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## FPGA Based Arrhythmia Detection

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### Abstract

This paper proposes a simple and reliable Field Programmable Gate Array (FPGA) based ECG Analysis system. Electrocardiogram (ECG) is important biomedical signal, which show the electrical activity of the heart. ECG waveform provides the valuable information for detection of abnormal heart diseases. For accurate analysis, ECG signal must be processed to remove the noise signal. Also, various features of ECG must be extracted for diagnosis of cardiac disorders. Thus, ECG signal processing includes two stages: Preprocessing and Feature Extraction. Preprocessing stage removes noise from the raw ECG signal and the feature extraction stage extracts diagnostic information from the ECG signal. The main objectives of the work are (i) ECG signal enhancement using Empirical mode decomposition (EMD) based method. (ii) Detection of R peaks which is the first step towards automatic detection of cardiac arrhythmias in ECG signal. The proposed system can detect three different arrhythmias. 94.76% accuracy of the proposed method is achieved in detecting the different heart Arrhythmias correctly by using subset of data records from the MIT-BIH database. The system is implemented using Verilog HDL and Xilinx Spartan 3E FPGA respectively.

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### 1. Introduction

Electrocardiogram (ECG) is one of the important tools used by the cardiologists to analyze the ECG waveforms in diagnosis of various diseases and monitoring the conditions associated with the heart. It is obtained by placing electrodes on the skin of the patient. It provides information of a human heart like disturbances in heart rhythm, abnormalities in the electrical impulses etc. Signal corruption takes place due to noise [1] and artifacts during the transmission of ECG. The characteristics of ECG signal vary due to different types of noises like Power Line Interferences, Baseline drifts, Motion Artifacts, EMG, Instrumentation noise etc. Such a noisy signal analyzation bound to give erroneous results. Thus it is important to denoise or enhance the ECG signal. A number of methods have been implemented for the Enhancement of ECG signal. These include use of Neural Networks, PCA, Filter banks [2], ICA [3], Adaptive Filtering [4], wavelet transform [5-7] etc. In this paper, we

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used a recent technique called Empirical Mode Decomposition (EMD) which is a time frequency analysis method suitable for mainly non linear and non stationary signals like ECG. After Enhancement, ECG Feature extraction involves extracting useful information like R peaks, detection of different heart arrhythmias etc. As R wave is the most dominant wave in the ECG signal, we detect the R peaks calculate RR intervals and heart rate based on which different arrhythmias are detected. Here, we implemented a QRS detection algorithm, which detects R peaks by using Threshold Methodology. This design is implemented on Xilinx Spartan 3E FPGA board.

The paper is designed as follows: Section II describes the Theoretical aspects of empirical mode decomposition and QRS Detection Algorithms. Section III describes the methodology of the proposed techniques, Simulation and Synthesis results are shown in Section IV and the conclusions of the paper are shown in Section V. The block diagram of the proposed method is shown in Fig. 1.

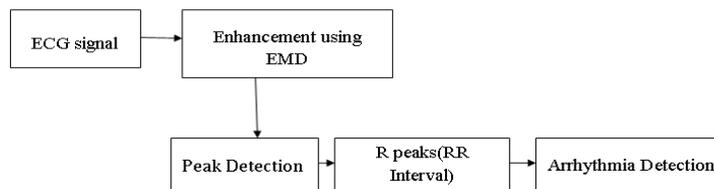


Fig.1 Block diagram of the proposed method

## 2. Theoretical Background

### 2.1 Empirical mode decomposition (EMD)

The EMD method which is a new non-linear technique has been recently developed by N.E Huang *et al.* [8] for representing the non stationary signals like ECG. The basic principle of EMD is to decompose a signal into a finite number of IMFs [17][18]. The extracted IMFs satisfy the following requirements:

- (a) The maximum difference between the number of extrema and the number of zero crossings must be one in the entire data set.
- (b) At any point, the mean value of envelope defined by local maxima and local minima is zero.

