Design and Implementation of a Data Acquisition System for R Peak Detection in Electrocardiograms

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Abstract: This paper presents a data acquisition system for the R peak detection in electrocardiograms. R wave is one of the most important sections of the QRS complex, which has an essential role in diagnosis of heart rhythm irregularities. This paper employs Hilbert transform and adaptive threshold technique for the detection of R-peak. The performance of the system was tested using standard ECG waveform records from the MIT-BIH arrhythmia database. In addition, tests were carried out using the sensors Single Lead Heart Rate Monitor for real-time data processing.

1 INTRODUCTION

The electrocardiographic signal (ECG), a representation of heart activity, ECG is the most popular device used in medicine and found the most precise tool in monitoring heart activity by the medical practitioners or cardiologists. More specifically, ECG is a strictly repetitive quasi-periodic signal synchronized by the heart, as a generator of bioelectric (Khandpur R., 2003). The ECG corresponds to a single heartbeat consisting of temporally distinct wave shapes: P wave, QRS complex, T wave and U wave. Algorithms for ECG beats detection focus on the QRS complex because of its short duration and high amplitude of R peak in the QRS complex (Pooja S. et al., 2017).

Accurate determination of the QRS complex, in particular, accurate detection of the R wave peak, is essential in computer-based ECG analysis. The position of its peak (R-peak) is the most evident feature. The distance between consecutive R-peaks (RR period) is an important parameter in the analysis of heart pathologies (Crema C., et al., 2016). RR period can be used for monitoring heart rate variability (HRV), one of the most valuable markers for detecting arrhythmias and noticing abnormal heart rhythm (bradycardia/tachycardia) (Crema C., et al., 2016). The study of the ECG morphology is usually performed starting from the detection of the time positions of R-peaks (Crema C., et al., 2016). However, this measurement is quite strenuous/challenging (Farahabadi H. et al., 2012). Several methods are used by experts to detect the R-peak. Difficulties arise primarily from signal noise, abnormalities that accompany the ECG signals, and the diversity of QRS wave forms.

In the last several years, research into R-peak detection using different approaches has been increasing, for example, Shin-Chi Lai (Chi Lai S. et al., 2014), presented a low-cost electrocardiogram signal recorder design based on an Arduino platform. The results showed that the algorithm is completely effective and can achieve higher-quality scores than those of other related approaches. Another relevant study, presented in (Farahabadi H. et al., 2012), developed an R-peak detection algorithm suitable for implementation in portable ECG acquisition systems. The algorithm is based on Hilbert transform, wavelet transform and adaptive thresholding, which showed less sensitivity to noise in comparison to other methods.

The purpose of this paper is design and build a data acquisition system for the detection of representative waves of an electrocardiogram by implementing the Hilbert transform and adaptive thresholds. The tests are performed with the standard databases MIT-BIH Arrhythmia and Single Lead Heart Rate Monitor to evaluate the results obtained from the implemented methods in this document.

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2 MATERIALS AND METHODS

In this section, we present the architecture of the graphic interface developed for acquisition of ECG signals. Our approach is presented in stages, each of which explains the design and creation of the adaptative thresholds for the detection of representative points in the signal.

2.1 General Architecture

The general architecture of the methodology is presented in following block diagram (Figure 1).

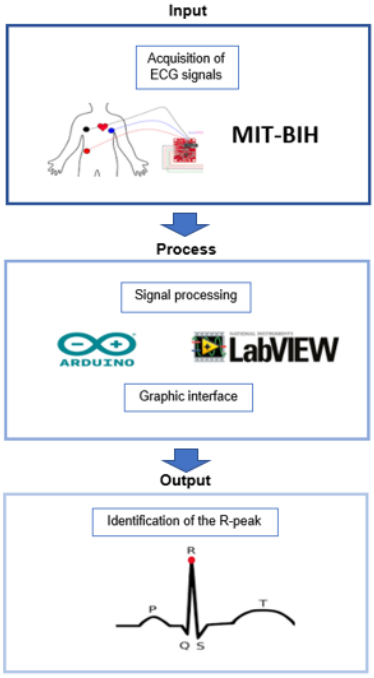

Figure 1: General architecture.

