Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 181 (2021) 957–964

Procedia Computer Science

www.elsevier.com/locate/procedia

CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies 2020

QRS Peaks, P and T Waves Identification in ECG

Renan Costa[1,2], Thaís Winkert[2] , Aline Manhães[2] and João Paulo Teixeira[1,3*]

[1]*Instituto Politécnico de Bragança (IPB), Bragança 5300, Portugal*

[2]*Federal Center for Technological Education of Rio de Janeiro, Av. Maracanã 229, Rio de Janeiro, Brazil*

[3]*Research Centre in Digitalization and Intelligent Robotics (CEDRI), Applied Management Research Unit (UNIAG) - IPB, Braganca 5300, Portugal*

Abstract

The cardiovascular electrocardiogram signal presents noises that include low and high frequency components that interfere in the automatic identification and classification of the QRS peaks, P and T wave. Pre-processing techniques based on moving average and *detrend* function was used to smooth the ECG signal and remove local tendencies. Noise filtering methods based on FIR digital filters were implemented with the purpose of reducing interferences of the baseline and high frequency noise. For the localization of the R peak, an adaptive threshold, based on the Pan-Tompkins algorithm was applied. The other peaks, P-Q-S-T, were found from the search for highs and lows in a pre-determined zones. Pop-up windows were implemented to improve the accuracy of the semi-automatic localization. The developed algorithm obtained an accuracy of 98.09% in the QRS complex identification and 96.29% for the whole peaks under the MIT-BIH Arrhythmia Database.

Keywords: ECG features, Cardiac Diagnosis, Smoothing ECG, QRS recognition, P wave recognition, T wave recognition.

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: joaopt@ipb.pt

1877-0509 © 2021 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies 2020
10.1016/j.procs.2021.01.252

1. Introduction

Heart-related diseases are the leading cause of death worldwide. According to the World Health Organization (WHO), in its 2018 World Health Report [1], cardiovascular disease summed 17.9 million deaths. Related to this, in recent years the trend towards automated electrocardiogram analysis has gained strength as a means of disease prevention. The electrocardiogram (ECG) is a widely used diagnostic tool and essential in clinical cardiology practice. It acts in the capture and recording of electrical signals generated by the heart's activities in its cardiac cycles. Its tracing consists of several deflections caused by activation, depolarization and repolarization of cardiac cells (P-QRS-T) [2-3]. ECG is one of the most common noninvasive tools used for doctors to diagnose heart disease [2]. Therefore, the use and processing of the ECG signal is of vital importance.

ECG observations have traces of electrical signals from various activities of different parts of the body because they are acquired on the body surface. The main issues in bio-signal processing, such as ECG, are reducing noise, isolation and signal identification from different sources [4]. ECG analysis to detect clinical pathologies should be as accurate as possible [5]. In addition, by accurate analysis, it is considered the correct identification of the QRS complex, the on-set and off-set of P and T waves was well as its magnitudes.

From the data obtained from the ECG and its generated electrical signal, this paper describes, as its main objective, the reliable identification of R peaks, the Q and S points, and P and T waves. As part of the extraction process, initially the captured signal is smoothed, therefore it is necessary to reduce the interference found in the acquisition process [6-7]. From this stage, the parameters can be identified using signal-processing techniques, highlighting the important and crucial data for cardiac analysis. With the aid of artificial intelligence tools, the parameters found could be processed and classified according to the presence or absence of pathologies.

The results reported in this paper intends to contribute to the long term objective of develop a system to automatically carry out the analysis, test reporting, and computer-aided preliminary diagnosis of ECG signals obtained from a patient, to support the final medical diagnosis decision [8].

Such systems that automatically interpret the ECG can be useful in the absence of a cardiologist in remote placed where the medical access is difficult, or it can also support the cardiologist himself for a final diagnosis.

