International Journal on Applications in Engineering and Technology
Volume 2: Issue 3: March 2016, pp 6-.12 www.aetsjournal.com ISSN (Online) : 2455-0523

VLSI Based ECG QRS Complex Detector

Aashiqa Rismi.I[1],Gayathri.G[2],Kowsalya.C[3],Mohankumar[4]
[1,2,3]PG scholar, [4]Assistant professor, Department of ECE
Dr.Mahalingam College of Engineering and Technology,pollachi,India

***Abstract*—Detection of QRS complex in ECG signal is required to determine heart rate and study of cardiac disorders. ECG signals are usually affected by noise of low and high frequency. To improve the accuracy of QRS detectors with minimal computational cost and resource without noise multiscale mathematical morphology method have been proposed. The Multiscale Mathematical Morphology method is used to suppress background noise and baseline wandering from original ECG signal. The major advantage of this method is that it does not require any prior knowledge of frequency spectrum. Then the multiframe modulus accumulation is act as a low-pass filter to enhance the QRS complex and improve the SNR ratio.Our method produces the low power consumption of 118mW with 3V supply when compare with 218mW in method like wavelet based ECG detection. The codes for the algorithm are compiled in Xilinx 8.1i software and simulated in Modelsim SE 6.3f. The experiments are carried out on the database created by our own based on a standard ECG report.**

Keywords*—ECG detector; Multiscale mathematical morphology;multiscaled product;soft thresholding;Modelsim.

I. INTRODUCTION

The recent growing demands of healthcare applications such as tele-health care, implantable medical devices, body-area monitoring devices, etc., the considerable research efforts are focused on designing electronic biomedical devices using integrated circuit (IC) technology. Those integrated circuits which on implementation require compactness, reliability, low energy consumption and efficient. Because electronic biomedical devices deals with patients life.

One of the most commonly implementable biomedical devices is the cardiac pacemaker, which is widely used to detect, monitor and guarantee the patient’s heart-beating rate within a safe range by using ECG QRS complex detector. The ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis.

The aim of our project is to design an efficient ECG detector with high detection accuracy and low power consumption for implantable cardiac pacemaker[1]. ECG being a non-stationary signal, the irregularities may not be periodic and may show up at different intervals. Pacemaker which is implemented inside the human body depends on high detection accuracy and reliability.

Once it is implanted inside human body, the pacemaker is expected to operate over several years without changing the battery[2],[3]. To avoid repeated surgeries due to battery exhaustion, low power consumption is another extremely important design requirement for IPIC. According to previous research work, while the analog circuits including amplifiers and bias circuit take about half of the overall power consumption, the digital logic circuit including the ECG detector is the second power hungry block, which utilizes 15% or more. Thus our basic objective is to come up with a simple method having less power consumption and high detection accuracy in the ECG detector.

This objective has motivated us to search and experiment with various techniques. We have implemented enhancement using Multiscale Mathematical Morphology method. The effectiveness multiscale filtering used for removal of noises in ECG signal was explained in [4],[5].In [6] and [7] algorithm for impulsive noise suppression and background noise normalization was proposed. The experiments are carried out on the database created by our own based on a standard ECG report and the results shows good accuracy.

In this paper we present a novel algorithm to detect QRS complexes in ECG signals with very low computational complexity. In Section II we study the characteristic aspects of ECG. In Section III we review some of the methods described in the literature that should be avoided in order to reduce the computational complexity and energy consumption of a QRS detector. Then, Section IV describes details of our proposed MMM method. In section V described the performance obtained by the algorithm when tested against our own based on a standard ECG report. Finally Section VI presents the conclusions.

II. THEORETICAL ASPECTS OF ECG

A. Human Heart

The heart, located in the mediastinum, is the central structure of the cardiovascular system. It is protected by the bony structures of the sternum anteriorly, the spinal column posteriorly, and the rib cage. There are two nodes in the heart which acts as natural pacemaker,

- Sino atrial (SA) node is the dominant pacemaker of the heart, located in upper portion of right atrium. It has an intrinsic rate of 60–100bpm.
- Atrio ventricular (AV) node is a part of AV junctional tissue. It slows conduction, creating a slight delay before impulses reach ventricles. It has an intrinsic rate of 40–60 bpm.
- Normally, the SA Node generates the initial electrical impulse and begins the cascade of events that result in a heart-beat. For a normal healthy person the ECG comes off as a nearly periodic signal with depolarization

followed by repolarization at equal intervals. However, sometimes this rhythm becomes irregular.

