to remove general arterial interference and to limit the ECG bandwidth between 1Hz and 50Hz. After that, Pan & Tompkins method [64] is used to indicate R waves. With

detected R points, T points can be located by cross-checking on the maximum points of ECG and all the zero-crossing points of dECG. In their research, the noise band is at range [0.42 0.46] cpb, and $P_{0.5}$ is the maximum value at range [0.47 0.5] cpb by considering potentially TWA frequency shifting. In [3] artificial generated Gaussian noise is added to the ECG recordings with SNR varying from -30dB to 30dB. Moreover to assess the performance in the presence of non-stationary noise, real muscle artifact (MA) and electromyography (EMG) noise were taken from MIT BIH noise stress database. Fidutial points are selected at the onset by employing mechanism for QRS and T-wave detection.

TWA analysis

Figure 2.8 presents the main steps proposed by Rosembaum et al. [65] to separate between the ECG signal of a normal subject from those susceptible to sudden cardiac death.
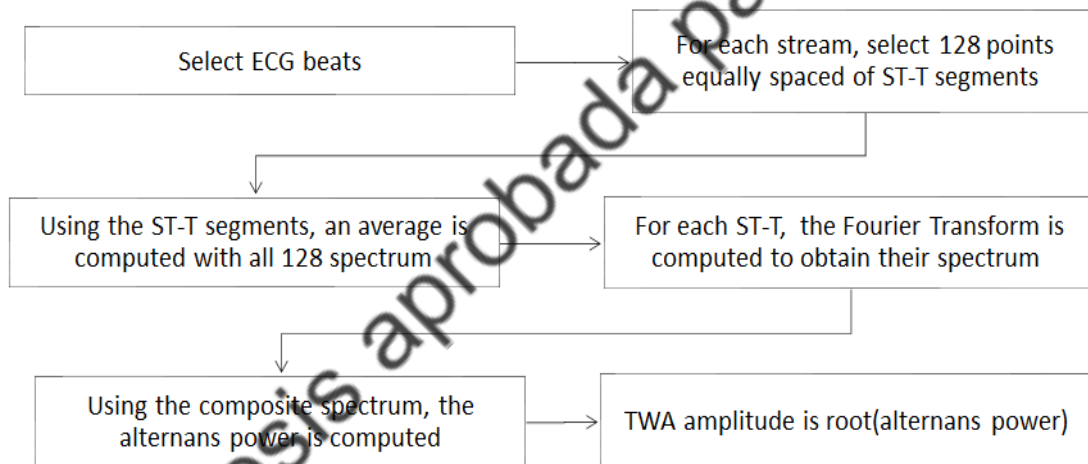

Figure 2.8. Main steps of the SM methodology to compute alternans amplitude.

Paper [37] defines the ECG signal as $X = x_i$, where $x_i \ for \ i = 1...n$ is one beat in the signal. To compute TWA, two ECG beats groups are created. The even beats x_{2*i} correspond the group A and odd beats x_{2*i-1} is in the group B. Modified moving average are calculated for group A and for group B. T-wave alternans is computed using the maximum absolute value of the difference between the averaged beats A and averaged beats B. The segment ST- and T-wave are used to compute the modified moving average.

Under the supposition of random Gaussian noise, the method [36] finds the presence of TWA. Two alternative templates are used to describe the use of the template-matched filter detector (TMFD): the median (TMFD-1) and the mean (TMFD-2). In the SNR region

between -15 dB and 35 dB, this approach performs better than the correlation method. When the detection probability is maximized in Gaussian noise, the performance of TMFD−1 is comparable to that of SM, but Laplacian noise results in a 2 dB degradation. The bias of the TMFD approaches SM under improved signal conditions (SNR = 25 dB) for alternate magnitudes $> 40 muV$ in the Gaussian case and for magnitudes $> 20 muV$ with genuine noises.

In work [28], when there are phase shifts in the register and with some noise, EMMA outperforms MMA in all cases by 25%. The experiments under different baseline wandering conditions also demonstrated that EMMA is more robust than MMA.

In [21], the Receiver Operating Characteristics (ROC) is used to evaluate the results. In a ROC curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points of a parameter. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish between two diagnostic groups (diseased / normal). In the method Adaptive SM, ROC were computed for each method with the area under the curve indicating relative TWA signal discrimination. NMF-Adaptive SM had the greatest area under the ROC (0.92) followed by the SM's Kscore of (0.77), SM without the Kscore (0.74), and MMA (0.70) $(p < 0.001)$. By ROC curve analysis, TWA discrimination with NMF-Adaptive SM was superior to SM with k-score $(p < 0.001)$.

The estimated accuracy comparison in [3] is carried out in terms of relative bias (Rb), standard deviation and mean square error (MSE). Extended Kalman smoother (EKF) and Unscented KF (UKF) provide an advantage of 10dB in achieving best Rb=O. UKF provides a higher Rb at low SNRs (-20dB).

In SM, the stratification of risk is analyzed by means of the maximum alternating magnitude, this value is associated with a high level of risk of SCD if it is greater than or equal to 60 μ V during an ambulatory and routine test greater than or equal to 47 μ V after an episode of myocardial infarction. SM in a method that requires a stable heart rate of 105-110 beats per minute over a period of time, using a specialized exercise protocol, pharmacological agents or atrial pacing. Due to these restrictions, approximately 20-40% of the tests are classified as "indeterminate", either due to factors related to the patient such as the inability to reach the target heart rate, excessive ventricular ectopia, atrial fibrillation or technical problems as noise in the recording.

MMA [37] is a time domain approach that consists of continuously estimating the average

beat of even and odd beats calculated in T waves or $ST - T$ complexes. Normally, the TWA level is reported every 10 or 15s, which makes the MMA more versatile and more appropriate in ambulatory recordings. The MMA method can be applied in stress tests and ambulatory tests, however, the exact values of the thresholds have not yet been defined to calculate the maximum alternating magnitude, resulting in the classification of the tests being around 75% accuracy.

Conclusions

In this chapter, the state of the art has been presented focusing on the detection and quantification of the amplitude in the T-wave to determine the risk of SCD. According this MMA and SM are the most used methods. It can be seen that the accuracy improves but only in certain cases and under certain conditions, which complicates a comparison between methods since the same database or the same sample size is not used. On the other hand, the proposed methods are tested using either synthetically generated signals or using the physionet database. The reliability of current systems is still debatable because their results are not enough robust.

In this context, it is important to develop new methods to detect and quantify the alternation of the T wave to overcome the results presented in the state of the art. For this, we will use the current computational power and new AI techniques, which will allow us to develop new efficient and lightweight algorithms for improving the efficiency of SCD detection

Chapter 3

PROPOSED METHODOLOGY

Contents

In bioengineering and clinical cardiology, the issue of early detection of SCD risk factors is still open [10]. In this way, this chapter presents the proposed methodology that allows to detect SCD using TWA as risk stratification index and features dictionaries learning. Figure 3.1 shows a summary of the processes developed.
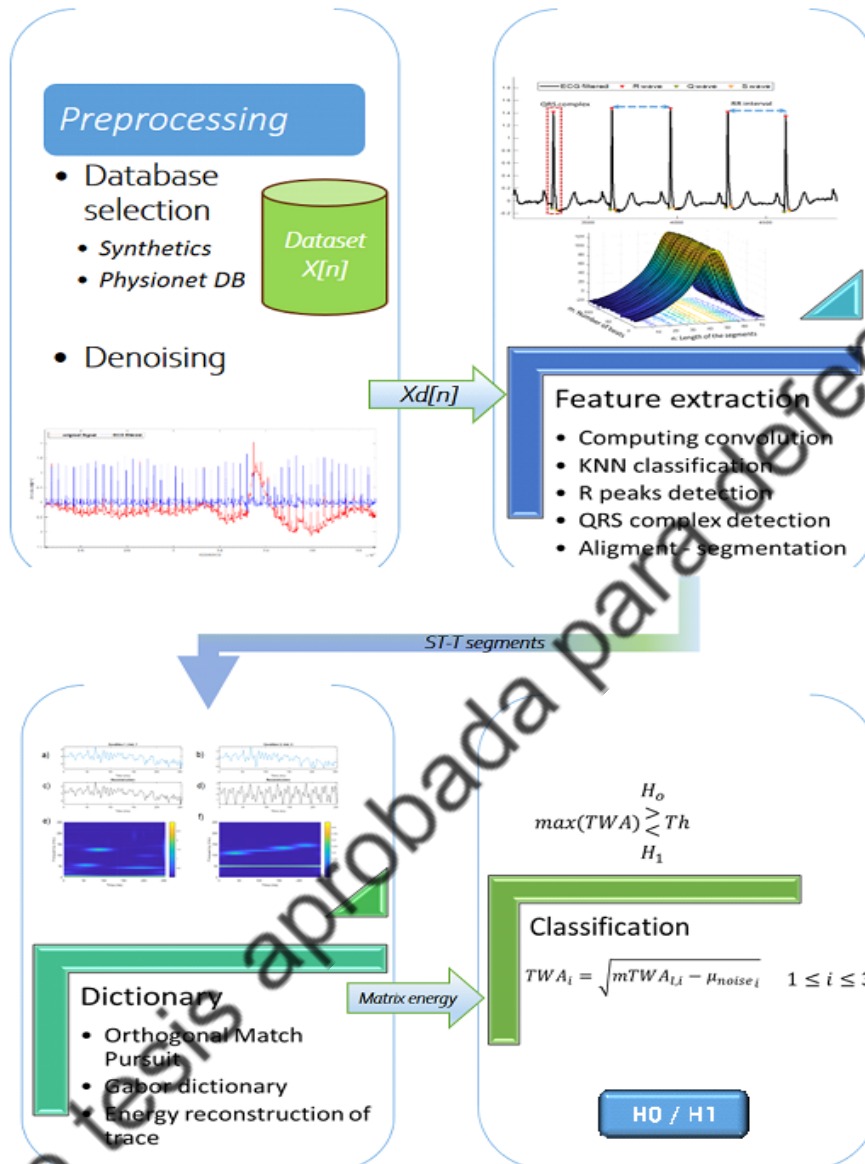
Figure 3.1. Summary of proposed methodology. Source: Authors

