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DENOISING AND FEATURE EXTRACTION OF ECG USING DISCRETE WAVELET TRANSFORM

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Abstract: *Electrocardiogram plays a vital role in heart disease diagnosis. ECG contains very important clinical information about the cardiac activities of the heart. ECG signal is affected by noises such as baseline wandering, power line interference, electromagnetic interference and high frequency noises during data acquisition. In this paper, DWT has been used for denoising the ECG signal by discarding the coefficients containing noise. Also QRS complexes are detected and used to locate the Q peaks, R peaks and S peaks using PTB diagnostic ECG Database and manually annotated database.*

Keywords: *ECG, Discrete Wavelet Transform, Multi resolution analysis, Quadrature mirror filters*

I. Introduction

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. The ECG signal and heart rate reflects the cardiac health of human heart. Any disorder in heart rate or rhythm or change in the morphological pattern of ECG signal is an indication of cardiac arrhythmia. It is detected and diagnosed by analysis of the recorded ECG waveform. A typical ECG beat is shown in Figure 1. The amplitude and duration of the P-QRS-T-U wave contains useful information about the nature of disease related to heart. In the normal sinus rhythm (normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds. The QRS interval is from 0.04 to 0.12 seconds. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute [1]. In clinical environment during acquisition, the ECG signal encounters various types of artifacts. The primary interest are power line interference, external electromagnetic field interference, noise due to random body movements and respirational movements, electrode contact noise, electromyography (EMG) noise, and instrumentation noise. These noises degrade the signal quality, frequency resolution and strongly affect the morphology of ECG signal containing important information. It is essential to reduce disturbances in ECG signal and improve the accuracy and reliability for better diagnosis. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis [2].

A lot of work has been done in the field of ECG signal analysis using various approaches and methods. The basic principle of all the methods however involves transformation of ECG signal using different transformation techniques including Fourier Transform, Hilbert Transform, Wavelet transform etc. Physiological signals like ECG are considered to be quasi-periodic in nature. They are of finite duration and non stationary [3]. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG. On the other hand, wavelet transform, which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals [4]. For computerized determination of wave peaks and corresponding onset and offset points, QRS detection is the starting point. QRS location is represented by R peak index, or QS peak index in case of positive R absent. In time domain processing of samples, the individual fiducial points are determined with respect to the corresponding QRS index of the same beat by window search of appropriate width using magnitude and slope based criteria. Since ECG morphology varies among different age groups, communities and subcontinents, in addition to numerous types of cardiac diseases, there exists no golden rule for detection of the wave boundaries accurately. In an attempt to develop more accurate algorithms for extraction of features different approaches are used. Some algorithms are based on mathematical models [5]. A simple, mathematical based method along with the concept of data structure is used to obtain the complex. A new mathematical based QRS detector using CWT is explored in. Some other approaches like matched filters, ECG slope criteria, second order derivatives, wavelet transforms [6] are also studied. In, a multi-scale QRS detector including a method for monophasic P and T waves was proposed. Method based on evolutionary optimization process is reported for wave delineation. ECG beats are classified by neuro-fuzzy networks where predefined feature vectors are used [7]. A rule mining based method is developed, where ischemic beats are identified by extraction of features followed by feature discretization and rule mining. ECG features was also extracted using linear predictive coding in [8]. Natalia et al. [9] have analysed first derivative based QRS detection algorithm. A wavelet based soft decision techniques is proposed for identification of patients with cognitive heart failure [10], it uses power spectral density and soft computing techniques for the purpose. Feature measurement of ECG beats based on statistical classifier is explored in. Integration of independent

component analysis and neural networks for ECG beat classification is also an effective technique for classification of ECG beats. A method of analysis of Myocardial Infraction is explored using discrete wavelet transform in [11].

