Respuestas, 24 (2) May - August 2019, pp. 89-99, ISSN 0122-820X - E ISSN: 2422-5053

Respuestas
Journal of Engineering Sciences

RESPUESTAS

Original Article https://doi.org/10.22463/0122820X.1835

Techniques of Acquisition and Processing of Electrocardiographic Signals in the Detection of Cardiac Arrhythmias

Técnicas de Adquisición y Procesamiento de Señales Electrocardiográficas en la Detección de Arritmias Cardíacas

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How to cite: G. Barbosa-Casanova, D. Cardozo-Sarmiento, M. Llera, A. Orozco-Duque y H, Andrade-Cicedo "Techniques of Acquisition and Processing of ElectrocardiographicSignals in the Detection of Cardiac Arrhythmias". *Respuestas*, vol. 24, no. 2, pp. 89-99, 2019.

Received on September 10, 2018; Approved on December 19, 2018

ABSTRACT

Keywords:

Ambulatory Monitoring, Electrocardiogram, Signals Processing Cardiac, Arrhythmias, Type MD-12.

The development of ambulatory monitoring systems and its electrocardiographic (ECG) signal processing techniques has become an important field of investigation, due to its relevance in the early detection of cardiovascular diseases such as the arrhythmias. The current trend of this technology is oriented to the use of portable equipment and mobile devices such as Smartphones, which have been widely accepted due to the technical characteristics and common integration in daily life. A fundamental characteristic of these systems is their ability to reduce the most common types of noise by means of digital signal processing techniques. Among the most used techniques are the adaptive filters and the Discrete Wavelet Transform (DWT) which have been successfully implemented in several studies. There are systems that integrate classification stages based on artificial intelligence, which increases the performance in the process of arrhythmias detection. These techniques are not only evaluated for their functionality but for their computational cost, since they will be used in real-time applications, and implemented in embedded systems. This paper shows a review of each of the stages in the construction of a standard ambulatory monitoring system, for the contextualization of the reader in this type of technology.

RESUMEN

Palabras clave:

Monitoreo Ambulatorio Electrocardiograma Procesamiento de Señales Arritmias cardíacas, Tipo M-12.

El desarrollo de sistemas de monitoreo ambulatorio y sus técnicas de procesamiento de la señal electrocardiográfica (ECG) se han convertido en un importante campo de investigación, debido a su relevancia en la detección temprana de enfermedades cardiovasculares, tales como arritmias. La tendencia actual de esta tecnología está orientada al uso de equipos portátiles y dispositivos móviles como los Smartphones, que han sido ampliamente aceptados debido a sus características técnicas y a su integración, cada vez más común, en la vida diaria. Una característica fundamental de estos sistemas es su capacidad de reducir los tipos más comunes de ruido mediante técnicas de procesamiento de señales digitales. Entre las técnicas más utilizadas se encuentran los filtros adaptativos y la Transformada Discreta Wavelet (DWT, por sus siglas en inglés), los cuales han sido implementados exitosamente en diversos estudios. Así mismo, se reportan sistemas que integran etapas de clasificación basadas en inteligencia artificial, con lo cual se aumenta el rendimiento en el proceso de detección de arritmias. En este sentido, estas técnicas no solo son evaluadas por su funcionalidad, sino por su costo computacional, debido a que deben ser utilizadas en aplicaciones en tiempo real, e implementadas en sistemas embebidos. Este documento presenta una revisión del estado del arte de cada una de las etapas en la construcción de un sistema de monitoreo ambulatorio estándar, para la contextualización del lector en este tipo de tecnologías.

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Introduction

According to the World Health Organization (WHO), the main cause of death in the world are cardiovascular diseases, which claim the lives of approximately 17.9 million people a year, this means more than 31% of the total deaths that occur in the world. More than three-quarters of these deaths occur in low- and middle-income countries, mainly due to the absence of early detection and timely treatment programs [1].

Sudden cardiac death is the leading cause of death in Western countries and is mainly due to cardiac arrhythmias such as ventricular fibrillation and malignant ventricular tachycardia [2]-[6], which are dangerous arrhythmic events leading to death if defibrillation is not applied to the patient within a few minutes [7]. According to the American Heart Association (AHA) report, in the United States, between 2014 and 2015, cardiovascular disease cost an estimated 351.2 billion dollars [8]. Likewise, the report "European Cardiovascular Disease Statistics 2017", shows that these diseases constituted an estimated cost for the European Union of two hundred thousand million euros during 2015 [9]. This represents a serious public health problem, and at the same time generates a challenge in the detection and diagnosis of cardiac arrhythmias.