2.2 ECG Signal Acquisition

The ECG signal acquisition process is presented in a stage diagram (Figure 2), that shows each of the steps of the implementation.

a) **ECG acquisition method.** The signals are captured by means of pads placed on the surface of the skin.

b) **Identification of electrodes and their locations.** The pads are placed on the surface of the arms and on the right leg.

c) **Cleaning the identification area.** The areas where the pads are placed are cleaned to ensure a good connection.

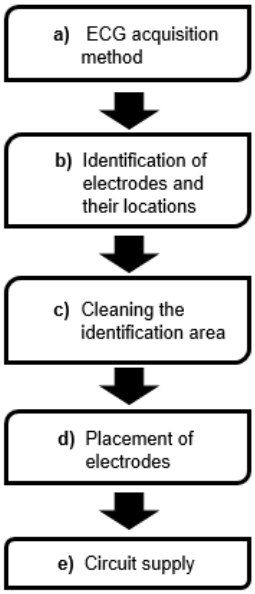

Figure 2: Stages of signal acquisition.

d) **Placement of electrodes.** The sensor pads are placed according to the manufacturer's recommendations. The closer to the heart the pads are, the more precise measurement is.

e) **Circuit supply.** The power supply of the sensor is carried out through the board pins.

2.3 Sensor Connection of the Single Lead Heart Rate Monitor

The sensor board has a special design that can be adapted to the Arduino. The connections between the sensor and Arduino are predetermined for optimal performance. The specifications for the product operation are presented in detail below.

2.3.1 Pin Connections in the Arduino

The AD8232 Heart Rate Monitor has nine connections from the IC that can be soldered to pins, wires, or other connectors to operate the monitor with an Arduino or another board (Analog Devices, 2013). We connect five out of the nine pins to the Arduino board. The five pins are labeled GND, 3.3v, OUTPUT, LO-, and LO+ (Table 1).

2.3.2 Sensor Pad Placement

After the electronic connections are established or made, the pads are placed on the indicated body parts. The following recommendations can help improve the signal quality (Quiceno A. et al., 2007):

Table 1: Connection specifications (Analog Devices, 2013).

Board Label	Pin Function	Arduino Connection
GND	Ground	GND
3.3v	3.3v Power Supply	3.3v
OUTPUT	Output Signal	A0
LO-	Leads-off Detect -	11
LO+	Leads-off Detect +	10
SDN	Shutdown	Not used

- It is recommended to snap the sensor pads onto the leads before placing the pads on the body.
- The closer to the heart the pads are, the better the measurement, as shown in Figure 3.
- The cables are color coded to help identify the proper placement (Table 2).
- Minimize movement while taking a measurement.
- Use fresh pads for each measurement. The pads loose the ability to pass signals after multiple applications.
- The sensor placement may have to be adjusted for each individual.
- Hair is not a good conductor.

Table 2: Color identification (Analog Devices, 2013).

Cable color	Signal
Black	RA (Right Arm)
Blue	LA (Left Arm)
Red	RL (Right Leg)

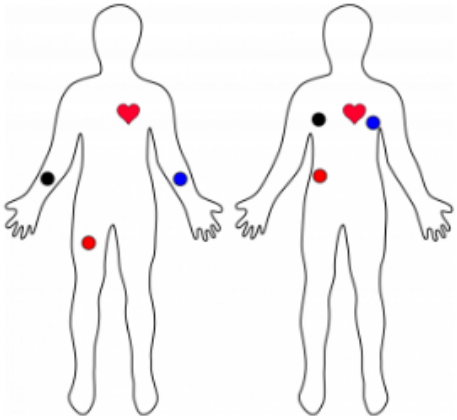

Figure 3: Typical sensor placement (Analog Devices, 2013).

