Real-time Electrocardiogram (ECG) signal analysis and Heart Rate determination in FPGA platform

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by

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Dedicated
to
The Dreams and Sacrifices
of my Dear Ones
who Love me a Lot.

Department of Electrical Engineering
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Certificate

This is to certify that the thesis entitled **"Real-time Electrocardiogram (ECG) signal analysis and Heart Rate determination in FPGA platform "** *by* **Manas Rakshit**, *submitted to the National Institute of Technology, Rourkela for the award of Master of Technology in Electrical Engineering, is a record of bonafide research work carried out by him in the Department of Electrical Engineering, under my supervision. I believe that this thesis fulfills part of the requirements for the award of degree of Master of Technology. The results embodied in the thesis have not been submitted for the award of any other degree elsewhere.*

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Most real spirit is to achieve a goal through a way of perfection. The achievement which I have gain cannot be possible without the cooperation of numerous personalities.

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Manas Rakshit

Abstract

Heart disease is one of the leading cause for death of people globally. According to a recent study by the Indian Council of Medical Research (ICMR), about 25 percent of deaths in the age group of 25- 69 years occur because of heart diseases. Electrocardiogram (ECG) is one of the primary tool for the treatment of heart disease. ECG is an important biological signal that reflects the electrical activities of the heart. A typical ECG signal consists of mainly five components namely P, Q, R, S and T wave. Amplitude and morphology of each component contains numerous medical information. The automated detection and delineation of each component in ECG signal is a challenging task in Bio-medical signal processing community.

In this research work, a four stage method based on Shannon energy envelope has been proposed in order to detect QRS complex in ECG signal. Peak detection of the proposed algorithm is amplitude threshold free. To evaluate the performance efficiency of the proposed method standard MIT-BIH arrhythmia ECG database has been used and get an average accuracy of 99.84%, Sensitivity 99.95% and Positive Predictivity value 99.88%.

To detect and delineate P and T waves, an algorithm based on Extended Kalman Filter (EKF) with PSO has been proposed. For performance examination, standard QT ECG database has been used. The proposed algorithm yields an average Sensitivity of 99.61%and Positive Predictivity of 99.00% for the ECG signal of QT database.

A long term automatic heart rate monitoring system is very much essential for standard supervision of a critical stage patient. This work also includes a field programmable gate array (FPGA) implementation of a system that calculate the heart rate from Electrocardiogram (ECG) signal. FPGA provides easy testability that allows faster implementation and verification option for implementing a new design. FPGA-based design can act as a bridge for converting from a software algorithm to a dedicated hardware design based on Application-specific integrated circuits (ASICs). In this work a five stages methodology using basic VHDL blocks has been implemented that can detect the heart rate from a typical ECG signal.

Keywords: Electrocardiogram (ECG), Extened Kalman Filter (EKF),Field Programmable Gate Array (FPGA), Particle Swarm Optimization (PSO), Shannon Energy, VHSIC Hardware Description Language (VHDL)

List of Acronyms

Acronym	Description
ECG	Electrocardiogram
Na	Sodium
K	Potasium
SA Nde	Sinoatrial Node
AV Node	Atrioventricular Node
FPGA	Field-programmable Gate Array
DRWC	Dominant Resceled Wavelet Coefficient
FND	False Noise Detection
FRD	False R Detection
PSO	Particle Swarm Optimization
EKF	Extended Kalman Filter
SNR	Signal to Noise Ratio
ASICs	Application Specific Integrated Circuit
BPF	Band-pass Filter
FIR	Finite Impulse Response
IIR	Infinite Impulse Response
Se	Sensitivity
Acc	Accuracy
DER	Detection Error Rate
PPV	Positive Productivity
TP	True Peak
FN	False Negative
FP	False Positive
VHDL	VHSIC Hardware Description Language

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Chapter 1

Introduction

1.1 Introduction

Electrocardiogram (ECG) is an important biological signal that reflects the electrical activities of heart system. A lot of cardiac decisions can be taken from the amplitude and morphology of a typical ECG signal [1]. ECG signal is produced by the movement of Na+ and K+ ions, which causes depolarization and repolarization into heart cell [2]. An ECG signal has a typical amplitude of 0.2 mv and to monitor ECG signal there is requirement of frequency range 0.1 to 120 Hz [3]. ECG signal can be collected by placing suitable electrodes at standard locations on the human skin. A particular ECG signal has mainly five components namely P, QRS complex and T wave. Every wave in ECG has a normal value of amplitude and duration [4]. Whenever there is any defect in heart system the normal morphology of these waves are changed and by detecting the change in ECG wave cardiac diseases are identified.

In order to monitor an ECG signal, two type methods are available. In manual detection method, ECG signal, taken from a patient body printed on a standard graph paper and checking visually clinician takes the decisions. This manual detection method is not suitable for a long-term monitoring system, and whenever we get an ECG from a patient body, a lot of noises accumulate with it, so proper detection is not an easy task. On the hand in automatic ECG monitoring system ECG signal is processed through a computer system that is suitable for long-term monitoring.

1.2 Human Cardiac System and ECG signal generation

Human Cardiac system consists of several parts and heart is the central organ of the human cardiac system. Through cardiac system, total blood circulation process has been throughout the whole body. A pictorial diagram of human cardiac system has been described in Figure 1.1

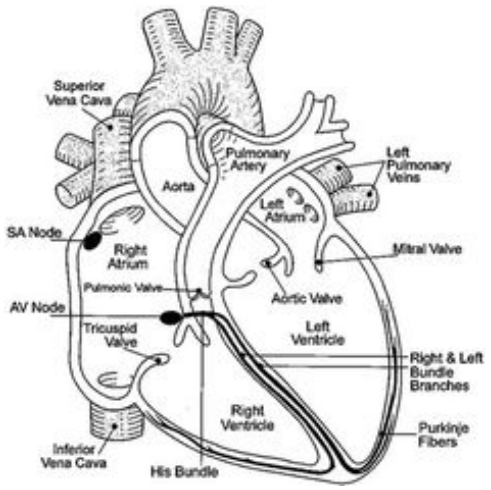

Figure 1.1: Human Cardiac System.

A human heart is separated into two sections left and right,which are subdivided divided into two chambers, the upper chamber is known as atrium where the lower one is ventricle.The atriums are blood receiving chamber where ventricles are blood transmitting chambers. The atria, attached to ventricles by fibrous, non-conducting tissues that keep them electrically isolated [5]. The tricuspid valve isolates right atrium and right atrium, where mitral valve separates left atrium and left ventricle[6].

De-oxygen blood from the whole body is received to the right part by superior and inferior vena cava. Then the blood is passed into the right ventricle through the tricuspid valve and from that it is passed to lungs through pulmonary atria. Oxygen filled blood is collected from lungs through the pulmonary vein to the left atrium that transferred to the left ventricle through mitral value. Then this purified blood is spreaded throughout the whole body through the aorta. Now during this cardiac process positive ions Na+ in blood flowing through the cell membrane of the heart cell, so a voltage potential has been created between heart inside cells and the outside cells [7]. This processÂăisÂăknown as depolarization. Again similar to depolarization, in repolarization positive ions K+ flowing out from the cell membrane and creates a potential difference. When the potential difference is larger than the a threshold value the primary pacemaker of heart that is SA node produces an electrical pulse. This electric impulse travels to the right and left atrium causing them to contract and generates the first component of ECG that is the P-wave. After contraction of the atrium, the electrical pulse arrives at AV node that is responsible for contraction of the ventricle. This contraction of ventricles causes QRS complex. Then the signal is passed through His bundle and left and right Bundle Branches and spreaded through Purkinje fibre. This effect causes the depolarization of ventricle and generation of the T wave. The typical flow of this electrical signal has been described in Figure 1.2. By place in suitable electrodes in the standard locations of the human body, this ECG signal is collected and processed.

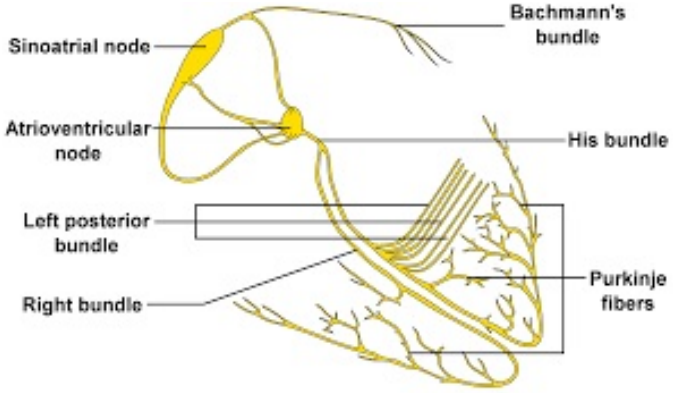

Figure 1.2: ECG Signal Flow.

1.3 ECG signal components

A typical ECG signal consists of mainly five components namely P wave, QRS complex and T wave. Figure 1.3 shows the components of ECG signal. Table1.1 presents a description of the components of a typical real ECG signal.

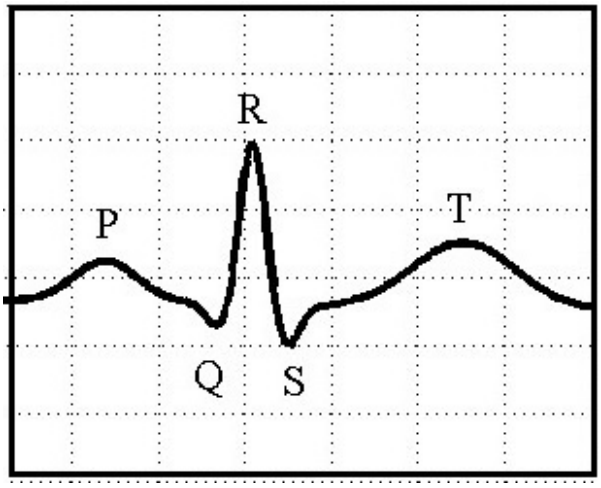

Figure 1.3: ECG Signal Components.

Table 1.1: Description of Components of ECG signal.

