



A QUADRATIC SPLINE WAVELET BASIS ON LOW POWER ECG SIGNAL SCRUTINY FOR BIOMEDICAL APPLICATIONS

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Abstract

Heartbeat classification and R-wave location are widely used to detect the health condition of the people. Nowadays, several types of development were made towards the biomedical application. At present many methods were there to process the ECG signal. While processing P, Q, R and S signal the accurate value of ECG signal output is obtained. The condition of the patients heartbeat is analyzed by using Electrocardiogram. ECG waveform analysis has been used to identify whether the heartbeat rate is normal or abnormal. A novel method has been proposed to feature extract based on FPGA by using the QSW algorithm to rectify the problem. The QSW

method removes the low power noises from the input ECG after a signal is passed through the feature extraction part and is used to partition the ECG signal into heartbeat without noise. The output shows that the patient condition is normal or abnormal and it also shows whether the patient has any disease or not. The proposed design is simulated and comparison parameters are obtained in Quartus II software.

Keywords: Electrocardiogram (ECG); QRS complex detection; heartbeat classification; Quadratic Spline Wavelet(QSW); Short-Term Autocorrelation(STAC)

1 INTRODUCTION

A heart is the most sophisticated organ of the human being and its related diseases are to be identified with greater accuracy in short time and it requires immediate detection. A Quartus II software implemented classification system consumes low power consumption in real time circumstances, which is provided below. Thus, we need to develop a low power classification system.

Electromyography (EMG) is a diagnostic procedure and it evaluates the health condition and it records the electrical activity of skeletal muscles. The PAT is a widely used method, which is based on the amplitude threshold technique exploiting the fact that R peaks have higher amplitudes compared with other ECG wave peaks. Finally, the zero-crossing method [4] is used to position the R-wave face based on DWT result.

Adaptive sampling is projected in several works to adapt the sampling rate based on the performance of the input data. Thus it is more often used to reduce power consumption of the whole system. However, the adaptive sampled signals were mixed with noises and it is mainly based on the time domain characteristics. There is a high prospect that the low frequency sampled region may contain R-waves.

The classification is done [3] for original ECG signal. In order to explain the problem, an improved QSW algorithm is projected to locate the R-wave point of sampled ECG signals and to classify the heart rate. KNN is a method to classify different types of data based on the majority of the nearest neighbors [7]. The rest of the

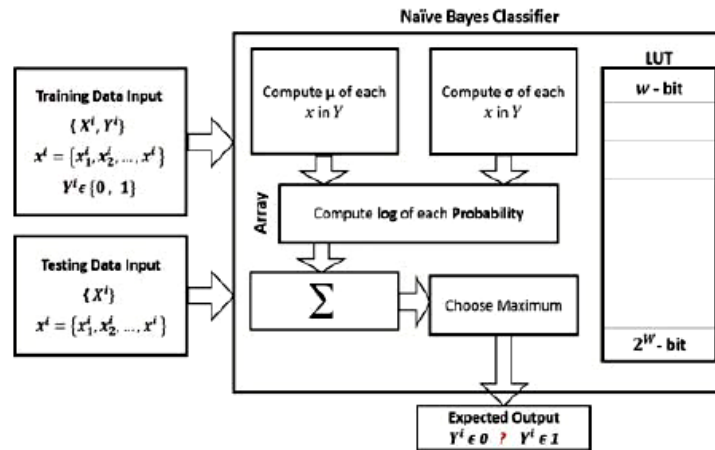


Figure 1: The Architecture of classifier

paper is organized as follows: Section 2 describes the processing and filtering of ECG signal; Section 3 shows about T and P waves; Section 4 details the construction of the whole system; Section 5 shows the results and Section 6 makes a conclusion.

