A Novel Low Complexity On body CVD Classifier ASIC Design Methodology

Sandeep Kumar Tiwari

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Sandeep

(Signature)

SANDEEP KUMAR TIWARI

(– Student Name –)

EE12M1031

(Roll No)

Approval Sheet

This thesis entitled "A Novel Low Complexity On body CVD Classifier ASIC Design Methodology" by Sandeep Kumar Tiwari is approved for the degree of Master of Technology from IIT Hyderabad.

External Examiner

V. Siva Ram Krishna
Ashudeb Dutta

Internal Examiner

for Ashudeb Dutta

Adviser

Co-Adviser

Chairman

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Dedication

Dedicated to my Family, True Friends and Gurus

Abstract

Due to increasing rate of cardiac disorders in developed and developing countries Continuous on body monitoring of ECG signal using the concept of IoT and Body Sensor Network has become the necessity. In this work we are proposing a novel low complex, low power algorithm and architecture for E.C.G. classification which can be incorporated in present era of IOT and Body Sensor Network. Rather than going for Artificial Intelligence based pattern matching and complex DSP algorithm we have used the simplicity of Hurst exponent and Haar wavelet for filtering out anomalous E.C.G. signals and normal ones. Modification has been presented on standard Hurst Exponent method to improve its classification quality which out performs the standard methods available for anomalous E.C.G classification in terms of number of anomalies which can be classified and the classification efficiency as well. The simulation result shows 98.6% accuracy in four E.C.G. databases MITDB of MIT-BIH. Along with the algorithm we propose its corresponding low complex architecture exploiting algorithm architecture holistic design view.

The proposed Architecture has been synthesized using $UMC130nm$ technology and it occupies $0.14mm^2$, while state of the art method requires $0.7mm^2$. Similarly the power consumption for proposed design is $26nW@1kHz$ while state of the art method consumes $182.94nW@1kHz$. The low power and less area are the key parameter which makes this design better suited for ASIC implementation.

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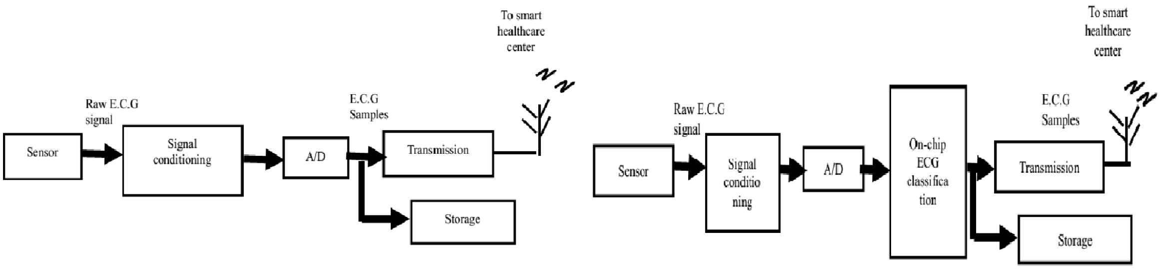
Chapter 1

Introduction

1.1 Motivation

The electrocardiography (ECG) which measures electrical activity signal of the heart has a very important role in heart disease diagnosis. Cardiac arrhythmia (popularly known as abnormal condition of heart) measured by ECG are potentially connected to symptoms of a heart disease[1,2]. Recently, automatic heart beats classification has attracted much interest for research because it can save cardiologist from looking for arrhythmia beats in a sheer amount of ECG heart beats data. Automatic classification will enable cardiologist to diagnose cardiovascular disease (CVD) timely and to make home care possible. The early detection of cardiac diseases e.g. Arrhythmia helps in prolongation of life and enhances the quality of life. So, there is a need of monitoring the condition of heart.

For over a century ECG (Electro Cardio Gram) has been popular choice among doctors for diagnosis of heart because of its fairly informative and non-invasive nature[3]. Detection of arrhythmia is a critical step in administering aid to a cardiac patient. It can be present in a healthy heart and be of minimal consequence. To detect its presence patients are hooked to cardiac monitors in hospitals. A physician is required for visual inspection of arrhythmia. Visual inspection is tedious and physician dependent task. It invites certain human errors to creep in. So, algorithms were developed to detect arrhythmia automatically [4]. Most of these algorithms had good classification efficiency of more than 96%, but the procedure itself lacks modern concept of telecardiology, IoT, body sensor network, pervasive computing and most importantly personal health care [5] [6] [7]. However with the advent of IoT (Internet Of Things) and body sensor networks there is trend of continuous monitoring[10]