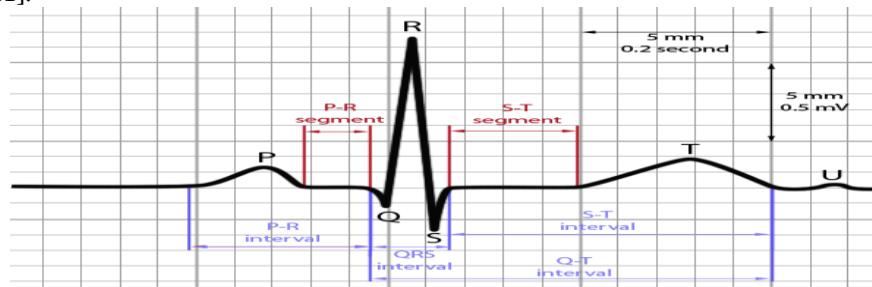


Figure 1 ECG waveform.

II. The Discrete Wavelet Transform

The discrete wavelet transform represents a one-dimensional signal $S[n]$ in terms of shifted versions of a low-pass scaling function of multi resolution analysis (MRA) and shifted and dilated versions of a prototype band-pass wavelet function of MRA. From a signal processing point of view the discrete wavelet transform is a mathematical function that involves multiplication and addition operations to convolve the signal of interest with a predefined wavelet. In the field of signal processing, the implementation of the wavelet transform is performed using filter banks. In a wavelet transform system, the signal is convolved with a pair of maximally decimated quadrature mirror filters (QMF). These filters are related to wavelet and scaling functions. The structure is presented in Figure 2:

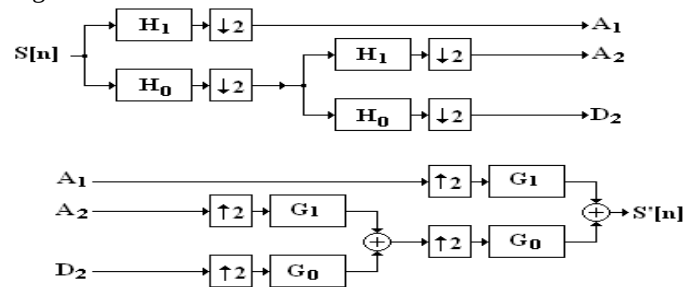


Figure 2 – 2nd order DWT decomposition and reconstruction structure

The coefficients are ordered using two dominant patterns, one that works as a smoothing filter (like a moving average), and one pattern that works to bring out the "detail" information of the data. These are performed by a quadrature mirror filter pair which split in half the frequency band after every decomposition. To eliminate the redundancy from the signal, after every filtering a downsampler is applied to reduce to half the number of coefficients. In the present work Daubechies wavelet is chosen although the Daubechies algorithm is conceptually more complex and has a slightly complicated computations yet this algorithm picks up minute detail that is missed by other wavelet algorithms, like Haar wavelet algorithm. Even if a signal is not represented well by one member of the Daubechies family, it may still be efficiently represented by another. The wavelet analysis of ECG signal is performed using MATLAB software.

III. Noises in ECG Signal

A. Power line interference

Inward of all electric current consumer apparatus an electromagnetic field is generated that assist to the outward situated electric network generated base-harmonic and their harmonics caused perturbations. Unfortunately these disturbances exists inward all electric appliances, and with proper screening their effect can be decreased but not abolished. The base frequency of this noise is place dependent, for example 50Hz in India.

B. Electrode contact noise

The improper contact of the electrodes interrupts for a short period the connection between patient and measuring system, creating the electrode contact noise. The loss of contact can be permanent or intermittent, as in case when a loose electrode is brought in and out of connection with the patient's skin as a result of vibration or movement. This switching action at the input of measuring apparatus generates an abrupt, high amplitude artifact that decays to isoelectric line exponentially, since the ECG signal is usually capacitively coupled to the system.