3.1. Framework

Based on the three principal observed stages in the review for TWA analysis. A framework to detect SCD is presented by combined SM and DL properties. Four principal stages have been developed: a) Preprocessing, b) feature extraction, c) compute dictionary and d) classification. Figure 3.2 shows, step by step, all processes implemented in the methodology to detect TWA for determining the risk of SCD.
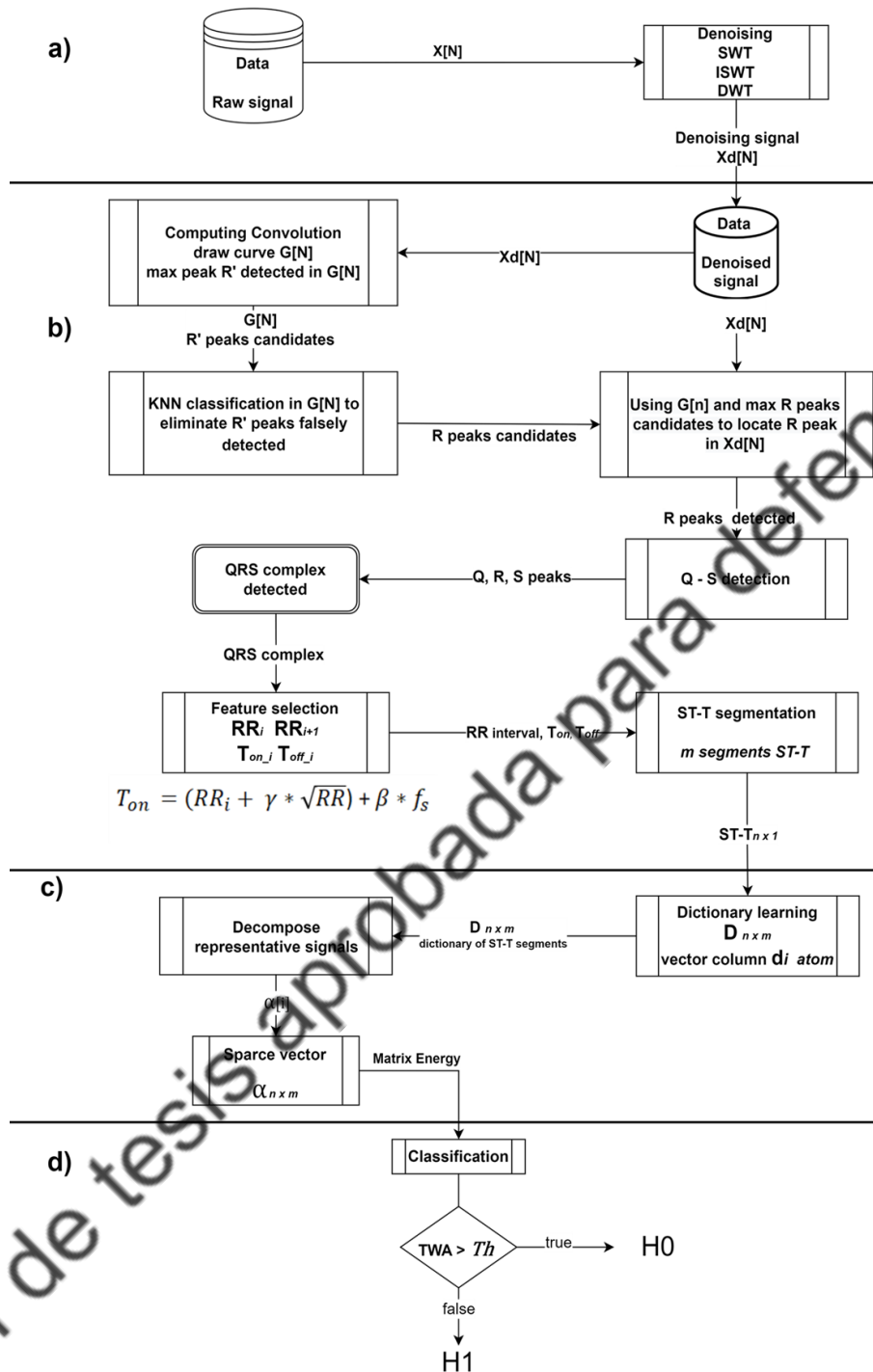
Figure 3.2. SCD by TWA framework. It consists of 4 steps: a) *Preprocessing:* Database selection and denoising signal, b) *Feature selection:* fidutial points detection and alignment/segmentation of T waves, c) *Dictionary:* compute dictionary learning and d) *Classification:* TWA detection

3.2.   Preprocessing

In this stage, two tasks have been carried out: database selection and denoising.

3.2.1.   Database Selection

The databases used in this research are the following: MIT-BIH Arrhythmia Database (mitadb) [66], T-wave alternans Database (twadb) [67], and QT Database (qtdb) [68].

In this thesis an algorithm is developed to detect the QRS complex. The qtdb and mitadb databases were used to evaluate this algorithm. On the other hand, the databases mitadb and twadb were used to evaluate the proposed methodology.

- Each recording in the **mitadb** has a 30 minutes period, making up a total of 24 hours' worth of ECG data. These recordings relate to 48 patients. At 360 samples per second, the signals were digitally processed. Additionally, there are files in this database that have annotations created by two highly qualified cardiologists. These specifications enable us to recognize the beginning and end of the waves in the ECG. Around 110,000 beats make up mitadb.

- 100 multichannel ECG records recorded at 500 Hz can be found in **twadb**. Patients with myocardial infarction, transitory ischemia, ventricular tachyarrhythmias, and other conditions that increase the risk of sudden cardiac death are among the participants, along with healthy individuals in the control group and artificial instances with calibrated levels of T-wave alternans. In this study, 36 data were employed in the experimental to validate the suggested framework.

- **qtdb** contains 49 records, which are distributed as follows: There are 15 records in the MIT-BIH Arrhythmia Database, 6 in the MIT-BIH ST Change Database, 12 in the MIT-BIH Supra-ventricular Arrhythmia Database, 10 in the MIT-BIH Normal Sinus Rhythm Database, 4 in the MIT-BIH Normal Sinus Rhythm Database, and 2 in the Sudden Death Database.

3.2.2.   Denoising

The disturbances or unwished signals may be of physiological, environmental origin or due to the acquisition and registration equipment. Different filtering techniques have been proposed for noise reduction:

- **Infinite Impulse Response Filter (IIR):** To eliminate power-line interference, an IIR filter is employed. This kind of electronic filter exhibits a response that depends on both the values of the input signal and the response's prior values [69].

- **Finite Impulse Response Filter (FIR):** The response of this filter can only be based on a limited set of input signal levels. As a result, regardless of the filter, its impulse response will depend on the filter's coefficient count and be steady and of finite duration.

- **Wavelet Transform (WT):** WT is a powerful method for analyzing non stationary signals, such as the ECG. Wavelets allow both time and frequency analysis of signals. The WT is defined as [70]:

$$W_f(s, \tau) = \int f(t)\psi_{s,\tau}^*(t)dt$$

The wavelets are generated from the translation and change of scale of a same wavelet function $\psi(\tau)$, called the "mother Wavelet", and is defined as:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right),$$

where s is the scale factor, and τ is the translation factor.

The discrete wavelet transform (DWT) examines a signal as a linear combination of the product of the mother wavelet's coefficients and the wavelet coefficients added together [71]. Equation 3.1 is the DWT of $X[N]$ that is the discrete signal of $X(t)$ [30]. Equation (3.1) is the DWT of the discrete signal $X[N]$, and N is its size.

$$DWT(s, \tau) = 2^{\frac{-s}{2}} \sum_N X[N]\psi^*(2^{-s}N - \tau) \tag{3.1}$$

DWT is also known as wavelet filter banks. This tool uses two filters: a high pass filter and a low pass filter that allows to decompose the signal in different frequency scales.

There are several methods based on the DWT to reduce the noise that is presents in the ECG signal (considering such noise as Gaussian white, variations in the baseline and power line) [71], [72], [73].

The Stationary Wavelet Transform (SWT), a technique for non-stationary signals like the ECG, serves as the foundation of the suggested methodology. The SWT's implementation is based on the work of [71]. The order of the SWT in this study is $M = 3$, and the simplest mother wavelet (the Haar wavelet) is utilized. The inverse stationary wavelet transform (ISWT) is then computed after that. This method enables the detection of particular signal
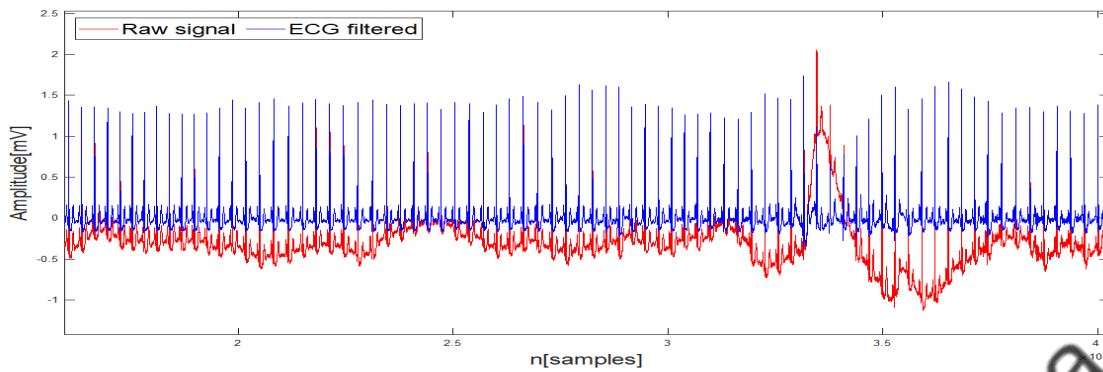
Figure 3.3. One example of ECG signal filtering: mitadb record 101m (female, age 75), using the algorithm above describe.

elements like motion artifacts, outliers, and QRS complexes. DWT is utilized to remove intrinsic noise, and a set of thresholds are determined to get the filtering coefficient. The strategies previously mentioned have been used in this study to generate the denoising signal $Xd[N]$ in order to enhance the signal $X[N]$. Figure 3.3 shows a raw ECG signal. After that DWT was applied, the baseline wander was improved and the power line interference was satisfactorily reduced.

3.3. Feature Extraction

The analysis of specific segments of the ECG is a common non-invasive technique for the diagnosis of cardiovascular diseases. In this sense, the accurate identification of specific points in the ECG could help to improve results in a clinical application such as heart arrhythmia [1], [3], [29]. The ECG segmentation process can be performed manually and may offer reliable results when it is done by expert clinicians. However, this method is tedious and time consuming. So, many researchers have been interested in automatic ECG segmentation. Signal processing techniques and computing systems are tools that allow to develop automatic methods for segmentation and interpretation of the ECG. In this context, it is important to develop efficient algorithms that allow accurate detection of EGC fiducial points. The first step for this segmentation process is to delineate the QRS complex, which means to detect the onset, the peak, and the offset of the waves. An accurate delineation of the complex will allow to delineate other components like P and T waves, RR and QT intervals, ST segments, or any other morphological parameters. However, ECG automatic segmentation is a hard task due to different aspects such as the difficulty to identify the small amplitude of the P wave, this due to interference arising from the movement of electrodes

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or muscle noise. The P and T waves can be biphasic, this increase the difficulty to an accurately determination of their onsets and offsets. Otherwise, some ECG cycles may not contain some waves or segments, for example, the P wave may be missing. Some techniques have been proposed for feature extraction on the ECG, some of them are based on wavelet transforms and techniques using machine learning approaches [53], [74]–[78].