The limits of automatic diagnosis systems are known, facing the Myocardial infarction (MI), also known as a heart attack, due to the ST-segment elevation. Also, Hyperacute T waves, Winter ST-T complex, Wellens' syndrome, as well as myocardial infarction in the presence of left bundle branch block, paced rhythm or left ventricular hypertrophy, among others, are diagnostic challenges [9-10]. Therefore, contributions still need to improve the accurate P, T and QRS waves identification for automatic diagnosis.

The article consists of five sections. Section 2 presents the materials used in the work. Section 3 discuss the methodology used, namely, the pre-processing and the identification methods. Section 4 presents the results obtained with the proposed algorithm and its discussion. The last section presents the conclusion of the work and future research.

2. Materials

The ECG signals used in this paper were from the PhysioBank – physiologic signal archives for biomedical research database [11] and the file chosen for the selected signal samples was the MIT-BIH Arrhythmia Database [12].

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000. 24-hour ambulatory ECG recordings were collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. The remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well represented in a small random sample [12].

In most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes were also placed on the chest.

Recordings were digitalized at 360 samples per second per channel with 11-bit resolution over a 10 mV range [12].

Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110 000 annotations in total) included with the database [13].

The materials and annotations were used as the standard for evaluation in this work

3. Methodology

This section describes the signal processing techniques used over the ECG signals to a semi-automatic process to identify the QRS complex and P and T waves.

The ECG signal is subject to a pre-processing phase in order to remove low and high frequency noise components due to baseline and contact noise generated by some movement and bad contact of the surface electrodes.

It follows the R peak identification over the ECG signal. This procedure was carefully developed because the remaining identification waves are based in the R peak position.

Starting from the R peak the P and T waves are identified.

3.1. Preprocessing

ECG signal characteristics have traces of electrical signals from various activities of different parts of the body because they are acquired on the body surface [4]. In a process of identification of the parameters found in the ECG, the removal of this noise from the existing activities in the obtained signal is paramount. If the ECG signal being studied has a high noise level, this identification task becomes even more complicated [5].

The process of removing such interference has as its initial phase the cancellation of the DC component and the removal of the baseline. The second objective is to smooth the ECG signal removing the high frequency noise. For these purposes, a smooth function was implemented, subtracting from the original ECG the smoothed signal. This function is a moving average with a window length of five samples (N=5). Then, in cascade form, the signal is applied to a *detrend* function, to remove the linear trend of the signal. This *detrend* function identifies break points in the signals were the tendency changes and then removes the best straight line fit between each pair of breakpoints. This procedure removes local tendencies over the whole signal including the baseline. Figure 1 presents the results of this procedure for removing the baseline and the tendencies over an ECG of 60 s length.

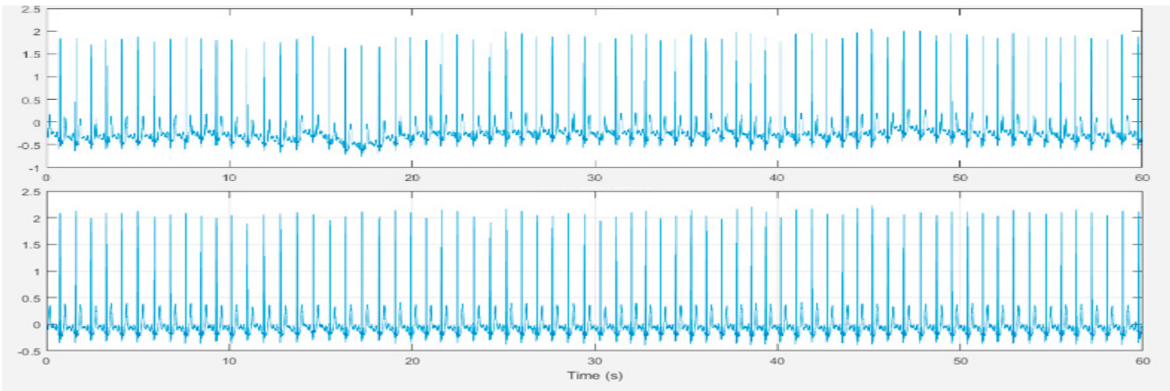

Fig. 1. Comparison between original (above) and smooth/*detrend* signal (below) by adjusting baseline and tendencies.

