CALIFORNIA STATE UNIVERSITY, NORTHRIDGE

QRS DETECTION USING WAVELET TRANSFORM

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By

Anuja Nanavati

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The thesis of Anuja Nanavati is approved:

Dr. Ali Amini Date

Dr. Vaughn Cable Date

Dr. Xiyi Hang, Chair Date

California State University, Northridge

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ABSTRACT

QRS Detector using Wavelet Transform

By

Anuja Nanavati

Masters of Science in Electrical Engineering

The electrocardiogram (ECG) provides information about the heart. ECG is a biological signal which generally changes its physiological and statistical property with respect to time, tending to be non-stationary signal. For studying such types of signals wavelet transforms are very useful. The most striking waveform when considering the ECG is QRS wave complex which gives the R wave peak which is time-varying. This report describes an algorithm for detection of QRS complex using the Wavelet transform. This detector is reliable to QRS complex morphology and properties which changes with time and also to the noise in the signal. The performance of the Wavelet transform based QRS detector is illustrated by testing ECG signals from MIT Arrhythmia database. We also compare the performance of Wavelet based QRS detector with detectors using Derivative based method. From the comparison, the Wavelet detector exhibited superior performance for different ECG signals like multiform premature ventricular contractions, bigemy and noisy signals.

I. INTRODUCTION

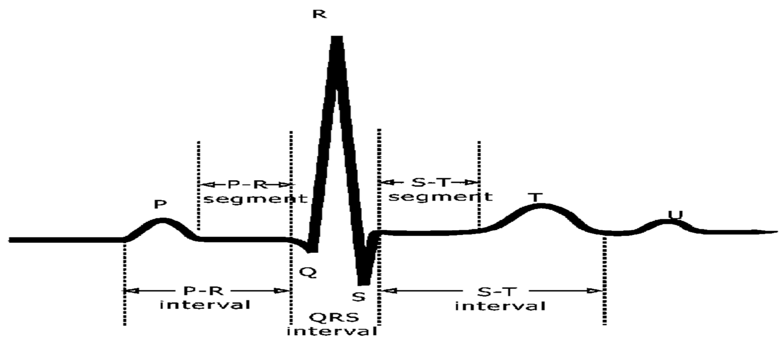

Fig. 1 ECG Waveform and its components

The Electrocardiogram (ECG) is known as the recording of the heart's electrical functioning. It provides information about the heart's strength and functioning capability. During a single cardiac cycle there are different feature points known as the P wave, QRS complex and the T wave. Specifically QRS wave is used to detect arrhythmias and identify problems in regularity of heart rate [1]. It is complicated to detect the R wave which is the highest point of the QRS complex because it is changing with time and is corrupted with noise, baseline wandering due to different patient conditions [2]. Sometimes, in an ECG signal, QRS complexes may not always be the prominent waves because they change their structure with respect to time for different conditions, so they may not always be the strongest signal sections in an ECG signal. The identification of the QRS complex can be greatly hindered due to the presence of P or T waves with similar characteristics as QRS [3, 4]. Also, the ECG signal can be affected and degraded by other sources such as noise in a clinical environment like patient condition, baseline wandering due to respiration, patient movement, interference of the input power supply, contraction and twitching of the muscles and weak contact of the ECG electrodes [4]. Therefore, it is crucial for the QRS detector to avoid the noise

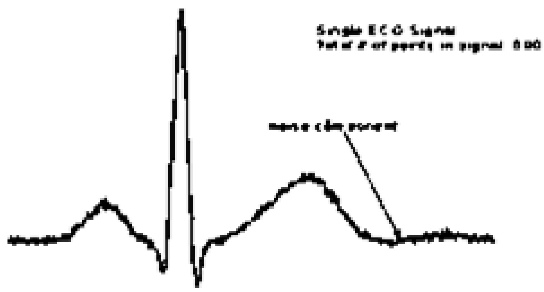

Fig. 2 ECG with noise and artifacts

interference and correctly detect QRS complexes even when the ECG signal varies with respect to time. Also the chances of getting human error are high if the ECG is monitored visually. It is a complicated task and it increases chances of loss of important clinical related information. Therefore lot of efforts has been made to avoid this problem by developing various analog and digitized systems for ECG analysis. Digitized systems have proved to be more efficient as compared to analog systems, which make it possible to retrieve information rapidly for storage of important data and techniques to present that data which is prominent for whose clinical usage. Many approaches used or proposed in the past have been complicated and use a great deal of time, e.g., nonlinear transforms, artificial neural networks, and genetic algorithms. Real time approaches, on the other hand, can be used to monitor the R wave complexes and thus determine the correct heart rate [5].

As per [6], the current QRS detectors can be divided into the preprocessor level and the decision level. The preprocessor level is useful to determine & enhance the QRS wave and the decision stage is useful in thresholding the

QRS enhanced signal. The preprocessor level performs linear and nonlinear filtering of the ECG. Initially, a band pass filter is used for suppressing the noise along with P and T waves. This emphasizes on the R wave which has a greater slope. A derivative or square nonlinear transform is then applied to enhance the high frequency QRS complexes and certain rules are used to determine the presence or absence of QRS complexes in the signal. The signal can also be smoothed by using moving window integration which gives the short duration estimate of the signal energy. Thus, a signal energy detector with limited time duration is developed using window analysis. Thus, it is possible to skip the false beats and identify the missed detections by the selection of the size of the window. A small window allows very less information to accumulate but a large window allows large information and energy which can pass over the threshold value easily. Therefore, it can be observed that the fixed bandwidth of the band pass filter does not adapt to the changes in QRS complex band width and the fixed window does not adapt to variations in the QRS complex duration in the frequency and time domains respectively. Sometimes, the bandwidth of the QRS complex may be different due to different patients and variations in time durations. It may happen that with this condition the QRS complex overlaps with the noise.

The main drawback with the methods mentioned above is they do not adapt to the variations in the QRS complex structure, a disadvantage of a band pass filter technique which prefixes the bandwidth is that it does not accurately provide useful information for the time-varying morphology of the QRS complex. Thus it is required to have a general adaptive method that fights the limitations of the above mentioned problems which covers the spectral and temporal variations in the QRS morphology efficiently.

