Prediction of Sudden Cardiac Death from Electrocardiogram Signal.

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Abstract

Sudden Cardiac Death (SCD) is an unexpected natural death caused by cardiovascular problems. SCD is one of the leading causes of death in the world and represents over 50% of deaths from cardiovascular disease, ranking second as the leading cause of death only after cancer. Ventricular fibrillation (VF) is the most common peculiarity that leads to SCD. The survival rate decreases by approximately 10 % per minute for patients after the onset of VF. Analysis of electrocardiograms (ECG) and heart rate variability (HRV) signals provides the information needed to make an effective prediction of SCD. Researchers have used different types of features (time, frequency, time-frequency, and nonlinear) and automatic learning algorithms to predict SCD from ECG signals. The proposed method seeks to detect an SCD event with more time prediction than current work since a more advanced prediction is vital given that medical specialists have little time to apply preventive or reactive techniques to counteract an SCD event. Based on the hypothesis that Orthogonal Matching Pursuit (OMP) and Singular Values Decomposition (SVD) should provide similar accuracy to the traditional approaches, but with a longer time to predict a nearby SCD event; this thesis proposes to implement a methodology based on OMP and SVD to define a criterion for the detection of ECGs associated with an SCD signal or a normal ECG signal. To validate the efficiency of the proposed methodology, the MIT / BIT data set consisting of several ECG signals from patients with SCD and normal heart rhythm signals will be used. The results obtained were compared with the most recent state-of-the-artwork.

Resumen

La muerte súbita cardiaca (SCD, *Sudden Cardiac Death*) es una muerte natural inesperada causada por problemas cardiovasculares. La SCD es una de las principales causas de muerte en el mundo y representa más del 50% de las muertes por enfermedades cardiovasculares, ocupando el segundo lugar como la principal causa de muerte solo después del cáncer. La fibrilación ventricular (VF, *Ventricular Fibrillation*) es la peculiaridad más frecuente que conduce a un SCD. La tasa de supervivencia disminuye aproximadamente un 10% por minuto para los pacientes después del inicio de la VF. El análisis de electrocardiogramas (ECG) y señales de variabilidad del ritmo cardiaco (HRV, *Heart Rate Variability*), proporcionan la información necesaria para lograr una predicción efectiva de un SCD. Los investigadores han utilizado diferentes tipos de características (tiempo, frecuencia, tiempo-frecuencia y no lineales) y algoritmos de aprendizaje automático para predecir SCD a partir de las señales de ECG. El método propuesto busca predecir un evento de SCD con un mayor tiempo que los trabajos actuales, ya que una predicción con mayor anticipación es vital, puesto que los especialistas médicos tienen poco tiempo para aplicar técnicas preventivas o reactivas para contrarrestar un evento de SCD. Basados en la hipótesis de que Orthogonal Matching Pursuit (OMP) y Singular Values Decomposition (SVD) deben proporcionar una precisión similar a la de los enfoques tradicionales, pero con un mayor tiempo de predicción de un evento SCD próximo; se propone implementar una metodología basada en OMP y SVD para definir un criterio para la detección de ECG asociados con una señal de SCD o con una señal de ECG normales. Para validar la eficiencia de la metodología propuesta se utilizará el conjunto de datos del MIT/BIT que consta de varias señales de ECG de pacientes con SCD y de señales de ritmos cardiacos normales. Los resultados obtenidos se compararán con los trabajos más recientes del estado de arte.

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Chapter 1

Introduction

Sudden cardiac death (SCD) is an unexpected death caused by cardiovascular problems that atrophy heart function. (Rea and Page, 2010) and with or without a history of heart disease (Deo and Albert, 2012; Fishman et al., 2010). In general, SCD occurs within an hour after the onset of symptoms although the person has no history of a fatal heart condition (Myerburg, 2005). SCD accounts for more than 50% of all deaths from cardiovascular disease (Rea and Page, 2010), ranking second as the leading cause of death only after cancer (Passman, 2013). SCD is a vital challenge for clinicians, as it can be experienced in individuals with no history of heart diseases.

Numerous heart diseases lead to SCD, however, the death of 84% of patients with SCD is mainly caused by ventricular tachyarrhythmias (including ventricular tachycardia (VT) and ventricular fibrillation (VF)) and 16% is due to bradyarrhythmia (BA) (Shen et al., 2007). These arrhythmias often lead to SCD, which makes the heart unable to pump blood effectively. Although SCD may be due to several pathologies, the VF is an underlying quality in most SCD episodes. The survival rate decreases approximately 10% per minute for patients after VF onset (Rea and Page, 2010). The VF is the main cause that leads to SCD (Passman and Goldberger, 2012), representing about 20% of SCD episodes, which is considered the main problem that can detonate an SCD (Pagidipati and Gaziano, 2013; Zheng et al., 2015). Therefore, an early prediction of SCD in a person that is suffering a VF is of great value for timely intervention and increasing the survival rate.

Being able to predict an SCD is of vital importance to prevent death since there are several cardiopulmonary resuscitation alternatives to counteract them, much attention has recently been drawn to the public access defibrillation (PAD) procedure as a way of rescuing patients from impending death after the collapse. However, this success rate of cardiac function restoration depends primarily on when first aid is given to stimulate the heart (Aziz et al., 2010). However, it is preferred to prevent the onset of SCD by providing medical aid before the collapse occurrs, which raises the question of

whether or not it would be possible to have warning systems capable of recognizing cardiac arrest half an hour before the crisis (Fang et al., 2009). In recent works, efforts were focused on this severe health problem with the goal of developing an efficient way of predicting the SCD using multiple invasive and non-invasive techniques (Huikuri et al., 2003; Hallstrom et al., 2005; La Revere, 1998). A strategy among the classes of risk predictors is the clinical marker, such as electrocardiogram (ECG) measurements. Experts from around the world are working on these heart problems to predict SCD before its onset by using ECG signals (Huikuri et al., 2003; Acharya et al., 2015b). Several research papers published in the literature achieve an effective prediction of SCD using ECG and heart rate variability (HRV) signals that are extracted from ECG signals. ECG is one of the most important physiological signals to identify cardiac abnormality and electrical conductivity characteristics since it graphically represents the electrical activity of the heart.

Recent works have experimented with the characteristics of the ECG or HRV signal to detect the fine changes that occur within the signals and identify the unique characteristics that can prevent the risk of SCD. In the prediction of SCD, researchers have used different types of characteristics (time, frequency, time-frequency and non-linear) and machine learning algorithms to predict SCD from ECG and HRV signals to design a biological marker. To date, researchers have predicted SCD before 25 minutes of its onset through the use of intelligent signal processing methods (Vargas-Lopez et al., 2020). However, this prediction has been made by evaluating two classes: normal signal and SCD signal.

The SCD signals from the database used in the related works are from patients who already have a history of heart diseases, see **Section.** 4.1, so these SCD signals could be easily differentiated from normal signals by other features belonging to heart disease passed, and not necessarily because of the features belonging to an SCD event. That is why this evaluation may not be the most appropriate for these cases in which there are other features involved. Therefore we present a new evaluation approach to the prediction of the SCD, in which we handle seven classes: the normal signal and six sets of SCD signal. The SCD signal sets correspond to minutes before the SCD but after the minute of the analyzed SCD. This new evaluation approach is more appropriate since when comparing the SCD set with other sets that also have the features of past heart disease, this allows us to identify that the features extracted effectively belong to SCD features of the minute analyzed. Further, we propose a mainly focused on a linear method, with it is hoped to find a distinctive pattern that cannot be found with conventional linear methods. Thus, our methodology considers, normal signals

and SCD signals in an electrocardiogram could be distinguished if their information is decomposed by extracting the main components and a base of signals is generated to identify each group according to their particular features.

1.1 Problem statement

SCD is a vital challenge for clinicians, as it can be experienced in individuals with no history of heart diseases. Although there are different current methods to predict SCD, in general, all the methods detect the SCD 25 minutes before and this represents a problem since this time is not enough to apply the methods to counteract the event of SCD.

1.2 Project justification

Data from the World Health Organization (WHO) show that cardiovascular diseases are the number 1 cause of death globally, taking an estimated 17.9 million lives each year. Due to thousands of patients die every day because they do not receive treatment in time, there is a need to develop a methodology that allows to predict an SCD earlier.

This thesis seeks to offer an alternative technique based on scattered representations that can be used to predict an SCD event before it occurs. This will allow preparation against possible complications and give medical specialists the time necessary to apply the appropriate treatment, thus increasing the probability of survival.

1.3 Hypothesis

Normal signals and SCD signals in an ECG can be distinguished by analyzing the information provided by their sparse representations, which will improve the classification of the signals and thus Increased the prediction time of an SCD event.

1.4 Objectives

1.4.1 General objective:

Develop a methodology that increased the prediction time of SCD distinguishing between normal ECG signals and those close to an SCD episode based on the differences in their decomposition into elemental signals.

1.4.2 Specifics objectives:

- To extract the signal segments corresponding to several time intervals from the signals of the database for both groups (SCD/Control).
- To implement an algorithm for training with the generated signal segments for each time interval.
- To decompose the representative signals and identify the associated signals (SCD/Normal).
- To define a criterion to identify signals (SCD/Normal).
- To compare the results obtained with the most recent works of the state of the art.

1.5 Methodology

As a first step, it will be applied an automatic decimated as a function of time (t), to segment the ECG signal at different time intervals (previous minutes to the SCD). Then, the segments will be normalized to scale the ECG signals. In the training phase, two sets of signals (Training and Test) will be generated and then a features base will be trained for each group in each time interval by using OMP and SVD. Thus, the test signals will be decomposed into each base and the base that best decomposition reaches will correspond to the set in which the signal belongs.

1.6 Contributions

Along with this research work, two principal contributions were performed. We summarize them as follows: A novel methodology for the SCD event prediction to 30 min before the onset using the analysis of sparse representation from ECG signals. And a proposed evaluation that uses six classes of SCD signals and one class of Normal signals. Using different categories of SCD delivers an evaluation more suitable to find significant features of an SCD event since the SCD signals with which it is compared also have the same features of the previous heart diseases.

1.7 Organization of the thesis

This thesis has been organized as follows. In **Chapters** 2 and 3, the theoretical basis is presented, with the fundamental concepts for the development of our research and the previous works that determine the research location; each step in our methodology is discussed in **Chapter** 4; **Chapters** 5 describes our experimental framework to evaluate the feasibility of the proposed solution and the results achieved; finally, the conclusions and future work are presented in the **Chapter** 6.

Chapter 2

Theoretical Framework

In this chapter, we provide the technical knowledge used for SCD prediction. **Section** 2.1 shows relevant information about the SCD, such as epidemiology, consequences, and risk factors. **Section** 2.2, we present the most signals used for the SCD prediction. Finally, in **Section** 2.3, we describe the algorithms that are used for the training of dictionaries.

2.1 Sudden Cardiac Death (SCD)

Sudden Cardiac Death is a death occurring unexpectedly and is caused by cardiovascular problems up to an hour after the onset of symptoms (Lopshire and Zipes, 2006). Most of the occurrence of SCD is caused by ventricular tachycardia (VT) or ventricular fibrillation (VF), these are the main qualities that originate a cardiac arrest (Kokolis et al., 2006); all other cases are caused by events of bradycardia.

2.1.1 Epidemiology

Data from the World Health Organization (WHO) show that cardiovascular diseases are the number 1 cause of death globally, taking an estimated 17.9 million lives each year. The SCD accounts for more than 50% of all deaths from cardiovascular disease (Rea and Page, 2010), ranking second as the leading cause of death in the world only after cancer (Passman, 2013).