B. Phases Of Cardiac Cycle

There are two phases of the cardiac cycle.

- Systole: The ventricles are full of blood and begin to contract. The mitral and tricuspid valves close (between atria and ventricles). Blood is ejected through the pulmonic and aortic valves.
- Diastole: Blood flows into the atria and through the open mitral and tricuspid valves into the ventricles.

These phases occur in the human heart causes the heart beats and when it is recorded it is obtained as a wave which represents ECG signal.

C. Electrocardiogram

The electrocardiogram (ECG) is the record of variation of bioelectric potential on the body surface with respect to time as the human heart beats. It provides valuable information about the functional aspects of the heart and cardiovascular system.

The fig 1 shows each cardiac cycle in the ECG is normally characterized by successive waveforms known as P wave, QRS complex and T wave, so that time intervals between onset and offset of different waves are significant.

Because they reflect physiological processes of the heart and the autonomous nervous system .Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range is of 1–10 mV.

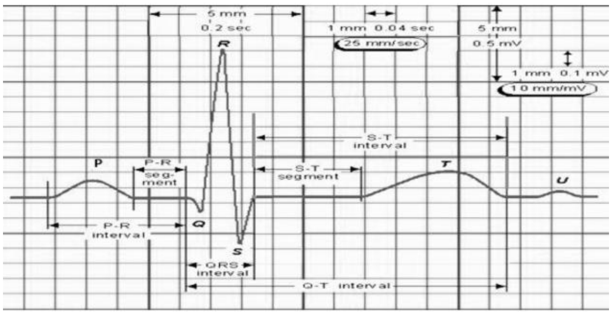


Fig. 1. Typical ECG Recording

III. LITERATURE SURVEY

In this chapter, we briefly review the prior real-time ECG detection algorithms. In addition, a state-of-the-art ECG detector for an energy-efficient IPIC, which uses the wavelet transform with decompositions in the time-frequency domain and time-scale domain, is also introduced.

Generally, ECG signals are corrupted by various types of noises generated from the human body. For example, the Electromyography (EMG) signal from muscle contraction and relaxation may cause a degradation of signal-to-noise ratio (SNR). Body movement also causes baseline drifts of variable DC-offsets. Many detection algorithms have been proposed to eliminate the noise effects and precisely detect the peak points of the ECG signal[8]-[13]. The hardware complexity and the detection performance of the previously proposed algorithms in the literatures are as follows.

A. Time Domain Analysis

J. Pan introduced a real-time ECG detector based on time domain analysis[8]. The major difficulty encountered in this approach is that extracting ECG signals by removing noises with a high-order flat band pass filter is quite difficult and the detection performance can be degraded. The higher order flat band pass filter is quite difficult to design and remove noises of high frequency and hence time domain analysis becomes necessary in the detection.

B. Neural Network Analysis

To achieve high detection performance, an artificial neural network (NN) algorithm was proposed in NN are highly sensitive to noise. The performance of the classifier can be significantly reduced if the NN is constructed with a proper architecture and trained with appropriate data. However, the building of the ECG statistic model can incur a large computational burden[9],[10]. Because a internal cardiac pacemaker requires hardware simplicity and compactness.

C. Frequency Domain Analysis

The frequency components of the QRS complex range from10 Hz to 25 Hz. So, most algorithms do not filter out high and low frequency noise. Hence to filter out high frequency noises in the signal a conventional method is urgently needed. Considering the trade-off between the hardware complexity and the detection accuracy, the wavelet based detection algorithm is generally considered as one of the most effective algorithms[11].

D. GLRT Based ECG Detector

The GLRT based wavelet ECG detector consists of wavelet filter banks (WFBs) , a generalized likelihood ratio test (GLRT) and a noise detector, the WFBs decompose the input ECG signals into sub-bands with two monophasic and biphasic outputs of W*fi* and W*fi+1*. The GLRT with threshold function estimates the heart-beating rate with the decomposed WFB outputs. Since the GLRT uses the maximum-likelihood estimation of unknown parameters, the implementation requires a more number of registers, adders and multipliers[13]. Hence it leads to time delay and high power consumption.