2.4 R-peak Detection

QRS complex detection is the basis of the of segmentation of ECG signals (Quiceno A. et al., 2007). The R-peak can be detected along with the P, T, and sometimes U waves. The QRS complex is a heartbeat detector that can be used to measure the RR interval to analyze heart rate variability and to detect arrhythmias. Various R-peak detection methods have been reported by researchers, but these methods do not work very well in pathological signals where the morphology of the QRS complex changes radically and ectopic beats occur frequently (Quiceno A. et al., 2007).

To be able to detect the representative R wave, we used three methods capable of distinguishing the dominant peaks of a signal and to improve the detection results: first, ECG filtering to remove noise; second, the Hilbert transform to detect dominant peak points in the signal; finally, an adaptive thershold to detect R-peaks.

2.4.1 ECG Filtering

A bandpass filter, is a type of filter that allows a certain range of frequencies to pass while attenuating other frequencies. This type of filter is built by combining a low-pass filter (Figure 4) and high-pass filter (Figure 5).

These filters are represented by standard continuous time system building blocks, integrators, amplifiers and sum connections.

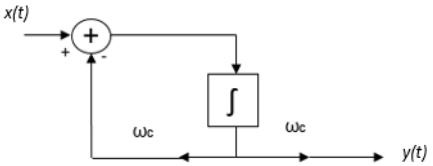

Figure 4: Low-pass filter (Roberts M., 2018).

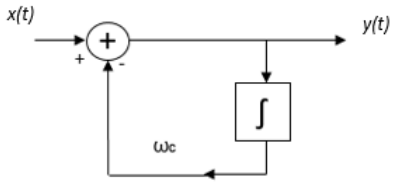

Figure 5: High-pass filter (Roberts M., 2018).

These two systems can be connected in series to form a bandpass filter, as shown in Figure 6.

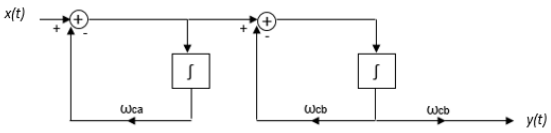

Figure 6: Bandpass filter (Roberts M., 2018).

2.4.2 Differentiation

The first derivative is applied to identify the minimum slope of the ECG signal, *i.e.*, the falling of the signal from R to S. In addition, the first derivative indicates the maximum slope points, *i.e.*, the rising of the signal from Q to R. The first derivative is expressed in the following equation:

$$\dot{y}(t) = \frac{\Delta y}{\Delta t} = \frac{y(t) - y(T_{previous})}{(t - T_{previous})} | t > T_{previous} \quad (1)$$

where t is the current time and $T_{previous}$ is the time of the last output.

2.4.3 Hilbert Transform

The Hilbert transform is one of the most important and common transforms used for the detection of the QRS complex and the R wave (Rabbani et al., 2011). The Hilbert transform is defined as (Benitez D. et al., 2001):

$$\hat{y}(t) = H\{\dot{y}(t)\} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\dot{y}(\tau)}{t - \tau} d\tau \quad (2)$$

Using Fourier identities, it is possible to show that the Fourier transform of the Hilbert transform of $\dot{y}(t)$ is given by (Benitez D. et al., 2001):

$$F\left\{(\hat{y})\right\} = -j\, sgn\, fF\{\dot{y}(t)\} \quad (3)$$

In the frequency domain, the result is obtained by multiplying the spectrum of $\dot{y}(t)$ by $j(+90^\circ)$ for negative frequencies and by $-j(-90^\circ)$ for positive frequencies.The result in the time domain can be obtained by performing the inverse Fourier transform. Therefore, the Hilbert transform of the original function $\dot{y}(t)$ represents its harmonic conjugate, as shown in Figure 7 (Benitez D. et al., 2001).