In this project, a method based on the discrete wavelet transform is tested. With the use of Wavelet transform (WT), the identification of R peak indicates the ECG signal recognition. The wavelet transform, is useful in biomedical signal processing. It is also useful in ECG characterization and QRS detection. Wavelet transform helps in getting accurate analysis and detection of small variations in the heart signal, characterization of ECG features in frequency and time domains and separation of ECG waves from noise, artifacts and baseline drifts. There are two factors in a Wavelet, a ’mother’ wavelet and a ’daughter’ wavelet. The mother wavelet is fixed in shape and then by changing its scales the wavelet functions obtained are the daughter wavelets. They have different time scales and bandwidths. At any particular scale, the signal and a scaled daughter wavelet with respect to time are convolved and it is known as the dyadic wavelet transform. This wavelet transform adapts to temporal and spectral variations in the signal to be analyzed by scaling of the mother wavelet. It has multi resolution capability. It can be given such that, for large scale values it shows low temporal and high spectral resolution and for low scale values high temporal and less spectral resolution. Thus, multi resolution feature of the wavelet transform has been used in various fields [7, 8]. More will be said later about wavelets in this report (Section II.) According to [9, 10], the discrete wavelet transform has been applied for ECG analysis like extraction of waves like P, R, T waves and detection of ventricular potentials. The QRS complex last for a very short time and wavelet transform is computed using a special wavelet that detects peaks for scales at the instance of occurrence of the complexes. Thus it can be assumed that QRS complexes are detected by noting the peaks in the wavelet transform across successive scales.

Many studies have been done on detection of QRS complex. Some have used up to four fixed scales to compute the wavelet transform [11]. In our approach of the analysis of QRS complexes, a specific wavelet is used and we compute the wavelet transform for at least two scales and if necessary we compute for one additional scale. This has a computational advantage over [11] as it dilates the signal and provides detailed information hidden in the signal as compared lower scale which compresses the signal and provides global information about the signal.

In this project we have mainly concentrated on R wave detection due to its primary significance but it is also possible to apply the algorithm to detect other waves such as P, T waves etc. as mentioned by the authors in [11] and[12]. A wavelet transform based QRS detector is described which overcomes noise and time varying nature of the QRS and we focus on the capability of the wavelet transform to detect transients in relation to the problems of QRS detection. We also use the MIT/BIH database for testing the algorithm and have compared the performance efficiency of our algorithm with another standard technique based on Derivatives using the same database. We found the wavelet transform based QRS detector to be robust when noise effects in the signal.

Section II; presents one of the standard methods the Derivative QRS detector, Section III; presents a review of the wavelet transform and its relevant properties and, in Section IV; this Wavelet transform QRS detector is compared with the derivative based method for QRS detection using the MIT/BIH Arrhythmia database.

II. DERIVATIVE BASED QRS DETECTOR

An initial filter stage is generally used by all QRS detection algorithms since the typical frequency components of QRS complex ranges from around 5Hz to 25 Hz. This is done before the actual QRS detection to suppress the remaining features in the ECG signal which are the P, T waves, noise and baseline drift. Noise and baseline drifts are suppressed by using a low pass filter while the other components like P and T waves are suppressed using a high pass filter.

Therefore, both the low and high pass filters combined together results into the application of a band pass filter with the cut off frequencies of 5 Hz and 25 Hz for QRS detection [26].

The high and low pass filtering is carried out separately for many algorithms. Some algorithms used only high pass filters [27-33]. Then the QRS complex is detected using the comparison with the threshold using the filtered signals. Some other decision rules are used to reduce the detections of false positives [26].

Usually in the older algorithms, the high pass filter was realized as a differentiator. Thus the QRS complex feature of having a large slope was used for its detection. The first order derivative of the ECG signal is shown in figure 1. The differentiator has the following difference equations [27-33]

$$y_1(n) = x(n+1) - x(n-1) \tag{10}$$

$$y_1(n) = 2x(n+2) + x(n+1) - x(n-1) - 2x(n-2) \tag{11}$$

$$y_1(n) = x(n) - x(n-1) \tag{12}$$

$$y_1(n) = \tilde{x}(n) - \tilde{x}(n-1) \tag{13}$$

where $\breve{x}(n) = \begin{cases} |x(n)| & |x(n)| \geq \Theta \\ \Theta & |x(n)| < \Theta \end{cases}$ (14)

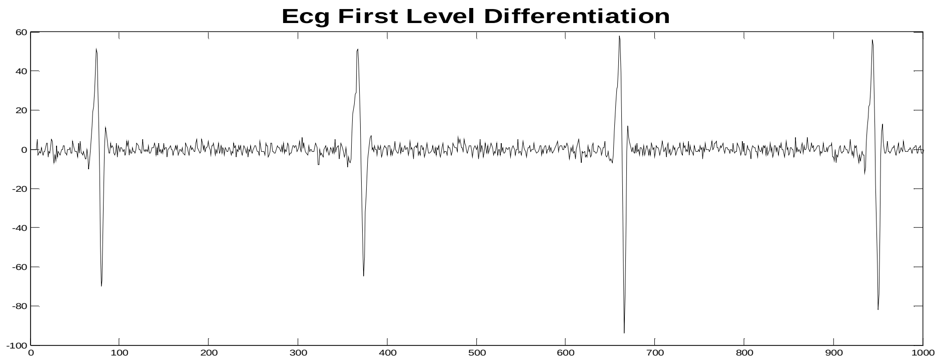

Fig.3. First order derivative of Ecg

and Θ is an threshold of the amplitude. Most of the times, the differentiator from Eq. (10) is used. As shown in figure 2, the second derivative is computed by some algorithms which is given by [27, 28]

$y_2(n) = x(n + 2) - 2x(n) + x(n - 2)$ (15)

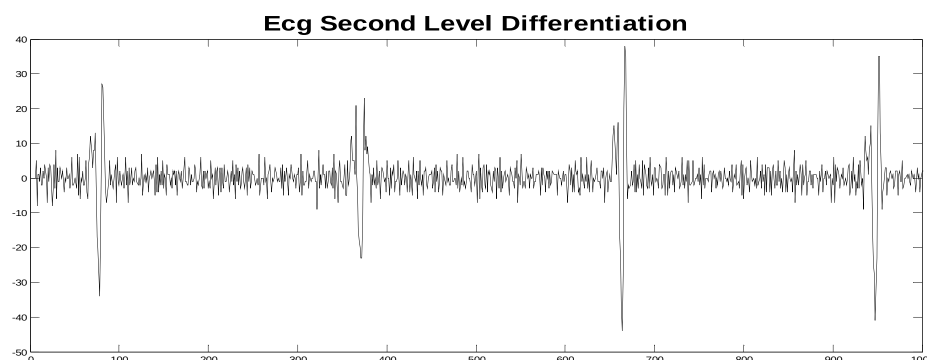

Fig.4. Second order derivative of Ecg

The typical features of such algorithms is given by z(n).