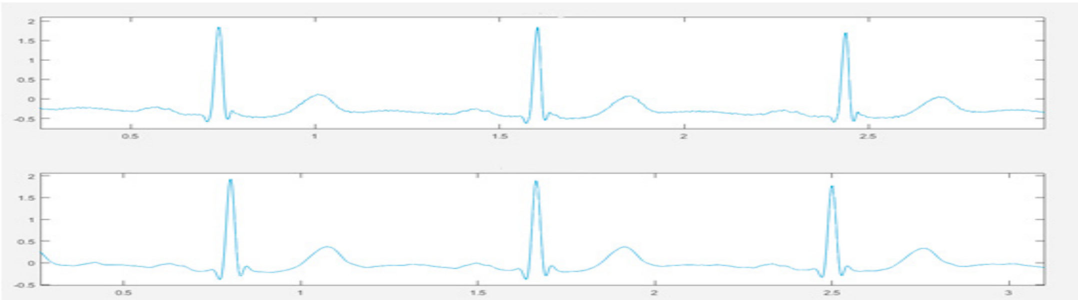

Fig. 2. Detail of 3 cardiac periods of the original ECG signal (above) and after smoothing (below).

It can be seen in Figure 1 that the smooth and *detrend* functions were able to achieve the smoothing sought by removing the linear bias of the signal. Figure 2 presents a detail of 3 cardiac period of the original and smoothed ECG. It can be seen that the original signal is more crumpling.

According to Smith [14], the filter present in the 'smooth' moving average function is an exceptionally good smoothing mode (time domain action), but an exceptionally bad low pass filter (the action in the frequency domain), justifying the need for more filters to reduce noise sources.

The next step is the application of FIR-type digital filters to reduce low and high frequency interference in the signal [8, 15]. Containing bandwidth between 0.25Hz and 30Hz, the result is obtained by sequentially applying a low-pass (order 30) and high-pass (order 6) filters.

The result can be seen in Figure 3, where the Fourier Transform (FFT) was applied to the analyzed signal (103) in order to better visualize and interpret the effects in the frequency domain caused by the proposed filtering process.

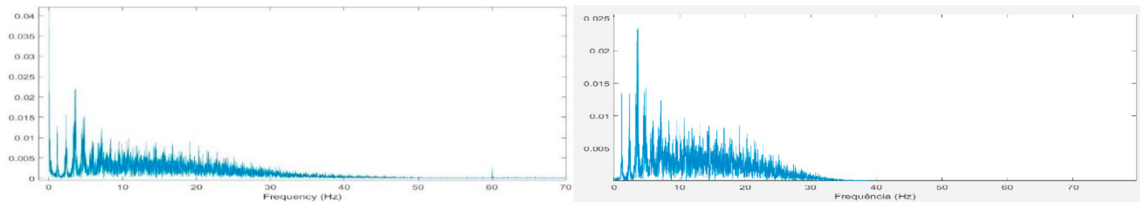

Fig. 3: Frequency components of MIT-BIH signal 103. Original (left), after the filtering process using the cascade FIR filters (right).

As a result of the original signal preprocessing through the low pass and high pass cascade filters, it can be seen that the method was able to reduce the noise, also eliminating the initial DC component and noise characteristics over 30 Hz. According to Blackledge [16], the presented filters process the signal to reduce interference, allowing the use of low-resolution limits to obtain high detection sensitivity.

3.2. Feature Extraction

The identification of events that occur in the ECG automatically and accurately is the main objective of this work. After the pre-processing steps, the interference has been smoothed and the identification of the curves present in the signal can now be recognized.