2 EXISTING METHODOLOGY

Some kinds of heartbeat types indicate a threat to life and it requires immediate detection. In this existing system DWT (Discrete Wavelet Transform) algorithm is being used to classify the heartbeats and KNN method is used as a classifier since the heartbeat types are highly related to RR-interval. Battery-power devices are the main trends for long-term monitoring of people's health condition. Adaptive sampling has been proposed to adapt the sampling rate based on the input data. An improved DWT algorithm is proposed to locate the R-wave point of sampled ECG signal. High sampling frequency is used for the possible R-wave area and low sampling frequency for none R-wave area and efficient power of 258.37mW is obtained within the time of 59.728ns by implementing in VLSI architecture using SMIC CMOS technology.

3 PROPOSED METHODOLOGY

A block diagram of heartbeat detector is shown in the Fig. 2, which is implemented for FPGA consisting of various blocks like summer, subtractor, registers, and accumulators. At each time instant four samples (each sample contains 8 bit) enters the block. The bits are subjected to wavelet transform filter for removal of noise. The noise removed samples are given to coarse and fine search where the samples are compared with QRS template. The R-peaks are detected and heart rate is found. The sampling frequency of the heartbeat detector is 360 Hz. The QSW is commonly used as the low-power noise reduction method for ECG. The hum-noise and baseline wander are well concealed using QSW.

(A) ECG Pre-processing stage

i) ECG Filtering:

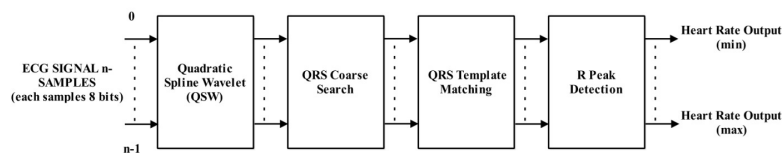


Figure 2: Block diagram of heartbeat detector

Bandpass filtering of ECG signal isolates the major QRS energy centered at 10 Hz, and attenuates the low frequencies characteristic of the P and T waves, baseline drift, and higher frequencies associated with electromyographic noise and power line interference. The main important point is not to lose the information carried by the ECG signal after being filtered out. The differential equations of the cascaded LPF and high-pass filter (HPF) are given in (1) and (2), respectively. The cutoff frequency of the LPF filter is 11 Hz, and it introduces a delay of six samples, whereas the HPF has a cutoff frequency and delay of 5 Hz and 16 samples, respectively. The coefficients of the filters are all integers and of power-of-two, which make them suitable for

hardware implementation.

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \quad (1)$$

$$y[nT] = x(nT - 16T) - 1/32[y(nT - T) + x(nT) - x(nT - 32T)] \quad (2)$$

ii) QRS Detection

To detect the QRS complex, the PAT method was used. The PAT is a widely used method, which is based on the amplitude threshold technique exploiting the fact that R peaks have higher amplitudes compared with other ECG wave peaks. With proper filtering of the signal, the method is highly capable of detecting the R peaks in every heartbeat using two threshold levels. Differentiation of the filtered signal is used to distinguish the QRS complex from other ECG waves by finding high slopes. Then, a nonlinear transformation is performed through point-to-point squaring of the filtered ECG signal in which it is important to emphasize the higher frequencies in the signal obtained from the previous step, which is normally characteristic of QRS complex. After that, integration is carried out by a moving time window to extract additional features, such as the QRS width.

Finally, adaptive amplitude thresholds are applied to the averaged signal to detect R peaks. Both the bandpass filtered signal and the averaged signal are stored in separate SRAMs for further analysis. Initially, the design reads the first 200 ECG samples from the SRAM, which stores the samples of the averaged ECG signal. The maximum value of these samples is set as an initial R peak and used to compute the initial value of the threshold Th , which is set to 50% of the peak value. Then, the value of every incoming sample is compared with Th , and only the sample value, which is greater than the threshold, is used in the next step. If none of the samples have a higher value than Th , the algorithm redefined the value of the threshold and set it to 30% of the peak value ($Thsb$).

