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Analysis of ECG Signal Using Base Filter Decomposition and Threshold Extraction

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Abstract: ***One of the scientific tests performed to diagnose Heart Diseases is through Electrocardiogram signals, which shows an electrical activity of the heart in terms of the waves. To diagnose Heart Diseases based ON ECG signal, a medical doctor obtained the features like amplitude of the waves QRS-complex, P-wave and T-wave and the time interval between the waves called R-R interval, P-R interval, S-T interval and Q-T interval. Since an ECG signals may be of different lengths and as being a non-stationary signal, the irregularity may not be periodic instead of showing up at any interval of the signal, a physician has to analyse the signals completely which is a time consuming process. Therefore, in the present study, an algorithm is developed to pre-process and to automatically extract the features from ECG signal based on Discrete Wavelet Transform (DWT) and De-noising factor. The developed algorithm initially performs pre-processing of a signal in order to remove Baseline Drift (De-trending) and to remove noise (De-noising) from the signal and then it uses the pre-processed signal for feature extraction from the ECG signal automatically. By using this algorithm the accuracy of the analysis can improved and the analysis time of an ECG signal can be reduced.***

Keywords: ECG; QRS-complex-wave; T-wave; R-R interval; P-R interval; S-T interval and Q-T interval; DWT; Baseline Drift; Denoising

1. Introduction

The extraction of high resolution cardiac signals from a noisy electrocardiogram (ECG) remains an important problem for the biomedical engineering community. Despite of the rich literature in this field, there are still many clinical applications that lack reliable signal processing tools to extract the weak ECG machinery contaminated with background noise and permit the measurement of subtle features in the ECG.

Depolarization occurs when the cardiac cell, which are electrically polarized, lose their internal negativity. The spread of depolarization travels from cell to cell, producing a wave of depolarization across the entire heart. This wave represents a flow of electricity that can be detected by electrodes placed on the surface of the body. Once depolarization is completed the cardiac cells are restored to their resting potential, a process called *repolarisation*.

This flow of energy takes in the form of ECG wave and is composed of P wave followed by QRS complex followed by T wave followed by U wave per cardiac cycle which is shown in figure 1.The P wave is a small low-voltage deflection away from the baseline caused by the depolarization of the atria prior to atria contraction. QRS-complex is the largest-amplitude portion of the ECG, caused by currents generated when the ventricles depolarize prior to their contraction. The T-wave is the result of ventricular repolarisation and finally the small U wave although not always visible, is considered to be a representation of the Papillary Muscle or Purkinje Fibres.

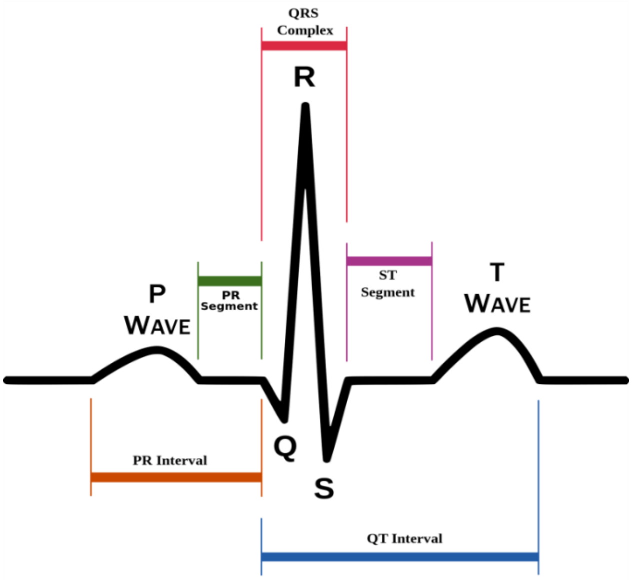

Figure 1: Typical ECG Signal

Many of the heart related diseases can be diagnosed by using the Electrocardiogram signals. In order to diagnose these diseases, a physician analyzes the signal and extracts the features like amplitudes of the waves and the time interval between them [2].