Components Name	Description	Amplitude (mv)	Duration (Sec.)
P wave	Atrial delorization	0.10-0.20	0.12
PR Interval	Starting of P wave to end of QRS complex	-	0.20
QRS complex	Ventricle delorization	1.00-1.20	0.08
T wave	Ventricle repolarization	0.12-0.30	0.16
QT Interval	Starting of QRS complex to the end of T wave	-	0.40
R-R interval	One cardiac cycle	-	0.80

1.4 Motivation

ECG wave reflects the electrical activities of the heart. Every component of ECG signal has a particular morphology, whenever any problem causes into the heart the typical morphology of the ECG wave has been changed. In medical treatment, these changes are detected by cardiation and decisions have been taken [8]. Now as ECG is a non-stationary wave so to monitor visually is not an easy task for a clinician and also it is a time-consuming process. When a patient is in severe condition and requires long time monitoring, so it is not possible for a doctor for long time supervision. So an automated ECG monitoring system is required. Again, when an ECG wave is collected from a patient body a lot of noise such as electromagnetic noise, baseline wander noise, patient breathing and moving noise have been accumulated with it so it become a tedious work for a clinician to take important decision by only monitoring it visually. So a computer based

automated ECG monitoring system is required. Not only for an adult patient, ECG wave has a great importance to know the condition of fetal in the maternal abdomen. By processing the fetal ECG, the actual condition of fetal can be known [9],[10]. The above information clears that ECG signal has a great importance in medical science, and ECG signal processing is one the essential part of Biomedical signal processing. This information motivates me to work my research in this field.

1.5 Objective of the thesis

According to the motivational information, we get that design of an automatic ECG monitoring system is popular research work in the field of Biomedical Signal Processing. In this research work my primary focus is

- To design QRS detection algorithm without any amplitude threshold. The developed algorithm should require a low memory buffer and low processing time which are the basic characteristic of a real-time monitoring system. If we can detect R-peaks of an ECG signal then corresponding heart rate can easily calculated (HeartRate $=\frac{60}{\text{R-Rinterval}}$bpm). So we have to prepare our algorithm such that it can faithfully determine the heart rate from the ECG signal.

- Apart from QRS complex other waves (P and T waves) also contain cardiac information. My thesis work also includes designing an algorithm that can detect P and T waves and also delineate by finding ON and OFF of the P and T waves from a real ECG signal.

- In the present FGPA based system is a popular one. FPGA system creates the hardware environment. My work includes designing FGPA based heart rate detection from a real ECG signal.

- To determine the efficiency of my proposed algorithms I have validated my proposed algorithm with standard ECG signal. In my work, I have used standard MIT-BIH and QT database to validate my proposed algorithms.

1.6 Thesis Organization

Including this chapter this thesis consists of five chapters. The remaining thesis orientation is as follows:

1.6.1 Chapter 2: Literature Survey

In this chapter the total literature survey of this work has been described. In order to get enough information about ECG wave signal processing, many literature review are undertaken. As my research are divided into twoÂăbasic parts, so literature review is also divided into twoÂăsection where first part consists information for detecting QRS complex, second one consists of information for detection of P and T-waves.

1.6.2 Chapter 3: Proposed Algorithms

In chapter 3 the implemented algorithms proposed in my thesis work have been described. This is also subdivided into three different parts to describe three proposed algorithms.

1.6.3 Chapter 4: Results and Discussion

Here total experimental results have been described. In chapter also divided into three parts to show the performance of each algorithm separately. In result and discussion stage, the performance of proposed work has been compared with previously established works.

1.6.4 Chapter 5: Conclusion, Future Scope and Publications

This is the last one. Here conclusive remarks and limitations of this work have been described. This part also contains the information about publications those have been made throughout this research. At last a brief future scope of this work has been described.

Chapter 2

Literature Survey

Since the last few year, ECG signal processing becomes a popular research topic in the field of biomedical signal processing. A number of research were taken by the different researcher in ECG signal processing. Few of these research idea enrich my knowledge to implement modified algorithms for processing of ECG. Here is the brief description of literature survey undertaken in this research work. As this research work has mainly three-part such as detection of QRS complex, P and T wave detection and delineation and last one FPGA implementation of the heart rate detection system, literature survey is divided as follows:

2.1 QRS Complex Detection

Pan and Tompkins (1985) [11] have proposed an algorithm for detection of QRS complex. This method is based on squaring and filtering process. According to this proposed algorithm raw ECG signal, has been passed through a low pass filter for noise extraction then differentiation and squaring operation have been performed. At last by typical peak detection operation R peaks are detected. This is one of the established QRS detection algorithms. Though it is a simple algorithm but accuracy is quite poor. Again as the peak detection is based on amplitude threshold do a suitable threshold value is required otherwise accuracy can be degraded.

Benitez *et al.* (2001) [12] have developed an algorithm for detection QRS complex using Hilbert Transform. This algorithm based on the zero crossing features of Hilbert transform. Primary steps of this method are filtering of raw ECG in order to remove noise, and then to get slope information first order differentiation has been performed. Hilbert Transform is used in order to detect peak locations. By applying this algorithm extraction of R peaks from large T, peaks is possible but this algorithm is quite complex. As Hilbert Transform is used here, so we have to go frequency domain and sampling of the signal are required, so a large amount of memory buffer is required.

Ghafffarl *et al.* (2008) [13] have proposed QRS detection algorithm in 2008. This algorithm is derived from the concept of the continuous wavelet transform. In order to emphasise QRS complex from other, he used dominant rescaled wavelet coefficient (DRWC). This method successfully detects QRS complex from long P and T peak signal, but accuracy degrades in few number of signals. The selected wavelet function for that data only suitable for that type of data morphology. If ECG morphology is changed, then the selected wavelet cannot give a better performance response. For random varying of the duration of QRS complex, the algorithm fails to detect QRS complex successfully.

Manikandan *et al.* (2012) [14] has proposed a new algorithm based on Shannon energy with Hilbert Transform. The primary stages of this algorithm as follows: first raw signal has been passed through a low pass filter for noise reduction then first ordered differentiation of the filtered signal has been performed to get slope information and remove low drift noise. After that Shannon energy envelope of the signal has been extracted. Here Shannon energy envelope is used in the place of squaring operation as it has benefits to amplify medium value components. If the square operation has been performed for low-value signal, then it is attenuated. After Shannon energy envelope extraction step, Hilbert Transform of the signal has been performed. Hilbert Transform has a particular characteristic to produce

zero crossing at the position of peak values. Now according to zero crossing point cross ponding R peaks locations have been detected. Though this method has a better accuracy than the previous methods but for the long pauses signal it detects a large number of false peaks as true R-peaks. Again as there is Hilbert Transform, so we have to go for frequency domain where a large number of the memory buffer is required in order to sample the input signal, which not suitable in a real-time environment.

Zhu *et al.* (2013) [15] have proposed a QRS complex detection algorithm based on Shannon energy envelope. This amplitude based on amplitude and time decision criterion based. The primary steps of this algorithm, at the initial stage for noise filtering band pass filter is used. Then in order to get the slope information first order differentiation is performed. After that Shannon, energy envelope has been extracted from the differentiated signal. At peak, detection stage to detect False Noise Detection (FND) and False R Detection (FRD) in uses amplitude and time duration criteria. This algorithm shows better accuracy than the previously established methods and Hilbert Transform problem in the previous algorithm has been solved by this algorithm.The major drawback of this method is that it uses amplitude threshold that degrades accuracy for low amplitude ECG signal.

Apart from these Different methods for detecting R peaks in ECG are artificial neural network (ANN) [16] , heuristic methods [17], wavelet transform (WT) [18], [19], [13], [20], [21], empirical mode of decomposition [22]. Shannon energy [23].

2.2 P and T wave Detection

Thakor *et al.* (1991) [24] have proposed a method for noise cancellation and arrhythmia detection. This method is based on Adaptive Filter where a noise ECG has been choose as an input, and an impulse train of QRS wave has been chosen as reference. The basic strategy of the adaptive filter is to minimize the mean square error between the input signals to the reference signal. This method is applied in different arrhythmia detection problem and p wave detection method. The method successfully removed various artifacts but only P wave detection is possible, and accuracy is quite poor.

[25] proposed an algorithm for extraction of P and T wave based on Extended Kalman Filter. This method is based on Bayesian framework for estimation of denoised ECG from a raw ECG. For detection of peaks location, it used Bayesian estimation theory and to find the fiducial point it uses the width of corresponding wave component. This method has successfully detected wave components in ECG signal but for initialization of filter in this method requires operator interaction. For baseline fluctuation ECG signals the accuracy of this method is quite poor.

[26] proposed a Bayesian signal model for detection and delineation of P and T wave which is threshold free. To estimate the unknown parameters of Bayesian model Gibbs sampler is used.It creates complexity in the resulting posterior distribution. Apart from these Various techniques, based on nested median filter [27], adaptive filtering [24], low pass differentiation (LPD) [28], discrete cosine transform [29], hidden Markov model [30] and wavelet transform (WT) [31] have been proposed for automated extraction of P and T waves.

Chapter 3

Proposed Algorithms

In this research work, total task is divided into three parts. In the first part, the main focus will be the extraction of QRS wave in ECG signal. In the second part implementation of P and T wave, extraction algorithm is described and finally an FPGA-based heart rate detection system using ECG signal has been implemented.

3.1 Proposed Algorithm for QRS complex detection in ECG signal

The block representation of R peak detection algorithm is shown in Figure 3.1. This is divided into four stages namely pre-processing, extraction of Shannon energy envelope and peak finding logic followed by actual R peaks detection. In the pre-processing stage, noise is suppressed, and QRS complex is enhanced by using band pass filter, first order differentiation, and amplitude normalization respectively. In the Shannon energy envelope extraction stage, smooth Shannon energy envelope is produced by using Shannon energy calculation and moving average filter. In peak estimation logic stage, the pre-process for R peak detection is performed by using first order differentiation, amplitude normalization, and squaring, moving average filter. In actual(true) R peak detection stage, exact locations of R peaks are detected. The detailed discussion of each stage of Figure 3.1 is presented in the next subsections.

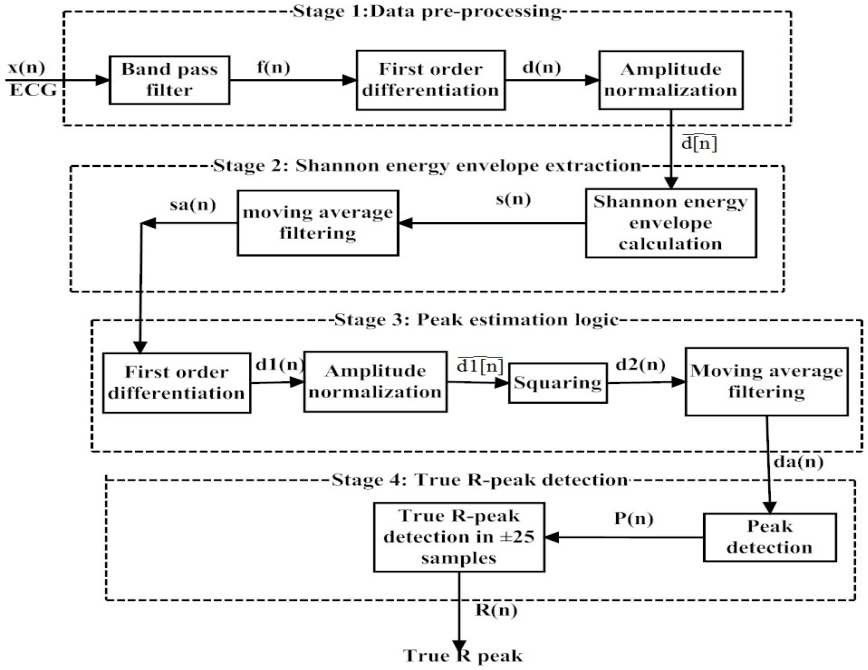

Figure 3.1: Block Diagram of Proposed Algorithm.