2.1.2 Prevalence

SCD is currently very prevalent in people with heart failure, and 50 % of deaths are attributable to it. Patients with heart failure have approximately 9 times the incidence of SCD than the usual population (Tomaselli and Zipes, 2004). The magnitude of the problem is supported by population studies showing an incidence of up to 12 per 1000 inhabitants per year of new diagnoses of heart failure (Blackledge et al., 2003).

2.1.3 Consequences

Immediate defibrillation is essential to restore cardiac activity in patients who suffer a VT or VF, failure to restore cardiac activity for a long period can lead to brain cognitive decline and even death. (Valenzuela et al., 1997). Although there is a significant decrease in cardiovascular mortality mainly due to therapeutic advances, deaths from SCD have not decreased in the same way, mainly because this condition has an unpredictable nature (Lopshire and Zipes, 2006). Cardiac arrest victims outside the hospital have an unfavorable prognosis as they have a survival rate of approximately 5% for patients who have suffered the main event. Besides, cardiac arrest survivors are more likely to experience an event again. (Tomaselli and Zipes, 2004).

2.1.4 Aetiology

Numerous heart diseases lead to SCD mainly, ventricular tachyarrhythmias (VTA), ventricular tachycardia (VT), ventricular fibrillation (VF), bradyarrhythmia (BA), coronary artery diseases (CAD), valvular diseases (RV), myocardial infarction (MI) and genetic factors (Murukesan et al., 2014). However, the death of 84% of patients with SCD is mainly caused by ventricular tachyarrhythmias (including VF and VT) and 16% is due to BA (Shen et al., 2007). The patients who present ventricular arrhythmia or have survived cardiac arrest, have a higher incidence of SCD, compared to adults with no history of heart diseases (Myerburg et al., 1998).

2.1.5 Risk factors

There are two periods in life when the risk of sudden death is particularly high: between birth and six months of age, and between the ages of 45 and 74. It is predictable that the risk of SCD increases with age, although there is a relative decrease in the octogenarian population and above due to other competing causes of death (Virmani et al., 2001). Epidemiological studies have revealed the median age of SCD patients to be 59 years. In the study by Kannel et al. (1987), 62% of all deaths from ischemic heart disease were sudden in males aged 45-54 years. This percentage increased to 58 percent and 42 percent in men aged 55-64 and 65-74, respectively.

SCD is more usual in males than females, especially in the younger population group, with a ratio of 7 to 1 in the 55-64 age group, and 2 to 1 in the 65-74 age group (Kannel and Thomas Jr, 1982). It is estimated that 75-90% of sudden death cases are present in males (Kuller et al., 1967; Liberthson et al., 1974).

Smoking, diabetes, hypertension, and a raised body mass index (BMI) increase the chances of having an SCD event (Kannel and Schatzkin, 1985). Smoking is a very important factor since the risk of suffering an SCD event is 2.5 times higher in smokers. (Virmani et al., 2001). Furthermore, in the study by Hallstrom et al. (1986), in survivors of cardiac arrest, the probability of recurrence of cardiac arrest was 27% in those who continued to smoke after the initial episode, on the other hand, the probability of recurrence of arrest heart rate was 19% in those who stopped smoking. This is probably mainly due to increased catecholamine release and platelet adhesiveness. Another important factor related to SCD is obesity, and a direct relationship between weight and the risk of SCD has been documented (Kannel and Thomas Jr, 1982).

2.2 Signals

To predict that an SCD event is approaching, we need some kind of information that can be quantitatively compared. In the medical field, different signals could help with this task. However, numerous recent works focused on the prediction of SCD have preferred to use the signals of electrocardiograms or signals that are derived from it since it measures the electrical activity of the heart graphically, performing the objective of having a quantitative measurement of the activity of the heart.

2.2.1 Electrocardiogram (ECG)

An electrocardiogram (ECG) is a graphic representation of the electrical activity of the heartbeat. With each beat, an electrical impulse (wave) travels through the heart. This wave causes the muscle to squeeze and pump blood since the heart. An ordinary heartbeat shows ECG the synchronization of the top and lower chambers.

The ECG consists of different waves, interval, and complexes, those are illustrated in the **Figure** 2.1, some of the most relevant are: the P wave that represents the depolarization of the atria, the QRS complex that represents the depolarization of the ventricles and the T wave that represents the repolarization of the ventricles. The QRS complex is mainly represented by 3 waves: the first negative wave that appears in the complex and that precedes an R wave is called Q; The first positive wave that appears in the complex is called R and the second negative wave that is inscribed after the R wave is called S.

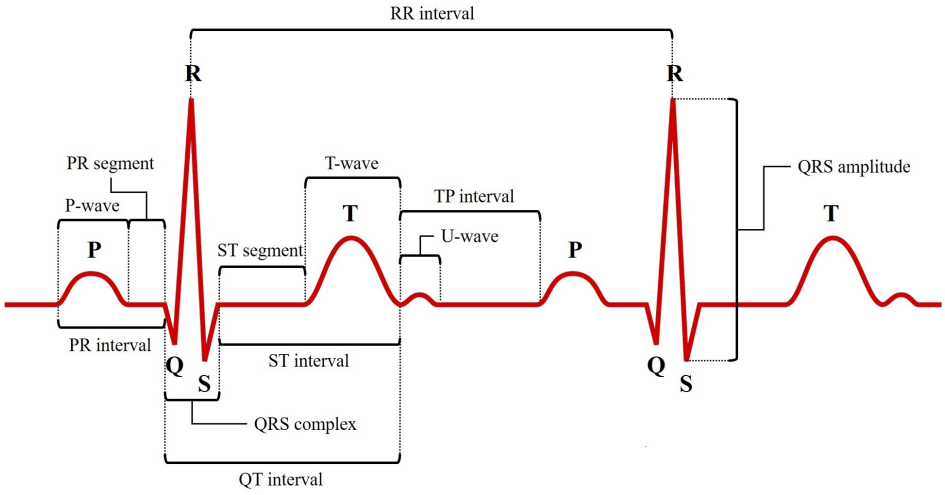


Figure 2.1: The classic ECG curve with its most common waveforms. Important intervals and measurement points are represented.

2.2.2 Heart Rate Variability (HRV)

Heart Rate Variability (HRV) is an index of autonomic function and a physiologic phenomenon of variation in the time interval between heartbeats. The extraction of the R to R peak intervals from the ECG signals constitutes HRV signals. In addition to ECG signals, HRV also plays a vital role in the clinical diagnosis of heart disease in recent decades (Jouven et al., 1999). ECG and HRV signals are not invasive, so they are useful for cardiac diagnoses.

2.3 Sparse representation

Sparse representation also knew as sparse approximation theory deals with sparse solutions for systems of linear equations. Techniques for detect these solutions and exploiting them in applications have found detect use in image processing, signal processing, machine learning, and medical imaging (Baraniuk et al., 2010; Rakotomamonjy, 2011; Papyan et al., 2017). For this reason we decided to use the sparse representations for the prediction of the SCD event.

2.3.1 Sparse signal

A signal x, considered as a vector in a finite-dimensional subspace of $\mathbb{R}^N$, is sparse if the most of its components are equal to zero, that is, if $\Lambda(x) = \{1 \leqslant i \leqslant N \mid x[i] \neq 0\}$ is of cardinality $k \ll N$. A k-sparse signal is a signal in which k of its elements have

a value other than zero. A signal not sparse can be converted to a scattered signal in an appropriate transform domain. For instance, if x is a sine, it is not sparse, but its Fourier transform is sparse. In general, we can represent a signal x as the linear combination of T elementary waveforms, also called atoms, such that

$$x = \Phi\alpha = \sum_{i=1}^{T} \alpha[i]\varphi_i, \tag{2.1}$$

where $\alpha[i]$ are representation coefficients of x signal in the dictionary $\Phi = [\varphi_1, ..., \varphi_T]$ (the $N \times T$ matrix whose columns are the atoms φ_i , in general normalized to a unit ℓ_2 norm, i.e., $\sum_{n=1}^{N} |\varphi_i[n]|^2 = 1$).

The signals or images x that are scarce in the dictionary ϕ are those with which the signal or image can be represented by superimposing a small fraction of the atoms in the dictionary.

2.3.2 Sparsity Terminology

An atom is an elemental signal that represents a model, that is, a vector with certain features of another signal. The atoms can be sinusoids, monomials, wavelets, and Gaussians. Using a set of atoms as structures, and employing linear superposition, more complex waveforms can be constructed by.

A dictionary Φ is an ordered set of atoms $(\phi_\gamma)_{\gamma\in\Gamma}$, where Γ is a countable set; that is, its cardinality $|\Gamma| = T$. The index γ can have different interpretations depending on the dictionary: in a Fourier dictionary (ie sinusoids) represents frequency, in the Dirac dictionary (also known as standard unit vector-based) represents the position, in the wavelet dictionary represents position scale, and finally, the index γ can have an interpretation of translation-duration-frequency for cosine packets and position-scale-orientation for the curvelet dictionary in two dimensions. Since a set of column vectors (atoms) make up a dictionary, the signal processing, a dictionary looks like an $N \times T$ matrix whose each column are the atoms.

Given a trained dictionary, two operations can be performed (analysis and synthesis). Analysis is the operation that tells us in a resulting vector of coefficients α which atoms of Φ are used in the reconstruction of the x signal: $\alpha = \Phi' x$. Synthesis is the operation with which we can reconstruct the signal x by superimposing atoms indicated in the vector α: $x = \Phi\alpha$. Analysis and synthesis are contrary to linear operations. In the case of overcomplete, Φ is not invertible and the rebuild is not unique.

2.3.3 Best Dictionary

The best dictionary is the one with the sparsest representation. However, if you work with a very large dictionary ($T \gg N$), the cost of computer time to calculate the coefficients would not make it very convenient α. Therefore, there is a direct relationship between the complexity of the analysis (the magnitude of the dictionary) and the time taken to calculate the coefficients. Some dictionaries have the advantage of using fast operators; these dictionaries are very high performance for data analysis. The Fourier dictionary is the well known, however many others have been proposed in the state of the art.

2.3.4 Dictionary learning

The main objective is to design an over-complete basis function from the available data (image or signals) for sparse compact representation. Given a set of images denoted by x_i, where i is the total number of images, the dictionary learning algorithm solves the following optimization, learning algorithm solves the following optimization,

$$\min_{D,\alpha} \sum_{i=1}^{T} \|x_i - D\alpha_i\|_2^2 \quad \text{s. t.} \quad \|\alpha_i\|_0 \leqslant \tau, \forall i \tag{2.2}$$

Here D is the dictionary learned and α_i the sparse representation for each data x_i. $\|.\|_0$ is the ℓ_0 norm that denotes the number of non zero elements in a vector and τ allowable maximum number of non-zero elements used for representation. Each column of the dictionary is often denoted as atoms. The k-Singular Value Decomposition (k-SVD) (Elad and Aharon, 2006b), so far the most popular algorithm for dictionary learning was introduced. The K-SVD algorithm also solves the optimization in **Equation** 2.2 as a two-step approach. First, the sparse solution is obtained by minimizing the following.

$$\min_{\alpha} \sum_{i=1}^{T} \|x_i - D\alpha_i\|_2^2 \quad \text{s. t.} \quad \|\alpha_i\|_0 \leqslant \tau, \forall i \tag{2.3}$$

The orthogonal matching pursuit (OMP) algorithm (Tropp and Gilbert, 2007) is used to solve **Equation** 2.2. The next step updates the dictionary using the sparse codes obtained from **Equation** 2.2. Instead of solving the dictionary as a least-square solution as other methods, the K-SVD updates each column of the dictionary, by

solving a low-rank approximation problem. The dictionary is updated by solving $\min_D \sum_{i=1}^{T} \|x_i - D\alpha_i\|_2^2$. The objective function is re-written as

$$\sum_{i=1}^{T} \|x_i - D\alpha_i\|_2^2 = \|X - \sum_{j=1, j\neq k}^{T} D_j \alpha^j - d_k \alpha[j]^k\|_2^2 = \|E_k - d_k \alpha^k\|^2 \tag{2.4}$$

Thus d_k is obtained by taking the singular value decomposition of $E_k = U\Sigma V$ and $d_k = U(:, 1)$. The k-SVD is done K times which is the number of columns in D in each iteration.