Generally, a normal ECG signal has the following amplitudes values: P-wave 0.25 mV, R-wave 1.6mV, Q-wave 25% of the R-wave, T-wave 0.1 to 0.5 mV; the time interval values: PR-interval 0.12-0.2s, QRS complex 0.04 to 0.12s, QT interval <0.42s and the heart rate of 60-100 beats/min [3]. Any change in the above said values indicates the abnormality of the heart. In the present study an algorithm is developed in order to extract the ECG features automatically. The developed algorithm initially decomposes the original ECG signal by using Discrete Wavelet Transform and Daubahies wavelet (db6) as mother wavelet. It removes the low frequency components in order to remove the Baseline Drift (De-trending) and removes the threshold high frequency components in order to remove the noise (De-noising) from the original signal. Then it uses the pre-processed signal to extract features from the ECG signal automatically. The sample ECG signals for the present study are obtained from MIT/BIH database via Physionet website [4] and stored in a text format. The MIT-BIH database contains many types of Electrocardiogram signals including both abnormal or unhealthy Electrocardiograms and normal Electrocardiograms, which are sampled at different rates. For example record 16272 is originally sampled at 128 Hz, record 30 was sampled at 250 Hz and record 113 was sampled at 360 Hz. Therefore, to process all the signals uniquely, all the samples must be re-sampled at 360 Hz before processing the ECG signal. Each selected ECG signal is of thirty minute duration, but only 5 minutes duration of the signal is used for processing in this study. The present paper is organized as follows. Section 2 gives a detailed description of Discrete Wavelet Transform. In section 3, a description of the developed algorithm for ECG feature extraction is presented. The Experiments and results of the present study are also given in this section and finally conclusion is given in section 4.

2. Discrete Wavelet Transform (DWT)

Signals can be analyzed by using a well known method called *Fourier Transformation*, which breaks down a signal into constituent sinusoids of different frequencies. i.e it transforms the signal from time based to frequency based. For many signals (stationary signal), Fourier Transform is extremely useful because the signals frequency content is of great important. But the serious drawback with this approach is in transforming to frequency domain, the time information is lost. So, it is not possible to tell when a particular event occurred through this approach. This drawback can be overcome by using *Short Time Fourier Transformation* (STFT). In a Short Time Fourier Transformation a signal is mapped in both frequency and time dimensions using a technique called Widowing. Though the time and frequency information is obtained at a time using this approach, it has a drawback that the size of the time window must be fixed for all frequencies. To overcome this drawback a most commonly used method called *Wavelet Transformation* [5] is used where it has a time window of variable size.

A *Wave* is an oscillating function of time or space, *Wavelets* are localized waves and they have their energy concentrated in time or space. The Transform of a signal is another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time- frequency representation of the signal and is well suited to the analysis of non-stationary signals [6] such as ECG. A Wavelet Transformation uses multi resolution technique by which different frequencies are analyzed with different resolutions. A Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies the Wavelet Transform gives good frequency resolution and poor time resolutions. One of the most frequently and commonly used Wavelet Transformation is the *Discrete Wavelet Transformation (DWT).* The discretization of Continuous Wavelet Transform is called as *Discrete Wavelet Transform (DWT).* The Discrete Wavelet Transform employs a dyadic grid (integer power of two scaling in *a* and *b*), orthonormal wavelet basis functions and exhibits zero redundancy. Using the dyadic grid wavelet**,** the discrete wavelet transform DWT can be written as:

$$Tm,n = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)dt$$

where Tm, n is known as the wavelet (or detail) coefficient at scale and location indices (m, n). *Multi-Resolution Analysis using Filter Banks Theory*: Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations and the scale is determined by up sampling and down sampling (subsampling) operations. The Discrete Wavelet Transform of a signal can be computed by passing it through the low pass and high pass filters as shown in figure 2**.** This is called the Mallat algorithm or Mallat-tree decomposition [7]. In figure 2**,** X[n] represents the original signal to be filtered, where n is an integer, G0 represents the low pass filer and H0 represents the high pass filter. At each level, the high pass filters produces detail information, d[n], while the low pass filters associated with scaling function produces coarse approximations, a[n].

