A

Dissertation

on

Detection of ECG signals using Wavelet based ECG Detector

submitted in

partial fulfilment of the requirement

for the award of the degree of

Master of Technology

in

VLSI Design and Embedded System

Submitted
by

Milova Paul
University Roll No. 2K12/VLS/13

Under the Guidance of

Dr. Rajiv Kapoor
Professor (HOD),
Department of Electronics and Communication Engineering
Delhi Technological University

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

2012-2014

Electronics and Communication Engineering Department
Delhi Technological University
Delhi-110042
www.dce.edu

CERTIFICATE

This is to certify that the dissertation titled "**Detection of ECG signals using Wavelet based ECG Detector**" is a bonafide record of work done by **Milova Paul, Roll No. 2K12/VLS/13** at **Delhi Technological University** for partial fulfilment of the requirements for the degree of Master of Technology in VLSI and Embedded System Design. This project was carried out under my supervision and has not been submitted elsewhere, either in part or full, for the award of any other degree or diploma to the best of my knowledge and belief.

(Dr. Rajiv Kapoor)
Professor (HOD)
Department of Electronics and Communication Engineering
Delhi Technological University

ACKNOWLEDGEMENT

I would like to express my deep sense of respect and gratitude to my project supervisor **Dr. Rajiv Kapoor**, Professor (HOD), Electronics and Communication Engineering Department, DTU for providing the opportunity of carrying out this project and being the guiding force behind this work. I am deeply indebted to him for the support, advice and encouragement he provided without which the project could not have been a success.

I would also like to acknowledge Delhi Technological University for providing the right academic resources and environment for this work to be carried out.

Last but not the least I would like to express sincere gratitude to my parents and my colleagues for constantly encouraging me during the completion of work.

Milova Paul

University Roll no: 2K12/VLS/13

M.Tech (VLSI and Embedded System Design)

Department of Electronics & Communication Engineering

Delhi Technological University
Delhi – 110042

ABSTRACT

Recent researches are focused on monitoring and processing of biomedical signals. Electrocardiogram (ECG) is a non- invasive technique which plays a very important role in detection and diagnosis of such signals. ECG is the recording of a signal which interprets the electrical activity of the heart over a period of time, which is detected by electrodes attached to the surface of the skin. This electrical activity is demonstrated by certain changes of electrical voltage on the body surface. And these changes are recorded by summarizing the electrical activity of all heart cells.

The digital signal processing algorithms which analyze ECG signals are mainly divided in three categories: time domain, frequency domain and time- frequency domain. The algorithm using time- frequency domain analysis overcomes the drawbacks suffered by earlier two methods. The time domain algorithms do not provide high quality results whereas, the frequency domain algorithms cannot specify the exact phase of the heart cycle during which changes take place.

The ECG signal is basically a non- stationary signal, as it changes its physiological and statistical property with respect to time and so wavelet transforms are a useful tool to study such types of signals. Wavelet Transform (WT) utilizes time- frequency analysis which is used for detection of ECG signals and their implementation.

In this work, the conventional wavelet based ECG detector has been studied in detail and simulated using MATLAB (R2012b). The design for detection of ECG signals has been extended to employ multiwavelet approach. This proposed ECG detector architecture has been simulated and verified in terms of its workability.

KEYWORDS: Electrocardiogram (ECG), Wavelet Transform (WT), Multi-scaled Product, Multi-wavelet Approach.

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CHAPTER 1

INTRODUCTION

1.1. Motivation

In the last fifteen years, huge part of the research has been focussed on the processing of biomedical signals. Therefore, in medical data analysis, automatic processing systems are frequently used. Electrocardiogram (ECG) plays a very important role in monitoring and processing of such signals. It is a non-invasive technique which is used for diagnosing cardiovascular diseases.

In our ever-changing society, everyone has a lot of responsibilities; stress is a major cause of poor job performance, illness and diseases. These major problems can be prevented by rapid detection of symptoms and proper medical action. And so, ECG detection systems were developed to cater this need.

ECG is the recording of a signal which interprets the electrical activity of the heart over a period of time, which is detected by electrodes attached to the surface of the skin. This electrical activity is demonstrated by certain changes of electrical voltage on the body surface [1]. And these changes are recorded by summarizing the electrical activity of all heart cells.

Mostly analysis of ECG signals are done using simple as well as sophisticated algorithms of digital signal processing, which can broadly be sorted in three groups: time domain, frequency domain, and time-frequency domain. Of these, the first two classes belong to the classical methods, but they suffer from drawbacks which are overcome by using algorithms employing time-frequency domain. Analysis using time domain algorithms suffer from low sensitivity, and so they do not provide high quality results. Whereas, frequency analysis although increases the sensitivity, but it cannot specify the phase of the heart cycle in which these changes originated.

The electrocardiogram (ECG) signal is basically a non-stationary signal, as it changes its physiological and statistical property with respect to time. Wavelet Transforms are very useful for studying such types of signals. Wavelet Transform (WT) is the algorithm that uses the time-frequency analysis and it has become popular as it can be easily implemented and its results can be easily verified. There are many variants of WT available and the selection of a particular type of WT depends on the specific application. These attractive features of employing wavelet transform for detection of ECG signals have captured the interest of designers to implement new versions of ECG detectors.

1.2. Research Objective

There has been a shift of trend to use wavelet transform for detection and processing of ECG signals in contrast to the previously used derivative ECG detectors. The wavelet based detectors offer high performance and provides rapid analysis and detection of different ECG signals. Hence this thesis provides a novel approach for using multiwavelets in the classical wavelet based ECG detector. The objectives formulated for this research work are:

- To establish an overview of basic ECG detectors and their characteristics
- In depth study of the fundamental working principle of ECG and the incorporation of wavelets in its detection process
- To simulate classical wavelet based ECG detector
- To introduce novel detector design employing multiwavelet approach
- Verification of proposed design using MATLAB simulations

1.3. Thesis Outline

The remainder of the thesis is organized as follows:

Chapter 2 contains a review of the basic literature related to ECG detectors. Different approaches starting from time domain analysis to neural network and wavelet transform analysis are discussed.

Chapter 3 describes the basic principle and working of ECG systems, which includes the study of different functional blocks and the importance of the QRS complex in a typical ECG wave.

The incorporation of wavelet transforms is introduced in Chapter 4. It starts with the brief introduction of Wavelet Transform along with its advantages over the classical Fourier Transform. Detailed explanation of ECG Detector with wavelet transform and multiscaled product is presented.

In Chapter 5, block by block simulation of the ECG Detector using multiscaled product is shown and relevant observations are drawn from the results. Also, the growing need of utilizing multiwavelets in the design is introduced.

Proposed design of Multiwavelet based ECG Detection System is provided in Chapter 6, the simulations and results are also verified concurrently.

Chapter 7 is the closing chapter of this report containing conclusion drawn in accordance with thesis objectives and discussion of future work in this area.

CHAPTER 2

LITERATURE REVIEW

2.1. Detection of ECG Signals

The detection of QRS complexes consists of two stages:

- Pre-Processing Stage:

  It is based on baseline wandering removal, high frequency noise removal and transformation of ECG waveforms to specific patterns.

- Decision Stage:

  It is to apply decision rules for QRS detection.

Many detection algorithms have been proposed in the literature to eliminate the noise effects and precisely detect the peak points of the ECG signal.

2.2. Literature Survey of ECG Detectors

2.2.1 Real Time ECG Detector Based on Time Domain Analysis – J . PAN (1985)

In this type of ECG Detector proposed by J. Pan, all the processing was done with integer arithmetic so that the algorithm can operate in real time. [1]

The signals in various steps of digital signal processing are shown in Fig.2.1.

First in order to attenuate noise, the original signal is passed to a digital band pass filter which is composed of cascaded high pass and low pass filters. Fig(b) shows the output of the digital band pass filter.

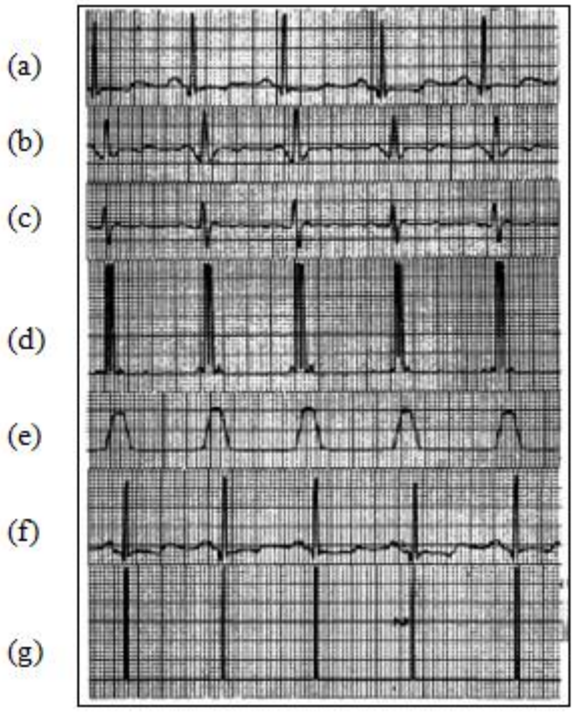

Fig. 2.1: QRS Detection Algorithm processing steps for a normal ECG.
(a) Original signal. (b) Output of Bandpass filter. (c) Output of Diffrentiator. (d) Output of squaring process. (e) Output of moving window integration. (f) Original ECG signal delayed by the total processing time. (g) Output pulse stream.

The next process after filtering is differentiation which is shown in Fig (c). This gives information about the slope of the QRS.

This process is followed by squaring [Fig (d)], which intensifies the slope of the frequency response curve of the derivative and restricts the false positives caused by the T- waves.

The next step after squaring is the moving window integration [Fig (e)], which produces a signal that includes information about both the slope and the width of the QRS complex.

Fig (f) is same as the original ECG [as in Fig (a)] except delayed by the total processing time of the detection algorithm.

Fig (g) shows the final output stream of pulse marking the locations of the QRS complexes after application of adaptive thresholds.

This detector used two sets of thresholds to detect the QRS complexes. One set thresholds the filtered ECG and the other set thresholds the signal produced by moving window integration. By using thresholds on both the signals the reliability is improved comparing to using one waveform alone.

The ECG is preprocessed with this digital band-pass filter which improves the SNR ratio and permits the use of lower thresholds than would be possible on the unfiltered ECG which increases the overall detection sensitivity.

There are two separate threshold levels in each of the two sets of thresholds, of which, one level is half of the other. The thresholds continuously adapt to the characteristics of the signal since they are based upon the most-recent signal and noise peaks that are detected in the ongoing processing of signals. If the program does not find a QRS complex in the time interval corresponding to 166 percent of the current average RR interval, the maximal peak detected in that time interval that lies between these two thresholds is considered to be a possible QRS complex, and the lower of the two thresholds is applied. Therefore, for storing past history of the ECG, a long memory buffer is not required and thus minimal computing time is needed to accomplish the procedure to look for a missing QRS complex.

(i) Band-pass Filter:

The band-pass filter reduces the interference of muscle noise, baseline wander, 60 Hz interference and T-wave interference. 5-15Hz is approximately the desirable passband to maximise the QRS energy. Since for this chosen sample rate band-pass filter could not be correctly designed, so a cascaded combination of a low-pass and a high-pass filter was used.

(ii) Derivative:

After filtering, the signal is differentiated to provide the slope information of the QRS complex. The transfer function used was,

$$H(z) = 1/8T\ (-z^{-2} - 2z^{-1} + 2z^{1} + z^{2})$$

(iii) Squaring Function:

After differentiation, point by point squaring of the signal is performed. The equation of this operation is,

$$y(nT) = [x(nT)]^2$$

This makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies (i.e. predominantly the ECG frequencies)

(iv) Moving Window Integration:

The main purpose of moving window integration is to obtain waveform feature information in addition to the slope of R wave. It is calculated from,

$$y(nT) = (1/N)\,[x(nT - (N-1)T] + [x(nT) - (N-2)T] + \ldots\ldots + x(nT)]$$

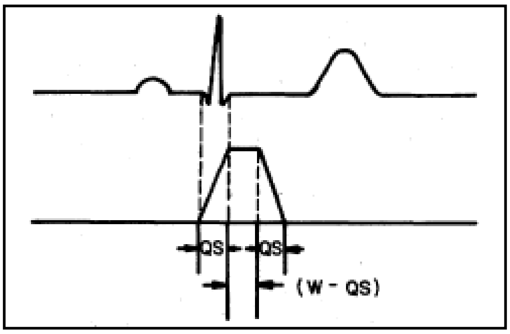

Fig.2.2: Relation of QRS complex to moving integration waveform

Drawbacks of J. Pan's ECG Detector

The major difficulty encountered in this approach was that extracting ECG signals by removing noises with a high order flat band-pass filter was quite difficult and the detection performance was degraded.

2.2.2 ECG signal detector using Artificial Neural Network – J. TOMPKINS (1994)

This ECG detector uses ANN i.e Artificial Neural Network for ECG detection and classification. An ANN model is a parallel, distributed, non-linear computing network that mimics the information processing structure of a biological neuron system, which makes it different from the conventional digital computer.[3]
This model used the feed forward multilayer perceptron (MLP), which has numerous applications in pattern classification, non-linear control, time series modelling and other areas.

In an ANN structure many simple, nonlinear processing elements, called neurons are interconnected via weighted synapses to form a network. Fig2.3 shows that the function of each neuron is to compute the weighted sum of all synapse inputs, subtract the sum from a predefined bias and pass the result through a threshold function whose output ranges between 0 and 1.

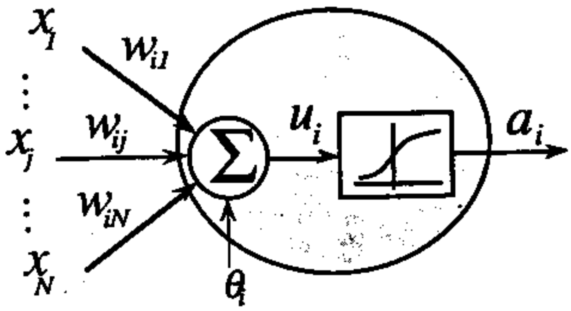

Fig.2.3: Basic ANN Structure

If these neurons are grouped together in layers with weighted synapses interconnecting only neurons in successive layers, the ANN structure is called an MLP model [Fig.2.4].

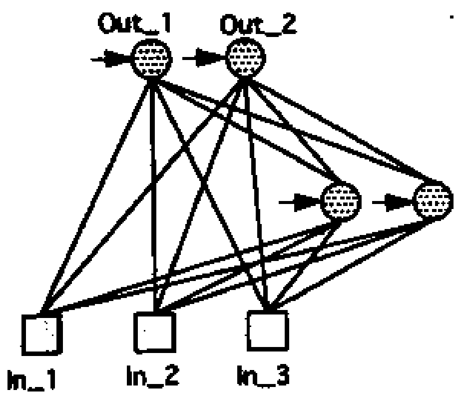

Fig.2.4: Multilayer Perceptron Model (MLP)

An MLP is capable of approximating any functional nonlinear mapping to arbitrary accuracy. The QRS detection system is shown as in Fig.2.5.

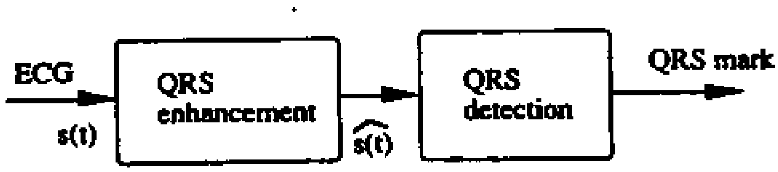

Fig.2.5: QRS Detection System

In the QRS enhancement phase, the background noise including P and T waves is removed so that the SNR is enhanced, this enhanced signal is then passed to the detection block to detect and mark the position of QRS complex.[3]

Here the electrocardiographic signal x(t) is assumed to be the superposition of the QRS complex s(t) and the background noise n(t). Therefore, x(t) = s(t) + n(t), and s^(t) is founded to be an approximation of s(t). This is done by the MLP model.

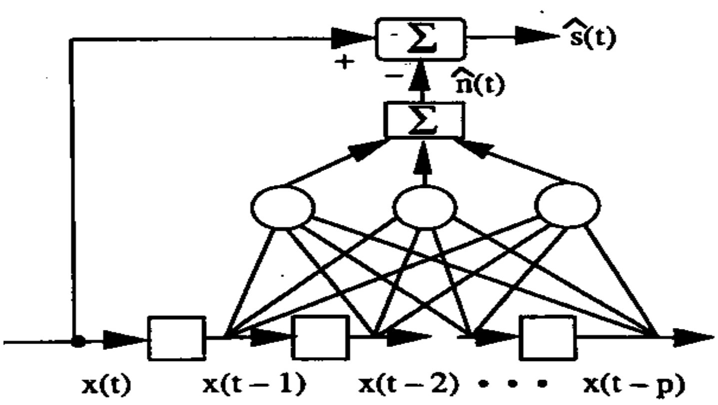

Fig.2.6: MLP based QRS Enhancement

Drawback of this model

This model incurred large computational burden which could be minimized.

