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# Comparative Study of QRS Complex Detection in ECG Based on Discrete Wavelet Transform

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*Abstract*— **A new robust algorithm for the QRS detection using the properties of the wavelet transform is proposed in this paper. Wavelet transform provide simultaneous time and frequency information. The algorithm has explained the effect of wavelet with different properties such as linearity and time frequency localization on the accuracy of QRS detection. The wavelet transform decomposes the ElectroCardioGram (ECG) signal into a set of frequency band. The proposed method identifies and detects the components of ECG signal such as QRS complex. The method also show the sharp results for ECG detection parameters. For the standard 24 hour Massachusetts Institute of Technology/Beth Isrel Hospital (MIT-BIH) arrhythmia database, this algorithm correctly reduces the error in detection of the QRS complexes.**

*Index Terms*- **ECG, QRS complex detection, Discrete wavelet transform, Multi resolution, Massachusetts Institute of Technology/Beth Isrel Hospital (MIT-BIH) ECG arrhythmia database.**

## I. Introduction

The ElectroCardioGraph (ECG) is the graphical representation of the electrical voltages generated during the cardiac activity. Since it reflects the rhythmic electrical depolarization and repolarization of the atria and ventricles, its shape, time interval and amplitude provide much information about the current state of the heart. One cardiac cycle of ECG shown in Figure 1. consists of the P wave, QRS complex, T wave, small U wave is usually visible in 50 to75 % of ECG. These signals are an essential tool for the diagnosis of cardiac abnormalities. A good performance of an automatic ECG analyzing system highly depends upon the accurate and reliable detection of the QRS complex. The QRS complex is the most crucial step in automatic electrocardiogram analysis such as arrhythmia detection and classification of ECG diagnosis and heart rate variability studies. The QRS detection provides the fundamentals for almost all automated ECG analysis algorithm. Accurate detection of QRS is an important issue in many clinical conditions.

The feature extractions of the ECG signal, consisting of many characteristic points, can detect the cardiac abnormalities. Therefore, the ECG signal was decomposed into time frequency representations using discrete wavelet transform. A number of techniques have been devised by the researchers to detect QRS complex. The QRS complexes originally developed by Pan and Tompkins [1] in assembly language for implementation on a Z80 microprocessor, but it takes less time and are easily implemented. The main drawback of this algorithm is that frequency variation in QRS complexes adversely affects their performance. Therefore a real time QRS detection algorithm in the C language was developed by Hamilton and Tompkins [2].

Though band pass filtering and temporal filtering of the signal are used for QRS complex detection, the selection of the bandwidth of the filter and the width of the sliding window is not a simple decision [3, 4].

The various researchers are conducted to explore effective signal analysis techniques for the detection of QRS complex [5-9].Wavelet analysis is a promising mathematical tool that gives good estimation of time frequency localization. A number of techniques have been attempted to use wavelets for QRS complex detection to overcome some of these issues [10-20]. In addition, wavelet analysis provides flexibility and adaptability. Also the researchers have the choice of the function and level of decomposition for this application. The goal of this paper is to present a preliminary investigation of the use of an optimal wavelet filter bank for characterization and classification of signal cycles in the ECG. It finds the abnormal waveform like PVCs in the ECG signal. This paper determines the appropriate wavelets for QRS detection.

## II. THEORY

### A. Wavelet Transform

The wavelet transform is a mathematical tool for decomposing a signal into a set of orthogonal waveforms

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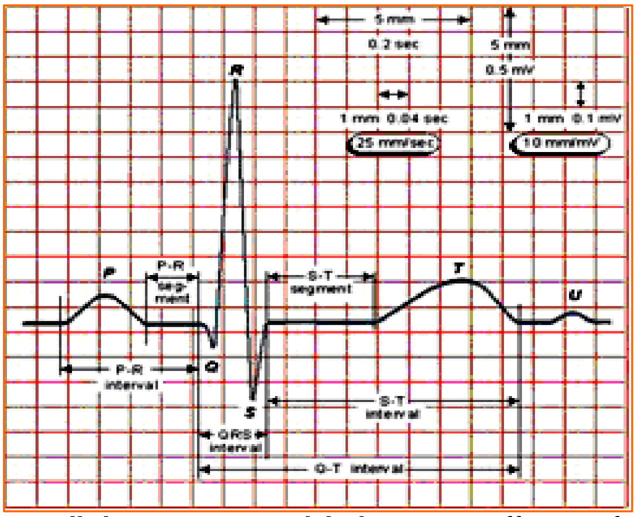
localized both in time and frequency domains. The decomposition produces coefficients, which are functions of the scale (of the wavelet function) and position (shift across the signal). We manipulate wavelet in two ways viz., translation and scaling. In the translation the wavelet along the time axis is shifted and adapts to slow down the wavelet activity. In the scaling, fast activity, sharp spikes are captured. In our approach we use four level discrete wavelet transform. This is called compactly supported orthonormal wavelets. Discrete Wavelet Transform (DWT) has two filters, a low pass filter (LPF) and a high pass filter (HPF).They are used to decompose the signal into different scales. The output coefficients of the LPF