It can be the differentiated signal itself [29, 30, 32]

$z(n) = y_1(n)$ (16)

or the cumulating of the magnitudes of first differential and second differential [34] as shown in figure 3,

$$z(n) = 1.3|\, y_1(n)| + 1.1|\, y_2(n)| \qquad (17)$$

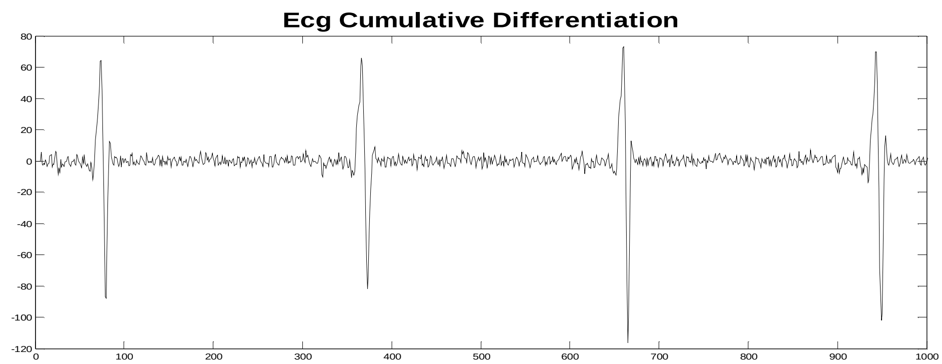

Fig.5. Cumulative first and second order derivative of Ecg

The comparison between the feature in the ECG and the threshold value gives the QRS complex. The selection of the threshold levels must be adaptive in nature and depend on varying signal morphology. When considering feature in equation 16, the threshold is proposed [29, 30, 32]

$$\Theta x = 0.3 \text{ to } 0.4 * \max [x] \qquad (19)$$

where the x is the signal segment and its maximum value is determined. This method of getting the threshold value is used in almost all QRS detectors. Then various decision rules are applied to avoid false positives by using various peak detection logics represented in figure 4 [26].

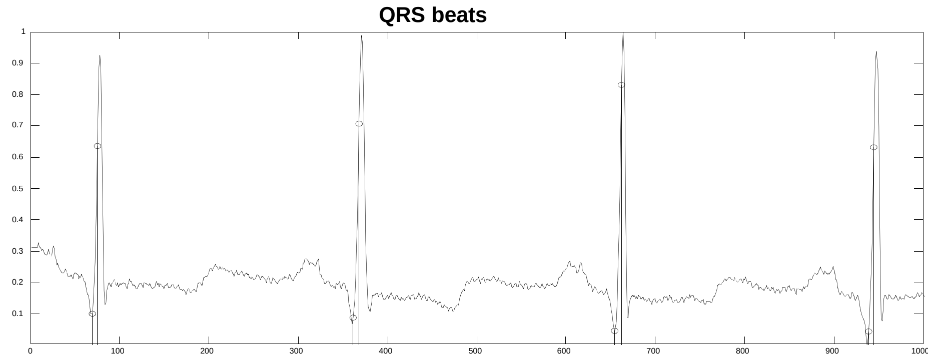

Fig.6. QRS complex in Ecg

Thus, derivative detection method is used for identification of QRS in ecg signal using cumulative differentiation technique. The performance efficiency of this method is compared along with the wavelet transform based method in topic IV.

III. QRS DETECTION USING WAVELET TRANSFORM

A. Definition of Wavelet Transform:

A representation of functions with respect to wavelets is known as wavelet transform. A continuous time signal is distributed into different scale components by using a mathematical function called wavelet. The "mother wavelet" is a fixed length waveform which is scaled and thus translated into "daughter wavelets". Wavelet transforms represents functions with discontinuities, sharp peaks and exhibits accuracy in reconstruction of signals which are non-stationary, non-periodic and finite in nature. Thus it is advantageous over Fourier Transforms for such cases [14]. According to the definition, as mentioned in [15] a function $\psi \in L^2R$ is called orthonormal wavelet if it is used to define a Hilbert basis. The Hilbert basis is designed as the family of functions $\psi_{jk}: j, k \in Z$ with of translations and dilations ψ,

$$\psi_{jk}(x) = 2^{\frac{j}{2}}\psi\left(2^{j}x - k\right), j, k \in Z \tag{1}$$

This is an orthonormal system and $\langle f \mid g \rangle$ is the standard inner product on L^2R.

$$\langle f, g \rangle = \int_{-\infty}^{\infty} \overline{f(x)}g(x)dx \tag{2}$$

It is complete if every function $h \in L^2R$ is expanded in the basis as

$$h(x) = \sum_{j,k=-\infty}^{\infty} c_{jk}\psi_{jk}(x) \tag{3}$$

with convergence of the series which is considered as norm. This represents wavelet series. As mentioned in [16], wavelet transform is in lines with the Fourier transform, which distinguishes the signal into a bank of functions which is called as the wavelet function system.

B. Wavelet Transform

The integral wavelet transform is given as below where $c_{j,k}$ are the wavelet coefficients.

$$\left[W_{\psi}f\right](a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} \overline{\psi\left(\frac{x-b}{a}\right) f(x)dx} \quad (4)$$

$$c_{j,k} = [W_{\psi}]\left(2^{-j}, k2^{-j}\right) \quad (5)$$

Here, a=2^{-j} varies the shape of a continuous wavelet and hence called the binary or discrete dilation or the stretching factor. b=k2^{-j} changes the position and displacement of a continuous wavelet and therefore is called the binary or dyadic position or the translation factor. This is called as a continuous wavelet transform because a, b are continuous [16].

C. Types of Wavelet Transform

The wavelet transform is given as infinite set of different transforms. Thus we see wavelet transform is used in very different situations and applications. We consider the property of orthogonal wavelets to set the division of transforms. Discrete transform uses orthogonal wavelets and continuous transform uses non orthogonal wavelets [17].

1) Continuous Wavelet Transform

When the continuous wavelet transforms is applied to the input signal it gives back an array of data which one dimension larger than the input signal in the time frequency domain. As here wavelet is used where data is highly correlated, therefore redundancy is large. This helps to see the results in a more humanistic and realistic format [17]. It is expressed as below, [18,19]

$$\mathrm{CWTx}(b, a) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) * g(\frac{t-b}{a})\ dt \tag{6}$$

where g(t) is the wavelet function for which a, b are dilation and translation factors respectively, a,b € R, a≠0.

