Wavelet based QRS detection in ECG using MATLAB

K.V.L.Narayana (Corresponding author)

Department of Electronics and Instrumentation Engineering, GITAM Institute of Technology,

GITAM University, Visakhapatnam, Andhrapradesh, India.

E-mail:kvl007in@yahoo.co.in

A.Bhujanga Rao

Department of Instrument Technology, Andhra University College of Engineering,

Visakhapatnam, Andhrapradesh, India

E-mail:dr_abrao@yahoo.com

Received: October 24, 2011

Accepted: October 29, 2011

Received: October 21, 2011

Abstract

In recent years, ECG signal plays an important role in the primary diagnosis, prognosis and survival analysis of heart diseases. Electrocardiography has had a profound influence on the practice of medicine. This paper deals with the detection of QRS complexes of ECG signals using derivative based/Pan-Tompkins/wavelet transform based algorithms. The electrocardiogram signal contains an important amount of information that can be exploited in different manners. The ECG signal allows for the analysis of anatomic and physiologic aspects of the whole cardiac muscle. Different ECG signals from MIT/BIH Arrhythmia data base are used to verify the various algorithms using MATLAB software. Wavelet based algorithm presented in this paper is compared with the AF2 algorithm/Pan-Tompkins algorithms for signal denoising and detection of QRS complexes meanwhile better results are obtained for ECG signals by the wavelet based algorithm. In the wavelet based algorithm, the ECG signal has been denoised by removing the corresponding wavelet coefficients at higher scales. Then QRS complexes are detected and each complex is used to find the peaks of the individual waves like P and T, and also their deviations.

Keywords: Electrocardiogram (ECG), AF2 Algorithm, MATLAB, Pan-Tompkins algorithm, Wavelet Transform, Denoising

1. Introduction

The ECG is nothing but the recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. The time domain method of ECG signal analysis 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 can be 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 electrocardiology. 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 opt 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. Electrocardiography has a basic role in cardiology since it consists of effective, simple, noninvasive, low-cost procedures for the diagnosis of cardiovascular disorders that have a high epidemiological incidence and are very relevant for their impact on patient life and social costs.

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 activity passing through the heart muscle which enables to find whether the parts of the heart are too large or overworked. 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, 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

.

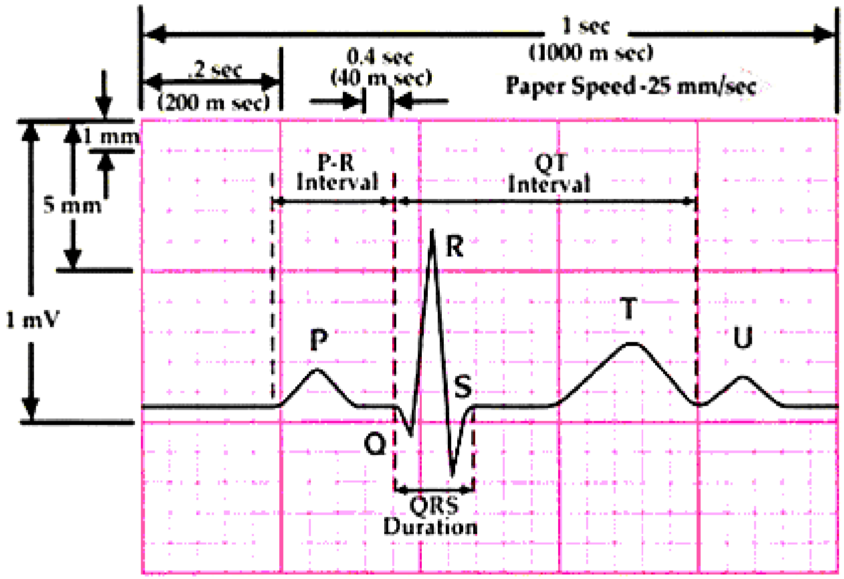

Figure 1. A typical cardiac waveform

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 provide 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.

