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Wavelet-Based ECG Signal Analysis and Classification

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***Abstract*—**This paper presents the processing and analysis of ECG signals. The study is based on wavelet transform and uses exclusively the MATLAB environment. This study includes removing Baseline wander and further de-noising through wavelet transform and metrics such as signal-to noise ratio (SNR), Peak signal-to-noise ratio (PSNR) and the mean squared error (MSE) are used to assess the efficiency of the de-noising techniques. Feature extraction is subsequently performed whereby signal features such as heart rate, rise and fall levels are extracted and the QRS complex was detected which helped in classifying the ECG signal. The classification is the last step in the analysis of the ECG signals and it is shown that these are successfully classified as Normal rhythm or Abnormal rhythm. The final result proved the adequacy of using wavelet transform for the analysis of ECG signals.

***Keywords*—**ECG Signal, QRS detection, thresholding, wavelet decomposition, feature extraction.

I. Introduction

THE ELECTROCARDIOGRAM (ECG) is a diagnostic tool used for studying the heart condition and detecting various heart diseases. This is done by measuring the electrical activity of the heart. Understanding such readings will help in the diagnosis process. The results may be minor or fatal. The ECG is used for recording the electric waves that are generated during a heart activity over a period of time. It has been used as a diagnostic tool for over 70 years. Doctors use ECGs to help in the detection of heart conditions such as arrhythmias and myocardial infarctions [1], [2].

The ECG signal consists of 6 waves. The P-wave, QRS complex, T-wave and an additional U-wave that exists in the latter part of the signal. The most important part of the ECG signal is the QRS complex which represents the excitation of the lower chamber of the heart. The QRS complex helps in the analysis and identification of any abnormality.

The advantages of an ECG machine is that it is safe, inexpensive and readily available but various factors affect an ECG signal such as movement of the patient's body, the movement of the electrodes that are placed on the patient's body, baseline noise, powerline interference, etc.

Due to the presence of such artifacts, it can be difficult to analyse and process the ECG signal since such artifacts may exhibit spikes that can be misread as cardiological rhythms. Therefore, noise and any undesired signals must be discarded or attenuated to ensure correct analysis and diagnosis. Removal of noise from an ECG signal is the first step that may help in further detections and analysis such as QRS detection, diagnosis of myocardial ischemia, diagnosis of atrial fibrillation etc. Various noise removal techniques have been applied to ECG signals and by far the best technique for de-noising is the wavelet transform [3], [4] and this is further debated in the literature review.

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II. Objectives of the Study

The aim of this study is to develop a diagnostic tool that may help medical experts in the diagnosis and treatment of certain heart diseases.

Various ECG signals taken from MIT-BIH Arrhythmia Database (Physionet) [5] will be processed using engineering techniques that will serve as a diagnostic tool.

An ECG signal may be corrupted with noise that might be so trivial and thus barely seen with the ECG machines. Such distortion makes it difficult to detect abnormalities accurately. The real ECG signal may include noise such as muscle noise and baseline wander causing the signal to have a deformed shape. Therefore removal of noise from the original signal is the first step towards ECG processing.

Detecting the QRS complex is the next step since it holds valuable data related to depolarization of the right and left ventricles of the heart. This will help in further analysis and detection of any abnormality. This can be achieved efficiently with the use of wavelet transform toolbox which is available in MATLAB toolboxes

III. Methodology

This study will focus on a number of techniques for ECG signal de-noising and the detection of QRS complex. Wavelet-based processing will be extensively studied and used throughout the process of achieving our proposed objectives. The implementation of these techniques will make use of an open access database (MIT-BIH database). The results will be further analysed for abnormality checks.

MATLAB environment is exclusively used in the implementation of the studied techniques with a focus on the wavelet built-in toolbox.

A. The ECG Signal

The ECG recording gives two kinds of information. One is the duration of the electrical wave which helps in figuring out if the electrical activity of the heart is normal, fast, slow or irregular whereas the second type is the amount of electrical activity passing through the heart muscle and this helps determine whether the heart is too large or overworked [6]

The frequency range of an ECG signal is between 0.01 and 300 Hz whereas the amplitude range is between 0.05 and 3mV.

The ECG is characterized by five peaks and valleys labeled by the letters P, Q, R, S, T. The P wave represents the wave of

excitation sweeping over the atrial walls whereas the parts labeled Q, R, and S represents the wave excitation in the ventricle walls. The T segment indicates the recovery of the ventricle walls. An additional U wave may also be present. Fig. 1 shows a typical ECG signal with all its waves.

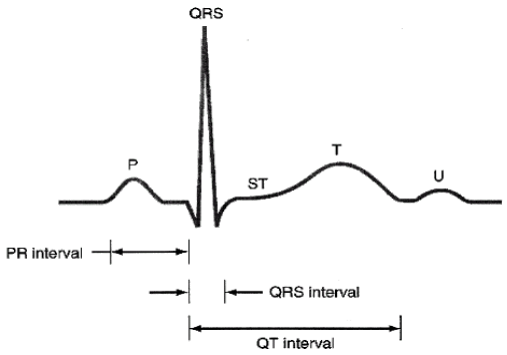


Fig. 1 Typical ECG Signal

P wave: It is the small sine wave that is in the beginning of the ECG which is about 0.1mv.

QRS complex: The Q represents a drop in voltage, R represents a large voltage peak and the S is another drop in voltage. The QRS complex is the most vital part of the ECG where it represents the depolarization in the ventricular systole phase.

T wave: It is represented by a small peak which follows the QRS complex. It represents the ventricular repolarization during the resting phase.

Variations in the distance between those waves and the peak values and the waveforms can help diagnose heart diseases and electrolyte imbalances.

In a normal state of the heart, the P-R interval is between 0.12 to 0.2 seconds. The QRS interval is from 0.06 to 0.10 seconds. The Q-T interval is less than 0.42 seconds and the normal heart rate ranges from 60 to 100 beats/minute.

Therefore, from the shape of the ECG signal, one can distinguish between a normal beating heart, a fast heart (Tachycardia) , a slow heart (Bradycardia) or heart problems such as AV block, Atrial Fibrillation etc.

Fig. 2 shows two examples of recorded ECGs, (a) represents a normal heart rhythm and (b) represents an irregular heart rhythm.

Fig. 2 (b) represents an ECG signal from a Fibrillating heart. It is obvious from the Fig. 2 that there is no obvious regular rhythm at all.

A patient suffering from a fibrillating heart may be monitored in a hospital with a monitor that keeps track of the heart rhythm. If fibrillation begins, a warning sound begins to alert the team of medics. They will try to pass an electric current through the chest wall in order to revive the heart back to its normal rhythm.

B. ECG Signal Pre-processing

Any signal may contain noise and artifacts that are within the frequency band that may exhibit similar characteristics as those of the ECG signal itself. Therefore it is very essential to de-noise the signal before any further diagnosis and analysis is performed. Two dominant artifacts present in ECG recordings are the High- frequency noise caused by electromyogram induced noise, powerline interferences, or mechanical forces acting on the electrodes, and the Baseline wander (BW), which is categorized as a low frequency noise that can be caused by patient respiration or motion,, changes in electrode impedance, or by other instruments. These artifacts severely affect the ECG signal and their removal is therefore required to ensure accurate clinical evaluation [7].

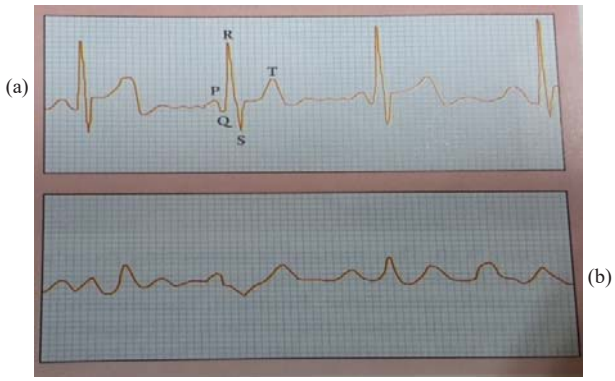


Fig. 2 Two Different Heart Conditions: (a) Normal Rhythm, (b) Irregular Rhythm [3]

In this work, we have focused on the methods that use wavelet transform for noise removal. These methods do not require any particular assumptions about the nature of the signal, permits discontinuities and spatial variation in the signal, and exploits the spatially adaptive multiresolution of the wavelet transform.

C. Wavelet Thresholding

In Discrete wavelet transform (DWT), the wavelets are sampled discretely which means that it transforms the time signal into discrete wavelets.

The wavelet decomposition process is iterative so that one signal is broken down into components which are the approximation and details. Fig. 3 represents the wavelet decomposition tree.

The approximations represent the low frequency components whereas the high frequency components are represented by the details.

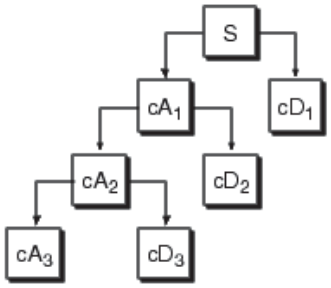


Fig. 3 Wavelet Decomposition

For the DWT, the mother wavelet is expressed by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{a}\right) a,\ b \in R,\ a>0,$$

where, 'a' and 'b' are the scaling and the shifting factor, respectively and R is the wavelet space.

