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A Simple FPGA Based ECG R Wave Peak Detection System For Heart Rate And Heart Rate Variability Calculation

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ABSTRACT
A simple and reliable Field Programmable Gate Array (FPGA) based ECG Analysis system is discussed in this paper. An R peak detection system is modeled that identifies the time instances at which the R peak occurred. The system first calculates the threshold value for the next peak detection cycle, by looking at the previous peak. The hardware design has accuracy in excess of 99% in detecting the beats correctly when tested with a subset of AF Termination Challenge Database. The design, implemented using a proprietary design tool (Xilinx ISE),uses 8%of the resources available in a small sized FPGA device (Xilinx Spartan® xc3s500) and is able to calculate the heart rate and heart rate variability of the signal in the given data base. A front end using Microsoft Visual Studio was also designed for interfacing with a PC to transfer data to the FPGA from the signal database and receive the calculated values for display and for testing purposes.

Keywords - ECG, FPGA, HR, HRV, QRS

I. INTRODUCTION

An electrocardiogram (ECG) represents cardiac signals generated by cardiac muscle fibers. It is by far the most common method used by cardiologists for determining the cardiac function in a non-invasive fashion. The accurate detection of QRS complex which consists of the peak of the R wave and QRS duration is an essential prerequisite for the reliable function of ECG analysis systems. Although automated ECG diagnosis generally involves detailed analysis of 12 lead ECG recordings, it is possible to identify abnormal heart activity from a limited number of features of the ECG such as the R-R interval, P and T waveform morphology, and ST segment changes. Because the vital importance of QRS detection in automated ECG analysis, there has been ongoing development of QRS detection algorithms over the past 20 years. These efforts have included approaches involving filter banks, wavelet analysis, neural networks, and other methods [1]-[7].
Earlier works were mainly based on linear or non-linear filter or filter banks methods [1],[2]. These methods use very simple models and require less computational power and are most suitable for embedded real-time monitoring applications. The drawback is that the precision of the QRS feature extraction is limited since the processing involves a limited range of frequencies of the ECG signals. Development of wavelet based QRS detection became increasingly popular in recent years [3],[4],[5]. With wavelet based analysis, each QRS complex corresponds to distinguishable features in the wavelet transform that can be used to identify the temporal location of the R wave. The ECG signal is evaluated over different scales in both the time-and frequency-domain whereby the ECG signal is decomposed into different response clusters which represent different frequency components of the ECG. This method is computationally involved and generates significant redundancy which represents a disadvantage that restricts its application in embedded real-time systems.Another method, template matching [7] has also been developed for QRS detection. This detects the position of the QRS complex by calculating the cross-correlation between a representative waveform template and the ECG signal of interest. The performance of the method can exhibit poor performance when there are variations in the ECG waveforms of the signals being analyzed. This is a significant deficiency when evaluating signals from individuals with various cardiac pathologies that inherently produce waveform variations. This paper describes the implementation of a potentially effective QRS detection algorithm that incorporates a slope vector waveform analysis. It allows for a fast and accurate search of the location of the peak of the R wave, QRS complex duration,

and RR interval yielding effective ECG feature extraction results. In addition, the required computations are considerably less than those associated with techniques such as a wavelet based analysis.

II. REVIEW OF LITERATURE

Shukla et al [8] in 'A Fast and Accurate FPGA based QRS detection System' describes a FPGA (Field Programmable Gate Array) system for ECG analysis that incorporates a QRS detection algorithm that has an accuracy of around 96% that utilizes approximately 76% of the device in question. The design consists of two stages: a preprocessing stage followed by a peak detection and median based threshold calculation stage. In their design a delayed version of the low passed signal is used to effectively obtain the location of the peak of the R wave in the original signal.Dokur et al [6] performed ECG waveform detection by using an artificial neural network. In their work the peak of the R wave is first detected and then feature vectors are formed by using the amplitudes of the significant frequency components of the DFT spectrum. The concept of a "Grow and Learn" process is then applied to analyze the ECG waveforms. The results in this paper presents the accuracy of the system, however the design complexity in terms of hardware or software is not mentioned.