In this work, a gradient signal function is calculated in order to locate R peaks in the signal. Subsequently, an algorithm based on K-Nearest Neighbors (KNN) is applied to eliminate false R peaks. A set of thresholds is calculated for detecting peaks Q and S. In addition, these thresholds allow to the signal to be segmented. The computational time for the overall process is also reported in the evaluation section.

The goal of this stage is to keep as much information in the TWA as possible while reducing the number of data points to be processed.

For extracting, peaks and waves of interest, different process was developed: Computing convolution, KNN classification, R peaks detection, QRS complex detection and alignment-segmentation of ST-T segments.

3.3.1. Computing Convolution

In order to calculate the signal gradient, a discrete convolution approach is used. The discrete convolution of Xd and V is given by:

$$G[n] = \sum_{i=-\infty}^{\infty} Xd[N-i]V[i] \qquad (3.2)$$

In this scenario, the output signal (gradient signal) is G, V is the impulse response and Xd is the input signal. In this case, Xd is the denoising ECG signal and V is the kernel given by $[1, -1]$. The ECG's QRS complex has an amplitude that is greater than the other waves, including the T, P, ST interval, and PR interval. In the ECG, the convolution aids in locating a wave with a higher gradient value than the other waves. Figure 3.4 presents the gradient signal $G[N]$ (red curve) that has been calculated for highlighting the most prominent points of the ECG signal.
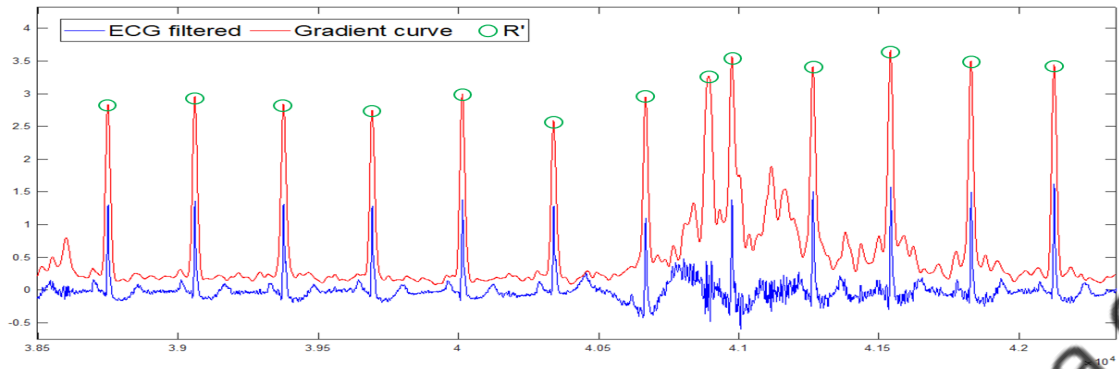
Figure 3.4. Gradient signal computed (red line) to detect maximum points R' (green marks) over G[N]: mitadb record 101m.

A set of max points (green marks) R' called *R' peaks candidates* has been detected in G. The goal is to use R' and detect R peaks inside $Xd[N]$ signal.

3.3.2. K-Nearest Neighbors Classification

A supervised machine learning approach called K-Nearest Neighbors (KNN) can be used to handle classification and regression issues. Figure 3.5 shows R' presented in $G[N]$. However, R' falsely detected are presented. In this case, KNN algorithm was applied to eliminate these ones as shows in Figure 3.6.
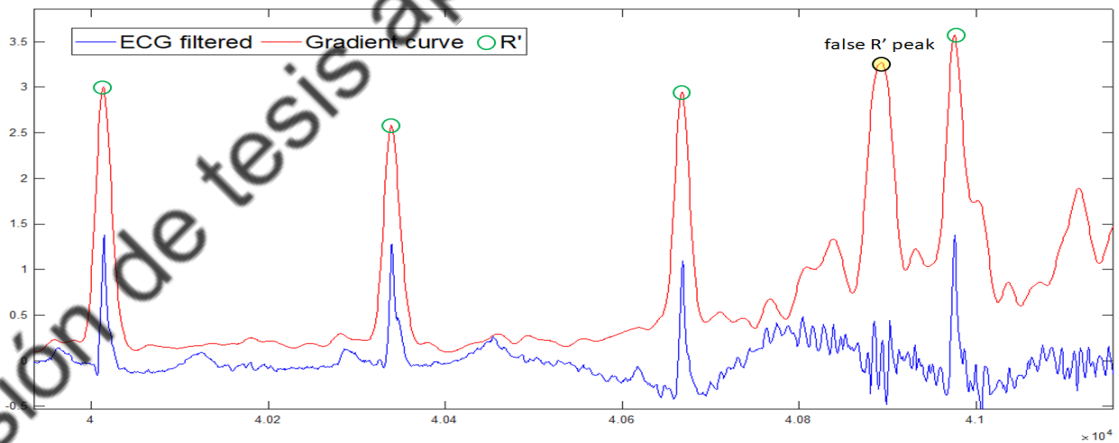
Figure 3.5. R' peaks falsely detected.
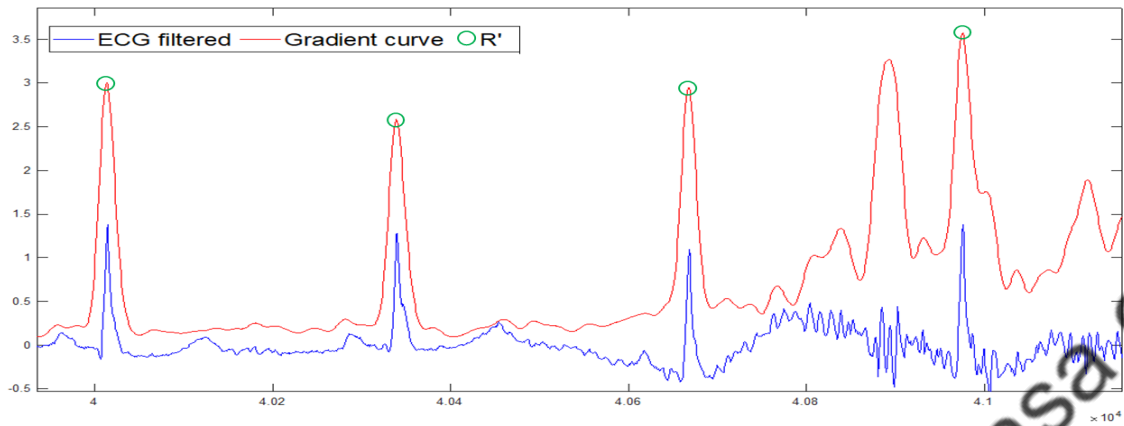
Figure 3.6. `KNN algorithm applied to eliminate false` R `peaks.  mitadb record 101m.`

KNN algorithm was trained with k=3 using Euclidean distance. After that for estimating the skill of KNN, the k-fold cross validation procedure with k=5 was implemented.

3.3.3.   R Peaks Detection

Let R' be a point with the greatest amplitude in gradient signal G after use KNN classification algorithm. Using R' peak and the threshold computed by equation (3.3)

$$\mu = 2 * \delta - R'distance \tag{3.3}$$

where $R'distance = R'_{i+1} - R'_i \quad with \quad 1 <= i < N$, and $\delta = 0.04 * fs$. The method construct a window of size μ to detect R-peaks on $Xd[N]$ signal. Figure 3.7 shows the process carried out to detect R-peak.
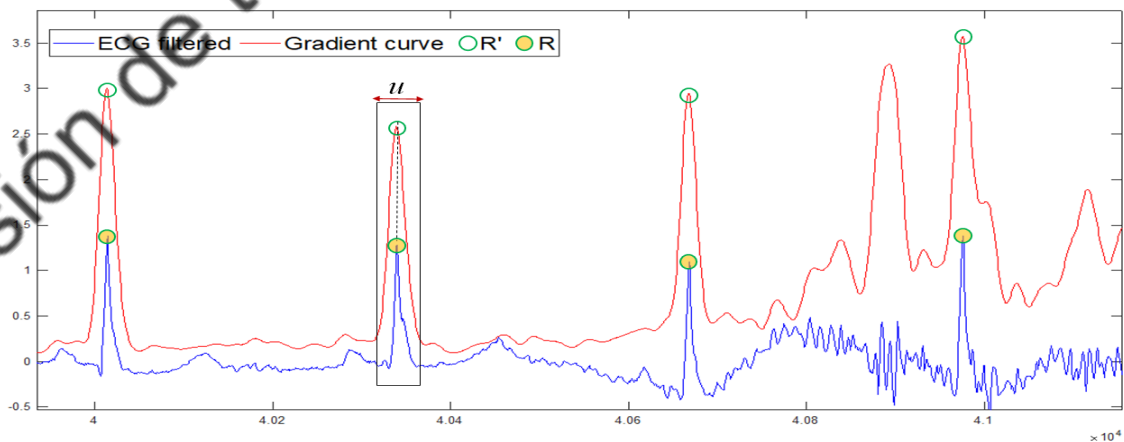
Figure 3.7. `R-peak detected in ECG signal` $Xd[N]$`:  mitadb record 101m.`

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Using R peaks, the technique looks for Q and S points to examine the signal. Finally, as illustrated in Figure 3.8, the QRS complex is found.
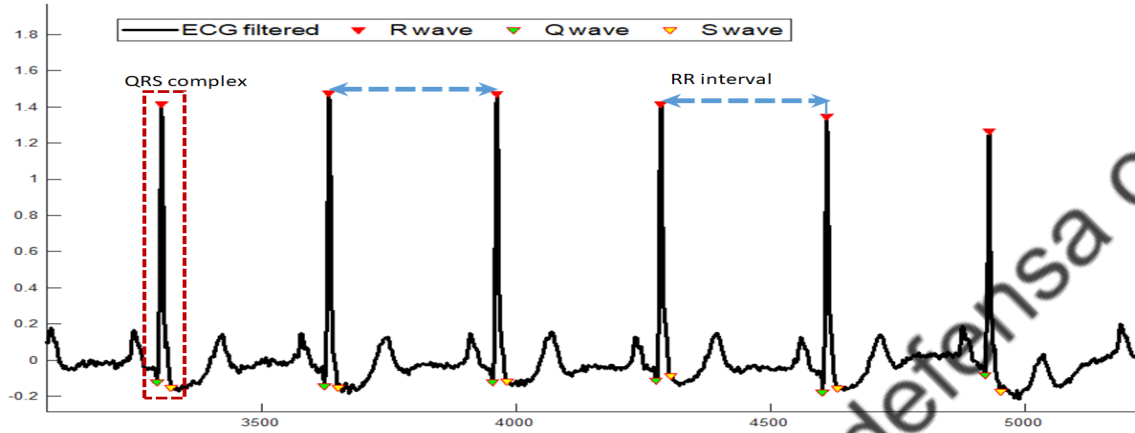
Figure 3.8. QRS complex and RR intervals. mitadb record 101m.