(a) State of the art telecardiology (b) Proposed method for telecardiology

Figure 1.1: Different telecardiology scenarios

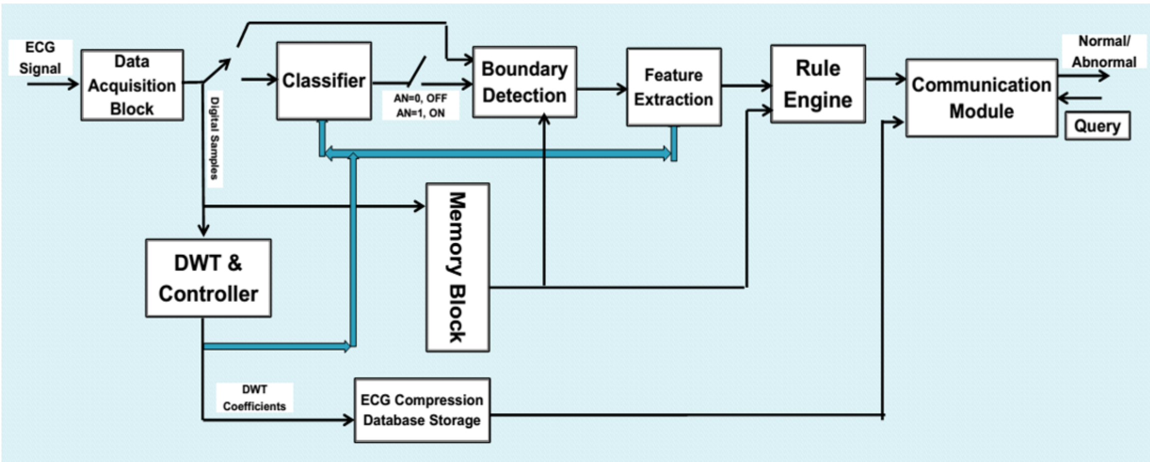


Figure 1.2: Proposed Next Generation Health Care Chip(NGHC)

of individual health and this data is send to a server where doctors can manually or automatically analyze it[9]. This technique with respect to heart is called Telecardiology. Telecardiology can be very useful for developing and under developed countries because of their less doctor to patient ratio. Fig.1.1a depicts a general telecardiology scenario. In telecardiology it is seen that most signals are normal and are of no interest for investigation and consume unnecessary power and bandwidth for wireless transmission. So power can be saved if classification of E.C.G is achieved on chip before transmission. Motivated with this idea a new telecardiology approach has been depicted in Fig.1.1a.

Fig.1.2 shows the block level implementation of next generation health care chip(NGHC). Here in this figure we have only concentrated on ECG signal only but it may include various other biosignals e.g. EEG, EMG, EOG, GSR etc. The classifier finds a vital role in these kind of applications. As we can see that classifier sits in between data acquisition block and other processing blocks. The classifier can be used as primary data filter to decide weather samples require detailed processing or not. Thus this kind of scheme can ignore normal samples which are of less significance. Hence this technique helps in reducing overall power consumption of chip by giving option of selective processing.

Any algorithm which has to be implemented on battery run chip has constraints of low power and low area which is not met by algorithms mentioned in ref. [4-7]as they were proposed for general purpose processor. Recently from our research group one robust classification technique based on Hurst exponent has been published [8] [9], which has shown to outperform the state of art classification approaches. However the main focus in that paper was to propose robust classifier but not on its application to remote personalized healthcare due to its computationally intensive nature. Therefore in this work we propose low complexity architecture of this classifier by exploiting architecture algorithm holistic design view so that it can be targeted to CPS (Cyber Physical System) or IOT enabled remote personalized healthcare application. Subsequently we propose an improved classification which is shown to perform better than that was proposed in [8] [9]. Along with the algorithm a low complexity architecture has also been proposed using algorithm architecture holistic design view. All the proposed architecture and algorithm are validated using MIT-BIH database and has been experimented on real hardware.