2.3.5 Applications of dictionary learning

Initially, a dictionary learning algorithm was applied in image de-noising application, where the dictionary is learned from small patches extracted (Elad and Aharon, 2006b,a) from a noisy image. The linear combination of the dictionary and the sparse codes were then exploited to provide a de-noised representation of the image. Methods have been developed for both grayscale (Elad and Aharon, 2006b,a) and color images. While de-noising has been one of the first applications to demonstrate the impact of dictionary learning in obtaining a sparse representation of the images, it has since been extensively used in other applications like image/signal segmentation, image/signal classification, visual tracking, event detection.

Chapter 3

Related Works

This chapter presents a review of the state of the art regarding SCD prediction and the current state of research in this field. All related works are discussed in detail with graphics explanations using block diagrams each of the methodologies. The approach and classification used by each of the works as well as the prediction time of the SCD event with your respective accuracy are principally compared. The recent methods for predicting an SCD event focus on extracting the particular features of the SCD signals and then differentiating them from the normal signals using these particular features of an SCD event. All of the methodologies present in this chapter use ECG signals from the MIT/BIH Normal Sinus Rhythm (NSR) database for signals from SCD patients and MIT/BIH Sudden Cardiac Death Holter (SCDH) database for signals from healthy patients. We present two sections of feature extraction from a signal depending on what type of signal the features are extracted from. **Section** 3.1 presents works with feature extraction from the HRV signal, and **Section** 3.2 presents works with feature extraction directly from the ECG signal.

3.1 Feature extraction from HRV signal

In this section, we present the methodologies that use features from the HRV signal. Analysis methods for HRV signal data exist in the time domain and frequency domain. In most cases, the previous works use features of those domains. The time feature extraction is simple and requires lesser computational time in comparison with the frequency feature extraction. Finally, some works use a combination of these feature extraction (frequency and time). This alternative considers that features combination provides a robust prediction.

In previous work, several trends have been proposed that address the problem of SCD prediction. As Shen et al. (2007) that introduced a personal cardiac monitoring system with a home approach, the system is mainly based on the identity verification of ECG signals, by analyzing the ECG signals the system can detect and therefore predict an SCD event minutes before. This system could be considered as one of the pioneering investigations in the prediction of an SCD. The system includes an ECG amplifier, NI DAQ card, laptop, LabView, and MatLab programs. Through a wavelet analysis, this study reaches a performance of 87.5 % in SCD detection. The classification also was tested with several artificial neural networks (ANN) but the maximal result reached was 67.44 %. In **Figure** 3.1 a block diagram of the methodology proposed by Shen et al. (2007) is presented.

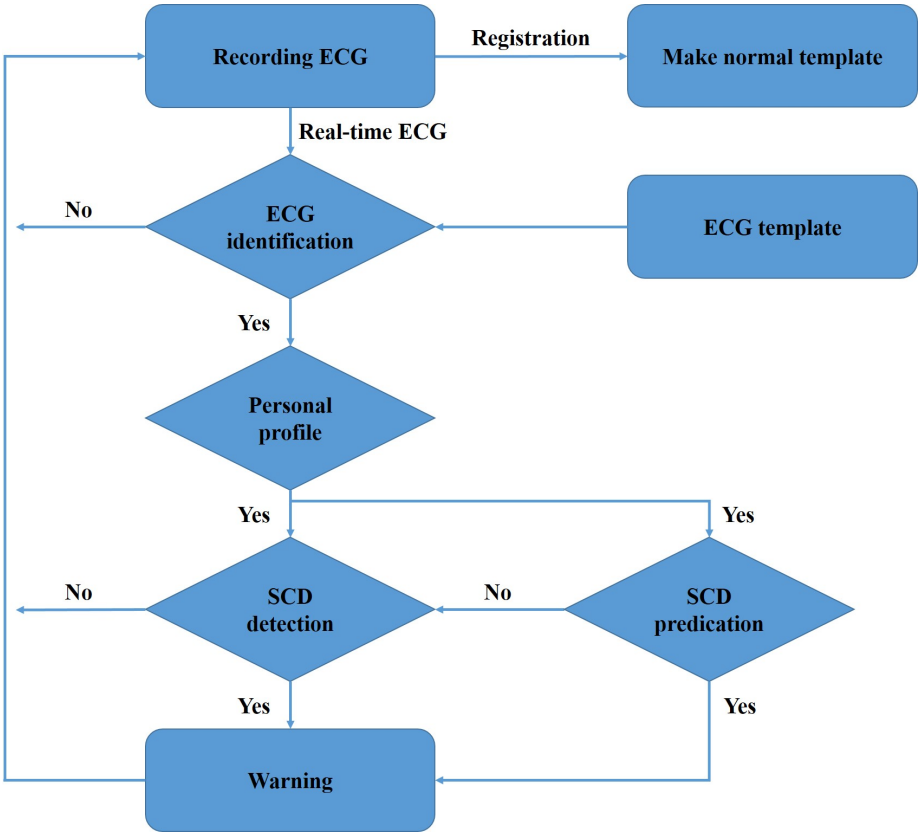


Figure 3.1: Block diagram of the method proposed by Shen et al. (2007).

Ebrahimzadeh et al. (2011) introduced an algorithm to predict SCD, analyzing the HRV signal using the classical and time-frequency methods. The first step was to use the minute of the ECG signal exactly at the event of cardiac death to calculate the HRV signal. Four features in the frequency domain and five features in the time domain were extracted from this HRV signal, which were used as classical linear features. Also, eleven additional features are obtained in the time-frequency domain using the Wigner Ville transform that was applied to the HRV signal. Principal component analysis (PCA) was applied to reduce the feature vector dimensions. By using a multilayer perceptron neural network (MLP) reaches 74.36% and 99.16% (precision) for classical features and time-frequency features, respectively. Besides, the accuracy of the k-Nearest Neighbor (k-NN) classifier was 73.87% and 96.04%. In **Figure** 3.2 a block diagram of the methodology proposed by Ebrahimzadeh et al. (2011) is presented.

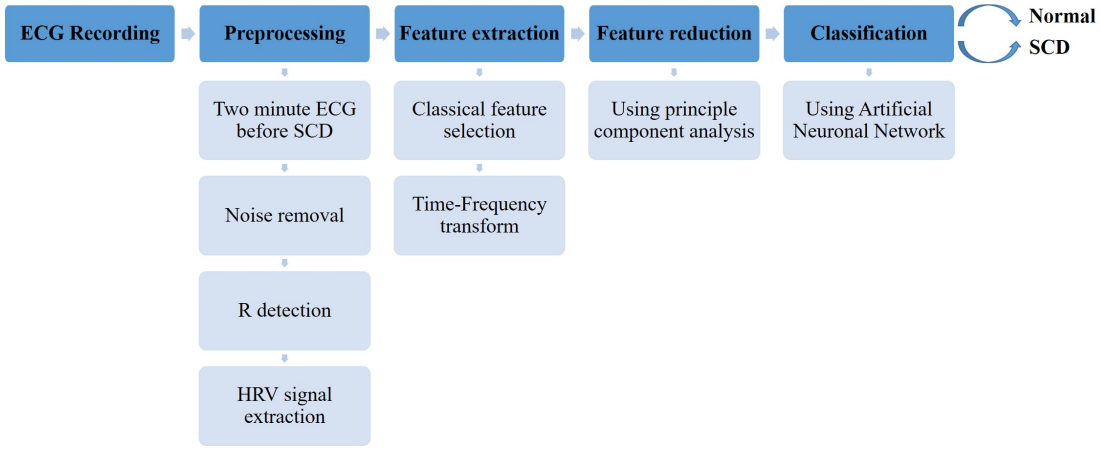


Figure 3.2: Block diagram of the method proposed by Ebrahimzadeh et al. (2011).

Afterward, Ebrahimzadeh et al. (2014) proposed to extract features from the HRV signal, using linear, time-frequency, and non-linear features. Then, the ECG signals of healthy people and people at risk for SCD are classified using k-NN and MLP. The classification rates for non-linear and time-frequency features were performed separately and combinedly. Was found that the combination of both has a better performance achieving greater precision. The results presented by Ebrahimzadeh et al. demonstrated that a combination of these features allows predictions of 99.73%, 96.52%, 90.37%, and 83.96% for the first four minutes before SCD occurs, respectively. In **Figure** 3.3 a block diagram of the methodology proposed by Ebrahimzadeh et al. (2014) is presented.

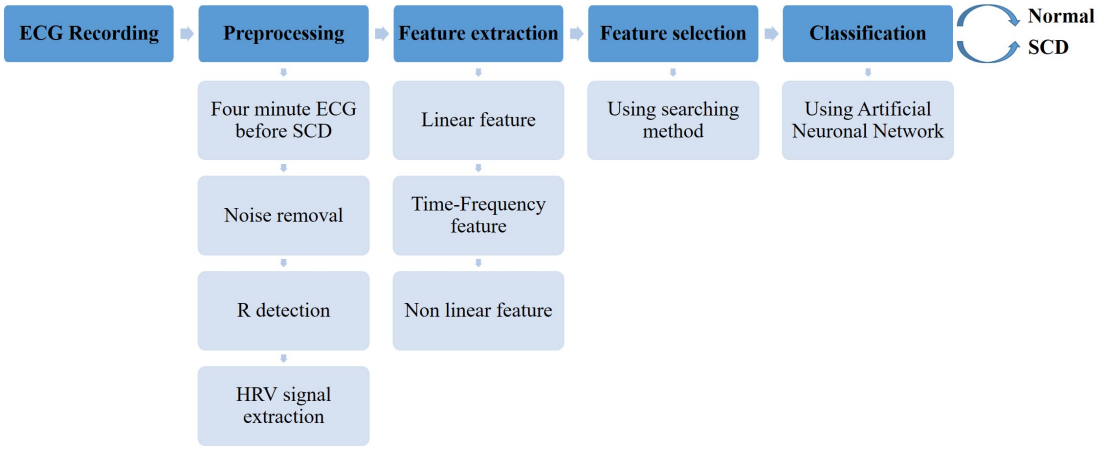


Figure 3.3: Block diagram of the method proposed by Ebrahimzadeh et al. (2014).

Acharya et al. (2015a) presented works on the prediction of SCD. In your first work, proposed an algorithm to detect and predict SCD autonomously by extracting features from HRV signals using Recurrence Quantification Analysis (RQA) and Kolmogorov complexity parameters. These features were tested by applying different classifiers for normal and SCD signals in the four minutes before SCD occurs. This method reaches an average precision of 86.8%, a sensitivity of 80%, and specificity of 94.4% using a k-NN classifier and a mean precision of 86.8%, a sensitivity of 85%, a specificity of 88.8% using a Probabilistic Neural Network (PNN). In **Figure** 3.4 a block diagram of the methodology proposed by Acharya et al. (2015a) is presented.