2) Discrete Wavelet Transform

The discrete wavelet transform represents the digital signal with respect to time using various filtering techniques. Various cutoff frequencies at multiple scales are used to analyze the signal. Filters perform the functions to process the signal. Scaling the filters in iterations produces wavelets. Scales are determined using up and down sample method. The use of filters provides the information in the signal. This uses low and high pass filters over a digitized input signal as displayed in figure 1 where x[n] represents input sequence. G_0 and H_0 represent the low and high pass filters respectively. The detail signals d[n] is given by H_0 and the approximations a[n] is given by G_0 at every level.

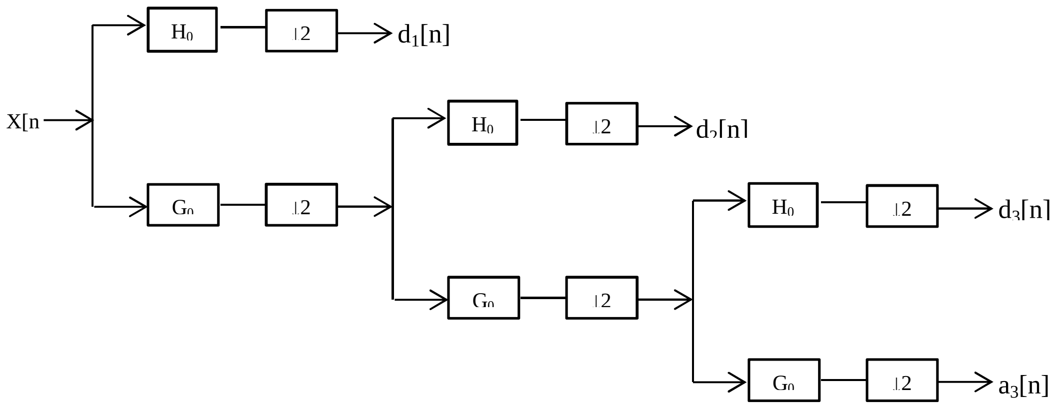

Fig.7. Three level wavelet decomposition tree

The anagram and errors in frequency values reduce to half due to the use of half band filters. They obtain signals with half the frequency band at every level of decomposition, thus increasing the frequency resolution to double. According to nyquist criterion, the filtration obtains the highest frequency of the signal to be ω/2 radians when originally it has ω radians requiring a sampling frequency of 2ω radians. This makes the signal to have half of the samples which results in time resolution to be divided into half and also leads to zero loss of information. The improved time resolution takes place at higher frequency range and improved frequency resolution at lower frequency range due to removal of half of the frequency components caused by half band low filters and decimation by two by high filters. The desired level is reached by continuous filtering and decimation process. The largest number of level is obtained through signal length. All coefficients from the end stage of decomposition are connected obtaining the DWT of the original input signal.

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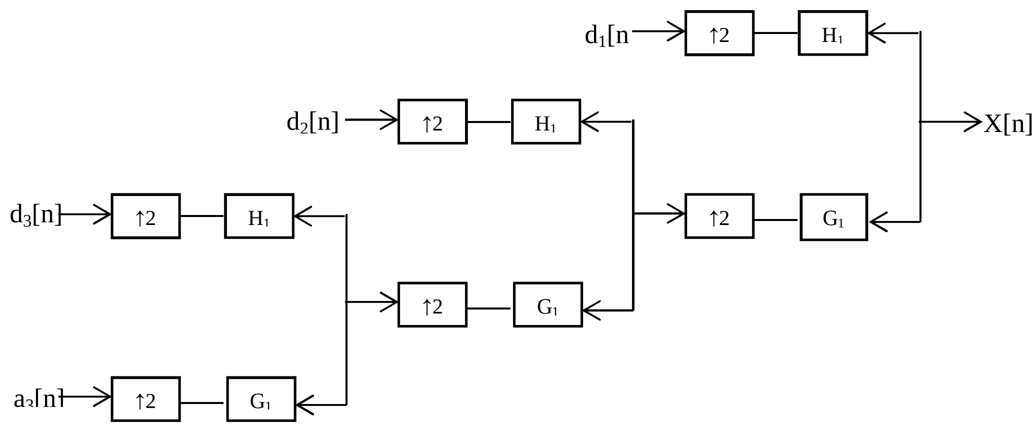


Fig.8. Three level wavelet reconstruction tree

Process of reconstruction is reverse in nature to the process of decomposition represented in figure 2. The coefficients are up sampled by two, passed through filters and then added. The number of levels in the reconstruction process is similar to the decomposition process.

When applied a data signal as an input to the discrete wavelet transform it gives back a same length data vector. It distinguishes the signal as a set of orthogonal wavelet functions. Generally, many data are almost zero in the vector obtained. Hence, the signal is decomposed with the wavelet coefficients same or less as the number of data points.

For the discrete wavelet transform, set of wavelet scales which are discrete in form are used. Its difference as compared to the continuous wavelet transform is that it breaks down the signal into orthogonal group of wavelets and when applied in the discrete time it is known as discrete time continuous wavelet transform. For the discrete transform redundancy is less. By using the scaling function that describes its scaling properties a wavelet can be constructed. The dilation equation is

$$\emptyset(x) = \sum_{-\infty}^{\infty} a_k \, \emptyset(Sx - k) \tag{7}$$

it has S as a scaling factor which is usually chosen as 2 and sometimes 3 for non-stationary and larger data signal. The scaling function should be orthogonal to the integral translate,

$$\int_{-\infty}^{\infty} \emptyset(x)\emptyset(x + l)dx = \delta_{0,l} \tag{8}$$

It must be orthogonal to its integer translate. Now such restrictions does not produce an unique solution so we can implement some more conditions which will give the results of all the equations which are a finite set of coefficients a_k which defines the wavelet along with the scaling function. The scaling function is an even integer N and it produces the wavelet. Thus, these set of wavelets are orthonormal which are used for decomposing the signal. The discrete wavelet transform algorithm is used for various implementations like pyramidal algorithm which is one of the oldest. Thus if the D is 2^N which is total data and L is the signal length, then the first half data D/2 with scale $L/2^{N-1}$ is calculate, then (D/2)/2data with scale $L/2^{N-2}$ and so on. This is done to finally get two data sets at scale L/2. These coefficients are used in recurrence to get data at all the scales. Thus the output array has the same length as the input [17]. Choice of the value of ‘a’ which is the dilation factor is crucial in determining property of the original main wavelet g (t). The multiresolution capability because of the varying bandwidth introduces different resolutions at various scales. The disadvantages of continuous wavelet transform are complex and redundant computations. Discretizing a or both a, b can help reduce the drawbacks and also if a is discretized, then the continuous wavelet transform is called as the discrete wavelet transform (DWT). The range of a is discretized along the scales 2^i where i=1,2,3,….. [3]. From [20] it is then defined as

$$\mathrm{DWTx}\left(\mathrm{b}, 2^{\mathrm{i}}\right) = \frac{1}{\sqrt{2^{\mathrm{i}}}} \int_{-\infty}^{\infty} \mathrm{x}(\mathrm{t}) \mathrm{g} * (\frac{\mathrm{t}-\mathrm{b}}{\mathrm{a}}) \mathrm{dt} \tag{9}$$