The algorithm explained in preceding sections for detecting QRS complex was released in the previous work [79]. The detection rate was 0.9976 and $0,998$ using mitadb and qtdb respectively 53397 beats were processed, 110 FN and 94 FP were detected.

3.3.4. Segmentation and Alignment of ST-T Segments

In this stage, a STT matrix contained the ST-T segments has been created. Using R peaks, the vector *dist* was created. This structure contains the RR intervals and it is used to detect the segment ST-T inside the interval. Let t_1, t_2, t_3 and t_4 be the variables that contains the limits of the segment, f_s is the sampling frequency and $distance$ is the vector where the RR interval size is stored. The algorithm detect the limits of each ST-T segment inside Xd using equation 3.4.

$$t_i = RR_i + \gamma * \sqrt{RR_i} + \beta * f_s \qquad i = 1, 2, 3, 4.$$ (3.4)

γ and β represent the experimental values that have been used in this work to detect the segments. Figure 3.9 indicates how is used the limits t_i to detect T_{on} (begin of the T wave) and T_{off} (end of the wave).

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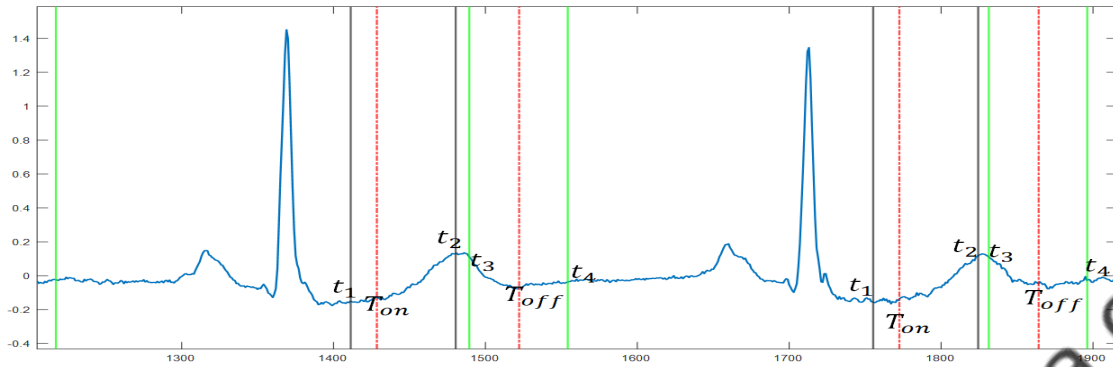
Figure 3.9. Limits t_i used to detect the ST-T segment. mitadb record 101m.

Algorithm 1 shows the process that has been implemented for detecting ST-T segments.

Figure 3.10 presents the result of the Algorithm 1. $STT_{m \times n}$ is the matrix where the ST segments detected in the signal were recorded; m is the number of beats located in the signal and n is the ST-T segment length.
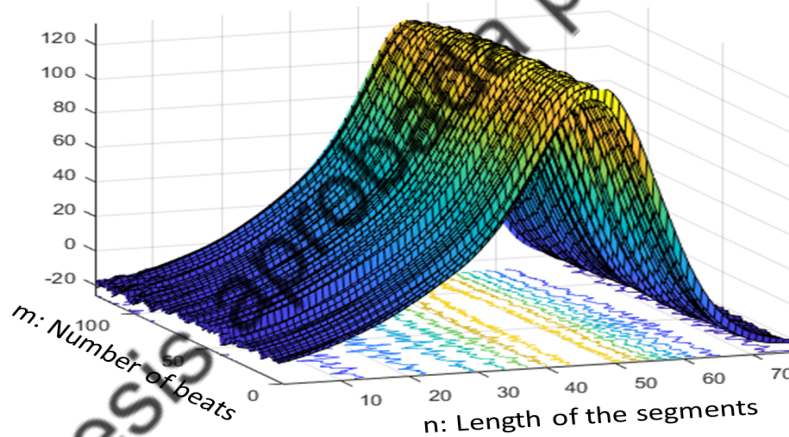
Figure 3.10. $STT_{m \times n}$ matrix composed of $ST - T$ segments detected over the ECG signal using Algorithm 1: m=128, n=76 in mitadb record 101m.

3.4. Dictionary

A dictionary learning process results in an over-complete dictionary. This process was carried out using two algorithms of signals analysis: Orthogonal Matching Pursuit (OMP) and Gabor dictionary (D).

Algorithm 1: ST-T detection and segmentation.

Input : R_{peaks}, Xd

Output : ST-T segments represented by an $STT_{m \times n}$ matrix.

// $M \leftarrow size(R_{peaks}) \leftarrow$ `numbers of beats`

// $N \leftarrow$ `length of ST segment`

// $dist \leftarrow$ `distance between R peaks`

for $i \leftarrow 1$ **to** M **do**

    $dist(i) \leftarrow R_{peaks(i+1)} - R_{peaks(i)}$

    if $dist(i) < 0.76 * f_s$ **then**

        $t_1 \leftarrow R_{peaks(i)} + 0.3 * \sqrt{dist(i)} + 0.02 * f_s$

        $t_2 \leftarrow R_{peaks(i)} + 0.3 * \sqrt{dist(i)} + 0.05 * f_s$

    end

    if $dist(i) < (1.13 * f_s)$ & $dist(i) >= 0.76 * f_s$ **then**

        $t_1 \leftarrow R_{peaks(i)} + 0.4 * \sqrt{dist(i)} + 0.1 * f_s$

        $t_2 \leftarrow R_{peaks(i)} + 0.4 * \sqrt{dist(i)} + 0.29 * f_s$

    end

    if $dist(i) > (1.13 * f_s)$ **then**

        $t_1 \leftarrow R_{peaks(i)} + 0.3 * \sqrt{dist(i)} + 0.1 * f_s$

        $t_2 \leftarrow R_{peaks(i)} + 0.01 * \sqrt{dist(i)} + 0.45 * f_s$

    end

    if $dist(i) < 0.72 * f_s$ **then**

        $t_3 \leftarrow R_{peaks(i)} + 0.18 * \sqrt{dist(i)} + 0.1 * f_s$

        $t_4 \leftarrow R_{peaks(i)} + 0.1 * \sqrt{dist(i)} + 0.32 * f_s$

    end

    if $dist(i) < (1.1 * f_s)$ & $dist(i) >= 0.72 * f_s$ **then**

        $t_3 \leftarrow R_{peaks(i)} + 0.1 * \sqrt{dist(i)} + 0.24 * f_s$

        $t_4 \leftarrow R_{peaks(i)} + 0.1 * \sqrt{dist(i)} + 0.42 * f_s$

    end

    if $dist(i) > (1.1 * f_s)$ **then**

        $t_3 \leftarrow R_{peaks(i)} + 0.1 * \sqrt{dist(i)} + 0.24 * f_s$

        $t_4 \leftarrow R_{peaks(i)} + 0.01 * \sqrt{dist(i)} + 0.49 * f_s$

    end

    $T_{on}(i) \leftarrow t_1 + abs(t_2 - t_1)/2$

    $T_{off}(i) \leftarrow t_4 - abs(t_4 - t_3)/2$

end

for $k \leftarrow 1$ **to** M **do**

    $STT_{(:,k)} \leftarrow Xd_{(T_{on}(k), T_{off}(k))}$

end

3.4.1. Orthogonal Matching Pursuit (OMP)

OMP is an iterative technique that breaks down a signal **x** into linear waveform expansions, which are generated from a comprehensive and redundant dictionary of functions D. This technique makes use of the orthogonal projections found in dictionary (atom) elements to successively approximate the signal.

The most common approach to construct time-frequency dictionaries is based on Gabor functions, which are Gaussian envelopes modulated by sinusoidal oscillation. To know which of the functions of these dictionaries most closely resembles a given signal, a measure of fit (similarity) between the analyzed signal and a known function is needed. This is achieved by means of the inner product.

Let **x** $= STT_{(:,k)}$ be the column of matrix that contains the ST-T segments after applying Algorithm 1. The trace **x** can be reconstructed according (2.2) like:

$$STT_{(:,k)} = \sum_{i=1}^{m} \alpha[i] d_i \tag{3.5}$$

where $\alpha[i]$ is a coefficient vector and d_i is the i-th optimal atom of the dictionary D involved in the decomposition.

3.4.2. Gabor dictionary

Gabor dictionary (D) is a collection of the wave forms knowing as atoms. Each atom d_i is represented from 3 characteristics: translation, length and frequency; as following:

$$g_\gamma(t) = \frac{1}{\sqrt{s}} w \left(\frac{t-u}{s} \right) e^{j2\pi\xi(t-u)} \tag{3.6}$$

The index γ is an element of the set $\Gamma = \Re^+ \times \Re^2$, w is the Gaussian function window $w(t) = \sqrt[4]{2} e^{-\pi t^2}$, the factor $\frac{1}{\sqrt{s}}$ normalizes to 1 the norm of $g_\gamma(t)$, the scale s controls the length of the waveform envelope, u is the time translation of the atom and ξ is the modulation frequency.

To efficiently represent any function, an appropriate countable subset of atoms $g_{\gamma_i}(t)$ must be selected with $\gamma_i = (s_i, u_i, \xi_i)$ [80]. So, $g_{\gamma_i}(t)$ is the i-th optimal atom to reconstruct the signal, represented by d_i.

3.4.3. Energy Reconstruction of Trace

The two algorithms described in above sections have been used to decompose the trace $STT_{(:,k)}$ in their sparse representation. Algorithm 2 presents the process carried out to

obtain time-frequency representation of each trace using the algorithm OMP and Gabor dictionary . The input variables of this algorithm are: the column vector $STT_{(:,k)}$ named the $trace$; the variable $numAtoms$ that contains the number of the atoms of the dictionary; n is the size of $ST - T$ segments and the number of $Iterations$.

Algorithm 2: Energy reconstruction of trace using Gabor Dictionary process.

