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Comparative Study of High Performance QRS Complex Detection on Electrocardiogram Signal

B. Khaleelu Rehman* Adesh kumar* and Paawan Sharma*

Abstract : In the today's scenario most of the people are suffering from heart related problems and hence it's necessary for the demand in the low cost, portable and efficient Electrocardiogram (ECG) for frequent heart monitoring. To make the entire system low cost, light weight and low power the ECG system is tested by using Modelsim simulator and it should be deployed on the Field Programmable Gate Array (FPGA). Apart from the deploying it is also important to choose the suitable algorithm that optimizes in terms of feature extraction accuracy and computation time. This paper compares two methods of ECG QRS complex detection the Pan and Tompkins algorithm and derivate based method on FPGA platform. The approach for the derivate based method is adaptive thresholding but not the fixed thresholding for the reason of robustness in real time QRS detection. The inputs are 24 records of 40 minutes; total 24 hours ECG data is obtained for MIT-BIH database, the standard database for the research purpose. Both the algorithms come with different outcomes in terms of computation speed and accuracy. Results reveals that pan and Tompkins algorithm shows the best accuracy with 98.89% on detecting of QRS complex as compared to the derivate-based method of 95.37% it takes less time *i.e.*, half of the computation time (A total of 16.42 minutes to compute 24 hours ECG data) on comparing with pan and Tompkins algorithm (A total of 45 minutes to compute 24 hours of ECG data).
Keywords : Electrocardiogram, Modelsim, adaptive thresholding, pan and Tompkins algorithm.

1. INTRODUCTION

At present, cardiovascular diseases have become a threat to human life and health for major diseases, and morbidity increases year by year. the prevalence rate of cardiovascular disease, morbidity and mortality upward trend continued, the death toll of about 40% of the number of deaths[1], therefore, focus on the prediction of cardiovascular disease diagnosis and prevention is an important significance.

2. ELECTROCARDIOGRAM

An electrocardiogram (EKG or ECG) is a test that checks for problems with the electrical activity of a heart. An EKG translates the heart's electrical activity into line tracings on paper. The spikes and dips in the line tracings are called waves. The heart is a muscular pump made up of four chambers. The two upper chambers are called atria, and the two lower chambers are called ventricles. A natural electrical system causes the heart muscle to contract and pump blood through the heart to the lungs and the rest of the body. The ECG is nothing but the recording of the hearts electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. Cardiac cells, in the normal state are electrically polarized. Their inner sides are negatively charged relative to their outer sides. These cardiac cells can lose their normal negativity in a process called depolarization, which is the fundamental electrical activity of the heart. This depolarization is propagated from cell to cell, producing a wave of depolarization that can

* Assistant Professor in Department of Electronics Instrumentation & Control Enginnering, University of Petroleum & Energy Studies, Dehradun, India. *E-mail : krehman@ddn.upes.ac.in, adeshkumar@ddn.upes.ac.in, paawan.sharma@ddn.upes.ac.in*

be transmitted across the entire heart. This wave of depolarization produces a flow of electric current and it can be detected by keeping the electrodes on the surface of the body. Once the depolarization is complete, the cardiac cells are able to restore their normal polarity by a process called re-polarization. This is also sensed by the electrodes

3. ECG QRS COMPLEX DETECTION AND RELATED WORK

The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P, QRS and T-waves reflect the rhythmic electrical depolarization and repolarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart

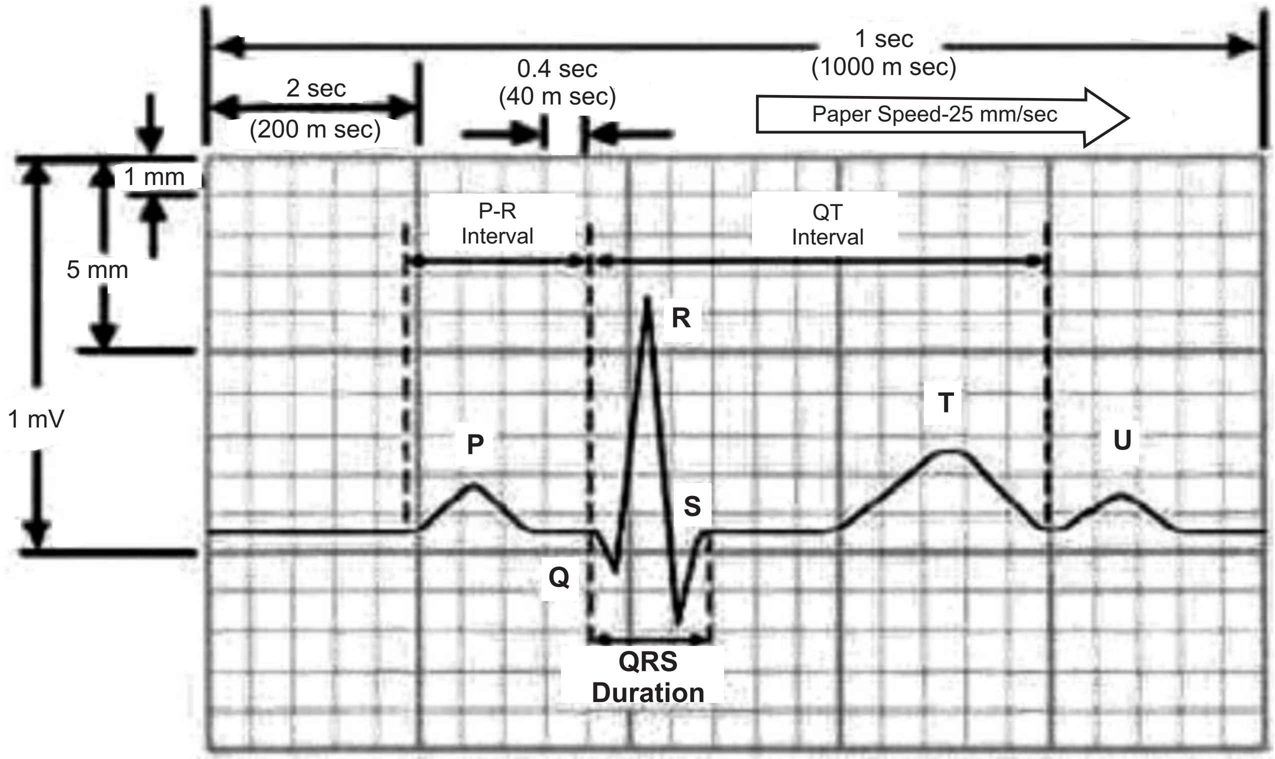

Figure 1: Electrocardiogram (ECG) wave

From the past many yeas most of the researches have been carried out to improve the best techniques in detecting the peaks, due to some problems such as noise incurred by power-line interference, T wave amplitude similar to QRS peaks and so on. Among all these research, two most common and widely accepted algorithms to detect QRS complex by detecting the R Peaks is Pan and Tompkins algorithm and derivative-based method algorithm.

A. Pan and Tompkins Algorithm

Pan and Tompkins algorithm comprises of preprocessing to remove noise and extract the location of QRS complex depending upon the information of slope and magnitude as shown in figure 1.Many researchers reported this pan and Tompkins algorithm[2-7].

From the figure 2 it is observed that the raw ECG data which is taken from MIT-BIH database is sent to the 15 Hz low pass filter then sent to 5Hz high pass filter. The main purpose of the filtering technique is to remove the noise that is incurred by electromyography interference, power line interference, and base line shift and other noise involved in the process[8]. The output from the filtering is then differentiated to increase the QRS slope information then passes through squaring to make the data positive values and further increases the difference between QRS peak and other peak next the data is smoothen by using window moving integrating and lastly pass through adaptive threshold to detect the peaks of the QRS.