The wavelet function g(t) must fulfill the constraint $\sum_{\mathrm{i}=-\infty}^{\infty} |\mathrm{G}(2^{\mathrm{i}}\mathrm{w})|^2 = 1$ where G(w) is fourier transform of the signal x(t).The discrete wavelet transform have similar results as a group of octave band filters due to the discrete sampling of scale parameter. The advantage of the discrete wavelet transform is reduction in computational complexity and redundancy and it has similar properties as the continuous wavelet transform such as linearity, shift covariance, scale covariance, etc. According to [20], if wavelet is selected as the first derivative smoothing function then the maxima of the absolute DWT shows the precise changes in the signal whereas the minima shows the slow variations in the signal. Thus we use discrete wavelet transform for QRS detection.

D. Other applications of Wavelet Transform

The detection of edges and compression of images are some of the other applications of wavelets that makes use of the property of alignment of maxima of the dyadic wavelet transform [20], [21] Also some other applications are pitch detection and quantification of the period of the pitch in signals of speech [22]. The applications of wavelet transform are in various fields since it gives information about the frequency and time of signal whose example can be given by the gait analysis which uses signal processing for its acceleration [23].

E. The Discrete Wavelet Transform QRS Detector

The Wavelet transform based QRS detection algorithm is described in Figure 3:

Consider a window length Lw and compute wavelet transform of the ECG signal for that length as the window section. The wavelet transform should be computed at the dyadic scales a= $2^i, i = i_m, i_{m+1}, \dots \dots i_u$. For this project the length is fixed and is set according to the sampling rate and amount of samples for each input data signal. Here, similar to [20], [21] and to [22], the QRS complexes are detected by using the property of the absolute value of dyadic wavelet transform. The property is that when transients occur in a signal with applied wavelet transform, the absolute value of wavelet transform at consecutive scales has maxima across those scales across the instants when transients occur. A threshold is set or given and for each scale of the wavelet transform and the maxima is located for the absolute value of the transform dyadic wavelet transform (b,2^i) which crosses over the threshold value. The best results are when the transients occur in a signal with applied wavelet transform, the absolute value of wavelet transform at consecutive scales has maxima across those scales across the instants when transients occur. A threshold is set or given and for each scale of the wavelet transform and the maxima is located for the absolute value of the transform dyadic wavelet transform (b,2^i) which crosses over the threshold value. The best results are when the threshold is set to 60 percent of the maximum value generally. Thus it varies according to the length of the peaks for every signal. Then we can get the peaks of the absolute value at scale a=2^i and at scale a=2^{i+1} by considering the number and the positions of the threshold maxima. If the result obtained is same number of peaks and the location of those peaks aligns within ±25 samples with respect to time over two consecutive scales, then QRS complexes are the positions of those maxima possibly. But, if the numbers of peaks is same but the positions are more than ±25 samples with respect to time, then the threshold data is pruned and the misaligned peaks are ignored.

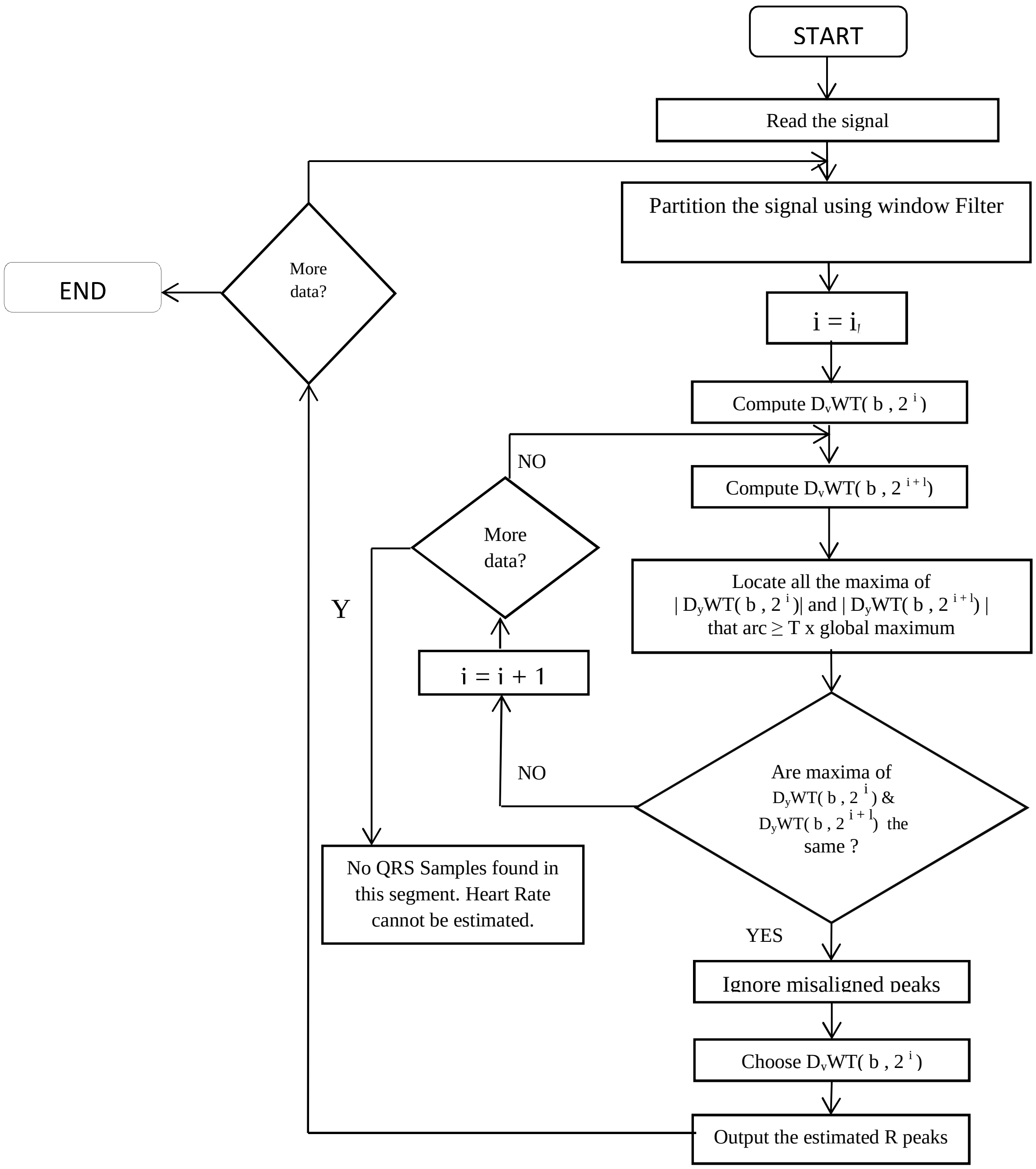
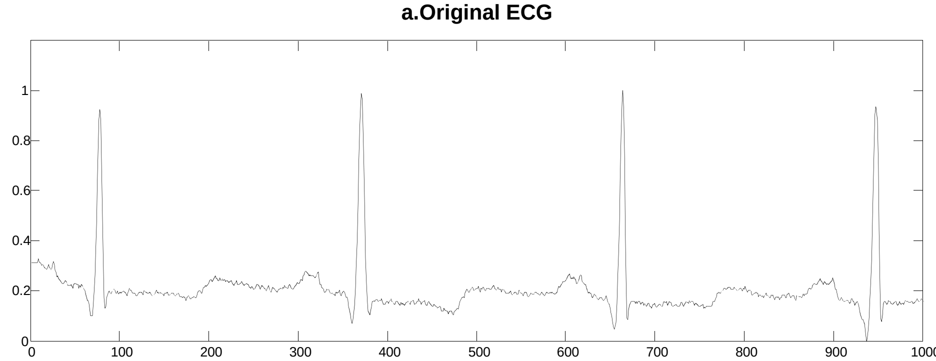