The first step to a good classification of the events that occur in the signal is an excellent recognition of each cardiac cycle, starting with the identification of the R peak. Then, follows the Q and S identification and finally the P and T waves identification.

3.2.1. R-Peak Identification

The correct identification of the R peak is of crucial importance for the identification of following waves. Therefore, some methods were experimentally compared, namely the use of wavelets, the methods developed by, Lopes [6-7], and the Pan-Tompkins method [17].

The discrete wavelets transform (DWT) [18-20] was also experimented using the decompositions levels 2, 3 and 4, with the mother wavelets Haar, Doubechies and Symmlets.

The method developed by Lopes [6-7] is based in the autocorrelation of the initial QRS over the whole ECG signal to find the high values of autocorrelation and then search the R peak near to the autocorrelation peak.

The Pan-Tompkins method [17] was used because it was the ability to adapt to changes in the ECG along the time and is less time-consuming process.

For this, the previously filtered signal is derived as a way to suppress the P and T wave, low frequency components. Analyzing the result obtained in the process, the signal is now squared, showing the presence of the most visible peaks, the R peaks. The next step is the threshold procedure of the algorithm developed by Pan-Tompkins [17], which adapts to the ECG signal changes by calculating estimates of signal operation and noise peaks. The adaptations over the signal is based in the use of the SPKI (general peak of a QRS wave) and NPKI (peak no related with QRS, noisy peak), the Thresholds I1 and I2. The value of these parameters are updated along the signal according to the magnitude of present peak and the Equations 1.

$$\begin{aligned} SPKI &= 0.125PeakI + 0.875SPKI \\ NPKI &= 0.125PeakI + 0.875NPKI \\ I1 &= NPKI + 0.25(\mathrm{SPKI} - \mathrm{NPKI}) \\ I2 &= 0.5I1 \end{aligned} \tag{1}$$

These threshold parameters are used to evaluate each peak after the signal been squared as R peak or just a noisy peak.

3.2.2. Q and S Peaks Identification

After finding the location of the R peaks of the signal, it is possible to identify the Q and S peaks, completing the QRS complex. The used method is based on Magalhães [21], for the localization of local minimums according to a presented sample threshold. For the Q wave, a range from the R-peak is determined from -5 to -20 samples where the minimum Q peak is searched. Similarly, the S wave is localized, but with a range from +1 to +25 samples where the minimum S peak is searched. At the sampling frequency of 360 Hz, one sample corresponds to 2.8 ms.

3.2.3. P and T Waves Identification

The location of the P and T waves are also based on the peaks, but because they are positive peaks, the maximum function with a previously delimited interval is used. For P peak, the values are -70 and -15 samples. For the peak T location, the values used are +25 and +130 samples. Since the sampling frequency is 360 Hz, Table 1 exemplifies the time interval to search for these peaks.

Table 1. Representation in seconds of threshold for identification of peaks Q, S, P and T.

	Interval in seconds	
Peak	Previous	Later
Q	-0,056	-0,014
S	0,003	0,069
P	-0,194	-0,042
T	0,069	0,361

The methods used to find Q and S peaks and P and T waves has very low processing requirements and presents good results since the ECG signal was previously smoothed.

A complementary method of adjustments was developed as a way to improve the results obtained in the identification of ECG parameters, due to the difficulty of identification at a fixed threshold range some particular P and T waves [21]. The method proposes the implementation of a user interface through pop-up windows, where it is possible to change the cutoff frequency, the order of previously used filters, and the limits of the search intervals for each peak. Thus, from the menu function established in a while, the values could be adapted to the morphology of each signal. The pop-up windows is supposed to be useful only in the initial part of the signal if errors are visually identified. These adjustments made by the pop-up windows are illustrated in Figure 4.