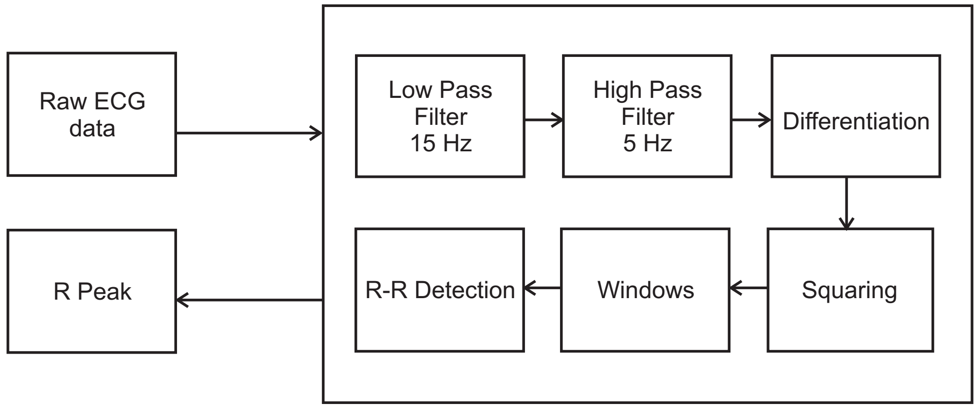

Figure 2: Pan and Tompkins algorithm

B. Derivative-based Method Algorithm

There is also another algorithm proposed by Balda [9] to detect QRS complex, so-called Derivative-based Method as shown in Fig. 3. This method had been reported by many researchers in [10 – 14].

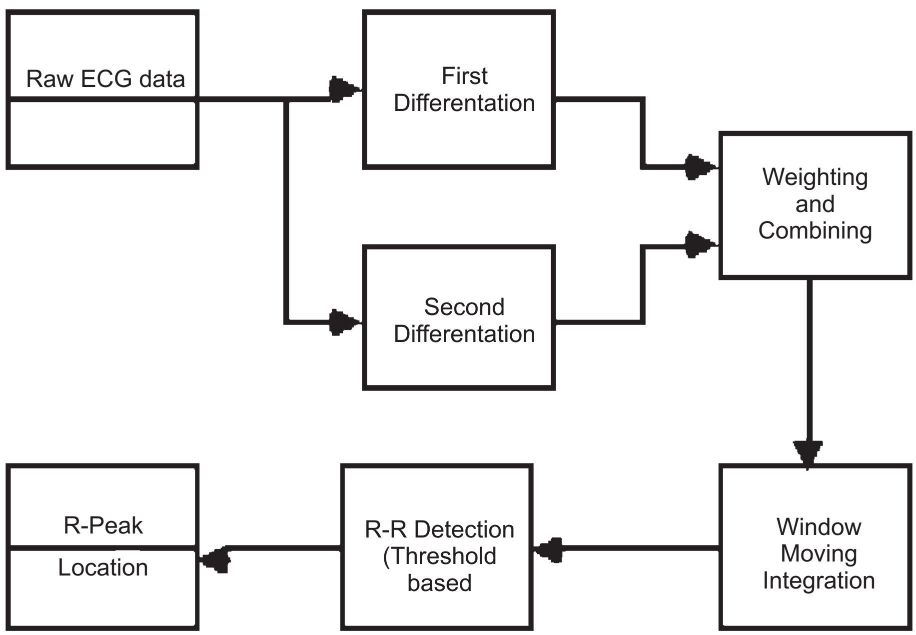

Figure 3: Derivative-based Method algorithm

Instead of filtering, this method uses first derivative and second derivative to differentiate the ECG raw data, respectively. Both of the derivation output signals is then weighted based on fixed coefficient and combined. The data is then smoothen using window averaging integration and pass through fixed threshold to detect the R peak. It is known that the Derivative-based Method is quite sensitive to noise especially to high frequency noises [15].

4. PROPOSED ALGORITHM AND SYSTEM ARCHITECTURE

In this section the detail implementation of the pan and Tompkins algorithm and the revised derivate-based algorithm is deployed by applying the adaptive thresholding rather than fixed threshold to increase robustness in real time QRS detection

A. Pan and Tompkins Algorithm with Adaptive Threshold

The raw ECG data is filtered using 15 Hz low pass filter and then 5 Hz high pass filter, as shown in equations (1) and (2) respectively

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

$$y(n) = y(n-1) + x(n)-x(n-32) \quad (2)$$

The filtered output is then differentiated as shown in equation (3) to enhance the slope information of QRS complex as it has the steepest slope in an ECG signal.