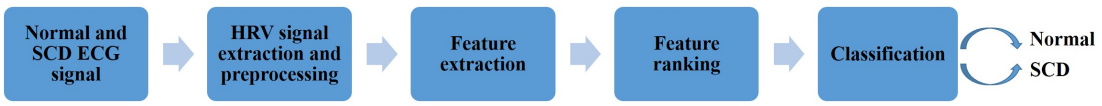


Figure 3.4: Block diagram of the method proposed by Acharya et al. (2015a).

Subsequently, Fujita et al. (2016) presented an algorithm to autonomously classify the characteristics of HRV signals from healthy patients at risk of SCD using non-linear techniques. The results show that they were able to predict an SCD event 4 min in advance, extracting the following non-linear characteristics in one-min intervals: Diffuse entropy (EF), Renyi entropy (REnt), Tsallis entropy (TEnt), Hjorth parameters (activity, mobility, and complexity), and energy characteristics of the Discrete Wave Transform (DWT) coefficients. These clinically significant characteristics obtained were classified and indicating a precision of 97.3%, 89.4%, 89.4%, and 94.7% for the

prediction of the SCD of the first four minutes before the start of the SCD respectively, employing an SVM classifier. In **Figure** 3.6 a block diagram of the methodology proposed by Fujita et al. (2016) is presented.

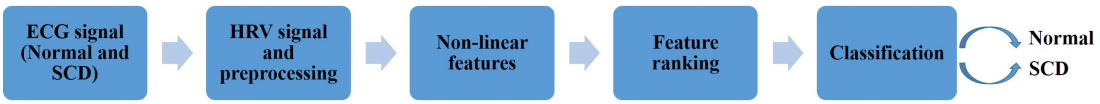


Figure 3.5: Block diagram of the method proposed by Fujita et al. (2016).

The work by Murugappan et al. (2015) can predict the SCD 5 min before the SCD Onset using HRV signals. A 1 min interval of the HRV signals of a patient with SCD was used to design the intelligent SCD prediction system, this interval corresponds to the 6th minute of the HRV signal, that is, 5 min before the start of SCD. The 1 min HRV signals from SCD and normal cardiac rhythm derived from the database were preprocessed using a digital filtering method to eliminate noise and artifacts present in HRV data. A set of time-domain features were extracted to classify the normal cardiac rhythm and SCA using two simple machine learning algorithms, k-NN, and Fuzzy classifier. They report a maximum mean classification rate of 93.71% and 83.43% 5 min before the onset of SCD is achieved using Fuzzy and k-NN, respectively.

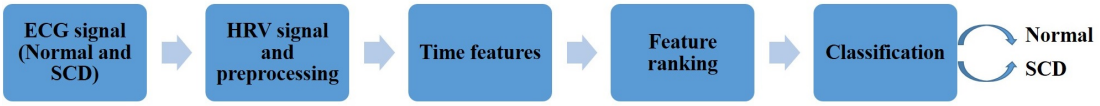


Figure 3.6: Block diagram of the method proposed by Murugappan et al. (2015).

Subsequently, Ebrahimzadeh et al. (2018) presented an approach for the selection of subsets of local features to extract features of non-linear, time-frequency, and classical processes. This approach selects features that differ from each minute interval before the SCD event. Once a combination of features is chosen, they are classified. The most significant characteristics are analyzed considering the predominance of their ranking. They demonstrate that SCD can be predicted 12 minutes before onset with an accuracy of 88.29% using the Multilayer Perceptron (MLP) classifier. In **Figure** 3.7 a block diagram of the methodology proposed by Ebrahimzadeh et al. (2018) is presented.

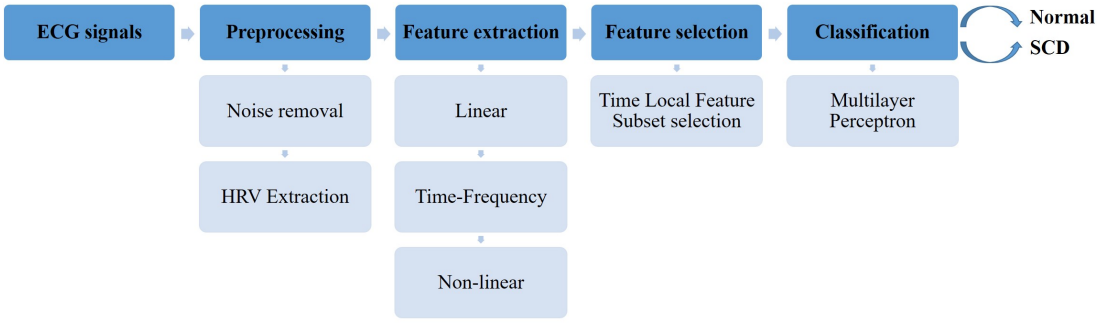


Figure 3.7: Block diagram of the method proposed by Ebrahimzadeh et al. (2018).

3.2 Feature extraction directly from ECG signal

In this section, we present methodologies that use features extracted directly from the ECG signal. This means that the jobs in this section use the signal as it was extracted from the patient. The processing of the ECG signal consists of two parts, the first one deals with the improvement of the signal and the second with the detection of events principally such as QRS complex, RR interval, P wave, and T wave.

Acharya et al. (2015b) introduced an integrated index for the prediction of SCD by analyzing ECG signals. The ECG signal was decomposed using second-level Discrete Wave Transform (DWT) to extract non-linear features. The characteristics used were fractal dimension (FD), Hurst exponent (H), trend-free fluctuation analysis (DFA), approximate entropy (ApproxEnt), sample entropy (SampEnt), and correlation dimension (CD). These non-linear characteristics, extracted directly from the ECG signal, are classified using the t value. Then, the integrated Sudden Cardiac Death Index (SCDI) is used employing a grouping of characteristics. To anticipate an SCD event up to 4 minutes before it occurs using a single numerical value four minutes before the SCD episode, the use of the SCDI is required. The efficiency of the SCDI was corroborated with four classifiers using the non-linear characteristics described. The combination of DWT and non-linear analysis of ECG signals was able to predict SCD with an accuracy of 92.11%, 98.68%, 93.42%, and 92.11% during the first, second, third, and fourth minutes before the appearance of the SCD respectively, using an SVM classifier. In **Figure** 3.8 a block diagram of the methodology proposed by Acharya et al. (2015b) is presented.

Figure 3.8: Block diagram of the method proposed by Acharya et al. (2015b).

Finally, we present the two most recent works on the prediction of SCD, on the one hand, Amezquita-Sanchez et al. (2018) presented a methodology to detect and predict an event of SCD using the homogeneity index (HI), the Wavelet Packet Transform (WPT), and a non-linear measurement for time-series signals that allow the extraction of characteristics from ECG signals. To classify the characteristics an Enhanced Probabilistic Neural Network (EPNN) was used. They report greater precision using a single non-linear characteristic and predict the risk of suffering an SCD event up to 20 minutes before onset with an accuracy of 95.8%.

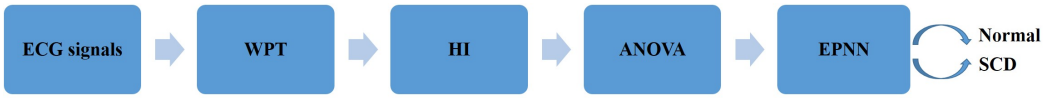


Figure 3.9: Block diagram of the method proposed by Amezquita-Sanchez et al. (2018).

In **Figure** 3.9 a block diagram of the methodology proposed by Amezquita-Sanchez et al. (2018) to detect and predict an SCD event is presented, which consists of 4 steps. In step 1, each minute interval of the ECG signals was examined using the WPT. Also, it was decomposed into a set of signals with specific frequency bands according to the level of decomposition. In step 2, for each frequency band, the HI value was calculated, in which the number of bands changes according to the level of decomposition. In step 3, using a one-way analysis of variance (ANOVA), for each frequency band the HI values were evaluated to determine which values are most significant to be used in the prediction of an SCD event. Finally, in step 4, elected characteristics were evaluated to predict an episode of SCD automatically using an EPNN classifier.

On the other hand, Vargas-Lopez et al. (2020) proposed a methodology that uses a combination of empirical mode decomposition, non-linear measurement entropy such as Higuchi fractal, and permutation, to extracted non-linear characteristics. The results obtained show that the methodology is capable of detecting an episode of SCD 25 min before it appears with an accuracy of 94% using a neural network.

Figure 3.10: Block diagram of the method proposed by Vargas-Lopez et al. (2020).

In **Figure** 3.10 a block diagram of the methodology proposed by Vargas-Lopez et al. (2020) is presented. This methodology used the patient's ECG signal as input and the following steps were applied. First, to separate the ECG signal into a set of frequency bands according to the information contained in the ECG signal, the Empirical Mode Decomposition (EMD) method was used. Then, the Katz Index (KI), the Box Dimension Index (BDI), the Higuchi index (HI), the Permutation Entropy Index (PEI), and the Shannon Entropy Index (SEI) were used. to examine the frequency bands obtained and evaluate which characteristics would be used for greater precision in the prediction of an SCD event. Then, using ANOVA, the most significant characteristics were selected. And finally, the selected characteristics are classified using an MLP neural network to automatically predict an episode of SCD minutes before onset.

3.3 Related works discussion

In this chapter, we present the most recent and relevant works on SCD prediction. **Table** 3.1 presents a summary of these methods that have been proposed for the prediction of SCD using the same data set. Data about the type of signal processed, the difference of the proposed approaches, the classifier used, and the minutes before the SCD event occurs with its respective accuracy were also included.

The main scheme for the research work on the prediction of SCD is based on extracting all the characteristics that are possible from the ECG signal or, where appropriate, the HRV signal, to then make a ranking of these features that better identify each type signal, and use the highest-ranked features as an indicator of belonging to each signal. These features are extracted and compared with the features of the input signal to be classified, and the signal is classified to the group of signals with which it shares the most characteristics. However, this process of extraction and ranking of characteristics has to be carried out whenever you want to classify a signal, making the methods that extend several characteristics could be harmed in the classification time, it could become a problem when dealing with a topic of SCD prediction where time is vital for patients with this condition.

Although several features extracted from a signal indeed provide greater precision, the latest research works reach a high classification precision using only two features. However, we believe that a methodology that does not rely directly on feature extraction might be a better alternative since the extraction and ranking of feature processes for signal classification would not have to be carried out.

SDC prediction methodologies have a variety of technical knowledge. In most cases, the methodologies that analyze the behavior of the signal (ECG or HRV) use global features and learning algorithms. These algorithms rank the features in each of the occurrences. However, sparse representations accomplish high performance in classification problems by not having to extract the characteristics each time the input signal is going to be classified. For this reason, we proposed an SCD prediction using the information of sparse representations and the use of a criterion. We use the sparse representations for SCD signal classifications and accordingly the prediction of an SCD event. Furthermore, this method needs the proper use of a criterion that will help us to classify these signals correctly.

Table 3.1: Previous works of SCD prediction from ECG and HRV signals.