C. Motion caused artifacts

The measured ECG signal is inseparable from alteration caused by the specific movements of the studied patient. Motion artifacts are transient but not step-like baseline changes caused by modification

in the electrode-skin impedance due to electrode motion. A typical cause of motion artifacts is assumed to be vibrations or movements of the subject. The shape of the iso-electric line perturbation can be considered to be a biphasic signal resembling one cycle of a sine wave with duration of 100-500ms and maximal amplitude that can reach 500% of the height of a normal QRS beat. The filtering of such a signal is considered to be hard, especially when the measured value reaches one of the limiting degrees. In this case the disturbed interval cannot be processed, so the highly altered QRS beats become unrecognizable.

D. Muscle contractions

Muscle contraction generates millivolt-level artifactual potentials. Usually these currents extinct each other so the recognition of QRS beats is not hardened, but they can decrease the detection rate of other waves, like P, S, T, U. The average value of the artifact is close to baseline with amplitude 10% of normal QRS and a duration of 50ms. Its frequency may vary from low components.

E. Breath caused baseline movement

The drift of the iso-electric line with respiration can be approximated with a sinusoidal component at the frequency of respiration added to the ECG signal. The amplitude of the drift may be at least five times smaller than the size of a normal QRS beat as the respiration frequency of a normal patient is about 0.15-0.30Hz.

IV. Methodology

The corrupted ECG signal is denoised by taking the DWT of noisy ECG signal and QRS peaks are detected. Figure 3 shows block diagram of noise removal and feature extraction of ECG signal:

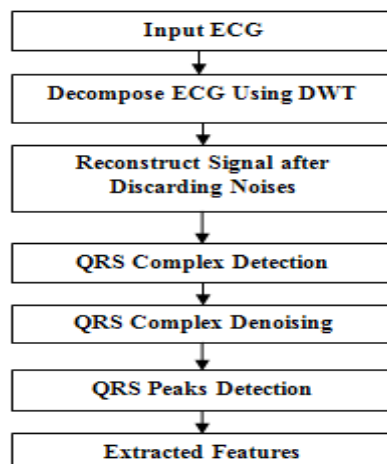


Figure 3 Block diagram of noise removal and feature extraction of ECG signal

ECG signal is obtained from PTB-DB database on physiobank ATM [12]. In PTB-DB database, sampling frequency of ECG signal is 1 KHZ and time duration is 10 seconds. Ten level decomposition has been used by which we get detailed coefficients (cd1-cd10) and approximation coefficient (ca1-ca10). Electrode contact noise and muscle contraction noises are high frequency noises and they are present in the frequency range of 250-1000 HZ. Coefficients containing these noise are cd1 (500-1000HZ) and cd2 (250-500HZ). Baseline line wandering noise is low frequency noise and present in the frequency range of 0.15-0.30 HZ. Coefficient contains this noise is ca10 (0-0.9765 HZ). By discarding these coefficients noise free ECG signal can be recovered. QRS region is obtained from the detail coefficients of the DWT decomposition. The QRS complex region mostly present in the cd4 and cd5 coefficients. In order to find QRS complex, all the coefficients except cd3 and cd4 has been removed and IDWT of all coefficients is obtained. In order to obtain denoised QRS region, threshold limit has been set to 174 such that QRS region is obtained by taking 180 sample and after that 200 sample values has been changed to zero [13].

Algorithm for denoised QRS region as follows:

SET Threshold

QRS_DET

1. $i = 1; k = 1;$
2. if $QRS_DET(i) > \text{Threshold}$, go to step 5;
3. $i = i + 1;$
4. go to step 1;
5. QRS region (k) = x + 180;

6. $k = k + 1$; $i = i + 200$;
7. go to step 1.

To find Q peaks, minimum peaks distance is set to 300 samples and threshold limits has been set between -500 and -800 on y-axis in which Q peaks exist then signal has been reversed after that peaks has been found.

To find R peaks, again minimum peaks distance have been set to 300 samples after that peaks has been found.

To find S peaks, minimum peaks distance has been set to 300 samples and signal has been reversed after that peaks has been found.