are called Approximation while the output coefficients of

Figure 1. Normal ECG waveform

the HPF is called Detail. The Approximation signal can be sent again to the LPF and HPF of the next level for second-level decomposition; thus we *can* decompose the signal into its different components at different scale-levels. In the wavelet analysis the filter decomposes the signal into frequency bands. In the wavelet synthesis the filter reconstructs the decomposed signal back into the original bands as shown in Figure 2.

The selection of filter determines perfect reconstruction and it also determines the shape of the wavelet. The approximation of the signal x (n) using wavelet orthonormal bases can be defined as

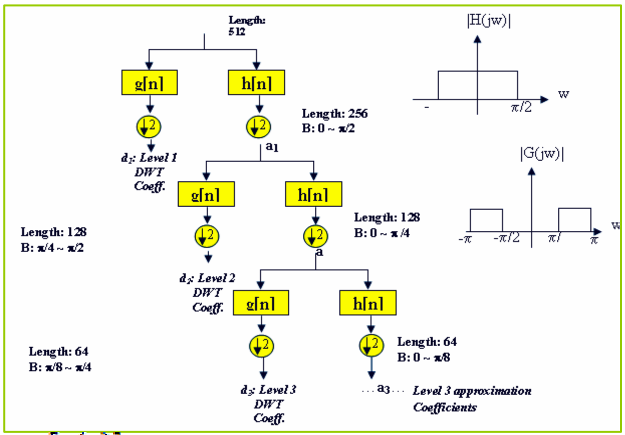
$$X(n) = D_{j,k}[x(n)] + A_{j,k}[x(n)] \qquad n \in Z \qquad (1)$$

where j - scale is the translation parameter

$D_{j,k}[x(n)]$ - represents the dilated signal as j level, j controls the dilation on contraction of the scaling function Φ(t)(father wavelet), k controls time position of the wavelet function ψ(t)(mother wavelet),

x -represents the sample number of the discrete signal x(n).

$n \in z$ -represents the set of integers.




$A_{j,k}[x(n)]$ -the approximation function.

Figure 2. The Signal decomposition by LPF and HPF into three levels

ψ(t) represents high frequency parts of the signal and Φ(t) represents smooth and low frequency parts of the signal. Discrete wavelet transform has number of advantages when applied towards ECG analysis. ECG feature extraction is preceded by a band pass or a matched filter to suppress the P and T waves and noises before sending the signal for characteristic detection.

### *B. Wavelet Selection for QRS Detection*

To determine the choice of the wavelets, the properties of the QRS must be examined. QRS has the highest slope, has a characteristic shape and the event is localized in time. The shape of the signal is maintained if the phase shift is linear. Thus one requirement of the wavelet is that it should be a symmetrical function. Time localization is important because the ECG events are transient. Spline wavelet is a bi-orthogonal wavelet. They are the first derivatives of smoothing functions and are symmetrical. The higher order of the spline wavelet results in the sharper frequency response. This is always desirable in wavelet transform. But the higher order spline wavelet is a longer coefficient series, leading to more computational time. Therefore the Cubic Spline wavelet in Figure 3. is assumed to have the high enough order for this application

$$\Psi(t) = \exp\left(-\frac{t^2}{\beta^2}\right)\cos(2\prod ft) - \lambda \qquad (2)$$

β- Attenuation factor, f - base frequency



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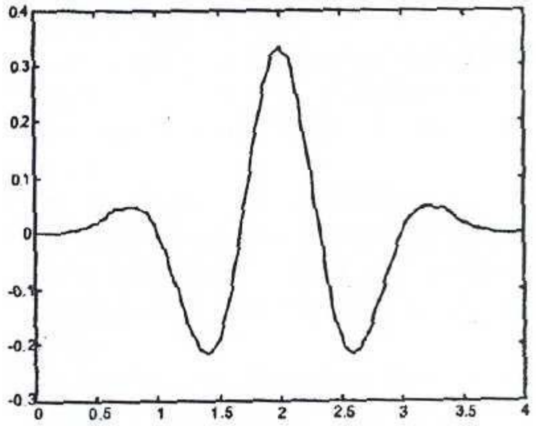

Figure 3. Cubic Spline wavelet

The Harr wavelet is compact in time and provides localization in time shown in Figure 4. This wavelet is discontinuous, and resembles a step function.