Author	Signal	Approach	Classification	Prediction time (Accuracy)
Shen et al. (2007)	HRV	Features: 4 • Time-frequency	MLP	2 min before (67.4%)
Ebrahimzadeh et al. (2011)	HRV	Features: 20 • Linear (9) • Time-frequency (11)	MLP	2 min before (91.2%)
Ebrahimzadeh and Pooyan (2013)	HRV	Features: 34 • Classical (9) • Time-frequency (11) • Non-linear (6)	MLP	4 min before (73.3%)
Murukesan et al. (2014)	HRV	Features: 34 • Time (15) • Frequency (13) • Non-linear (6)	MLP	2 min before (96.3%)

Continued on next page

Table 3.1: *Continued from previous page*

Author	Signal	Approach	Classification	Prediction time (Accuracy)
Ebrahimzadeh et al. (2014)	HRV	Features: 23 • Classical (9) • Time-frequency (11) • Non-linear (4)	k-NN	4 min before (83.9%)
Acharya et al. (2015a)	HRV	Features: 10 • Non-linear methods • Entropies	k-NN	4 min before (86.8%)
Acharya et al. (2015b)	ECG	Features: 18 • Non-linear	SVM	4 min before (92.1%)
Murugappan et al. (2015)	HRV	Features: 7 • Time	Fuzzy	5 min before (93.7%)
Fujita et al. (2016)	HRV	Features: 4 • Non-linear methods	SVM	4 min before (94.7%)
Ebrahimzadeh et al. (2018)	HRV	Features: 23 • Classical (9) • Time-frequency (11) • Non-linear (4)	MLP	12 min before (88.2%)
Amezquita-Sanchez et al. (2018)	ECG	Features: 1 • Non-linear (Homogeneity index)	EPNN	20 min before (95.8%)
Vargas-Lopez et al. (2020)	ECG	Features: 2 • Non-linear (Higuchi index and permutation entropy)	MLP	25 min before (94%)

*The MIT / BIH databases were used in all cases.

Chapter 4

Methodology

In this chapter, we present the proposed methodology to obtain 30 min of prediction of SCD event from ECG signals. For that, our method has four steps. First, we present the preprocessing of the input ECG signal (**Section** 4.2). Second, we decompose the input ECG signal is representative signals in (**Section** 4.3). Third, we training the dictionary with ECG signal (Normal and SCD) segments (**Section** 4.4). Finally, we identify associated signals with an SCD event through a criterion (**Section** 4.5).

In **Figure** 4.1 a block diagram of the proposed methodology is presented. First, a pre-processing (yellow block) is carried out in which it consists of segmenting the ECG signal in one-minute intervals, and then the signals are normalized. To dictionary training phase (blue block), first, will generate two sets of signals (Training and Test) and then you will train with the Training sets using OMP and SVD. Leaned ECG signal belonging to the test set will be decomposed into representative signals (green block), and finally, the decomposed signals are analyzed (red block) and which qualities belong to each type of signal are identified to define a criterion to classify them.

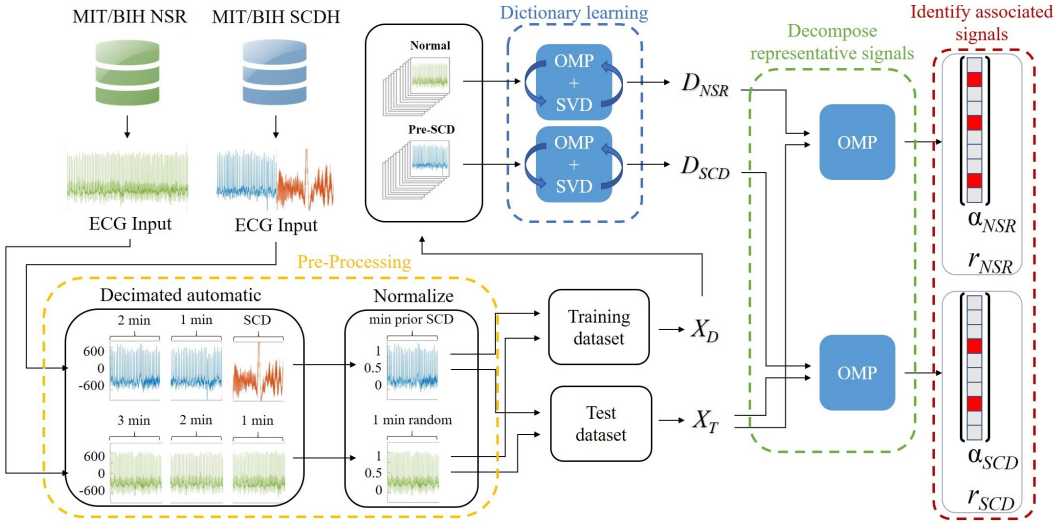


Figure 4.1: Block diagram for the proposed methodology.

4.1 Dataset

To evaluate our algorithm, we use data obtained from two international databases open access is used. The ECG signals (Normal and SCD) were obtained MIT/BIH Normal Sinus Rhythm Database (NSR) and MIT/BIH Sudden Cardiac Death Holter Database (SCDH). In the case of the NSR database includes ECG signals of 18 patients. Experts from the Arrhythmia Laboratory at Boston's Beth Israel Hospital confirmed that signals belong to subjects a normal heart rate. **Figure** 4.2 shows the ECG signal of a patient with normal cardiac rhythm.

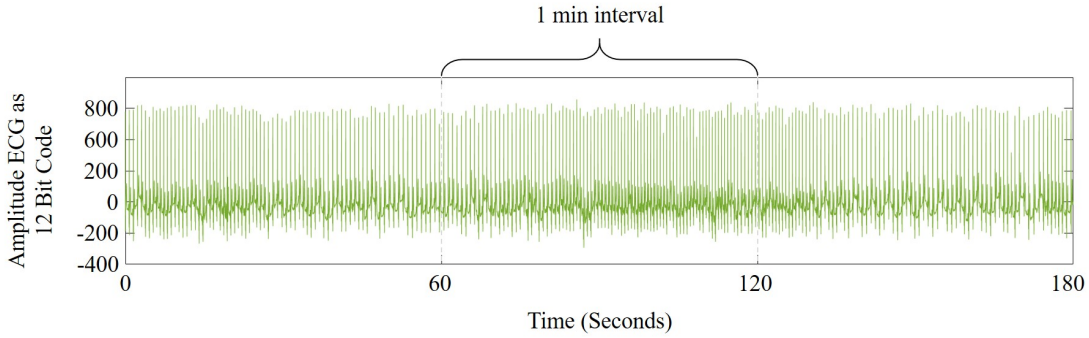


Figure 4.2: ECG signal of a patient healthy.

On the other hand, the SCDH database includes the ECG signals of 23 subjects with SCD caused by VF, these signals were obtained from the Boston area hospitals. Each signal has 24 hours recorded for each SCD patient and the exact time of the SCD. It is important to mention that only 20 SCD ECG signals were used for analysis because the other 3 signals present other heart alterations instead of present an SCD episode or a VF episode. **Figure** 4.3 shows the ECG signal from a patient with SCD during 2 min prior its occurrence and 1 min after its occurrence.

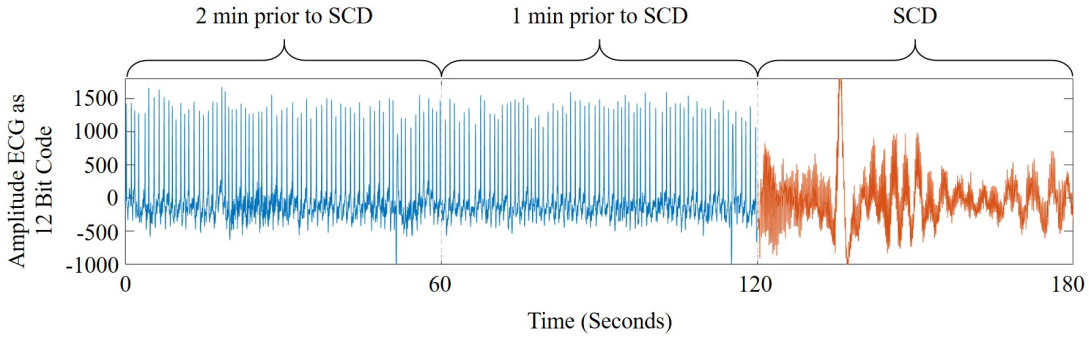


Figure 4.3: ECG signal of a patient with an SCD episode.

Table 4.1 summarizes some features of the used ECG signals. Clinical information of patients with SCD, sex, age, history, medication, the exact time of onset of SCD and more information about the patients, can be found in SCDH database.

Table 4.1: The dataset divided based on the age and gender in each class.

		Gender			Age	
	Total	Male	Female	Unknown	Range	Mean
SCD	23	13	8	2	17-82	60.31
Normal	18	5	13	-	20-50	34.33

4.2 Pre-Procesing

The signals from the databases were monitored for 24 hours but since the ECG signals correspond to different databases they using a different sampling frequency. In the SCDH database, a sampling frequency of 250 Hz was used, whereas in the NSR database a sampling frequency of 128 Hz was used, both digitalized with an analogic to digital converter of 12 bits. To maintain consistency between SCD and normal groups in this work the acquired ECG signals from the SCD group were down-sampled from 250 Hz to 128 Hz to match the sampling frequency of the normal group. The down-sampling was carried out by convolving the ECG signal with a low-pass Finite Impulse Response (FIR) filter.

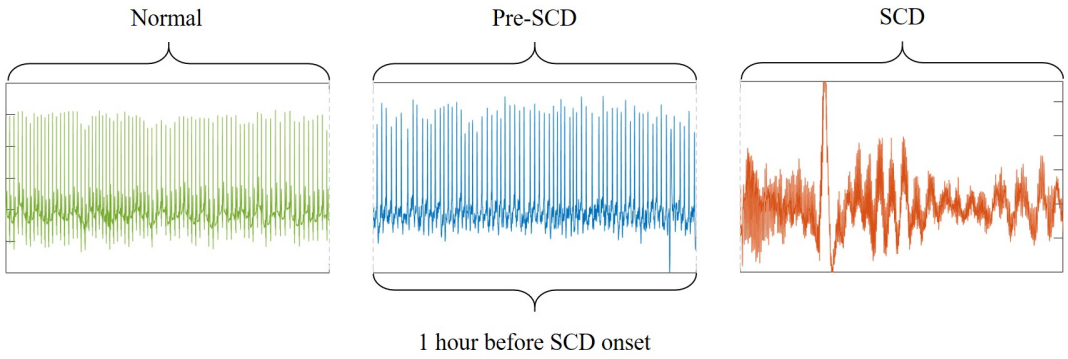
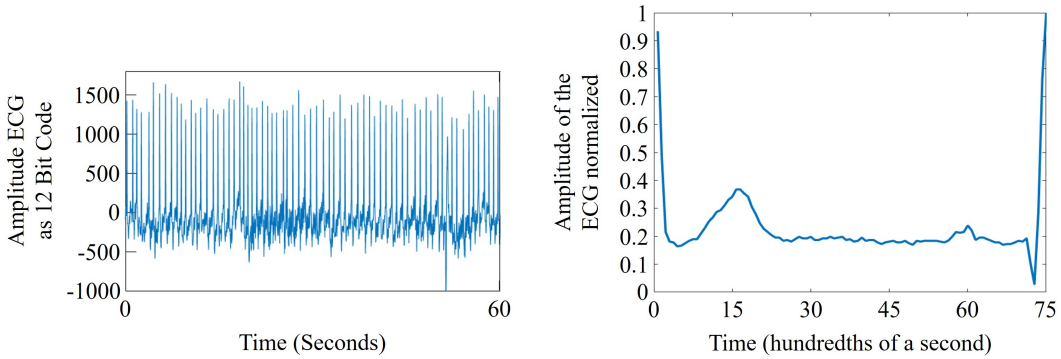


Figure 4.4: ECG with Normal signal, Pre-SCD signal and SCD signal from MIT-HIB dataset.