1.2 Literature Survey

Automated ECG classification has been of great interest after the advent of Digital computers. In late 90s high performance computers were used to assist cardiologist in detecting arrhythmia. Later on after the progress in signal progressing and availability of cheaper computing machine boosted the field of automatic ECG classification. ECG classifier classifies the signals in different classes. Here different classes are the diseases e.g ventricular tachycardia, atrial flutter, malignant ventricular tachycardia etc. Instead of manually annotate the ECG signals by experts such as doctors and cardiologists, which could take enormous time and efforts, we can automatically detect the types of ECG signal using computer. Various studies have been done for classification of different types of arrhythmia. ANN and its derivative have been used extensively for Arrhythmia classification. Some of them are combining Principal Component Analysis (PCA), wavelet transform (WT), Fuzzy C-Mean(FCM) with Artificial Neural Network (ANN) or Learning Vector Quantization-Neural network (LVQ-NN) for classifying the signal [14-17].Bayesian framework [18] has also been used. Fuzzy theory has also been applied on arrhythmia classification in paper [13], [18-20]. Few researchers explored Support Vector Machine(SVM) as a classifier [21-23]. Combination of different pattern search algorithm e.g Support Vector Machine(SVM,Particle swarm Optimization (PSO) have also been studied for ECG classification [20-23]. Hamid et.al presented comparisons feature extraction methods like PCA, DFT, DWT, Morphological based and integrated it with Artificial Neural Network(ANN) classifiers [24].

1.3 Contribution of Thesis

The main contribution of this work to current state of art work are:

- This work proposes a novel low complex algorithm for automated ECG classification which requires very less computing resources.
- A novel low complex automatic ECG classification architecture design methodology has been proposed which can be used for next generation health care chips.
- The proposed classifier help to reduce the power consumption in Telecardiology.
- This classifier reduces the power consumption of next generation health care chips. It can be used to avoid processing of normal signals as demonstrated in Fig.1.2.

1.4 Thesis Organization

Chapter 1: Is the introduction describing the motivation behind the work, literature survey, objectives and contributions of the present work.

Chapter 2: Describes the Background of ECG signal, types of ECG signal, basic method for ECG classification, Issues involved with ECG classification, wavelet transform and Hurst Exponent. The chapter concludes with description of Hurst exponent as classifier.

Chapter 3: Describes the Hurst exponent as CVD classifier and introduces about the modification which leads to superior classification results.

Chapter 4: Introduces to the proposed Low complex on body CVD classifier design methodology.

Chapter 5: Discussion on results obtained with algorithm and architecture.

Chapter 6: Presents the conclusion to the thesis as well as future directions of this work

Chapter 2

Background

2.1 Electrocardiography

Electrocardiography is the non-invasive process of collecting electrical signals generated by cardiac muscle during its operation.The heart produces different actuation signals which controls the functioning of cardiac muscles. ECG or EKG is the graph which shows the electrical activity of cardiac muscles with time.

2.2 ECG Recording

Conventionally ECG is recorded using 12 leads. It consist of four limb electrodes and six chest electrodes. Table2.1 shows the placements of leads on the body.

Table 2.1: Placement of leads on the body

Electrode name	Electrode placement
RA	On the right arm, avoiding thick muscle
LA	In the same location where RA was placed, but on the left arm
RL	On the right leg, lateral calf muscle
LL	In the same location where RL was placed, but on the left leg.
V1	In the fourth intercostal space (between ribs 4 and 5) just to the right of the sternum (breastbone).
V2	In the fourth intercostal space (between ribs 4 and 5) just to the left of the sternum.
V3	Between leads V2 and V4.
V4	In the fifth intercostal space (between ribs 5 and 6) in the mid-clavicular line.
V5	Horizontally even with V4, in the left anterior axillary line.
V6	Horizontally even with V4 and V5 in the midaxillary line.