Software QRS detection has been a research topic for more than 30 years. The evolution of these algorithms clearly reflects the great advances in computer technology. Whereas in the early years the computational load determined the complexity and therefore the performance of the algorithms, nowadays the detection performance is the major development objective. The computational load becomes less and less important. The only exception from this trend is probably the development of QRS detection algorithms for battery-driven devices. Within the last decade, many new approaches to QRS detection have been proposed by Rosaria Silipo and Carlo Marchesi (1998), by V.X. Afonso, W.J. Tompkins (1999); for example, algorithms from the field of artificial neural networks, genetic algorithms, wavelet transforms, filter banks as well as heuristic methods mostly based on nonlinear transforms.

2. Description of Algorithms

2.1AF2 Algorithm

This algorithm is an adaptation of the analog QRS detection scheme developed by "Both Fraden & Neuman (1980). A threshold is calculated as a fraction of the peak value of the ECG.

$$\text{Amplitude threshold} = 0.4 \max[X(n)], \quad 0<n<8191 \tag{1}$$

The raw data is then rectified:

$$Y0(n) = X(n) \quad \text{if } X(n) \geq 0 \quad 0 < n < 8191 \tag{2}$$

$$Y0(n) = -X(n) \quad \text{if } X(n) > 0 \quad 0 < n < 8191$$

The rectified ECG is passed through a low level clipper:

$$Y1(n) = Y0(n), \text{ if } Y0(n) \geq \text{amplitude threshold} \tag{3}$$

$$Y1(n) = \text{Amplitude threshold if } Y0(n) < \text{Amplitude threshold}$$

The first derivative is calculated at each point of the clipped, rectified array:

$$Y2(n) = Y1(n+1) - Y1(n-1) \quad 1 < n < 8190 \tag{4}$$

A QRS candidate occurs when a point in Y2 (n) exceeds the fixed constant threshold, Y2 (i) > 0.7.

2.2 Pan-Tompkins Algorithm

The QRS detection provides the fundamentals for almost all automated ECG analysis algorithms. Pan-Tompkins proposed a real-time QRS detection algorithm based on analysis of the slope, amplitude, and width of the QRS complexes of typical cardiac signal as shown in Fig. 1. The algorithm includes a series of filters and operators that perform derivative, squaring, integration, adaptive thresholding operations and search procedures, detailed in the next sections and shown in Figure 2.

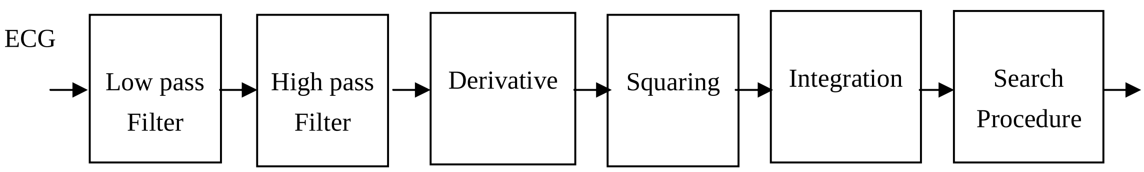

Figure 2. Steps in implementation of Pan-Tompkins Algorithm

2.2.1 Band pass Filtering

The band pass filter for the QRS detection algorithm reduces noise in the ECG signal by matching the spectrum of the average QRS complex. This attenuates noise due to muscle noise, power line interference, baseline wander, T wave interference. The pass band that maximizes the QRS energy is in the 5Hz-35Hz range. The filter implemented in this algorithm is composed of cascaded high pass and low pass Butterworth IIR filters.

2.2.2 Derivative Operator

The next processing step is differentiation, standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves. The derivative procedure suppresses the low frequency components of P and T waves, and provides a large gain to the high-frequency components arising from the high slopes of the QRS Complex.

2.2.3 Squaring

The squaring operation makes the result positive and emphasizes large differences resulting from QRS complexes; the small differences arising from P and T waves are suppressed. The high frequency components in the signal related to the QRS complex are further enhanced. This is a nonlinear transformation that consists of point by point squaring of the signal samples.

2.2.4 Integration

The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a suitable interval, advances one sample interval, and integrates the new predefined interval window. The half-width of window has been chosen as 27 to include the time duration of extended abnormal QRS complexes, but short enough that it does not overlap both a QRS complex and a T-wave. MA (moving average) filter extracts features in addition to the slope of the R wave. It is implemented with the following difference equation:

$$Y\,(nT) = \frac{1}{N[X(nT-(N-1)T)+---+X(nT)]} \qquad (5)$$

Where, N=1+2M is the number of samples in the width of the moving window. M is Half-width of moving average filter.