In general, the significant symptoms of SCD occur within one hour before its onset, even though the person does not have a history of a fatal heart condition (Myerberg, 1992). That is why Pre-SCD (1 hour before to SCD onset) signals are used to predict an SCD since they have more significant features that can be associated with an SCD event, see **Figure** 4.4. In these signals, the goal is to detect features that allow predicting the SCD using time windows of 1 min, as used by other authors such as (Acharya et al., 2015a,b; Fujita et al., 2016; Murugappan et al., 2015). In this work, only the first 30 min of ECG signal before the onset of the SCD is used. These 30 min are segmented into 1-min intervals, see **Figure** 4.5b. Additionally, for the normal group, a 1-min interval of each ECG signal is extracted randomly. In this work, we use the intervals: 5 min, 10 min, 15 min, 20 min, 25 min, 30 min before to SCD and the 1-min interval of normal ECG extracted randomly. These intervals were normalized since working with negative amplitude value could cause problems in signal processing, furthermore, to each of the intervals all possible R-R intervals were extracted. In a signal interval of one-minute, there are approximately 70 R-R intervals, since an R-R interval lasts approximately one second, see **Figure** 4.5b. These intervals R-R analyze to find differences between the SCD and Normal groups.



(a) A 1-min interval.

(b) A R-R interval.

Figure 4.5: (a) A 1-min interval of Pre-SCD signal and **(b)** A R-R interval of Pre-SCD signal from MIT-HIB SCDH dataset.

4.3 Decompose representative signals

4.3.1 Sparse signals

A signal $x_{n\times 1}$, considered as a vector in a finite dimensional subspace $\mathbb{R}^n$, is strictly or exactly sparse if most of its entries are equal to zero, i.e., if the set of values $F(x) = \{1 \leqslant i \leqslant n \mid x[i] \neq 0\}$ is of cardinality $y \ll n$. The signal x can be modeled as the linear combination of m elementary waveforms (atoms), such that

$$x \approx D\alpha = \sum_{i=1}^{m} \alpha[i] d_i \tag{4.1}$$

where $\alpha_{m\times 1}$ is the sparse representation of x containing the coefficients associated with the atoms (d_i) in a matrix dictionary $D_{n\times m}$ involved in the decomposition (Beckouche et al., 2013; Starck et al., 2010), see **Figure** 4.6.

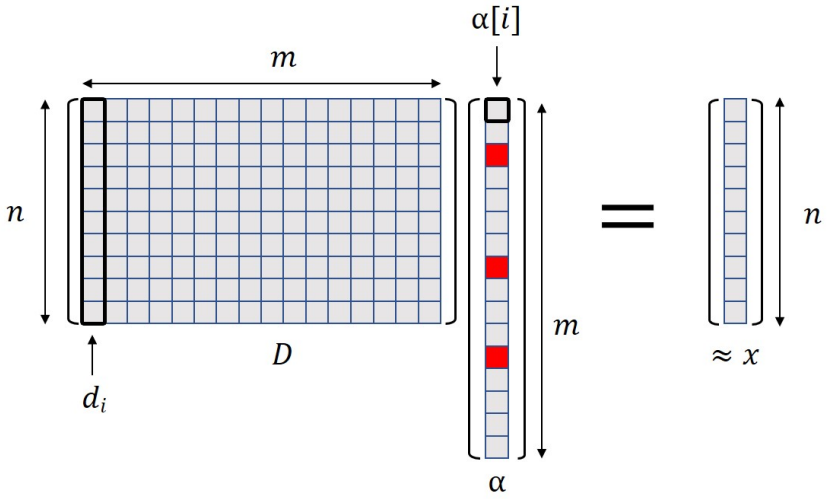
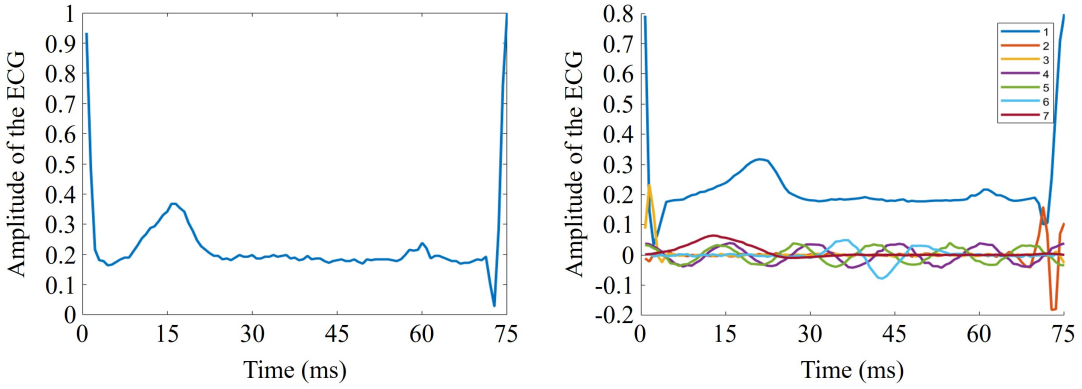


Figure 4.6: Diagram of the signal reconstruction (synthesis).

The signals x sparsed by D are those that can be written exactly as a superposition of a small fraction of the atoms in the basis (d_i). An atom d_i is an elementary signal of $n \times 1$ that represents part of the energy or features of a specific type of signals for which the dictionary was adapted. Thus, a dictionary is viewed as an $n \times m$ matrix whose columns are the atoms, and the atoms are considered as column vectors. When the dictionary has more columns than rows, $m > n$, is called overcomplete or redundant, and has the setting in which $x \approx D\alpha$. Given a dictionary, there are two possible operations to be performed on it: analysis and synthesis. The analysis is the operation

that obtains the sparse representation of a complete signal x by using the expression $\alpha = D'x$, where α is the resulting sparse vector and D' is the transpose dictionary. The synthesis is the operation of approximate reconstructing x by superposing atoms, using the **Equation** 4.1, as shown in **Figure** 4.6.

In previous work, overcomplete dictionaries have demonstrated high performance in classification tasks (Wright et al., 2010; Zhao et al., 2010). There are two different types of dictionaries depending on how they were created: a fixed dictionary and a learned dictionary. In the fixed dictionaries: the predefined signals provide a helpful analysis operation in reasonable processing time and are the best option when the signals have a good dispersion. On the other hand, learned dictionaries: implies a learning process in which the dictionary captures the information required to recognize the particular features of a set of signals. Although learned dictionaries consume more processing time, this option achieves a high performance when the signals to be processed are not well represented by the existing fixed dictionaries (Wright et al., 2010; Zhao et al., 2010; Valiollahzadeh et al., 2009).

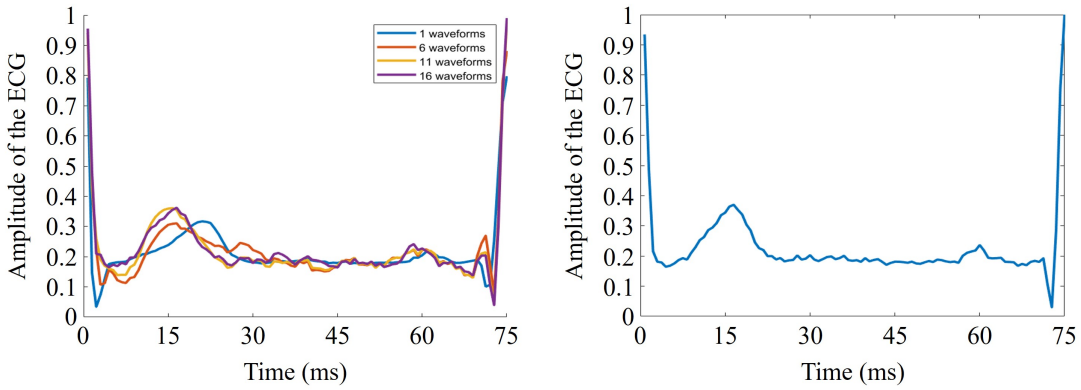


(a) Original signal. **(b)** Signal decomposed.

Figure 4.7: (a) Original signal and **(b)** signal decomposed in elementary waveforms

Once a dictionary has been defined, it is possible to obtain the sparse representation of the signals. For instance, **Fig.** 4.7a shows an R-R interval of the original ECG signal. This signal has been decomposed in atoms with their corresponding coefficients through the analysis operation. The atom d_i and its $\alpha[i]$ coefficient generate an elemental waveform that represents a part of the original signal (see **Equation** 4.1). **Figure** 4.7b shows seven of the sixteen elementary waveforms in which the original signal was decomposed. In **Figure** 4.8a shows its reconstruction through the synthesis operation by using a different number of waveforms (1 waveform, 6 waveforms,

11 waveforms, and 16 waveforms). The higher the number of signals used in the reconstruction, the features of the reconstructed and the original signal will be more similar (**Figure** 4.8b).



(a) Signal reconstruction.

(b) Reconstructed signal.

Figure 4.8: (a) signal reconstruction with a different number of atoms and **(b)** signal reconstruction with an all number of atoms.

4.4 Dictionary learning

An overcomplete dictionary is obtained by a dictionary learning process. In this work, the dictionary learning process is performed by two algorithms: Orthogonal Matching Pursuit (OMP) and k-Singular Value Decomposition (k-SVD). OMP, a greedy algorithm, reduces the resources requirements and obtains a sparse solution by performing the analysis operation given a dictionary Beckouche et al. (2013). After, K-SVD evaluates how accurate the dictionary is for decomposing the input signals. Both algorithms and their use in SCD prediction are explained in detail in this section.

4.4.1 Orthogonal Matching Pursuit (OMP)

The OMP algorithm searches an approximate solution through the combination of the atoms in D that minimize the error-constrained (**Equation** 4.2) sparse coding problem, where $\|\alpha\|_2 = \sqrt{\sum_i |\alpha_i|^2}$ is the ℓ_2 norm, and ε is the error threshold in the range $[0, 1]$. Thus, **Equation** 4.2 allows signal decomposition until reach an ε error level, therefore, the number of coefficients may vary from one signal to another.

$$\alpha = \arg\min_{\alpha} \|\alpha\|_0 \quad \text{s. t.} \quad \|x - D\alpha\|_2^2 \leqslant \varepsilon \tag{4.2}$$

The OMP error-constrained process is described in **Algorithm 1**, where the inputs are the dictionary D, the original signal x, and the minimum error ε, on the other hand, the outputs are α which is a column vector that contains the representative coefficients of the original signal x and the residual r_0, which represents the subtraction of the original signal with the reconstructed signal. The algorithm starts by ensuring that $e < \varepsilon$ and that $r_0 = x$ since the signal x has not yet been decomposed; I is the vector of dimensions $j \times 1$ that stores the indexes of the atoms involved in the decomposition of x. The OMP algorithm is an iterative process that chooses the optimal local solution from a set of possible solutions. In each iteration j, this process tries to find in D the atom d_i with the highest correlation to the current energy of the residual r_{j-1} (**Algorithm 1**, lines 3-4). The index of the i-th atom that fulfills the arg max condition is stored in the vector I at each iteration which helps to compile the submatrix D_I. To approximate the sparse coefficients, α is computed by taking into account only the atoms associated to the indexes in I, i.e. D_I, and the residual is updated as r_j containing the remaining energy of x that is not yet represented by $D_I\alpha$ (**Algorithm 1**, lines 5-6). Finally, e is estimated by the ratio between the energy remaining in r_j and the energy of the original signal (**Algorithm 1**, line 7). Thus, using OMP it is expected that the sequence of local optimum solutions leads to the global optimal solution α.