E. Wavelet Based ECG Detector

Compared to the previously published work, the main contributions and novelties of this work can be summarized as follows.

- The QRS detector of the previous work is based on GLRT as explained in the previous section. In this work, we exploited a multi-scaled product algorithm, which leads to significant power consumption reduction in hardware implementation.

- Although the use of the multi-scaled product algorithm achieves considerable power savings, detection accuracy is reduced compared to the previously published work. To boost the QRS detection accuracy, we used a soft-threshold algorithm, which can be implemented without large power and area overheads.

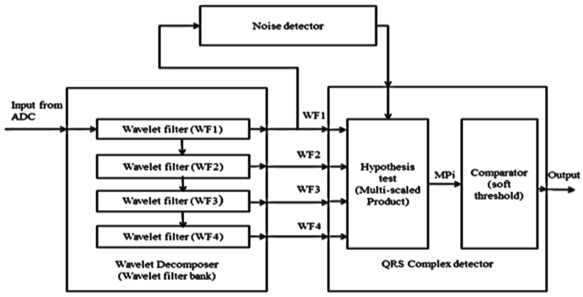


Fig. 2. Block Diagram of Wavelet Based ECG Detector

The components of the Wavelet Based ECG Detector are as follows

- Wavelet decomposer with WFBs
- Noise detector with zero-crossing points
- QRS complex detector, which replaces the GRLT and simple threshold function.

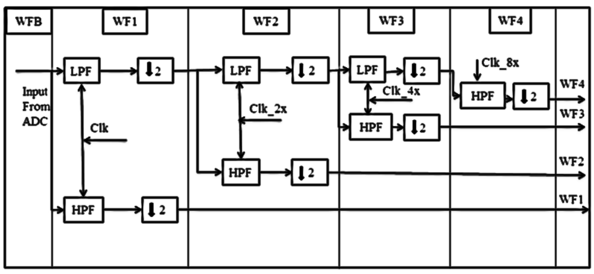


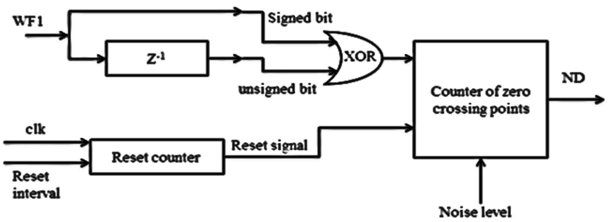
Fig. 3. Decimator based wavelet filter bank.

1) wavelet filter bank: The WFBs decompose the input ECG signals into sub-bandswith two monophasic and biphasic outputs of W_{fi} and W_{fi+1} . Due to its property of low computational complexity, the dyadic wavelet transform is generally considered suitable for implementing the ECG detector[14]. The above fig 3 shows the decimator based WFB. To implement the dyadic wavelet transformer, the decimator (down sampler) based architecture with the filter pairs of low-pass filter (LPF) and high-pass filter (HPF) have been proposed[15],[16]. The clock divider is used in between all the LPF and HPF for synchronization purpose. To reduce the number of registers, the lifting based structure is frequently used, which reduces the delay elements. It also reduces the arithmetic operations by constructing the lifting wavelets of the second generation wavelets. However, the lifting scheme cannot be applied to all types of wavelet function families. In the wavelet decomposer implementation, the decimator based architecture with the WFBs of thedyadic wavelet transform is employed. The down sampler of divided by 2 is used to down sample the frequency bands. Thus the wavelet filter is designed to remove noise in ECG signal.

2) Noise Detector: The noise level inside the ECG detector ismeasured 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 of the conventional noise detector is shown in fig 4(a). 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[17]. The comparator with noise thresholds, zero-crossing counts and a reset with a fixed interval time of no longer than 100 ms, 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 multiscaled product block. By using this noise detector, our ECG detector achieves robust ECG detection against phase-modulated noises rather than amplitude-modulated noises.