As soon as the demarcation of the samples that exist in the QRS complex region is done, the maximum value among them is set as a new R peak, and the threshold is updated accordingly

(50% of the last detected R peak). The process repeats itself, and the threshold is adjusted according to the last detected R peak. The last step in the QRS complex detection is to find the corresponding R peaks in filtered signal, which is done by subtracting the delay encountered due to the filters.

iii) T AND P WAVE DELINEATION

This method is based on adaptive search windows to distinguish T and P peaks accurately from noise peak. In each heartbeat, the QRS complex is used as a reference for the detection of T and P waves in which two regions are demarcated with respect to R peaks. These regions are then used to form the forward and backward search windows of the T and P waves, respectively, as shown in Fig.3. A forward search window is assumed to contain the T wave, and the boundaries are extended from the QRS offset to two third of the previously detected RR interval. Similarly, a backward search window for the P wave is identified and extended from the QRS onset backwardly to one-third of the previous RR interval. The position of T and P peaks is demarcated in their respective search windows by finding a local maximum or/and local minimum that is above the associated thresholds. The thresholds, given in (3) and (4), are modified in each heartbeat based on the most recent detected values in the last 3 s

$$T_{\text{waveth}} = \frac{T_{\text{Peak}}}{R_{\text{Peak}}} t_{\text{threshin}} \quad (3)$$

$$P_{\text{waveth}} = \frac{P_{\text{Peak}}}{P_{\text{Peak}}} P_{\text{threshin}} \quad (4)$$

From (3) and (4), and are set between 0.1 and 0.2 based on the most recent detected values in the last processing window. By comparing the local maximum or/and the local minimum points with the thresholds, the waveform morphology of each wave is identified [positive monophasic, inverted, or biphasic (+,)/ (, +)]. If the value of T or P peak is greater than the associated threshold, then the T or P wave has a positive monophasic waveform, and the local maximum is stored to give a probable

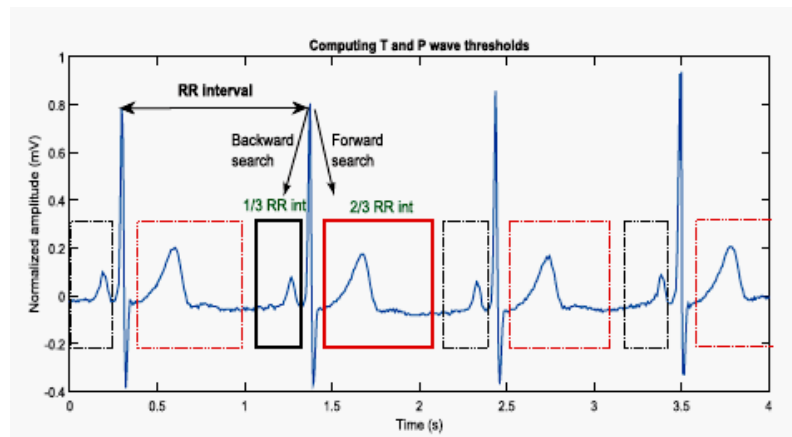


Figure 3: Formulation of T and P wave search windows with respect to the Previously calculated RR interval.

position of the peak. Otherwise, the waveform is identified as inverted, and the local minimum of the ECG signal within the same window is the correct peak. In case of a biphasic wave, both the local maximum and the absolute value of the local minimum should be greater than the threshold.

4 ONSET AND OFFSET POINT DELINEATION

The method traces the onset and offset values of the P-QRS-T waves by finding the sample corresponding to the zero slope of the entitled ECG signal. The sample point that has a zero slope and former to the peak is identified as the onset point. Similarly, the offset point is determined at another side of the peak. To solve this, the method adds another criterion for a correct delineation of the wave boundaries based on the fact that the fiducially points tend to merge smoothly with the iso-electric line. The iso-electric line is approximated as the average value of the beat signal after removing the QRS complex. This idea is utilized and combined with the zero slopes for an accurate and reliable delineation of the fiducially points. The general FSM, which illustrates the

delineation process of T and P waves, is shown in Figure 3.