Haar wavelet function ψ(t) is given by

$$\Psi(t) = \begin{cases} 1 & 0 \leq t \leq \frac{1}{2} \\ -1 & \frac{1}{2} \leq t \leq 1 \\ 0 & otherwise \end{cases} \qquad (3)$$

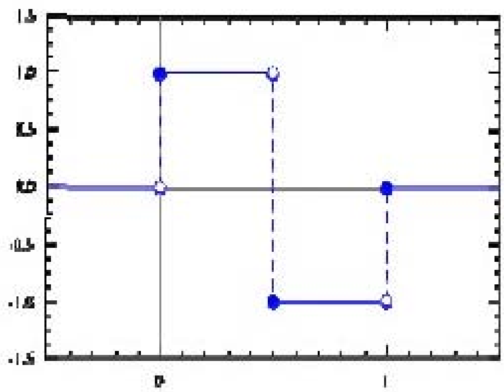

Figure 4. Haar wavelet

Choosing the wavelet of Daubechies4 (Db4) satisfy the following conditions.1.The compact and relative short support to represent the heart components in temporal selectivity 2.Assiociated scaling filters are near linear phase filters.3. Compact support and near from symmetry shown in Figure 5.

This paper analyzes a comparison of these wavelets.

### *C. Arrhythmia Database*

The Massachusetts Institute of Technology/Beth Isrel Hospital (MIT-BIH) arrhythmia database is used in this study [21]. The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-hrs recordings of 47 different individuals. Continuous ECG signals are band pass filtered at 0.1-100 Hz with 11 bit resolution over a 10mV in the range. The database contains annotation for both timing information and beat class information verified by independent experts. In this study, we chose a total of 10 records (containing total of 22273 beats) from the database, using modified-lead II signals in all files and utilizing the annotation information to locate beats in ECG signals. Cardiologists have manually identified the time of occurrence and classified the type of QRS complex anomaly for each record making it suitable for this study.

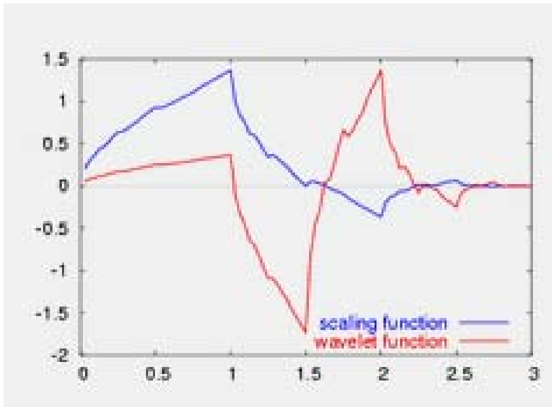


Figure 5. Daubechies4 wavelet

## III. METHODOLOGY

An ECG feature extraction system is based on the multiresolution wavelet transform. Detection of the R waves and the elimination of the abnormalities in the ECG signal is the important step in localizing the aim of this paper. In the feature extraction stage, the main ECG signal features are identified, following the steps presented below.

Step1: The selected ECG record, which is one of the MIT-BIH arrhythmia database records, is filtered by a band pass filter. All records are dual channel ECG signal. The wavelet transform used in ECG signal processing, breaks down the ECG signal into scales and makes it easier to analyze the ECG signal in different frequency ranges. The algorithm locates the maxima of the absolute of the discrete wavelet transform that exceeds the given threshold for each scale.

Step 2: Four level wavelet decomposition is performed using different wavelet transforms. The wavelet transform decomposes the ECG signal into different frequency scales where the ECG characteristics waveforms are indicated by zero crossings. The filter is used to detect the R peak based on the wavelet transform.

Step3: The QRS detection consists in finding the point R of the heartbeat, which is in general the point where



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the heartbeat has the highest amplitude. This detection allows also the evaluation of the heart beat rate by measuring the distance between two adjacent QRS segment of 150 ms window. The peaks corresponding to the R-waves are searched by the algorithm in the first wavelet. The maximums and minimums are searched within a search window set for five seconds to ensure that at least one peak that corresponds to a R-wave is within the search window.

Step 4: The discrete wavelet transform computed using cubic spline wavelet at the scales a=$2^1$, $2^2$ and $2^3$ respectively. The first wavelet is selected for R peaks which is greater than the adaptive threshold.

Step 5: An adaptive threshold value fixed is greater than that of R waves and less than the value of Premature Ventricular Contraction (PVC). After identifying the PVCs they are eliminated. The adaptive threshold algorithm allows the decision thresholds to adjust the signal quality changes and eliminate the need for manual adjustments when changing from patient to patient. Two types of adaptive threshold algorithm are used in this paper.

The first one uses the first wavelet where the maximums and the minimums that correspond to the QRS complexes are tracked by the algorithm. The second adaptive threshold algorithm also uses the first wavelet where the maximums and minimums are searched and the wavelet amplitude of the normal R waves is estimated. In the similar way, the wavelet filtering is applied to the ECG registration using Haar and Db4 wavelet. The detection of R waves in some signals was high which is shown in Figure 6. R wave delay calculations are very difficult. The wavelet transforms of some ECG signals were not accurately performed because of serious high frequency noise, baseline drift, and artifacts. The detection of R-waves in some signals was very difficult due to the presence of high amplitude peaks.