3.1.1 Data pre-processing

In reality a typical pathological obtained ECG is corrupted by numerous noises such that power line interface (50 Hz), motion artifact due to electrode, skin interface, patient breathing etc. Moreover ECG signal contains P wave, T wave other than QRS complex which are not interested in our work. So we need a filtering system to extract QRS complex. From the power spectral analysis of

various signal components in ECG signal, we observe that the maximum power density of QRS complex lies between 5-20 Hz. In our proposed method, the ECG is passed through a Chebyshev type I filter with bandwidth of [6-18] Hz.

After getting the filtered signal, we perform the first order differentiation of the signal to get the slope information. The first order differentiation is a high pass filter which attenuate lower frequency components (P and T wave)and passes higher frequency components (QRS wave). The mathematical implementation of the first order differentiation is shown below:

$$\mathrm{d[n]} = \mathrm{f[n+1]} - \mathrm{f[n]} \tag{3.1}$$

After filtering and differentiating the signal is normalized in order to scale its value up to 1. This is done for preparing the signal for Shannon energy envelope computation.

$$\widehat{\mathrm{d[n]}} = \frac{\mathrm{d[n]}}{\max(\,|\mathrm{d[n]}|\,)} \tag{3.2}$$

3.1.2 Extraction of Shannon energy envelope

After differentiating the ECG signal it becomes a bipolar signal. As our method is based on peak detection, so we have to transform the differentiated signal into a unipolar signal. Now for this transform there are some transform methods those can be applied. They are absolute value method, squared value method, Shannon entropy method, Shannon energy envelope method. The mathematical formulation of these methods is described below.

Absolute value:$\mathrm{y[n]} = |\mathrm{a[n]}|$
Squared value:$\mathrm{y[n]} = \mathrm{a[n]} \times \mathrm{a[n]}$
Shannon entropy value:$\mathrm{y[n]} = -\,|\mathrm{a[n]}| \times \ln(\,|\mathrm{a[n]}|\,)$
Shannon energy value: $\mathrm{y[n]} = -\,(\mathrm{a[n]})^2 \ln(\,(\mathrm{a[n]})^2\,)$

where $\mathrm{a[n]}, \mathrm{y[n]}$ are input and output for the above equations respectively.

In our proposed method we have used Shannon energy envelope method as it has some advantages over the others. Figure 3.2 shows that absolute value method produces same weight value irrespective of the input amplitude. Shannon entropy method attenuates high-intensity components and gives high preference to low intensity components. The squared value method gives an exponential weightage response to the high-intensity components which will make difficulties in order to detect low-intensity components. For Shannon energy method, middle-intensity components are more emphasised and other intensity values are attenuated which gives a better detection of R-peaks.

After achieving Shannon energy envelope by using Shannon energy calculation the signal is passed through a zero shift moving the average filter to get a smooth Shannon energy envelope. A moving average filter is nothing but a moving window integrator. The mathematical expression of a moving average filter is expressed below.

$$\mathrm{y(nT)} = \frac{1}{\mathrm{N}}\,[\mathrm{a(nT-(N-1)T)} + \mathrm{a(nT-(N-2)T)} + \ldots\ldots\ldots + \mathrm{a(NT)}] \tag{3.3}$$

The length of the moving average filter is an important parameter for this detection method. Generally the length of the moving average filter is taken approximately to the width of the QRS complex. If the length of moving average filter is too broad then for integration it takes the T wave also, again if the length of moving average filter is very narrower compared to the QRS complex, then for a single QRS complex it produces more spike which leads to an erroneous detection. In our proposed method we have taken a length of 65 samples moving average filter.

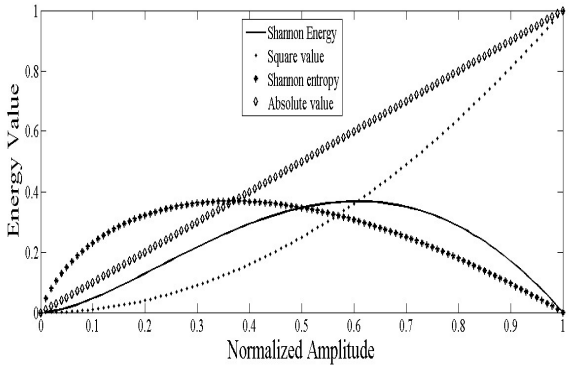

Figure 3.2: Comparison of energy value for different envelope method using normalized amplitude.

3.1.3 Peak Estimation Logic

In this stage we introduce some different approaches from the other R-peak detection technique based on Shannon energy. In [14] for detection of R peaks use Hilbert Transform but for Hilbert transform it requires more memory buffer again in [15] have used some amplitude threshold in the decision stage for extraction for true R peaks. To overcome these problems our R peak detection logic should be free from amplitude threshold. After Shannon energy envelope extraction stage we get smooth peak signal but it contains both true R-peaks and false R-peaks. In this stage we actually attenuate the false R-peaks and emphasise the true R-peaks. This is done by following steps.

It is natural that the amplitude value for true R-peaks will be quite high than the false peaks. So if we take the first order differentiation of the signal, then it stores the slope information of the true peaks but it reduces the slope information of the false peaks.

Now in order to scale the signal to 1 the amplitude normalization of the signal has been performed.

Now the signal is a bipolar signal and for peak detection we have to make it a unipolar signal. So we performed square operation. The amplitude of false peaks are very low so when we apply square operation of these peaks they will be completely attenuated. As a result true R-peaks are amplified and false R peaks are diminished. Then the signal has been passed through a smoothing filter(moving average filter) in order to get a polished peak signal. In our proposed technique we use a moving average filter of length 85 samples.

Now signal is ready for peak detection.This peak estimation logic stage is demonstrated in Figure 3.3

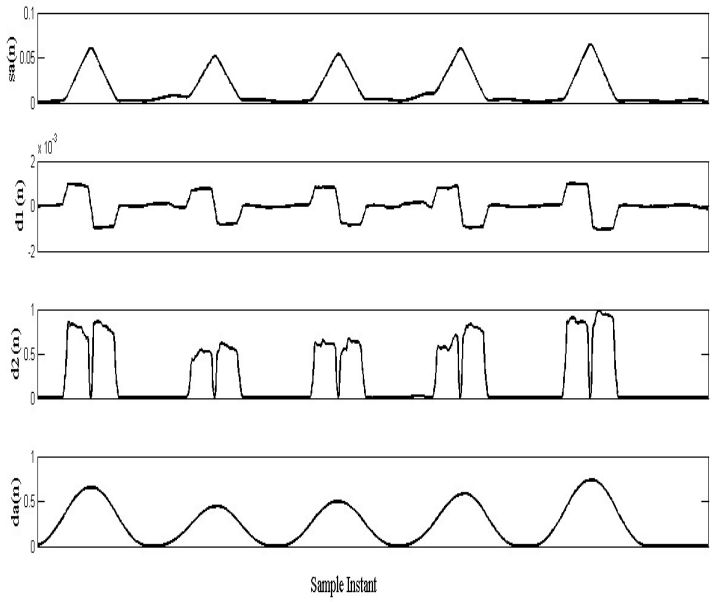

Figure 3.3: Different Signal processing steps of peak estimation logic stage.

3.1.4 True R peak detection

In this stage by applying peak finding algorithm R-peaks are detected. But experimentally shows that detected peak locations are slightly different from the actual positions of peaks in the experimental signal. So in order to find the real positions of R-peaks, an operation is incorporated which finds the actual time instant of peaks in the ECG signal by determining the maximum signal value within ± 25 locations of the identified locations in previous step.

In Figure 3.4 the total signal processing of the entire algorithm is shown, wherein Figure 3.4(h) red impulses indicate the extracted R peaks by proposed algorithm.

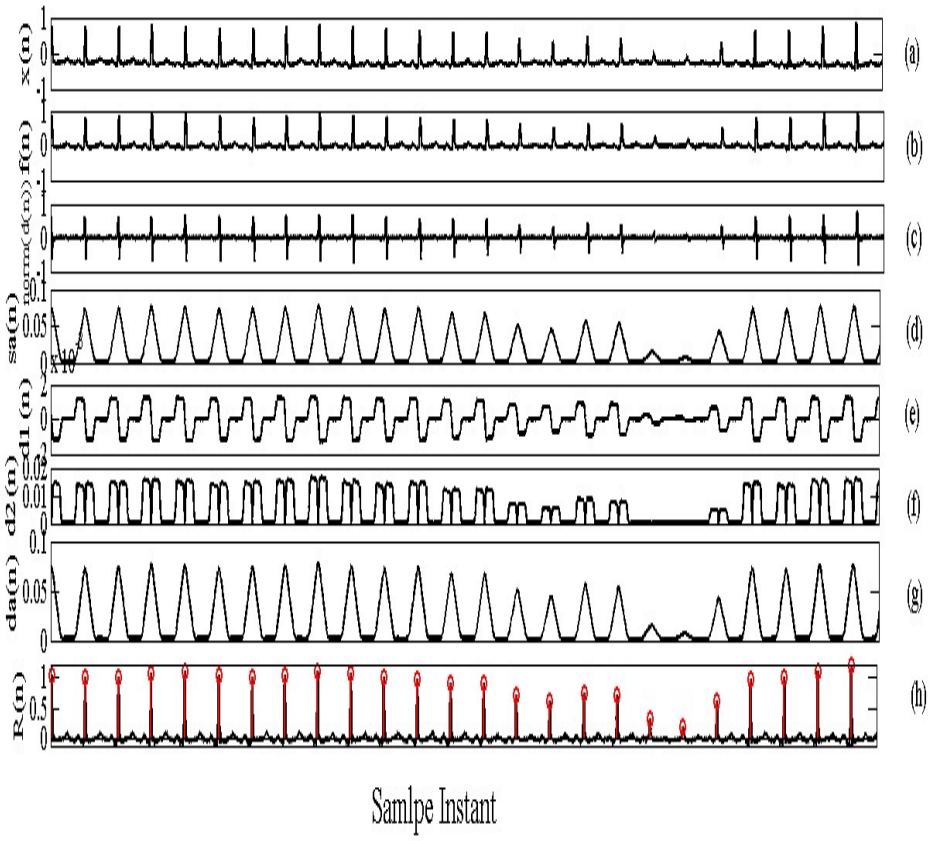

Figure 3.4: Total signal processing steps of the described method: (a) ECG data(Record 205). (b) Filtered signal. (c) Output of normalize operation. (d)Smooth Shannon energy envelope. (e) Differentiation of Shannon Energy envelope. (f) Output of square operation. (g) Output of moving average filter. (h) True detected R-peaks (Red colour impulses).