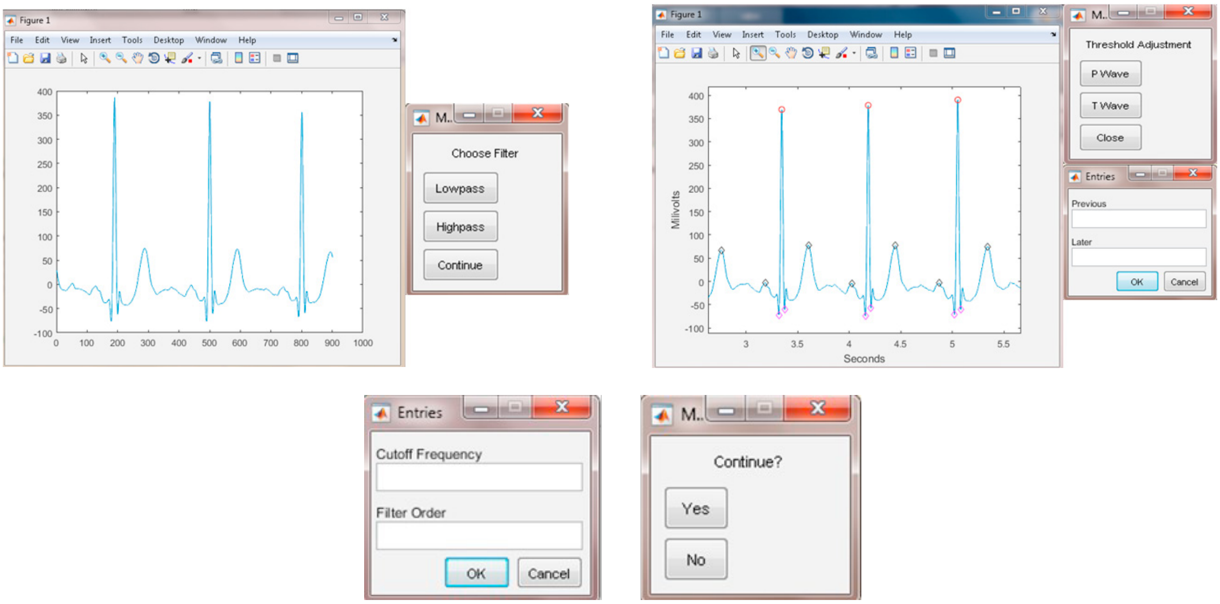

Fig. 4. Representation of the original signal and pop-up for digital filter adjustment, cutoff frequency and filter order and option through the threshold adjustment pop-up.

4. Results and Discussion

This section demonstrates the applicability of the analyzed methods and the implementation of the method proposed by the present work. As an example of the pre-processing process, the first 60 seconds of the MIT-BIH Arrhythmia Database signal 103 were used.

The next step, in the process of extracting the ECG parameters, was applied to the whole signal, that is, corresponding to 30 minutes of acquisition. As a way to compare and measure the accuracy of the method used, the algorithm was applied to the 48 signals available in MIT-BIH. The analyzed database presents a gold standard in the recognition of R peaks [12], labeled by two medical specialists. Thus, it is possible to determine the accuracy by comparing the number of hits found with the algorithm, and those found by the experts.

Table 2 presents the R-peak identification for 5 signals as example and the total/average for the all 48 signals. The dataset is composed with 48 signals of patients with an average age of 63,7 year old (for 2 of the patients the age were not registered - nr), and 26 of them are male (54%).

The proposed algorithm achieved a general accuracy of 98,09%. This value is higher than related works of: Pachauri and Bhuyan [22] using wavelets and achieving 96,65%; Jaswal, Parmar and Kaul, [23] achieving 95,74% using also Wavelets transform; Nanavati [24] that achieved 82,2% also with Wavelets transform and Magalhães [21] with 95,91%. Although, this result are lower than references: [17] with an accuracy of 99,3%; Yeh and Wang [3] with 99,75% and Park, et al. [19] which achieved an accuracy of 99,8% with the same dataset and an algorithm based on DWT. However, in contrast, the algorithm presented here is much simpler than the latter, which is an advantage for real time applications and only about 1% accuracy lower.