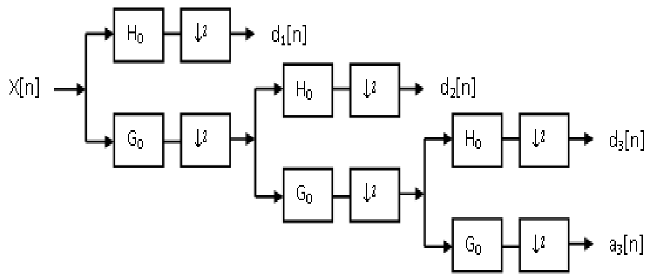

Figure 2: Three-level Wavelet Decomposition Tree

With this approach, the time resolution becomes arbitrary good at high frequencies, while the frequency resolution becomes arbitrary good at low frequencies. The filtering the decimation process is the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition. the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition.

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelets produces all the wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform.

Figure 4 illustrates some of the commonly used wavelet functions. The Haar wavelet is one of the oldest and simples wavelet. Daubaches wavelets are the most popular wavelets. The Haar, Daubeches, Symlets and Coiflets are compactly supported orthogonal wavelets. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

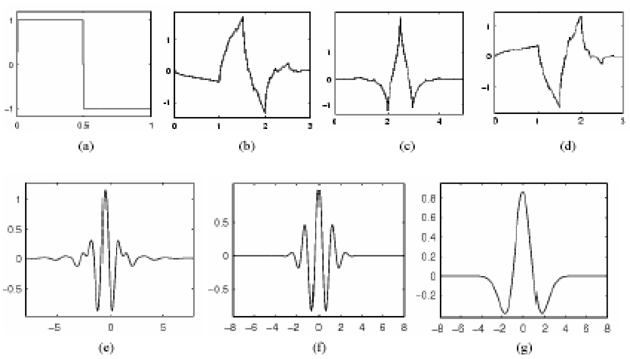

Figure 4: Wavelet Families (a) Haar (b)Daubachies4 (c)Coiflet1 (d)Symlet2 (e) Mayer (f) Morlet (g)Mexican Hat

3. Automatic Extraction of ECG Feature Using Discrete Wavelet Transform

When an Electrocardiogram is recorded many kinds of noises are also be recorded due to very low and high frequencies [8] , which causes an ECG to have baseline drift and noise in the signal and is very difficult to clinically diagnose. For proper diagnosis of ECG it is necessary to remove noise from the signal. A process of removing the baseline drift of a signal [9] is called as de-trending and a process of removing the noise [10] of a signal is called as de-noising. Both of these processes come under the preprocessing of an ECG signal. Once the signal is preprocessed then it can be used for further processing (extraction of ECG features). In the present study, an algorithm has been developed both to reprocess and to extract the features from ECG signal automatically by using Discrete Wavelet Transformation (DWT). The developed algorithm is implemented using MATLAB 7.3. In this study, in order to test the developed algorithm a *Record No 105 of MIT-BIH Arrhythmia* database is selected. In order to perform all these operations, the developed algorithm decomposes the obtained original ECG signal into corresponding Approximation and Detail coefficients up to 8 levels using *Discrete Waveletet Trasformation*. The mother wavelet or basis function that is used in the decomposition is *Dabachies6* (db6) [11]. The decomposed approximation and detail coefficients of the signal are cA1, cA2 . . . , cA8 and cD1, cD2. . . ,cD8 . The decomposed signal is then reconstructed to get original ECG signal components by using I*nverse Discrete Wavelet Transformation* (IDWT). The reconstructed approximation and detail coefficients of the signal are A1, A2 . . . ., A8 and D1, D2, … D8. Among these components, the components A8 and D8 have the lowest frequencies, the components A1 and D1 have the highest frequencies and between of these components have from lower to higher frequencies. Now the obtained individual reconstructed ECG components are used for both preprocessing and for extraction of ECG features automatically in the following way. In the present module, in order to test the developed algorithm a *Record No 105 of MIT-BIH Arrhythmia* is selected. The original ECG signal of length 800 samples for Record No 105 of MIT-BIH Arrhythmia is shown in figure 5**.**