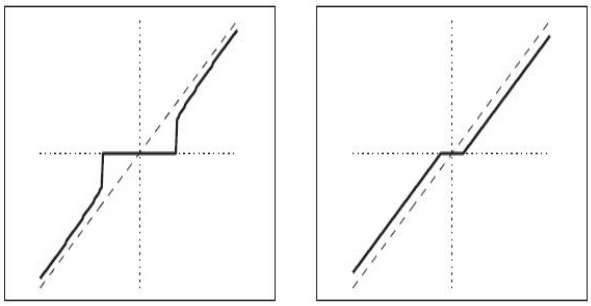
Daubechies wavelet is mostly used in ECG signal processing because it resembles the shape of the QRS complex.

The Discrete Wavelet transform uses a high level decomposition to eliminate the lowest frequency component. Thus the baseline wander can be eliminated at higher levels of decomposition. The main idea is to extract the approximation from the signal decomposed at a high level in order to remove the baseline wander. The high frequency noise can be eliminated from the detail coefficients as explained later. Selection of the decomposition level will depend on the signal itself. One can test many levels and calculate the SNR, PSNR and MSE and decide on which decomposition level gives the optimum result. Details of SNR, PSNR and MSE will be discussed later on in this paper.

Wavelet thresholding is the signal estimation technique that exploits the capabilities of signal de-noising. Thresholding methods can be categorized into two types such as hard thresholding and soft thresholding.

Even though each threshold has a default value of whether it exhibits soft or hard threshold, one can change the default value according to their needs. Soft thresholding provides smoother results in the sense that your signal becomes very smooth compared to the original state of the signal where as in hard thresholding it preservers the sharp edges and curves when compared to the soft threshold [8].

The choice of thresholding technique solely depends on the results we wish to achieve. Fig. 4 shows the difference between soft and hard thresholding.



(a) (b)

Fig. 4 Soft (a) and Hard Thresholding(b)

Decision can be made easier by calculating the Signal-to-Noise Ratio (SNR), Peak-Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). The goal is to get a low value for MSE and a large value for SNR as well as for PSNR.

D. ECG Signal De-noising

De-noising is the next stage of ECG signal processing. It is the process of removing noise while retaining the quality and details of the signal being processed. This process comes after the removal of baseline wander.

There are many ways for denoising ECG signals but the most widely used are mentioned.

1. Baseline Wander Removal

One of the most important types of noises that need to be eliminated is baseline wander (BW). It is a low frequency noise that makes the signal on the x-axis "wander" moving up and down rather than being straight across the zero axis which causes the entire signal to change in nature. This may be due to broken or corroded electrodes. The low-frequency parts of the signal are the most important parts since it carries the details of the signal. Fig. 5 shows a signal with baseline wander.

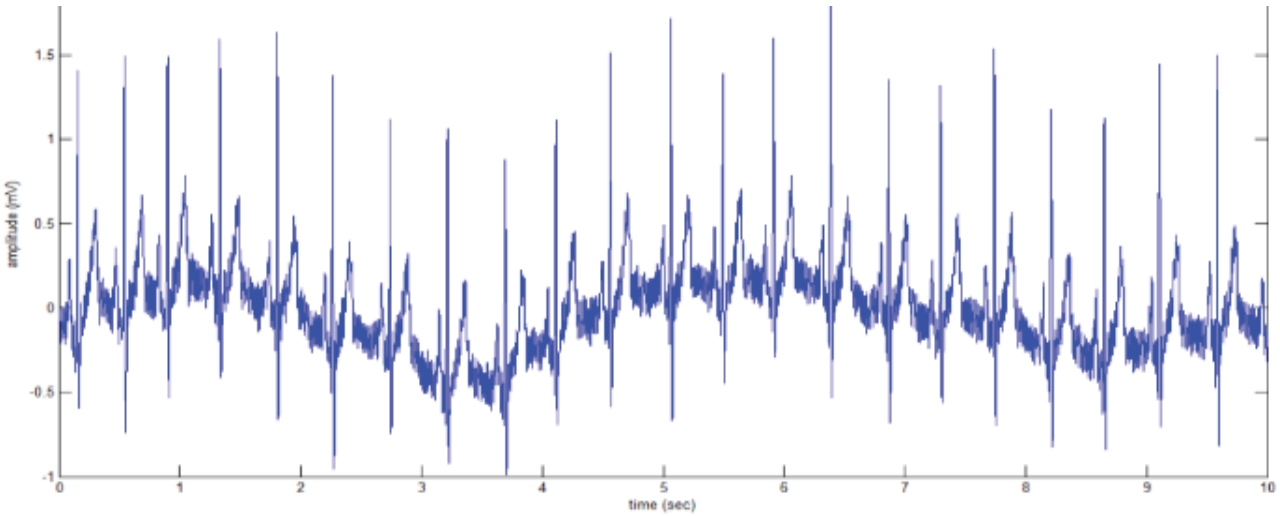


Fig. 5 ECG Signal with Baseline Wander

High pass filters can generally be used to remove baseline wander. One must choose an appropriate cut-off frequency for the filter in order to remove the baseline wander but not change the entire shape of the signal.

In our work, we have used the DWT with thresholding to remove the baseline wander which, as explained above, appears

at higher levels of decomposition, and also to remove the high frequency noise which mainly affects the detail coefficients.

E. QRS Detection

Detecting the QRS complex from the denoised signal is the most important part in signal analysis which helps in diagnosis [9].

As mentioned earlier, the QRS complex is the most vital part when it comes to detecting abnormalities, cardiac arrhythmia detection, calculating the heart rate and any other type of disorder since it holds most of the important details of the ECG signal. The most widely used techniques for QRS complex detection is using thresholds or wavelet transform.

The QRS complex may occur in a positive polarity R-peak and negative polarity R-peak where the R-peak goes to the negative side where the R-peak is downwards towards the negative instead of being upwards towards the positive pole. Fig. 6 shows the two different R-peak polarities.

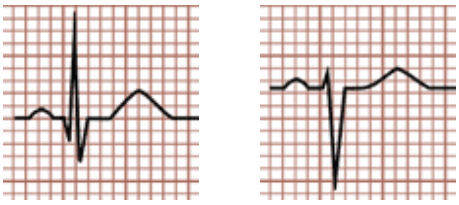
The most common is the positive polarity R-peak. The negatives ones rarely occur and it is due to extrasystole.

To detect the R peaks, two thresholds are usually used Adaptive Quantized Threshold and Dynamic Threshold.

F. Adaptive Quantized Threshold

Adaptive thresholding changes the threshold adaptively over any given data.

With adaptive thresholding, the QRS complex is detected by using an amplitude threshold of the signal being analysed. It defines a range of adaptive amplitude thresholds. If the detected peak exceeds the threshold, it is defined as the QRS complex otherwise the algorithm disregards that peak. In this method, it extracts the first derivative of the signal and uses zero-crossing threshold on the derivative extracted as well as on moving average filter.



(a)Positive Polarity (b)Negative Polarity

Fig. 6 Positive & Negative R Peaks

G. Dynamic Threshold

The difference in the algorithm is that Butterworth filter is used to remove the baseline wander and unwanted high frequencies. The signal is then filtered using a moving average filter. The QRS complex is the peaks with amplitude values exceeding the dynamic threshold. The dynamic threshold is defined here as the mean plus the standard deviation of the signal after passing through the average filter.

H. ECG Feature Extraction

Feature extraction is an important step in ECG signal processing. Without this step, diagnosis would be impossible. One must first extract certain features in order to study the ECG signal thoroughly. ECG Classification techniques include Fuzzy Logic, Artificial Neural Network, Genetic Algorithm, Bayesian, Hidden Markov Model and other techniques.

After detecting the QRS complex, we can extract certain features such as the R- wave peak and by detecting the R wave, we can calculate the heart rate. P-R interval and R-S interval represents the rise level and fall level respectively. Such features help us in classifying the ECG signal and detecting abnormality.

I. ECG Signal Classification

After extracting the features needed, we have to implement and test a classification scheme based on the knowledge provided from the medical field on the different heart rhythms and conditions. The classification scheme should categorize the ECG signals as normal heart rhythm or some specific heart condition based on the values obtained in the feature extraction phase.

A normal heart rate for instance is between 60 to 100 beats per minute, P-R interval is between 0.12 - 0.20seconds, a QRS complex duration of 0.06 - 0.10s and a Q-T interval of 0.44 s.

Any extracted values that are outside these ranges would indicate some type of heart condition.

There are various classification techniques which have been tested on ECG signals to ensure their proper classification [10], [11]. Due to time constraints, we have implemented in this work a simple scheme which is depicted in the diagram. Fig. 7 demonstrates the conditions and their classification.

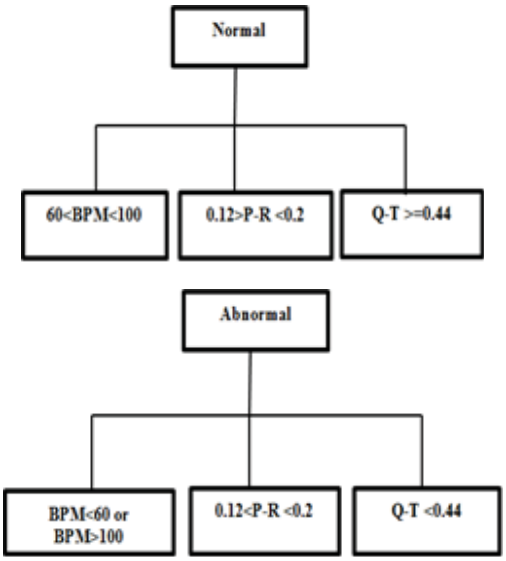


Fig. 7 Classification Overview of an ECG Signal

The ECG signal is said to be normal when the BPM is between 60 to 100 Beats/minute, P-R interval is between 0.12 and 0.20 seconds and the Q-T interval is said to be greater than or equal to 0.44 seconds. Any other condition is classified as an abnormal ECG signal. P-R interval represents the Rise level and the Q-T interval represents the Fall level.