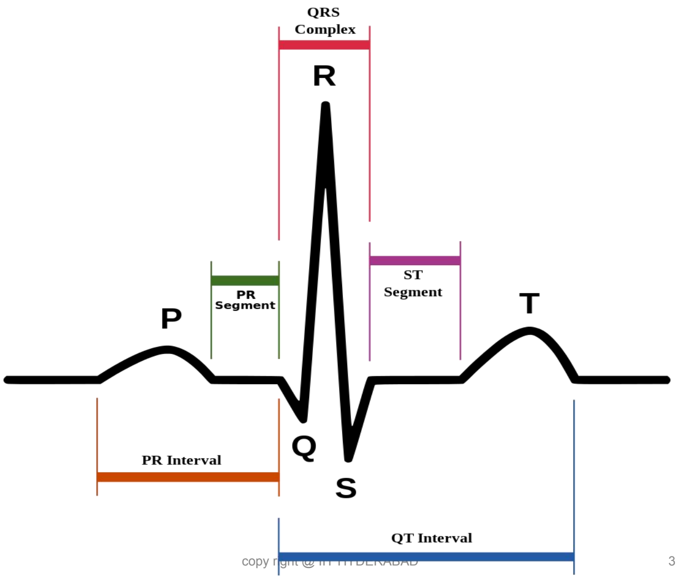


Figure 2.1: Sample ECG Waveform

2.3 ECG Signal

ECG signal is a low frequency signal with a typical range of 0.1 Hz to 150 Hz. Most of the power of ECG signal is concentrated below 35 Hz. The QRS wave lies in the range of 15 Hz to 25 Hz and P wave and T wave are mostly concentrated near 10 Hz. In time domain the signal is has a regular pattern at frequency of 60 to 100 beats per minute. ECG records having beats more than 100 Hz per minute may suffer from tachycardia. while on the other side if the heart beat rate is below 60 beats per minute, it may be the case of bradycardia. There are few exception to these general rules e.g. athletes. They have lower heart beat rate but still they are considered to be normal.

2.4 CVDs in This Thesis

Although there are many cardio vascular diseases, but in this thesis we have chosen to stick on three common CVD i.e. ventricular Tachycardia, malignant ventricular arrhythmia and atrial fibrillation. Ventricular tachycardia is a type high breathing rate disorder that starts in the bottom part of the heart. Atrial fibrillation (Afib) is characterized by rapid and irregular beating with symptoms of short breath, fainting and chest pain.

2.5 ECG Data Acquisition

Electrical signals of the patient heart can be sensed by putting electrodes on the body of patients. These obtained electrical signals need to conditioned properly before digital processing. Since ECG signals is effected by a lot of noise sources like motion artefact, Power line noise, base line wandering etc, so they need precise noise filtering and signal conditioning before feeding to ADC for digitization.

Electrocardiography (ECG), requires a precision analog front end instrumentation gain stage, filtering, and a high resolution analog to digital converter to achieve the highest performance. A typical ECG data acquisition system consist of Analog front end, and ADC.

Analog signal coming from the electrodes placed on the body of patient is first passed through a gain stage to boost the signal power. Typically the lower cut off frequency for ECG signals is considered to be 0.5 Hz. So after gain boosting the signals is passed through high pass filter having cut off frequency of approximately 0.5 Hz (can be adjusted according to application). The signals is again boosted and sent to low pass filter. Generally the cut off frequency for low pass filter is kept around 125 Hz. The filtered signal is again passed through instrumentation amplifier to increase the power level of the signal. Finally the signal gain is adjusted by putting a gain adjustment block so that the maximum SNR (signal to noise ratio) can be obtained at the ADC end. The conditioned signals coming from the AFE block is sent to ADC (Analog to Digital Conversion). ADC digitizes the signal. Generally 12 bit ADC is used for medical purpose but higher bits may also be used, especially for research purpose.

2.6 Discrete Wavelet Transform (DWT)

Discrete wavelet transform is a method of analysing signal in time frequency domain simultaneously. Fourier transform gives the complete detail of spectrum utilization by the signal, but the drawback of this method is that it gives no information about the time of occurrence of these frequency components. So, Fourier transform does not suit for real time application. Discrete wavelet transform takes finite no. of discrete sample of input signal and analyses for presences of frequency components. In DSP jargon this term is called analysing signals at different scales. There are many types of DWT e.g. DB1, DB2 etc. DB1 is known as HAAR wavelet. The mother wavelet of HAAR wavelet is a square wave. In HAAR wavelet we pass the signal through a chain of low pass and high pass filter. Fig.2.2 explains the process of HAAR wavelet analysis. Incoming signal is first passed through a combination of low pass and high pass filter, then the output of low pass filter is down sampled and