For analysis of the accuracy of remaining peaks contained in the ECG (P-QRS-T) with the use of the pop-up interface, only the signals that obtained identification of all R peaks present in the signal were selected. This option was taken because accurate identification of the R peak is paramount for the used methods based on thresholds starting from the R-peak position. The analyzed signals, comprised in their first 60 seconds, underwent adjustments in cutoff frequency values and filter order, together with changes in the P and T peak thresholds. Only about 30 seconds after the first 60 seconds, of each signal were used for this evaluation. The successful identification is detailed in Table 3.

The result can be considered satisfactory, because the proposed changes achieve an accuracy of 96.29%. A good rate, since identifying P and T curves are the most difficult to perform.

Table 2. Identification of R-peaks in the dataset.

Signal	Gender	Age	# R peaks	FP	FN	Acc
100	m	69	2273	0	1	99,96
101	f	75	1865	1	0	99,95
102	f	84	2187	0	0	100
103	m	nr	2084	0	1	99,95
…	…	..	…	…	…	97,89
234	f	56	2753	0	1	99,96
Total/Average		**63,7**	110159	203	1900	**98,09**

Table 3. Representation of the analyzed peaks P, Q-R-S and T of the algorithm.

Signal	# of Peaks	Failure	Acc
102	170	10	94,12
109	220	34	84,55
112	200	1	99,50
115	145	0	100,00
117	115	0	100,00
119	150	14	90,67
122	205	0	100,00
209	215	0	100,00
220	170	0	100,00
Total	1590	59	**96,29**

5. Conclusions

This paper proposes as a pre-processing the application of a moving average with length 5 to smooth the ECG signal, and a *detrend* function to remove the local and general tendencies very common in ECG signals. These techniques proved to result satisfactory in the experimented signals, but a low pass filter still be necessary to remove high frequency components. A cascade low and high digital FIR filters with cut-off frequencies between 0.25 and 30 Hz were used. These filters reduce the original ECG noise, satisfactorily eliminating signal interference, and removes the DC component.

Identification of the R-peak was implemented with the Pan-Tompkins algorithm that allow its adaptation along the time. This algorithm obtained a 98.09% accuracy over MIT-BIH Arrhythmia Database. This result improves over some previous published results, but do not achieve the state-of-the-art. Anyhow, due to its simplicity compared to algorithms witch perform about 1% better this algorithm can be considered useful for real time applications.

In the identification of all peaks (P-QRS-T) with the aid of the adaptive threshold pop-up window, an accuracy of 96.29% was achieved.

Considering the main objective the result of the work can be considered a satisfactory response in face of real signals.

Future work is already undergone and consists in selecting features based on the identified peaks to be used in a machine learning process to classify cardiac diseases.

The use and importance of signal processing and artificial intelligence to anticipate possible heart problems and to act quickly in their treatment can be vital to reduce the huge number of deaths because of cardiac disease. Research and development of interfaces that enable fast and accurate identification of real-time ECG parameters can be life-saving.

Acknowledgements

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020.