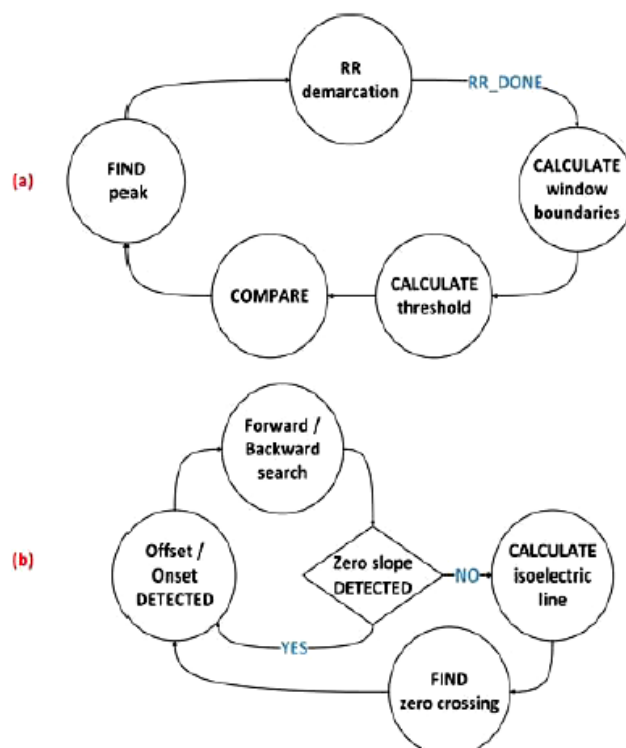


Figure 4: (a) Peak detection (b) Onset and offset delineation.

v) Feature extraction stage

The two main parameters is to be considered while developing a prediction system are the complexity and the accuracy of the feature extraction technique providing the best results. For example, if the technique that is used for the feature extraction requires complex transformation or data analysis of the ECG signal, this would increase the overall cost and complexity of the system, and thus, it will not be suitable for wearable biomedical devices. Furthermore, the extracted ECG features should show a

significant relevance in the detection (or prediction) of the targeted arrhythmia to guarantee maintaining a high accuracy. Usually, there is a trade-off between the complexity and the accuracy. We have performed statistical analysis techniques that are famous in the decision making in the biomedical research to choose the best discriminative ECG features that would maintain low system complexity and high accuracy.

The result has been found that the indicative characteristics of ventricular arrhythmia is obtained higher accuracy. The features include RR, PQ, QP, RT, TR, PS, and SP intervals. Figure 12 shows these intervals on ECG record.

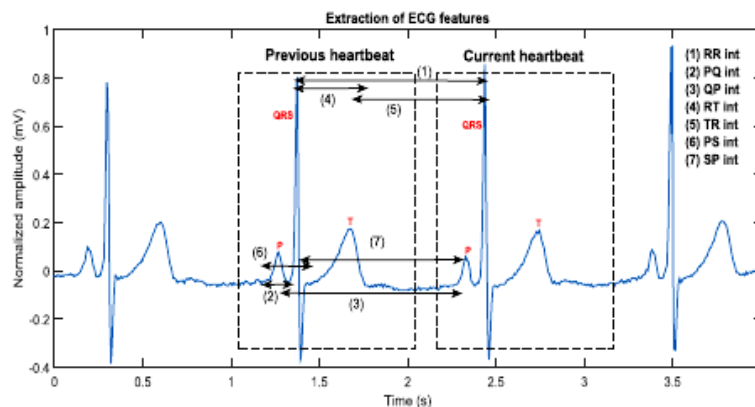


Figure 5: ECG feature extraction from two consecutive heartbeats.