$$Y(n) = \frac{1}{8} 2x(n)) + x(n-1)-x(n-3)-2x(n-4) \quad (3)$$

After the information of the QRS complex slope is enhanced, the signal is squared as shown in equation (4). This is to make all value positive and to magnify the difference between amplitude so that it is easier to differentiate between QRS complex with P wave or T Wave.

$$\mathrm{Y}(n) = [x(n)]^2 \quad (4)$$

Next, the signal is passed through a moving window integral as shown in equation (5). This is to smoothing the signal peaks so that the next analysis is less prone to error in QRS complex detection. The idea is by taking a mean of N sample data point consecutively and put it as a single data point, and the mean move from point zero to the end of the sample ECG data.

$$\mathrm{Y}(n) = \frac{1}{\mathrm{N}} [x(n-1) + x(n-2) + x(n-3) + \ldots\ldots\ldots\ldots.. x(n-\mathrm{N}) \quad (5)$$

The QRS complex is detected by applying adaptive threshold based detection. It is important to use adaptive threshold rather than fixed threshold because the amplitude of ECG is varying for each human. By using adaptive threshold this value will automatically adapt accordingly, without the need of changing the fixed threshold value on each ECG recording. To do this every detected peak is categorized either as Noise peak or Signal peak. This peak value will later determine the value of Signal Threshold and Noise Threshold.

Firstly, 2 seconds of ECG data is taken as sample set to determine the initial value of Noise Threshold, Signal Threshold, Signal Peak and Noise Peak as shown in equations (6) to (9).

Signal Peak = MAX (sample set) (6)

Signal Threshold = MAX (sample set)/3 (7)

Noise peak = MEAN(sample set) (8)

Noise Threshold = MEAN(sample set)/2 (9)

For the remaining of ECG data, if the current peak is higher than Signal Peak, than the point is considered as R peak. Note that certain parameters need to be updated from time to time as shown in equations (10) to (12) to adapt with the current peak amplitude.

Signal peak = 0.125(current pea) + 0.875(signal peak) (10)

Signal Threshold = Noisepeak + 0.25(Signalpeak–Noise peak) (11)

Noise Threshold = Signal threshold/2 (12)

After the R peak is classified, 0.3 seconds is mixed before the next peak is detection to prevent false peak detection. If the peak detected is less than threshold signal but higher than noise threshold then this peak is considered as the noise peak. Though there is no R-peak detection, the parameter still need to be updated as shown in equation (13) to (15).

Noise peak = 0.125(Current peak) + 0.876(Noise peak) (13)

Signal threshold = Noise peak + 0.25(signal peak–noise peak) (14)

Noise Threshold = Signal Threshold/2 (15)

B. Derivative-based Method with Adaptive Threshold

The derivative-based method is shown below First the raw ECG signal is differentiated by using first order and second order derivative, as shown in the equations (16) and (17) respectively

$$y_1(n) = x(n) – x(n–2) \quad (16)$$

$$y_2(n) = x(n) – 2x(n–2) + x(n–4) \quad (17)$$

Both the derivative output signals are the weighted and combined as shown in the equation (18)

$$y_3(n) = 1.3y_1(n) + 1.2\,y_2(n). \quad (18)$$

The data is smoothening using 8 point window averaging integration as shown in equation (19).

$$Y_4(NT) = (1/N)[Y_3(NT–(N–1)T) + Y_3(NT–(N2)T + \ldots\ldots\ldots Y_3(NT)] \quad (19)$$

For the R-peak detection, the adaptive threshold algorithm of pan and Tompkins as described in equations(6) to(15) is also applied in this derivative-based method instead of fixed thresholding.

5. SYSTEM ARCHITECTURE AND ANALYSIS RESULT

Figure 4 shows the overall system architecture of the proposed ECG processing. The Spartan 6 FPGA kit acts as the top-level module to execute both pan and Tompkins and derivate based method QRS detection algorithm as embedded software. The JTAG cable sends and receive the information from pc to FPGA.