IV. ECG Signal Database

The MIT-BIH database is a freely available resource intended for studies and research. It was launched in 1999. It has around 48 records ranging from normal sinus to abnormal sinus rhythms with lead II. Each record is 30 minutes long and sampled at a frequency of 360 hertz. The records are available in many formats such as .zip, .text, .mat etc. The user can have the option of the signal duration, the format of time and data. It can be easily downloaded as a MAT file to be loaded onto MATLAB.

We chose a few records including normal sinus rhythm, Tachycardia, Bradycardia, and signals with a mixture of abnormalities. In this work, our concentration is on Normal rhythm, Bradycardia and Tachycardia.

V. ECG Signal Pre-Processing

In this section, we will display the results of baseline wander removal as well as noise removal using penalize low, hard threshold available in wavelet's GUI.

A. Baseline Wander Removal

We first loaded the signal from MIT-BIH database in MATLAB. We normalized the signal to scale down the magnitudes to millivolts (mV). After that, we subtracted the signal mean from the normalized signal to yield a signal with zero bias. The signal of Normal Sinus Rhythm is displayed in Fig. 8.

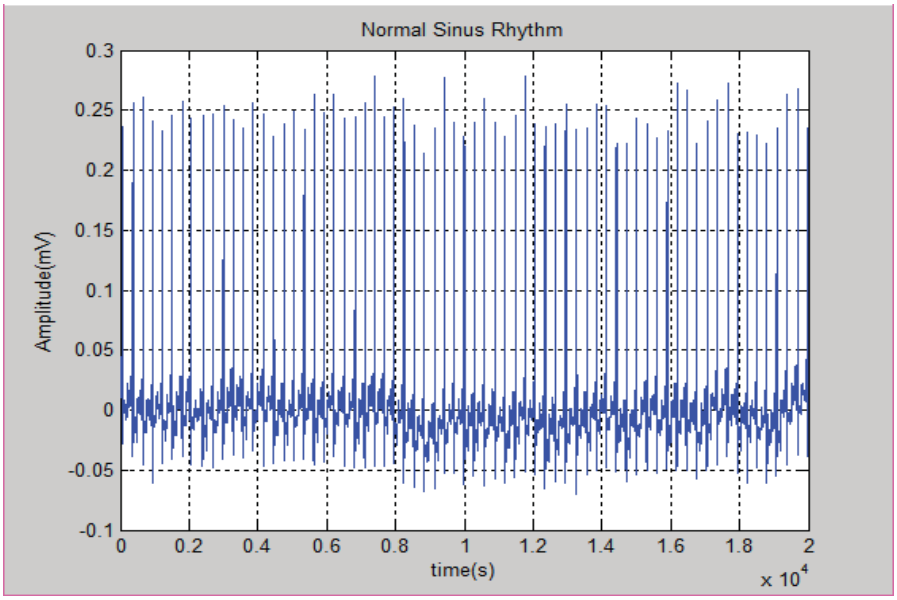


Fig. 8 Normal Sinus Rhythm ECG Signal with Baseline wander

Fig. 8 shows a normal sinus rhythm signal with baseline wander. The highest peak is around 0.27 mV. The peaks of a signal are referred to as the R-wave and the peaks that are down are referred to as the Q-wave and the S-wave. The next step would be removing the baseline wander which is using Wavelet Transform GUI.

When the GUI opens, we import the saved signal from workspace and choose the wavelet type and corresponding level. Daubechies 6 (db6) with level 10 has been chosen since the baseline wander is more obvious in level 10. Fig. 9 shows the wavemenu. We selected wavelet 1-D since our signal is one dimensional.

Fig. 10 shows the signal "s" loaded onto GUI. The signal is analysed using db6 level 10. The approximation and detail coefficients are displayed separately. The next step is to save the "approximation 10" so that we can perform a simple coding mechanism to remove approximation 10 from the signal in order to remove the baseline wander.

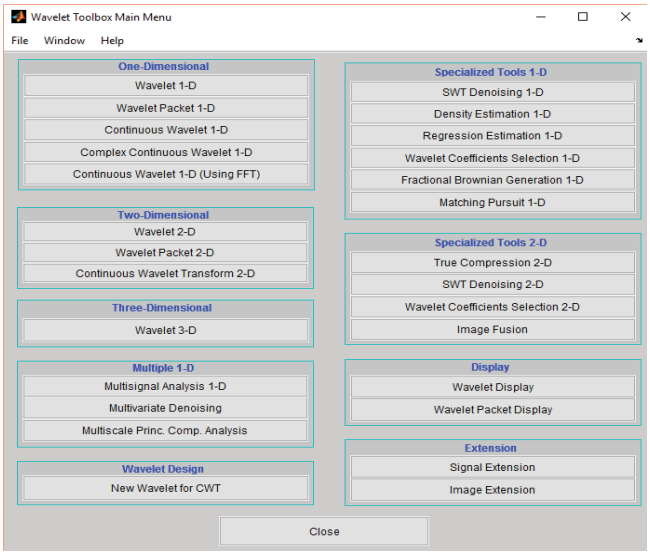


Fig. 9 MATLAB'S Wavelet GUI

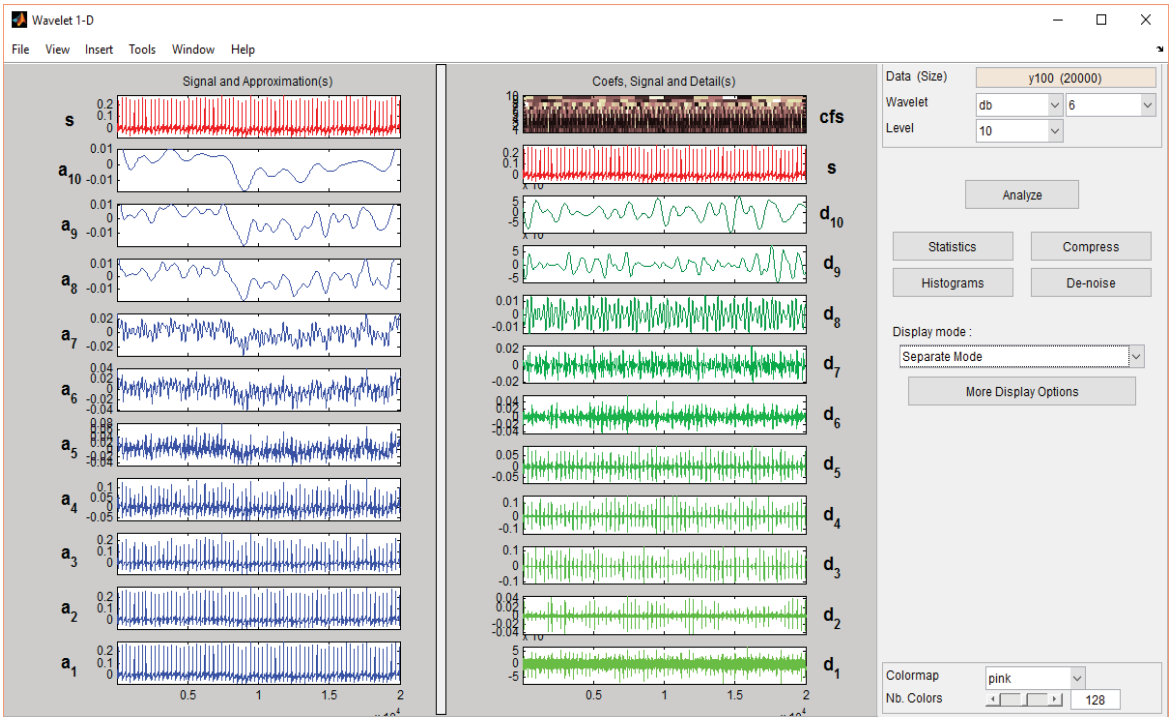


Fig. 10 Signal Loaded

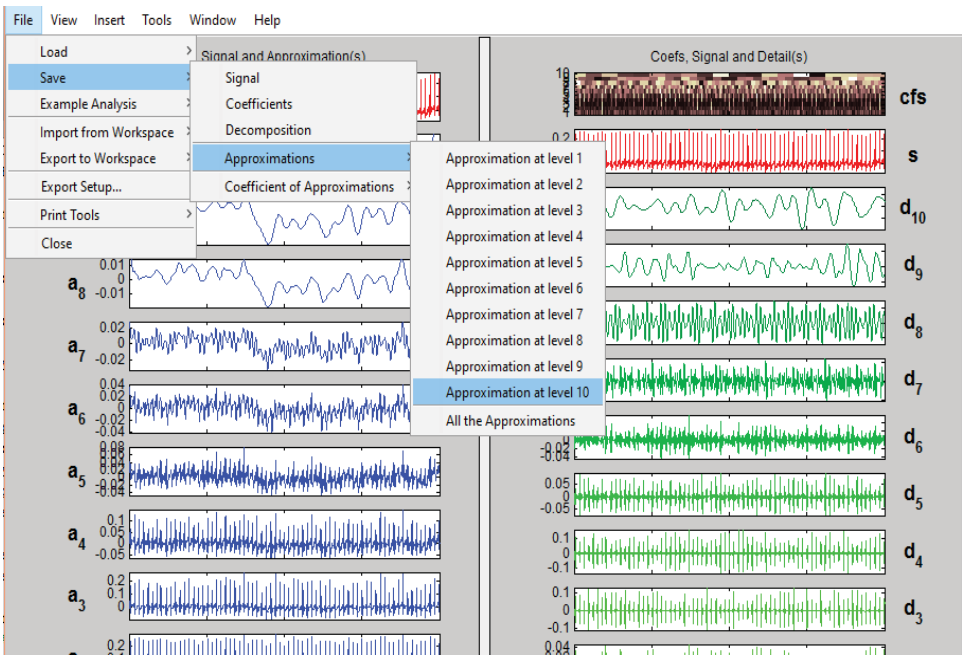


Fig. 11 Saving Approximation 10

Fig. 11 shows the procedure of saving the approximation 10. Baseline wander occurs in the approximation coefficients and as can be seen from the Fig. 10, the baseline wander is more intense in the approximation 10 this is the reason we need to save the approximation 10 to help us extract it from the original signal.