Fig.9. Flow chart of Wavelet Transform based QRS Detector [3]

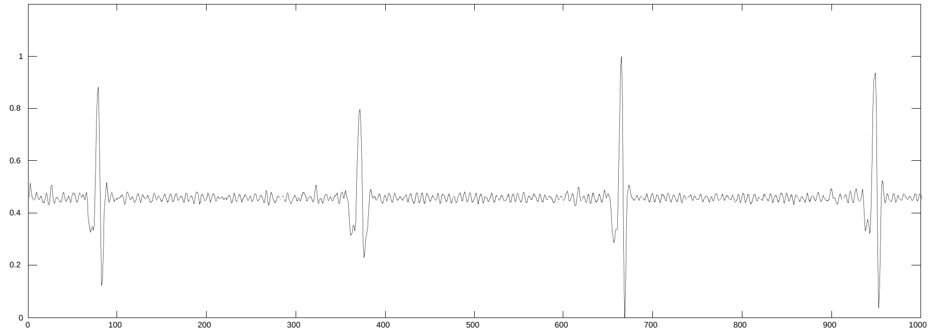
This algorithm is repeated for scales till i$\leq i_u$ when the number of peaks for two consecutive scales does no match; the wavelet transform is computed by considering the next scale. Thus, false peak detection is reduced by using this method.

The wavelet transform is computed at scales 2^i for all I but range of scales can be decided according to the nature of the input signal. We choose ‘coiflet’ in our algorithm because it is orthogonal and works with both continuous and discrete wavelet transforms. The scales are chosen such that they include the range of the QRS wave which is about 5 to 30 Hz which also reduces the noise occurrence in that range. The scale for the algorithm to begin is 2^{i_m} where i_m=1 which continues up to a maximum scale2^{i_u} where index$i_u = 3$. This is the maximum limit for the algorithm since it cannot be computed beyond this scale. Once the lowest and highest scales of the wavelet transform are chosen, it is computed at the lowest scale to the highest scale to obtain the matching peaks. Thus we compute the wavelet transform with three scales $2^1, 2^2$and 2^3 maximum to reduce computational complexity significantly. The computations of the wavelet transforms can be done simultaneously since it is independent of different scales. Fig.1 above displays the flow chart of the wavelet transforms based algorithmic program.

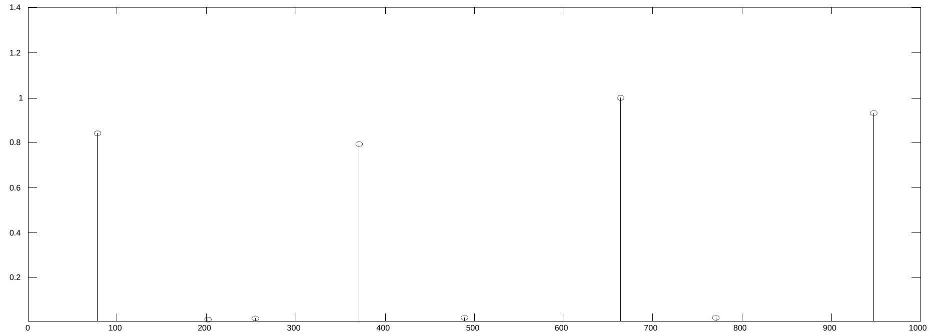
a.Original ECG



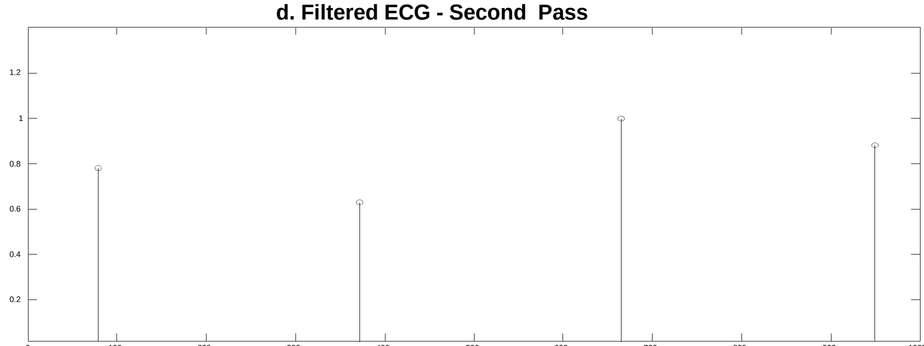
b. Wavelet Transformed ECG



c. Filtered ECG -First Pass



d. Filtered ECG - Second Pass



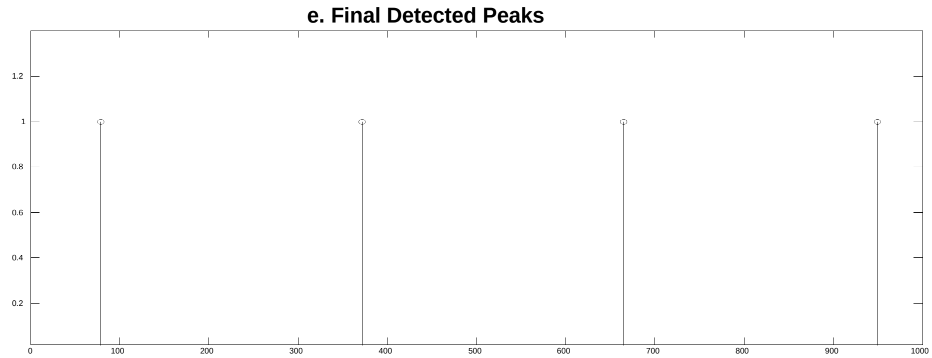


Fig.10. (a) Original unfiltered ECG signal, (b) Wavelet transform applied to the signal, (c) Signal filtered first pass, (d) Signal filtered second pass, (e) Final peaks detected.