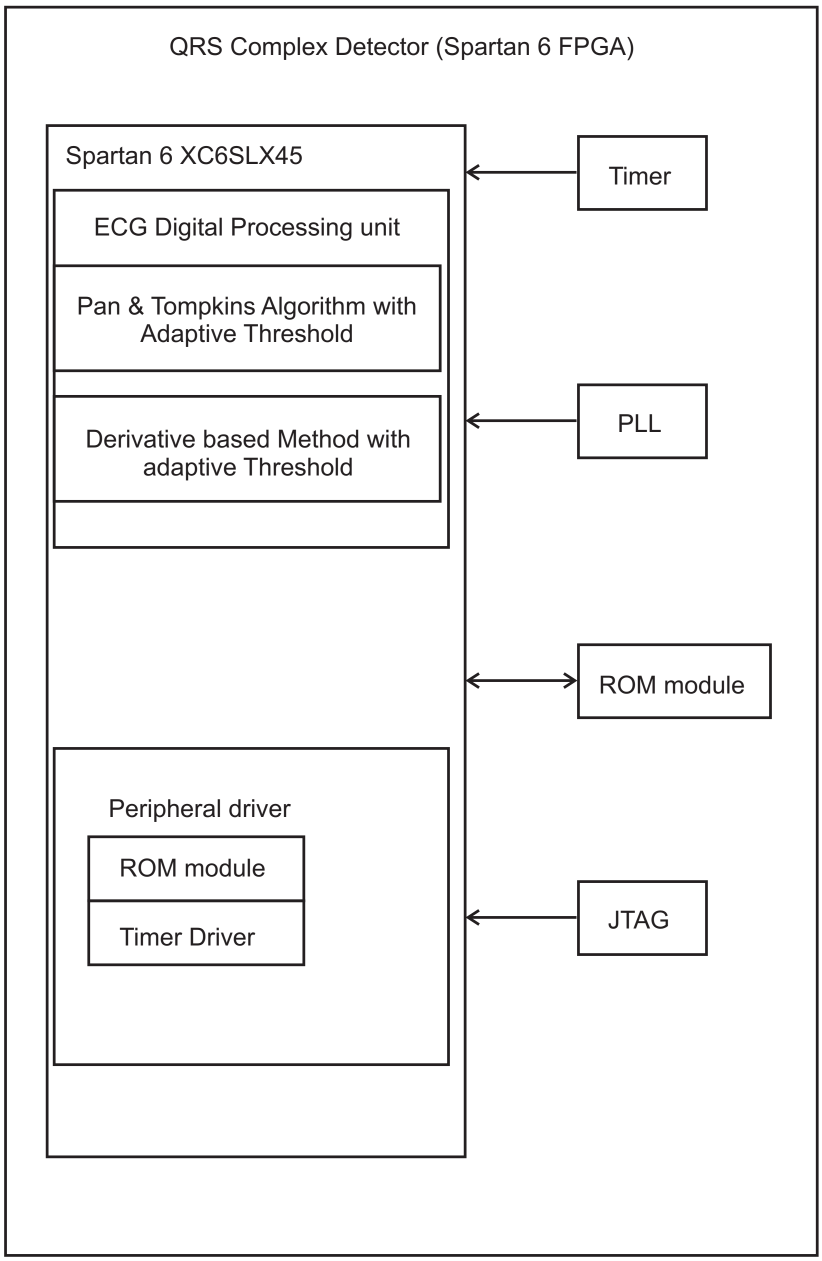

Figure 4: Hardware Design Architecture on Spartan 6 FPGA

The use of phase locked loop (PLL) increases the clock frequency by providing the clock speed of 130MHz to overall system architecture. Timer measures the computation time of each process. The complete system is dumped on Spartan 6 XC6SLX45 FPGA of XILINX development board to make the system portable and low cost. This platform provides the cost-effective because of ROM memory to the application due to large set of ECG data processing

The input of the raw ECG data is taken from physionet MIT-BIH[16] arrhythmia database which is used by researchers over the world as standard database for testing and benchmarking the ECG processing algorithm the data contains 24 records and each records 40 minutes long, The data is initially sampled at 350Hz but it is resampled to 200Hz to suit both the algorithms requirements and reduce the process memory.