V. Results

GUI has been used to obtain the features of ECG like DWT, Denoising, QRS, Denoised QRS and QRS peaks using push buttons as shown in Figure 4.

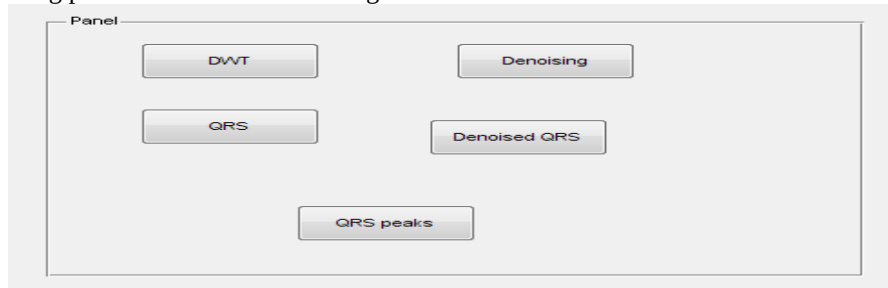


Figure 4 GUI of ECG feature extraction

Approximation and Detailed coefficients of one patient are shown in Figure 5. In which cd1, cd2 and ca10 contain noises. After removing noises by using IDWT denoised signal is shown in Figure 6. QRS complex is obtained by using thresholding, Denoised QRS complex is obtained by using algorithm and QRS peaks obtained are shown in Figure 7.