2.2.3 QRS detection using Wavelet Transform and Neural Network based adaptive filtering- Szilagyi (2000)

This ECG signal detector used both the neural networks and the concepts of wavelet transform to detect the QRS complexes [4]. This algorithm is based on adaptive neural network whitening filter, wavelet transform and adaptive long and short term prediction. It consists of following steps:

- ANN- based filtering
- Wavelet transform based QRS detection
- Generic algorithm to determine the optimal wavelet parameters in processing time

The adaptive behaviour of the filter is assured by coefficients computed through Least Mean Square Algorithm (LMS).

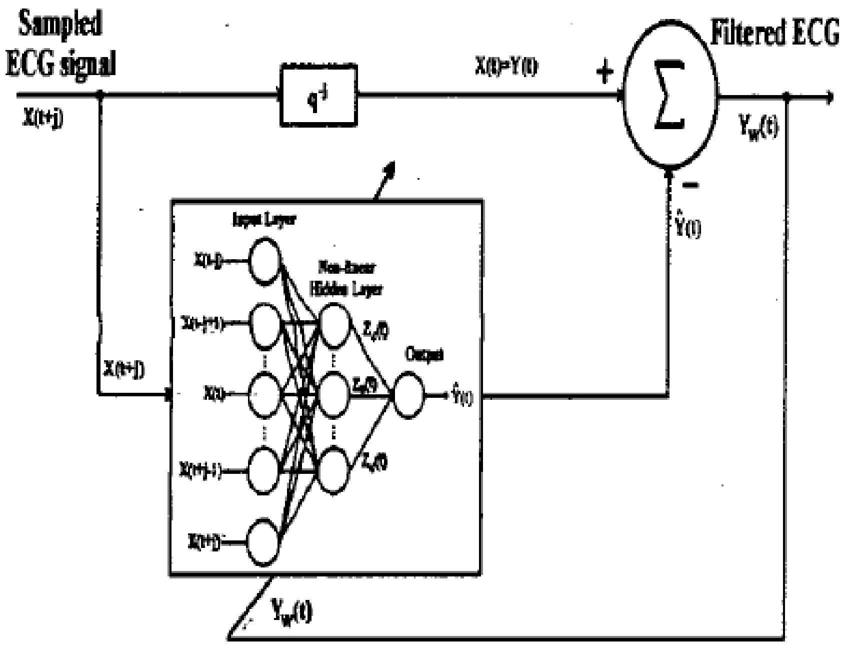

Fig.2.7: Structure of Adaptive Filter

Wavelets are one of the best transformation algorithms for QRS wave detection. The selected mother wavelet is,

$$\boldsymbol{\psi(t) = \frac{1}{\sqrt{2\pi}\,.\,\sigma}\,.\,e^{-\frac{t^2}{2\sigma}}\,.\,sin\,(\alpha.\,t.\,e^{-\beta|t|})}$$

where α and β is selected according to the highest frequency in the ideal ECG signal and σ is the variance used to modify the wavelets shape.

Drawbacks of this model

This model for ECG signal detection proved to be too complex for VLSI implementation.

2.2.4 Wavelet Transform based event detector for Cardiac Pacemaker-Olsson (2005)

This wavelet based ECG detector used wavelet filter banks (WFB) as a wavelet decomposer decomposing the input signals into many sub-bands. The WFB is a combination of a biphasic (antisymmetric) and a monophasic (symmetric) filter function [5]. The basic block diagram can be modelled as,

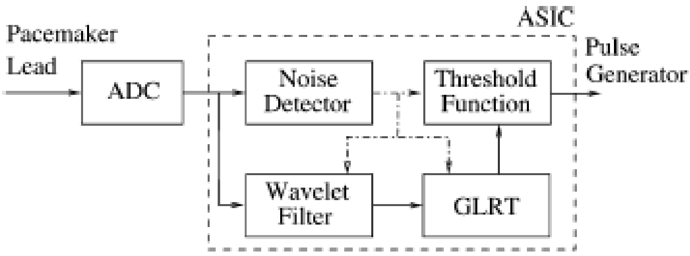

Fig.2.8: ECG Detector with WFB and GLRT

The GLRT i.e Generalized likelihood ratio test block processes the output of the wavelet filter bank before subjecting it to threshold rule. A basic GLRT block can be modelled as,

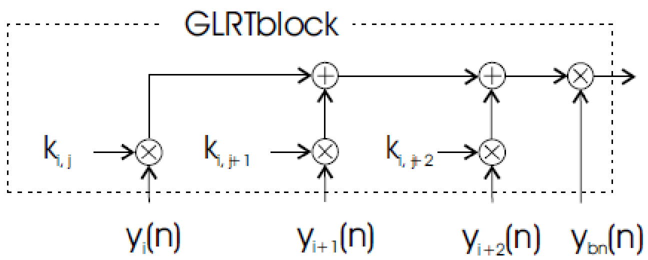

Fig.2.9: Typical GLRT Block

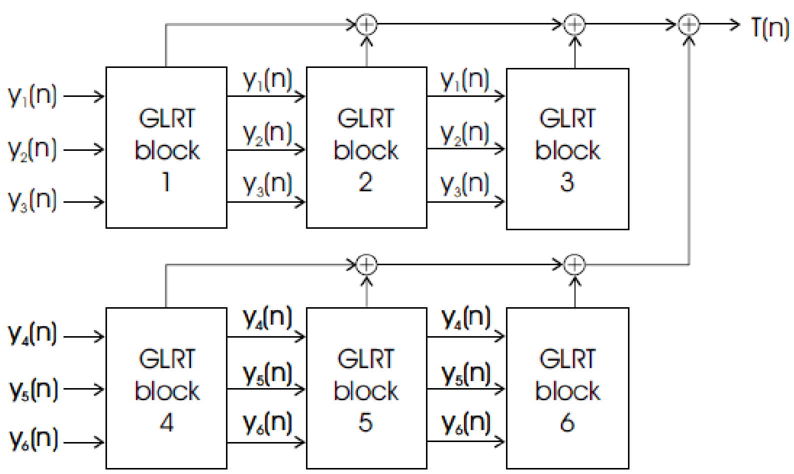

Fig. 2.10: A schematic block diagram employing GLRT

The transfer function of the biphasic wavelet filter bank is modelled as,

$h_{1,b}(n) = g_b(n)$

$h_{2,b}(n) = f(n) * g_b(2n)$

$h_{3,b}(n) = f(n) * f(2n) * g_b(4n)$

.

.

.

$h_{q,b}(n) = f(n) * ..... * f(2^{q-2}n) * g_b(2^{q-1}n),$

where q ϵ [2.4] is the scaling factor. The case q=1 is not considered as no filtering is defined a priori. The functions $g_b(n)$ and $f(n)$ are defined as,

$f(n)$ = [1 3 3 1] and $g_b(n)$ = [-1 1]

The block diagram of this conventional ECG detector can be shown in Fig.2.11.

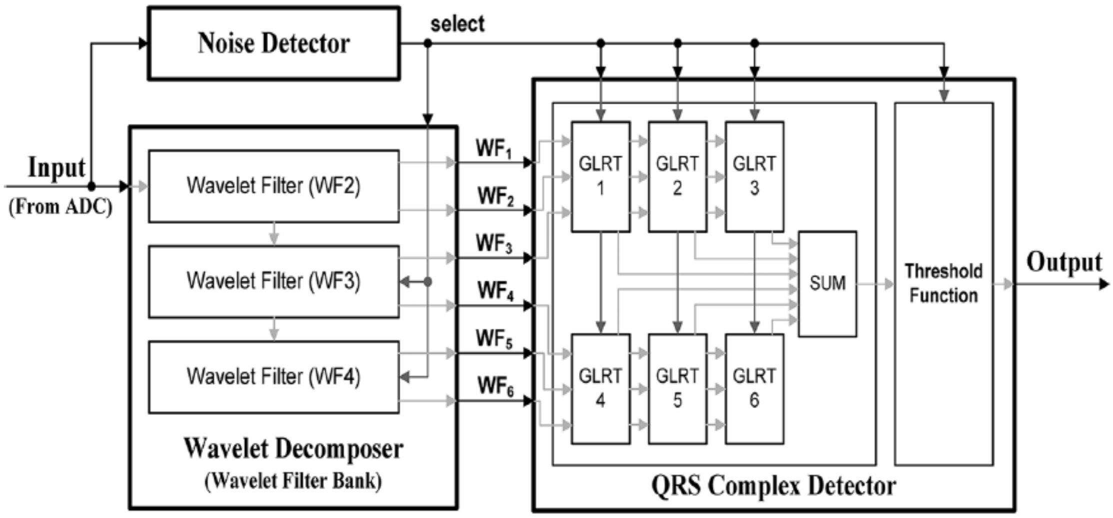

Fig.2.11: Conventional ECG Detector

The WFB's decompose the input ECG signals into sub-bands with two monophasic and biphasic outputs of WF_i and WF_{i+1}. With the decomposed WFB outputs, the GLRT with threshold function estimates the heart beating rate. The noise detector determines the operation mode according to the SNR of the input ECG signal, thereby reducing the power consumption.

Wavelet Decomposer:

The dyadic wavelet transform (DWT) is generally considered suitable for implementing the ECG detector due to its property of low complexity, as in [5]. To implement the dyadic wavelet transformer, both the decimator based and the undecimator based architectures with filter pairs of low-pass filter and high pass filter have been shown.

The transfer function of LPF and HPF of fig are,

$H(z) = 1+3z^{-1}+3z^{-2}+z^{-3}$

$G(z) = 1-z^{-1}$

Where, H(z) and G(z) are the transfer functions of LPF and HPF respectively in the WFB's.

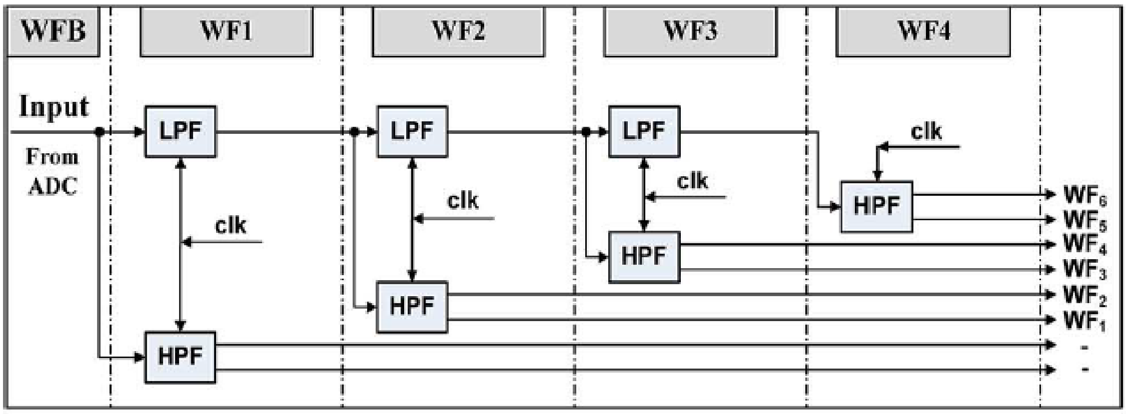

Fig.2.12: Undecimator based wavelet filter bank

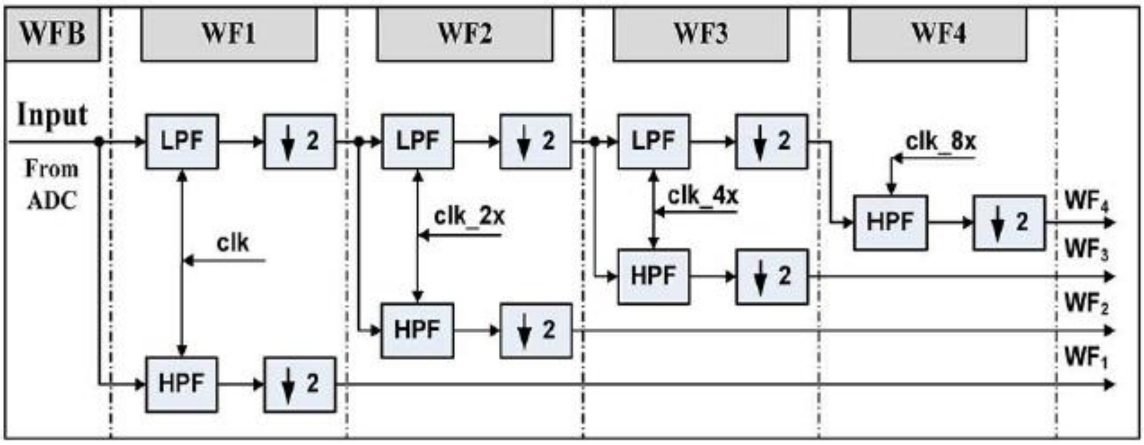

Fig.2.13: Decimator based wavelet filter bank

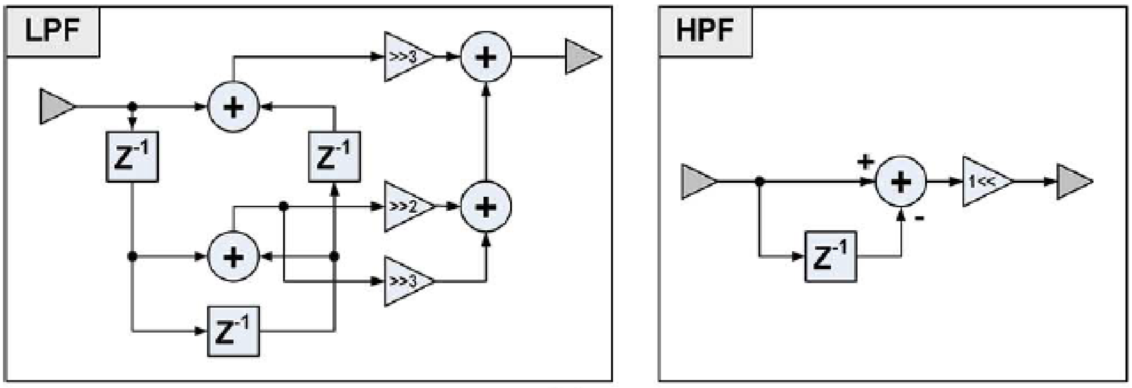

Fig.2.14: Schematic of LPF and HPF in filter banks

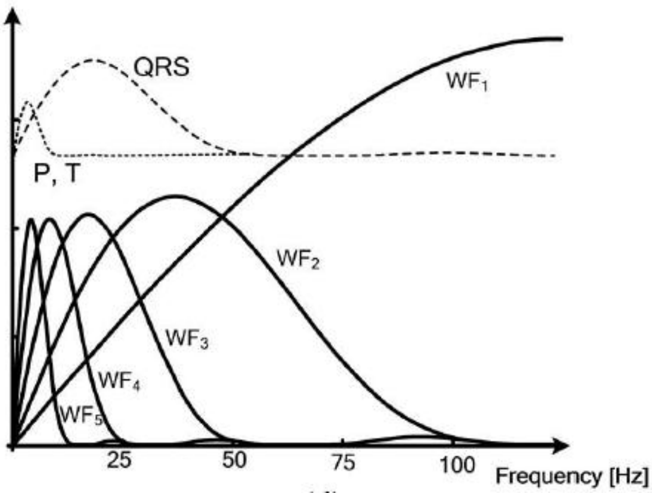

Fig.2.15: Frequency response of wavelets filter banks

QRS complex detector:

This block uses the hypothesis testing of the GLRT. The implementation of each GLRT block requires a considerable number of registers, adders and multipliers as the GLRT uses the maximum likelihood estimation of unknown parameters, shown in fig. The GLRT determines the presence of R-waves according to the test computations expressed as,

$$T(n) = x(n)^{T} \mathbf{H}(\mathbf{H}^{T}\mathbf{H})^{-1}\mathbf{H}^{T} x(n)$$

Where x(n) is the input to the WFB and **H** is the linear combination matrix of representative functions.