3.2 Proposed Algorithm for Detection and Delineation of P and T wave in ECG signal

The schematic block representation of the P and T wave extraction algorithm is shown in Figure 3.5. It consists of five stages namely pre-processing, phase assignment, optimization parameter estimation using PSO, denoised ECG signal estimation logic, P and T wave detection and delineation logic. In the pre-processing stage, we have removed baseline wander and power line interference from the ECG signal. In the phase assignment stage at first R peak is detected by using a Shannon energy envelope method, described in the previous section and then phase is assigned to the ECG according to the detected R peaks. We have used PSO framework for calculation of optimized parameters of the ECG component in the ECG and set the parameters of EKF. In the fourth stage, EKF framework is used to estimate the denoised ECG. Finally in the P and T wave detection and delineation logic, square operation is used with the denoised ECG signal and optimized phase parameters calculated by PSO for detection and delineation of P and T waves.

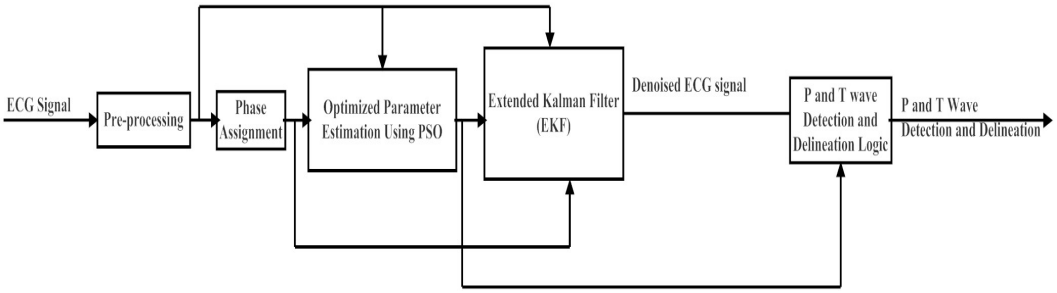

Figure 3.5: Block diagram of proposed methodology for P and T waves detection and delineation in ECG.

3.2.1 Pre-processing

The main aim of the pre-processing stage is to remove the baseline wander and power line interference from the ECG signal.Baseline wander noise is one of the common noise present in a typical ECG signal. It fluctuates the baseline from the reference axis of ECG signal. Various filters can be used to remove baseline wander noise such as two-stage moving window median filter(MD2), single stage moving window median filter(MD1), two stage moving average filter(MA2), low pass filter(LP), band pass filter using noise stress database(BPF) [32]. In my experiment, I have used two-stage median filter for removing the baseline wander noise. Figure 3.6 show that for different input SNR in case of two-stage median filter the output SNR improvement is highest. So I have used two-stage median filter for this particular problem.At first,the ECG signal is passed through a median filter with a window size of 200 ms which removes the P waves and QRS complexes. Then a median filter with window size of 600 ms removes the T waves and power line interference. The filtered signal represents the baseline wander which is then subtracted from the ECG recording to get the baseline wander removed ECG signal. Figure 3.7 shows the complete signal processing steps of two-stage median filter.

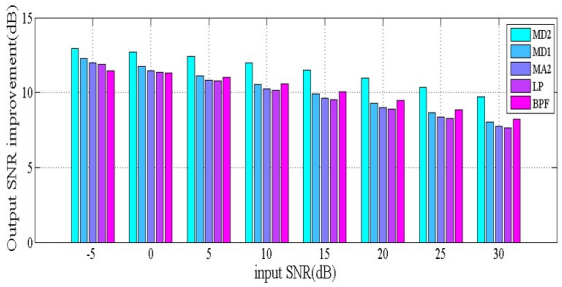

Figure 3.6: Comparison of mean SNR improvements achieved in different input SNRs for BW removal based on two-stage moving window median filter(MD2), single stage moving window median filter(MD1), two stage moving average filter(MA2), low pass filter(LP), band pass filter using noise stress database(BPF).

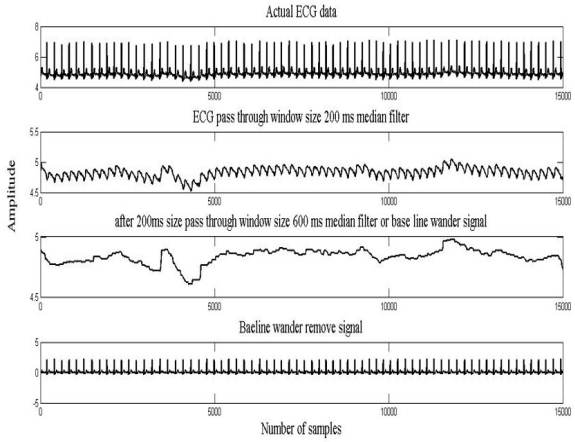

Figure 3.7: Baseline wander removed ECG signal.

In a typical ECG electromagnetic noise is present in the frequency range of 50 Hz. A notch filter centered at 50 Hz is implemented through a 50 tap finite impulse response filter to remove the power line interference. The complete steps for removing of electromagnetic noise has been described in Figure 3.8

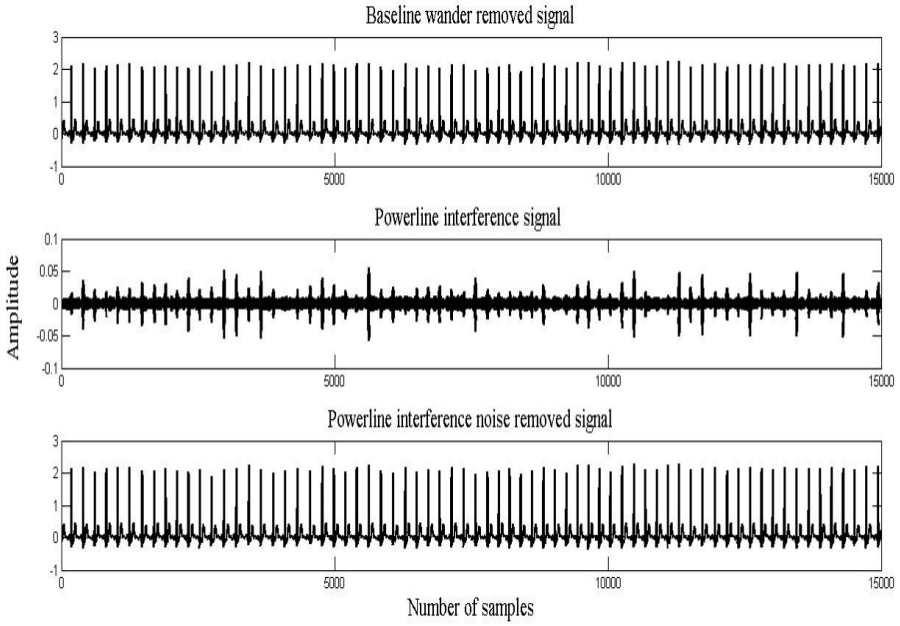

Figure 3.8: Baseline wander removed ECG signal.

3.2.2 Phase Assignment

The main aim of the phase assignment stage is to detect R peak in the ECG signal and then to assign the phase to each sample of the signal according to the detected R peak. In this stage, a Shannon energy envelope method is applied to detect R peak the ECG. We have used the concept of R peak detection of the ECG as explained in our proposed method above. The phase to each sample of ECG was assigned by using R-peaks of ECG.

Here φ_k = phase of ECG which varies between $-\pi$ to π. Assign phase $\varphi_k = 0$ when k=sample number where R peak is detected. The phase difference between two consecutive R peaks is 2π. Let $nlen$ = number of samples between the two nearest R peaks. Each sample is assigned a phase $\frac{2\pi}{nlen}$ more than the phase of previous sample. Then 2π is subtracted from the phase of the sample where the phase of the sample is more than π and less than 2π because the phase of the sample is between $-\pi$ to π. The phase assignment of ECG signal of sel103 QT database has been described in Figure 3.9

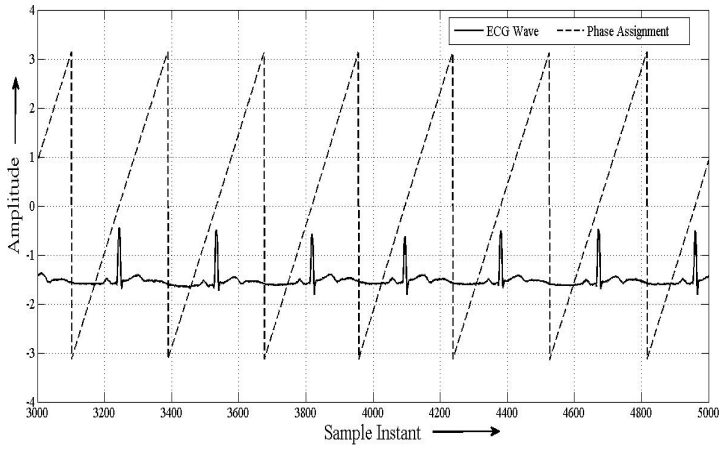

Figure 3.9: Phase assignment of ECG of sel103 QT database.

3.2.3 Optimized Parameters Estimation Using PSO

The main aim of the optimization parameters estimation stage is to calculate optimized parameters of single cycle of the ECG envelope by using PSO. For modeling of a single cycle of ECG envelope, a set of optimized parameters (amplitude, width, phase) related to components of the ECG (P, Q, R, S and T wave) is required. In our proposed method for finding these optimum parameters we have applied PSO method.

Templates of ECG like mean of ECG, standard deviation of ECG and mean of phase are required for estimation of optimized parameters by using PSO. We have calculated the templates of ECG (mean of ECG, standard deviation of ECG, mean of phase) as explained in [33].

PSO is a stochastic random optimization process which is inspired by the behaviors of social animal like swarm of fish, flock of birds [34]. It is one of the powerful evolutionary technique that is capable to optimize a nonlinear equation with the least number of solution parameters. The basic concept of PSO lies in the fact of social sharing information [35]. For each solution variable a swarm of particles are taken. Movement of each particle is controlled by its current position and velocity. At each step, each particle remembers its local best position and global best position. For each variable, the optimum position of particle denoted as global best where local best denoted the last updated optimum position of the corresponding particle. Optimality of a particle is checked according to the problem statement [36].