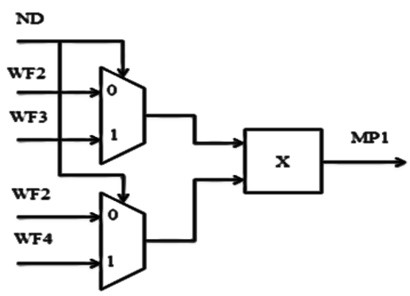
3) QRS Complex Detector: TThe QRS complex detector is designed so as to achieve high detection accuracy and low power consumption in the ECG detector. The combinations of the following two effective algorithms were used.

- Multi-scale product-hypothesis test
- Soft-threshold Algorithm-comparator



(a)

International Journal on Applications in Engineering and Technology
Volume 2: Issue 3: March 2016, pp 6-.12 www.aetsjournal.com ISSN (Online) : 2455-0523



(b)

Fig. 4. (a) Schematic diagram of Noise detector. (b) D Schematic diagram of Multi-scaled product.

4) Multi-scaled product: The multi-scaled product of WFB outputs can be expressed as follows

MPI =π1WFI1

where I is the sub-set of WFB outputs. This is very similar to the edge detection observed in digital image processing. With the multiple scaled signals WFI containing thewavelet coefficients, the nonlinear combination MPI tends to reinforce the peaks while suppressing noises. According to the noise information from the noise detector, the multi-scaled product selects the wavelet filter banks to reconstruct the ECG signal without noises and to detect QRS signals.

*5) Soft-Threshold Algorithm:*In order to remove the failure occurred in the QRS complex detection, the soft-threshold algorithm[18], which uses variable thresholds rather than a hard threshold, is presented. The soft threshold filter Hs shrinks the wavelet coefficients above and below the threshold. Soft thresholding reduces coefficients toward zero with the known minimum RR interval of 200 ms or less. In fact, we focused to avoid the duplicated detections in the case of fast ECG signal. To implement the soft-threshold algorithm, only a single 8-bit counter is required. Since the counter is composed of simple adders and occupies a small area with low power consumption, higher detection accuracy was achieved with very small hardware overheads using the soft-threshold algorithm.

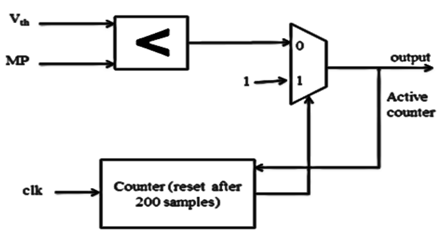


Fig. 5. Schematic diagram of Soft-threshold algorithm.

F. Drawback Of Wavelet Based ECG Detector

Our method of signal enhancement and QRS complex detection using wavelet decomposer and QRS complex detector is novel, efficient method having high detection accuracy and considerable power consumption for implementation. But each LPF and HPF contains several adders, shifters and delay elements. It leads to some power consumption. so, our proposed method is to reduce power consumption when compared with all previous techniques.

IV. Proposed System

A. Multi-scaled Mathematical Morphology

Mathematical morphology is a set-theoretic method of image analysis providing a quantitative description of geometrical structures. A morphological operation is actually the interaction of a set or function representing the object or shape of interest with another set or function of simpler shape called structure element[19]. The geometry information of the signal is extracted by using the structure element to operate on the signal. The shape of the structure element determines the shape information of the signal that is extracted under such an operation. Such operators serve two purposes, i.e., extracting the useful signal and removing the artifacts. The block diagram of multiscale mathematical morphology is shown in the fig 7.

The two principal morphological operations are *dilation* and *erosion* . Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded.

1) Dilation: The dilation process is performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution. The difference is in the operation performed. It is best described in a sequence of steps:

1. If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel.
2. If the origin of the structuring element coincides with a 'black' in the image, make black all pixels from the image covered by the structuring element.

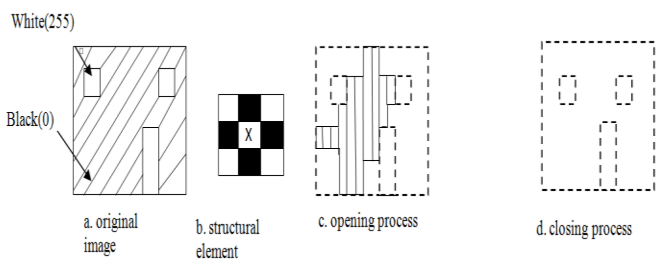


Fig. 6. Illastration of poening and closing operation.