The number of detected QRS complex is measured and compared with MIT-BIH actual number of QRS complex annotation. Computation time consumption of both algorithms is measured using timer module.

Table 1 shows the processing result of all 24 ECG records based on pan and Tompkins with adaptive threshold algorithm, in terms of R-peak detection accuracy and total computation timing performance. Table II and figure 5 show the computation timing performance and graph analysis of each processing task by using database #100 as shown below.

Table 1

Pan And Tompkins Algorithm results emulation on FPGA Processor

Database Number	*Actual Number peaks*	*Peaks detected*	*Accuracy(%)*	*Computation time(s)*
#100	2220	2220	100.00	47.45
#101	1834	1834	99.78	55.16
#102	2140	2136	99.98	51.17
#103	2098	2098	100.00	49.45
#104	1987	1976	97.89	54.38
#105	2019	1998	98.79	52.35
#106	2387	2360	99.45	57.41
#107	2198	2198	100.00	55.43
#108	1876	1869	98.69	54.38
#109	2154	2155	99.95	56.39
#110	3079	3076	99.90	56.29
#111	2484	2602	95.46	56.84
#112	1886	1571	83.30	56.42
#113	2154	2155	99.95	56.39
#114	2427	2422	99.79	56.46
#115	1886	1571	83.30	56.73
#116	1619	1615	99.75	56.34
#117	2753	2752	99.96	56.33
#118	2601	2603	99.92	56.41
#119	2262	2256	99.73	56.48
#120	1518	1520	99.87	56.34
#121	2154	2155	99.95	56.39
#122	3363	3362	99.97	56.28
#123	2539	2543	99.84	56.55
#124	2137	2131	99.72	56.46
Average	2178	2140	98.89	56.24

Table 2

Computation time for QRS detection on MIT-BIH database # 100 using pan & Tompkins

Process	*Time taken(s)*
Low pass filter	8.41
High Pass filter	7.34
Differentiation	9.51
Smoothing	26.23
Adaptive thresholding	4.34
Total	55.83