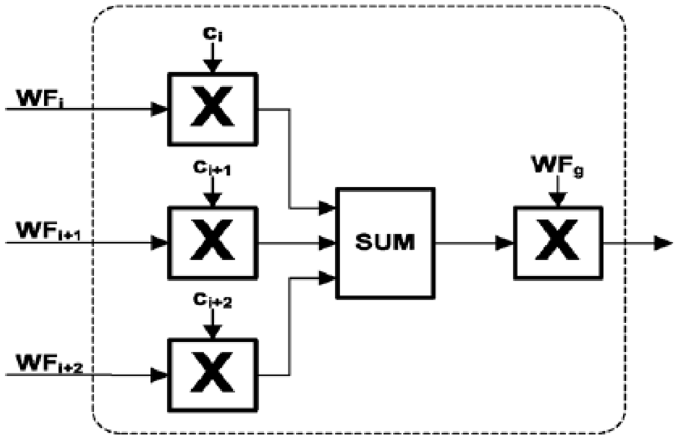

Fig.2.16: Conventional GLRT Block

Noise Detector:

The noise level inside the ECG detector is measured by counting the number of zero crossing points in a certain time interval. Therefore, the noise detector can be simply implemented using a counter of zero crossing points, a XOR gate and a reset counter. The schematic if the conventional noise detector is shown in Fig.2.17.

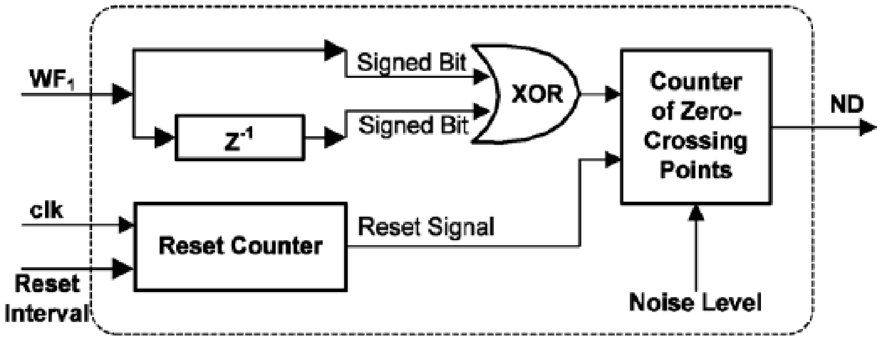

Fig.2.17: Noise Detector

The XOR gate detects the zero crossing points by comparing the sequential signs of the ECG input signal, which presents the difference between the current input and the previous input signals. The comparator with noise thresholds, zero crossing counts and reset with a fixed time interval, detects the SNR of the input ECG signal.

According to the detected SNR, the noise detector selects the operation mode and provides the control signal to GLRT.

Drawback of this model:

Large numbers of computations were required to calculate the zero crossing points which increased the power consumption of the detector.

2.2.5 QRS detection processor using Quadratic Spline Wavelet Transform – (2012)

This model basically focussed on detecting the QRS complexes for a wireless ECG acquisition system. There are essentially three functional blocks in this model:

- An analog front end for amplification and filtering
- An analog to digital convertor for digitization
- A wireless transmitter for delivering data to back end unit

To save power and increase the accuracy of the device QSWT i.e. Quadratic Spline Wavelet Transform, feature extraction and decision making stages are used.

In a typical ECG wave the RR interval is sufficient to calculate the Heart Rate Variability (HRV) of a person [11]. This used a 10-bit SAR ADC and wireless modules which transmitted data in different formats (QRS detection result, raw ECG or both).

The basic model for processor can be shown in Fig.2.18.

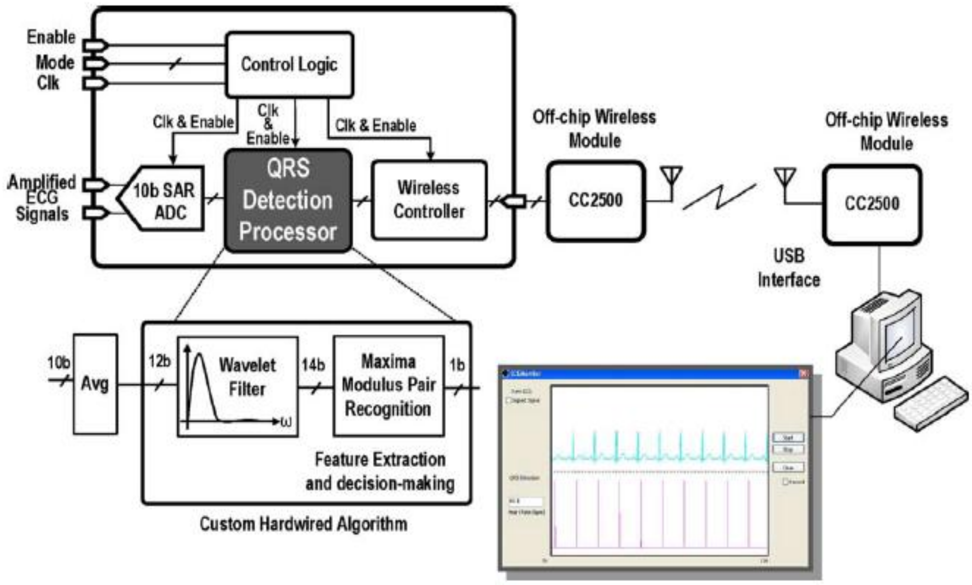

Fig.2.18: QSWT based QRS detection processor

There are three stages:

(i) **Quadratic Spline Wavelet Transform**:

The QSWT provides highest detection accuracy compared to other detection methods [16]. The Fourier transform characterizing its frequency response is shown as,

$$\psi(\omega) = i\omega \left[\frac{(\sin \omega/4)}{\omega/4}\right]^4$$

The corresponding filter coefficients are,

$$h(x) = \left[\frac{1}{8}\ \frac{1}{8}\ \frac{1}{8}\ \frac{1}{8}\right] \qquad g(x) = [-2\ 2]$$

(ii) **Feature extraction**:

This is performed by,

(a) Zero crossing detection
(b) Peak (zero derivative) detection
(c) Threshold adjustment

These features are extracted parallel to minimize clock rate and decrease power.

According to information given by these, FSM's change state on finding positive and negative peaks, a zero crossing point and a opposite direction peak and give the markings of temporal locations of QRS complexes.

Two FSM's are used where,
FSM1- is used for decision making
FSM2- is used for marking QRS complex positions according to signals from FSM1.

Four states in FSM are:
-seen_none
-seen_peak
-seen_zero
-seen_neagtive

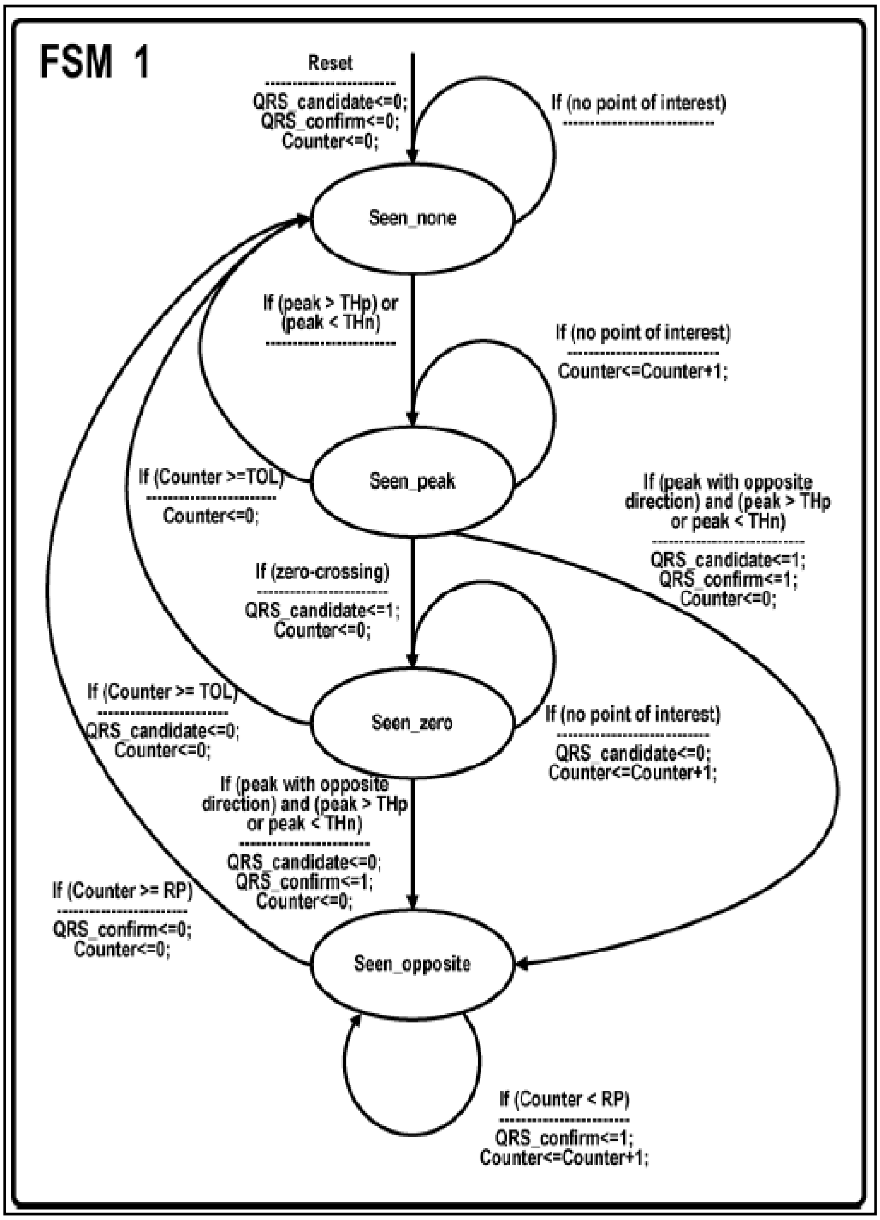

Fig.2.19: FSM 1 in QSWT based detector

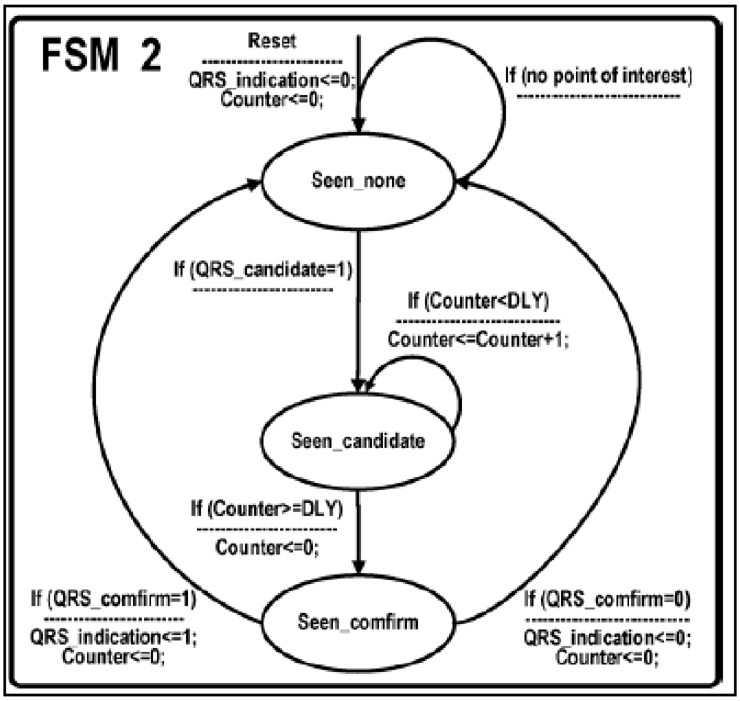

Fig.2.20: FSM 2 in QSWT based detector

The modulus maxima pair recognition structure which uses both the FSM's is shown in Fig.2.21.

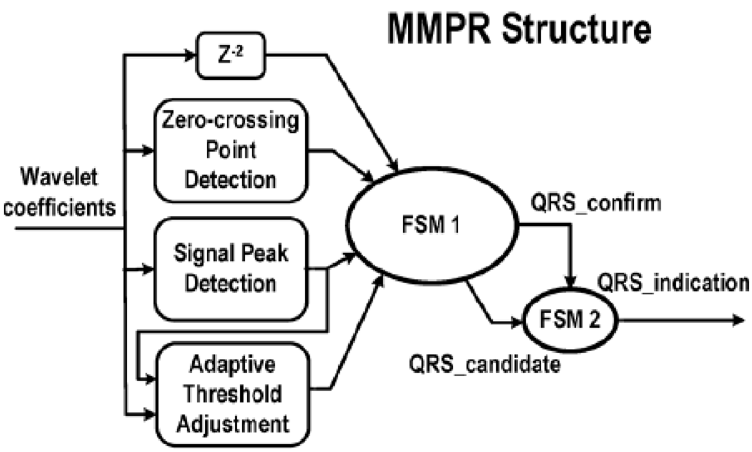

Fig.2.21: MMPR structure for QSWT based detector

Special decision rules are applied based on the FSM's output to mark down the temporal locations of the QRS complexes.

Drawbacks of this design

This ECG detector suffered from poor accuracy which could be further improved.

2.2.6 Wavelet Based ECG detector using Multi Scaled Products –(2013)

This model leads to significant power consumption reduction in hardware implementation, but the detection accuracy trades off, so to compensate it a soft threshold algorithm is used which can be implemented without large power and area overheads [13]. Therefore, the combination of multi-scaled product and soft threshold algorithm leads to a low power and highly reliable QRS detector.

The block diagram of the ECG detector which consists of a wavelet decomposer with WFB's, a noise detector with zero crossing points and a QRS complex detector, which replaces the GLRT and simple threshold functions used earlier.

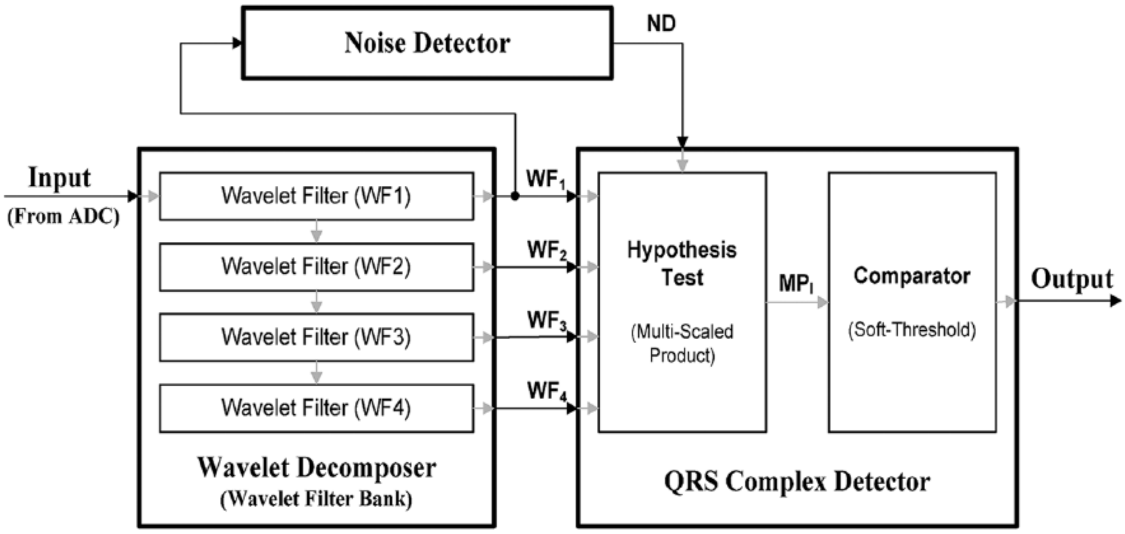

Fig.2.22: ECG detector using multi scaled products

CHAPTER 3

BASICS OF ELECTRO CARDIO GRAM (ECG)

3.1 Introduction to ECG

ECG is the recording produced by Electrocardiography, which is a transthoracic (across the thorax or chest) interpretation of the electrical activity of the heart over a period of time, as detected by electrodes attached to the surface of the skin [7].

An ECG is used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart, such as a Pacemaker.

Basically ECG is an instrument to trace heart’s electrical activity.

3.2 Block Diagram of ECG

The basic block diagram of ECG acquisition system consists of three stages:

- Input stage
- Processing stage
- Output stage

These stages in detail are shown in Fig.3.1.