Notation:

$$A \oplus B$$

2) Erosion: The erosion process is similar to dilation, but we turn pixels to 'white', not 'black'. As before, slide the structuring element across the image and then follow these steps:
1. If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel.
2. If the origin of the structuring element coincides with a 'black' pixel in the image, and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from „black" to a 'white'.
Notation:

$$A \Theta B$$

3) Opening and Closing: These two basic operations, dilation and erosion, can be combined into more complex sequences. The most useful of these for morphological filtering are called opening and closing. Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image. See Fig 4, for the illustration of the opening process.
Notation:

$$A \circ B = (A \Theta B) \oplus B$$

Closing consists of a dilation followed by erosion and can be used to fill in holes and small gaps. we see that the closing operation has the effect of filling in holes and closing gaps. Comparing the left and right images from Fig. 5, we see that the order of operation is important. Closing and opening will generate different results even though both consist of erosion and dilation[20].
Notation:

$$A \bullet B = (A \oplus B) \Theta B$$

In mathematical morphology, opening is erosion followed by dilation and closing operation is dilation followed by erosion. Both operations act as morphology filters having clippings. Here 'i' represents ith element in 'L'length structure element. Other common operators are top hat and bottom hat operators, which contain opening and closing with two different orders.

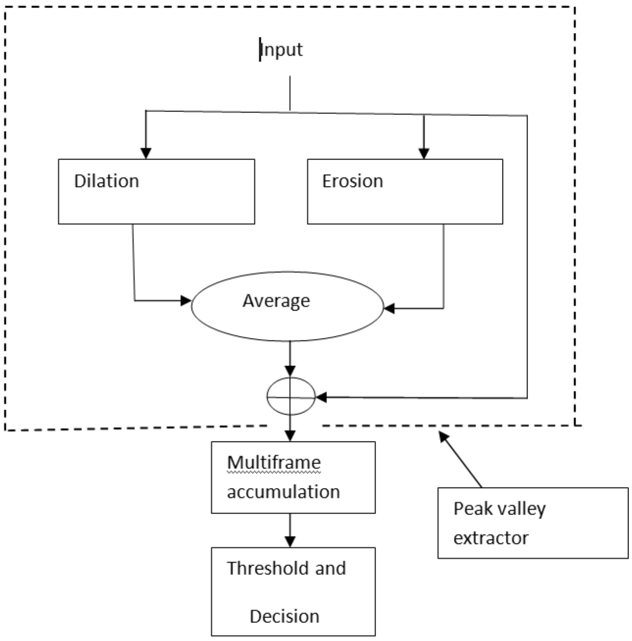


Fig. 7. Block diagram of proposed system.

4) Multiframe Accumulation: The absolute value of the above output is then combined by Multiple-frame accumulation, which is much alike energy transformation[21],[22]. The energy accumulation process is expressed as follows.

$$s(n) = \sum_{i=n-[\frac{q}{2}]}^{n+[\frac{q}{2}]} |v(i)|$$

where the value of q denotes the possible maximum duration of the normal QRS complex.

5)Decision and Threshold: An adaptive threshold is used as the decision function in connection with the proposed transformation for QRS detection. Usually, the threshold levels are computed signal dependent such that an adaption to changing signal characteristics is possible. For the signal produced by above equation, it is proposed that the required adaptive threshold is a function of the maximum of the transformed ECG waveform S(n).

$$T = \begin{cases} 0.1\ \text{Max}, & \text{Max}<3 \\ 0.3\ \text{Max}, & 3\leq\text{Max}\geq 7 \\ 0.13\ \text{Max}, & \text{Max}>7 \end{cases}$$

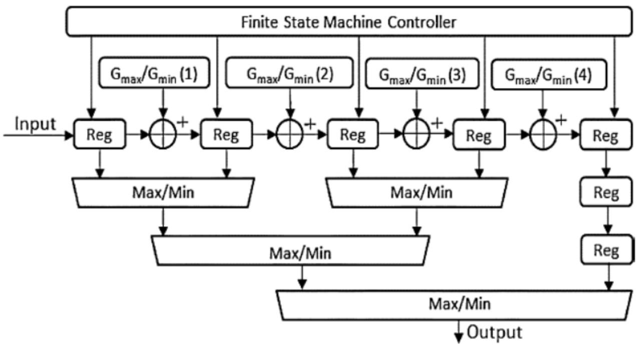


Fig. 8. Proposed Architecture for Opening and Closing Operation (5 Scale).