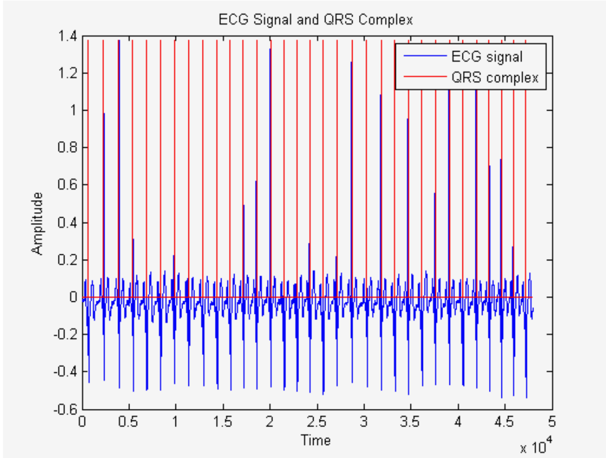


Figure 6. Detection of QRS complex

## IV. Results And Discussions

The analysis of algorithm was tested using ECG registration from MIT-BIH arrhythmia database which is internationally adopted. The algorithm has been developed in the MATLAB environment with a Wavelet Toolbox. In this work we have only used the modified limb lead II. The database contains 48 records which contains about 30 minutes ECG data. Here 10 records are used to evaluate the algorithm. The results obtained are summarized in Table I. The ten records contain 22273 beats. It provides a comparison of the use of the wavelets of the different wavelets for detection of the QRS complex. The speed of detection is very fast. A False Negative occurs when the algorithm fails to detect an actual QRS quoted in the corresponding annotation file of the MIT-BIH record and a false positive represents a false beat detection.

**Table I : Validation Results For The Proposed QRS Detection Algorithm Applied To MIT-BIH Arrhythmia Database Using Different wavelets**

| | Cubic Spline wavelet | | | | | Haar wavelet | | | | Db4 wavelet | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Record | Total beats | NBU beats | FP beats | FN beats | DE (%) | NBU beats | FP Beats | FN beats | DE (%) | NBU beats | FP beats | FN beats | DE (%) |
| 100 | 2272 | 11 | 0 | 0 | 0.48 | 21 | 5 | 4 | 0.92 | 13 | 1 | 3 | 0.57 |
| 105 | 2543 | 8 | 1 | 0 | 0.31 | 15 | 3 | 1 | 0.58 | 12 | 3 | 2 | 0.47 |
| 108 | 1775 | 7 | 2 | 1 | 0.39 | 18 | 5 | 8 | 1.0 | 13 | 3 | 2 | 0.73 |
| 115 | 1953 | 12 | 2 | 1 | 0.61 | 20 | 7 | 5 | 1.02 | 14 | 5 | 2 | 0.71 |
| 118 | 2278 | 9 | 4 | 0 | 0.17 | 18 | 6 | 4 | 0.79 | 15 | 5 | 3 | 0.65 |
| 124 | 1473 | 6 | 1 | 0 | 0.41 | 18 | 7 | 5 | 1.22 | 10 | 4 | 3 | 0.67 |
| 200 | 1972 | 18 | 2 | 1 | 0.91 | 30 | 9 | 4 | 1.52 | 11 | 8 | 3 | 0.56 |
| 202 | 2102 | 7 | 1 | 0 | 0.33 | 19 | 8 | 5 | 9.03 | 14 | 8 | 3 | 0.66 |
| 212 | 2649 | 21 | 0 | 0 | 0.4 | 32 | 7 | 3 | 1.20 | 25 | 4 | 1 | 0.94 |
| 215 | 3256 | 11 | 1 | 3 | 0.34 | 22 | 8 | 5 | 0.67 | 15 | 5 | 2 | 0.46 |
| Total | 22273 | 110 | 14 | 6 | 0.43 | 213 | 205 | 44 | 0.98 | 142 | 46 | 24 | 0.64 |

NBU - Number of beats Undetected, FP- False Positive, FN - False Negative, DE – Detection Error



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## CONCLUSIONS

A novel, effective, and noise tolerance QRS detection algorithm based on Cubic Spline wavelet transform is more suitable for this application because it reduces the probability of error in the detection of the QRS complex. The usefulness of the properties of the wavelet transform for QRS detection has been studied in this paper and a new QRS complex detector has been proposed. Through adaptive threshold all relevant noise are removed of the signal allowing the utilization of simple detection logic for the QRS detection. The main advantage of this kind of detection is less time consuming for long time ECG signal.

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