For a given particle P_{ij} at k^{th} iteration position and velocity updating formulae are given below.

$$v_{ij}^{k+1} = w.\, v_{ij}^{k} + C_1\, R_1(p_{lij}^{k} - p_{ij}^{k}) + C_2\, R_2(p_{gi}^{k} - p_{ij}^{k}) \tag{3.4}$$

$$p_{ij}^{k+1} = p_{ij}^{k} + v_{ij}^{k+1} \tag{3.5}$$

Here i and j varies from 1 to NP and 1 to NG respectively. Where NP is number of particles in the swarm and NG is the number of variables in the problem.

Here v_{ij}^{k+1} = velocity of the ith particle of jth variable at iteration k+1, p_{ij}^{k+1} = position of the ith particle of jth variable at iteration k+1, w=inertia weight factor, C_1 and C_2 are acceleration constant, R_1 and R_2 are random values.

We have intelligently applied PSO for calculation of optimum parameters of the ECG. The suitable step for finding optimum parameters of the ECG for one cycle by using PSO as follows:

Step 1: Initialize the swarm by assigning random position value of the particles for the phase value of P, Q, S, T wave within the range of waves as given in paper[37].The random phase value for P,Q, S, T are in ranges $\frac{-\pi}{3} \pm 0.2$, $\frac{-\pi}{12} \pm 0.2$, $\frac{\pi}{12} \pm 0.2$, $\frac{\pi}{3} \pm 0.2$ respectively. We have set R wave has phase zero.

Step 2: Fitness value (mean square error) of each particle is calculated. This is done by finding the amplitude value of mean of ECG correspond to each swarm (phase value) and calculated the error by subtracting the modeled ECG getting from each set of parameters using synthetic dynamic ECG model [37] from ECG mean value. Finally, mean square error is calculated from the error.

Step 3: Our main aim in PSO is to minimize mean square error. For each individual particle update local best position (p_{lij}^{k}) according to current fitness value.

Step 4: For each variable find the global best position (p_{gi}^{k}) by comparing the fitness value of the corresponding particles.

Step 5: Update the position and velocity of each particle according to equation (3.4) and (3.5).

Step 6: Go to step-2 until maximum iteration is reached or convergence condition(mean square error<= 0.001) is achieved.

We have got optimized parameters to model maternal ECG for one cycle at maximum iteration is 100, $C_1 = C_2 = 2$, $w_{\min} = 0.4$, $w_{\max} = 0.9$.

3.2.4 Denoised ECG signal Estimation logic

In denoised ECG signal estimation logic stage, we have used EKF for estimate the denoised ECG signal.

The goal of the extended Kalman filter is to estimate the state of a discrete time controlled process [38]. Consider a state vector X_{k+1} governed by a nonlinear stochastic difference equation with measurement vector Y_{k+1} at instant $k+1$ [39]

$$X_{k+1} = f\,(X_k) + W_k \tag{3.6}$$

$$Y_{k+1} = h\,(X_{k+1}) + V_{k+1} \tag{3.7}$$

Where W_k and V_k represent process noise and measurement noise, $f(.)$ defines system dynamic function and $h(.)$ defines measurement function. Here $E[W_k W_k^T] = Qn$ and $E[V_k V_k^T] = Rn$. Qn and Rn are the covariance of process noise and measurement noise respectively which are calculated from the mean and standard deviation of the ECG [33]. In this study, a synthetic dynamic ECG model[37] is used to estimate denoised ECG from the raw ECG. One ECG signal can be expressed as the sum of five Gaussian functions defined by their peak amplitude, width and center, denoted as α_i, b_i, and ϕ_i respectively.

$$Z(\theta) = -\sum_{i \in W} \alpha_i \exp(\frac{-(\theta - \phi_i)^2}{2\, {b_i}^2}) \tag{3.8}$$

Each Gaussian function models one of the five waves $W = \{P, Q, R, S, T\}$ of heart beat. The state vector X_k in equation (3) is defined as $X_k = [\ \theta_k \quad Z_k\ ]^T$, where the θ_k is phase and Z_k is amplitude of the ECG. The state process $f(.)$ is:

$$\theta_{k+1} = (\theta_k + w\delta) \bmod (2\pi) \tag{3.9}$$

$$Z_{k+1} = -\sum_{i \in W} \frac{\alpha_i\, w_f \delta\, \Delta\theta_{i,k}}{{b_i}^2} \exp(\frac{-\Delta\theta_{i,k}}{{b_i}^2}) + Z_k \tag{3.10}$$

Where w_f is the phase increment.

$\Delta\theta_{i,k} = (\theta_k - \phi_i) mod(2\pi)$ and $w =$ the angular velocity of the trajectory as it moves around the limit cycle.

The equation (3.6) represents the state equation and a description of the state equation is given above. The next step of the extended kalman filter is an observation equation as represented in equation (3.7).

Observation data $Y_{k+1} = [\ \varphi_{k+1} \quad S_{k+1}\ ]^T$ where $\varphi_{k+1} =$ the phase of ECG which is between $-\pi$ to π and is explained in phase assignment subsection. S_{k+1} is the amplitude of the ECG at an instant $k+1$.

The measurement function $h(X_{k+1}) = X_{k+1}$.

In this stage we have initialized the parameters of the extended Kalman filter such as initial state $\widehat{X_0}$ and initial covariance P_0.

$$\widehat{X_0} = [\ -\pi \quad 0\ ]^T$$

$$P_0 = \begin{bmatrix} (2\pi)^2 & 0 \\ 0 & 10 \max(|S|)^2 \end{bmatrix}$$

Computation of Extended Kalman Filter

For $[k = 0, 1, 2.....N]$

State prediction :$[\overline{X_{k+1}} = f(\overset{\wedge}{X_k})]$

State prediction covariance :$\overline{P_{k+1}} = \nabla f_x\ P_k\ \nabla {f_x}^T + Qn$

$$\nabla f_x = \begin{bmatrix} 1 & 0 \\ -\sum\limits_{i \in w} \frac{\alpha_i w_f \delta}{{b_i}^2}(1 - \frac{\Delta\theta_i^2}{{b_i}^2}) exp(\frac{-\Delta\,\theta_i^2}{2{b_i}^2}) & 1 \end{bmatrix}$$

$$Sg = \nabla h \, \overline{P_{k+1}} \, \nabla h^T + Rn$$

$$\text{As } h\left(\overline{X_{K+1}}\right) = \overline{X_{K+1}}$$

$$\text{So } \nabla h \; = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\text{Kalman Gain: } Kg = \overline{P_{k+1}} \, \nabla h^T Sg^{-1}$$

$$P_{K+1} = \overline{P_{K+1}} - ((Kg)Sg(Kg^T))$$

$$\widehat{X_{k+1}} = \overline{X_{k+1}} + Kg\left(Y_{k+1} - h\left(\overline{X_{k+1}}\right)\right)$$

3.2.5 P and T wave Detection and Delineation Logic

The main aim of this stage is to detect and delineate P and T wave (detect P ON position, P OFF position, P Peak, T ON position, T OFF position, T Peak). The optimized phase of P and T wave, calculated by PSO has been compared with the phase value correspond to each estimated ECG sample using EKF. The exact location of P and T peak can be found by searching the maximum signal value within ±30 of the identified location in the previous step. In order to find on and off position of P and T wave we first squared the estimated denoised ECG. Then we have detected the valley point of both sides of detected peak locations (P and T peak) which gives location of on and off position of P and T wave (delineation). Figure 3.10 demonstrates the delineation logic of P and T waves(T-On, T-Off, P-On, P-Off).

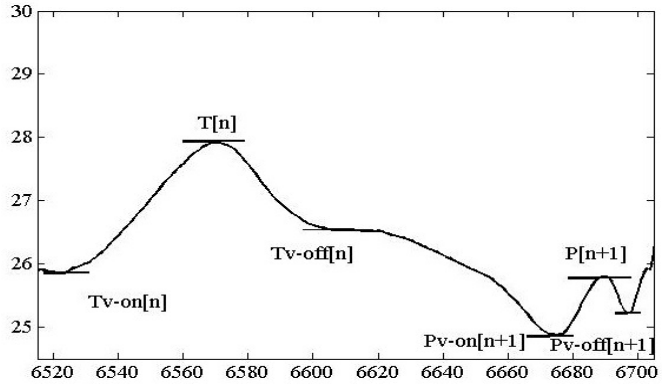

Figure 3.10: Valley point detection logic.

3.3 Heart Rate determination from an ECG signal in FPGA platform

Heart Rate detection is one of the basic clinical jobs to determine the condition of a patient. Heart rate can easily be calculated from ECG signal. In an ECG

signal if the locations of R-peaks are known then heart rate can easily determine by the following formula: HeartRate $=\frac{60}{\mathrm{R-Rinterval}}$bpm. A real-time QRS detection algorithm has been proposed in this research work, this algorithm can extended for heart rate detection also. In this section, we implemented the design in field programmable gate array (FPGA). FPGA is a very popular field to design a hardware environment [40]. FPGA provides easy testability allow faster implementation and verification option for implementing a new design [41]. Field Programmable Gate Array (FPGA) allow rapid prototyping and quick programming [42]. FPGA based design can act as a bridge in converting from a software algorithm to dedicated hardware design based on Application-specific integrated circuits (ASICs). In this section, a brief description of the primary jobs those are undertaken to design the heart rate detection algorithm in FPGA.

3.3.1 Data Conversion

The amplitude value of a typical ECG signal is in real numbers format. But real number format is not compatible for FPGA. For the implementation of ECG signal in FPGA, two formats are present (i) fixed point format, (ii)Floating point format.Here fixed point format has been used because it is easier to understand and implement, require less memory and less processor time. We have converted the real number to 16 bits fixed-point format. The amplitude of the ECG signal ranges between -15 to 15. So we have multiplied the number with 2^{11} . Then we convert to the nearest integer and if the number is positive we represent the binary form of the number. If negative, at first convert the number into the binary then represent the number as $1's$ complement of the binary number.

3.3.2 Filtering

In our proposed method, the ECG is passed through a finite impulse response (FIR) band-pass filter with Kaiser window with a bandwidth of [6-18] Hz. We have used FIR band-pass filter with Kaiser Window for easier implementation and avoid complexity compare to the infinite impulse response (IIR) filter [43]. [44]. We have used direct form-I for implementation of FIR band-pass filter. The mathematical representation of direct form-I:

$$\mathrm{Y} = \sum_{\mathrm{n=0}}^{\mathrm{N-1}} \mathrm{a(n).b(n)} \tag{3.11}$$

Here Y=output of the band-pass filter, a is shifted matrix, b is the coefficient matrix shown in Figure 3.11 and N is the length of the coefficient matrix. The block diagram for FPGA implementation of the band-pass filter (equation-1) shown in Figure 3.11. We have calculated coefficients of FIR band-pass filter (coefficient matrix) with Kaiser Window with a bandwidth of [6-18] Hz. We have used Filter Design Toolbox (FDT) in MATLAB for calculation of coefficient matrix [45]. We have converted the each coefficient from the real number to the 16 bits fixed-point format by using the algorithm 1 and store in the coefficient matrix. We have used shifted form to store the input values. The length of the shifted matrix is 31 because the length of the coefficient matrix is 31. In shifted matrix, all the values in shifted matrix shift one unit right and store input at zeroth location (shifted

matrix (1 to 30) =shifted matrix (0 to 29) and shifted matrix (0) =X (n)).Where input is X (n) (real ECG converted to fixed point format) at instant n.