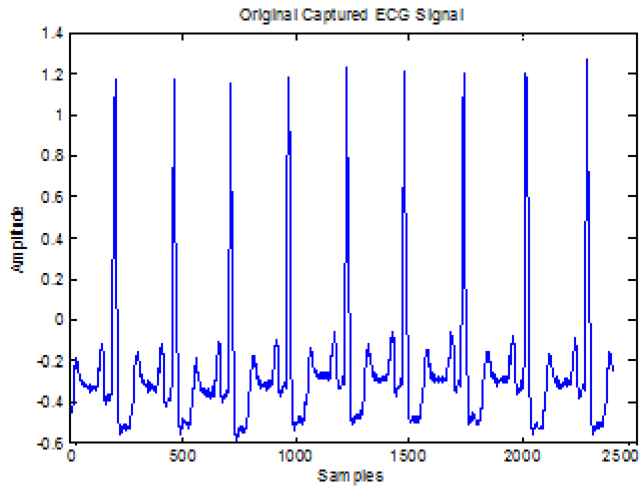

Figure 5: The original ECG signal of Record No 105 of MIT-BIH Arrhythmia Database

After decomposition, the individual reconstructed components of the ECG signal of length 3600 samples are shown in figure 6. Now the obtained components are used for both preprocessing and extracting the features from the ECG signal.

3.1 ECG Preprocessing

When an Electrocardiogram is recorded many kinds of noises are also be recorded due to very low and high frequencies [8], which causes an ECG to have baseline drift and noise in the signal, and is very difficult to clinical diagnosis. For proper diagnosis of ECG, it is necessary to remove noise from the signal. A process of removing the baseline drift of a signal [9] is called as de-trending and a process of removing the noise [10] of a signal is called as de-noising. Both of these processes come under the preprocessing of an ECG signal. Once the signal is preprocessed then it can be used for feature extraction.

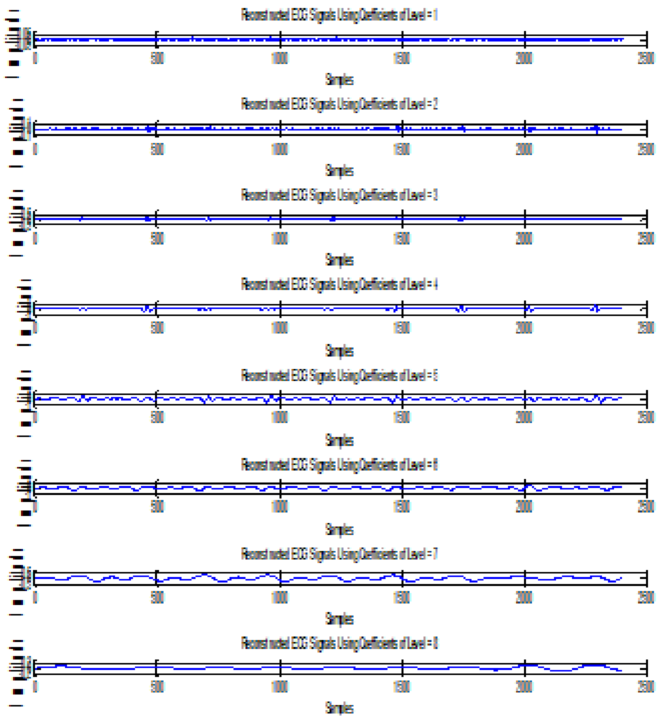

Figure 6: Reconstructed Approximation and Detail Components of the ECG signal

3.2 ECG Baseline Drift Removal

Since the low frequency components cause the signal for baseline shifting, these components must be deducted to have a signal without baseline drift. In this study, the low frequency components of a decomposed signal are A8 and D8. Therefore, to remove the baseline drift, the developed algorithm removes these components from the original ECG signal. Thus, the problem of baseline shifting is solved. The original and detrended ECG signal of length 800 samples is shown figure7.