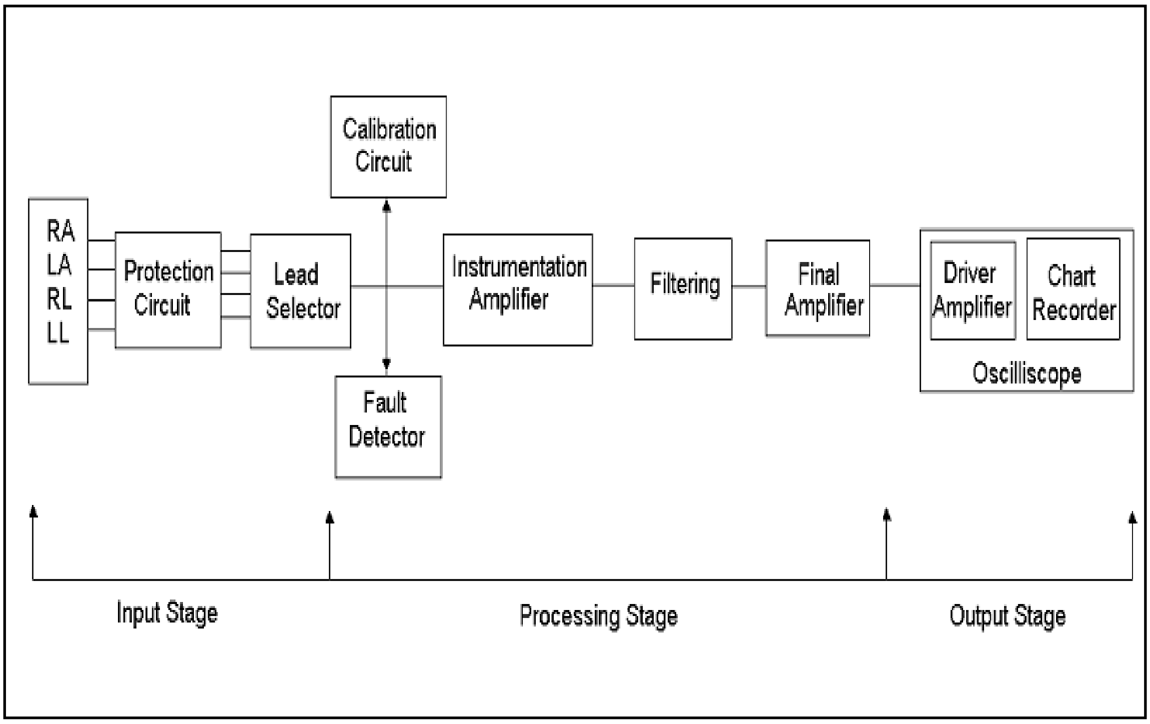

Fig.3.1: ECG Block Diagram

These stages are explained in detail as follows:

- **Input Stage**

  The input stage receives the signal from the ECG leads which are RA (right arm), LA (left arm), RL (right leg), LL (left leg). This stage consists of Protection circuit and a Lead Selector.

  - Protection Circuit :

    It protects the system from high level voltages or DC shock used to resuscitate heart attack patients.

  - Lead Selector:

    This design consists of switches which connect the patient leads to either non-inverting terminal (+) or inverting terminal (-) or CM of the amplifier.

- **Processing Stage**

  This stage consists of Calibration Circuit, Fault Detector, Instrumentation Amplifier and Filtering Blocks.

- Calibration Circuit :

  This circuit consists of resistive network connected to a voltage source that provides 1mV as its output. This is used to check the amplifying factor of the system before using the ECG machine.

- Fault Detector :

  Faults can be detected manually or automatically, depending on the operating modes and how much quickly the system needs to be restored. For systems that require human interfaces, the failures can be detected by human visual and/or auditory sensors.

- Instrumentation Amplifier :

  This is a kind of differential amplifier with input buffer amplifiers, which eliminate the need for input impedance matching thus, make it suitable for test equipment purposes. The differential gain of the instrumentation amplifier can be changed by simply changing the value of R_{gain}. These are used where great accuracy and stability of circuit are required.

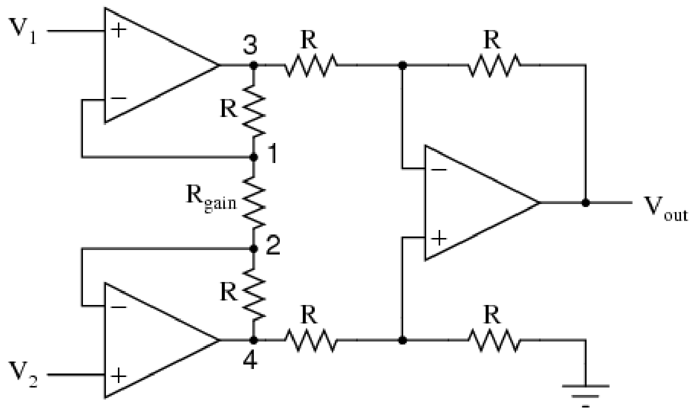

Fig.3.2: Instrumentation Amplifier

- Filters :
  (i) Low Pass Filter :

  These filters filter out the signal at frequencies higher than the filter's cut off frequency.

(ii) High Pass Filter :

It passes high frequencies and attenuates low frequencies. Also, they are used to filter out the undesired low frequency components from the main high frequency signals. They are used in applications which require the rejection of low frequency signals.

(iii) Notch Filter :

This is required to eliminate the 50Hz interference, which comes from the power lines carrying this frequency in close proximity to patient and equipment.

- **Output Stage**

  The output stage mainly consists of Oscilloscope which is a graph displaying device. It observes the change of an electrical signal over time, describes a shape which is graphed against a calibrated scale.

A typical Electrocardiogram (ECG) machine is shown in Fig.3.3.

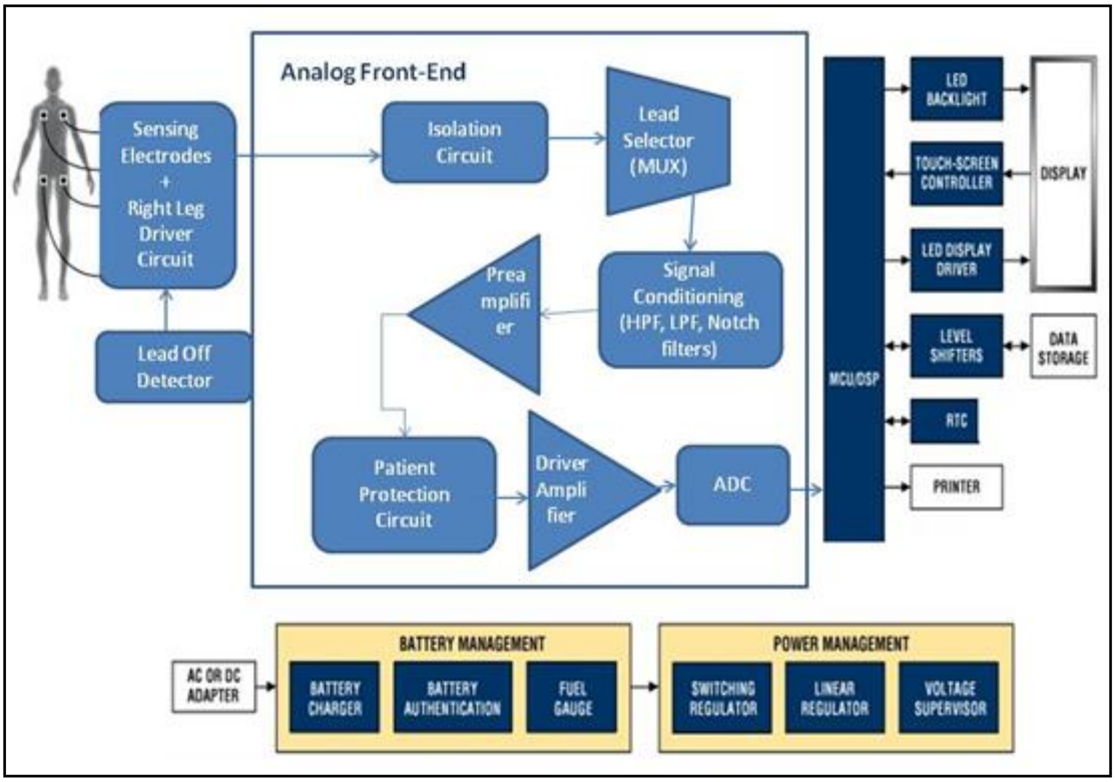

Fig.3.3: ECG Machine

Functional Blocks of ElectroCardioGraph (ECG) Machine

1. Sensing electrodes
2. Protection Circuit
3. Lead selector (Multiplexer)
4. Lead fail detectors
5. Calibration signal
6. Preamplifier
7. Isolation circuit
8. Driven right leg circuit
9. Driver amplifier
10. Wilson network
11. ADCs
12. Microcomputer/controller cum Digital Signal Processor
13. Digital level shifters
14. Display & Data storage
15. I/O expanders for user interface
16. Battery and power management

3.3 Working of ECG

The basic working of ECG can be summarised as follows:

- A total of 10 electrodes are placed on the patient
- Electrical impulses are picked up by them

- The voltage change is sensed by measuring the current change across 2 electrodes- a positive electrode and a negative electrode.
- If the electrical impulse travels towards the positive electrode then this results in a positive direction [fig.3.4]
- If the impulse travels away from the positive electrode then this results in a negative direction

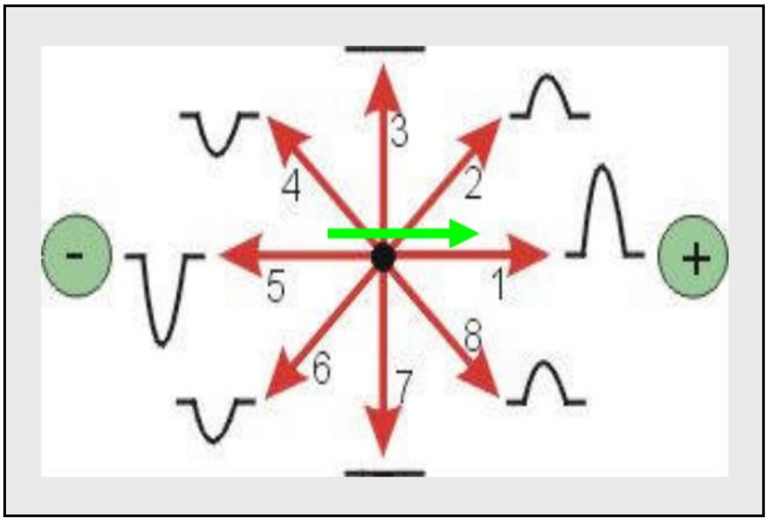

Fig.3.4: ECG Working

3.4 A Typical ECG Wave

Generally ECG is characterised as a recurrent sequence of three waves including the P wave, the QRS complex (combination of Q, R and S waves) and T wave.

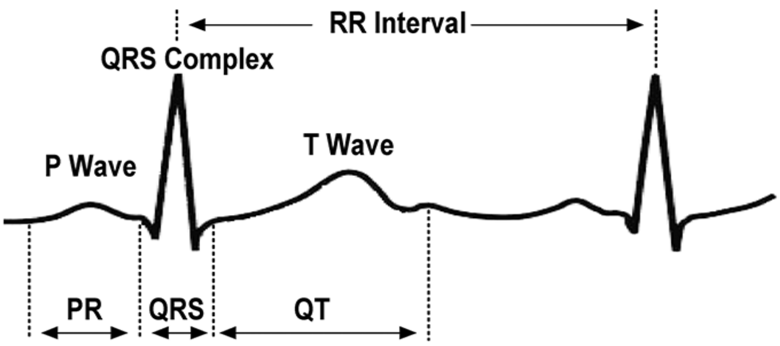

Fig.3.5: Typical ECG wave

Among the three waves, the QRS complex generally has more energy with higher amplitude than P and T waves over the RR interval (interval between two adjacent R waves) [Fig.3.5]. To precisely monitor the heart-beating rate of the patients, accurate detection of QRS complex (or R wave) is required.

There are two main reasons why QRS detection becomes challenging:

- ECG signal is likely contaminated by much noise and artifacts, such as powerline interference, electrode contact noise, baseline wandering, quantization noise, aliasing etc.
- The wide variations of QRS morphologies and rhythms from abnormal ECG's and interpersonal variations.

Therefore, a QRS detector must be robust over noise and disturbance.

CHAPTER 4

WAVELET BASED ECG DETECTOR

4.1. Introduction of Wavelet Transform

Wavelets, based on time scale representations, provide an alternative to time-frequency representation based signal processing. The shifting (or translation) and scaling (or dilation) are unique to wavelets [14]. Wavelets are represented by dilation equations as opposed to difference or differential equations. They maintain orthogonality with respect to their dilations and translations. Wavelets decompose the signal at one level of approximation into approximation and detail signals at next level. Thus, subsequent levels can add more detail to the information content.

A **wavelet** is a wave-like oscillation with amplitude that begins at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation". Wavelets are a mathematical tool, which can be used to extract information from many kinds of data, including audio signals and images. Mathematically, the wavelet is a function of zero average, having the energy concentrated in time:

$$\int_{-\infty}^{\infty} \psi\,(t)dt = 0$$

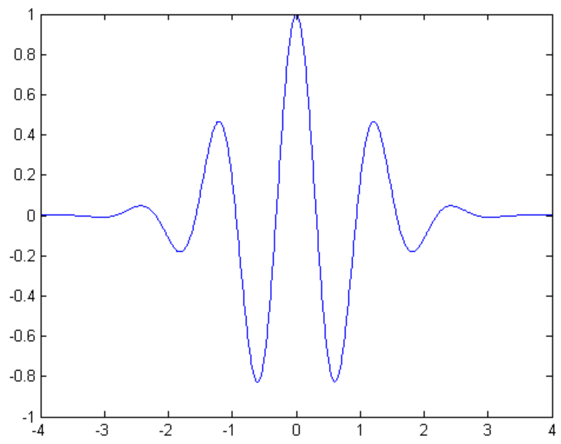

Fig.4.1: A Typical Wavelet

4.2. Wavelet Transform

There are different kinds of signal transforms which are available in the literature like Fourier Transform, Cosine Transform etc. the main reason for performing any type of transform on the signal is solely concerned with extracting certain properties of the signal which are confined to certain domains like Fourier Transform is used to extract the signal properties in the frequency domain [5]. But there were certain drawbacks or missing information in all the conventional transforms which compelled the scientists to think of a novel approach of perceiving a signal to extract its properties. Therefore, wavelet transform was born. These shortcomings were-

- The Fourier Transform was unable to determine the properties of a signal at the time of an interruption since it was confined to only a single domain. Wavelet transform overcomes this limitation as they are localized in both time and frequency.

- Due to the dual domain localization of wavelet transform, they are much more flexible to calculate the interruption factor and thus are a useful tool in digital signal processing systems.

- Wavelets provided a multi-resolution analyses, i.e they allowed both high time and frequency resolution.

4.2.1. Short Time Fourier Transform

Firstly, to overcome these drawbacks of earlier transforms, something called **Short Time Fourier Transform** (STFT) came into picture. This mainly focussed on non-stationary signals as conventional Fourier Transform was only meant for stationary signals [7].

In this STFT, windowing techniques was used i.e. the complete non-stationary signal was broken down into small signals with the help of windows, which made it stationary for a short duration of time determined by the length of the windows chosen as shown in Fig.4.2.

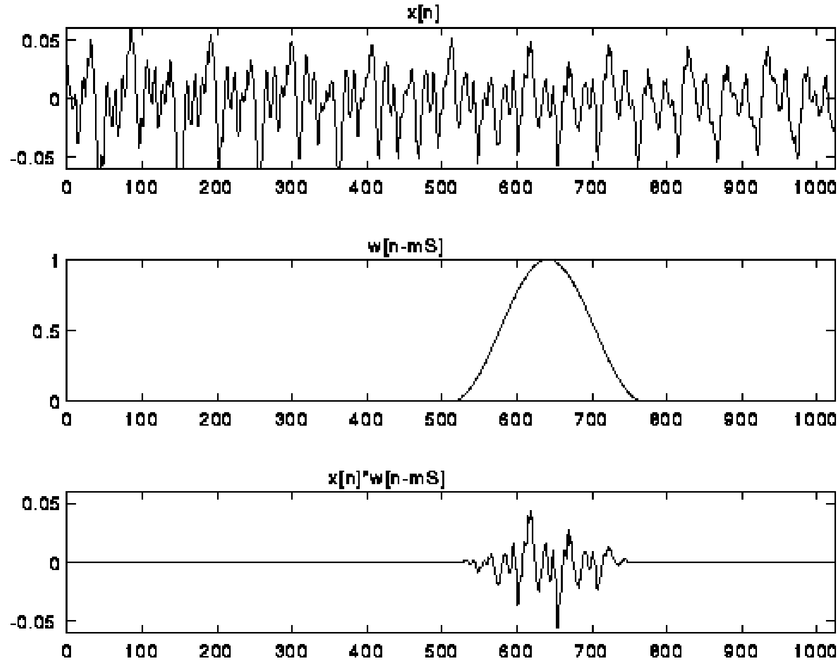

Fig.4.2: Windowing in STFT

If compared with the normal Fourier transform then, equations differ as:

$F(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t}\, dt$ ------- Normal Fourier Transform

$STFT(\tau, \omega) = \int_{-\infty}^{+\infty} f(t)\, w(t-\tau)e^{-j\omega t}\, dt$ ------- STFT

But Short Time Fourier Transform was also not able to fully model the non-stationary signals since its main drawback was the constant size of the windows i.e. when the window size was chosen very small, it provided a good time resolution but poor frequency resolution and similarly when the window size was chosen large enough then time resolution degraded and frequency resolution improved but it could not provide good time and frequency resolution both simultaneously. And also, having a constant window size meant that we must have all the information regarding that particular signal, but since the signal is a non-stationary signal so having its full content is not possible. Now, these shortcomings paved the road for wavelet transform, which enabled various sizing of windows so that a proper time and frequency resolution can be achieved.