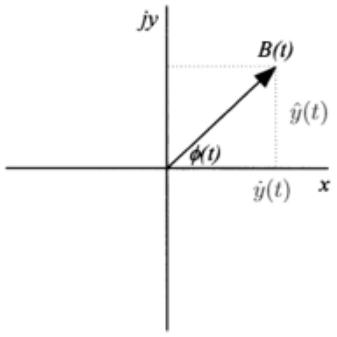

Figure 7: Complex representation of the envelope (Benitez D. et al., 2001).

The analytic signal or pre-envelope of a real signal $\dot{y}(t)$ can be given by expression (Benitez D. et al., 2001):

$$y(t) = \dot{y}(t) + j\hat{y}(t) \quad (4)$$

While the envelope $B(t)$ of $y(t)$ is defined as (Benitez D. et al., 2001):

$$B(t) = \sqrt{\dot{y}^2(t) + \hat{y}^2(t)} \quad (5)$$

2.4.4 Adaptive Threshold

The adaptive threshold is composed of a pair of thresholds called an upper limited threshold (u_{th}) and the lower limited threshold (l_{th}). The upper limited threshold is defined by Eq. (6).

$$u_{th} = 0.65 \times a \quad (6)$$

The lower limited threshold is defined by Eq. (7).

$$l_{th} = 0.15 \times a \quad (7)$$

where the maximum value is obtained at $B(t)$. In each stage of the threshold, the numbers of the peaks detected above the upper and lower thresholds and the total number of the detected peaks are calculated (Rodriguez R. et al., 2017).

Nu_{th} = Number of R-peaks detected by u_{th}.
Nl_{th} = Number of R-peaks detected by l_{th}.

The threshold values are updated by means of the iteration equation; meanwhile, the numbers of the peaks detected by the upper and lower limits are different. The value of u_{th} is updated using (Rodriguez R. et al., 2017):

$$u_{th}(t+1) = u_{th}(t) - w\Delta \quad (8)$$

The value of l_{th} is updated using:

$$l_{th}(t+1) = l_{th}(t) + w\Delta \quad (9)$$

where error weight $w = 0.125$, and $\Delta = u_{th}(t) - l_{th}(t)$, which is the difference between the two defined limits (Rodriguez R. et al., 2017).

3 EXPERIMENTAL RESULTS

This work was developed in LabVIEW. Three tests were conducted to cross-check the functionality. Case study 1 and 2 were performed with the MIT-BIH database, and case study 3 was conducted with Single Lead Heart Rate Monitor sensors.

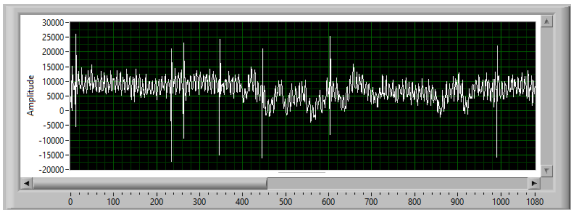

Figure 8: Original ECG signal from the MIT-BIH arrhythmia database (Case Study 1).

3.1 Case Study 1

To run the tests, we selected the *100.art* file from the MIT-BIH database (Figure 8).

The graph consists of two axes, with 1080 steps for the horizontal axis *(X)* and μV for the vertical axis *(Y)*. The graph shows the noise plot; therefore, the results are inefficient for the development of the thesis. We included a bandpass filter with a frequency of 5 to 15 Hz to remove the noise.

In the second part, we applied a bandpass filter and calculated the first derivative. Then, the Hilbert Transform was applied, resulting in a signal envelope with better resolution. Furthermore, the adaptive threshold technique was applied for the identification of u_{th} and l_{th} (Figure 9).

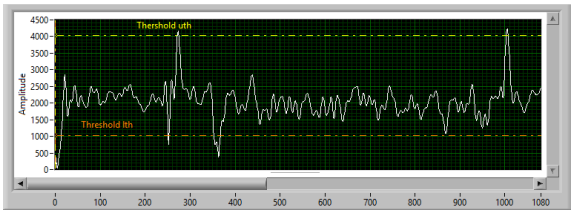

Figure 9: Envelope of the ECG signal (Case Study 1).