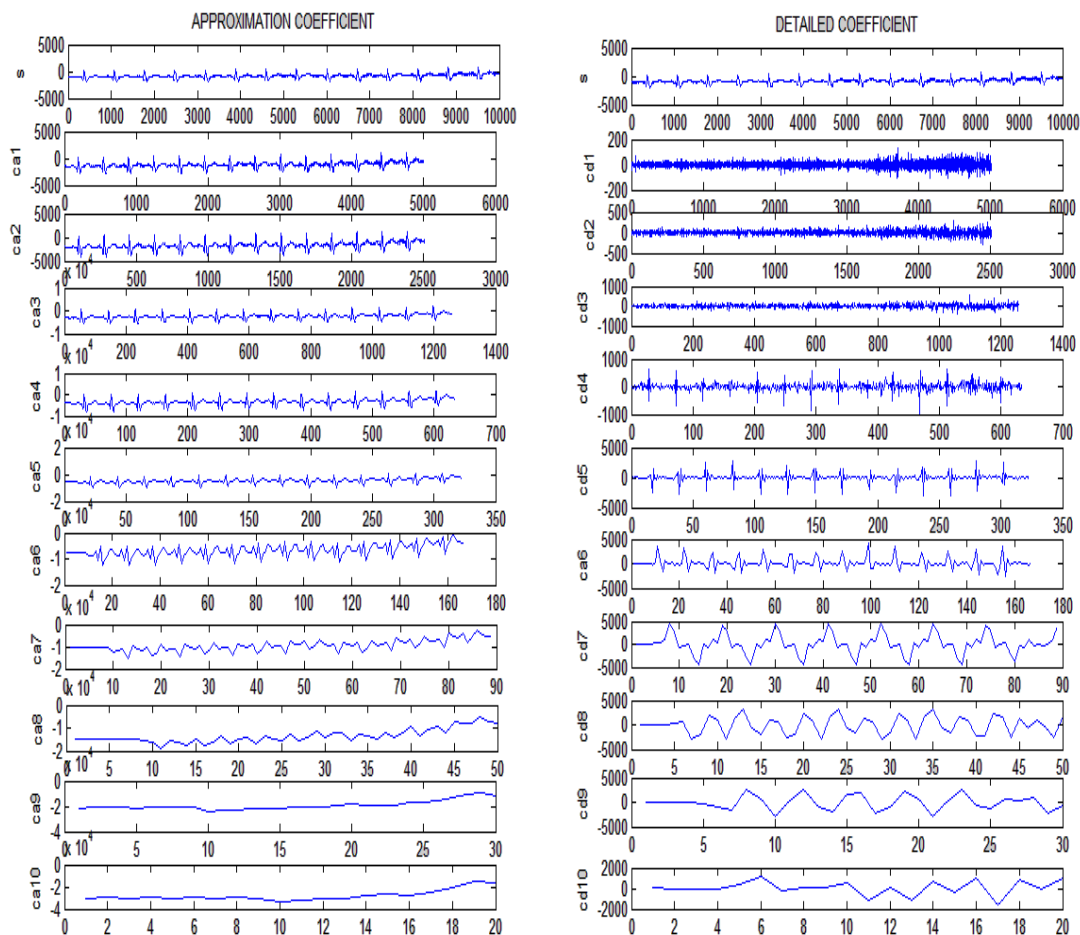


Figure 5 Approximation and Detailed coefficients

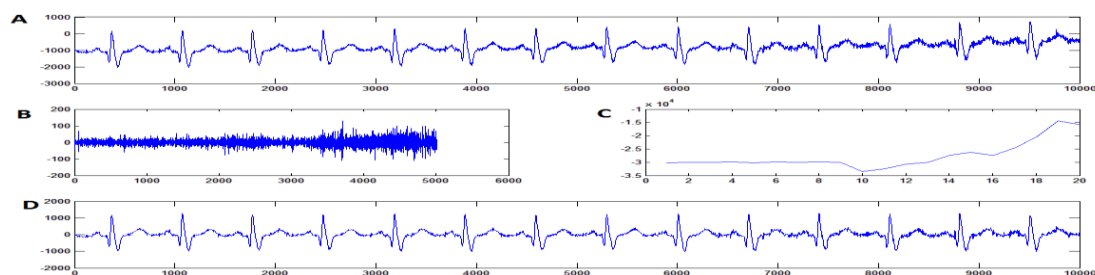


Figure 6. a. Original ECG signal, b. High Frequency Noise, c. Low Frequency noise, d. Denoised ECG signal

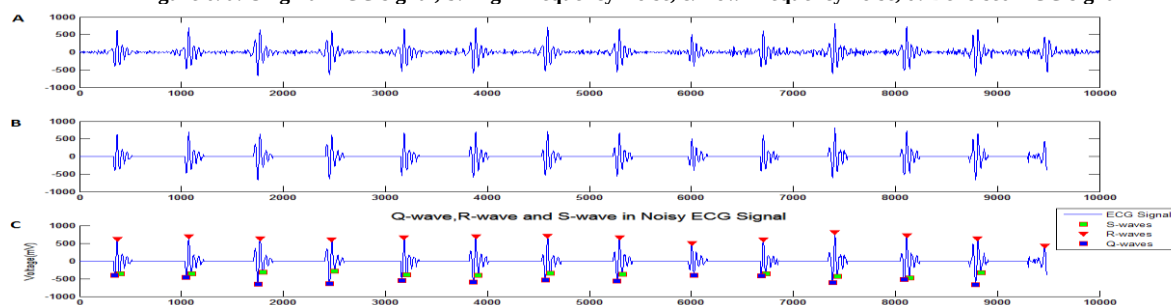


Figure 7 a. QRS complex, b. Denoised QRS complex, c. QRS peaks

VI. Conclusion

The proposed method uses multiresolution feature extraction using DWT, from ECG signal. This paper also explores multiresolution analysis for identification of various frequencies present in an ECG signal. The noise frequencies are also identified and eliminated. Reconstruction scales are selected on the basis of the power spectra of different parts of the signal, which eliminates various noise and artifacts and the interference of other part of the signal while extracting a particular wave or complex. Also QRS complexes are detected and used to locate the Q peaks, R peaks and S peaks. These peaks can be used to tell abnormalities present in ECG such as arrhythmia, Sinus Tachycardia, Atrial Fibrillation, Flutter and Supraventricular Tachycardia (SVT) and Bradycardia. The simulation is done using MATLAB software.

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