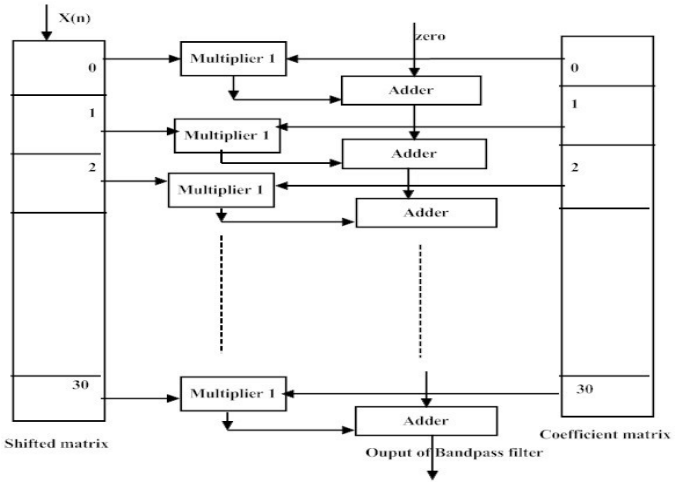

Figure 3.11: Block diagram of FPGA implementation of the band-pass filter.

3.3.3 R Peak Detection

For peak detection, we have used two previous samples with current samples of moving average filter output. Let three samples are a, b, c then b to be peak b should be more than a and c, for that we have used subtraction operation. We find d=a-b and e=c-b by using 2 subtraction block, then we have checked whether d and e are negative or not (d (31) =$'1'$ and e (31) =$'1'$). When these are negative, we assign that as the peak and that location we put as $'1'$ otherwise $'0'$.

But experimentally shows that detected peak locations are slightly different from the actual positions of the peaks in the experimental signal. So to find the real positions of actual R-peaks, we have searched the maximum amplitude within 50 previous samples of the identified location.

We have used 50 previous samples of actual ECG signals from the identified location. Then we find the maximum amplitude of that 50 samples by using subtraction operation and distance between the highest amplitude in 50 samples and identified the location calculated.

The current location automatically incremented by one when we give sequential inputs.

Finally subtracting the distance from the current location we got the R peak.

3.3.4 Heart Rate Detection

After ECG extraction, heart rate can be calculated using the interval between two consecutive detected R-peaks of the ECG signal. Heart rate between two consecutive R-peaks=$\frac{1}{T}$ bits/min = $\frac{60\,f_s}{n}$ bits/min.

Where T= R-R interval of the two consecutive R-peaks in minute, =sampling frequency, n=number of samples between the two successive R peaks.

Here fs=360

We first convert 60*fs to binary value consist of 32 bits. Then we calculate n by using subtraction algorithm, where inputs are two consecutive R-peak locations.

Then by using division operation calculate heart rate where inputs are binary values of 60*fs and n.

3.3.5 System Synthesize Information

After implementation of this proposed FPGA system, it is synthesized to check whether it is possible to implement it in the available hardware system. In this work, the proposed system has been synthesized in Vertex 5. The synthesized report as follows. Figure 3.12 shows the device utilization summary of the proposed system, where Figure 3.13 displays the RTL model of the system.

Device Utilization Summary (estimated values)			[-]
Logic Utilization	**Used**	**Available**	**Utilization**
Number of Slice Registers	5728	607200	0%
Number of Slice LUTs	88456	303600	29%
Number of fully used LUT-FF pairs	188	93996	0%
Number of bonded IOBs	114	700	16%
Number of BUFG/BUFGCTRLs	1	32	3%

Figure 3.12: Device Utilization Summary of the proposed FPGA System.

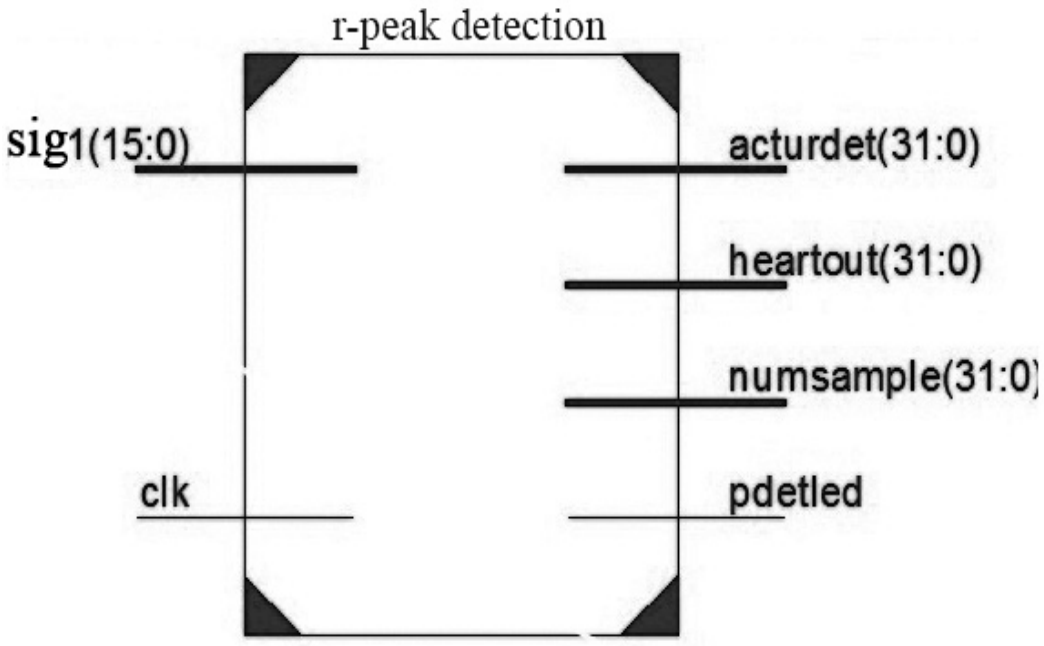

Figure 3.13: RTL of the proposed FPGA System.

Chapter 4

Results and Discussion

In order to evaluate the efficiency of proposed methods, the performance of these methods has been evaluated on real ECG signals.

4.1 Experimental ECG Database

In my research work, two real ECG databases have been used namely MIT-BIH Arrhythmia Database and QT Database.

4.1.1 MIT-BIH Arrhythmia Database

MIT-BIH Arrhythmia Database is one of the major contributions of cooperative work of Boston′s Israel Hospital Laboratory and MIT laboratory. This database was introduced in 1980 and the main contents of this database are standard material for evaluation of arrhythmia detection [46]. This database consists 48 half hours two-channel ECG recording obtained from 47 subjects studied by the BIH Arrhythmia Laboratory [47].

The sampling frequency of the digitized ECG signal is 360 samples per second per second with 11-bit resolution over a 10 mV range.

4.1.2 QT Database

QT database is one of the popular real databases that is used in different research work [28]. It is used as a reference for finding the validity of an automated ECG components delineation algorithm. It consists of two channel real ECG signal collected from various subjects. It is an annotated by the cardiologist for a minimum of 30 beats per channel [31]. The cardiologist annotation of QT database is being done by two leads where in this work annotation is one using single lead. To find the performance of the proposed technique the annotation result of this technique have been compared with manual annotation of QT database [48].

4.2 Simulation Software

A couple of software have been used in this work. For software simulation, MATLAB 2012B has been used. For FPGA system design, Xilinx ISE 14.2 has been used. Like the arrangement of Proposed Algorithms, result and discussion section also divided into three part as follows.

4.3 Result and Discussion for QRS Detection Algorithm

To evaluate the performance of our proposed R peak detection method, we require three parameters namely true positive (TP), false negative (FN) and false positive (FP) from detected R peak. Here TP is the number of correctly detected R peaks, FN is the number of missed R peaks, FP is the number of noise spikes detected as R peaks. Sensitivity (Se) and positive predictive value (+P) and detection error rate (DER) and accuracy (Acc) are calculated using TP, FN and FP by the following equations respectively.

$$\text{Se} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{4.1}$$

$$+\text{P} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{4.2}$$

$$\text{DER} = \frac{\text{FP} + \text{FN}}{\text{TP}} \times 100\% \tag{4.3}$$

$$\text{Acc} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \times 100\% \tag{4.4}$$

The performance of the proposed R-peak detection method for 48 ECG recording of the MIT-BIH arrhythmia database is summarized in Table 4.1. The proposed method detects a total number of 109474 true peaks. It also produces 58 false negatives (FN) and 116 false positive (FP). The average accuracy of the proposed method is 99.841% but for individual detection accuracies vary from 99.26% to 100%. In Table 4.2. The performance of the proposed method on MIT-BIH arrhythmia database is compared with other existing methods. It shows that our proposed method has a better accuracy than the other methods like wavelet transform techniques, differential operation method, Pan-Tompkins algorithm, Shannon energy with Hilbert transform technique, Shannon energy technique

In MIT-BIH arrhythmia database, records 104,108,203,228 contains high-grade of noise that′s why the accuracy of the method for these records are comparatively weaker than other records. Record 103 contains low amplitude QRS complexes and baseline drift, the performance of the proposed method for this record is shown in Figure 4.1

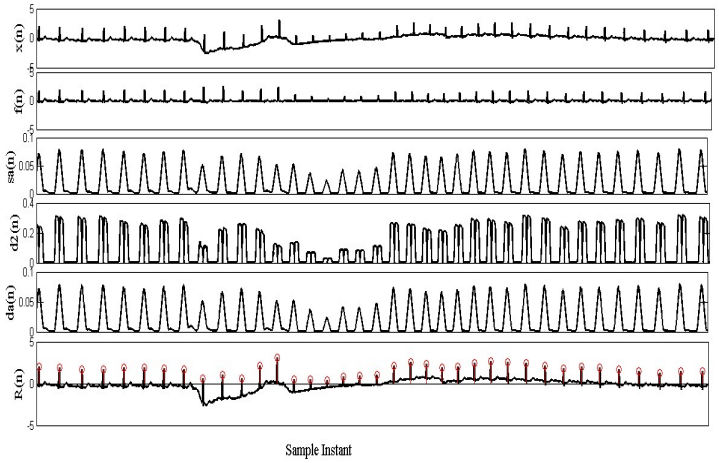

Figure 4.1: Performance of the proposed method for Record 103 (Low amplitude QRS complexes and baseline drift.)