Then, the second part of the thresholds was implemented. The thresholds were positioned in the same way and the same number of the peaks were detected.

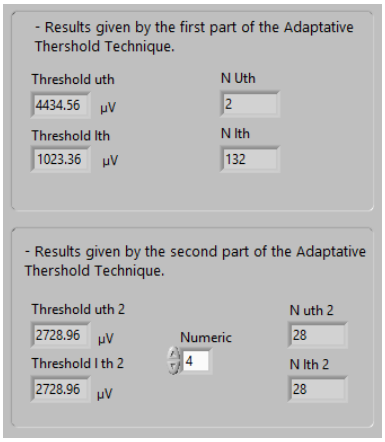

Figure 10: The results obtained by the adaptive threshold technique (Case Study 1).

The thresholds u_{th} and l_{th} are positioned in the same way (Figure 11).

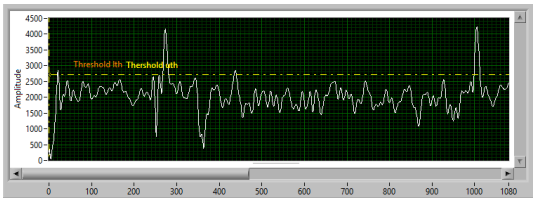

Figure 11: Adaptive threshold application in the ECG signal envelope (Case Study 1).

The R-peaks of the ECG signal were detected based on the location of the peaks obtained from the envelope of the signal (Figure 12).

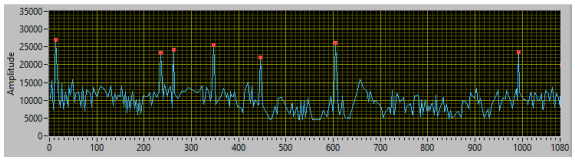

Figure 12: R-peaks of the ECG signal (Case Study 1).

3.2 Case Study 2

In case study 2, we selected the *104.art* file from the MIT-BIH database. As in case 1, the graph consisted of two axes: 1080 steps for the horizontal axis *(X)* and μV for the vertical axis *(Y)*. We included a bandpass filter with a frequency of 5 to 15 Hz (Figure 13).

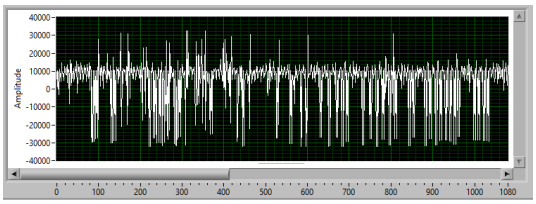

Figure 13: Original ECG signal from the MIT-BIH arrhythmia database (Case Study 2).

We implemented the first derivative and the Hilbert transform to obtain a signal envelope with a better resolution. Furthermore, the adaptive threshold technique was applied to identify u_{th} and l_{th}.

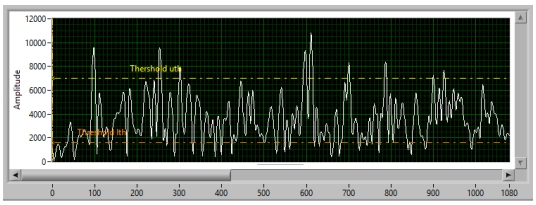

Figure 14: Envelope of the ECG signal (Case Study 2).

The thresholds were updated with the second part of the adaptive threshold technique and the same numbers of peaks were obtained with the upper and lower thresholds. Figure 15 presents the obtained peaks and the values for each threshold.

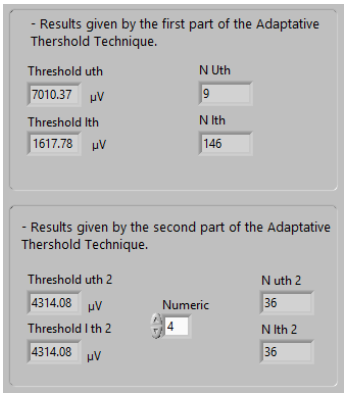

Figure 15: The results obtained by the adaptive threshold technique (Case Study 2).