3.3 ECG De-noising

Though the low frequency components are removed from the original signal, still it may have noise due to high frequency components. In order to remove the noise from ECG signal, it is required to identify which components contain the noise and then these identified components are removed from the detrended signal. When a signal is decompose by DWT, the successive approximations becomes less and less noisy as more and more high frequency information is filtered out of the signal. But, in discarding all the high frequency information many of the original signal's sharpest features are lost. Optimal de-noising requires a more subtle approach called *thresholding* [12]. This involves discarding only the portions of the details that exceed a certain limit.

The developed algorithm uses global thresholding option, which is derived from Donoho-Johnstone fixed form thresholding strategy for an un-scaled white noise. By using the developed algorithm, the identified high frequency components are D1, D2. These components must be filtered by applying a threshold. Then the thresholded components are removed from the de-trended signal.

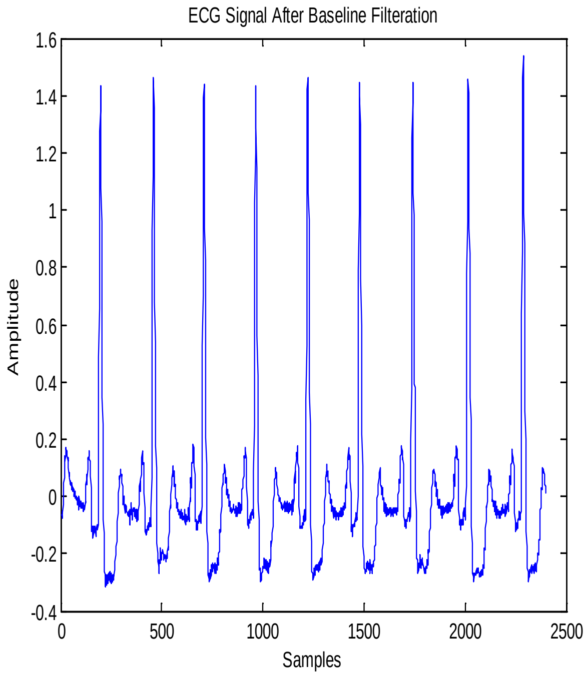

Figure 7: The De-trended ECG Signal

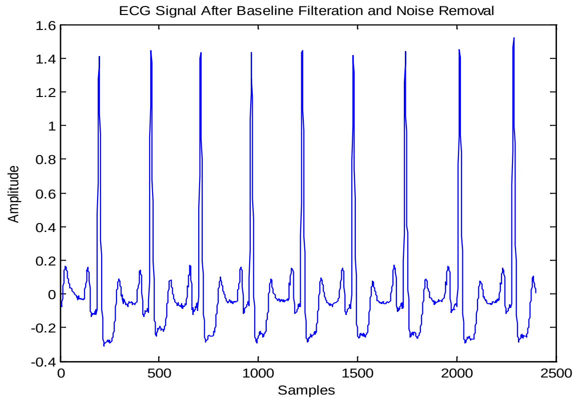

Figure 8: De-noised ECG signal

The denoised ECG signal of length 800 samples is shown in figure 8.