The method used for the detection of arrhythmias is the electrocardiogram (ECG), which records the electrical activity of the heart through electrodes positioned on the surface of the body. The voltage variations detected by the electrodes are caused by the depolarization and repolarization of the heart cells, which together make the heart perform its function as a pump, sending blood to all organs of the body. The standard ECG is a test that lasts approximately 10 minutes, during which the signal is taken and the morphology of its waveform and its behavior over time are analyzed in order to detect anomalies in the heart rhythm [10]-[16].

There are types of arrhythmias whose symptoms manifest sporadically, and therefore are not detected during the standard ECG test, due to the short time of the test [4], [5]. In these cases, ambulatory ECG (ECGA) monitoring of 24 hours or more, also called Holter, is used. This type of monitoring allows the ECG signal to be stored and recorded while the patient is performing routine activities. The ECGA can be used to assess arrhythmias (symptomatic and asymptomatic) in patients at high risk of sudden death and to evaluate the efficiency of treatments performed on patients already diagnosed [10], [17], [18].

People with symptoms of cardiovascular disease, or those who have already been diagnosed, need a continuous cardiac monitoring system because their lives are at risk [19]. In addition, the lack of early detection allows these diseases to reach a state in which their treatment is increasingly complex [20].

Holter is not the only ambulatory monitoring technique, other current techniques include the use of portable devices called "cardiac event monitors", which allow long-term monitoring, weeks and even months. The characteristics of these devices include the ability to detect, store, transmit, and analyze the ECG signal; they are also lightweight and comfortable so that their use does not represent a nuisance to the patient [20]-[22].

Cardiac event monitors are used in two main ways. The first is on-site monitoring, in which the ECG signal acquired from the patient is processed and analyzed directly in the device, i.e., it is not transmitted. This type of monitoring has a low energy consumption, since it only uses the wireless transmission modules to send alerts; however, its capacity to analyze and process the ECG signal is limited. The other form of monitoring is known as off-site, where the ECG signal acquired from the patient is transmitted through wireless modules to a base station where it is processed and analyzed. This type of monitoring allows for more reliable detections, due to the high processing capabilities of the base stations [20].

Specialists are in charge of diagnosing cardiac anomalies through the analysis of the ECG signal. This process is based on the interpretation of the morphology of the ECG signal and other parameters such as the R-R interval and the QRS complex

[19], [23]. In long ECG recordings, the task of determining comparison points and calculating parameters is a tedious and time-consuming job for specialists. Therefore, it is necessary that ambulatory monitoring devices have recognition algorithms of high sensitivity and specificity, which allow the automatic detection of abnormal ECG signals. The fundamental principle of these algorithms is based on signal processing techniques and pattern recognition [19], [23], [24].

This article presents a review of the state of the art of ambulatory monitoring techniques and ECG signal processing for the detection of cardiac arrhythmias. This article is organized as follows: Section 2 describes different acquisition schemes for ambulatory monitoring; Sections 3 and 4 present signal processing techniques for noise elimination and ECG signal classification; finally, Section 5 presents the conclusions obtained.

Materials and methods

This study included the most relevant papers resulting from a search focused on electrocardiographic signal acquisition and processing techniques for the detection of cardiac arrhythmias. The key words “ambulatory arrhythmia monitoring”, “ECG signal processing”, “non-invasive ECG monitoring” and “detection of abnormal ECG signals” were used. The databases consulted were ScienceDirect, Scopus, Google Scholar, SpringerLink and PubMed. Articles published in English in the last eight years from international journals or conferences were included. For the final selection, the impact generated by the research was taken into account according to the summary and conclusions of each article.

Acquisition schemes for ambulatory monitoring

A trend in the development of systems for ambulatory cardiac monitoring are devices with low energy consumption hardware and low-end microcontrollers. These devices allow the acquisition of the ECG signal through electrodes connected directly to the patient’s torso. The signal conditioning process is carried out by electronic circuits and by the microcontroller; the latter is also in charge of detecting the R wave and calculating the heart rate from the measurement of the R-R intervals obtained. The acquired data are sent to mobile devices or computers, through wireless modules, to be stored, visualized and analyzed information [25]-[28]. Some of these devices have sensors that allow additional records such as acceleration, temperature [25] and blood pressure [27].