References

[1] World Health Organization, (2018). ICD-11 for mortality and morbidity statistics.
[2] Maleki M., Alizadehasl A. and Haghjoo M., (2017) “Practical Cardiology”. Elsevier.
[3] Yeh, Y. and Wang, W., (2008) “QRS complexes detection for ECG signal: The Difference Operation Method”. Computer methods and programs in biomedicine 91: 245–254.
[4] Vaseghi, S. V., (2006) “Advanced Digital Signal Processing and Noise Reduction”. John Wiley & Sons.
[5] Mehta, V.;Chaudhary, M. and Garg, D., (2016) “Generalized Noise reduction in ECG WAVES using optimal selection of Filters”. International Journal of Engineering & Scientific Research.
[6] Teixeira, J. P. and Lopes, V., (2011). “Help system for medical diagnosis of the electrocardiogram”. 1st International Conference on Serious Games and Applications for Health, 95-102.
[7] Teixeira, João Paulo and Lopes, Vanda. (2011). “Electrocardiogram Events Detection”; in M. M. C. Cunha, J. Varajão, P. Powell, R. Martinho (Editors) ENTERprise Information Systems Communications in Computer and Information Science, Volume 221, pp 307-316, Springer, ISBN 978-3-642-24351-6.
[8] Teixeira, J. P. & Ferreira, A., (2015). “Ambulatory Electrocardiogram Prototype”. Procedia Computer Science - Elsevier, Volume 64, 2015, Pages 800–807.
[9] Ayer, A. and Terkelsen, C. J., (2014). “Difficult ECGs in STEMI: lessons learned from serial sampling of pre- and in-hospital ECGs”, Journal of Electrocardiology.
[10] Vivian G. and Alexandra J. Lansky, (2012). “Interventions for ST Elevation Myocardial Infarction in Women”. Interventional Cardiology Clinics.
[11] Goldberger A.L.; Amaral L.A.N.; Glass L.; Hausdorff J.M.; Ivanov P.Ch.; Mark R.G.; Mietus J.E.; Moody G.B.; Peng C.K. and Stanley H.E., (2000) “Components of a New Research Resource for Complex Physiologic”. Circulation 101(23): 215-220.
[12] Moody G.B. and Mark R.G., (2001). “The impact of the MIT-BIH Arrhythmia Database”. IEEE Eng. in Med. and Biol. 20(3): 45-50.
[13] Mark RG, Schluter PS, Moody GB, Devlin, PH, Chernoff, D., (1982). “An annotated ECG database for evaluating arrhythmia detectors”. *IEEE Transactions on Biomedical Engineering* 29(8):600.
[14] Smith, S. W., (1997). “The Scientist and Engineer’s Guide to Digital Signal Processing”. California Technical Pub 1.
[15] Oppenheim, A. V. (2010). Signals and Systems. Prentice-Hall
[16] Blackledge, J., (2006). “Digital Signal Processing”. Horwood Publishing 2.
[17] Pan, J. and W. Tompkins., (1985) “Real Time Algorithm detection for QRS”. IEEE Trans. Eng. Biomed Eng, 32(3): 230-236.
[18] Addison, Paul S., (2005). “Wavelet transforms and the ECG: a review”, Physiological Measurements, 26 R155–R199.
[19] Park, Jeong-Seon; Lee, Sang-Woong and Park, Unsang, (2017). “R Peak Detection Method Using Wavelet Transform and Modified Shannon Energy Envelope”, Journal of Healthcare Engineering: 4901017.
[20] Rodrigues, Pedro M. and Teixeira, João Paulo, (2013). “Alzheimer’s Disease Recognition with Artificial Neural Networks” - chapter 7 (pag. 102-119) of the book “Information Systems and Technologies for Enhancing Health and Social Care”, by Ricardo Martinho, Rui Rijo, Maria Manuela Cunha and João Varajão. IGI Global. DOI: 10.4018/978-1-4666-3667-5.
[21] Magalhães, W. V. C., (2012). Sistema de análise para eletrocardiograma. Centro Universitário de Brasília (UniCEUB).
[22] Pachauri, A., & Bhuyan, M., (2009). “Robust detection of R-wave using wavelet technique” International Conference on Signal Processing Communication and Networking, Singapore, World Academy of Science, Engineering and Technology, Vol. 56.
[23] Jaswal, G., Parmar, R., & Kaul, A., (2012). “QRS detection using wavelet transform”. International Journal of Engineering and Advanced Technology (IJEAT), 1(6), 2249-8958.
[24] Anuja Nanavati, (2012). “QRS Detection Using Wavelet Transform”. Master thesis of Science in Electrical Engineering, California State University, Northridge.