Input : $trace, numAtoms, n, Iterations$

Output : D, α

// The random numbers of dictionary D are elements normally distributed, with
    mean 0, variance 1 , and standard deviation 1

// r is the residue

// nrS is the number of samples

// nrT is the number of trials

// nrC is the number of channels

$[nrS, nrT, nrC] \leftarrow size(trace)$

$trace \leftarrow reshape(trace, [nrS * nrT, nrC])'$

$D \leftarrow randomDistribution(nrC, numAtoms)$

for $i \leftarrow 1$ **to** n **do**
    $\alpha \leftarrow OMP(trace, D, Iterations)$
    $r = trace - D * \alpha$
    for $j \leftarrow 1$ **to** $numAtoms$ **do**
        $I \leftarrow Find(\alpha(j, :) > 0)$
        if $I == 0$ **then**
          | continue
        end
        $Subset \leftarrow r(:, I) + D(:, j) * \alpha(j, I)$
        $GaborData \leftarrow GaborFunction(Subset)$
        $D(:, j) \leftarrow rAtom(Subset, GaborData)$
        $\alpha(j, I) \leftarrow rSignal(Subset, D)$
        $EnergyTrace(j, I) \leftarrow rEnergy(Subset, D)$
        $r(:, I) \leftarrow Subset - D(:, j) * \alpha(j, I)$
    end
    $Energy(:, :, i) \leftarrow EnergyTrace$
end

The algorithm begin with a random dictionary that contains elements normally distributed, with $mean = 0$ and $variance = 1$. The OMP function used in this work and developed by [81] required three parameters (the trace, the dictionary D and the number of iterations). When the OMP function is executed, the matrix sparse α is computed. Then, residue r

is calculated. The information recorded in these matrices are used in the Gabor functions to compute the data for updating the dictionary, the sparse representation and the energy of the trace. Finally a data structure $Energy$ is obtained. Figure 3.11 shows, the spectral representation calculated by Algorithm 2.
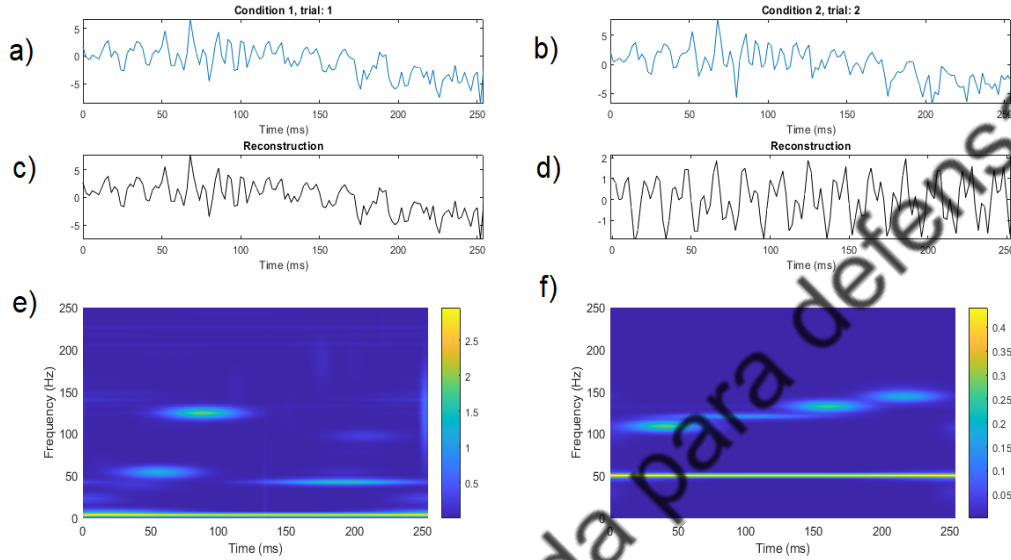
Figure 3.11. Time-Frequency representation of $ST - T$ segments recorded in matrix $STT_{m \times n}$ using OMP (128 samples; 2 trials; 100 atoms; 1 channel): Signal mitadb 101m. In a) trace $STT_{(:,1)}$; b) trace $STT_{(:,2)}$; c) and d) reconstructed the traces using OMP and D are presented; e) and f) frequencies detected inside the signals a) and b) respectively.

Using the energy signal $Energy$ obtained by algorithm 2, a mean sub-matrix V is created. V is the mean of $Energy^l_{k \times m}$ where $k = 64$ and corresponds to the sample size. The matrix V of dimensions $k \times n$ has been factorized into two matrices W and H having dimensions $k \times r$ and $r \times n$ respectively, where r is the order of the decomposition as following:

$$V \approx WH = \sum_{i=1}^{r} W_{(:,i)}H_{(:,i)} \tag{3.7}$$

Once equation (3.7) has been applied, the result obtained was W, that is called feature matrix and H, that is the coefficient matrix (weights associated with W). The main task is to separate the matrix into alternans components (AC) and noise components (NC). In this sense,

$$V = AC + NC \tag{3.8}$$

The size of matrix V is $k \times n$. However, the last 16 rows of the matrix have been chosen

because the frequency band of interest are located in this matrix position according [15].

Three matrices, w_1, w_2, and w_3, have been produced using $r = 3$ in (3.7). These ones represent the primary elements with comparable spectrum properties. The related alternans component w_q is chosen as the deconstructed component with the largest magnitude. Equation (3.7) can be written as follows:

$$V = w_q h_q + \sum_{\substack{i=1 \\ i \neq q}}^{r} w_i h_i \qquad 1 <= i <= 3 \tag{3.9}$$

According to (3.8) and (3.9), the value of the alternans component is

$$AC = w_q h_q \tag{3.10}$$

Let $mTWA = w_q$ be, the matrix that contains the alternans values of the trace. The rest of the equation (3.10) is the NC according (3.8). Thus, $mTWA$ have been used for classification.

3.5. Classification

Finally, a classification stage has carried out following the rule: $if \ max(TWA_i) > Th$ then H_0 is chosen instead of H_1. Th is a threshold, which is experimentally fixed.

$$TWA_i = \sqrt{(mTWA_{l,i} - \mu_{noise_i})}, \qquad 1 <= i <= 3; \tag{3.11}$$

Where, μ_{noise} is the NC and l is the row that contains the alternans energy values. According to [15], the frequency band of the noise is between $[0.36 - 0.49]$ cpb and the magnitude of 0.5 cbp for TWA energy. Algorithm 3 shows the process to compute the alternans value of the signal.

Algorithm 3: Compute the alternans value.

Input : $Energy$

Output : H_0 or H_1

// $[k, m, n] \leftarrow size(Energy)$

// $A_{k \times m}$ is a matrix with zero values

$A \leftarrow mean(Energy, 2)$

$V \leftarrow A(k - 15 : k, :)$

$[W, H] \leftarrow factorization(V, 3)$

$B \leftarrow W(1 : 15, :)$

$nmean \leftarrow mean(B)$

$nstd \leftarrow std(B, 0)$

for $i \leftarrow 1$ **to** 3 **do**
| $\quad TWA(1, i) \leftarrow real(sqrt(W(16, i) - nmean(i)))$
end

$q \leftarrow argmax(TWA)$

if *TWA(q) > Th* **then**
| $\quad H_0$
| **else**
| | $\quad H_1$
| **end**
end

Chapter 4

EVALUATION

Contents

The principal issue for evaluating the proposed framework is the lack of annotated databases. Generating synthetic data bases is a task accepted in the field [2], [5], [12], [28], [36], [82]. In this sense, to evaluate the methodology, a set of synthetic signals was constructed. Also, a set of real signals have been selected from the Physionet database [67].

4.1. ECG Synthetic Signals

In this work, for constructing the synthetic signals 2 groups have been considered:

4.1.1. Group1: Selected Signals from MIT-BIH Arrhythmia Database

Table 4.1 presents the ECG records that have been taken from MIT-BIH Arrhythmia database (mitadb) [66], [83]. According to work presented by [5], the selected signals satisfy the following criteria: (1) Only signals having more than 99% of their heartbeats labeled as

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"normal" are considered candidates, and (2) only candidates without TWA are taken into consideration.

Table 4.1. Dataset used for generating synthetic ECG. Source [5]

Record	Lead
117	2
121	1
	2
122	2
123	1
	2

Figure 4.1 presents the base beats used to generate the synthetic signals using mitdb.

a) mitdb117 lead 2

b) mitdb121 lead 1

c) mitdb121 lead 2

d) mitdb122 lead 2

e) mitdb123 lead 1

f) mitdb123 lead 2
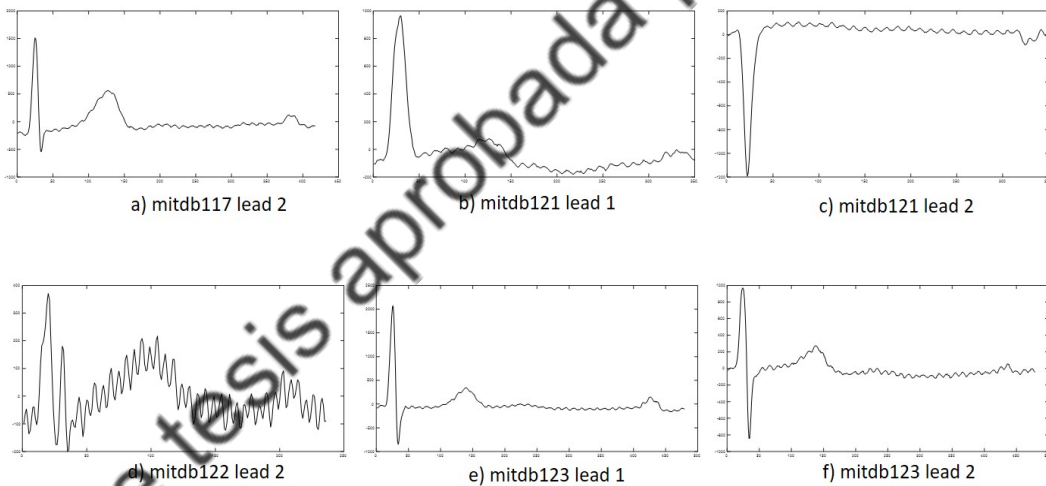
Figure 4.1. Base beats to generate synthetic signals using mitdb.

4.1.2. Group 2: Selected Signals from T-Wave Alternans Challenge Database

The proposed methodology uses TWA analysis to evaluate SCD. In this context, signals that contain this pathology should be considered. From the T-Wave Alternans Challenge Database (twadb) [66], [67], six single beats have been taken from the ECG signals, the same number of signals as group 1. Table 4.2 shows the characteristics of the selected signals. Column 1 is the name of the record within the twadb. Column 2 is the reference

rank derived from the ranks assigned by challenge entries. High ranks correspond to records with larger amounts of TWA. Column 3 specifies the data collection from which each record originates (see Table 4.7). The original record's name, which was used to create the twadb record, is listed in column 4. Reference of each record at [84]. The following criteria have been considered for selecting the different base beats: (1) The reference rank of the signals is considered to select the base beat. Signals with TWA and without TWA were therefore considered. (2) Healthy people and people with different cardiac conditions were selected.