In Fig 8(a), an ECG signal of 3600 samples is plotted. In Fig 8(b), the magnitude of DWT computed. In Fig 8(c), the magnitude of DWT is plotted with various peak locations with first pass filter at smaller scale of wavelet. In Fig. 8(d) the signal is plotted with peak locations. In Fig. 8(e) and (f) the final signal at maximum wavelet scale is plotted with final filtered peak locations representing R peaks. Since the noise is not filtration is not optimized, the number of peaks and their positions mismatch at low wavelet scales mismatch. This results into many false peak detections corresponding to noise. At this point the algorithm declares that there are QRS complexes present in the segment and estimates their locations as the location of the peaks. We compute the DWT at most at three scales as it gives the match of peak number and positions and also reduces complexity. Since computing the DWT at any one scale is independent of computing the DWT at any other scale, the computation can be performed simultaneously. This helps in implementation of the DWT based QRS detector at real time.

IV. NUMERICAL EXPERIMENT

In this project, we have used MIT/BIH Arrhythmia database as the testing signals [32]. The MIT/BIH Arrhythmia Database has 48 half hour segments of two-channel ambulatory ECG recordings which are obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. From a set of collection of 4000 24 hour ECG recordings, twenty three recordings were selected at random and the rest 25 recordings have significant arrhythmias which are picked up from the same set too. There are 360 samples per sec over a 10mV range of energy. These records are annotated by the cardiologists. The directory of the MIT/BIH Arrhythmia database has all the 48 records along with their reference annotation files available on PhysioNet. Both the channels are independent of each other and can be analyzed independently [32]. The first 23 records which are from 100 to 124 inclusive along with some missing records in between are those selected randomly and the other 25 records which are from 200 to 234 inclusive, again with some records missing are those which have variety of clinically important features. Each of those records is slightly over 30 minutes in length.

The first 23 records are used to represent the various waveforms and artifacts to help test the detector to show its efficiency in regular use to detect certain irregular heart conditions and arrhythmias. Records in the remaining portion which are 25 records possessing complex heart conditions like ventricular, arrhythmias and other abnormalities. Various records out of these 48 records are selected due to its wide range of features to emphasize on beat and rhythm features, morphological variations of the QRS complex or noise detection to present significant challenges to arrhythmia detectors to prove their efficiency; The subjects involve in all these records are 25 men aged from

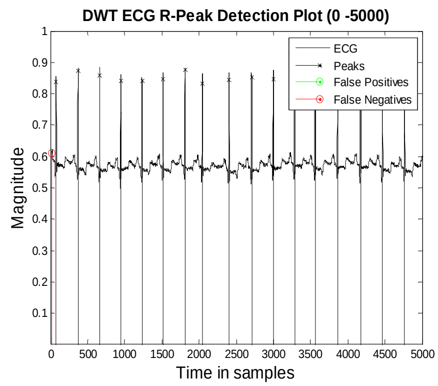
32 to 89 years and 22 women aged from 23 to 89 years. The MIT/BIH database is widely used among database users [33]. The analysis of signal is done with the use of the window filter in the Wavelet based detector. The window length is fixed depending on sampling rate and number of samples for a certain duration of the signal. The signal is applied with the fast Fourier transform to remove the lower and unwanted frequencies. The window is then optimized to get feature extracted high frequency data. When the signal is analyzed in the first pass there can be errors in the detections due to usage of a non-causal window but in second pass we can overcome the error by optimizing the window size. During the implementation of both the Wavelet transform based and Derivative based QRS detectors, in the first example; we check the performance capability of the algorithm by selecting a random record, which is mitdb/100 here. In the second example, we test its performance to noisy signals by using the ECG corrupted with noise and baseline wandering mitdb/203 and the later examples give their performance to two different arrhythmias. The signal having PVC's with multiform nature is given by mitdb/200. The QRS complexes that do not occur with the regularities and do not rise as per the regular rhythm are known as PVC's. Bigemy is where two QRS complexes occur and changes between slow and fast rates which are shown by mitdb/228. A 10 sec portion of each data signal from the MIT/BIH arrhythmia database is considered to obtain visual clarity and it is plotted.

A. Results and Discussion

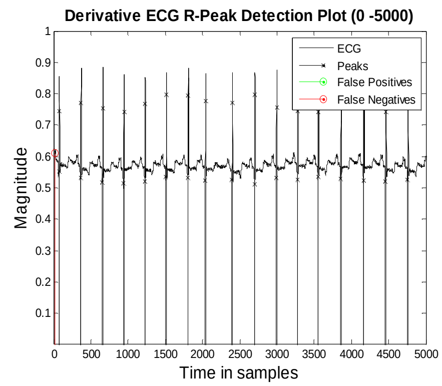
The results obtained when implementing the algorithm of wavelet transform based QRS detector using different MIT/BIH databases in MATLAB software is as follows. We consider only lead MLII since most of the high frequency components and maximum information is available in it as compared to the second lead.

