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Detection of QRS Complex in ECG Signal using Wavelet Transform and Thresholding Technique

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Abstract :-The Electrocardiogram is a powerful tool that provides the remarkable information about the cardiac disorders. QRS complex detection in ECG signal is very important for finding some cardiac disease. QRS complex has been detected by wavelet transform. Symlet-4 wavelet has been used for QRS detection. In the wavelet transform, thresholding also an important parameter for obtaining the higher output. The Rigersure type threshold gives highest sensitivity of 99.34%.The analysis has been done on ECG data files of the MIT-BIH Arrhythmia Database. Index termsecg, QRS complex detection, discrete wavelet transform, Multi resolution analysis, threshold.

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I. Introduction

Importance of the biometric signal monitoring has increased recently for securing patient lives through detection of emergencies and abrupt changes in patient conditions. Some cardiac problems can occur during normal daily activities and may not be present or disappear when the patient is hospitalized. For this reason cardiac patients are particularly dependent on long term monitoring equipment and

on-line electrocardiogram (ECG) data transmission that can provide information for preventive diagnosis in advance. The ECG is nothing but the

recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. Cardiac cells, in the normal state are electrically polarized. Their inner sides are negatively charged relative to their outer sides. These cardiac cells can lose their normal negativity in a process called depolarization, which is the fundamental electrical activity of the heart. This depolarization is propagated from cell to cell, producing a wave of depolarization that can be transmitted across the entire heart. This wave of depolarization produces a flow of electric current and it can be detected by keeping the electrodes on the surface of the body. Once the depolarization is complete, the cardiac cells are able to restore their normal polarity by a process called re-polarization. This is also sensed by the electrodes [1]. The ECG as shown in Figure 1 records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. Any ECG gives two kinds of information. One, the duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or slow or irregular and the second is the amount of electrical energy passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked. Figure 1 A typical cardiac waveform [2] Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mv. The ECG signal is characterized by five peaks and valleys labeled by the letters P, Q, R, S and T. In some cases we also use another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T and P waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The QRS complex is the most striking waveform within the ECG. Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provides much information about the current state of the heart. Due to its characteristic shape it serves as the basis for the automated determination of the heart rate, as an entry point for classification schemes of the cardiac cycle, and often it is also used in ECG data compression algorithms. In that sense, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. Can be performed [3]. The earlier method of ECG signal analysis was based on time domain method. But this is not always sufficient to study all the features of ECG signals. So, the frequency representation of a signal is required. To accomplish this, FFT (Fast Fourier Transform) technique is applied. But the unavoidable limitation of this FFT is that the technique failed to provide the information regarding the exact location of frequency components in time. As the frequency content of the ECG varies in time, the need for an accurate description of the ECG frequency contents according to their location in time is essential. This justifies the use of time frequency representation in quantitative electro cardiology. The immediate tool available for this purpose is the Short Term Fourier Transform (STFT). But the major draw-back of this STFT is that its time frequency precision is not optimal. Hence we obtain a more suitable technique to overcome this drawback. Among the various time frequency transformations, the wavelet transformation is found to be simple and more valuable. The wavelet transformation is based on a set of analyzing wavelets allowing the decomposition of ECG signal in a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG components in this time segment and frequency band [4].