The choice of the duration of the sliding window results in a tradeoff between false and missed detections. A large number of QRS detection schemes are described by B.U.Kohler, C.Hennig, and R.Orglmeister (2002). The ability to detect the presence of disorder of concern and percentage of detection peaks that are actually present i.e. sensitivity & efficiency, of Pan-Tompkins algorithm are more than 99%. The computational load is also low.

2.3Wavelet transform

A wavelet is simply a small wave which has energy concentrated in time to give a tool for the analysis of transient, nonstationary or time-varying phenomena such as a wave shown in Figure 3.

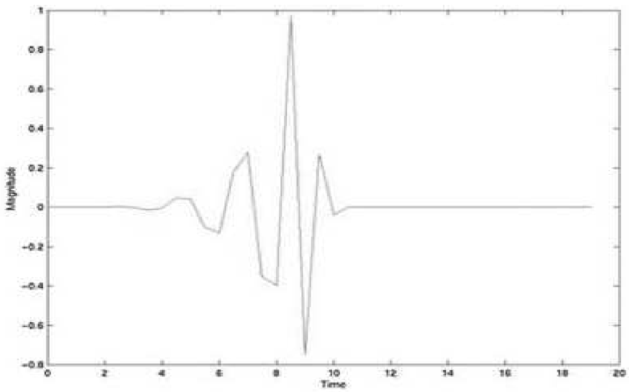

Figure 3.Wavelet function.

A signal as the function of f(t), can often be better analyzed and expressed as a linear decomposition of the sums: products of the coefficient and function. In the Fourier series, one uses sine and cosine functions as orthogonal basis functions. But in the wavelet expansion, the two-parameter system is constructed such that one has a double sum and the coefficients with two indices. The set of coefficients are called the Discrete Wavelet Transform (DWT) of f(t). Namely called a wavelet series expansion which maps a function of a continuous variable into a sequence of coefficients much of the same way as Fourier series dose with the main useful four properties. The representation of singularities, the representation of local basis functions to make the algorithms adaptive in-homogeneities of the functions, also they have the unconditional basis property for a variety of function classes to provide a wide range of information about the signal. They can represent smooth functions. In the wavelet transform, the original signal (1-D, 2-D, 3-D) is transformed using predefined wavelets. The wavelets are orthogonal, orthonormal, or biorthogonal, scalar or multiwavelets. In discrete case, the wavelet transform is modified to a filter bank tree using the Decomposition/ reconstruction given in Figure 4.

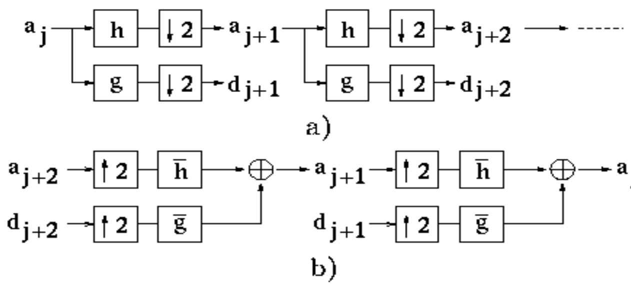

Figure 4. Filter bank tree of a) Decomposition and b) Reconstruction

The wavelet transform is a convolution of the wavelet function $\psi(t)$ with the signal $x(t)$. Orthonormal dyadic discrete wavelets are associated with scaling functions $\varphi(t)$. The scaling function can be convolved with the signal to produce approximation coefficients S. The discrete wavelet transform (DWT) can be written as

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)dt \qquad (6)$$

By choosing an orthonormal wavelet basis $\psi_{m,n}(t)$ we can reconstruct the original. The approximation coefficient of the signal at the scale *m* and location *n* can be written as

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\phi_{m,n}(t)dt \qquad (7)$$

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

$$x_0(t) = x_M(t) + \sum_{m=1}^{M} d_m(t) \qquad (8)$$

Where the mean signal approximation at scale *M* is

$$x_M(t) = S_{M,n}\phi_{M,n}(t) \qquad (9)$$

And detail signal approximation corresponding to scale *m*, for finite length signal is given by

$$d_m(t) = \sum_{n=0}^{M-m} T_{m,n}\psi_{m,n}(t) \qquad (10)$$

The signal approximation at a specific scale is a combination of the approximation and detail at the next lower scale.

$$x_m(t) = x_{m-1}(t) - d_m(t) \qquad (11)$$

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 based algorithm has been implemented using MATLAB software. MATLAB is a high performance; interactive system which allows to solve many technical computing problems. The MATLAB software package is provided with wavelet tool box. It is a collection of functions built on the MATLAB technical computing environment. It provides tools for the analysis and synthesis of signals and images using wavelets and wavelet packets within the MATLAB domain.