Fig. 12 displays the result after subtracting the approximation 10 from the noisy signal.

As can be seen from Fig. 12 the baseline wander that occurred along the x axis is removed from the original signal. This was done by basic subtraction of approximation 10 from the signal and loading it onto GUI.

1. Record 205, Sinus Tachycardia

The same steps that were performed for Record 100 are repeated for displaying Sinus Tachycardia.

Fig. 13 displays the noisy Tachycardia signal with baseline wander along the x- axis. The highest peak in this case is almost

0.27mW. Approximations and details coefficients are shown in Fig. 14 when decomposed using db6 level10. The same thing applies here when we speak about baseline wander which is more prominent in approximation 10.

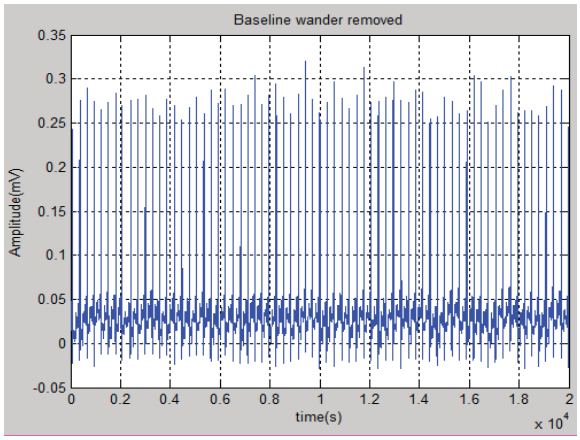


Fig. 12 Baseline Wander Removed

Fig. 15 displays the result after extracting approximation 10 and hence baseline wander is removed. Other types of noise still occur and they are extracted further using db6 level 2 as shown in the forthcoming results.

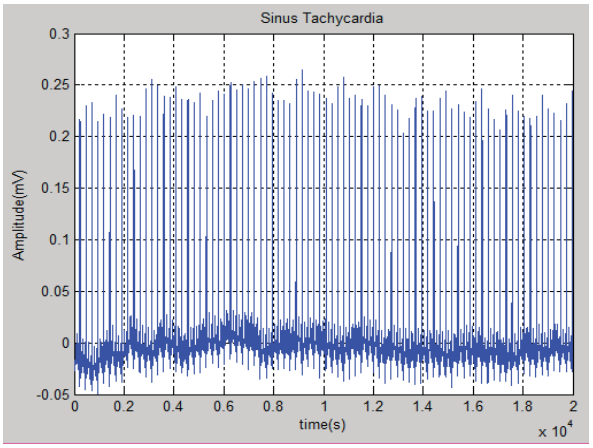


Fig. 13 Tachycardia with Baseline Wander

2. Record 232, Sinus Bradycardia

Fig. 16 displays the signal that belongs to the record 232 which is diagnosed as Sinus Bradycardia from MIT-BIH database. The signal exhibits has baseline wander and in order to remove the baseline wander, we decomposed the signal using db6 level 10 and then extracted approximation 10 which contains the baseline wander. As can be seen from Fig. 16, the baseline wander is pronounced and the signal is distorted. The highest peak is 0.15 mV and the lowest R-wave peak is 0.07 mV. The Q and S waves have a negative value.

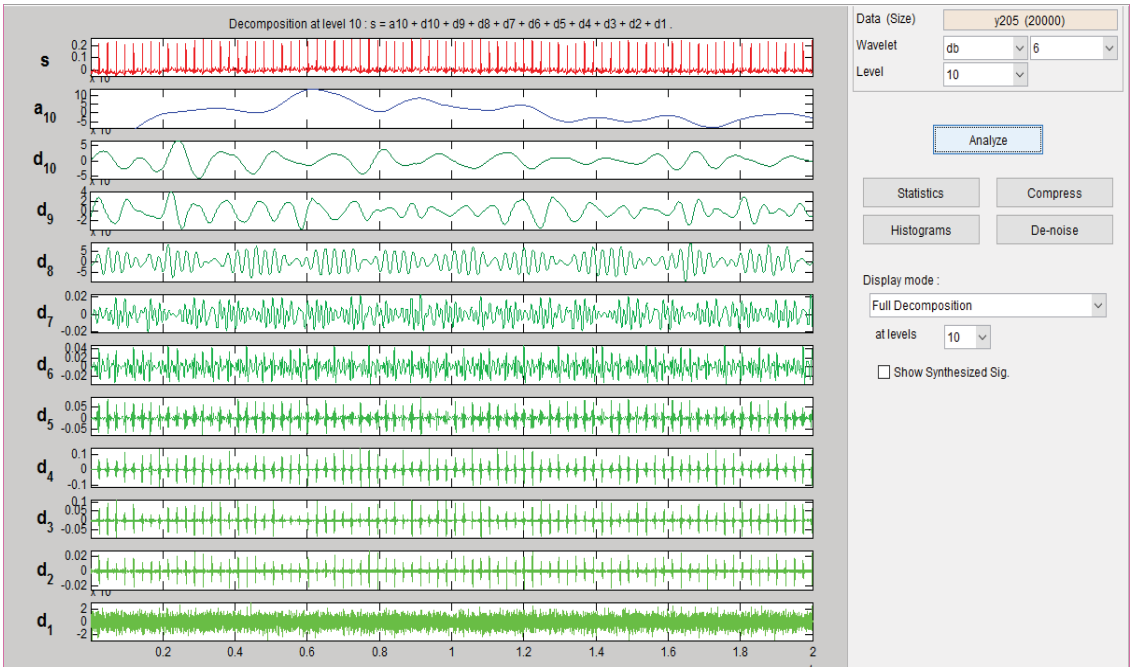


Fig. 14 Sinus Tachycardia's Approximation and Detail Coefficients

Fig. 17 displays the approximations and details coefficients of the signal Sinus Bradycardia. The same thing is considered here when it comes to the baseline wandering. It is more prominent in approximation 10.

The signal after baseline removal is illustrated in Fig. 18. The signal still contains noise which is removed further using db6 level 2.

B. Noise Removal

After baseline wander removal, we need to remove other noises that are present in the signal. For that, we constructed a table with different Daubechies types and their corresponding levels. We calculated their SNR, PSNR and their MSE. The

results are shown in Table I.