A systematic way to extract the IMFs is called the Sifting Process and its algorithm is given below

#### A. Sifting Process

Step 1) Identify all the maxima and minima of the original signal  $x(t)$ . Interpolate between maxima and minima to obtain  $x_{\max}(t)$  and  $x_{\min}(t)$ .

Step 2) The mean or average between the two envelopes is calculated as  $x_{\text{avg}}(t) = [x_{\max}(t) + x_{\min}(t)]/2$

Step 3) The candidate IMF  $d_1(t)$  is calculated i.e.

$d_1(t) = x(t) - x_{\text{avg}}(t)$ . Here  $d_1(t)$  is given as the input to the next iteration process.

As the resulting signals do not carry significant physical information after a certain number of iterations. To prevent this, we go for some boundary conditions. The sifting process is stopped by limiting the normalized

standard deviation (nstd) [9] where

$$SD = \sum_{t=0}^{L-1} \frac{|d_{k-1}(t) - d_k(t)|^2}{d_{k-1}^2(t)}$$

The Standard Deviation is set between 0.2 and 0.3[3] to obtain proper results.

Step 4) Check whether  $d_k(t)$  fulfils the conditions that defines an IMF.

i. If  $d_k(t)$  is not an IMF, treat  $d_k(t)$  as the Original data  $x(t)$  and repeat Steps (1–4) up to  $k$  times until  $d_k(t)$  becomes an IMF.

ii. If  $d_k(t)$  is considered as a first IMF  $h_1(t)$ , then residue  $r_1(t)$  is calculated as

$$r_1(t) = x(t) - d_k(t).$$

$$h_1(t) = d_k(t)$$

Step 5) In order to extract the second IMF,  $r_1(t)$  is given as the input to the next round of sifting process.

Repeat the steps from (1–5) (sifting process) to find other IMFs

$$h_1(t), h_2(t), \dots, h_n(t).$$

Step 6) The sifting process is stopped until the residue function  $r(t) = x(t) - \sum_{i=1}^n h_i(t)$  becomes a monotonic

function in which no more IMF's can be extracted.

Thus, the original signal  $x(t)$  is decomposed into the  $n$  IMFs  $h_1(t), h_2(t), \dots, h_n(t)$  and a final residue signal which can be denoted as

$$x(t) = \sum_{k=1}^N h_k(t) + r_N(t)$$

Where  $N$ = no of rounds of sifting process performed on the given signal  $x(t)$ .

## 2.2 QRS Detection Algorithms

The QRS complex is one of the most distinct features in an ECG waveform. Amplitude, width and its morphology play a very important role in the diagnosis of various cardiac ailments. Many new approaches vary from the use of Hilbert Transform [16], wavelet transforms [15], which are mostly based on non-linear transformations [10]. The frequency components of QRS complex of ECG waveform is from 10 to 25 Hz. Therefore low pass filter is needed for suppressing noise and the attenuation of P and T waves. The filtered signal is then used to extract the R Peak by comparing it to a threshold value.

## 3. Methodologies

### 3.1 Enhancement Technique Using EMD

In EMD Technique, Enhancement of ECG signal is done by expressing the noisy ECG signal as the sum of a series of IMFs. The noisy components are mostly found in the initial IMFs [I3] among the finite set of IMFs generated. It is important to determine whether noise is present in a particular IMF or not. In order to determine

this, Spectral Flatness (SF) measure is used here. The proposed denoising method using EMD is shown in Fig 2 and the different steps to be followed are explained below