Other equipment for ambulatory monitoring has the ability to detect arrhythmias on site, i.e. the process of detecting cardiac rhythm anomaly is done directly on the device. This process is carried out through digital signal processing algorithms, which are developed to be implemented in embedded systems [15], [29]-[34]. The type and amount of cardiac anomalies detected by the devices may vary from one device to another. Some have the ability to detect anomalies such as: atrial fibrillation [29], myocardial infarction and atrioventricular block [34]. Others detect ventricular fibrillation [15], premature ventricular contraction, pause, tachycardia, and bradycardia [30]. Another device detects changes in the ST segment level [32]. There are also devices that detect abnormal ECG signals or arrhythmias, without identifying the type of abnormality [31], [33]. On the other hand, some of these devices have additional functions that allow the sending of information at the moment of the detection of an anomaly in the ECG signal. This process is carried out by means of a GPRS module [15], [31], or through the mobile phone, via text message [34] or a 3G network [30].

Other authors propose the use of ambulatory monitoring systems for ECG signals based on mobile devices such as smartphones or tablets. This is due to the increased processing capacity, internet connectivity, and integration ability of these devices; moreover, they have evidently become an important part of daily life [12], [35]-[39]. These systems can be classified into two groups according to the use of the mobile device. To the first group belong those systems in which the mobile device is used as an interface to display, store and transmit the ECG signal, i.e. arrhythmia detection is not performed in the device. This type of system consists mainly of a sensor device, a Smartphone and a remote server. The sensor device is responsible for the acquisition, amplification, filtering and analogto-digital conversion (ADC) of the ECG signal; in addition, it is responsible for the transmission of information to the Smartphone via a wireless connection, usually Bluetooth. The next component of the system is the Smartphone, which allows to visualize, store and send to a remote server, by means of connections such as GPRS, WiFi or 3G, the acquired information. On the other hand, the remote server allows healthcare professionals to view, analyze and store the information received [40]-[45]. The second group consists of systems in which the detection of cardiac anomalies is performed on the mobile device. They consist mainly of two parts, the first is a sensor device, which acquires the ECG signal directly from the surface of the patient's body, performs a preprocessing and sends it to the mobile device, usually via Bluetooth connection. The second part is the Smartphone, which is in charge of detecting the anomaly in the heart rhythm, by means of detection and classification algorithms, which were implemented through mobile applications (apps) that have been designed using Integrated Development Environments such as Microsoft Visual Studio, Eclipse Helios, LabVIEW Mobile Module and tools such as Android NDK [5], [11], [18]. Among the anomalies detected by these systems are reported: abnormal beats [11], [18], right branch block, premature ventricular contraction, normal and accelerated heartbeat fusion [5], escape heartbeat, premature atrial contraction, atrioventricular block, tachycardia and bradycardia [37].

Noise reduction techniques

A comparison of ECG records acquired at rest with those obtained through ambulatory monitoring systems shows that the latter present different types of interference [46]. The most common are: deviation from the baseline, interference from the power line, interference from electromyographic signals (EMG) [47], and motion artifacts. This is one of the main problems with ambulatory monitoring systems, since such interference corrupts the ECG signal, hinders its interpretation, and can lead to misdiagnosis [48], [49]. To remove these interferences from the ECG signal, signal processing techniques based on the use of adaptive filters or the Wavelet transform [46], [48]-[50] are used.

Berset and his collaborators proposed two different methods to eliminate noise caused by motion artifacts. The first is based on the use of an adaptive Least-mean-square sign-error filter (LMS-SE) along with the impedance signal between the skin and the electrode (ETI), which is used as a reference signal. The second method consists of using the independent component analysis (ICA) technique, in which it is assumed that the independent component (IC) with the greatest kurtosis is preserved, while the other ICs are made zero before performing the inverse ICA transformation, in order to obtain a filtered ECG signal [46].

Mithun and his collaborators, propose for the EMG noise reduction the use of the Wavelet coefficient threshold, through a function that combines the characteristics of hard and soft threshold. On the other hand, for the noise reduction of motion artifacts they propose the use of the Wavelet coefficient limitation, which uses a threshold that excludes the coefficients that represent the ECG without noise, and significantly attenuates the motion artifacts [48].

Kim and his collaborators proposed a method to reduce noise caused by baseline deviation and motion artifacts through the use of a two-stage Least-Mean-Square Adaptive Filter (LMS) cascade. The first stage is a fourth-order adaptive LMS filter, which detects and reduces noise caused by deviation from the baseline. The second stage is an adaptive sixteenth order LMS filter with an adaptive step-size algorithm, which is responsible for reducing high frequency noise that is superimposed on the ECG signal, and non-stationary noise caused by sudden motion artifacts [49].