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II. Methodology

Figure 2 Block Diagram of QRS detection of ECG Base Line Correction – As shown in figure 2 the selected ECG record, which is one of the MIT-BIH arrhythmia database records ware applied for base line correction. Base-line drift can sometimes caused by variations in temperature and bias in the instrumentation and amplifiers. Its frequency range generally below 0.5 Hz. To remove baseline drift we subtract the main signal from its mean value. Wavelet transforms - the wavelet transform is a convolution of the wavelet function ψ(t) with the signal x(t). Orthonormal dyadic discrete wavelets are associated with scaling functions φ(t). The scaling function can be convolved with the signal to produce approximation coefficients S. The discrete wavelet transform (DWT) can be written as $\boldsymbol{Tm}, \boldsymbol{n} = \boldsymbol{x}\ \boldsymbol{t}\ \boldsymbol{\psi m}, (\boldsymbol{t})\boldsymbol{dt}\ \infty\ -\infty$ By choosing an orthonormal wavelet basis ψm,n(t) we can reconstruct the original [5]. The approximation coefficient of the signal at the scale m and location n can be written as $\boldsymbol{Sm}, \boldsymbol{n} = \boldsymbol{x}\ \boldsymbol{t}\ \boldsymbol{\phi m}, (\boldsymbol{t})\boldsymbol{dt}\ \infty\ -\infty$ But the discrete input signal is of finite length N. So the range of scales that can be investigated is 0 < m < M. Hence a discrete approximation of the signal can be written as $\boldsymbol{xo}\ \boldsymbol{t} = \boldsymbol{xM}\ \boldsymbol{t} + \boldsymbol{dm}(\boldsymbol{t})\ \boldsymbol{M}\ \boldsymbol{m}=\mathbf{1}$ where the mean signal approximation at scale M is xm(t) = SM,nφm,n(t) and detail signal approximation corresponding to scale m, for finite length signal is given by $\boldsymbol{dm}\ \boldsymbol{t} = \boldsymbol{Tm}, \boldsymbol{n\psi m}, \boldsymbol{n}(\boldsymbol{t})\ \boldsymbol{M}-\boldsymbol{m}\ \boldsymbol{n}=\mathbf{0}$ The signal approximation at a specific scale is a combination of the approximation and detail at the next lower scale [5]. Xm(t)=xm-1 (t)-dm(t) Multiple-Level Decomposition - The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree shown in figure 3. Figure 3 Wavelet Decomposition Tree [3] De-noising is an interesting application of wavelet transforms [6]. In this research work, the properties of wavelet transforms have been employed to recover a signal from the signal with noise. The process of filtering can be broken into further steps which are: 1. Denoising 2. Decomposition 3. Threshold 4. Reconstruction The signal was denoised at the third and fifth level, and then the difference of this level has been taken for further analysis. Squaring- This makes all the results positive and emphasizes the QRS complex because the amplitude of the signal is increased. Moving Window Integrator- The signal is passed through a Moving Window integrator. A Moving Window integrator is used because there are multiple peaks within the duration of a single QRS; the integrator takes an average of N samples, where N Where N is the number of samples in the width of the integration window. Adaptive Threshold- Signal peaks are defined as those of the QRS complex, while noise peaks are those of the T waves, muscle noise, etc. After the ECG signal has passed through the band pass filter stages, its signal-to-noise ratio increases. Two sets of thresholds are used, each of which has two threshold levels. The set of thresholds that is applied to the waveform from the moving window integrator is if PEAKI is the signal peak SPKI = 0.125 PEAKI + 0.875 SPKI if PEAKI is the noise peak NPKI = 0.125 PEAKI + 0.875 NPKI THRESHOLD I1 = NPKI + 0.25 (SPKI – NPKI) THRESHOLD I2 = 0.5 THRESHOLD I1 Decision - If the value of the sample is greater than the given threshold then there is a peak, this is the Rpeak in the QRS complex. These are stored in an array, which notes the sample number as they occurred in the record. This gives the time (and sample number) of the R wave in the QRS complex. For locating the Q wave find the minimum point of the left side of R-peak. Similarly, determine the S wave by searching the minimum point on right side of the R peak [7].