Wavelets provides multi-resolution analysis i.e. -

- Analyze the signal at different frequencies with different resolutions.
- Good time resolution and poor frequency resolution at high frequencies.
- Good frequency resolution and poor time resolution at low frequencies.
- More suitable for short duration of higher frequency; and longer duration of lower frequency components.

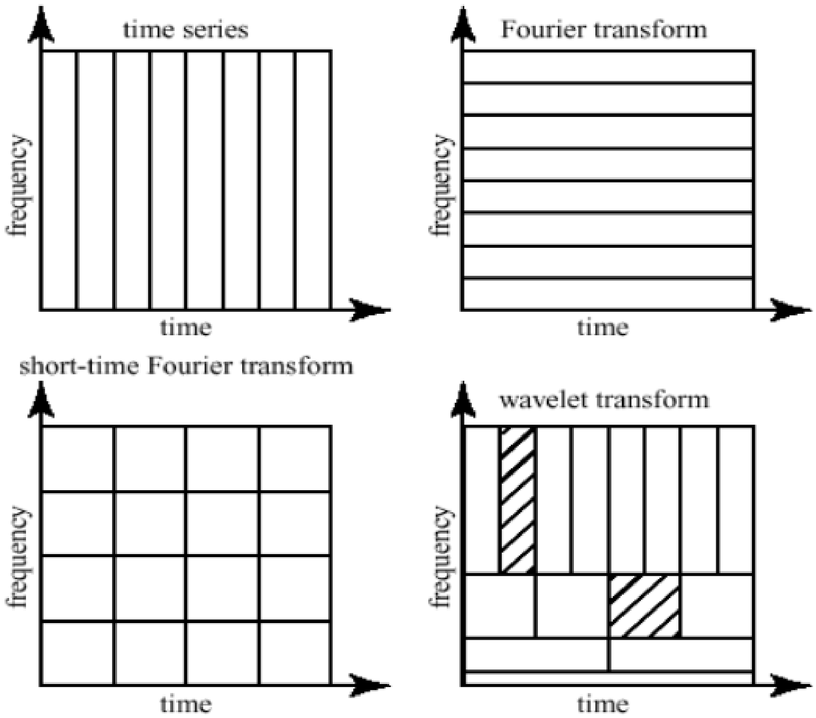

Fig.4.3: Multiresolution Analyses by wavelet transform

Wavelet transforms can be of Continuous or discrete wavelet transforms. Discrete wavelet transform (DWT) is one of the useful and efficient signal decomposition methods with many interesting properties [18]-[21]. This transformation similar to Fourier transform can provide information about frequency contents of signals. However unlike Fourier transform, this approach is more natural and fruitful when applied to non-stationary signals, like speech and images. The flexibility offered by DWT allows the researchers to develop and find the right wavelet filters for their particular application. The wavelet transforms are well suited for analyzing physical situations where signal contains discontinuities and sharp spikes.

With each wavelet type, there is a scaling function (called the *mother wavelet*) which generates an orthogonal multiresolution analysis as,

$$CWT_x^{\psi}(\tau, s) = \psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) \,.\, \psi^* \left(\frac{t-\tau}{s}\right) dt$$

Where, τ = translation (the location of the window),

s = scale and,

$\psi^* \left(\frac{t-\tau}{s}\right)$ = mother wavelet

4.3. Wavelet Filter Realization

A Discrete wavelet transform performs a multistage signal decomposition using a filter bank structure shown in Fig.4.4. This filter bank structure comprises of a low pass and a high pass filter, each followed by decimation by two [19].

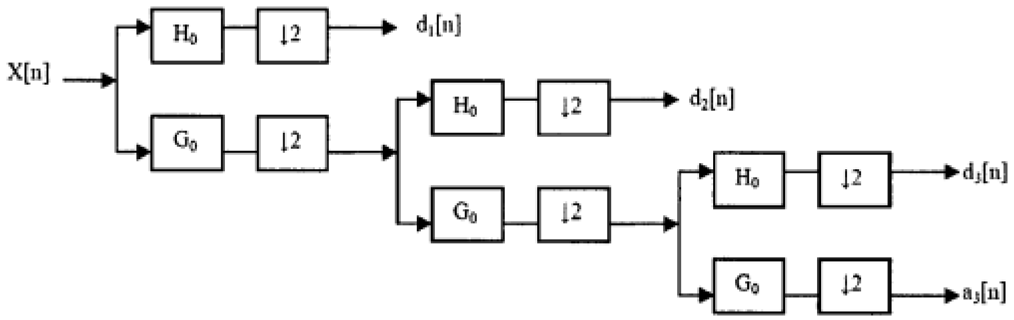

Fig.4.4: A three level wavelet decomposition system

The decimated low pass output from the preceding stage acts as the filter bank input for the succeeding stage and so on. Accordingly, any number of stages can be cascaded to produce wavelet based decomposition.

Similarly synthesis or reconstruction of the original signal can also be done in the same manner as decomposition system shown in Fig.4.5.

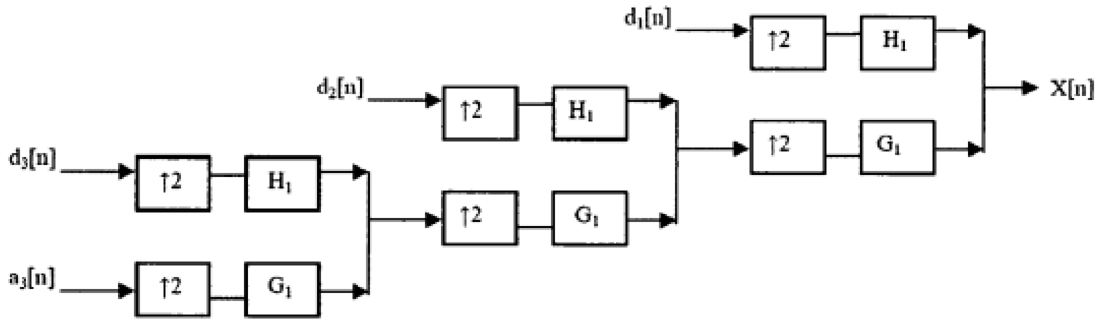

Fig.4.5: A three level wavelet synthesis system

4.4. ECG Detector using Multi Scaled Products

The block diagram of the ECG detector consisting of a wavelet decomposer, a noise detector with zero crossing points and a QRS complex detector is shown in fig below.

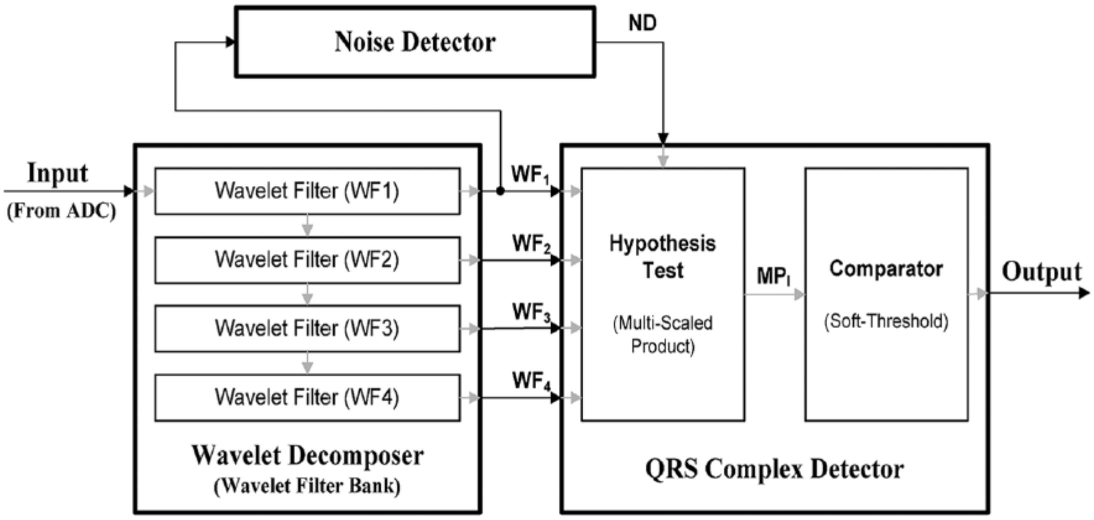

Fig.4.6: Multi scaled products ECG Detector

The Noise Detector Block has been explained in detail in Chapter-2 of this report.

4.4.1. Wavelet Filter Bank

The transfer function of LPF and HPF of fig are,

$H(z) = (1+3z^{-1}+3z^{-2}+z^{-3}).1/8$

$G(z) = (1-z^{-1}).2$

Where, H(z) and G(z) are the transfer functions of LPF and HPF respectively in the WFB's.

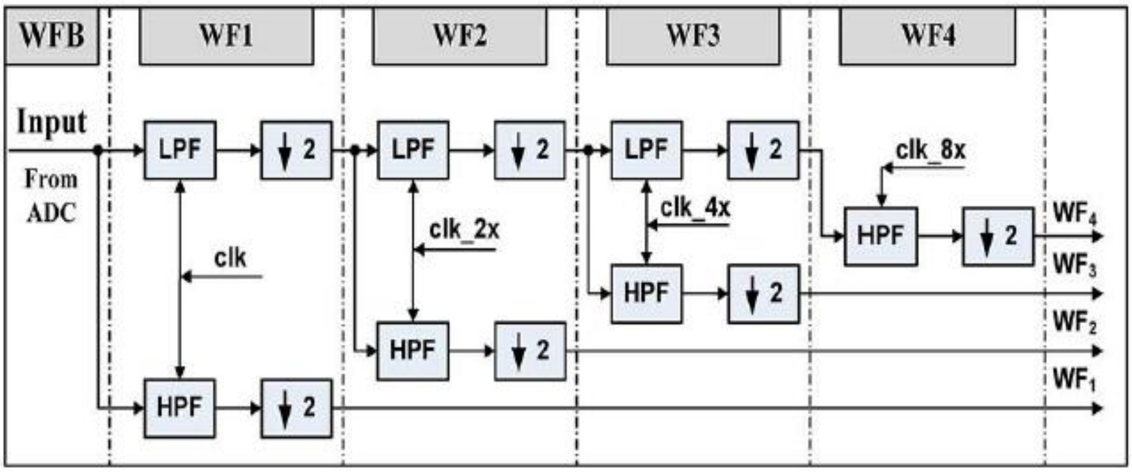

Fig.4.7: Decimator based wavelet filter bank

Here the high pass and low pass filters are implemented in direct form as shown in Fig.4.8.

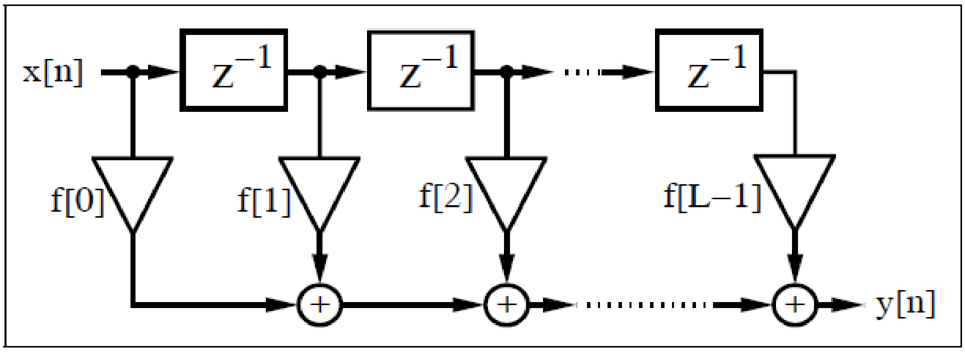

Fig.4.8: FIR implementation of high pass and low pass filters

4.4.2. Multi Scaled Products

The multi-scaled products of the WFB outputs can be expressed by,

$$MP_I = \prod_I^N |WF_I|$$

Where I is the subset of WFB outputs.

With multiple scaled signals containing the wavelet coefficients, the nonlinear combination MP_I tends to reinforce the peaks while suppressing noises.

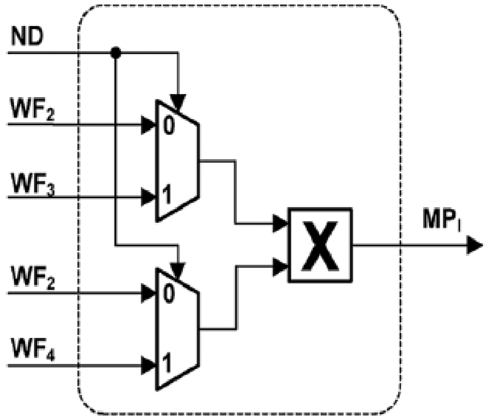

Fig.4.9: Multi scaled products algorithm

According to the noise information from the noise detector, the multi scaled products selects the wavelet filter banks to reconstruct the ECG signal without noises and to detect QRS signals.

4.4.3. Soft Threshold Algorithm

Here a soft threshold algorithm is used which employs variable thresholds rather than a hard threshold as shown in Fig.4.10.

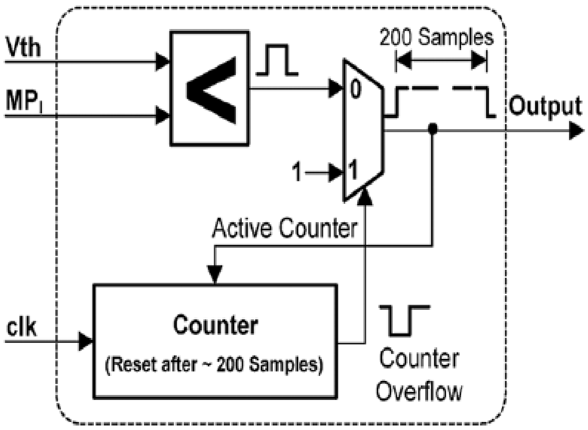

Fig.4.10: Soft Threshold Algorithm

With the known minimum RR interval of 200ms, the adoption of soft threshold can remove the errors. When the comparator detects the QRS complex at which the output of the comparator goes high, the threshold is changed to a higher value. The changed threshold is kept while 200 samples pass over T point signal [11]. To implement a soft threshold only a single 8-bit counter is required.

CHAPTER 5

SIMULATION RESULTS

5.1. ECG Detector using Multiscaled Products

As described in Chapter 4, the ECG Detector using Multi-scaled products comprises of a wavelet decomposer, a noise detector, a multi scaled product algorithm block and a soft threshold algorithm block. Detailed simulations of these blocks are done using MATLAB (R2012b).

5.1.1. Wavelet Decomposer

The filter coefficients for LPF and HPF are taken as,

[1/8 3/8 3/8 1/8] for H(z) i.e. for LPF and

[2 -2] for G(z) i.e. for HPF.