a. DWT QRS detector

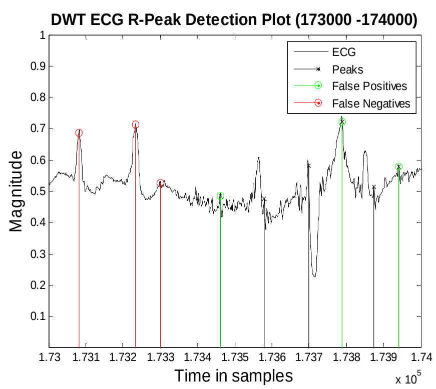
b. Derivative based QRS detector



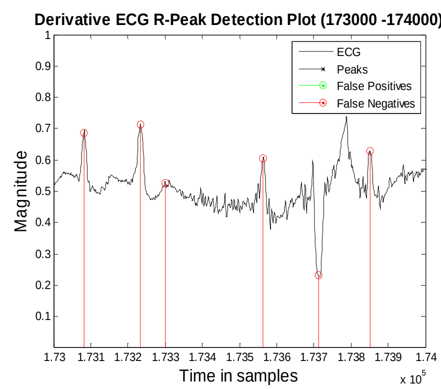
mitdb 100



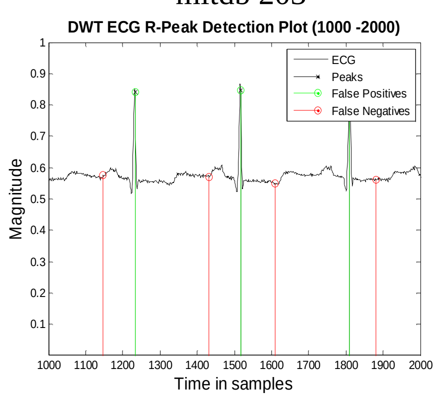
mitdb 100



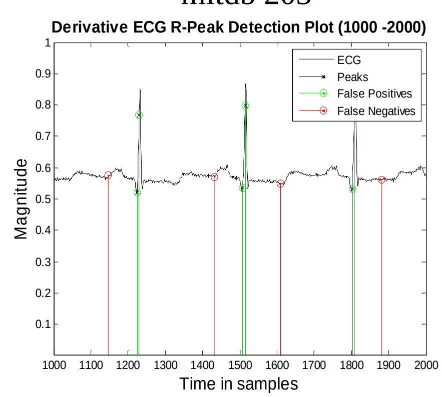
mitdb 203



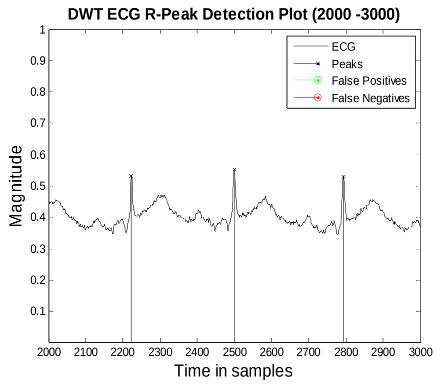
mitdb 203

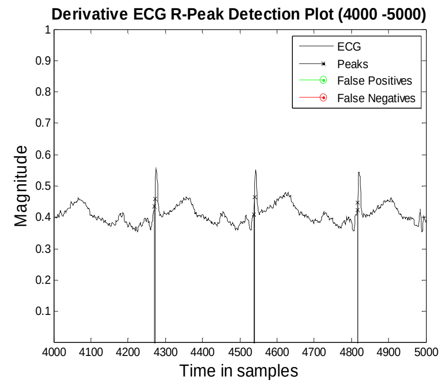


mitdb 200



mitdb 200





mitdb 228 mitdb 228

Fig.11. (a) DWT QRS detector for mitdb100, mitdb203, mitdb200, mitdb228

(b) Derivative based QRS detector for mitdb100, mitdb203, mitdb200, mitdb228

B. Overall Performance

We have applied two different algorithms on problematic ecg signals but actually to check the performance capability of the algorithm can only be done when it is tested on larger data. The result error rates of both algorithms are listed in tabular form below (refer figure 11). Even when there is presence of noise in the ECG signal, the QRS detectors should have a good performance. Thus we summarize the performance of the Wavelet based and Derivative based QRS detector with the use of channel 1 ECG from MIT/BIH Database. The figure 17, displays the performance efficiencies of both the algorithms.

MIT Arrhythmia Database(650000 samples)		Performance of DWT QRS Detector			Performance of Derivative based QRS Detector		
Signal	No. of beats	F_p	F_n	% error	F_p	F_n	% error
100	2273	76	1	3.4	159	1	7
203	2980	429	1887	77.7	61	2889	98.9
200	2601	605	118	27.7	424	1737	83.4
228	2053	303	84	18.8	119	640	36.9

Fig. 12. Performance of QRS Detectors

V. CONCLUSION

In this project, a QRS detection algorithm was designed based on the Wavelet transform. We have described the properties of the wavelet transform necessary for ECG signal processing. Significantly, the property of correlation between the onset of the local maxima of signal and dyadic scales is used. The performing capability of this detector was checked by testing the algorithm on MIT/BIH Arrhythmia database. Also, comparison of these results to Derivative based QRS detection algorithms was obtained. The wavelet transform base QRS detector displayed better performance than the other algorithm based on differentiation. Also, for all the cases presented in the simulation, the wavelet based detector did not miss as many QRS complexes as the derivative based other algorithm did which was indicated by the number of false negatives values. Thus the performance capability of the wavelet based QRS detector can be improved by optimization of the threshold. Thus, we can say that the wavelet based detector is robust to noisy signals and is flexible in analyzing the time varying structure of ECG data which are the main advantages over the existing techniques. In this study, we make use of a fixed threshold and optimize further the peak location selection. Future work guarantees the improved performance by the use of adaptive thresholding and peak pruning techniques [3].

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[3] Wavelet Transform-Based QRS Complex Detector

Shubha Kadambe,* Member, IEEE, Robin Murray, and G. Faye Boudreaux-Bartels

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VII. APPENDIX

WT- Wavelet Transform
DWT- Discrete Wavelet transforms
CWT- Continuous Wavelet transforms
x(n)- Input Signal
y(n)- Output Signal
Θ- Threshold value of amplitude of the signal
Θx- 0.3 to 0.4 * max(amplitude of signal)
Ψ- Wavelet function
$L^2(R)$ - Hilbert space for square integral functions
j,k – Integers used for scaling the wavelet function ψ
c- Wavelet coefficients
$a=2^{-j}$ – binary dilation
$b=k2^{-j}$ – binary position
$[W_\psi f](a, b)$- Integral Wavelet transform
G0, G1- Low pass filters
H0, H1- High pass filters
$\emptyset -$ Dilation value for wavelet transforms
S- Scaling factor of dilation of Wavelet transform
$\delta -$Integral dilation equation
N- even integer representing scaling function in wavelet transform
D- multiple of N
L= length of input signal
i-integer values
i_m - start value of scale for wavelet transform (usually 1)
i_u- end value scale for wavelet transform (usually 3 for ecg signal)
mitdb100- Signal 100 from MIT-BIH Arrhythmia Database
mitdb203- Signal 203 from MIT-BIH Arrhythmia Database
mitdb200- Signal 200 from MIT-BIH Arrhythmia Database
mitdb228- Signal 228 from MIT-BIH Arrhythmia Database
F_p- False Positives in Peaks
F_n- False Negatives in Peaks