Algorithm 1: Orthogonal Matching Pursuit

input : D, x, ε
output: α, r_j
ensure: $I = (), r_0 = x, e = \varepsilon + 1, j = 0$

1 **while** $e < \varepsilon$ **do**
2 $\quad j = j + 1$
3 $\quad i = \arg\max |D' r_{j-1}|$
4 $\quad I(j) = i$
5 $\quad \alpha = (D_I)^{-1} x$
6 $\quad r_j = x - D_I \alpha$
7 $\quad e = \frac{\|R\|_2}{\|x\|_2} * 100$
8 **end**

4.4.2 k-Singular Value Decomposition (k-SVD)

Several algorithms have been used to adapt the dictionary values to the type of signals that we are dealing with. This process is known as dictionary learning and its goal is to provide an accurate basis for the sparse representation. Algorithm k-SVD allows adapting an overcomplete dictionary (D) to the features of a particular set of M training signals ($X \in \mathbb{R}^{nxM}$). This adaptive process consists of K iterations in which the dictionary is improved to achieve an accurate sparse representation of the signals in X.

$$\min_{\alpha,D} \|X - D\alpha\|_2^2 \quad \text{s. t.} \quad \|\alpha_l\|_0 \leqslant N \tag{4.3}$$

A dictionary can be adapted to recognize the characteristics of a specific type of signal as presented above, for this task several algorithms have been used to adjust the dictionary values to the kind of signals that we are using with. K-SVD is an algorithm that allows the learning process to adequate a basis according to a set of signals, therefore it is called dictionary learning (**Algorithm** 2). This adaptive process is composed of K iterations in which the dictionary is adjusted to achieve an accurate sparse representation of the signals in X. The K-SVD inputs are an initial dictionary D_0, a set X of M training signals of the same type, and a given number K of iterations; according to literature, between 10 and 20 iterations are required Aharon et al. (2006); Mairal et al. (2008). On the other hand, the output is the dictionary D_K what is the trained dictionary adapted to signals X. The dictionary D_0 is initialized with random samples or random values. The final aim is to capture the essential features of the signal set in a final learned dictionary D_K. First, the matrix of sparse representations, α_k of dimensions $m \times M$, is obtained by using OMP and the dictionary D_{k-1} (**Algorithm** 2, line 2). Since OMP has analyzed a set of signals of the same type, the α_k matrix should contain some common atoms in the decomposition of the signals. It is assumed that if an atom takes part in the decomposition of several signals then it adequately represents part of the energy of the signals in X and must be preserved; otherwise, it must be recomputed. Then, the m atoms of D_{k-1} are analyzed to know their participation in α_k. For this, it is obtained the set of signals w in which the j-th atom takes part (**Algorithm** 2, line 4). After that, the matrix α_w is created with the signals in w, and its j-th row is set to 0 to perform a signal reconstruction without the participation of the j-th atom. Then, the residual matrix (R) is computed by the difference of values between the original signals set X and the product of the current dictionary with the

current coefficients (**Algorithm** 2, lines 5-6). Now SVD computes R to find the most accurate values for the j-th atom and its respective sparse coefficients ($d_j \alpha_j$). The SVD decomposition of the residual is designated by $R = U\Sigma V'$, where U are the eigenvalues, V are the eigenvectors and Σ is a diagonal matrix that include the singular values in descendent order (**Algorithm** 2, line 7). The update of the j-th atom of the dictionary (d_j) is computed by the first column of U (u_1) and the update of the coefficient vector α_j is computed through the first column of V (v_1) multiplied by $\Sigma(1,1)$ (**Algorithm** 2, line 7-8). Therefore, it is assumed that in the first iterations D_{k-1} does not provide an accurate decomposition α_k however that the capacity of the dictionary for representing X improves as k increases until reaching D_K.

Algorithm 2: k-Singular Value Decomposition

input : D_0, X, K
output: D_K (trained dictionary adapted to X)
ensure: $k = 0$

1 **for** $k = 1, 2, ..., K$ **do**
2 $\alpha_k = OMP(D_{k-1}, X, \varepsilon)$
3 **for** $j = 1, 2, ..., m$ **do**
4 $w = \{l \in 1, 2, ..., M \mid \alpha_k[j, l] \neq 0\}$
5 $\alpha_w[j, w] = 0$
6 $R = X_w - D_k \alpha_w$
7 $[U\Sigma V] = SVD(R)$
8 $d_j \in D_k = u_1$
9 $\alpha_j \in \alpha_k = v_1 \Sigma(1, 1)$
10 **end**
11 **end**

4.5 Identify associated signals

The usual scheme used for SCD ECG signal categorization consists in compare an input signal x with the features of two classes, normal and SCD (**Figure** 4.9). Conditioned by the similitude of x with the learned classes, the classifier can determine the corresponding class for x. Since signals may contain a large amount of information, it is important to seek which features can represent them in a simplified way to feet the classification process. Usually, a feature extraction process is applied to generate the new simplified signal representation called feature vector. The variety of features that

can be computed for a signal is vast and may depend on whether the most common features for that signal type or a ranking parameter, as the t-value.

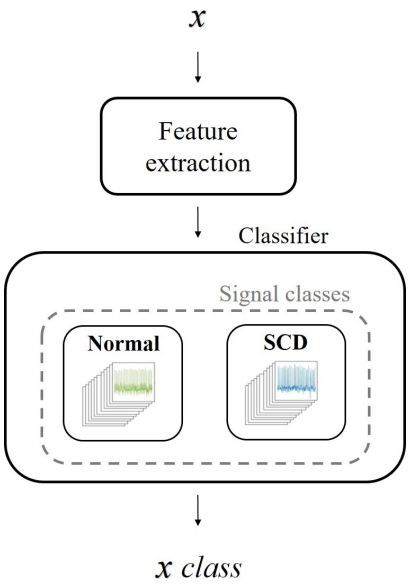


Figure 4.9: Usual scheme used in SCD ECG signal classification.

Applying a sparse representation to ECGs using α as a feature vector, it is expected that, this representation helps to distinguish among the different ECG signals (normal and SCD). Several dictionaries must be generated to identify such changes at different prediction minutes since the aim is early detection of changes in the signal that could be associated with a possible SCD. In this case, will be analyzed intervals at 5 min, 10 min, 15 min, 20 min, 25 min, and 30 min previous SCD. Then, a set for each class, i.e. the normal signals and signals at each time interval, is created as $C = \{NSR, 5min, 10min, 15min, 20min, 25min, 30min\}$. Dictionary learning, through K-SVD (**Algorithm** 2), is performed to generate the dictionaries adapted to the features of each signal set. Thereby, it is acquired a set of trained dictionaries $DT = \{D_{NSR}, D_{5min}, D_{10min}, D_{15min}, D_{20min}, D_{25min}, D_{30min}\}$ to obtain the most accurate decomposition of each kind of signals. Is expected that for a signal of class C_i its respective dictionary DT_i can sparse them properly through OMP given that signal features change depending on the proximity to the SCD event, and are more relevant as they approach an SCD event (**Algorithm** 1).

In this work, the α vector obtained through the sparse representation, supply a simplification of the signal that can be used as a feature vector for signal classification, and the ranking of the features is not necessary. The information in α can be evaluated to find the higher similitude between the features of signal x and a trained basis in DT.

For instance, it can be supposed that a dictionary that has learned the characteristics of a certain type of signal must acknowledge a signal of the same type more easily than learned dictionaries of other signal types, as reported in Díaz-Hernández et al. (2014).

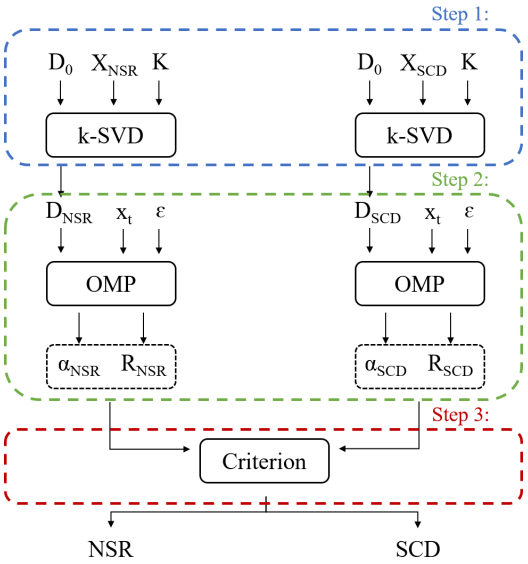


Figure 4.10: Block diagram of the classification process.

A way to measure the recognition of the signal that each dictionary in DT computes is by assessing the sum of α coefficients. For instance, if x_{c1} is a signal of class c1 then the dictionary D_{c1} can represent the signal without generate high coefficients because most of the x_{c1} features are already contained in the atoms energy of D_{c1}. The sparse representations together with the minimum sum criterion of absolute coefficients of α, have been shown to perform well in classification problems (Díaz-Hernández et al., 2014), for this reason, all evaluations with this classification criterion have been performed. In **Equation** 4.4 the Minimum Sum Criterion of Absolute Coefficients of α (MSACα) is described, and in **Figure** 4.10 is shown the general classification process via sparse representation using MSACα as classification criterion.

$$i = \arg\min_{c} \sum_{i=w} | \alpha_c[i] | \tag{4.4}$$

Chapter 5

Experimental Framework

In this chapter, the prediction of an SCD event from ECG results processed by sparse representations under the proposed scheme is presented and discussed. The datasets from MIT/BIH NSR and SCDH (**Section** 4.1) were used to evaluate the performance of sparse representations in the characterization of normal and SCD signals. The R-R intervals from each 1-min sets mentioned in the **Section** 4.2, and corresponding to classes in C, were used for the training and test stages. For each class in C, the signals were randomly selected to divide it into the test and training subsets. 2-fold cross-validation repeated ten times was computed to assure that signal selection does not influence the final results. Thus, a single dictionary was trained for each class in C, obtaining the set of dictionaries DT. The classification of the test signals was computed by obtaining their sparse representation with all the trained dictionaries and evaluating them with **Equation** 4.4. The obtained classification was compared with the label of the dataset. Moreover, the results were also compared with those obtained in the related works.

The quantitative evaluation was performed using signals comparisons of our classification with the signal label of the dataset. To provide quantitative results and compare them with the related works, we used accuracy, a measure based on the numbers of true positives, true negatives, false positives, and false negatives. The proposed method is evaluated using accuracy (Acc), as present in the **Equation** 5.1, where the TP refers to true positives i.e. the correctly predicted SCD signals, TN refers to true negatives i.e. the correctly predicted Normal signals, FN refers to false negatives i.e. the incorrectly predicted Normal signals, and FP refers to false positives i.e. the incorrectly predicted SCD signals.

Accuracy (Acc): the ratio of correct predictions to the total predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{5.1}$$

5.1 Experiments and tests

In this section, to evaluate the robustness the proposed methodology were tested using the a evaluation implemented in the state of the art (common scheme, see **Figure** 4.9) that consider the normal and SCD signal classes. **Table** 5.1 shows the results of one of the tests performed and its metrics.

Table 5.1: Results of test 1.

Minute Before SCD	TP	TN	FP	FN	Acc(%)
5	382	258	55	1	92.0
10	375	290	62	5	90.8
15	369	271	68	1	90.3
20	373	332	64	4	91.2
25	383	281	54	2	92.2
30	397	331	40	0	94.8

The results show that, in general, the used criterion (**Equation** 4.4) for sparse representations reaches a high number of correct predictions. The accuracy (Acc) indicates that it is possible to reach a correct classification of ECG SCD signals greater than 90% which indicates a reliable detection. The general evaluation of the ten tests with the average measures and standard deviation for the time intervals before SCD onset are shown in **Table** 5.2. As observed, the results obtained achieve high precision and small deviation.

Table 5.2: Measures for the ten tests of ECG SCD classification through sparse representations.