Kesel brener et al [9] in 'Nonlinear high pass filter for R-wave detection in ECG signal' presented a simple and easily implemented method for R-wave detection from ECG signals. Their method is based on subtraction of a filtered version of signal from the original signal. Threshold detection is then performed on the filtered signal. Their results are presented for a simulated signal with sinusoidal and step baseline drifts as well as ECG complex shape changes. The design described in this paper [9] incorporates a filter as the initial stage in FPGA implementation. After passing through the filter the signal is processed further in the time domain to detect the interval between the peaks of the R waves.

A novel technique for the detection of QRS complexes in electrocardiographic signals that is based on a feature obtained by counting the number of zero crossings per time segment is presented by Kholer et al [10]. This seems to be a rather simple method to detect R peaks but results in an algorithm that provides a sensitivity of 99.70% and a positive predictivity of 99.57% when evaluated against the MIT-BIH arrhythmia database.

III. SYSTEM OVERVIEW

The ECG data is taken from standard AF (Atrial Fibrillation) Termination Challenge Database [11] and noise is added to it utilizing MatLab code, the software used was MathWorks, Matlab Version 7.7.0.471 (R2008b). The code is included in appendix II. The noise added is a white band noise, centered at 60 Hz. The ECG data containing the white noise is now inputted to the FGPA board (Spartan 3E – Starter Kit) via an RS-232 interface. The signal values are first processed on a 12th order low pass filter with a cut-off frequency of 16 Hz. The values are then fed to a block that calculates the HR (heart rate) and HRV (heart rate variability) which is described in detail in the experimental procedure. The values of the HR and HRV are then provided to the computer via the same RS-232 interface for graphical representation.

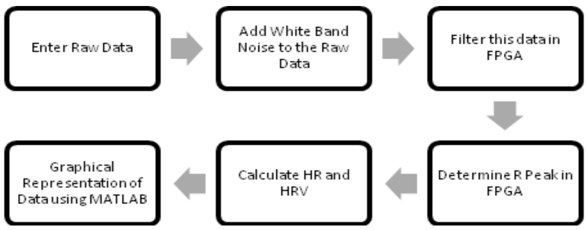

Fig. 1 System Overview

IV. EXPERIMENTAL PROCEDURE

Step 1: Finding initial R peak

The stream of sample is traversed and the first peak is identified. This is done by selecting the highest value that is observed before a reducing slope is reached. Then this peak is tested for its desirability by comparing it with parameters such as maximum and minimum possible beats per minute (bpm) which is 220 and 40 respectively. For the AF Termination Challenge database the sample rate was 128 samples per second. Hence 35 and 192 sample difference was received between the beats for maximum and minimum beats per minute. Using the minimum possible beats per minute, the first beat correctness is tested. This is achieved by looking for a peak greater than the first peak in the interval, 192/2 = 96. If a peak higher than the first peak is found out in this interval, it is assigned as the first peak for the minimum beats per minute. In case two significantly large peaks are reached where either can be the first peak, the initial one will be considered as the first peak.

Step 2: Determine Threshold

Threshold is equal to half the R peak value and is updated at run time whenever the R peak value is updated.

Step 3: Identify Upcoming R peaks

The system looks for the peak as soon as the rising edge crosses the threshold value.

Step 4: Calculate Heart Rate and Heart Rate Variability

After every R peak is detected, the Heart Rate and Heart Rate Variability is calculated as follows:

Considering the first heart beat occurred at time instance T1 and the second occurred at time instance T2, the heart rate is calculated in by the FPGA that is determined by the following formula:

$$HeartRate(H.R.) = \frac{60}{(T2 - T1)} beatsperminute$$

The Heart Rate Variability is then calculated using two successive readings of the heart rate. Let the two successive readings of heart rate be H.R.1 and H.R.2, the variability is calculated by formula:

$$HeartRateVariability(H.R.V.) = \frac{H.R.2 - H.R.1}{H.R.1}$$

Hence readings of heart rate and heart rate variability for every heart beat are calculated.

V. RESULTS

The signal obtained from the data, Learning-set\n01 of AF Termination Challenge Database file, when plotted is as depicted in the following graph, fig. 2

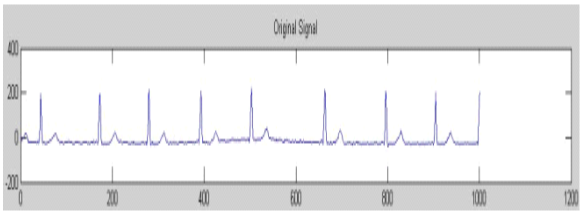

Fig. 2 Waveform of Original Signal

After passing the values through the MATLAB code [from appendix II], for the addition of white band noise, the signal in fig. 3 is received. This signal is next fed to the FPGA board.