To attenuate the noise caused by baseline deviation and power line interference, Orozco-Duque and his collaborators implemented a method based on the Discrete Wavelet Transformed (DWT), which consists of decomposing the signal into frequency scales using the fast DWT and threshold according to the level of the signal-to-noise ratio [50].

Some authors group or classify the techniques mentioned according to the context of their application; for example, Saxena et al. [51] suggest the following methodologies to cover problems related to power line interference: Finite Impulse Response Filters (FIR), Infinite Impulse Response Filters (IIR), DWT and Adaptive Normalized LMS Filters, where the linkage of two new methods to the previously named FIR and IIR filters can be observed. The first being those whose response to the imposed against an input of finite length is also of finite duration; the second, as its name indicates, related to infinite responses, constituted as outgoing-input digital feedback filters.

For the case where an ECG signal is affected by a power line interference with a frequency of 50 Hz or 60 Hz (depending on the country), the results of the effects of each of the filters cited in [51], vary depending on three evaluation conditions, the Signal / Noise Ratio (SNR) obtained; the Mean Square Error (MSE); finally, the Mean Absolute Error (MAE), shown in Table 1.

Table I. Comparison of performance of different filters to interferences of the power line

Filter	SNR	MSE	MAE
FIR	$\cong 28$	$\cong 0.06$	$\cong 0.17$
IRR	$\cong 30$	$\cong 0.03$	$\cong 0.05$
DWT	$\cong 40$	< 0.01	$\cong 0.02$
LMS	$\cong 50$	$\cong 0.001$	$\cong 0.02$

Adapted from [51]

For each type of noise, specific techniques have been developed in the literature and even groups or methodologies for its reduction; but, more generally, the type of filter to be used could be classified, in terms of the noise source, as indicated by Shetty [52], for interference by baseline deviation (frequencies less than 1 Hz), low-pass filters should be used; for power line interference (frequency range 50/60 Hz), band-pass filters should be used; finally, for interference from EMG signals (frequencies greater than 100 Hz), high-pass filters should be used.

Similarly in [52], a comparison is made, using the SNR as the evaluation parameter, for four well-known IRR filters: Butterworth, Chebyshev-I, Chebyshev-II and Elliptic. Filters such as Elliptic and Chebyshev-I generate the best results in noise reduction characterized by baseline deviation (High-Pass Filters); notwithstanding the above, this last filter (Chebyshev-I) decreases its performance over the other three presented for noise processing based on power line interference. A similar analysis can be found in the research of Bhogeshwar and his collaborators, where a balance is made between the same filters and the same evaluation parameter, but applied to Low Pass filter structures for the treatment of electromiographic signal interference.

Finally, considering the revisions made, Table 2 is constructed with the methods and types of filters used, according to the interferences that produce noise in the ECG signals.

Classification Techniques

The ECG signal classification is an important tool for diagnosing different types of heart disease. The evaluation of these signals by experts is a tiring task and can take a long time, therefore the use of automatic detection systems for different types of ECG signals is presented as an option that can facilitate analysis and diagnosis [19], [54]. On the other hand, some arrhythmias may be asymptomatic, and at the same time precede some type of potentially fatal cardiac anomaly, for this reason, real-time automatic classification and detection of arrhythmias is critical in cardiac monitoring systems[55], [56].

Chin and his collaborators propose an algorithm for heart rate classification using the cross-correlation technique, along with a peak-valley detector and a trained diffuse k-NN classifier. This algorithm is capable of differentiating between normal sinus rhythm and ventricular tachycardia with a sensitivity of 93.5% and a specificity of 92.5% [57].

Raghavendra and his collaborators report the use of a method based on the dynamic time warping algorithm (DTW), with which they achieved the detection of normal beats and seven different types of arrhythmias, with an accuracy of 98.18%. This method calculates the DTW distance that exists between each acquired beat and the training beats, and uses as classification criteria the minimum DTW distance value obtained [55].

Table II. Methods for Attenuating Noises in ECG Signals

Noise Mitigation Proposals	Method	Type of Noise in ECG Signal Recording			
		Base Line Deviation	Power Line Interference	EMG Signal Interference	Artefacts in Motion
Berset and partners (2012)	Adaptive Filter LMS-SE				✓
	Independent Component Analysis				✓
Mithun and partners (2011)	Wavelet Coefficients Threshold			✓	
	Limitation of Wavelet Coefficients				✓
Kim et al. (2012)	Two Stage Adaptive LMS Filter	✓			✓
Orozco-Duque and collaborators (2013)	DWT	✓	✓		
Saxena (2019)	FIR		✓		
	IIR		✓		
	DWT		✓		
	Standard Adaptive Filters LMS		✓		
Shetty (2014)	Pasa-Baja Filters (<1 Hz)	✓			
	Band-Pass Filters (50/60 Hz)		✓		
	High-Paste Filters (>100 Hz)			✓	
	IIR (Elliptic)	✓	✓		
	IIR (Chebyshev-I)	✓			

Nambiar and his collaborators used block-based neural networks (BbNN), and trained using genetic algorithms (GA), for the detection of ventricular ectopic beats and supraventricular ectopic beats, with an accuracy of 99.64%. In this method they use as characteristics the polynomials obtained as a result of the Hermite evaluation performed on the preprocessed ECG signal [56].