3.4 Extraction of ECG Features QRS complex

Since the peaks of R waves in the ECG signal have the largest amplitude values among the other waves, identifying the QRS complexes of an ECG signal by using the developed algorithm is an easy task. To detect the R waves, the developed algorithm removes the very low and very high frequency components from the ECG signal. In this study, the detail components of D3, D4 and D5 show the QRS complex more clearly comparing with other components. Therefore, the algorithm keeps these components and removes the other low frequency and high frequency components. The R waves of ECG signals are shown in figure 9**.**

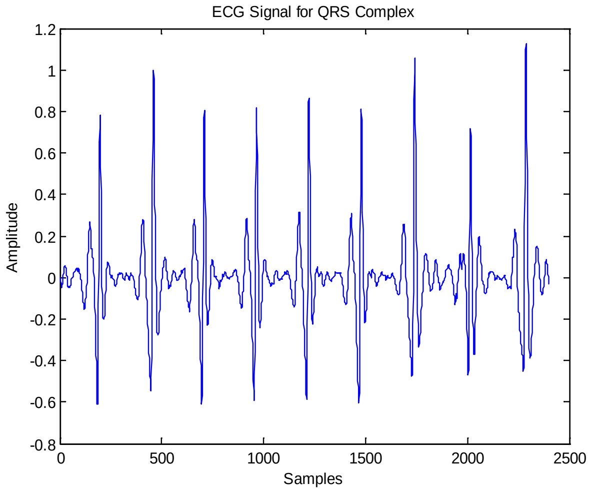

Figure 9: R-waves of the ECG Signal

3.5 R Waves of the ECG Signal

To make the R wave more noticeable, the obtained signal is squared, which is shown in figure 10**.** Since the obtained signal has pseudo peaks, a lower limit is applied to remove these pseudo peaks (thresholding), which is shown in figure 11. Once the R-peaks are identified then it can be used by the developed algorithm to automatically calculate the amplitude values of R waves and the time intervals between them.

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Once the R peaks are determined then based on these peaks the Q and S peaks are detected. Generally, the Q and S peaks occurs about the R peak within 0.1 second. Therefore, to make the peaks more noticeable, the developed algorithm removes all the detail components of the signal up to D5 from the signal. The approximation signal is remained same. The first negative deflection to the left of the R-peak is denoted as Q-peak and the first negative deflection to the right of the R peak is denoted as S peak. In the figure 12, the left point about the R peak denotes the Q-peak and the right point about the R peak denotes the S peak. Once the R-peaks are identified then it can be used by the developed algorithm to calculate the amplitude values of Q and S waves automatically.

3.6 P and T-waves

The extreme of the signal before and after zero crossings about QRS complex denotes the P and T waves. The detected zero crossings of the signal about the P and T peaks are the onset and offset points of the waves respectively. To make the P and T peaks more noticeable, the developed algorithm keeps the details D4 to D8, which are shown in figure 13. Once the