Table 4.1: Performance evaluation of R peak extraction algorithm on MIT-BIH arrhythmia database ECG signal with the duration of 30 minutes.

DATA NO	TP	FN	FP	Se (%)	+P (%)	DER (%)	Acc (%)
100	2272	1	0	99.96	100.00	0.04	99.96
101	1866	0	2	100.00	99.89	0.11	99.89
102	2187	0	0	100.00	100.00	0.00	100.00
103	2084	0	0	100.00	100.00	0.00	100.00
104	2255	0	4	100.00	99.82	0.18	99.82
105	2581	5	5	99.81	99.81	0.39	99.61
106	2000	3	5	99.85	99.75	0.40	99.60
107	2136	1	0	99.95	100.00	0.05	99.95
108	1762	5	8	99.72	99.55	0.74	99.27
109	2532	0	3	100.00	99.88	0.12	99.88
111	2124	0	4	100.00	99.81	0.19	99.81
112	2539	0	1	100.00	99.96	0.04	99.96
113	1795	0	0	100.00	100.00	0.00	100.00
114	1879	0	4	100.00	99.79	0.21	99.79
115	1954	0	6	100.00	99.69	0.31	99.69
116	2405	5	1	99.79	99.96	0.25	99.75
117	1535	0	1	100.00	99.93	0.07	99.93
118	2276	2	5	99.91	99.78	0.31	99.69
119	1985	2	4	99.90	99.80	0.30	99.70
121	1866	0	4	100.00	99.79	0.21	99.79
122	2476	0	0	100.00	100.00	0.00	100.00
123	1520	0	5	100.00	99.67	0.33	99.67
124	1628	0	8	100.00	99.51	0.49	99.51
200	2610	0	4	100.00	99.85	0.15	99.85
201	1962	1	2	99.95	99.90	0.15	99.85
202	2136	0	2	100.00	99.91	0.09	99.91
203	2981	9	8	99.70	99.73	0.57	99.43
205	2655	1	0	99.96	100.00	0.04	99.96
207	1857	3	5	99.84	99.73	0.43	99.57
208	2948	7	3	99.76	99.90	0.34	99.66
209	3003	2	0	99.93	100.00	0.07	99.93
210	2633	1	2	99.96	99.92	0.11	99.89
212	2748	0	0	100.00	100.00	0.00	100.00
213	3250	1	2	99.97	99.94	0.09	99.91
214	2264	0	2	100.00	99.91	0.09	99.91
215	3362	1	0	99.97	100.00	0.03	99.97
217	2208	0	1	100.00	99.95	0.05	99.95
219	2154	0	0	100.00	100.00	0.00	100.00
220	2048	0	0	100.00	100.00	0.00	100.00
221	2427	0	1	100.00	99.96	0.04	99.96
222	2482	0	1	100.00	99.96	0.04	99.96
223	2606	0	0	100.00	100.00	0.00	100.00
228	2053	0	5	100.00	99.76	0.24	99.76
230	2256	0	2	100.00	99.91	0.09	99.91
231	1571	0	0	100.00	100.00	0.00	100.00
232	1780	0	4	100.00	99.78	0.22	99.78
233	3070	8	2	99.74	99.93	0.33	99.68
234	2753	0	0	100.00	100.00	0.00	100.00
Total	109474	58	116	99.95	99.88	0.16	99.84

Record 232 contains a number long pauses in the ECG signal. Our proposed method has a better response to this signal shown in Figure 4.2. Record 106 has tall T waves, and it contains continuously varying QRS complex. Detection performance of the expressed method for this signal is shown in Figure 4.3.

Table 4.2: Comparison of performance of our proposed method with other methods for detecting R peaks using MIT BIH database

Method	Total beats	FN	FP	Se (%)	+P (%)	DER (%)	Acc (%)
Proposed method	109,532	58	116	99.95155	99.88416	0.164668	99.84131
PSEE [15]	109,494	93	91	99.92	99.92	0.168	99.832
WT [18]	104,184	65	112	99.94	99.89	0.17	99.83
SEHT [14]	109,496	79	140	99.93	99.87	0.2	99.8
DOM [49]	109,809	58	166	99.95	99.85	0.204	99.796
WT [31]	109,428	220	153	99.8	99.86	0.34	99.66
WT [13]	110,159	322	120	99.89	99.7	0.402	99.599
PT [11]	109,809	507	277	99.54	99.75	0.712	99.288

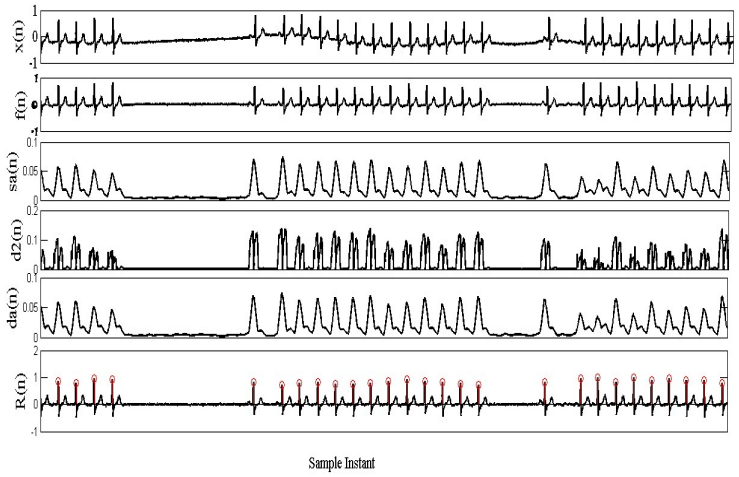

Figure 4.2: Performance of the proposed method for Record 232 (Long pauses.)

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4.3.1 Result and Discussion for P and T wave Detection and Delineation Algorithm

In order to evaluate that how much efficiently our proposed method is working on ECG signals of QT database we have need three parameters True Positive (TP), False Positive (FP), False Negative (FN) respectively. Where TP is the number of correctly detected the delineation points(P ′On′, P ′Off′, P-Peak, T ′On′, T ′Off′, T-Peak), FN is the number of missed delineation points((P ′On′, P ′Off′, P-Peak, T ′On′, T ′Off′, T-Peak). FP is the number of noise detected as delineation points((P ′On′, P ′Off′, P-Peak, T ′On′, T ′Off′, T-Peak). In our evaluation process, we have separately calculated these three parameters corresponds to every peak (P and T) and "ON"and "OFF"position of P and T waves. With the help of these parameters Sensitivity(Se), Positive Predictivity (PPV) have been calculated for 1 minute ECG signals of QT database. In Table4.3 the performance of our proposed method has been compared with formally established methods. In Figure 4.4 and Figure 4.5. a pictorial description of detected and delineated P and T waves of ECG signals namely sele0133, sel230 (QT database) have been described respectively.

Formulae for calculating Sensitivity (Se) and Positive Predictivity (PPV) have

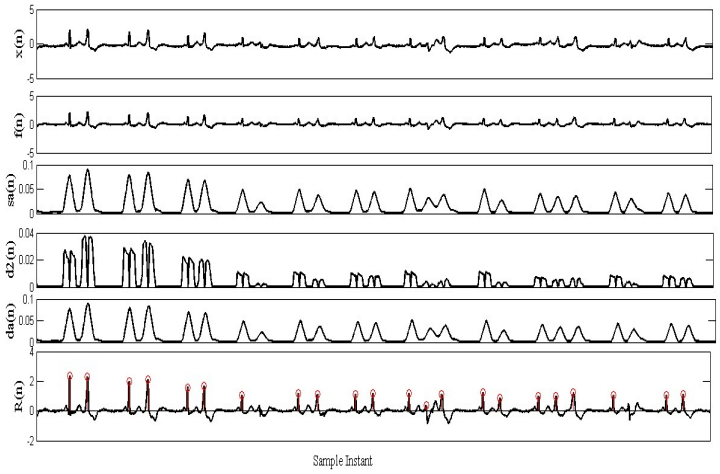

Figure 4.3: Performance of the proposed method for Record 106 (Continuously varying QRS complex and tall T wave.)

been expressed below.

$$\text{Se} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{4.5}$$

$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{4.6}$$

Table 4.3: Comparison of the average Se and average PPV for all record of QT ECG database with signal length 1 minute

Algorithm	Parameter	P 'On'	P	P 'Off'	T 'On'	T	T 'Off'
Proposed Work	Se(%)	97.80	99.61	98.33	99.04	99.61	96.12
	PPV(%)	98.40	100	99.70	99.42	100	96.50
WT[31]	Se(%)	98.87	98.87	98.75	98.87	99.17	99.17
	PPV(%)	91.03	91.03	91.03	98.03	97.79	97.79
EKF[25]	Se(%)	97.7	99.7	97.7	98.70	99.00	98.70
	PPV(%)	98.17	98.17	97.17	99.17	98.74	97.74

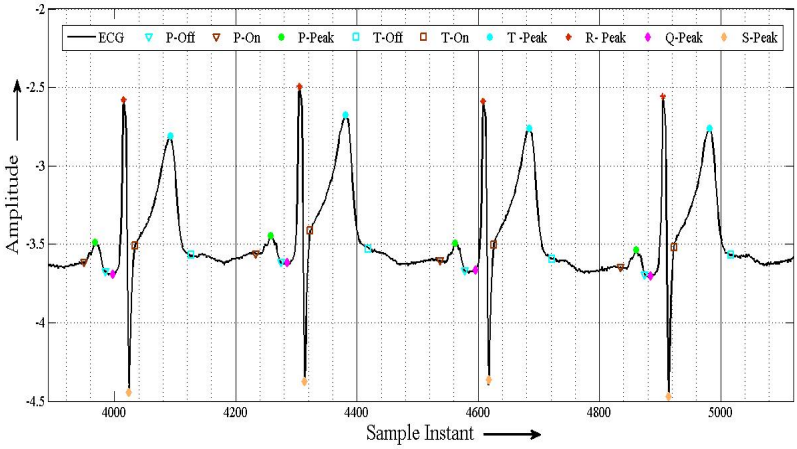

Figure 4.4: P wave and T wave extraction for ECG signal sele0133 (QT database).