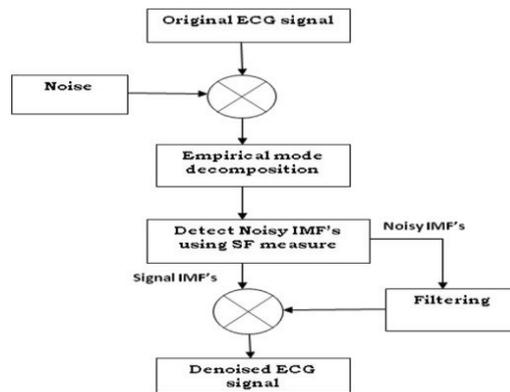


Fig 2: Block diagram of proposed ECG Denoising method

The lower order IMFs correspond to higher frequency components and the higher order IMFs with lower frequency components. Since the frequency of ECG signal ranges from 0.05 to 100 Hz [13], the spectrum of noisy IMFs will be relatively flat compared to signal IMFs which are concentrated on short range of frequencies. The different steps to be followed are explained below

Step1: The ECG signals are taken from MIT-BIH arrhythmia data base [14]. Consider  $x(t)$  as the original signal and  $n(t)$  as the noisy signal. The noisy ECG signal  $s(t)$  is obtained as  $s(t) = x(t) + n(t)$ .

Step2: Now the EMD algorithm is applied to the noisy ECG signal in order to decompose the signal into finite set of IMFs.

Step3: The number of noisy IMFs,  $n$ , can be obtained by calculating the Spectral Flatness (SF) measure for each IMF. And compare it to a threshold value  $T$ . The Spectral Flatness is given as

$$SpectralFlatness = \frac{\sqrt[L]{\prod_{n=0}^{L-1} H(n)}}{\sum_{n=0}^{L-1} H(n)}$$

If the Spectral Flatness is above the threshold  $T$  for the 1<sup>st</sup>  $n$  IMF's then they are considered as noisy IMFs. The threshold value  $T$  is taken as 0.09. Here  $L$ =Length of the signal.

Step 4: Using a band pass Butterworth filter of order 10 with pass band of 40-60Hz [12], the 1st IMF is filtered since significant part of the high frequency content of ECG is in this range. The remaining noisy IMFs are filtered using low pass butter worth filter of same order with cut off frequency of 60Hz to extract the significant signal components.

Step 5: The original ECG signal is obtained by adding the filtered IMFs and the remaining signal IMFs. The reconstructed signal  $\hat{x}(t)$  is given by

$$\hat{x}(t) = \sum_{k=1}^n \tilde{h}_k(t) + \sum_{k=n+1}^N h_k(t) + r_N(t)$$

Where  $\tilde{h}_k(t)$  is the filtered version of  $h_k(t)$ .

### 3.2 R peak Detection Using Difference Operation Method

One of the approaches based on filtering suggested by Yun-Chi Yeh [11] was implemented in the hardware with a few modifications. Difference Operation Method [11] is one of the simple and fast methods in detecting QRS complexes. The basic principle of this method is to find the R peak by applying difference operation to the ECG signal. Complex mathematical calculations such as cross-correlation, Fourier transform etc. are not involved in this method. It mainly involves finding the difference signal or the derivative. Therefore basic calculus is used for finding the peak points. The algorithm for the difference operation method is described below: The difference operation is first implemented according to the following steps:

- Step1) Take the original ECG signal as  $x(t)$  and derivative signal as  $d(t)$ .
- Step2) the difference or derivative signal of  $x(t)$  is given as  $D(t) = x(t) - x(t-1)$ .
- Step3) Then the difference signal is passed through a low pass filter to obtain  $xd(t)$ .
- Step4) Threshold logic is applied for finding the peak points.

Design:

The design can be divided into two main sections. The first section is the pre-processing stage. This was where the derivative and filtering are implemented. The second section is the peak detection stage where the peaks are detected. The block diagram of the proposed design is shown below:

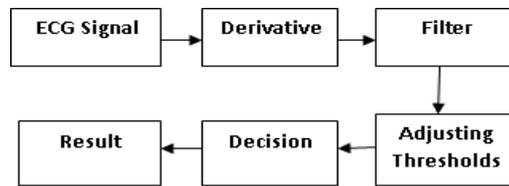


Fig 3: Block Diagram of DOM Method.

#### A) Pre-Processing Stage

Below Fig 4(a)-4(c) show the stages that are involved in the Preprocessing Stage.