For the classification of heartbeats, Raj and his collaborators propose the use of a three-layer feedforward neural network, trained with the backpropagation algorithm, which receives as inputs the Wavelet coefficients obtained from each beat by means of the DWT. This method differentiates between normal and abnormal beats, the latter being classified into seven types of arrhythmias, with a sensitivity of 97.57% and a specificity of 99.59% [6].

Thomas and his collaborators presented a method for the detection of five types of heartbeats, based on the use of a three-layer artificial neural network (ANN), trained using the backpropagation algorithm with an adaptive learning cup. This ANN receives as inputs the characteristics extracted from the QRS complex (AC power, curtosis, asymmetry, and timing information), along with the wavelet complex coefficients obtained from the fourth and fifth levels of decomposition of the Double Tree Complex Wavelet Transform (DTCWT) applied to the QRS complex. With this method they obtained a sensitivity of 88.60% and a specificity of 96.18% [19].

For the detection of premature ventricular contraction, Orozco-Duque and his collaborators developed a Vectorial Support Machine (SVM), which can be implemented in a microcontroller due to its low computational cost. This SVM uses as a characteristic vector the ten main components obtained by applying the technique “analysis of main components” (PCA) in the Wavelets coefficients. This method presents a sensitivity of 96.47% and a specificity of 97.18% [50].

Finally, considering the revisions made, Table 3 is constructed with the techniques used for the classification and detection of arrhythmias.

Conclusions

The development of ambulatory monitoring techniques and ECG signal processing for the detection of arrhythmias in real time, has been a very active research area during the last years. In this article we reviewed the current status and trends in these techniques, and observed that those ambulatory monitoring techniques that are based on the use of mobile devices such as Smartphones, are widely accepted by researchers, due to the processing capacity, possibility of internet connection, portability and integration ability that such devices have. Other advantages of using Smartphones in ambulatory monitoring are the ease of acquisition and acceptability by the patient, since these devices have become an integral part of daily life.

Different signal processing techniques have been developed for noise reduction and classification of the ECG signal acquired during ambulatory monitoring. In the pre-processing phase, it was observed the use of techniques based on adaptive filters or DWT, with which they achieved the reduction of some of the most common types of noise present in the signal. On the other hand, in the classification phase it was observed that those methods based on the use of ANN or SVM present a high performance in the process of detection of anomalies in the cardiac rhythm. Likewise, the development of techniques for noise reduction and classification is oriented to have a low computational cost, which allows them to operate in real time and be implemented in embedded systems. On the other hand, there is a need for research in the acquisition phase to improve the quality of the signal in the records made on an outpatient basis. Both in the pre-processing and classification phases, there are open research problems, mainly in the implementation of new mathematical tools

Table III. Techniques Used for the Classification and Detection of Cardiac Arrhythmias

Proposals for ECG Signal Classification	Classification Technique	Tests			Classification
		Sensitivity	Specificity	Precision	
Chin and collaborators (2011)	Fuzzy Classifier k-NN	93.50%	92.50%	-	Heart Rate
Raghavendra and his collaborators (2011)	*Algorithm Dynamic Time Warping*	-	-	98.18%	Detection of Normal Beats and Arrhythmias
Nambiar and its collaborators (2012)	Neural Networks Based on Genetic Blocks and Algorithms	-	-	99.64%	Ectopic Ventricular and Supraventricular Beats
Raj and his collaborators (2015)	Red Neuronal Feedforward	97.57%	99.59%	-	Normal and Abnormal Heartbeats
Thomas and his collaborators (2015)	Artificial Neural Network Backpropagation	88.60%	96.18%	-	Heartbeat
Orozco-Duque and his collaborators (2013)	Vectorial Support Machine	96.47%	97.18%	-	Premature Ventricular Contraction

to improve the performance of classifiers and the development of classification algorithms that can be adapted to the characteristics of each patient and the conditions of signal acquisition.

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