The guideline in selecting the threshold, , is given by where Max is determined from the current signal segment which is within the range of millivolts. The upper and lower bounds of Max will be subject to the selection of structure elements Detection of QRS complexes equals to the distinguishing of a group of consecutive positive and negative peaks. As mentioned above, originating from 2-D image processing, mathematical morphological technology extracts the effective information based on shapes in the image, not pixel intensities methods.

V. Simulation and Result Analysis

The following are the simulation results and inferences obtained from the analysis of proposed method of ECG detector. The better results are obtained against our own ECG signal based on original ECG signal.

The simulation of the wavelet ECG detector is performed. The codes are compiled and executed in Modelsim SE 6.3f software. The compiled output of the decimator filter of the WFB, the Noise detector and the QRS complex detector are shown in fig 9. The codes are compiled in Xilinx ISE 8.1i using VHDL program and the resulting design summary and power summary are shown in fig 10 and fig 11.

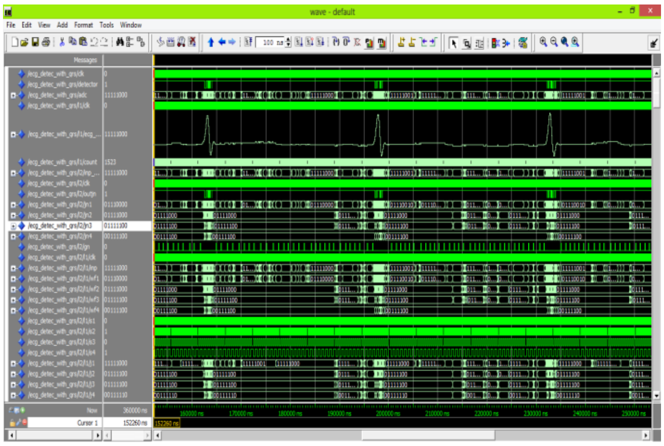


Fig. 9. QRS Complex Detector Output.