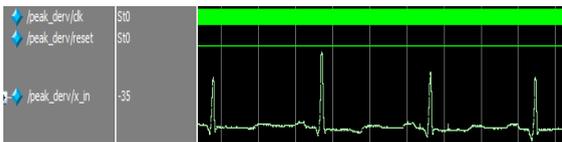


Fig 4(a) Input ECG Signal(x(t))



Fig 4(b) Derivative(xd(t))



Fig 4(c) Filtering (LPF)(xdf(t))



Fig4(d) Peak detection(xdfp(t))

Fig 4: Step by Step Representation of various stages in DOM Method

#### B. Peak Detection stage

**Threshold Methodology:**

We consider the initial Threshold value as 30% of the maximum value of all samples. Then the input sample is compared to the threshold value. All the data samples below the threshold value are removed. Then we search for three consecutive samples among which peak value can be detected. A sample value is considered as a peak value such that if its preceding and succeeding values must be less than the sample value i.e. if n is a sample then its preceding n-1sample and its succeeding n+1sample must be less than the sample n. Then n is considered as the peak value. Thus peak is detected based on the Threshold Methodology. The result of Peak detection stage is shown in the above Fig 4(d).After detecting the R peaks, calculate the R-R interval and Heart Rate to detect Arrhythmias.

**C. Heart Rate and Arrhythmia Detection:**

For detection of Arrhythmias, first we need to know the Heart rate of different Arrhythmias. It is shown in the below Table I.

$$\text{Heart Rate} = (60/\text{RR Interval}) \text{ BPM}$$

Heart Arrhythmias	Heart Rate(BPM)	RR Interval(s)
Normal Sinus Rhythm(NSR)	60-100	0.60-1.0
Atrial Fibrillation	>350	random
Atrial flutter	240-360	0.167-0.250
Atrial Tachycardia	160-240	0.25-0.375
Ventricular tachycardia(VT)	110-250	0.24-0.545
Ventricular Fibrillation	<250	<0.240
Sinus Tachycardia(ST)	>100	-
Super Ventricular Tachycardia(SVT)	140-240	-
Sinus Bradycardia	50-60	-

Table I: Heart rate and RR interval for different Heart Arrhythmia

In this work, we considered four different data records to detect different arrhythmias. The detected arrhythmias are Atrial Fibrillation, Sinus Tachycardia, Ventricular Tachycardia and Normal Sinus Rhythm. The results are shown in the below Fig (9-12).

**4. Simulation and Synthesis Results**

The proposed method is evaluated by using MIT-BIH Normal Sinus Rhythm database (nsrdb), Supra Ventricular Arrhythmia database (svdb), Atrial Fibrillation database (afdb) and Arrhythmia database (mitddb). The effectiveness of the proposed method in detecting the diseases with the overall accuracy of 94.76% is shown in the below Table II. Fig 5 shows the Denoising result using EMD. Fig 6 shows the result of Top level Design. Fig 7 and Fig 8 shows Block Diagram and synthesized RTL schematic of top level of our proposed design.