(iii) Classification stage

The choice of classifier was the naive Bayes. The naive Bayes the classifier is easy to build with no complicated iterative parameter estimation, which makes it particularly useful for hardware implementation. It assumes naive and strong independent distributions between the feature vectors, and this assumption was met since all the extracted ECG features were independently analyzed and assessed from the beginning. The

architecture of the classifier is implemented, as shown in Figure 5.

iv) Heartbeat Detection Algorithms

Extracting R-waves with threshold determination is a general approach. Recently, various statistical approaches have been proposed for noise-tolerant threshold calculation. However, both misdetection and false detection are increased in wearable healthcare systems by noise from various sources such as myoelectric signals from muscle and electrode movements because the power consumption and electrode distance of the wearable sensor are strictly limited to reduce its size and weight. More robust approaches to prevent incorrect detection are autocorrelation and template matching because these algorithms use the similarity of QRS complex waveforms and because they have no threshold calculation process.

Autocorrelation has been used in a non-invasive monitoring system, but the method necessitates numerous computations to calculate the average heart rate over a long duration (30s). A short-term autocorrelation (STAC) technique was proposed for heart rate detection in our previous work. For this work, we implemented the combination algorithm of quadratic spline wavelet (QSW) filter and two-stage STAC based heartbeat detection. The QSW is commonly used as the low-power noise reduction method for ECG. The hum-noise and baseline wander are well suppressed using QSW. Nevertheless, it is difficult to remove these noises solely by using QSW because it has a similar frequency range of the QRS complex. Therefore, in the next step, we used a noise tolerant heartbeat detection algorithm.

In the existing system Discrete Wavelet Transform algorithm were used and the output power 258.37mW and delay 59.728ns is obtained and in the proposed, Quadratic Spline Wavelet algorithm is used in this the power and delay is reduced to 235.58mW ,18.019ns in cyclone II platform.

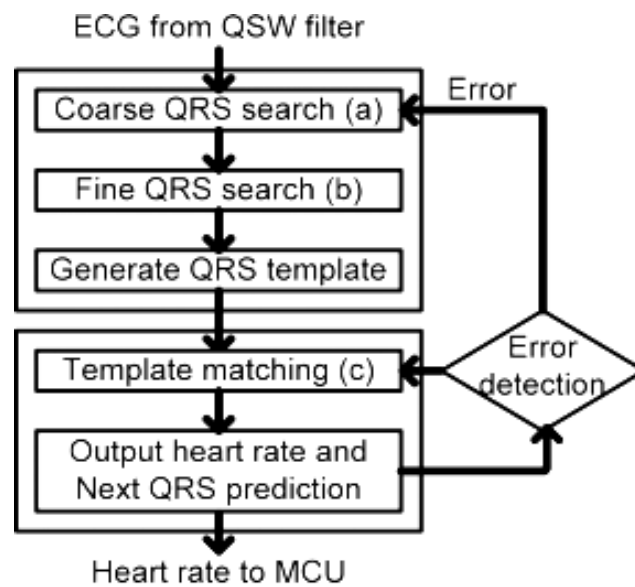


Figure 6: Flowchart of heartbeat detection algorithm.

Table 1: Comparison of Power and Delay.

PARAMETERS	EXISTING	PROPOSED
ALGORITHM	Discrete Wavelet Transform	Quadratic Spline Wavelet
PLATFORM	Cyclone II	Cyclone II
POWER(mW)	258.37	87.58
DELAY(ns)	59.728	18.577

5 SIMULATION RESULTS AND DISCUSSION

FPGA consisting of various blocks like summer, subtractor, registers, and accumulators. At each time instant four samples (each sample contains 8 bit) enters the block. The bits are subjected to wavelet transform filter for removal of noise. The noise removed samples are given to course and fine search blocks where the samples are compared with QRS template. The R-Peaks are detected and heart rate is found. The sampling frequency of the heartbeat detector is 360 Hz. The QSW is commonly used as the low-power noise reduction method for ECG. The hum-noise and baseline wander are well suppressed using QSW.