Table 4.2. Sources and reference rankings for a certain record in the T-Wave Alternans Challenge Database

Name of twa record	Reference rank	Source type	Source record name
twa00	1	sdd	sddb/30
twa01	91	syn	stwdb/c111
twa03	51	ptb	ptbdb/patient093/s0367lre
twa06	87	syn	stwdb/d109
twa10	7	nsr	nsrdb/19090
twa39	22	ptbc	ptbdb/patient243/s0472_re

The base beats used to generate the synthetic signals using twadb are presented in Figure 4.2.

a) Base beat twa00   b) Base beat twa01   c) Base beat twa03

d) Base beat twa06   e) Base beat twa10   f) Base beat twa39
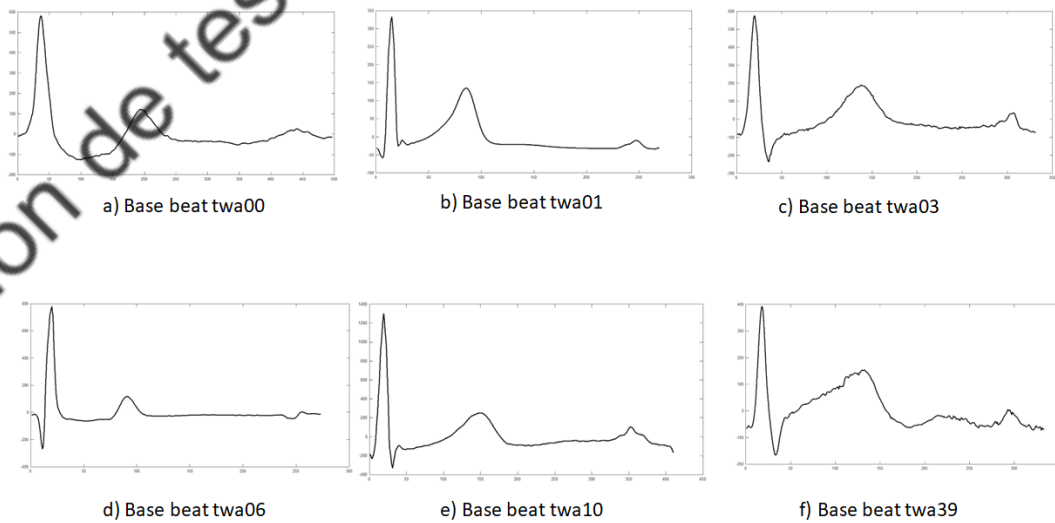
Figure 4.2. Base beats to generate synthetic signals using twadb.

4.1.3.   Creation of Synthetic Signals

Algorithm 4 shows the process implemented to obtain the synthetic database. The base beats were recorded in the matrix $baseBeat_{r \times c}$. The algorithm creates a ECG synthetic signal of 128 beats each one in the variable $synthetic$. After that, a value of alternans and noise is added and registered in $SyntheticECG$ variable.

Algorithm 4: Process to construct synthetic signals

Input : $baseBeat_{r \times c}$

Output : $Synthetic_{ECG}$

// r number of base beats used to generated the synthetic signals

// c size of each base beat

// nb number of beats

// $synthetic$ matrix that contains 128 beats

// $baseBeat_{r \times c}$ matrix that contains samples of selected records from twadb and
    mitdb

$nb = 128$

$baseBeat = [mitdb117_2(1, 1 : c); ...; twa39(1, 1 : c)];$

r=size(baseBeat)

for $i \leftarrow 1$ **to** r **do**
    $synthetic = [\quad]$
    $b = baseBeat(i, :)$
    for $k \leftarrow 1$ **to** nb **do**
        $synthetic = [synthetic \quad b^T]$
    end
    $a = read(\text{value of alternans})$
    $n = read(\text{GaussianNoise})$
    $SyntheticECG = synthetic + a + n$
end

The alternans values (V_alt) considered in this work are based on the paper [5] where $35\mu V < V_alt < 145\mu V$. The Gaussian noise is added at the based signal. Table 4.3 shows different values of alternans and noise levels that have been combined to generated the synthetic signal using twadb and mitadb.

Table 4.3. Values of alternans and level of noise that have been combined for generating synthetic signals using twadb.

Number of samples	Alternans (μV)	Noise (dB)	Number of beats
12	0	0	768
48	0	20 30 40 50	6144
48	10	20 30 40 50	6144
48	20	20 30 40 50	6144
48	50	20 30 40 50	6144
48	100	20 30 40 50	6144
48	200	20 30 40 50	6144
		Total of beats	38400

Using 12 base beats (6 base beats twa and 6 base beats mitdb) and combining them with different values of alternans and noise, a total of 300 synthetic ECG signals have been generated. So, 38400 beats were tested. Table 4.4 shows 25 synthetic signals. A total of 3200 beats generated. For example, signal artificial092 has 128 beats, an alternans value of $50\mu V$ and a noise level of 30 dB.

Table 4.4. Synthetic signal generated using twa06 real signal from twadb [67].

Synthetic signal	Number of beats	Alternans value (μV)	Noise level (dB)
artificial004	128	0	0
artificial079	128	0	20
artificial080	128	0	30
artificial081	128	0	40
artificial082	128	0	50
artificial083	128	10	20
artificial084	128	10	30
artificial085	128	10	40
artificial087	128	20	20
artificial088	128	20	30
artificial089	128	20	40
artificial090	128	20	50
artificial091	128	50	20
artificial092	128	50	30
artificial093	128	50	40
artificial094	128	50	50
artificial095	128	100	20
artificial097	128	100	40
artificial098	128	100	50
artificial099	128	200	20
artificial100	128	200	30
artificial101	128	200	40
artificial102	128	200	50
Total of beats	3200		

Figure 4.3 presents the results obtained using the algorithm 4. To generate the synthetic signal the base signal used is twa06 from twadb. In a) the ECG synthetic signal, b) ECG synthetic signal + 200 μV of alternans value added (Gaussian wave form) c) synthetic signal + alternans + 30 dB of noise added (Gaussian).
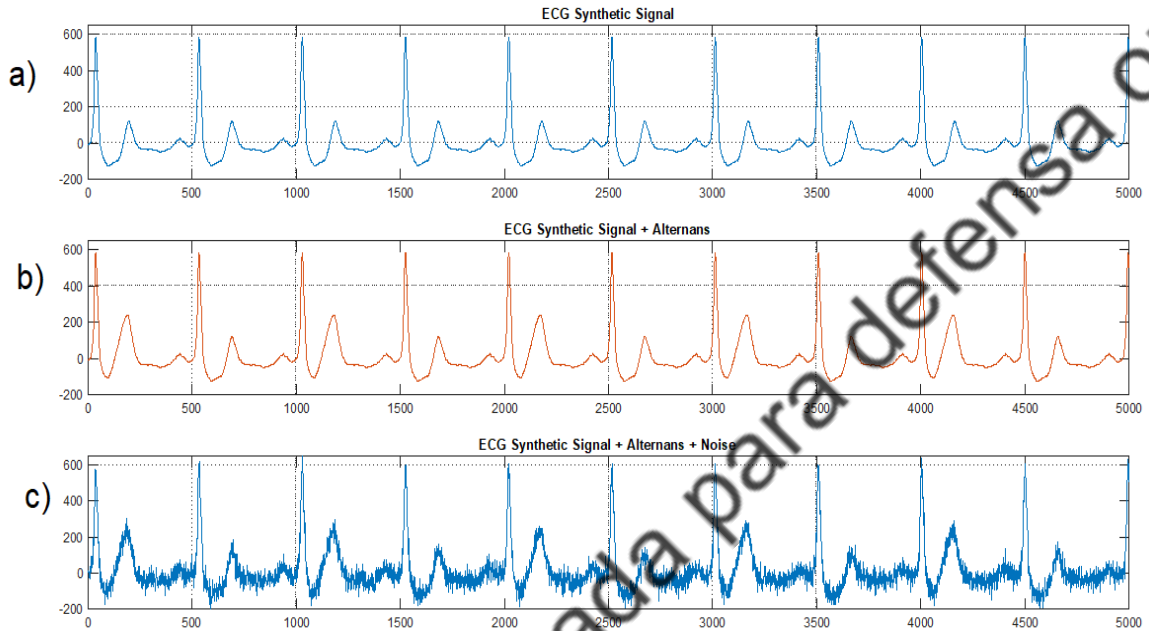
Figure 4.3. Synthetic signal using base beat twa06.

On the other hand, Table 4.5 shows 25 synthetic signals. A total of 3200 beats generated.

Table 4.5. Synthetic signal generated using twa00 real signal from twadb [67].

Synthetic signal	Number of beats	Alternans value (μV)	Noise level (dB)
artificial001	128	0	0
artificial007	128	0	20
artificial008	128	0	30
artificial009	128	0	40
artificial010	128	0	50
artificial011	128	10	20
artificial012	128	10	30
artificial013	128	10	40
artificial014	128	10	50
artificial015	128	20	20

Continue on the next page.

Synthetic signal	Number of beats	Alternans value (μV)	Noise level (dB)
artificial016	128	20	30
artificial017	128	20	40
artificial018	128	20	50
artificial019	128	50	20
artificial020	128	50	30
artificial021	128	50	40
artificial022	128	50	50
artificial023	128	100	20
artificial024	128	100	30
artificial025	128	100	40
artificial026	128	100	50
artificial027	128	200	20
artificial028	128	200	30
artificial029	128	200	40
artificial030	128	200	50
Total of beats	3200		

Figure 4.4 shows the synthetic signal generated using twa00. In a) the ECG synthetic signal, b) ECG synthetic signal + 200 μV of alternans value added (Gaussian wave form) c) synthetic signal + alternans + 20 dB of noise added (Gaussian).
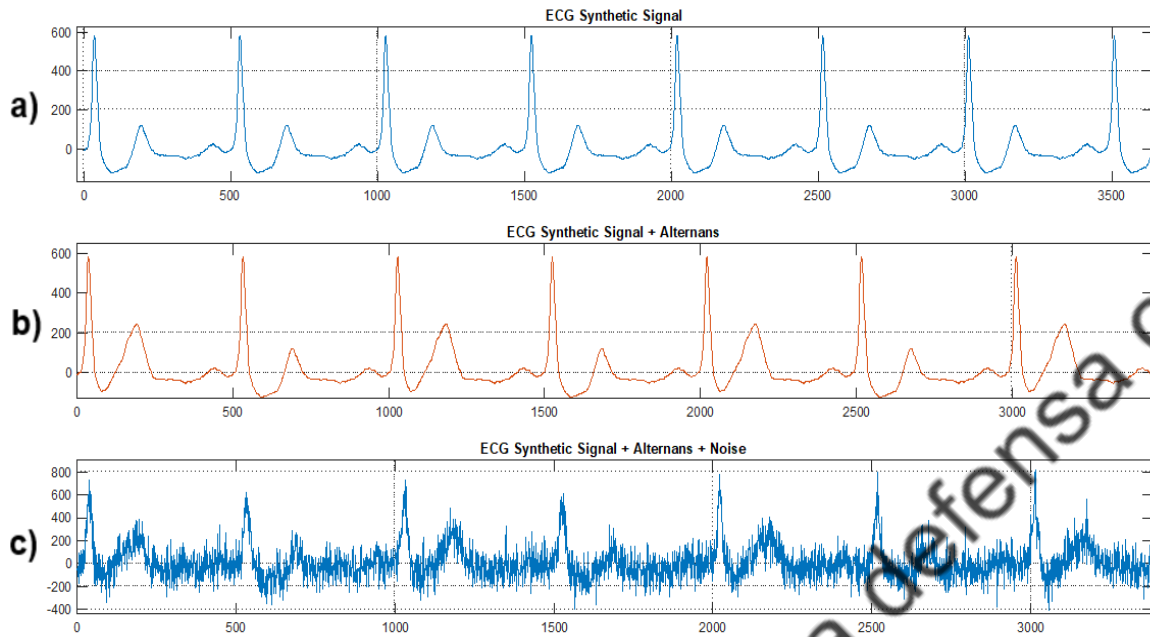
Figure 4.4. `Synthetic signal using base beat twa00.`

Table 4.6 presents the synthetic signals using mitdb. A total of 3200 beats have been generated.