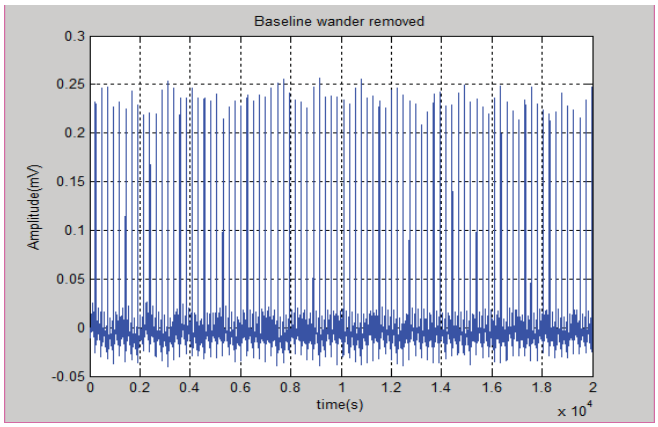


Fig. 15 Tachycardia with Baseline Wander Removed

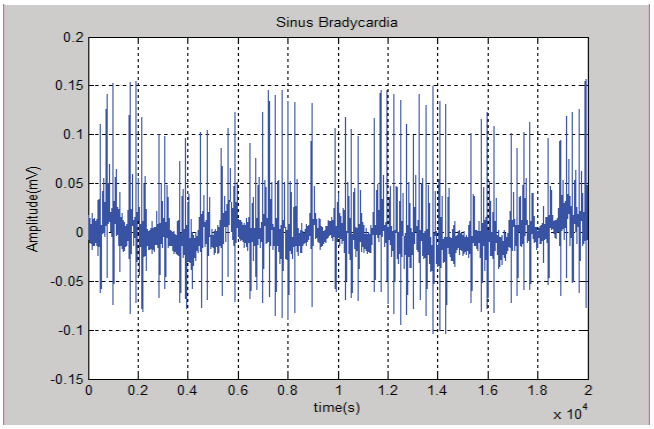


Fig. 16 Sinus Bradycardia with Baseline Wander

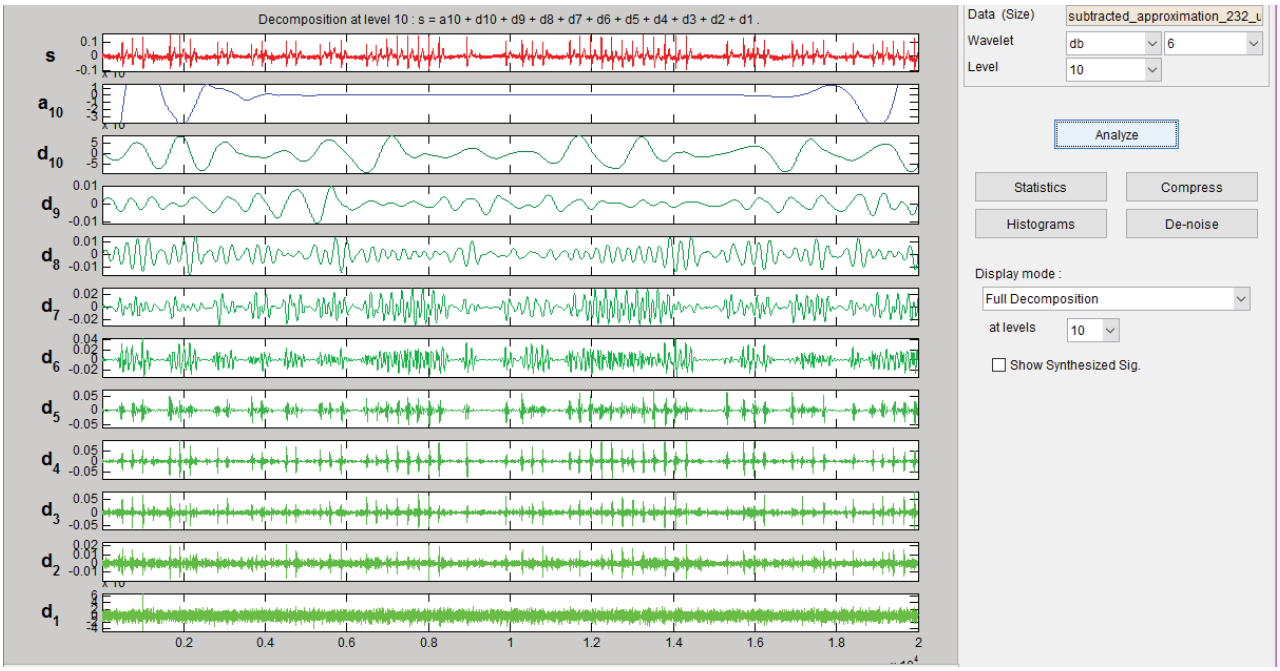


Fig. 17 Approximations and Details of Sinus Bradycardia

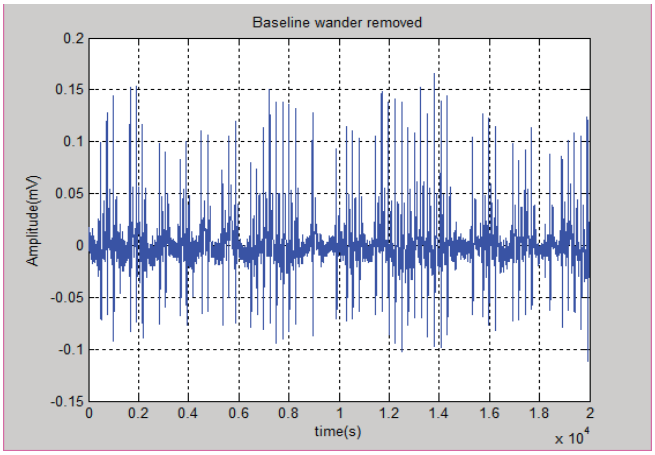


Fig. 18 Sinus Bradycardia with Baseline Wander Removed

Based on the results shown in Table I, we can conclude that the best wavelet type is db6 level 2 since it has the highest SNR and PSNR and low MSE. After choosing the wavelet type and its corresponding level, we applied all the available thresholds that are suitable for processing signals.

Table II shows the results of different types of thresholds and their corresponding SNR, PSNR and MSE.

Based on the results obtained in Table II, we chose penalize_low, with hard thresholding for all the signals being analyzed. The results of the decomposition as well as the thresholding is demonstrated in what follows.

1. Record 100, Normal Sinus Rhythm

As can be seen from Fig. 20, the signal is baseline free and free of unwanted noise. The signal is now ready for further analysis which is detecting the QRS complex.

2. Record 205, Sinus Tachycardia

Fig. 21 demonstrates the decomposed signal along with the de-noised signal using penalize low, hard threshold.

TABLE I
CHOOSING WAVELET TYPE BASED ON SNR, PSNR & MSE

Wavelet/level	SNR	PSNR	MSE
Db2/2	16.4576	15.8162	0.0021
Db2/4	4.9737	4.3324	0.0015
Db2/6	3.0569	2.4156	0.0011
Db2/8	2.6948	2.0534	9.9771e-04
Db4/2	19.9512	19.3098	0.0021
Db4/4	5.0238	4.3825	0.0015
Db4/6	3.0647	2.4234	0.0011
Db4/8	2.6812	2.0399	9.9275e-04
Db6/2	21.6791	21.0378	0.0021
Db6/4	5.2518	4.6104	0.0015
Db6/6	3.0726	2.4313	0.0011
Db6/8	2.6854	2.0441	9.9588e-04
Db8/2	20.7660	20.1247	0.0021
Db8/4	5.1713	4.5300	0.0015
Db8/6	3.0771	2.4358	0.0011
Db8/8	2.6809	2.0396	9.9321e-04

TABLE II
TYPES OF THRESHOLD WITH THEIR CORRESPONDING SNR, PSNR & MSE

Type/soft_or_hard	SNR	PSNR	MSE
Fixedform/soft	19.3481	35.7851	5.6663e-04
Fixedform/hard	19.3481	35.7851	5.6663e-04
Rigorous/soft	19.3481	35.7851	5.6663e-04
Rigorous/hard	19.3481	35.7851	5.6663e-04
Heuristic/soft	19.3481	35.7851	5.6663e-04
Heuristic/hard	19.3481	35.7851	5.6663e-04
Minimax/soft	19.3481	35.7851	5.6663e-04
Minimax/hard	19.3481	35.7851	5.6663e-04
Penalize_high/soft	23.2248	39.6387	5.6866e-04
Penalize_high/hard	25.8087	42.3197	5.7179e-04
Penalize_medium/soft	25.2698	41.7206	5.6960e-04
Penalize_medium/hard	28.5058	45.0168	5.7249e-04
Penalize_low/soft	25.8216	42.2792	5.6984e-04
Penalize_low/hard	29.2520	45.7630	5.7261e-04

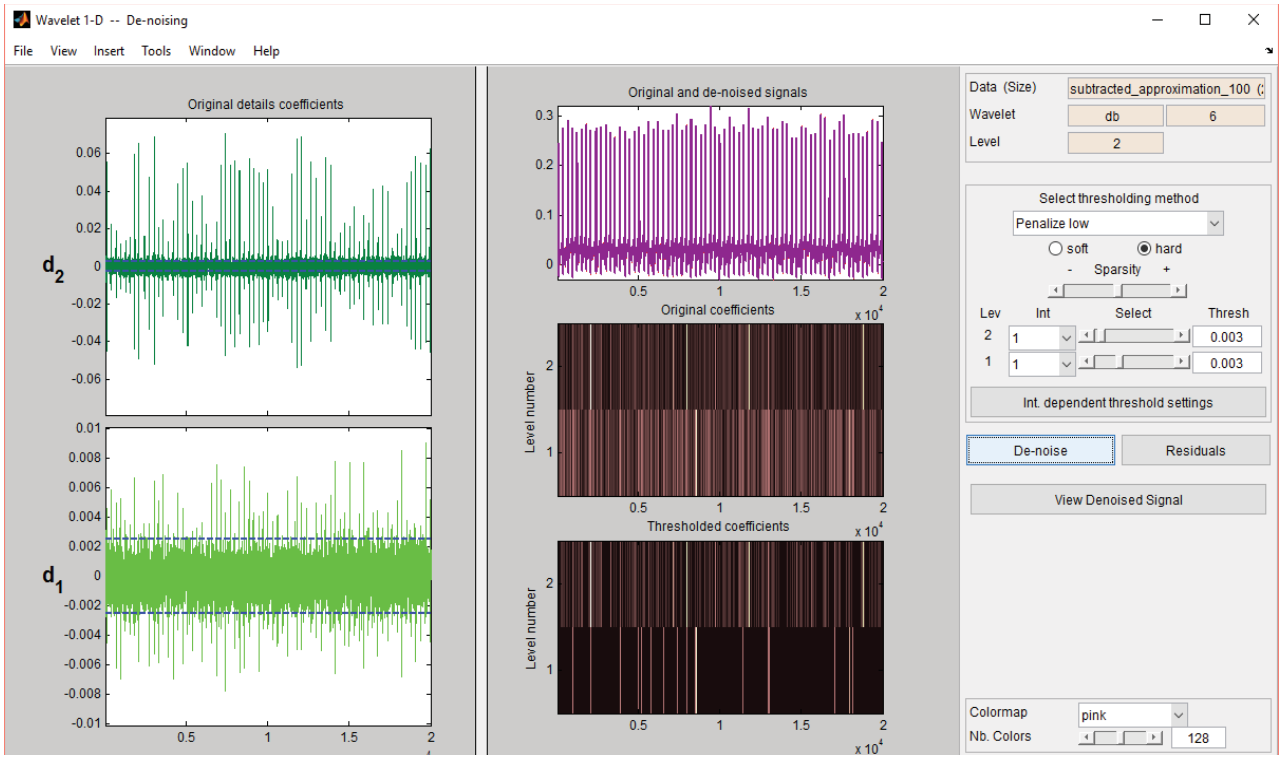


Fig. 19 Normal Sinus Rhythm de-noised via thresholding

Fig. 19 demonstrates the decomposed signal along with the denoised signal using the penalize_low, hard threshold. The result of the de-noised signal is shown in Fig. 20.