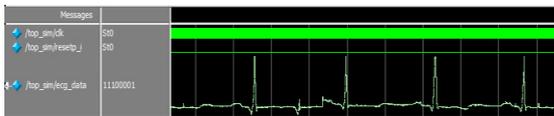


Fig 5(a) Input ECG Signal

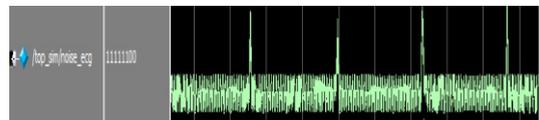


Fig 5 (b) Noisy ECG Signal

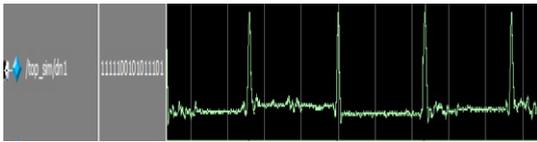


Fig 5(c) Denoised Signal

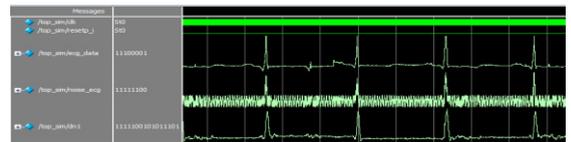


Fig 5 Overall Simulation Result of Denoising Using EMD

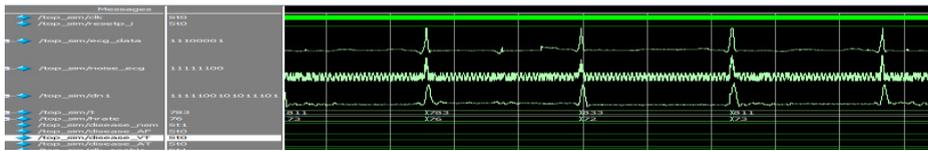


Fig 6: Simulation result of Top Level design (Both denoising and Heart Rate Calculation)

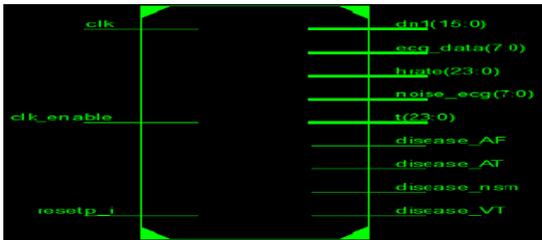


Fig 7: Block Diagram of our proposed design

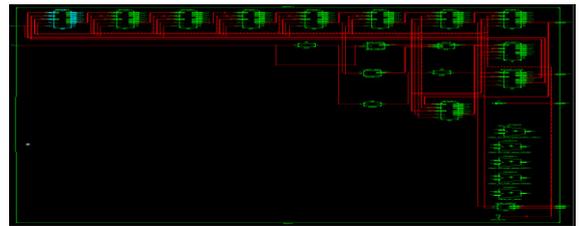


Fig 8: RTL Schematic generated by the Synthesis Tool.

Fig (9-12) shows the Simulation Results of four different data records calculating Heart Rate and detecting corresponding Arrhythmias.

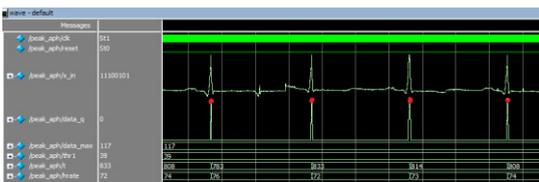


Fig 9: Record 100(Red point indicates R peak)

Heart Rate – >60-100 BPM,  
Detected Disease: Normal Sinus Rhythm

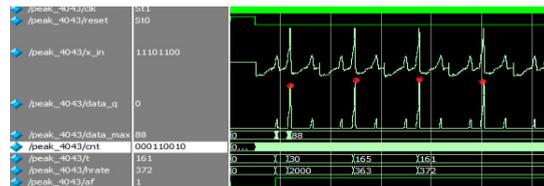


Fig10: Record 4043  
Heart Rate – >350 BPM  
Detected Disease: Atrial Fibrillation