Table 4.6. Synthetic signal generated using mitdb123 lead I real signal.

Synthetic signal	Number of beats	Alternans value (μV)	Noise level (dB)
artificial200	128	0	0
artificial201	128	0	20
artificial202	128	0	30
artificial203	128	0	40
artificial204	128	0	50
artificial205	128	10	20
artificial206	128	10	30
artificial207	128	10	40
artificial208	128	10	50
artificial209	128	20	20
artificial210	128	20	30
artificial211	128	20	40
artificial212	128	20	50

Continue in the next page.

Synthetic signal	Number of beats	Alternans value (μV)	Noise level (dB)
artificial213	128	50	20
artificial214	128	50	30
artificial215	128	50	40
artificial216	128	50	50
artificial217	128	100	20
artificial218	128	100	30
artificial219	128	100	40
artificial220	128	100	50
artificial221	128	200	20
artificial222	128	200	30
artificial223	128	200	40
artificial224	128	200	50
Total of beats	3200		

Figure 4.4 shows the synthetic signal generated using mitdb123. In a) the ECG synthetic signal, b) ECG synthetic signal + 200 μV of alternans value added (Gaussian wave form) c) synthetic signal + alternans + 30 dB of noise added (Gaussian).
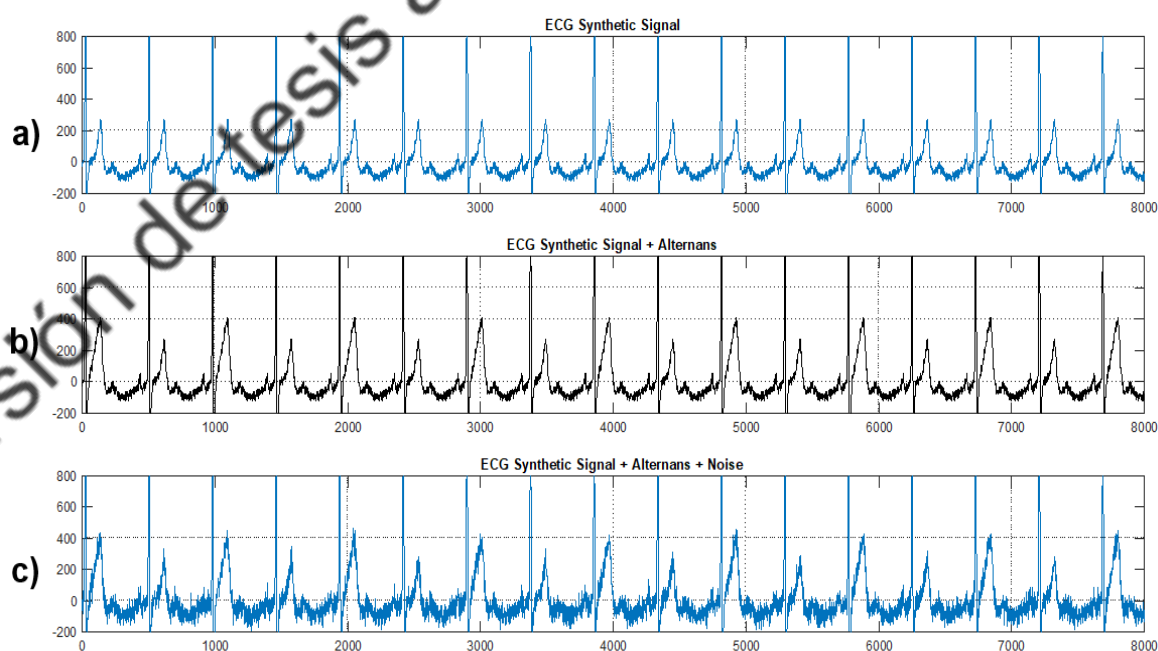

Figure 4.5. `Synthetic signal using base beat mitdb123 lead I.`

Finally, 300 synthetic signals have been generates named artificial001, artificial002, ..., artificial300. Each signal is composed by 128 beats. A total of 38400 beats have been processed.

4.2. ECG Real Signals

For evaluating the methodology, a set of real signal have been selected from Physionet database [66]. Table 4.7 shows the samples used for the performance evaluation of the methodology.

Table 4.7. Distribution of 36 records in twadb used for evaluating the methodology. Source [67]

Database	Record
PTB Diagnostic ECG Database (patients) (ptb)[85]	14
Long-Term ST Database (lts)[66]	4
St. Petersburg Institute of Cardiological Technics 12-lead (inc) [66]	2
Sudden Cardiac Death Holter Database (sdd) [86]	2
MIT-BIH Normal Sinus Rhythm Database (nsr) [66]	6
PTB Diagnostic ECG Database (healthy subjects) (ptbc)[85]	6
synthesized ECGs with TWA (syn) [87]	4
Total	36

4.3. Evaluation Metrics

Four metrics have been used for evaluating the proposed method: precison, sensitivity, specificity and accuracy.

1. **Precision** is the degree to which measurements of the same thing agree with one another.

$$\text{Precision, } P_r = \frac{TP}{(TP + FP)} \tag{4.1}$$

2. **Sensitivity** is the ability of a test to accurately identify true positives (patients out of those who do have TWA).

$$\text{Sensitivity, } S_e = \frac{TP}{(TP + FN)} \tag{4.2}$$

3. **Specificity** is the capacity of the test to appropriately reject healthy patients devoid of TWA. A diagnostic test effectively detects true negatives.

$$\text{Specificity, } S_p = \frac{TN}{(TN + FP)} \tag{4.3}$$

4. **Accuracy** Accuracy can be defined as the possibility that a patient was correctly categorized.

$$\text{Accuracy, } A_c = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.4}$$

It has been considered as: true positive (TP) if the method detects alternans and confirm the presence of TWA; false negative (FN) if the algorithm does not detects alternans but TWA is presented in the signal; true negative (TN) if the algorithm does not detects alternans in a signal without alternans ; and false positive (FP) if the method detects a false TWA.

4.4. Results

The results shown in these sections have been divided in two stages: Results obtained using the QRS complex detection algorithm and results obtained using SCD detection algorithm (TWA + dictionary learning).

4.4.1. Results Obtained Using QRS Complex Detection

Table 4.8 shows the results obtained using the algorithm 1 proposed in the stage of signal segmentation. The algorithm has processed 53397 beats, 110 FN, 94 FP. According to (4.2), (4.3) and (4.4), the detection rate is 99.80%, Sensitivity (Se) is 99.79% and the specificity is 99.82%.

Table 4.8. Results of evaluating the proposed method for QRS complex detection using MIT-BIH QTDB.

Data	Peaks	Detected peaks	TP	FP	FN	Se (%)	Sp (%)
sel30m	1019	1009	1009	10	0	99	100
sel100m	1134	1134	1134	0	0	100	100
sel102m	1088	1088	1088	0	0	100	100
sel103m	1048	1048	1048	0	0	100	100

Continue in the next page.

Data	Peaks	Detected peaks	TP	FP	FN	Se (%)	Sp (%)
sel104m	1113	1109	1109	4	0	99,6	100
sel114m	870	865	865	5	0	99,4	100
sel116m	1186	1186	1186	0	0	100	100
sel117m	766	766	766	0	0	100	100
sel123m	756	756	756	0	0	100	100
sel14046m	1260	1260	1260	0	0	100	100
sel14157m	1092	1085	1083	9	2	99,2	99,8
sel14172m	663	663	663	0	0	100	100
sel15814m	1036	1037	1036	0	1	100	99,9
sel16265m	1031	1031	1031	0	0	100	100
sel16272m	851	851	851	0	0	100	100
sel16273m	1112	1112	1112	0	0	100	100
sel16420m	1063	1063	1063	0	0	100	100
sel16483m	1087	1087	1087	0	0	100	100
sel16539m	922	922	922	0	0	100	100
sel16773m	1008	1008	1008	0	0	100	100
sel16786m	925	925	925	0	0	100	100
sel16795m	761	761	761	0	0	100	100
sel17152m	1628	1628	1628	0	0	100	100
sel17453m	1047	1047	1047	0	0	100	100
sel213m	1642	1642	1640	0	2	100	99,9
sel221m	1240	1250	1238	2	9	99,8	99,3
sel223m	1037	1309	1305	2	2	99,8	99,8
sel230m	1077	1077	1077	0	0	100	100
sel231m	731	731	731	0	0	100	100
sel232m	863	866	863	0	3	100	99,7
sel233m	1533	1531	1529	4	15	99,7	99
sel301m	1352	1351	1335	7	9	99,5	99,3
sel302m	1501	1499	1495	2	4	99,9	99,7
sel306m	1039	1039	1039	0	0	100	100
sel307m	854	854	853	1	1	99,9	99,9
sel308m	1291	1296	1264	6	32	99,5	97,53

Data	Peaks	Detected peaks	TP	FP	FN	Se (%)	Sp (%)
sel310m	2011	2011	2011	0	0	100	100
sel803m	1026	1026	1026	0	0	100	100
sel808m	904	903	903	1	0	99,9	100
sel811m	704	704	704	0	0	100	100
sel820m	1159	1159	1159	0	0	100	100
sel821m	1558	1558	1558	0	0	100	100
sel840m	1179	1180	1179	0	1	100	99,9
sel847m	804	804	798	7	6	99,2	99,3
sel853m	1115	1113	1113	2	0	99,8	100
sel872m	990	990	990	0	0	100	100
sel873m	859	859	859	0	0	100	100
sel883m	893	893	893	0	0	100	100
sel891m	1353	1311	1304	48	7	96,44	99,46
Total	531 81	53397	53304	110	94	99,79	99,82

Therefore, the proposed method has been evaluated using the MIT-BIH Arrhythmia databases. The algorithm is applied to channel I of 48 records with a duration of 30 minutes, 109494 beats have been processed and evaluated. The detection has been considered as true positive (TP) if the proposed method detects the QRS complex, false negative (FN) if the algorithm does not detect the QRS complex and false positive (FP) if the method detects a false QRS complex and this is considered as positive. Further, time from preprocessing stage to fiducial points detection is showed (Time (s)).

Table 4.9 contains 8 columns, the first one shows the number of processed signals; in the second column, the number of beats in the signal is shown according MIT-BIH arrhythmia DB; third, fourth and fifth columns show the TP, FP, FN respectively. In the next columns, the percentage rate and time of process of each signal is shown. The proposed method has processed 109,494 beats and it has produced 273 FN beats and 129 FP beats. The detection failure is 405 beats.