The de-noised signal is shown in Fig. 22. It displays the resulting signal after removing the baseline wander as well as other unwanted noise. the signal is properly alligned across the x-axis with clear QRS complexes.

3. Record 232, Sinus Bradycardia

The decomposed signal along with the de-noised signal using penalize low form threshold are shown in Fig. 23 and Fig. 24.

As can be seen from Fig. 24, the baseline wander is removed as well as other noise that was present in the signal. With this de-noised signal, calculating the PSNR, SNR and MSE is more accurate and QRS complexes are easily detected.

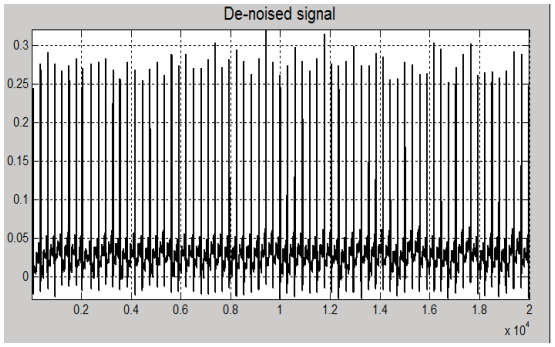


Fig. 20 De-noised Signal

VI. QRS Detection

For this step, we have developed an algorithm which takes the result of the de-noised signal and detects the QRS complex. The algorithm is based on finding the peaks of each interval. By that we can then find the minimum peak distance and amplitude. Detecting the position of each interval is very crucial and needs to be treated with total accuracy in order to achieve better QRS complex detection.

A. Sinus Bradycardia

The de-noised signal along with its R-wave and S-wave are shown in Fig. 25.