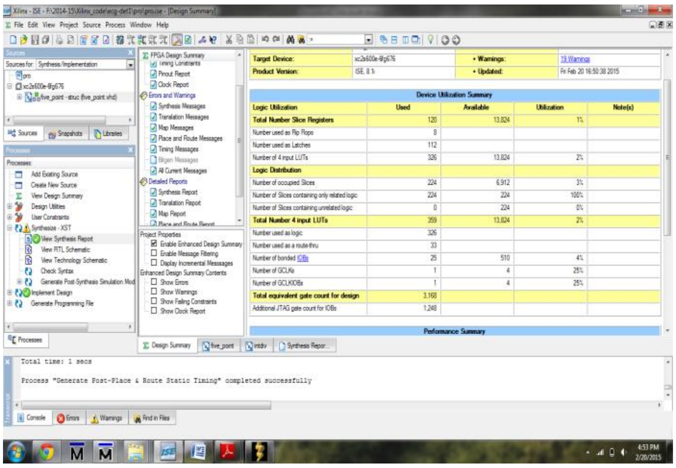


Fig. 10. Design Summary of Proposed ECG Detector

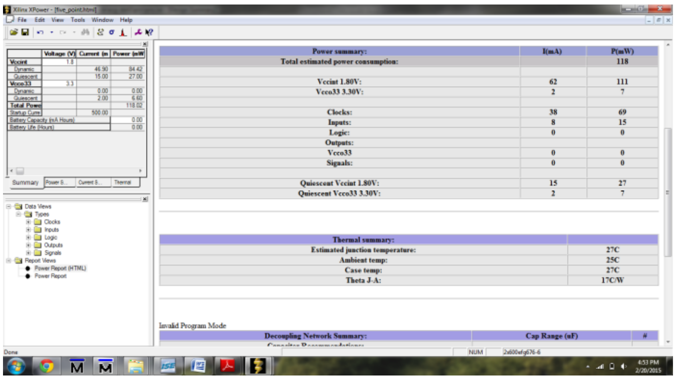


Fig. 11. Power Summary of ECG Detector

VI. Conclusion

Our sole objective of this project was to develop a method for efficient analysis of ECG signal. In this piece of work, we have proposed a novel method of enhancement of ECG signal using Multiscale mathematical morphology. This method has low power consumption of 118mW with 3 V supply voltage when compare with wavelet based ECG detector which consumes the total power of 218mW.Thus our method of signal enhancement and QRS complex detection is novel, efficient with high detection accuracy and considerable power consumption for implementation. Hence best suited for analysis of ECG signal for implantable cardiac pacemaker. The process of enhancement can be modified using more evolved techniques. Research needs to be done for finding more efficient methods for signal enhancement.

REFERENCE

1. Astrom M, Olmos S, and Sornmo L, "Wavelet base event detection in pacemakers," in Proceedings 23rd Annual Engineering in Medicine and Biology Society International Conference, Istanbul, October 2001, vol. 3, pp. 2121–2124.

2. Kay S.M and Gabriel J.R, "An invariance property of the generalized likelihood ratio test," IEEE Signal Processing Letter, vol. 10, no. 12, pp. 352–355, December 2003.
3. Kohler B.U., Hennig C and Orglmeister R, "The principles of software QRS detection," IEEE Engineering Medical Biology Magazine, vol. 21, no. 1, pp. 42–57, January–February 2002.
4. Martinez J.P., Almeida R, Olmos S, Rocha A.P and Laguna P, "A wavelet-based ECG delineator: Evaluation on standard databases," IEEE Transactions Biomedical Engineering, vol. 51, no. 4, pp. 570–581, April 2004.
5. Rodrigues J.N., Olsson T, Sornmo L and Owall V, "Digital implementation of a wavelet-based event detector for cardiac pacemakers," IEEE Transactions Circuits System I, Registerd Papers, vol. 52, no. 12, pp. 2686–2698, December 2005.
6. Szilagyi S.M and Szilagyi L, "Wavelet transform and neural-network based adaptive filtering for QRS detection," in Proceedings 22nd Annual International Conference IEEE Engineering in Medicine and Biology Society, Chicago, July 2003, vol. 2, pp. 1267–1270.
7. Wong L.S.Y., Hossain S, Ta A, Edvinsson J, Rivas D.H and Naas H, "A very low-power CMOS mixed-signal IC for implantable pacemaker applications," IEEE Solid-State Circuits, vol. 39, no. 12, pp. 2446–2456, December 2004.
8. J. Pan and W. J. Tompkins, "A real time QRS detection algorithm," IEEE Trans. Biomed. Eng., vol. 32, no. 3, pp. 230–236, Mar. 1985.
9. J. Hu and S. Bao, "An approach to QRS complex detection based on multiscale mathematical morphology," in Proc. 3rd IEEE Int. Conf.Biomed. Eng. Inform. (IEEE BMEI 2010), 2010, p. 725.
10. C.-H. N. Chu and E. J. Delp, "Impulsive noise suppression and background normalization of electrocardiogram signals using morphological operators," IEEE Trans. Biomed. Eng., vol. 36, no. 2, pp. 262–273, Feb. 1989.
11. W. Hu, W. Yu and A. Luo, "Impulsive noise suppression using morphological operators," in Proc. Of the IEEE Conf. Aerospace and Electron. vol. 1, pp.336-339,Geb 1995.
12. P. E. Trahanias, "An approach to QRS complex detection using mathematical morphology," IEEE Trans. Biomed. Eng., vol. 40, no. 2, pp.201–205, Feb. 1993.
13. F. Zhang, J. Tan, and Y. Lian, "An effective QRS detection algorithm for wearable ECG in body area network," in Proc. Int. Conf. IEEE Biomed. Circuits Syst., Montreal, ON, Canada, Nov. 2007, pp.195– 198.
14. N. V. Thakor, J. G. Webster, and W. J. Tompkins, "Optimal QRS detector, "Med. Bio. Eng. Computer. vol. 21, pp. 343–350, May 1983.
15. F. Gritzali, "Towards a generalized scheme for QRS detection in ECG waveforms," Signal Process., vol. 15, pp. 183–192, Sep. 1988.
16. http://www.physionet.org/physiobank/database/