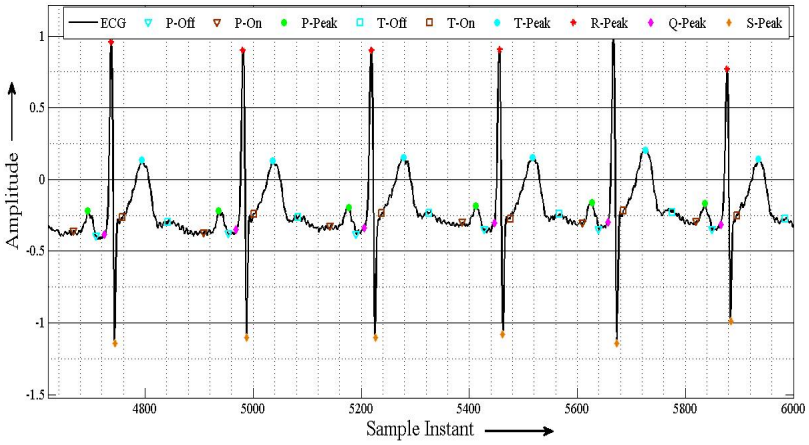

Figure 4.5: P wave and T wave extraction for ECG signal sel230 (QT database).

4.3.2 Result and Discussion for Heart Rate Determination in FPGA Platform

Performance the proposed heart rate calculation system is evaluated by using real ECG database namely MIT-BIH arrhythmia database. The proposed method is implemented on Xilinx. From the Xilinx, we got the location of the actual R-peaks of the ECG.
Figure 4.6,Figure 4.8 and Figure 4.10 present the actual R peak location and heart rate using Xilinx from 101, 106 and 116 of MIT-BIH arrhythmia database respectively. Figure 4.7, Figure 4.9 and Figure 4.11 present the placement of detected actual R peak on the ECG signal from 101, 106 and 116 of MIT-BIH arrhythmia database.

Finally Figure 4.12 shows the result of R peak detection and heart rate calculation from 203 of MIT-BIH arrhythmia database. From the above analysis, it is found that actual R peak detection is encouraging even with ill-conditioned data, which has been shown in Figure 4.13.

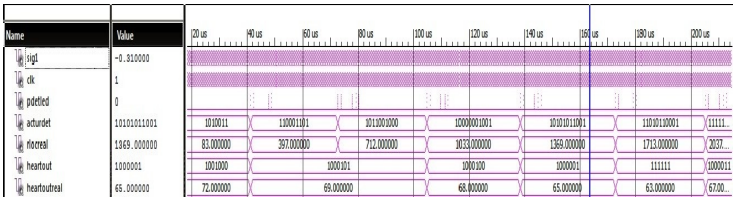

Figure 4.6: Detection of R peak location and calculation of heart rate using Xilinx from 101 of MIT-BIH arrhythmia database.

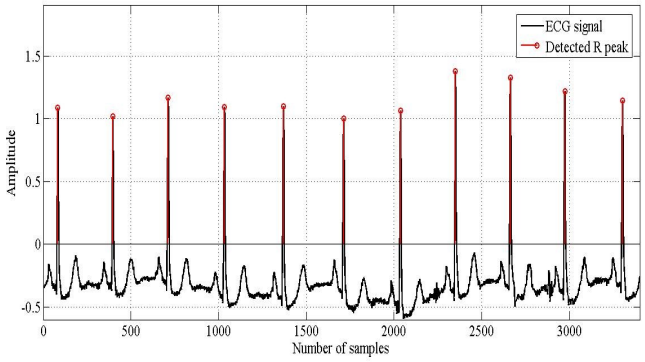

Figure 4.7: Placement of extracted peaks of the ECG signal with id 101 of MIT-BIH arrhythmia database.

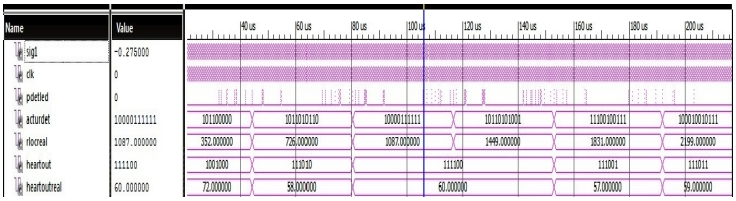

Figure 4.8: Detection of R peak location and calculation of heart rate using Xilinx from 106 of MIT-BIH arrhythmia database.

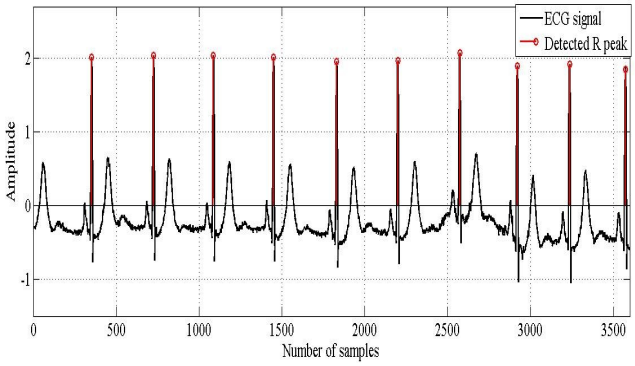

Figure 4.9: Placement of extracted peaks of the ECG signal with id 106 of MIT-BIH arrhythmia database.

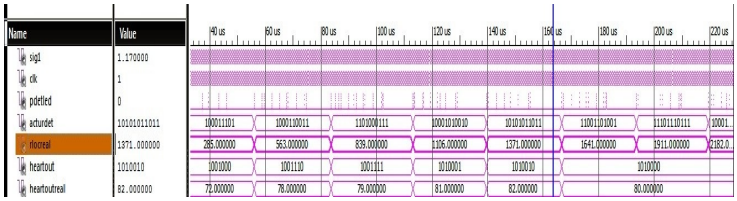

Figure 4.10: Detection of R peak location and calculation of heart rate using Xilinx from 116 of MIT-BIH arrhythmia database.

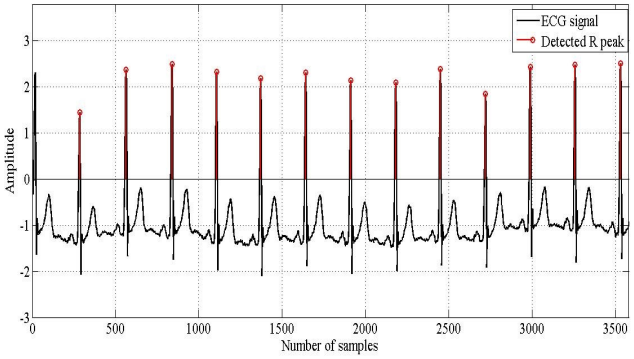

Figure 4.11: Placement of extracted peaks of the ECG signal with id 116 of MIT-BIH arrhythmia database.

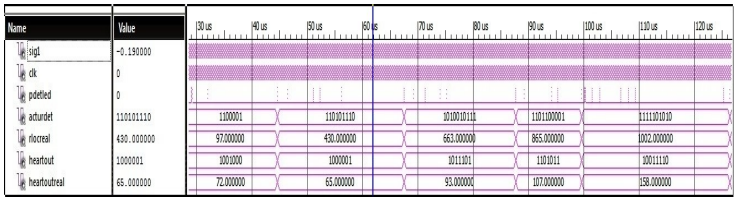

Figure 4.12: Detection of R peak location and calculation of heart rate using Xilinx from 203 of MIT-BIH arrhythmia database.

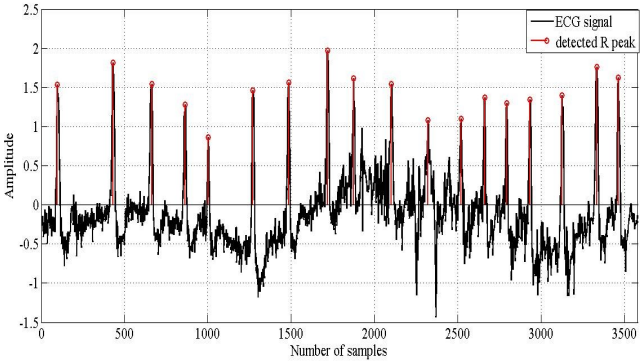

Figure 4.13: Placement of extracted peaks of the ECG signal with id 203 of MIT-BIH arrhythmia database.

Chapter 5

Conclusions, Future Scope and Disseminations

5.1 Conclusions

This research work mainly deals with signal processing of Electrocardiogram (ECG) signal. The primary focus of this work is to design real-time ECG analyzer that include real-time ECG components detection and real-time heart rate detection system. At the final it has been focused to implement an FPGA-based heart rate detection system. At the completion of this research work, a number of matters can be concluded.

- A real-time QRS detection method has been implemented. The proposed method detection logic is amplitude threshold free and the processing time of the proposed method is very less which is suitable for real-time application.
- The efficiency of the proposed method has been validated with real ECG database namely MIT-BIH arrhythmia database. The proposed method shows an average Accuracy of 99.84% and Sensitivity of 99.95 % for MIT-BIH arrhythmia database.
- The performance of the proposed work has been compared with existing method namely Shannon energy with Hilbert Transform, Peak Shannon energy method, Wavelet Transform method etc.
- For detection and delineation of P and T waves, a method based on EKF with PSO has been proposed in this research work. In this proposed method for initialization of Kalman Filter, no operator interaction is required, and PSO is used here for finding the set of optimized parameters for modeling a complete ECG envelope.
- The validation of this proposed method has been evaluated using real ECG database namely QT database. This method shows an average Sensitivity of 99.61% and Positive Productivity of 100% for P wave and for T wave an average Sensitivity of 99.61% and Positive Productivity of 100%.
- The proposed method can successfully extract the baseline wander noise and Electromagnetic noise for ECG signal.
- The performance of the proposed work has been compared with existing method namely Low pass Detector (LPD) method and Wavelet Transform (WT) method.
- In this research work an FPGA-based heart rate detection system has been proposed. The heart rate detection system has been implemented using VHDL environment and it can detect heart rate from a typical ECG signal.
- The performance of this FPGA system has been evaluated in VHDL Test Bench environment and for input the ECG signals from MIT-BIH arrhythmia database have been used.

5.2 Future Scope

This work implements a couple of methods in order to detect and delineate all the components of a typical ECG signal. However for future scope aspect following works can be done in future.

- Better accuracy model can be developed with modification of the algorithm.
- Automatic Cardiac disease detection with the hardware interface.
- Fetal status determination using abdominal ECG.
- Biometric application.

5.3 Disseminations

- **M. Rakshit**, D. Panigrahy, P.K. Sahu,"EKF with PSO Technique for delineation of P and T Wave in electrocardiogram(ECG) Signal",2nd IEEE conf. DOI: 10.1109/SPIN.2015.7095293, Page(s): 696 - 701.
- D. Panigrahy,**M. Rakshit**, P.K. Sahu,"An efficient method for fetal ECG extraction from single channel abdominal ECG",IEEE conf. College of Engg. Pune (paper presented).

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