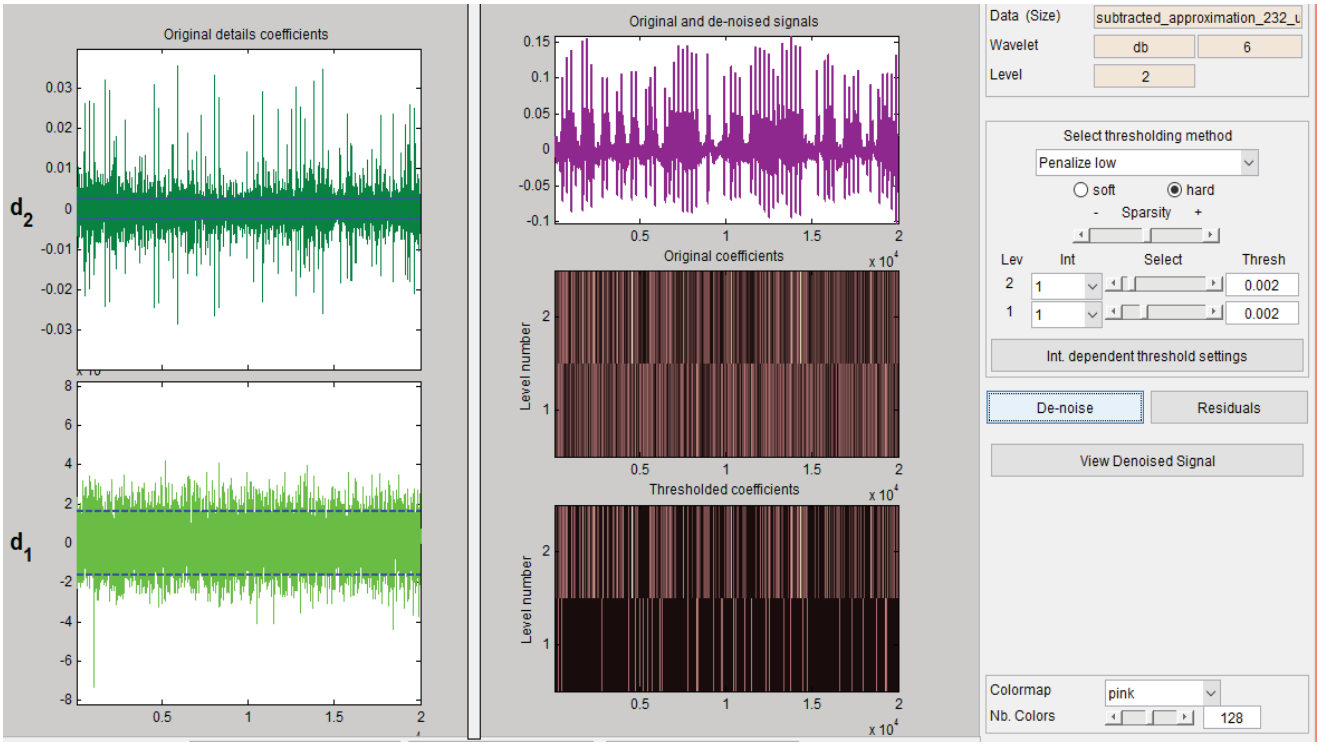


Fig. 21 De-noised Signal Using Penalize_Low, Hard

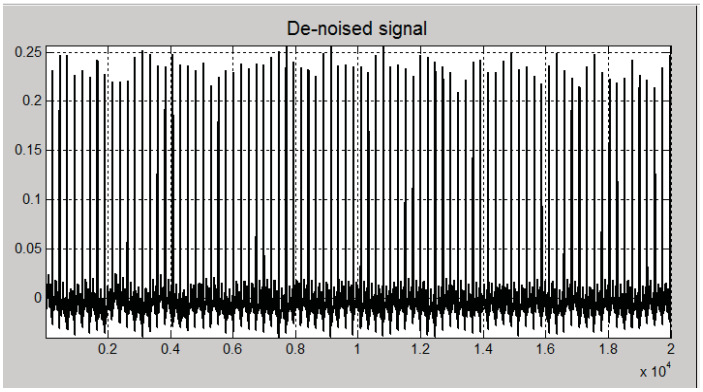


Fig. 22 De-noised signal

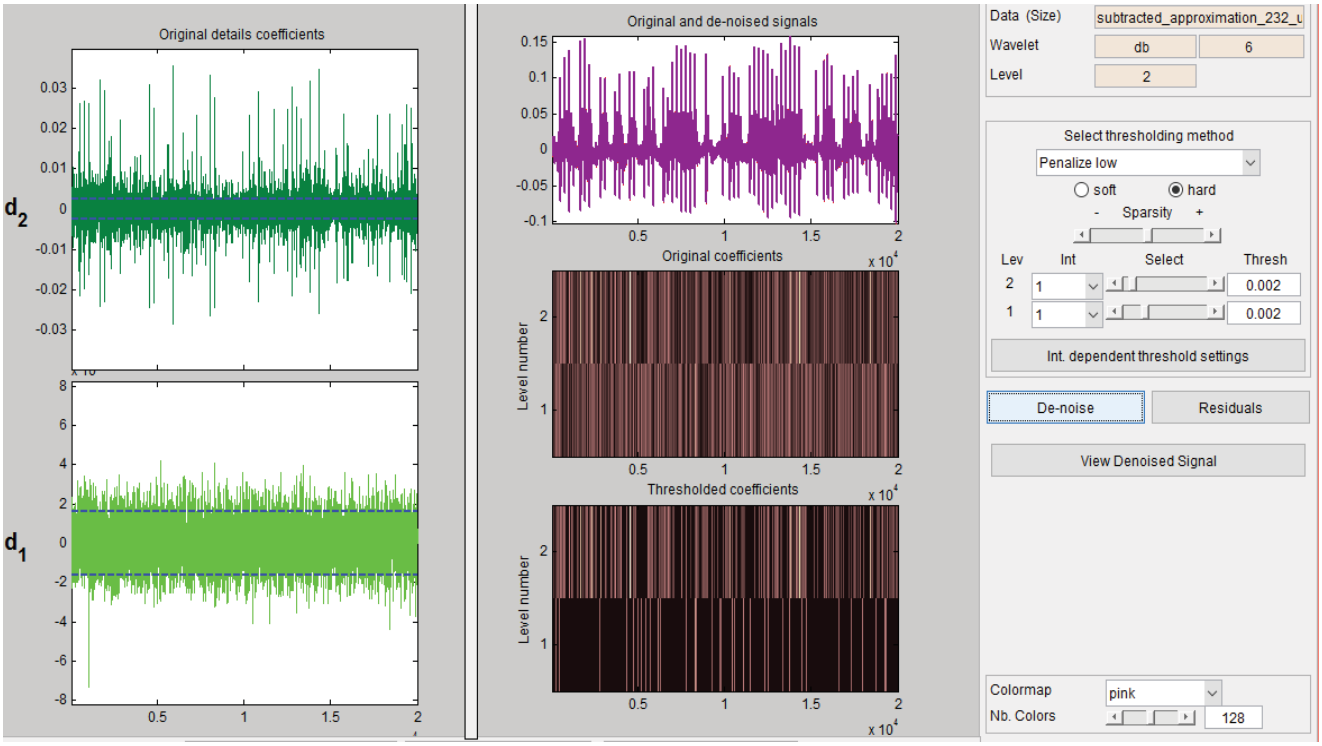


Fig. 23 Bradycardia De-noised Using Penalize- Low, Hard

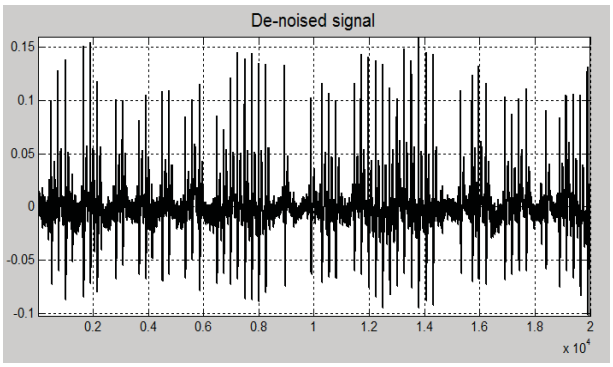


Fig. 24 The de-noised signal

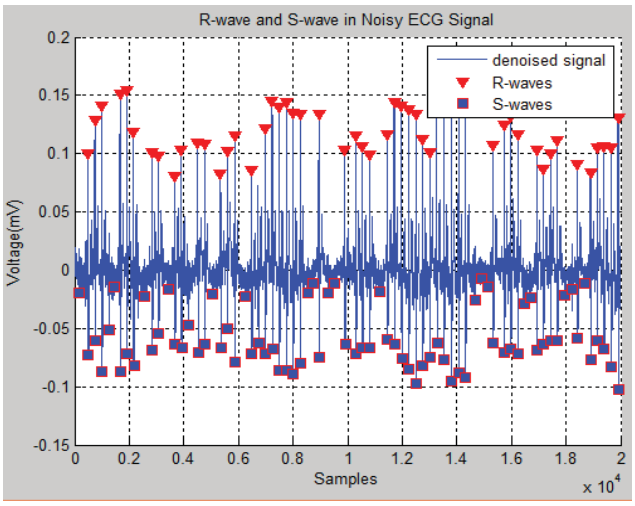


Fig. 25 R-waves and S-waves Detected

As can be seen in Fig. 25, the highest and lowest R-waves are detected in red colour. The highest and lowest S-waves are also detected and marked in blue. Both waves are marked along the de-noised signal.

Fig. 26 displays the QRS complex in the signal. As can be seen from the figure, the Q-waves are displayed in Green and, R-waves are displayed in red and the S-waves are displayed in blue. All peaks whether high or low are detected and marked.

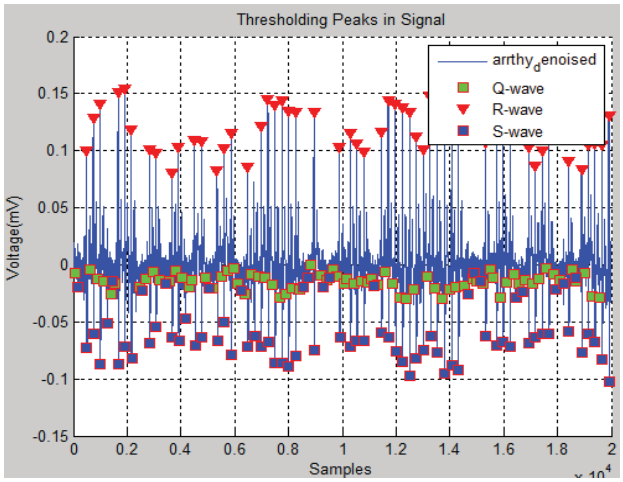


Fig. 26 QRS Complex Detected

B. *Normal Sinus Rhythm*

The detection of the R-waves and the S-waves of a normal sinus rhythm is illustrated in Fig. 27.

As can be seen from Fig. 27 the highest Q-wave peak is 0.33 mV and the lowest is almost 0.26 mV. The S-waves are close to each other and the number of peaks of R-waves are similar to the S-waves which is considered as a normal rhythm.

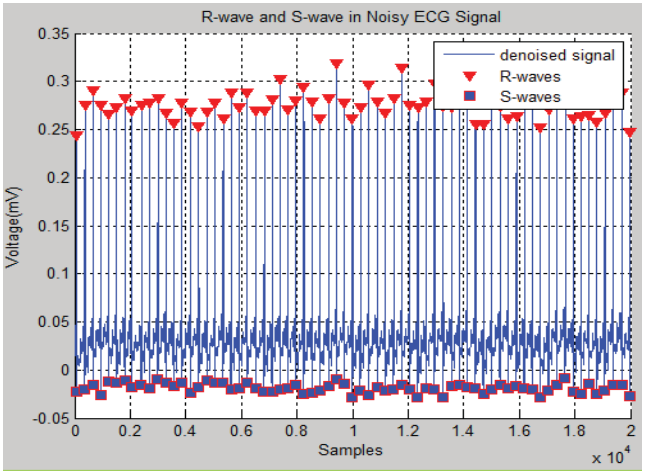


Fig. 27 R-waves and S-waves Detected

Fig. 28 displays the QRS complex of a normal sinus rhythm.

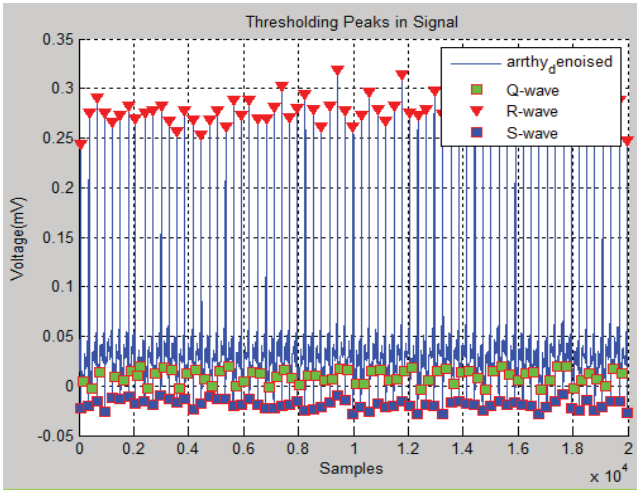


Fig. 28 QRS Complex Detected

As can be seen from Fig. 28, the QRS complex is in equal length with regards to the peaks. This type of signal is considered as normal.

C. Sinus Tachycardia

The R-waves and S-waves for Sinus Tachycardia are displayed in Fig. 29. As can be seen from Fig. 29, the highest R-waves is 0.26mV and the lowest is almost 0.215mV.

The QRS complex on si nus tachycardia is shown in Fig. 30. As can be seen in Fig. 30, the time interval between the QRS complexes is too short and the waves are very close to each other, this is considered as a fast heart rhythm which is referred to as tachycardia.

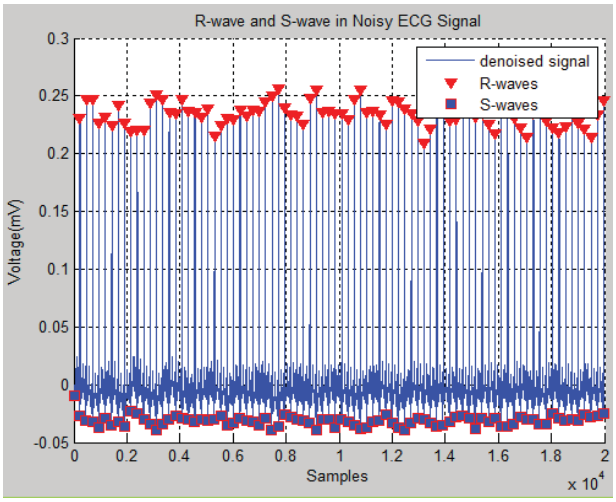


Fig. 29 R-waves and S-waves

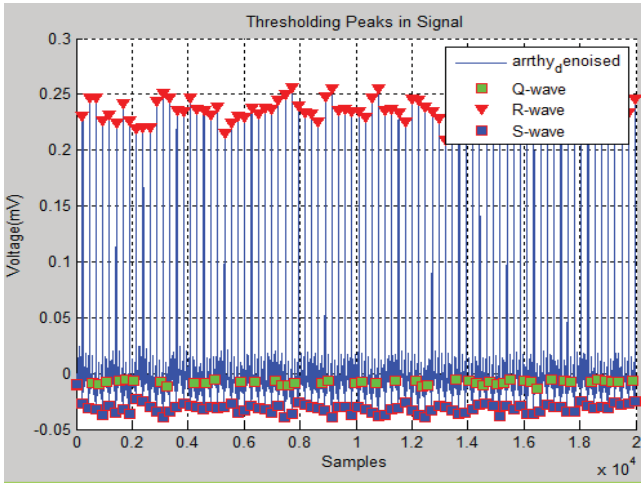


Fig. 30 QRS Complex Detected

VII. Feature Extraction

After detecting the QRS complex, feature extraction can be easily implemented. The features that we extracted from the QRS complex are: heartbeat, Rise level and fall level. The rise level corresponds to the distance between the Q-wave and the R-wave whereas the fall level corresponds to the distance between the R-wave and the S-wave. The results from the command window are displayed in Fig.31.