III. Result

Accurate detection of different waves which forming the cardiac cycle is a crucial steps in analysis of ECG.. Most of the studies based around wavelet transformation identify 97.5% of ECG waveforms. Especially the wavelet transformation is worth investigating in QRS complex detection. Some authors use wavelet technique for identification of the ECG changes resulting from acute coronary artery occlusion and are able to identify specific detailed time frequency components of ECG signal, which are sensitive to transient ischemia and eventual restoration of electrophysiological function of the myocardial tissue. For performance evaluation, an ECG record from the MIT-BIH Arrhythmia database was imported in the form of matlab file. In testing phase proposed algorithm was applied to all 45 records of the MIT-BIH Arrhythmia database on lead ML2. The database provides two channels of ECG data sampled from patients at a rate of 360Hz. Figure 4 QRS point on ECG The algorithm was able to detect the QRS complex more accurately as shown in Figure 4 above. The value of false positive and negative shown in Table 1. Performance was analyzed using the following parameters:- Sensitivity (%) = $TP\ TP{+}FN$ Positive predictive (%) = $TP\ TP{+}FP$ Detection error rate (%) = $FP + FN\ Total\ number\ of\ QRS\ complex$ Where, TP = Number of true positive beat detected FP = Number of false positive beat detected FN= Number of false negative beat detected TN = Number of true negative beat detected Table 1 Value of False positive & negative of QRS detection Record sym4 FP FN 100 0 0 101 0 0 103 0 0 Record sym4 FP FN 105 1 0 106 2 0 107 3 0 109 8 0 111 0 0 112 0 0 113 1 0 114 6 0 115 0 0 116 0 0 117 0 0 118 3 0 119 0 0 121 0 0 122 0 0 123 1 0 124 24 0 200 0 0 201 1 0 202 3 0 203 0 0 205 20 0 207 4 0 208 0 0 209 2 0 210 0 0 212 1 0 213 0 0 214 3 0 215 0 0 217 0 0 219 1 0 220 5 0 221 0 0 222 0 0 223 0 0 228 0 44 230 0 0 231 3 0 232 1 0 233 0 0 234 0 0 Total 93 44 As wavelet denoising consists four types of thresholds (heursure, rigrsure, minimaxi, sqtwolog), so it is important to find out which threshold gives 0 10 20 30 40 50 60 -0.5 0 0.5 1 ECG Signal with Q-R-S points 1 1.2 1.4 1.6 1.8 2 2.2 2.4 2.6 2.8 3 -0.5 0 0.5 1 ECG Signal with Q-R-S points the higher response. For this, the signal was tested in the algorithm using different thresholds on all 45 signals. Table 2 shows output of some signal and final comparison of all signals shown in Table 3. Table 2 Value of False positive & negative of different types of denoising Thresholds Record Heursure Rigrsure FP FN FP FN 100 0 0 O 0 101 1 0 1 0 103 0 0 0 0 105 0 0 0 0 114 3 0 0 0 Record Sqtwolog Minimaxi FP FN FP FN 100 0 0 0 0 101 1 0 0 0 103 0 0 0 0 105 0 0 0 0 114 0 0 0 0 Table 3 Comparison of different Thresholds Threshold Sensitivity Positive Predicitivity Detection Error Heursure 98.61 97.49 3.82 Rigrsure 99.34 97.49 3.22 Sqtwolog 98.62 97.61 3.7 Minimaxi 98.62 97.67 3.64 Table 3

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shows the comparison of different threshold on the basis of sensitivity, positive predictivity and detection error. According to detection error rigrsure gives best response among other types of threshold. IV CONCLUSION Development of an algorithm based on the wavelet transforms, to detect the QRS complex was the main contribution of this paper. Wavelets with their variable time frequency resolution and properties such as MRA and high number of vanishing moments provide an effective way to analyze a signal. The process of the signal filtering can be performed in quick time following this approach. The wavelet was decomposed for analysis of ECG signal up to level 5 gives high & low frequency component of the signal. The Rigrsure threshold shown the low detection rate, therefore sym4 with rigrsure provided best response for QRS detection of ECG. Wavelet Transform opens the door for further analysis of other kind of Biological signal (EEG, EMG**) also.**

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