Minute Before SCD	Accuracy (%)
5 minute before	94.4 ± 2.8
10 minute before	93.5 ± 2.7
15 minute before	92.7 ± 3.1
20 minute before	94.0 ± 3.1
25 minute before	93.2 ± 3.5
30 minute before	95.3 ± 2.5

The average accuracy that was obtained in **Table** 5.2 enables comparison among available methods in the literature and the proposed approach. **Table** 5.3 presents the most recent similar methods that have been proposed for the prediction of SCD using the same data set. Data about the type of signal processed, the difference of the proposed approaches, the classifier used, and the minutes before the SCD event occurs with its respective accuracy were also included.

Table 5.3: Comparison results.

Author	Signal	Approach	Classification	Prediction time (Accuracy)
Shen et al. (2007)	HRV	Features: 4 • Time-frequency	MLP	2 min before (67.4%)
Ebrahimzadeh et al. (2011)	HRV	Features: 20 • Linear (9) • Time-frequency (11)	MLP	2 min before (91.2%)
Ebrahimzadeh and Pooyan (2013)	HRV	Features: 34 • Classical (9) • Time-frequency (11) • Non-linear (6)	MLP	4 min before (73.3%)
Murukesan et al. (2014)	HRV	Features: 34 • Time (15) • Frequency (13) • Non-linear (6)	MLP	2 min before (96.3%)
Ebrahimzadeh et al. (2014)	HRV	Features: 23 • Classical (9) • Time-frequency (11) • Non-linear (4)	k-NN	4 min before (83.9%)
Acharya et al. (2015a)	HRV	Features: 10 • Non-linear methods • Entropies	k-NN	4 min before (86.8%)

Continued on next page

Table 5.3: *Continued from previous page*

Author	Signal	Approach	Classification	Prediction time (Accuracy)
Acharya et al. (2015b)	ECG	Features: 18 • Non-linear	SVM	4 min before (92.1%)
Murugappan et al. (2015)	HRV	Features: 7 • Time	Fuzzy	5 min before (93.7%)
Fujita et al. (2016)	HRV	Features: 4 • Non-linear methods	SVM	4 min before (95.3%)
Ebrahimzadeh et al. (2018)	HRV	Features: 23 • Classical (9) • Time-frequency (11) • Non-linear (4)	MLP	12 min before (88.2%)
Amezquita-Sanchez et al. (2018)	ECG	Features: 1 • Non-linear (Homogeneity index)	EPNN	20 min before (95.8%)
Vargas-Lopez et al. (2020)	ECG	Features: 2 • Non-linear (Higuchi index and permutation entropy)	MLP	25 min before (94%)
Our work	ECG	Sparse representations	MSACα	30 min before (95.3%)

*The MIT / BIH databases were used in all cases.

5.2 Additional experiments

Although the previous evaluation (**Section** 5.1) provides a quantitative comparison metric between the state of the art of SCD prediction, it might not be the most appropriate for this case, since evaluation uses only two classes, comparing Normal signals with SCD signals. These SCD signals belong to patients with a history of heart disease (SCDH). Thus, the entire signal behaves differently than a Normal signal, not just in the minutes before an SCD event. Using the previous evaluation (**Section** 5.1) the SCD signals could be easily classified by the features of prior heart diseases rather than the particular features of an SCD event. For this reason, we make an experimental evaluation, which uses six classes of SCD signals and one class of Normal signals. Using different categories of SCD, the evaluation is more suitable to find significant features of an SCD event since the other SCD signals with which it is compared also have the same features of the previous heart diseases. Also, having a class of Normal signals it could have an approximate of the last evaluation (**Section** 5.1) using only the accuracy of this class. For evaluating the robustness of the proposed methodology we perform 10 tests to each 1-min interval predictions using this evaluation. The results in one of the tests using each interval of minutes before to SCD as classes are presented in **Table** 5.4, i.e., it presents a confusion matrix of the minutes before to SCD, also the number of signals used and the accuracy of each class.

Table 5.4: Confusion matrix obtained with the experimental scheme in one of the tests.

	Normal	**05 min**	**10 min**	**15 min**	**20 min**	**25 min**	**30 min**	Total signals	Acc.
Normal	**382**	1	14	16	7	11	5	436	97.5%
05 min	0	**136**	29	32	25	10	27	259	87.1%
10 min	0	34	**77**	64	43	27	50	295	79.0%
15 min	0	23	39	**112**	56	14	28	272	81.7%
20 min	0	25	35	47	**133**	21	75	336	81.4%
25 min	0	34	30	39	38	**51**	85	283	83.1%
30 min	0	38	80	39	29	48	**44**	278	76.7%

Table 5.5 presents the average accuracy of the ten tests performed for each 1-min intervals (5 min, 10 min, 15 min, 20 min, 25 min, and 30min) before SCD onset using the evaluation experimental, in addition to the standard deviation of the accuracy results of each prediction SCD interval. Unlike previous studies using ECG signals (Amezquita-Sanchez et al., 2018; Vargas-Lopez et al., 2020), it can be seen from the

results in **Table** 5.5 that the longer the distance from the start of an SCD event, the more difficult it is to be able to predict the SCD with high accuracy; with these results from ten tests performed to different minutes before the start of SCD was obtained an average accuracy of 80.5% for an SCD event 30 minutes in advance. The purpose of the experimental evaluation is comparing SCD signals with the same conditions of a history of heart disease, therefore it is an evaluation with more equal conditions.

Table 5.5: Obtained accuracy for each prediction interval using proposed evaluation.

Minute Before SCD	Accuracy (%)
Normal minute	96.3 ± 1.4
5 minute before	86.2 ± 0.9
10 minute before	78.4 ± 1.6
15 minute before	80.1 ± 2.1
20 minute before	81.0 ± 1.3
25 minute before	83.8 ± 1.0
30 minute before	80.5 ± 2.8

5.3 Experiments summary

In this thesis, a new method of SCD prediction is proposed by using sparse representations, and analysis of the ECG signal. For this method, the ECG segments several minutes before (5 min, 10 min, 15 min, 20 min, 25 min, and 30 min) SCD onset are used for analysis. At every 1-minute interval of the ECG signals, all R-R intervals are extracted from 1-minute intervals of signals. After using sparse representations to decomposed the R-R intervals in the elementary waveforms with significant features, we using a criterion (MSACα) to separate the SCD signal from a Normal signal.

Results show that the proposed methodology yields an average accuracy of over 95.3 % for predicting an SCD episode 30 min before its occurrence. Also, we presented an experimental form of evaluation, since according to the MIT/BIH databases, the SCD signals belong to patients with a history of heart disease, and using the standard evaluation, the SCD signals could be classified by characteristics other than the SCD. For this reason, we decided to compare SCD signals of different predictions with each other in addition to comparing it with the Normal signal. The results obtained using experimental evaluation are an overall average accuracy of 80.5%, 30 min before to SCD event. The comparison between the state of the art approaches and the one proposed in this study highlights the fact that the suggested method has the capacity

for SCD prediction through analyzing without processing ECG signal, different from other approaches they use the HRV signal; for the use of the HRV signals, they have to be applied further signal processing strategies to correctly detect the R-R intervals required to estimate the HRV signal which increases the computational and accordingly the time to execute diverse methodologies (Shen et al., 2007). Moreover, feature ranking is a common task in other works. Still, it is a complicated process because the behavior of some features may change in time, making necessary a feature evaluation per minute to identify which features better represent that specific interval Acharya et al. (2015a). Since sparse representations provide a simplified description of the signal, α can be used as a feature vector, avoiding feature ranking. Also, it was found that the normal and SCD signals can be identified with high precision using a simple criterion instead of a classifier.

Acharya et al. Acharya et al. (2015a) also proved a simple evaluation by using the Sudden Cardiac Index (SCDI) for detecting SCD up to 4 minutes before the onset. Concerning previous works, it was proven that it is possible to reach an SCD detection up to 30 minutes before with high accuracy. Prediction of an SCD 30 min before the event is a difficult task since more than 50% of people do not suffer any symptoms or signs before an SCD onset (Raka et al., 2017). Anticipation is vital since medical specialists have little time to apply preventive or reactive techniques to counteract SCD, increasing the survival chance. Thus Normal signals and SCD signals in an ECG can be distinguished by analyzing the information provided by their sparse representations since the learned dictionaries perform a different decomposition of the signals according to their particular characteristics. Furthermore, using a criterion that considers the information associated with the elementary waveforms may significantly increase the classification of the signals thus prediction time.

Chapter 6

Conclusions

SCD is one of the main causes of death. Every day thousands of patients die because they are not treated on time. Higher anticipation of an SCD episode is vital to medical specialists can apply the timely treatment, increasing the possibility of surviving the event. In this work, a new methodology based on sparse representation techniques is presented for SCD prediction using ECG signals. In addition to presenting an experimental evaluation for validating the methodologies of prediction of SCD avoiding misclassification due to features that do not belong to the SCD event.

Our methodology has the next steps. First, we perform a preprocessing consisting of automatic decimated as a function of time (t), to segment the ECG signal, and then the ECG signals segments are normalized to scale the ECG signals. Then, we perform two sets of signals (Training and Test) will first be generated and then training dictionaries with the Training sets using OMP and SVD. Finally, the ECG signal introduced belonging to the Test set is decomposed into representative signals, to are be identified what features belong to each type of signal to be able to classify them. For the above, we define a criterion to differentiate them.

Regarding the experimental results, ten complete experiments were carried out using both evaluations employed the signals from the SCDH and the NSR. These ECG signals were used for both training and testing of the proposed methodology. The experiments included the dictionary learning, sparse, and signal classification steps, which were performed to guarantee the reliability of the results provided by the methodology. Each experiment used a different set of signals, which were randomly chosen, to avoid selection bias. The obtained results show that by using learned dictionaries, sparse representations, and a suitable criterion, a high time of prediction can be reached. We used a criterion based on the sum of absolute coefficients with which was possible be achieve to predicted 30 min before the SCD event. The prediction reaches a general average accuracy of 95.3% and 80.5% with the evaluation reported in other works and the experimental evaluation respectively.

For the proposed evaluation, we are based on that SCD signals belong to patients with a history of heart disease SCDH. Thus, the entire signal behaves differently than a Normal signal, not just in the minutes before an SCD event. For this reason, we believe that an evaluation that compares fragments of the same SCD signal with each other is a more fair and adequate evaluation to ensure that we are working with the characteristics of an SCD event.

The results reported in this work indicate that our methodology is feasible and promising. Together, the sparse representations and the used criterion proved to obtain higher time prediction of the SCD event that the reported in other works. Moreover, it is important to remark that the dictionary learning process is performed completely automatic which represents an advantage over on methodologies, where a verification step is required.

Finally, we can conclude that the methodology presented in this work provides a longer time prediction with relatively high accuracy and a low computational cost. Thus, the proposed method can be implemented in a system embedded to allow for a continuous and portable monitoring system for the patients; which would provide higher anticipation to specialists to apply the timely treatment.

6.1 Future works

The results obtained in this thesis have demonstrated the feasibility of a higher time SCD prediction from the ECG signal. Based on these results, we propose as future work:

- To conduct further tests and study the experimental evaluation to support the conjecture that it is a more suitable evaluation than the traditional evaluation for the classification of normal and SCD signals.
- To implement our proposed methodology using a different dataset even will be tested with other datasets of rhythm disturbances heart, such as arrhythmia. We will explore the implementation of our methodology to validate his consistency.
- To reach a longer prediction time before an SCD without losing accuracy.

6.2 Publications

J. R. Velázquez-González, H. Peregrina-Barreto, J. J. Rangel-Magdaleno, J. P. Amezquita-Sanchez (2020). **Prediction of Sudden Cardiac Death from Electrocardiogram Signal via Sparse Representations.** *Biomedical Signal Processing and Control.* Submitted

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