Fig. 31 indicates the following:

Beats/minute = 140.4000
Rise level: -0.7478
Fall level: 0.0795

Based on the results obtained, it is considered to be Sinus Tachycardia since the heart beat is above 100 beats/minute and the rise level is 0.12 seconds and the fall level is 0.44 seconds.

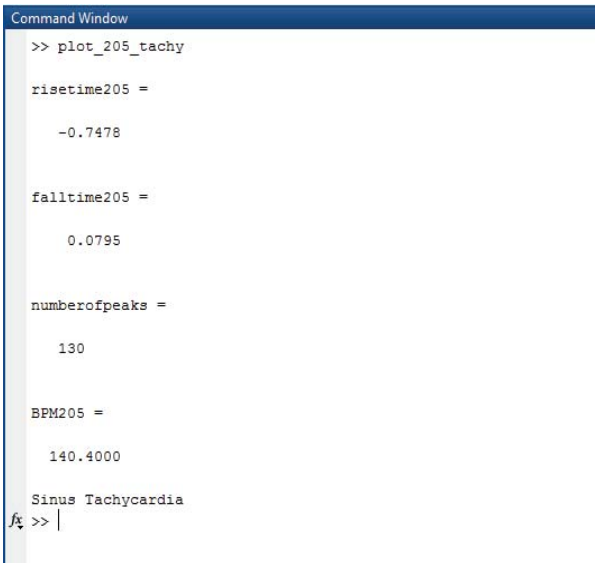


Fig. 31 Results of Feature Extraction from MATLAB

VIII. ECG Classification

This is the last stage in ECG signal analysis. After extracting the features, we must be able to classify those features further to analyse and detect abnormalities.

In our work, we implemented a simple classification scheme to categorize the signal as Normal heart rhythm, Tachycardia or Bradycardia.

If the heart beat is between 60 to 100 BPM, the rise level is between 0.12 and 0.20 and the fall level is greater or equal to 0.44, then the signal is of a normal rhythm.

If the heart beat is above 100 BPM and the rise level is greater than 0.20 and the fall level is less than 0.44, then the signal is said to be of type tachycardia.

The last criteria is if the heart beat is lower than 60 BPM or the rise level is greater than 0.20 and the fall level is less than 0.44, then the signal is said to be of type bradycardia.

Fig. 32 shows the hierarchy that explains the concept with regard to Beats/minute, rise level and fall level

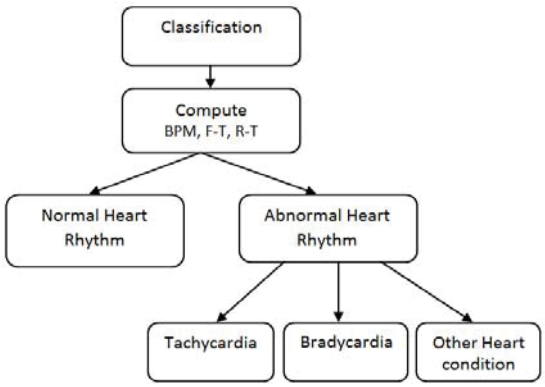


Fig. 32 Classification with regard to BPM, Rise level & Fall level

Figs. 33-36 display the results of classification in the command window in MATLAB.

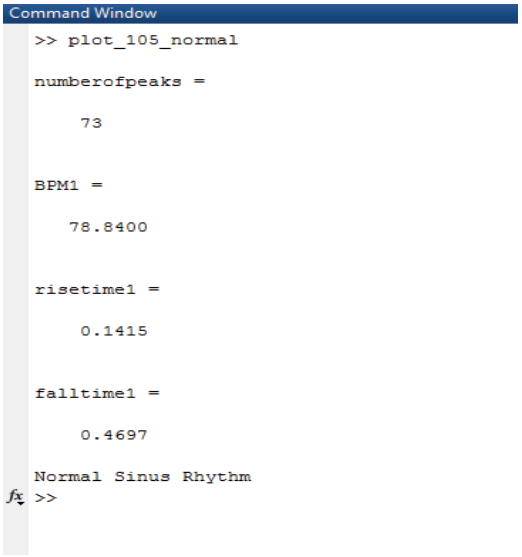


Fig. 33 Classified as Normal Sinus Rhythm

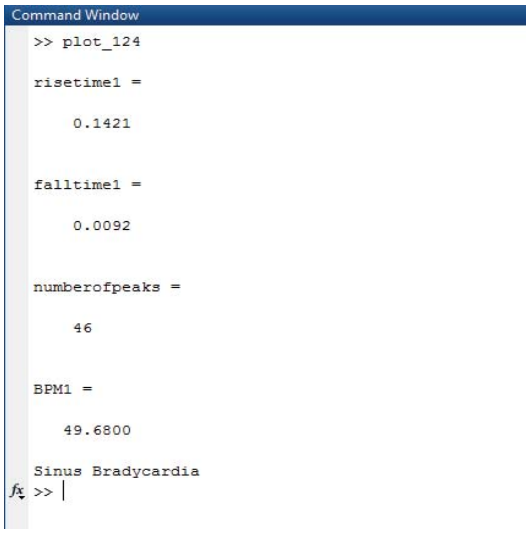


Fig. 34 Classified as Sinus Bradycardia

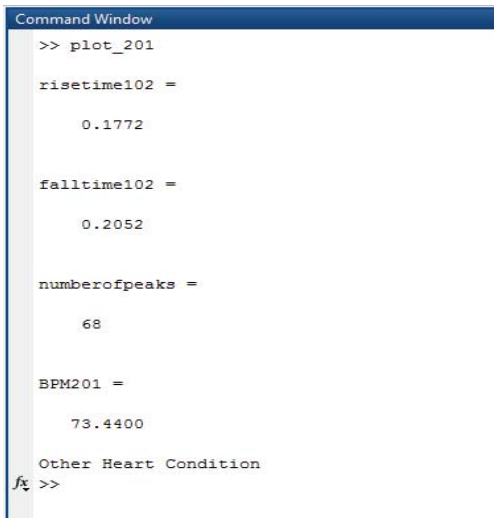


Fig. 35 Classified as Sinus Tachycardia

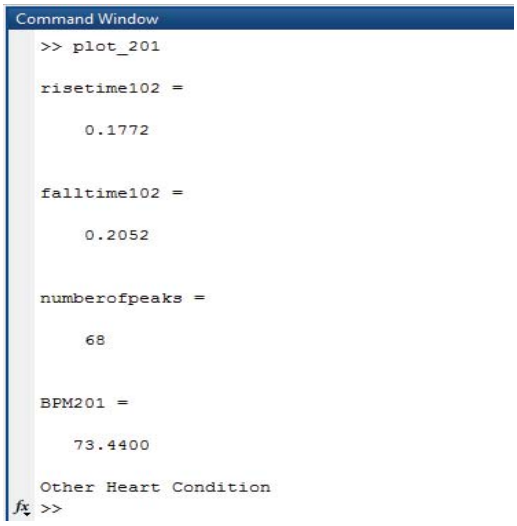


Fig. 36 Classified as Other Heart Condition

The results of feature extraction from different signals are listed in Table III.

TABLE III
CALCULATED FEATURES

	BPM	Rise level	Fall level
Signal 1	140.4000	-0.7478	0.0795
Signal 2	57.24000	0.2946	0.0830
Signal 3	141.4800	0.6419	0.2995
Signal 4	70.24400	0.2944	0.5432
Signal 5	173.4000	-0.8772	0.3210

IX. CONCLUSION

In this study , we performed de-noising with different wavelets and all the thresholds available in the MATLAB's wavelet toolbox for signals and came up with the conclusion that db6 level 2 together with penalize low, hard threshold gave the best result for all the signals tested.

QRS complex detection is made easier after de-noising using wavelets and so the locations of the intervals were found giving the fact that a simple observation must be made on where the locations are.

Feature extraction depends on the QRS complex detection and their location and time intervals. Calculating the heart beat is very important and it is the basis of any abnormality detection. The rise level and fall level helped us in detecting the P-R interval as well as the Q-T interval respectively.

The classification procedure is important and the analysis wouldn't be complete without it. One must classify the features extracted from the signal in order to detect what type of abnormality occurs. With such a mechanism, doctors can easily abnormalities with a click of a button.

ECG signals are always corrupted with noise. Some are of high frequency and some are of low frequency. We need to remove all types of noise but at the same time the useful characteristics of the signal must not be heavily distorted.

Baseline wander is one of the most common types of noises that may occur in a signal. It appears as a trend in the ECG recording and makes the analysis of the signal difficult and prone to inaccuracy. Wavelet decomposition was used in this study to extract the baseline wander from the signal.

After extracting the baseline wander, other types of noises have further been removed. The Penalize-low, hard threshold, technique was used for the de-noising by thresholding the detail coefficients at each level of decomposition.

QRS complex was next detected through a mechanism. The peaks of each interval (Q, R and S) was found. We found the minimum peak distance between two consecutive Q waves, R waves and S waves as well as the minimum peak amplitude.

For Q-wave and S-wave, we inverted the signal since they exist almost under the 0 axis and may have negative values.

After detecting the QRS complex, feature extraction was performed which enabled us to proceed with a classification of the ECG signals based on these features. The features extracted were examined to classify the signal into four main categories which are Normal Sinus Rhythm, Abnormal Rhythm be it Tachycardia (Fast) or Bradycardia(low) heart rhythm, or any other heart condition. The effectiveness of the proposed automatique classification was demonstrated with various types of ECGE signals.

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