3. Detection of QRS Complex

The detection of the QRS complex—specifically, the detection of the peak of the QRS complex, or R wave—in an electrocardiogram (ECG) signal is a difficult problem since it has a time-varying morphology and is subject to physiological variations due to the patient and to corruption due to noise. Since the QRS complexes have a time-varying morphology, they are not always the strongest signal component in an ECG signal. Therefore, P-waves or T-waves with characteristics similar to that of the QRS complex, as well as spikes from high frequency pacemakers can compromise the detection of the QRS complex. In addition, there are many sources of noise in a clinical environment that can degrade the ECG signal. These include power line interference, muscle contraction noise, poor electrode contact, patient movement, and baseline wandering due to respiration. Therefore, QRS detectors must be invariant to different noise sources and should be able to detect QRS complexes even when the morphology of the ECG signal is varying with respect to time. Most of the current QRS detectors can be divided into two stages as shown in Figure 5.: a preprocessor stage to emphasize the QRS complex and a decision stage to threshold the QRS enhanced signal.

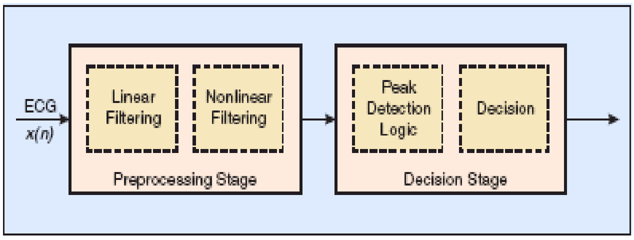

Figure 5.Common Structure of the QRS Detectors

Typically, the preprocessor stage consists of both linear and nonlinear filtering of the ECG.

4. Results and Discussion

The various algorithms have been implemented using MATLAB to find QRS complex only and tested with data available from MIT/BIH arrhythmia data base. The ECG record 100.dat of ten seconds duration as shown in Figure 6 has been used to validate the algorithms and the following things are observed.

- AF2 algorithm is fast in detecting QRS complex in comparison to Pan-Tompkins algorithm

  Delay of low-pass filter=16msec

  Delay of high-pass filter=64msec

  Delay of derivative filter=8msec

  Delay of slope finding step in AF2=4msec

  Delay of Moving Window Integration=60ms

  The total delay in AF2 algorithm is 84ms and in case of Pan-Tompkins algorithm, it is 148ms.So, Pan-Tompkins algorithm causes 64msec more delay than AF2 algorithm.
- The Moving Window Integration of Pan-Tompkins algorithm gives both width and slope information of QRS, but it costs 150ms delay.
- The delay in AF2 can further be reduced by skipping the low pass filter step if we try to find only the QRS. Since AF2 is highly immune to high frequency noises. But this step is needed for P wave detection.
- Due to the large delay caused the memory requirement is also high in Pan-Tompkins's algorithm, whereas in AF2 algorithm memory requirement is very less.
- Pan-Tompkins's algorithm does not give the information about the amplitude of R-peak, which is also to be found.
- The choice of the MWI window width 'W' is to be made with following considerations: If 'W' is very large it will result QRS and T waves being merged. If 'W' is too small a value could yield several peaks for a single QRS. A window width of 'W'=35 is found to be suitable for sampling rate=360Hz.
- The no. of beats in one minute is found to be 70-89 for record 100 of MIT/BIH Arrhythmia Database. Thus for 2 sec; the no. of beats can vary from 2 to 3. The no. of QRS complexes detected for AF2 Algorithm is 3 where as Pan-Tompkins Algorithm results 3 QRS complexes as shown in Figure 7. With respect to number of false detections or missed detections both algorithm do not defer much.
- The discrete wavelet transforms: The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high frequency components. The original signal we could consider as the approximation at level 0,denoted by A0.The words "approximation" and "detail" are justified by the fact that A1 is an approximation A0 taking in to account the low frequencies of A0.where as the detail D1 corresponds to the "high frequency" correction. The approximations and details of ECG record 100.dat are shown in Figure 8. to Figure 10.

$$S=A1+D1;\ A1=A2+D2;$$

$$A2=A3+D3;\ A3=A4+D4;$$

$$S=A4+D4+D3+D2+D1.$$

Scale	1	2	3	4
Resolution	1	1/4	1/8	1/16.