Table 4.9. Some results of evaluating the proposed methodology using MIT-BIH Arrhythmia DB

Data	Peaks	Detected peaks	TP	FP	FN	Rate%	time(s)
101	1865	1865	1865	0	0	100	3.81
107	2137	2137	2137	0	0	100	3.58
111	2124	2124	2124	0	0	100	3.87
114	1879	1881	1876	3	3	99.8	3.07
200	2601	2608	2598	3	10	99.6	5.83
203	2980	2973	2973	0	7	99.76	5.72
210	2650	2630	2623	7	27	98.9	6.12
213	3251	3246	3246	0	5	99.8	3.37
217	2208	2222	2208	14	0	100	5.79
230	2256	2256	2256	0	0	100	5.03
Total	109494	109350	109221	129	273	99.76	4.15

Hence, according to equations (4.2), (4.3) and (4.4), the detection rate is 99.76%, the S_e is 99.67% and the S_p is 99.73%. The average processing time is 4.15 seconds, by using a laptop DELL Inspiron N4050, Core i5 2.40-GhZ with 8GB RAM.

In order to evaluate the performance of this experimental study, the methodology developed has been compared with the well-known SM method. The first one is Pan Tompkins algorithm [64], that is a referent in the literature to detect the fiducial points. The second one is the method proposed by Saini et al. [88] that allows detect the points of interest using a KNN approach.

In the proposed algorithm a convolution was calculated, a gradient curve $G[n]$ was used to detect maximum points inside $G[n]$, this process allow to detect R peaks candidates in a ECG signal $X[n]$. The KNN approach is used to eliminate maximum point falsely detected in $G[n]$. After that, the R peaks are located using a window of size u in $X[n]$, this innovation improves the detection rate.

The proposed method works properly as a QRS detector for the employed databases, and it provides a satisfying high performance in difficult distorted records of MIT-BIH.

Table 4.10. Comparison of the performance of the proposed method with other algorithms for the MIT-BIH database and QT database.

Database (Annotations)	QRS Detector	Paper	Detection rate (%)
mitadb (109,809 beats)	A real-time QRS detection based upon digital analysis of slope, amplitude and width.	[64]	99.30
mitadb (109,966 beats)	QRS detection using K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases.	[88]	99.81
mitadb (109,494 beats)	Proposed method	–	99.76
qtdb (86741 beats)	An improved QRS complex detection method having low computational load.	[89]	99.8
qtdb (53181 beats)	Proposed method	–	99.8

4.4.2.   Results of SCD Detection by Using TWA and Dictionary

Performance evaluation using synthetic signals

In Table 4.11, the artificial signals have been classified by noise value. A total of 4608 beats with $noise = 20dB$ have been tested using twa base beats.

Table 4.11. Results of evaluating method using synthetic signal grouping by noise value $= 20\,dB$

Synthetic signals	Number of beats	Alternans (μ V)	Noise (dB)	Detection
artificial011	128	10	20	FN
artificial015	128	20	20	TP
artificial019	128	50	20	TP
artificial023	128	100	20	TP
artificial027	128	200	20	TP
artificial035	128	10	20	FN
artificial039	128	20	20	TP
artificial043	128	50	20	TP
artificial047	128	100	20	TP
artificial051	128	200	20	TP
artificial059	128	10	20	FN
artificial063	128	20	20	TP
artificial067	128	50	20	TP
artificial071	128	100	20	TP
artificial075	128	200	20	TP
artificial083	128	10	20	FN
artificial087	128	20	20	TP
artificial091	128	50	20	TP
artificial095	128	100	20	TP
artificial099	128	200	20	TP
artificial107	128	10	20	TP
artificial111	128	20	20	TP
artificial115	128	50	20	TP
artificial119	128	100	20	TP

Continue in the next page.

Synthetic signals	Number of beats	Alternans (μ V)	Noise (dB)	Detection
artificial123	128	200	20	TP
artificial131	128	10	20	TP
artificial135	128	20	20	TP
artificial139	128	50	20	TP
artificial143	128	100	20	TP
artificial147	128	200	20	TP
artificial007	128	0	20	TN
artificial055	128	0	20	TN
artificial031	128	0	20	TN
artificial079	128	0	20	TN
artificial103	128	0	20	TN
artificial127	128	0	20	TN
Total of beats	4608			

The results are: $A_c = 0.89$, $S_e = 0.87$, $Sp = 1$. In the cases when the values of noise are: 30, 40 y 50 dB, the results obtained are: $A_c = 1$, $S_e = 1$, $Sp = 1$.

Table 4.12 shows a subset of the artificial signals grouped by alternans values and is composed by 25 signals with $alternans = 10\ \mu V$.

Table 4.12. Results of evaluating method using synthetic signals that have an alternans value $= 10$ μV

Synthetic signals	Number of beats	Alternans (mu V)	Noise (dB)	Detection
artificial011	128	10	20	FN
artificial012	128	10	30	TP
artificial013	128	10	40	TP
artificial014	128	10	50	TP
artificial035	128	10	20	FN
artificial036	128	10	30	TP
artificial037	128	10	40	TP
artificial038	128	10	50	TP

Continue in the next page.

Synthetic signals	Number of beats	Alternans (mu V)	Noise (dB)	Detection
artificial059	128	10	20	FN
artificial060	128	10	30	TP
artificial061	128	10	40	TP
artificial062	128	10	50	TP
artificial083	128	10	20	FN
artificial084	128	10	30	TP
artificial085	128	10	40	TP
artificial086	128	10	50	TP
artificial107	128	10	20	TP
artificial108	128	10	30	TP
artificial109	128	10	40	TP
artificial110	128	10	50	TP
artificial131	128	10	20	TP
artificial132	128	10	30	TP
artificial133	128	10	40	TP
artificial134	128	10	50	TP
Total of beats	3072			

The result obtained is $A_c = 0.83$ using 3072 beats. Grouping the signals using alternans values of 20, 50, 100, 200 μV, the result is $A_c = 1$ in all cases.

Using twadb, the algorithm classified 116 signals as TP, 29 signals as TN, 4 signals as FN and 1 signal as FP. Using equations (4.2), (4.3) and (4.4) the quality of the proposed methodology was verified. The results obtained with the proposed methodology are: 0.96 of Accuracy; 0.97 of Sensitivity and 0.97 of Specificity.

Performance Evaluation in Real Signals

Table 4.13 shows the results obtained using reals signals. According to equations (4.2) and (4.3). Sensitivity is $S_e = 0.8$; Specificity is $S_p = 0.8$ and the Accuracy is $A_c = 0.81$.

Table 4.13. Results of evaluating the method using twadb.

Database	Record	Detection	Accuracy
PTB Diagnostic ECG Database Myocardial Infarction	03	TP	0.85
	11	TP	
	18	TP	
	19	TP	
	20	FN	
	31	TP	
	36	TP	
	40	FN	
	41	TP	
	48	TP	
	49	TP	
	53	TP	
	54	TP	
	83	TP	
Long-Term ECG Database	07	TP	0.75
	32	TP	
	85	FN	
	92	TP	
St Petersburg INCART	12	TP	1
	27	TP	
Sudden Cardiac Death Holter Database	00	FN	0.67
	08	FN	
	45	TP	
	63	TP	
	68	TP	
	95	TP	
PTB Diagnostic ECG Database Healthy People	39	TN	0.75
	46	FP	
	55	TN	
	60	TN	
MIT-BIH Normal Sinus Rhythm Database	10	TN	0.83
	23	TN	
	61	TN	
	62	TN	
	71	TN	
	93	FP	
Total	36		0.81

In order to evaluate the performance of this experimental study, the methodology developed has been compared with well-known SM method [39] using the software *TWAnalyser: A T-wave alternans detector* [90] available in Physionet. Table 4.14 summarizes the value of accuracy obtained.

Table 4.14. Value of accuracy obtained in the experimentation using TWADB.

Method	Accuracy
TWA and Dictionary Learning	0.81
Spectral Method using TWAnalyser software	0.64

In this experimental study, 300 artificial signals generated using the 12 base beats of twadb and mitdb and 36 real signals available in Physionet Data [67] have been tested. Using dictionary learning and time-frequency representation, an algorithm was implemented. The signals have been selected with alternate presences and alternate absences. According to Table 4.14 the implemented method improves the accuracy by 20% compared to the software TWAnalyser. To improve the robustness of the method, synthetic signals have been generated so that the threshold value can be adjusted. Thus, if the $TWA = 0\mu V$ then the threshold Th value was between 0 μV and 5 μV, and the result achieved was a true negative. On the other hand, when the synthetic signals presented TWA values between 10 μV and 200 μV; the proposed method sent a true positive for $Th >= 5\mu V$. In this sense, the experimental Th was fixed in this study.

Chapter 5

CONCLUSION AND FUTURE WORKS

Contents

The conclusions and upcoming projects for the thesis are presented in this chapter.

5.1. Conclusion

An innovative strategy for forecasting sudden cardiac death is presented in this research. In this context, a review of the state of the art was necessary. The papers analysed are focusing on the detection and quantification of the amplitude in the T-wave to determine the risk of SCD. According this MMA and SM are the most used methods. It can see that the accuracy improves but only in certain cases and under certain conditions, which complicates a comparison between methods since the same database or the same sample size is not used. On the other hand, the methods analysed are tested using either synthetically generated signals or using the physionet database.

In this work, the first task was to develop an efficient algorithm to detect the QRS complex following two steps. The first step is denoising, which allowed signal enhancement to obtain the relevant sections. The second step is the QRS point locations; for this, the gradient of the signal has been calculated and used to improve the R point detection. The QRS detection algorithm has obtained a detection rate of 0.997 and 0.998 for Arrhythmia DB and QTDB respectively.

Next, a dictionary has been computed by a dictionary learning process. Two algorithms have been used to build it. OMP has obtained a sparse solution by performing the analysis

operations given a dictionary. After, GD evaluates the accuracy of the dictionary to decompose the input signals. So, the energy of the signal obtained in this process is used to detect TWA.

The first experimental study shows an accuracy of 0.96 using artificial signals and 0.81 using real signals respect to the algorithm implemented by Physionet that shows an accuracy of 0.64 detecting TWA using the spectral method.

5.2. Future Works

This work presents a non-invasive methodology for predicting sudden cardiac death. The proposed algorithms have been implemented and the results obtained show improvements in predictions. However, execution time should be a task we need to improve. The suggested algorithms may be used in electrical device work in the future.

One limitation for evaluating our work was obtaining recorded databases. In this sense, an algorithm was developed to generate synthetic signals and evaluate the methodology. In future work, a standardized, registered database should be generated for use by the scientific community. Also, in a subsequent research, particular characteristics of patients could be taken into account, for example: geographical location, age, sex, and co-existing diseases. Another line of research could consist of changing the classification method or using another risk stratification index, which could somehow improve the results obtained.

In this work, Gabor dictionaries were used to develop the methodology. In a future work one could analyze another type of dictionaries such as those built using singular value decomposition.

Chapter 6

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