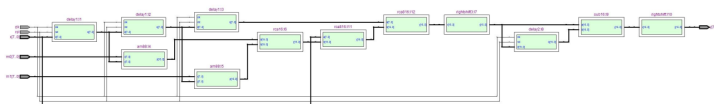


Figure 7: RTL View of QSW algorithm

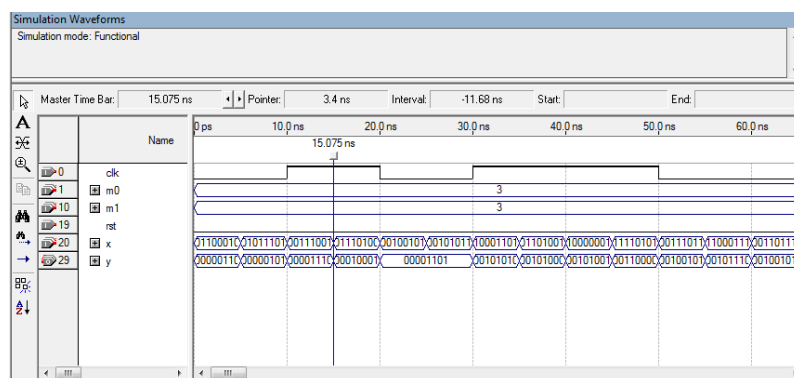


Figure 8: Simulation Waveform QSW

Flow Status	Successful - Tue Feb 06 10:29:30 2018
Quartus II Version	9.1 Build 222 10/21/2009 SJ Web Edition
Revision Name	QSW
Top-level Entity Name	QSW
Family	Cyclone II
Met timing requirements	Yes
Total logic elements	294 / 4,608 (6 %)
Total combinational functions	293 / 4,608 (6 %)
Dedicated logic registers	42 / 4,608 (< 1 %)
Total registers	42
Total pins	34 / 158 (22 %)
Total virtual pins	0
Total memory bits	0 / 119,808 (0 %)
Embedded Multiplier 9-bit elements	0 / 26 (0 %)
Total PLLs	0 / 2 (0 %)
Device	EP2C5F256C6
Timing Models	Final

Figure 9: Logic Element of QSW

PowerPlay Power Analyzer Status	Successful - Tue Feb 06 10:43:23 2018
Quartus II Version	9.1 Build 222 10/21/2009 SJ Web Edition
Revision Name	QSW
Top-level Entity Name	QSW
Family	Cyclone II
Device	EP2C5F256C6
Power Models	Final
Total Thermal Power Dissipation	87.58 mW
Core Dynamic Thermal Power Dissipation	15.98 mW
Core Static Thermal Power Dissipation	18.12 mW
I/O Thermal Power Dissipation	53.47 mW
Power Estimation Confidence	Low: user provided insufficient toggle rate data

Figure 10: Power Analysis of QSW

Timing Analyzer Summary									
	Type	Slack	Required Time	Actual Time	From	To	From Clock	To Clock	Failed Paths
1	Worst-case tsu	N/A	None	18.577 ns	m1[0]	delay2:18delayflip1:11q[8]	--	clk	0
2	Worst-case tco	N/A	None	23.130 ns	delay1:12q[1]	y[7]	clk	--	0
3	Worst-case tpd	N/A	None	26.703 ns	m1[0]	y[7]	--	--	0
4	Worst-case th	N/A	None	0.202 ns	x[5]	delay1:11q[5]	--	clk	0
5	Clock Setup: 'clk'	N/A	None	66.65 MHz (period = 15.004 ns)	delay1:12q[1]	delay2:18delayflip1:11q[8]	clk	clk	0
6	Total number of failed paths								0

Figure 11: Power Analysis of QSW

6 CONCLUSION

This paper presents the construction of the heartbeat classification system for adaptive sampling ECG signals. An optimized QSW algorithm is projected, which greatly improves the detection accuracy of R-wave points under noise. The result has been found that the indicative characteristics of ventricular arrhythmia is obtained higher accuracy. The main important point is not to lose the information carried by the ECG signal after being filtered out. This also guarantees the high accuracy of heartbeat classification. The accurate heart rate can be calculated by using this algorithm and it also greatly reduces the power and delay of QSW algorithm.

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