5. Conclusion

Since the application of wavelet transformation in electrocardiology is relatively new field of research, many methodological aspects (Choice of the mother wavelet, values of the scale parameters) of the wavelet technique will require further investigations in order to improve the clinical usefulness of this novel signal processing technique. Simultaneously diagnostic and prognostic significance of wavelet techniques in various fields of electro cardiology needs to be established in large clinical studies.

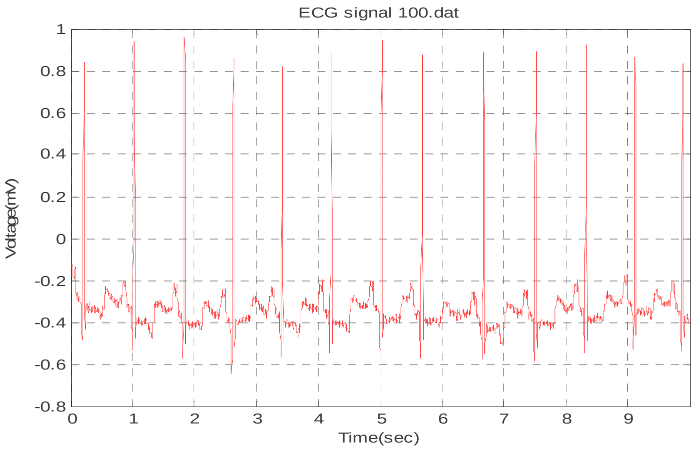

Figure 6. The ECG record 100.dat of 10 sec duration

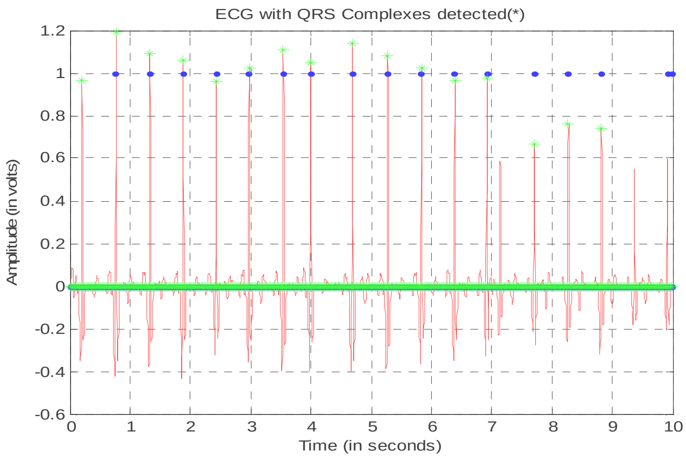

Figure 7. ECG record 100.dat with QRS Complex detection

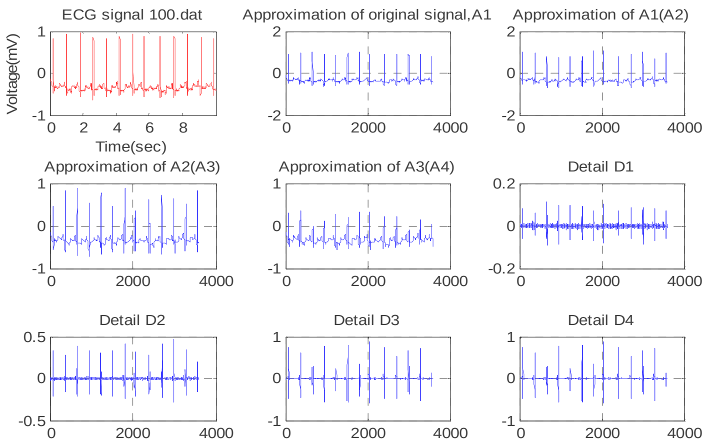

Figure 8. Wavelet based analysis of ECG record 100.dat

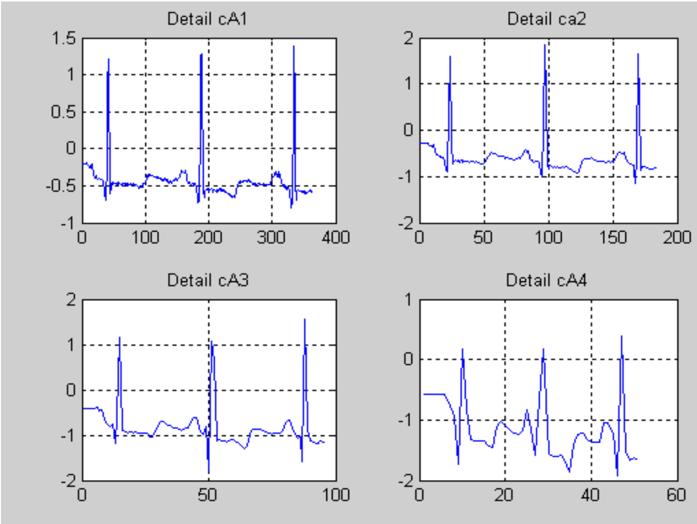

Figure 9. Approximations A1 to A4

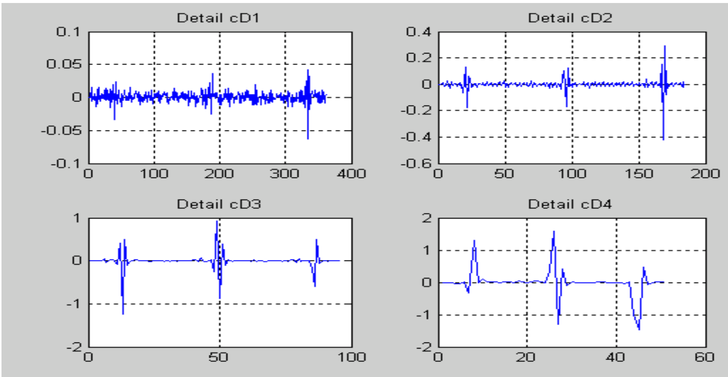

Figure 10. Details cD1 to cD4

References

B.U.Kohler, C.Hennig, & R.Orglmeister (2002), “The principles of software QRS detection”, *IEEE Eng. Med. Biol. Mag.*, vol. 21, pp. 42–57.

C. Li & C. Zheng (1995), “Detection of ECG characteristic points using wavelet transforms”, *IEEE Trans. Biomed. Eng*., vol. 42, no.1, pp. 21–28.