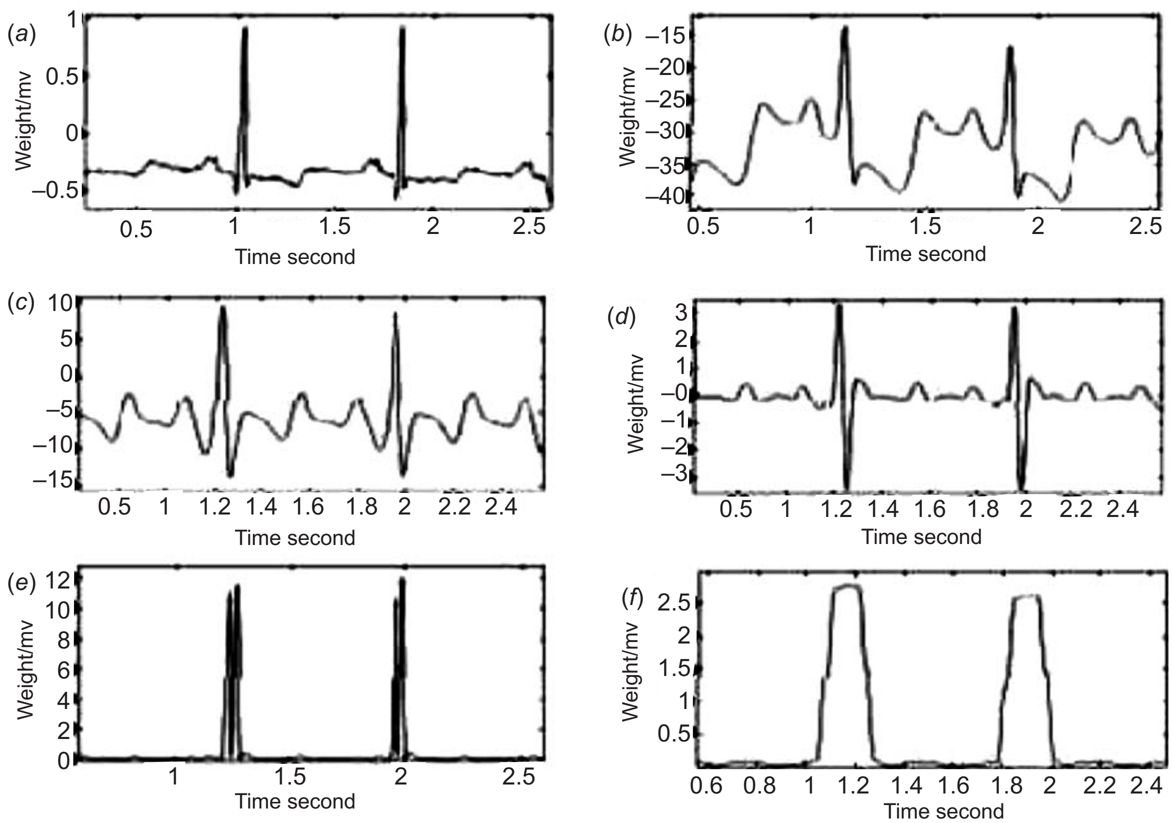

Figure 5: (*a*) ECG signal in tape #100 (*b*) ECG signal after 15 Hz low pass filter (*c*) ECG signal after 5 Hz High Pass Filter (*d*) ECG signal after differentiation (*e*) ECG signal after squaring (*f*) ECG signal after Moving Window Integration

6. RESULTS AND DISCUSSION

24 records of 40 minutes ECG data of QRS detection were processed using pan and Tompkins algorithm and derivate-based method with adaptive thresholding. The average accuracy of the QRS detection using pan and Tompkins algorithm is 98.89% which is slightly better than average accuracy 96.75% achieved by using derivate based approach that is 96.75%.This is because of the fact that the derivate based method will not use filtering techniques like low pass and high pass because it is sensitive to the noise. This shown as high noise record for example #101, #120, #122 the detection accuracy is significantly low on derivate-based method and producing outlines because of this detection accuracy of derivative-based method decreases significantly compared to the pan and Tompkins algorithm.

However on the other hand the computation timing performance using Spartan 6 FPGA kit as embedded software execution, Derivative based method only consume the average of 22.33 seconds to compute 45 minutes ECG data compared to pan and Tompkins that take 56.5 seconds. This is 63% reduction in processing computation time. The average moving integration or smoothing part is the main reason of the time difference. Pan & Tompkins use 32 point moving window integration for 200 Hz sample. In contrast, Derivate-based method just needs 8 points of moving window integration. As a result, derivative-based method is reducing a significant amount of the algorithm computation time.

Table 3

Derivate-based method result emulation FPGA processor

Database Number	*Actual Number peaks*	*Peaks detected*	*Accuracy (%)*	*Computation time(s)*
#100	2753	2748	99.82	22.18
#101	2208	2204	99.82	22.34
#102	2053	2362	86.88	22.55
#103	2605	2609	99.85	22.27
#104	3363	3369	99.82	22.34
#105	1897	1907	98.34	21.45
#106	2262	2272	99.56	22.32
#107	2753	2748	99.82	22.18
#108	2256	2262	99.73	22.27
#109	1763	2648	66.57	22.26
#110	2256	2262	99.73	22.27
#111	1865	1874	99.52	22.31
#112	2605	2609	99.85	22.27
#113	2476	2477	99.96	22.26
#114	2084	2084	100.0	22.26
#115	2539	2546	99.73	22.30
#116	1780	1793	99.27	22.36
#117	2154	2155	99.95	22.17
#118	3079	3076	99.90	22.55
#119	2484	2602	95.46	22.34
#120	1862	2381	78.20	22.52
#121	2154	2155	99.95	22.56
#122	1886	1571	83.30	22.36
#123	1834	1834	99.78	23.32
#124	2140	2136	99.98	23.01
Average	2288	2321	95.37	22.33

Table 4

Computation time for QRS detection on MIT-BIH database #100 derivate based method

Process	*Time taken(s)*
First Derivate	2.31
Second Derivate	4.15
Weighting	8.51
Smoothing	8.23
Adaptive thresholding	0.67
Total	22.26