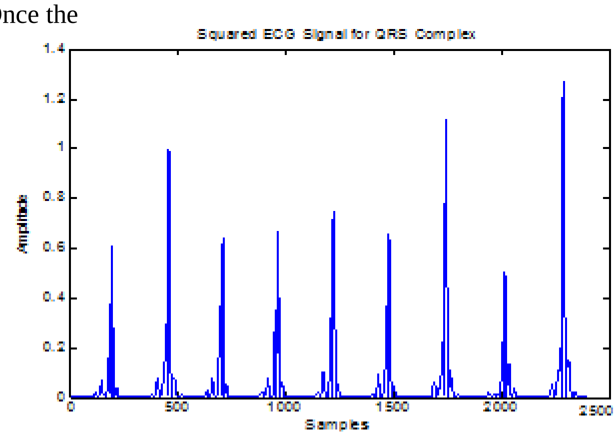

Figure 10: The Power of R-waves of the ECG Signal

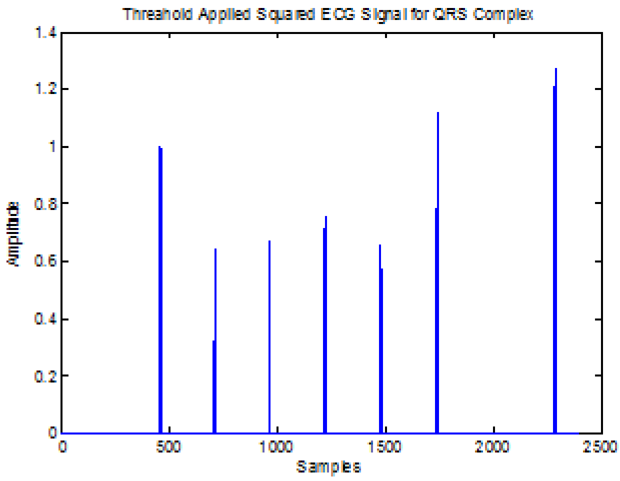

Figure 11: Thresholded R-waves of the ECG Signal

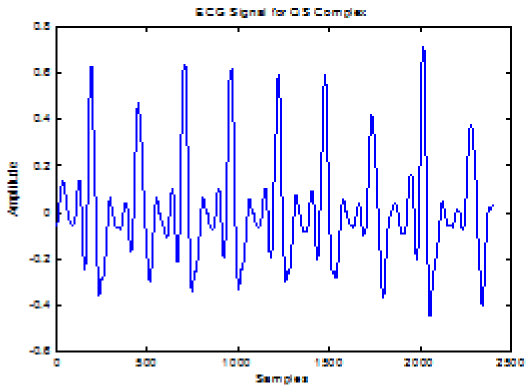

Figure 12: The Q and S-waves of the ECG Signal

P and Q peaks are identified then it can be used by the developed algorithm to calculate the amplitude values of P and T waves automatically

3.7 RR-Interval

The R-R interval of an ECG signal is the time interval between the R-waves. In order to determine the R-R interval of a signal, the developed algorithm determines the difference between the two consecutive R wave locations based on the identified R waves. Since these interval values are not constant throughout the signal, it indicates the abnormality of a heart rate. Also the number of heart beats per minute calculated (number of R-R intervals) by the developed algorithm is 60.

3.8 The P and T waves of the ECG Signal

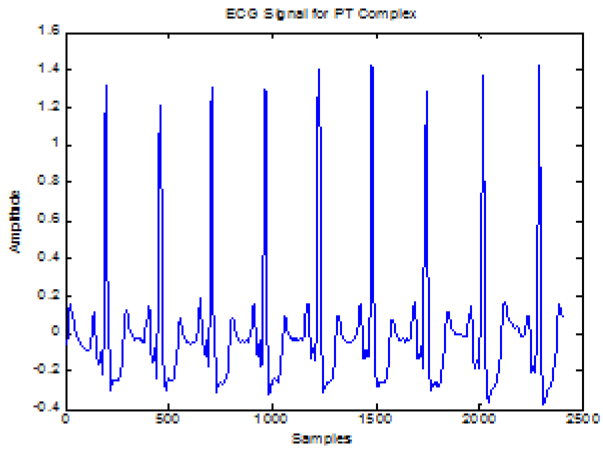

Figure 13: The P and T waves of ECG Signal

a) P-R Interval

Once the P and R waves are identified, it can be used by the developed algorithm to determine P-R intervals. In order to determine P-R interval, the developed algorithm determines the interval between the onset of P waves and onset of Q waves.

b) S-T Interval

Once the S and T waves are identified, it can be used by the developed algorithm to determine S-T intervals. In order to determine S-T interval, the developed algorithm determines the interval between the onset of S waves and offset of T waves

c) Q-T Interval

Once the Q and T waves are identified, it can be used by the developed algorithm to determine Q-T intervals. In order to determine Q-T interval, the developed algorithm determines the interval between the onset of Q waves and offset of T waves.

In above feature extraction use threshold values for the accuracy of the signal this proposed methodology is use by us to denoising and de trending the signal.

4. Conclusion

As the abnormality of heart beat can be showing up at any interval of ECG signal, it is difficult to physicians for manually analyze and to extract the features and also it is a time consuming process. Therefore, the proposed developed algorithm can be used to automatically extract features from ECG signal which increases the accuracy and reduces the time. Thus the performance of the proposed algorithm is increased.

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