The thresholds u_{th} and l_{th} were updated to the same values as in Figure 15. The initial values of the thresholds were $u_{th} = 0.5$ and $l_{th} = 0.1$. After some testing, the initial values were changed to 0.65 and 0.15, which resulted in substantial improvement in R-peak identification.

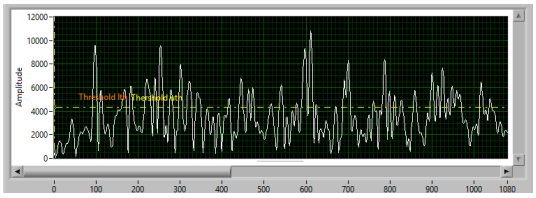

Figure 16: Adaptive threshold application in the envelope of the ECG signal (Case Study 2).

The R-peaks of the ECG signal were detected based on the locations of peaks obtained from the signal envelope (Figure 17).

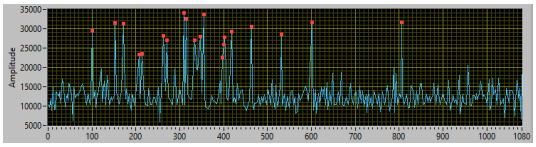

Figure 17: Original signal with the peak identification (Case Study 2).

3.3 Case Study 3

The signal for the last test case was recorded in real time from a Single Lead Heart Rate Monitor sensor. Figure 18 shows the placement of the pads in the indicated areas. Figure 19 presents the sensor and Arduino Mega connections. The data were recorded on a 19-year-old man.

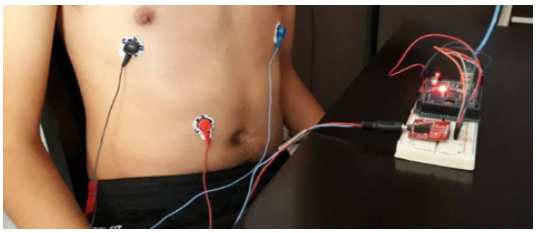

Figure 18: Pad placement and sensor connections (Case Study 3).

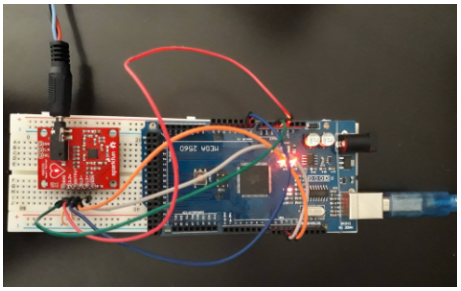

Figure 19: Arduino Mega and Single Lead Heart Rate Monitor sensor connections (Case Study 3).

The real-time signal is shown in Figure 20. The x-axis shows the time, and the y-axis shows the signal amplitude in mV. The recorded signal has minimal noise because the sensor included a filter, which resulted in a well-defined signal. Figure 21 presents the envelope of the signal obtained from the Hilbert transform. The scale of the envelope changes in relation to the ECG signal because the first derivative is used.

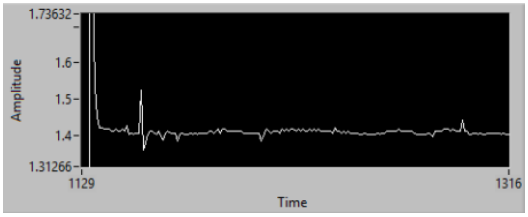

Figure 20: ECG signal recorded by the sensor (Case Study 3).

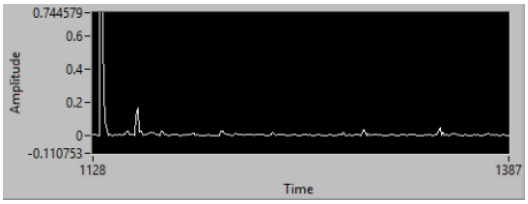

Figure 21: Envelope of the ECG signal (Case Study 3).