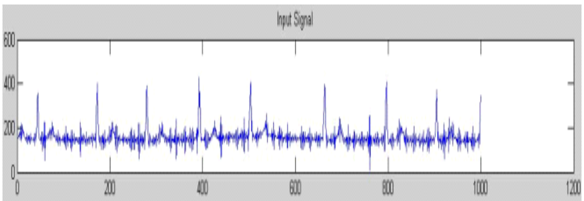

Fig. 2 Waveform of Signal with Noise

The first block in the FPGA is a low pass filter that smoothens the above signal by removing noise and gives the following graph, fig. 4

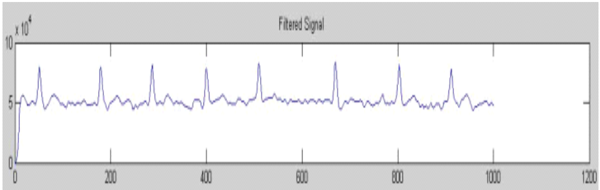

Fig. 3 Waveform of Filtered Output

As the values of the above signal passes through the processing block on FPGA to obtain the R peaks, the algorithm stamps the time instance at which the R peak occurred and to depict the same the following view graph is plotted as in fig. 5.

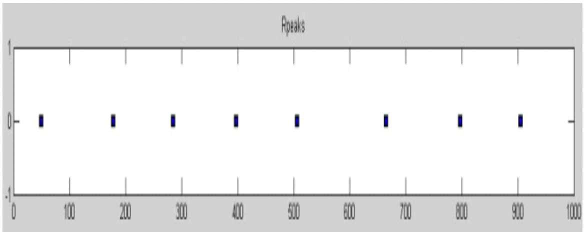

Fig. 4 Waveform indication R Peaks

The FPGA processing block also produces the values of the H.R. and H.R.V. for every value of time instance for the R peak as visible in the following figures 6 and 7. Figure 6 plots the heart rate after detection of every R-Peak whereas figure 7 plots Heart Rate Variability after calculation of every Heart rate.

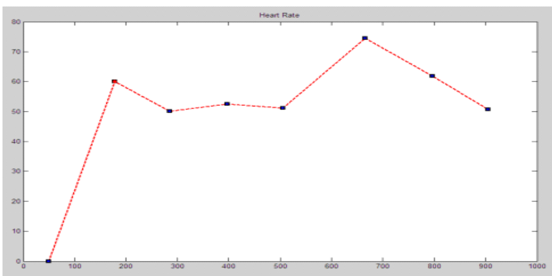

Fig. 6 Waveform representing Heart Rate

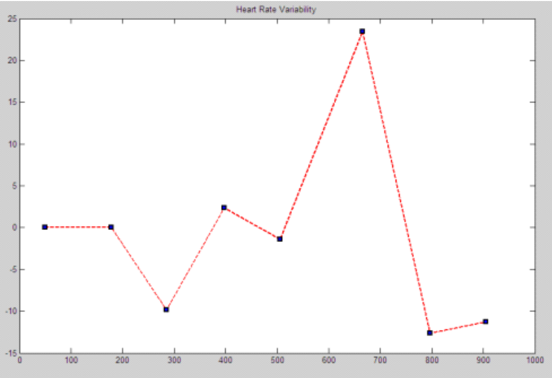

Fig. 5 Waveform representing Heart Rate Variability

Result analysis: The implementation was fed with various data files for a number of times and the following observations were made:

Table 1: Result Analysis

Data Set	Number of trials	Actual Beats	Average missed Beats	Efficiency
Learning-set\n01	10	76	3	99.96%
Learning-set\n02	10	73	4	99.94%
Learning-set\n03	10	50	1	99.98%
Average Efficiency				**99.96%**

VI. CONCLUSIONS

As it can be seen from the result analysis, table 1, the algorithm gives result 99% and higher, if calculated with average missed beats in the test data after passing the test data for multiple times through the implementation. This may not be the best result for the system as compared to the various systems previously developed [1-10] systems where huge data sets were tested. The design of this system is simple and low cost implementation as it requires very less hardware for implementation. Finally the algorithm is simple for the detection of heart rate and heart rate variability.

VII. ACKNOWLEDGMENT

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