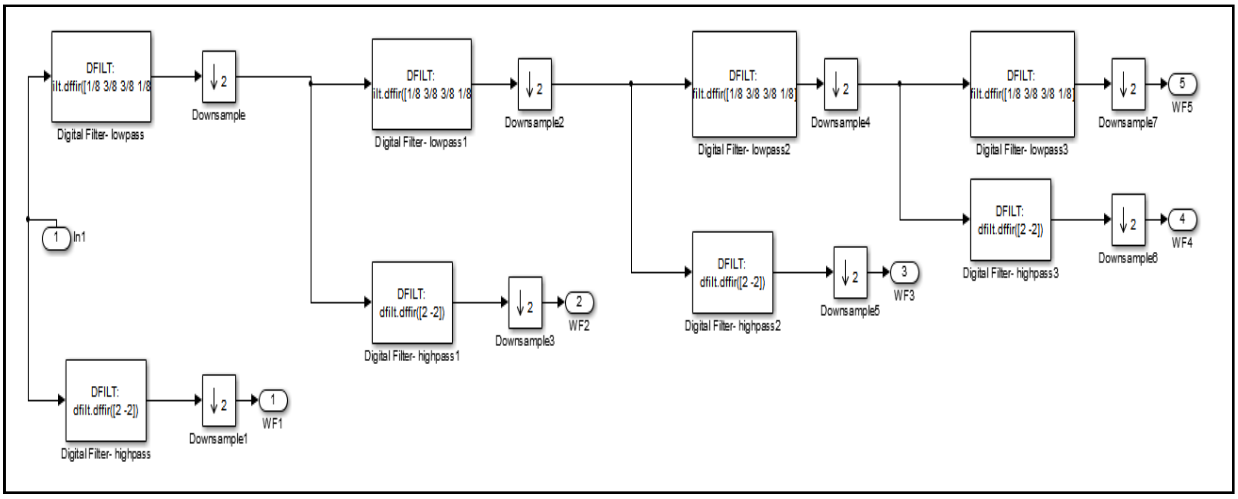

Fig.5.1: Schematic of Wavelet Filter Bank

5.1.1.1. Filter Responses of LPF and HPF:

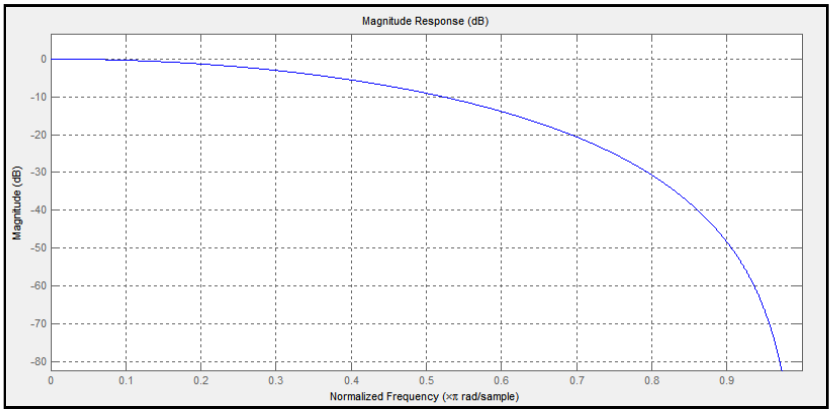

Fig.5.2: Low Pass Filter Response

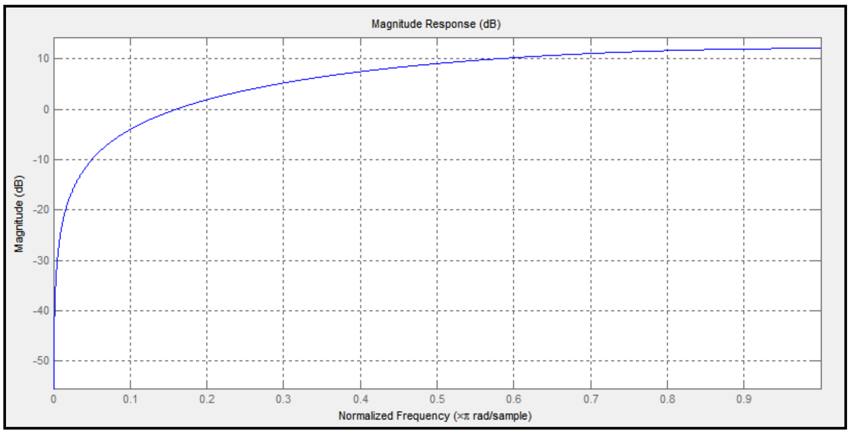

Fig.5.3: High Pass Filter Response

5.1.1.2. Individual Blocks of Wavelet Filter Bank:

- **WF1:**

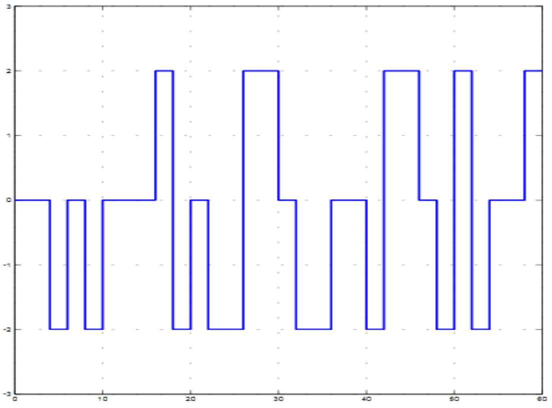

Fig.5.4: Output – WF1

- **WF2:**

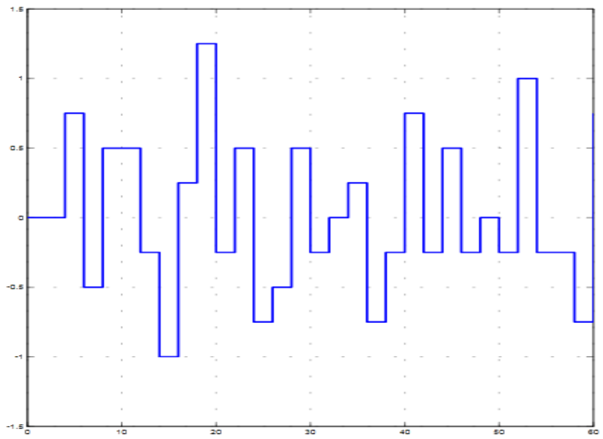

Fig.5.5: Output – WF2

- **WF3:**

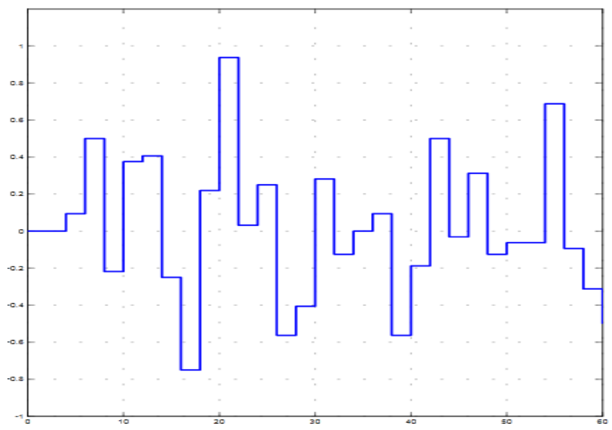

Fig.5.6: Output – WF3

- **WF4:**

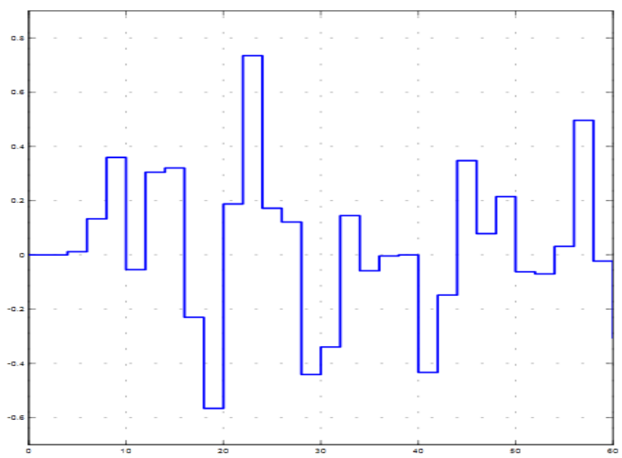

Fig.5.7: Output – WF4

- **WF5:**

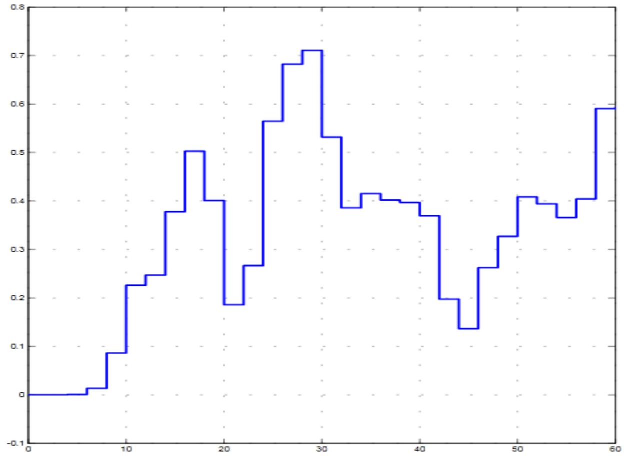

Fig.5.8: Output – WF5

5.1.2. Noise Detector

As explained in Chapter 2, the noise detector measures the noise level in the signal by counting the number of zero crossings in a certain time interval.

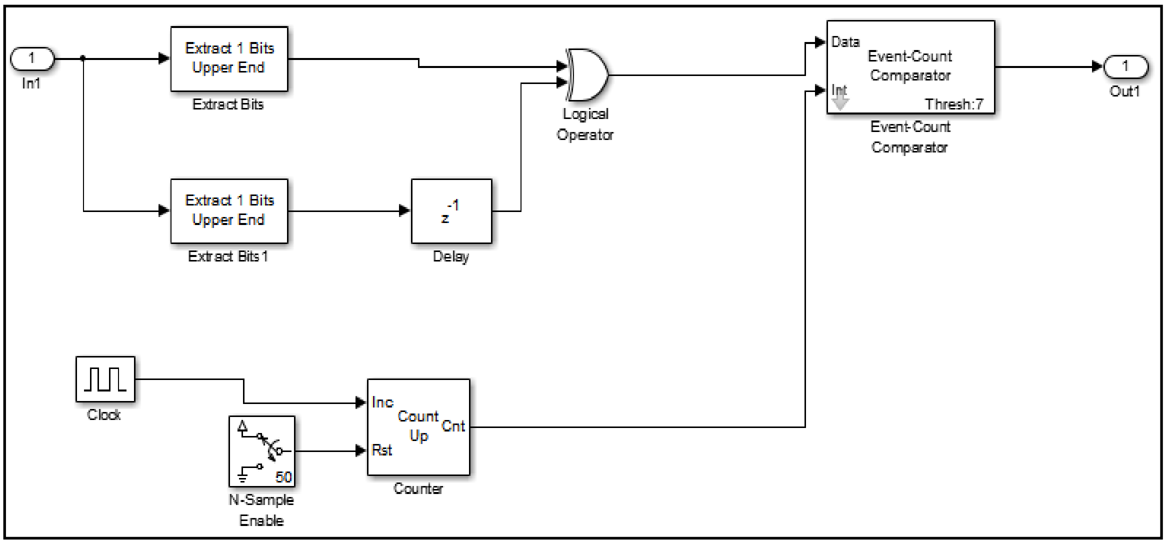

Fig.5.9: Schematic of Noise Detector

5.1.3. Multi Scaled Product

Its role is to select the wavelet filter banks according to the noise information for reconstruction of the ECG signal.

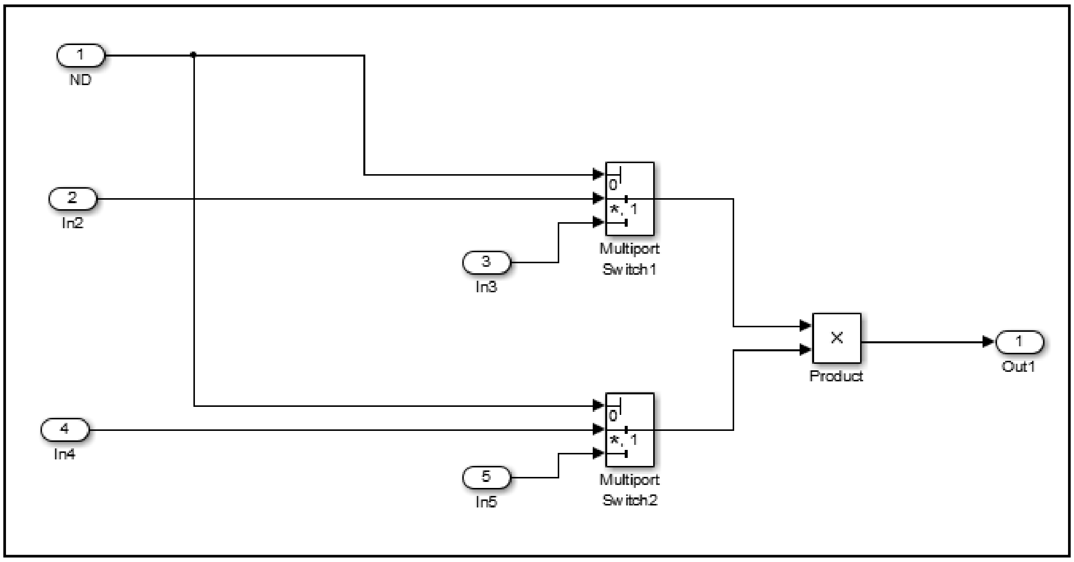

Fig.5.10: Schematic of Multi Scaled Product Block

5.1.3. Soft Threshold Algorithm

The adoption of soft threshold can remove the computation errors as the threshold is changed to a higher value when the comparator detects a QRS complex.

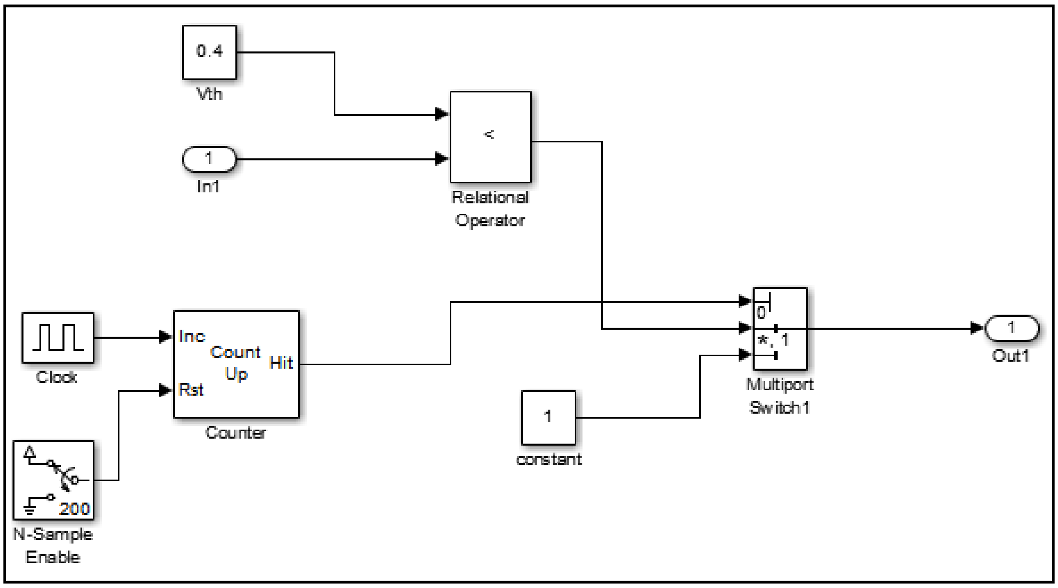

Fig.5.11: Schematic of Soft Threshold Algorithm Block

5.2. Overall Schematic and Waveforms

The overall ECG Detector can be shown in Fig.5.12. and the output waveforms of different blocks are shown subsequently.

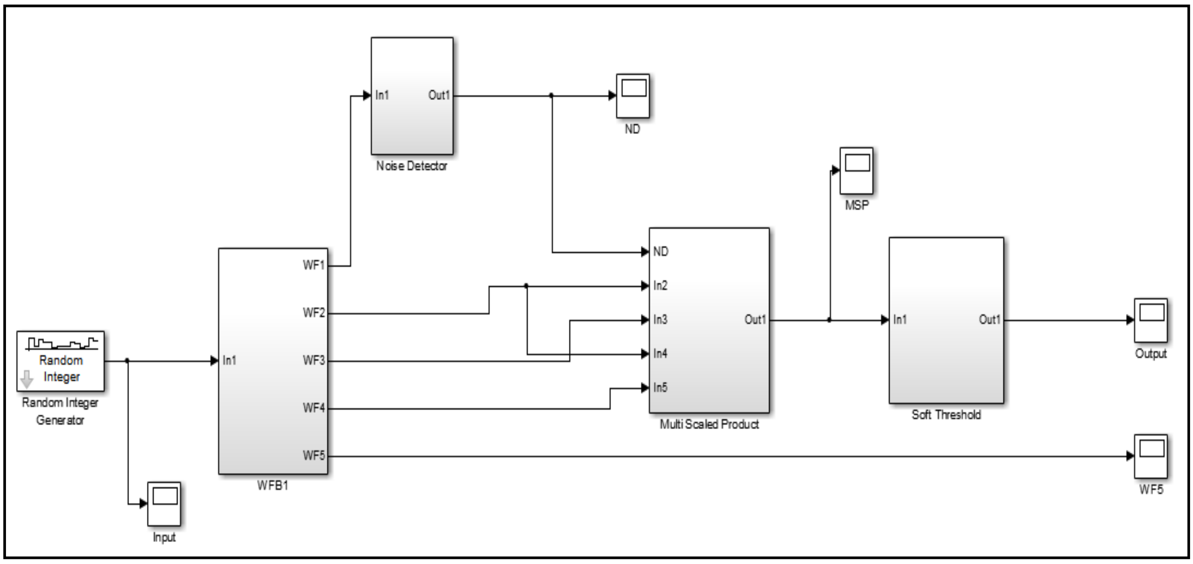

Fig.5.12: Overall Schematic of ECG Detector

The output of the Noise Detector Block is shown in Fig. 5.13.