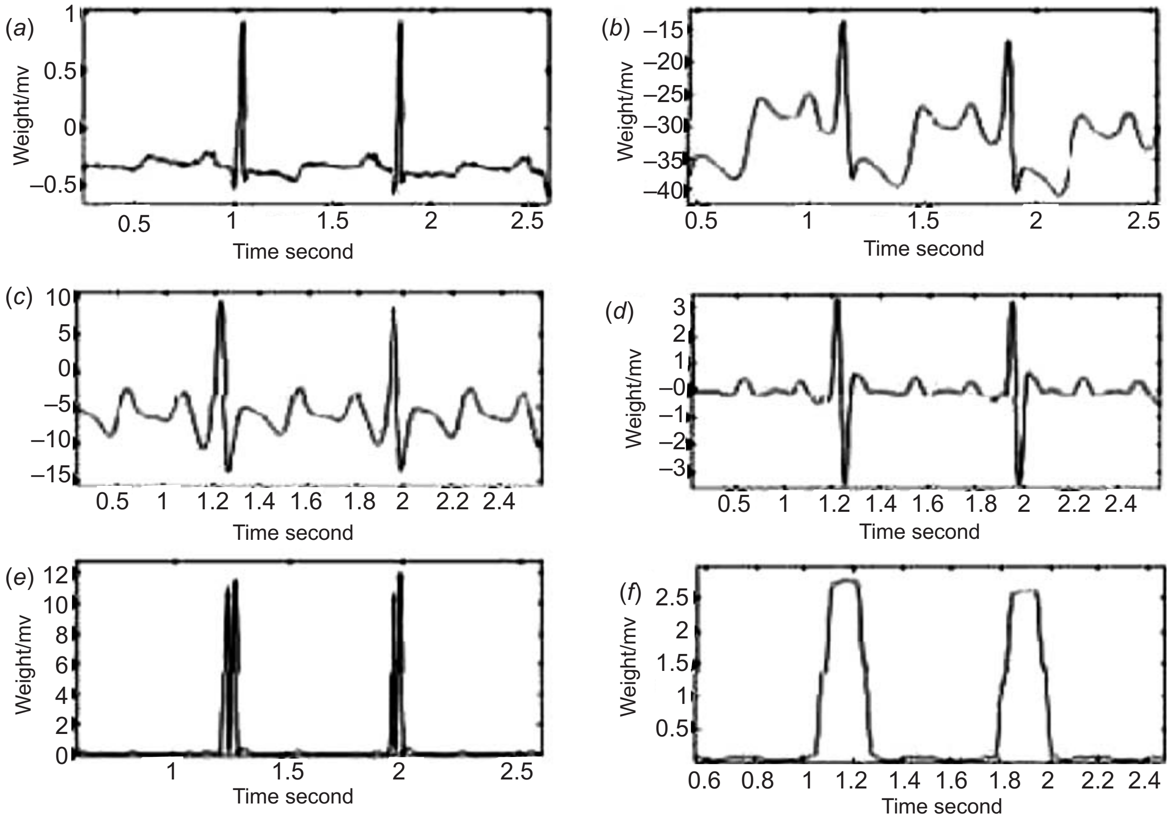

Figure 6 : (*a*) ECG signal in tape #100 (*b*) ECG signal after first derivative (*c*) ECG signal after second derivative (*d*) ECG signal weighting and combining (*e*) ECG signal after Moving Window Integration

7. CONCLUSION

A detailed comparison has been made between pan and Tompkins and derivative-based method algorithms for QRS detection of ECG signal. A novel adjustment had been made to derivate-based method algorithm by applying adaptive thresholding instead of fixed thresholoding so that they are more robustness in real-time ECG QRS detection both the algorithms rum on Spartan 6 FPGA processor as embedded software execution. The algorithm is implemented using VHDL and simulated using Modelsim simulator and the bit file is dumped using FPGA. The complete system architecture is discussed in the proposed algorithm. Results reveal that pan and Tompkins shows a better accuracy, but Derivative-based method consume significantly lesser time for computation timing performance. For future works, depend on application and priority, any of them can be applied for real-time ECG processing and hardware accelerator on FPGA implementation either as a standalone ECG device to accelerate the ECG processing further.

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