4 CONCLUSIONS AND FUTURE WORK

A method for R complex detection in ECG signals is presented. The proposed method has a significant effect on the detection of R-peaks and outperforms other methods. The paper proposed a system capable of detecting the representative R-peaks in an ECG, taking as test cases the MIT-BIH arrhythmia database and the Single Lead Heart Rate Monitor sensor. This detection is necessary for the analysis and diagnosis of several cardiac abnormalities. However, because of several artifacts and the variable morphology of each person's ECG signal, different techniques have been applied for the R-peak detection.

Different stages have been applied in the development of the R-peak detection method, such as implementation of a bandpass filter (for the signal from the MIT-BIH arrhythmia database), the first derivative, the Hilbert transform, and the adaptive threshold technique.

The developed system enables the identification of R-peaks in ECG signals. However, there are several potential directions for future research. Therefore, the following directions for future research are porposed:

- Real-time signal classification to identify different types of arrhythmias.
- System implementation in mobile devices for mobile telemedicine.
- Signal averaging to enhance the representative waves of ECG signals.

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REFERENCES

Rabbani H., Parsa M., Farahabadi E. and Farahabadi A., R-Peak Detection in Electrocardiogram Signal Based on an Optimal Combination of Wavelet Transform, Hilbert transform, and Adaptative Thersholding, *Journal of Medical Signals and Sensors*, vol. 1, no. 2, pp. 91-98, ago. 2011.

Khandpur R. (2003). *Biomedical instrumentation*. New Delhi: Tata McGraw-Hill Publishing Company.

Pooja S., Agrawal M., and Singh L., Automatic Detection of the R Peaks in Single-Lead ECG Signal, *Circuits Syst Signal Process*, New York, March 27, 2017, pp. 4637-4652.

Crema C., Depari A., Flammini A. and Vezzoli A., Efficient R-Peak Detection Algorithm for Real-time Analysis of ECG in Portable Devices, *IEEE Sensors Applications Symposium (SAS)*, Catania, Italy, pp. 1-6, ago. 2016.

Farahabadi H., Farahabadi E. and Rabbani H., Detection of QRS Complex in Electrocardiogram Signal Based on a Combination of Hilbert Transform, Wavelet Transform and Adaptive Thresholding, *IEEE International Conference on Biomedical and Health Informatics*, Hong Kong, China, Jan. 5-7, 2012, pp. 170-173.

Chi Lai S., He You S., Wei D. and Tin Gao S., Low-Cost and Low-Complexity Electrocardiogram Signal Recorder Design Based on Arduino Platform, *Tenth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, Kitakyushu, Japan, August 27-29, 2014, pp. 309-312.

Analog Devices. (2013). AD8232 Heart Rate Monitor Hookup Guide. Web page: https://learn.sparkfun.com/tutorials/ad8232-heart-rate-monitor-hookup-guide

Quiceno A., Castellanos G., Avendao L. and Ferrero J., Optimización en el Desempeño de Algoritmos de Detección de Complejos QRS, *Revista Avances en Sistemas e Informática*, vol. 4, no. 1, pp. 145-154, ago. 2007.

Roberts M. (2018). *Signals and Systems*. New York: McGraw-Hill Education.

Benitez D., Gaydecki P., Zaidi A. and Fitzpatrick A., The Use of the Hilbert Transform in ECG Signal Analysis, Computers in Biology and Medicine, pp. 400-406, 2001.

Rodriguez R., Martínez E., Torres R., Bila J. and Mizera-Pietraszko J., Adaptive Threshold, Wavelet and Hilbert Transform for QRS Detection in Electrocardiogram Signals, *Lecture Notes on Data Engineering and Communications Technologies*, vol. 13, pp. 1-10, 2017.