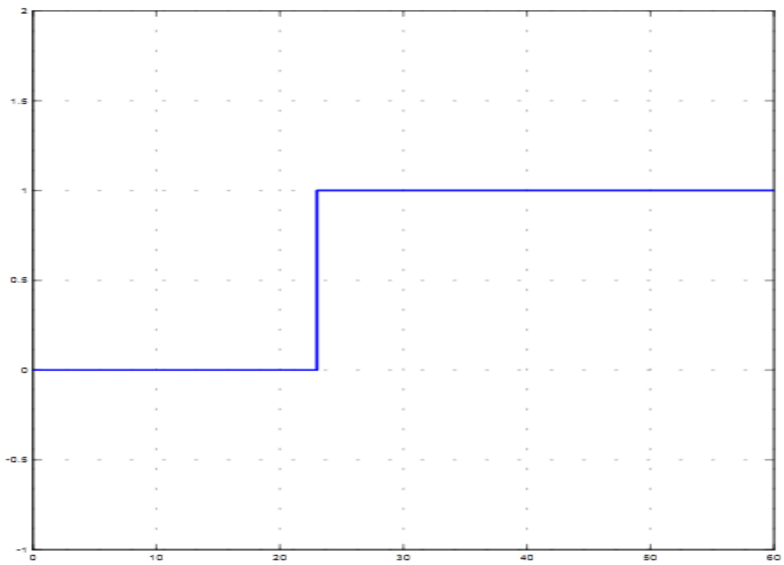

Fig.5.13: Noise Detector Output

The outputs of Multi Scaled Product and Soft Threshold Block are depicted in Fig. 5.14. and Fig.5.15. respectively.

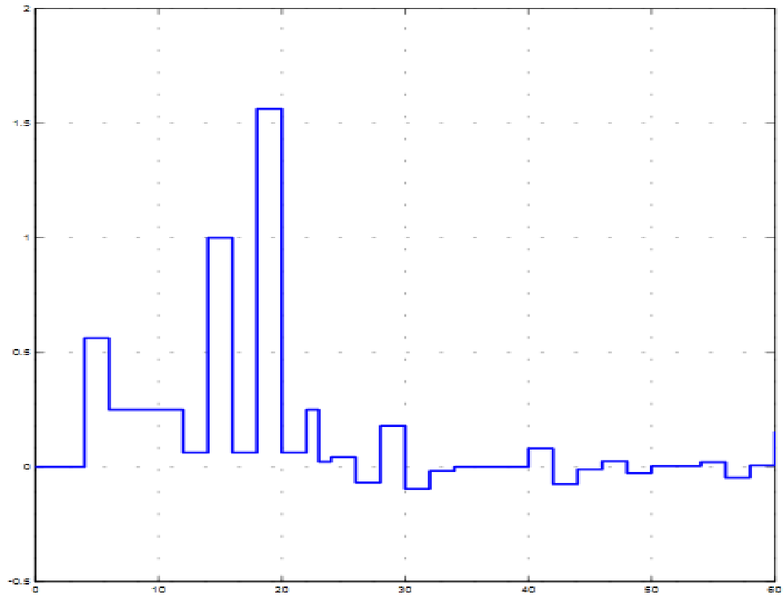

Fig.5.14: Multi Scaled Product Block Output

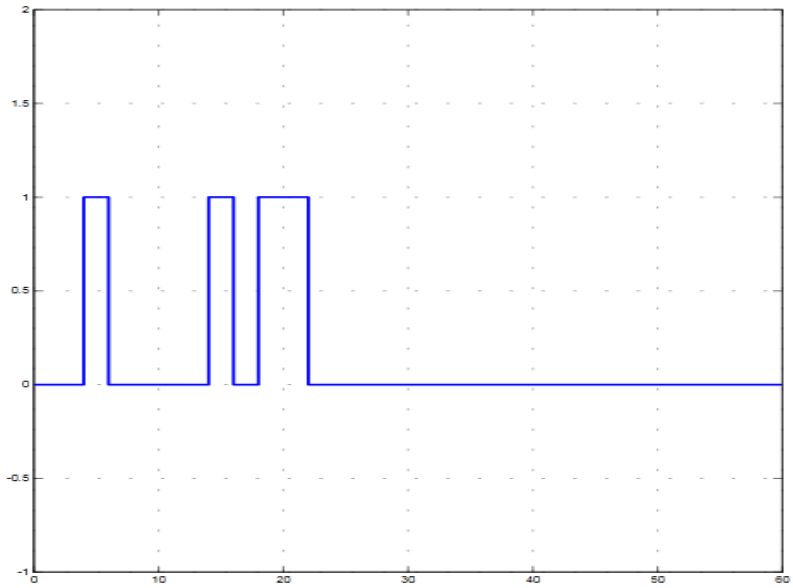

Fig.5.15: Final Soft Threshold Output

5.3. Observations

As the noise detector output goes high at 23rd sampling time instant, because the noise threshold in this case has been set to 7 (5-7 for normal human being), so it activates WF3 and WF4 wavelet bank, which is shown in Fig.5.14. The approximated output is the output of the last stage of low pass filter which here is WF5 shown in Fig.5.8.

Therefore, the final comparator detects valid QRS complexes till the noise detector output goes high, clearly shown in Fig.5.15.

5.4. Future Design

Up till now, we have seen how wavelets are effectively used in filter banks for ECG detection. A new dimension can be added by employing the notion of multiwavelets in this design. Theoretically, multiwavelets use more than one scaling function and more than one mother wavelet to represent a given signal. And therefore, they possess many advantages over scalar wavelets. Although preprocessing is required in multiwavelets which may lead to increase in computations but, overall signal compression, detection and denoising is better than uniwavelets. The implementation of multiwavelet based ECG Detector is proposed in the following Chapter.

CHAPTER 6

MULTIWAVELET BASED DESIGN

6.1. Introduction to Multiwavelets

We are already familiar with wavelets which are a useful tool for signal processing applications. Till now only scalar wavelets are used i.e. wavelets generated by one scaling function. Using more than one scaling function leads to the notion of Multiwavelets, which have several advantages compared their scalar counterparts.

The first construction for polynomial multiwavelet was given by Alpert, who used them as a basis for the representation of certain operators. Later, Geronimo, Hardin and Massopust constructed a multi-scaling function with two components using fractal interpolation.

A typical multiwavelet filter bank with C as the low pass filter and D as the high pass filter is shown in Fig.6.1.

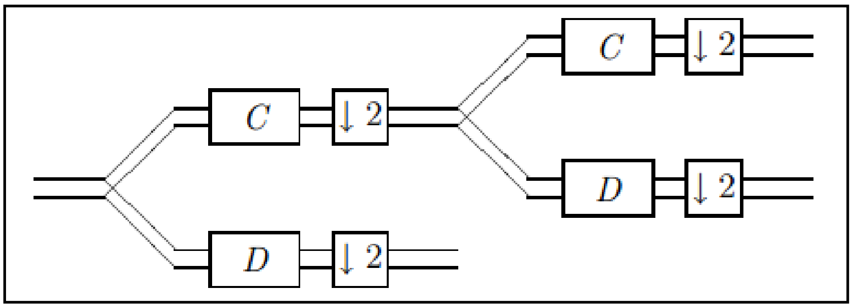

Fig.6.1: Multiwavelet Filter Bank, iterated once

Multiwavelets differ from scalar wavelet systems in requiring several input streams to the filter bank i.e. the coefficients of low pass and high pass filters in multiwavelets are N×N matrices and during the convolution they must multiply vectors instead of scalars. There are two methods for obtaining such a vector input stream from a one-dimensional signal and those are repeated row technique and approximation-based preprocessing.

In the repeated row technique, the signal is repeated in order to get two input rows from the given input signal. These two identical rows are fed to the multi filter bank. This technique introduces an oversampling of the data by a factor of two. Although these oversampled representations are useful in feature extraction but they require a lot of calculation. This scheme is not suitable for data compression applications where one is seeking to remove redundancy and not increase it. In the case of one-dimensional signals the "repeated row" method is convenient to implement.

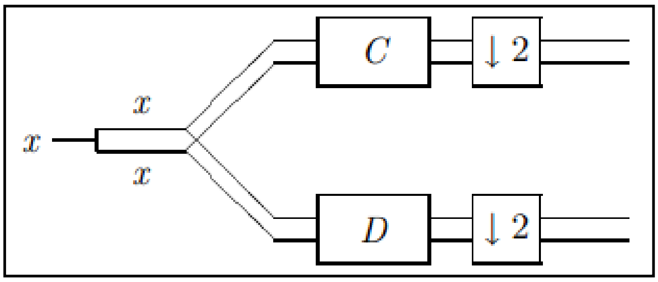

Fig.6.2: Multiwavelet Filter Bank with "repeated row" inputs

Another way to get input rows for the multiwavelet filter bank is to preprocess the given scalar signal, this although effective requires extra hardware and computations.

6.2. Multiwavelet based ECG Detector

In the previous ECG detector, a single wavelet filter bank was used as a wavelet decomposer block. In order to employ multiwavelets into this design, two sections of wavelet filter banks are used, which are alternatively selected with their respective multiplexers. Here, the approximated signal which is the output of WF5 is also shown. The timing of the control signal of the multiplexers is to be controlled according to the need of application. To ease the design, the function of selection of the wavelet filter banks is done with the help of two multiport switches. The overall proposed design is depicted in Fig.6.3.

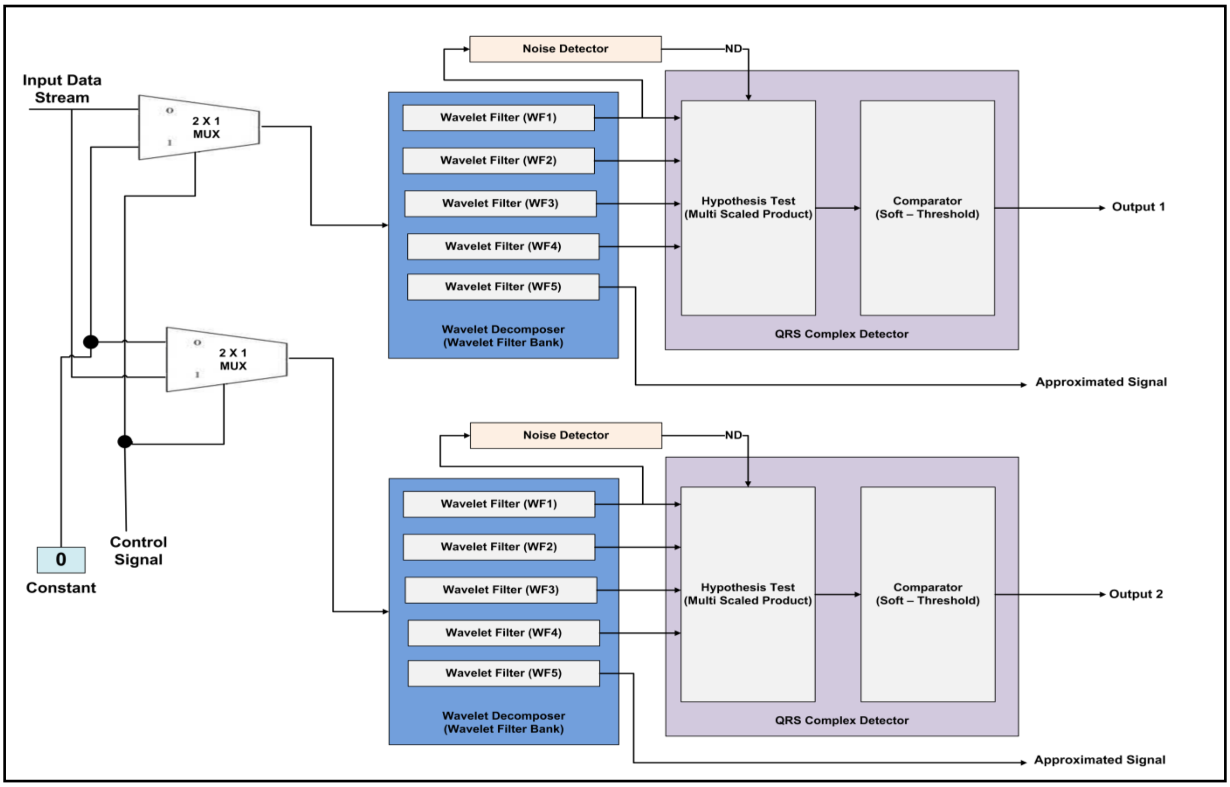

Fig.6.3: Proposed Multiwavelet ECG Detector

6.3. Proposed Design and Simulations

In this section, the multiwavelet design is implemented using MATLAB (R2012b) and the simulations results are shown subsequently.

Here, the two sections of ECG detector paths are alternatively selected by two multiport switches, whose control signal timing is varied according to the application. For the first sampling time duration, the first ECG detector path gets activated and provides Output_1 and similarly for the next sampling time duration the second path gets activated and provides Output_2. This is a multiwavelet ‘m’-stage design where m has been fixed as 2. Further ‘m’ could be increased as per the requirement of the application.

The MATLAB schematic of multiwavelet ECG detector is shown in Fig.6.4. and the output simulations follow.

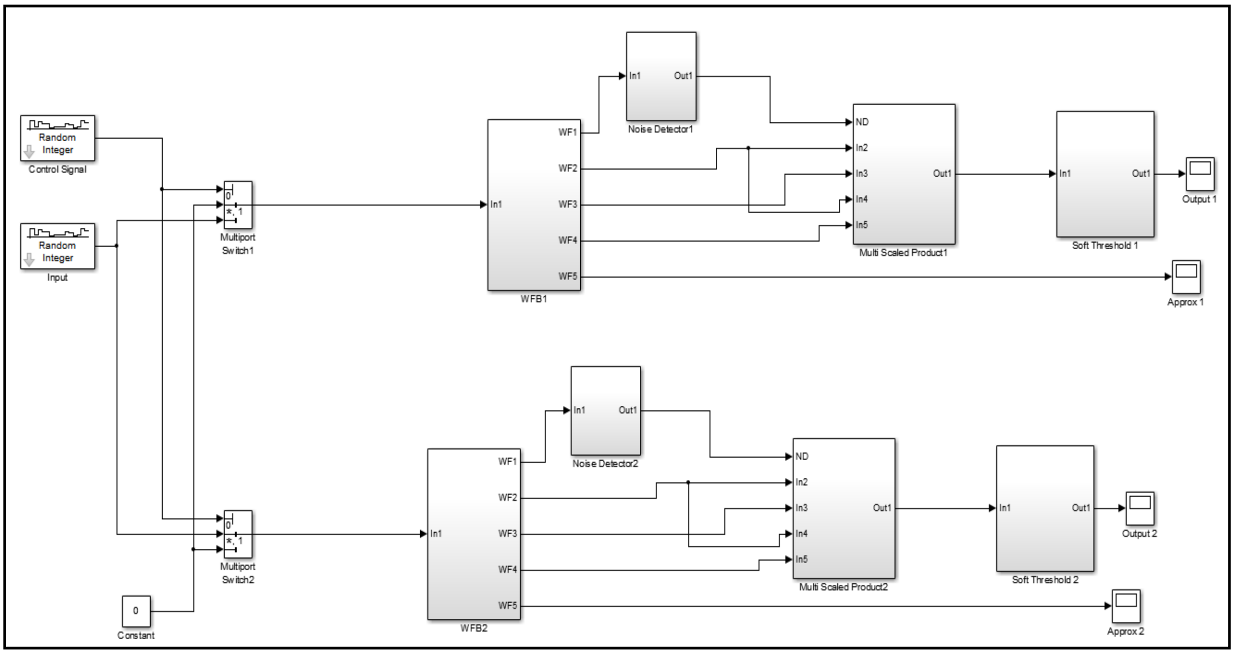

Fig.6.4: Schematic of proposed ECG Detector

The control signal (with sampling time 20) and the input are shown in Fig.6.5 and 6.6 respectively.