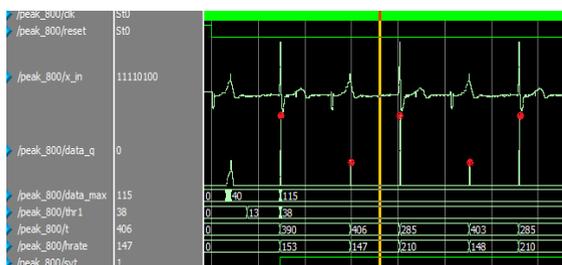


Fig 11: Record 800  
Heart Rate – >110-260 BPM

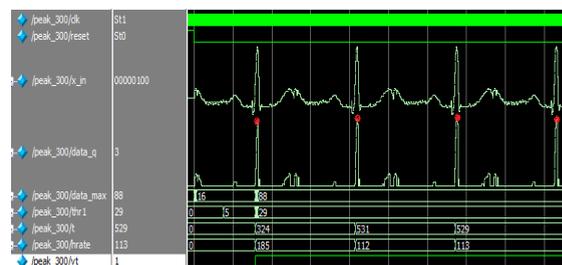


Fig 12: Record 300  
Heart Rate – >100 BPM

Detected Disease: Ventricular Tachycardia

Detected Disease: Sinus Tachycardia

The proposed model is implemented upon XILINX SPARTAN XC3S500 FPGA board processor.

**DISEASE DETECTION IN FPGA:**

Different types of Arrhythmias detected in FPGA through LED glow taken from data records of MIT-BIH Database is shown in the below figures(14-16):

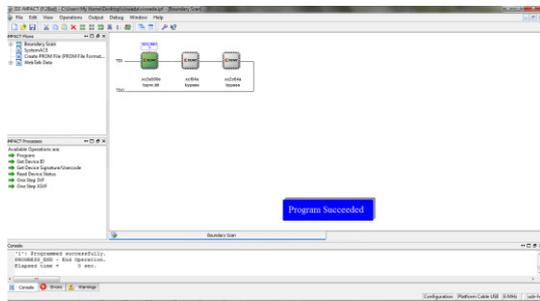


Fig13: FPGA Implementation output



LED-E9 GREEN  
NORMAL SINUS  
RHYTHM

ORANGE LED  
INDICATING  
SUCCESSFUL  
FPGA DUMPING

Fig14:Green Light(LED-E9) indicating the detected one as **NORMAL SINUS RHYTHM**

**RECORD-4043**



LED-D11 GREEN  
DISEASE  
DETECTED-  
ATRIAL  
FIBRILLATION

ORANGE LED  
INDICATING  
SUCCESSFUL  
FPGA DUMPING

Fig15:Green Light(LED-D11) indicating the detected disease as **ATRIAL FIBRILLATION**



LED-C11 GREEN  
DISEASE  
DETECTED-  
VENTRICULAR  
TACHYCARDIA

ORANGE LED  
INDICATING  
SUCCESSFUL  
FPGA DUMPING

Fig16:Green Light(LED-C11)indicating the detected disease as **VENTRICULAR TACHYCARDIA**

Cardiac disease	No.of data sets used for testing	No.of data sets correctly classified	No.of data sets mis-classified	Accuracy (%)
NSR	20	20	0	100
AF	25	23	2	92
SVT	26	24	2	92.3
Over all accuracy				94.76

Table II: shows accuracy rate of the algorithm in detecting three diseases i.e. Normal Sinus Rhythm, Supra Ventricular Arrhythmia and Atrial Fibrillation tested with the respective MIT-BIH Databases.

## 5. Conclusions

An efficient method for arrhythmia detection has been developed based on heart rate. EMD based method for denoising of ECG signal is proposed in which Automatic detection of noisy IMFs is done using Spectral Flatness measure. After Enhancement, R Peak detection, the most relevant feature of an ECG waveform is done using Threshold methodology. Once R peak is detected, RR interval is calculated to estimate the heart rate for arrhythmia detection. This design is implemented on Xilinx Spartan 3E FPGA board using Verilog language. The implemented design tool (Xilinx ISE), uses only 38% of the resources available in a small sized FPGA device (Xilinx Spartan XC3S500) and is able to compute the heart rate of the signal and detect the arrhythmia (through LED). The performance of proposed method is evaluated using different arrhythmia data records of MIT-BIH databases. Till now the analysis is done with R-peak but in future the work will go on with the other peaks too as some heart arrhythmias depends not only on the R-R interval but also P, T waves. Our system can't detect those kinds of arrhythmias. The algorithm can be modified further to calculate all the ECG parameters automatically at the output. Thus, it can be used for the processing of real time ECG signals in future.

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