Cuiwei Li & Chongxun Zheng (1993), “QRS detection by wavelet transform”, *Proceedings of Annual Conference on Eng .in Med. and Biol.*, vol. 15, pp.330-331.

J. Fraden & M.R. Neumann (1980), “QRS wave detection”, *Med. Biol. Eng. Comput.*, vol. 18, pp. 125-132.

P. Trahanias & E.Skordalakis (1990), “Syntactic pattern recognition of the ECG,”, *IEEE Trans. Pattern Anal. Machine Intelligence*, vol. 12, pp. 648-657.

Rosaria Silipo & Carlo Marchesi, member IEEE (1998), “Artificial Neural Networks for Automatic ECG Analysis”, *IEEE transactions on signal processing*, vol.46, No.5.

V.X. Afonso, W.J. Tompkins, T.Q. Nguyen, & S. Luo (1999), “ECG beat detection using filter banks”, *IEEE Trans. Biomed. Eng*., vol. 46, pp. 192-202.

D.C.Reddy. (2005), *Biomedical signal processing principles and techniques* (1st edition), New Delhi: Tata McGraw- Hill Publishing Company Limited.

K.V.L.Narayana & A.Bhujanga Rao (2010), "A Knowledge-Based Approach to Cardiac Signal Analysis using Lab VIEW", *Proceedings of the IEEE International Conference on Power, Control and Embedded Systems*", MNNIT, Allahabad.

Massachusetts Institute of Technology, MIT-BIH ECG Database. [Online] Available: http://ecg.mit.edu