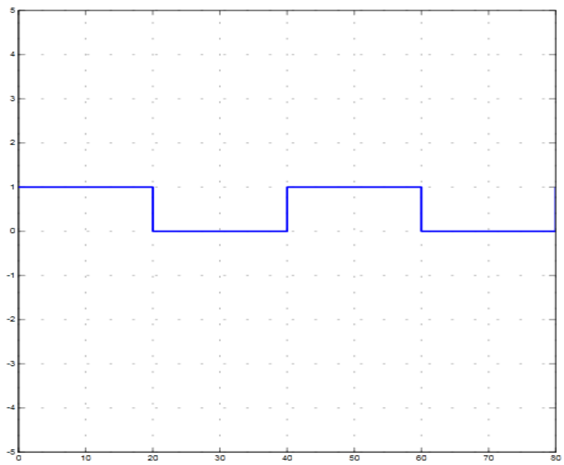

Fig.6.5: Control Signal

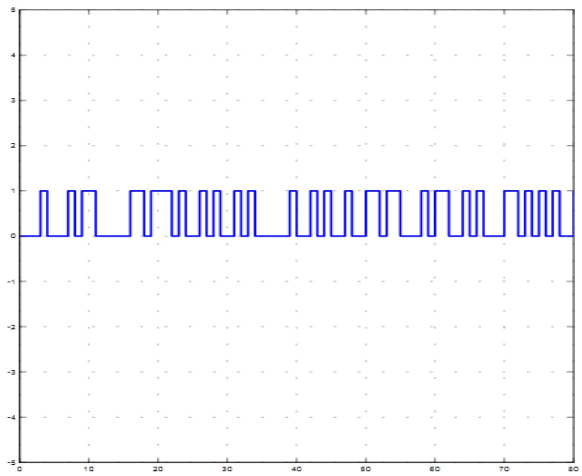

Fig.6.6: Input Signal

The control signal goes high for every alternate 20 sampling time instants, and in these durations, the respective ECG detector paths gets activated and gives the desired output.

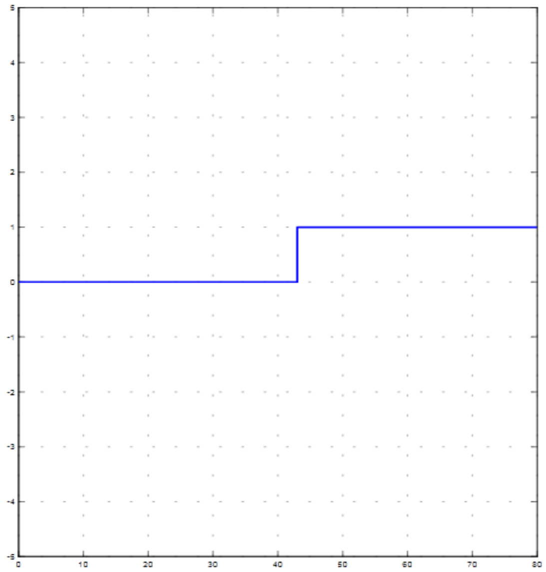

Fig.6.7: Noise Detector 1 Output

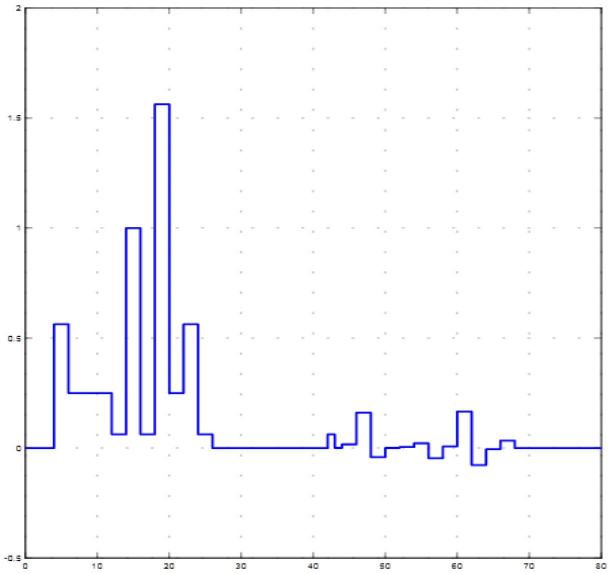

Fig.6.8: Multiscaled Product 1 Output

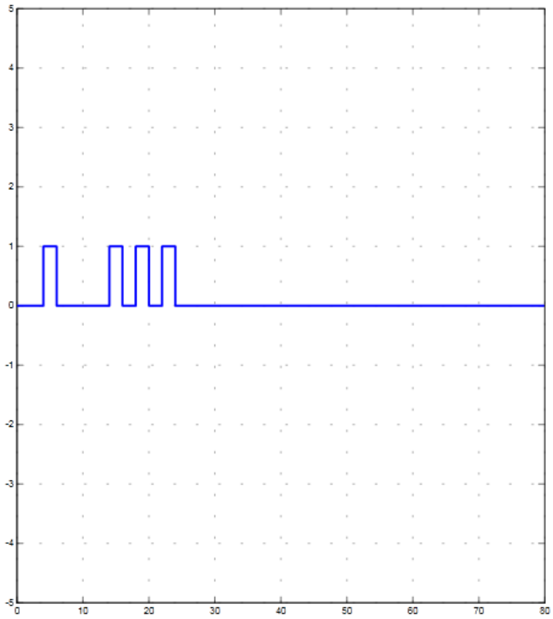

Fig.6.8: Output 1

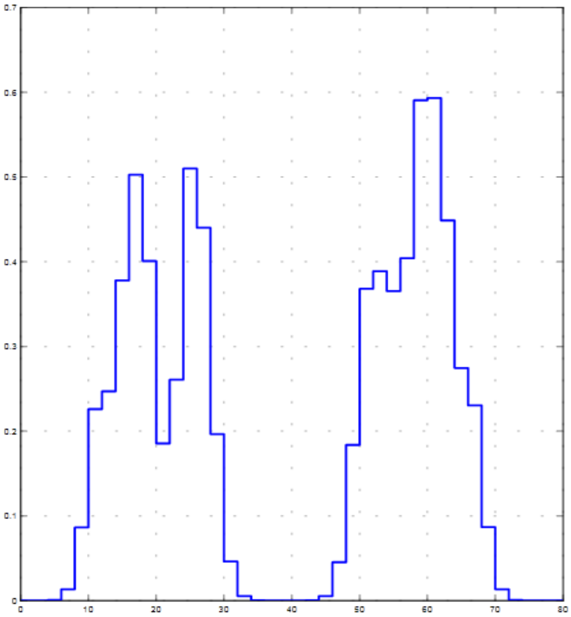

Fig.6.9: Approximated Signal 1

Observations for ECG Detector path 1:

The ECG detector path 1 works for sampling time duration 0-20 and 40-60. The noise detector goes high at 41st time instant, so the comparator could not detect a valid QRS complex after the noise detector output goes high. Therefore, for the first 20 samples Output 1 of ECG detector path 1 provides valid QRS complexes.

Similar waveforms are obtained for ECG detector path 2 as illustrated follows.

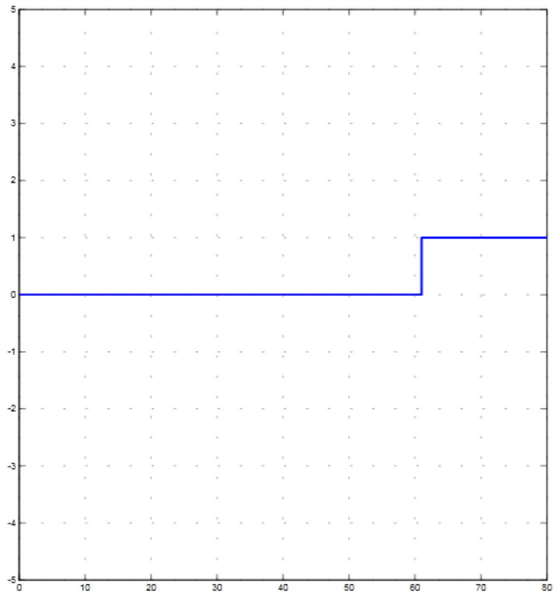

Fig.6.10: Noise Detector 2 Output

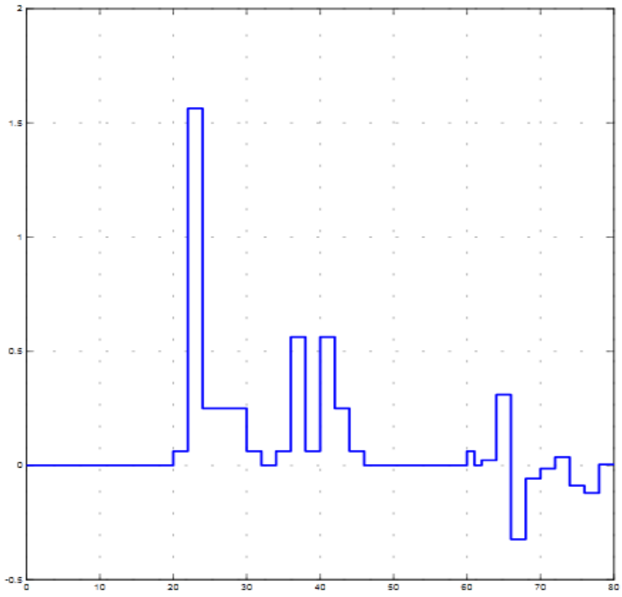

Fig.6.11: Multiscaled Product 2 Output

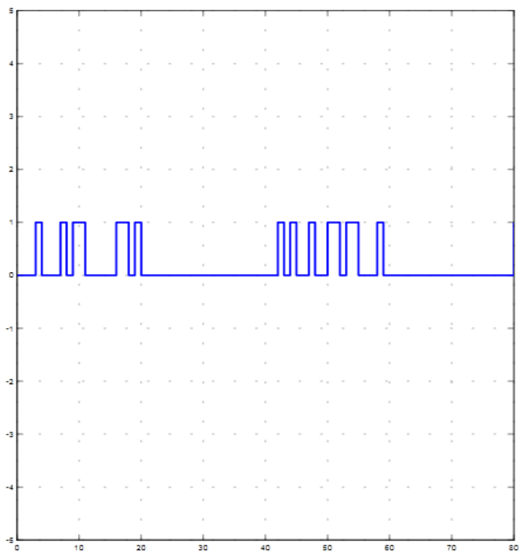

Fig.6.12: Multiport 1 output

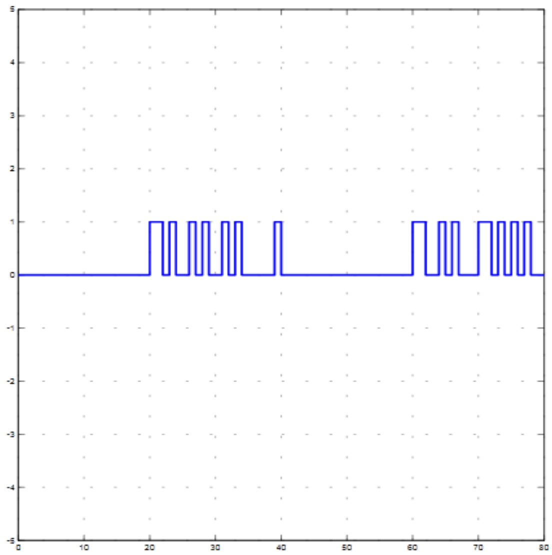

Fig.6.13: Multiport Output 2

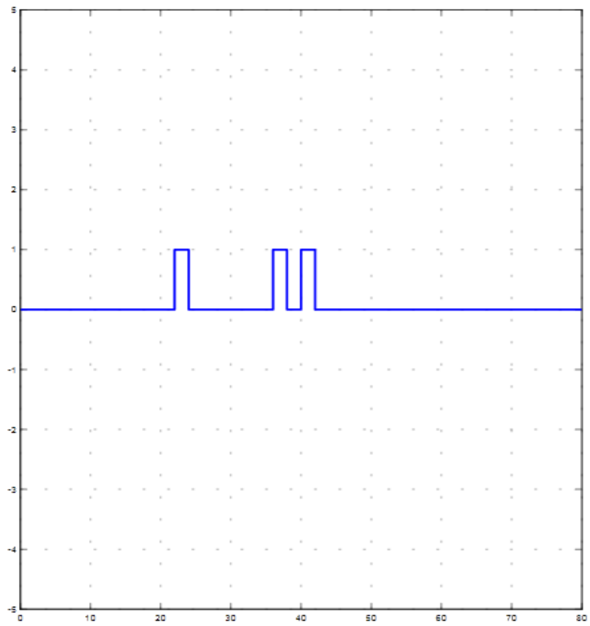

Fig.6.14: Output 2

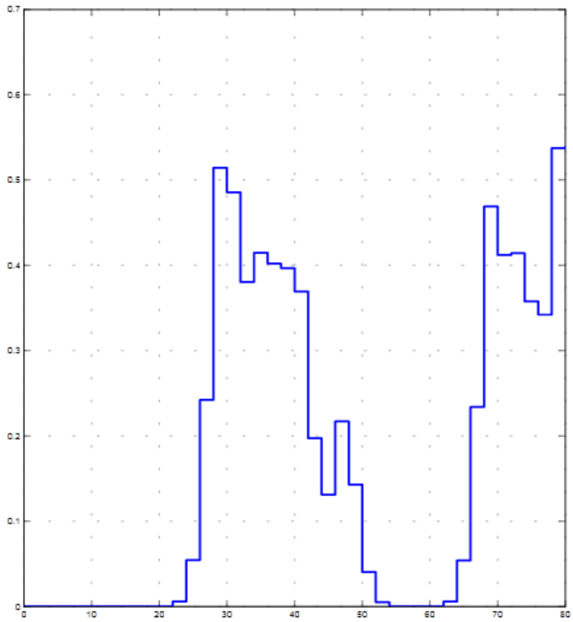

Fig.6.15: Approximated Signal 2

Observations for ECG Detector path 2:

This path 2 gets activated for 20-40 and 60-80 sampling time durations. The noise detector output goes high at 60th time instant, as a result of which the comparator could not detect a valid peak during this interval. Also the output of Multi Scaled Product Block degrades after the noise detector output goes high, since then it has to activate WF3 and WF4 banks of the wavelet filter banks.

Therefore, this proposed multiwavelet ECG detector design behaves in the exact manner as it is intended to i.e. depending on the timing of the control signal, the ECG detector paths gets activated and provides the necessary QRS complexes as output.

6.4. Advantages of Multiwavelet

We know that Multiwavelets contain multiple scaling functions, whereas scalar wavelets contain one scaling function and one mother wavelet. This leads to a greater degree of freedom in constructing wavelets. The features that are considered to be important for signal processing applications are, short support, orthogonality, symmetry and vanishing moments. A scalar wavelet cannot possess all these properties at the same time, but a multiwavelet system can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments). Therefore, multiwavelets provide superior performance as compared to scalar wavelets.

The increase in degree of freedom in multiwavelets is obtained at the expense of replacing scalars with matrices, scalar functions with vector functions, and single matrices with block of matrices. But as explained, prefiltering is an essential task which needs to be performed for any multiwavelet based application.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1. Conclusion

In this thesis, methods for ECG signal detection using wavelet transform have been discussed. This project describes different variants of wavelet based ECG detectors, of which multi scaled product based detector is given special importance. And finally this approach is extended to implement a novel multiwavelet based ECG detection system.

- Chapter 2 presented an in depth literature review of ECG detectors. This chapter started by discussing the first classical time domain based ECG analysis by J. Pan, followed by Tompkins ECG detector using artificial neural network. Subsequently, detection techniques using both wavelet transform and neural networks are discussed. This chapter was closed with the introduction of multiscaled product based ECG detector.
- Chapter 3 enclosed the basic underlying principle of ECG machines explaining with an explicit block diagram and discussing various functionalities of the fundamental parts of ECG Detection System.
- Chapter 4 introduced the basics of wavelet transform and its inherent nature in overcoming the disadvantages of Fourier Transform. Also, how wavelets prove to be a useful tool for detection of ECG signals is presented. This chapter was closed with the detailed explanation of Multi Scaled Product based ECG Detector.
- The Multi Scaled Product based ECG Detector was simulated and the results were verified with relevant observations summarized in Chapter 5 of this report. The growing requirement for multistage wavelets or multiwavelets is introduced at the end of this chapter.
- And finally, the basics of multiwavelets and a novel approach of employing multiwavelets in the world of ECG detectors was presented in Chapter 6, along with its superior advantages over scalar wavelets.

7.2. Future Work

In this section some topics for future developments are listed:

- To validate the power consumption and noise sensitivity of the multiwavelet based ECG detector design, and introduce considerable changes to make them tolerable within limits.
- To further extend the design for many stages of multiwavelets and verify its characteristics.
- To check for performance and detection error rate for different ECG signals corresponding to MIT-BIH Arrhythmia Database.
- The desirable continuation of this work would be to implement it in a commercial hardware synthesis ECG Detector Design.

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