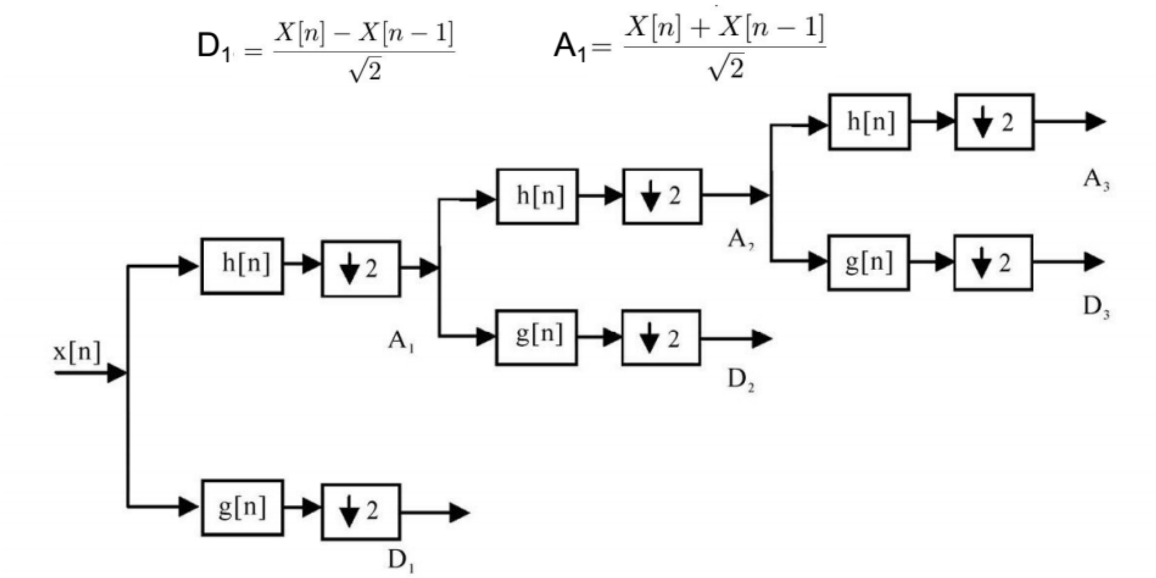


Figure 2.2: DWT using Haar wavelet

passed to next stage. In next stage again the signal is passed through low pass and high pass filter and then down sampled. This step is repeated till $log_2(no.Of input samples)$.

2.7 Evaluation of Classifier

A classifier classifies the given inputs in different classes. The classification done by real classifier is prone to error i.e if we talk in terms of binary classifier the classifier and consider two class e.g. Normal and abnormal, then it is possible that some normal signals may be classified as abnormal and some abnormal signals may be classified as normal. So, a evaluation method is require to measure the accuracy of classifier. In this thesis we have used binary classifier, so we will talk about evaluation of binary classifier.

Binary classifier can be evaluated by confusion matrix table. Below table2.2 shows the confusion matrix. There are few terms terms related to binary classifiers which are listed below.

Table 2.2: Confusion Matrix for Binary Classifier

Label/Classified Output	**Normal**	**Abnormal**
Normal	TN	FP
Abnormal	FN	TP

True Positive: The signals which are labelled as abnormal and also classified as abnormal.

False Positive: Signals which are labelled as normal but classified as abnormal.

True Negative: Signals which are labelled as normal and classified as normal.

False Negative: Signals which are labelled as abnormal but classified as normal.

Based on the above obtained data we can define few parameters for performance of classier which are discussed below.

Sensitivity

Sensitivity relates to the test's ability to correctly detect patients who do have a condition. Consider the example of a medical test used to identify a disease. Sensitivity of the test is the proportion of people known to have the disease, who test positive for it. Mathematically, this can be expressed as: $sensitivity = \frac{TP}{FN}$

Specificity

Specificity relates to the test's ability to correctly detect patients without a condition. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as: $specificity = \frac{TN}{TN + FP}$

Chapter 3

CVD classification Algorithm

3.1 Introduction

In literature survey we have seen that there are many CVD classification algorithms available e.g. ANN based classification, SVM based CVD classification and BDD based CVD classification. All of the above mentioned methods use artificial intelligence to classify the CVDs, because of which the primary architecture of Classifier becomes computationally complex in nature. Here in this work we have used Hurst exponent as basis for the CVD classification. Later we have proposed modification to the state of the art Hurst exponent based CVD classifier that improves the classification efficiency. This chapter describes step by step formulation of algorithm for CVD classification.

3.2 History of Hurst Algorithm

The Hurst Exponent is used as measure of long term memory of a time series signal. Hurst exponent was evolved in the field of hydrology for determining the optimum size of dam for Nile River. The term Hurst exponent or Hurst coefficient was derived from the Name of Harold Edwin Hurst who was research lead in this studies. This research gave life to a statistical methodology for distinguishing random from non-random systems and to identify the persistence of trends. Many years later while investigating the rectal nature of financial markets especially the tendency of a time series signal to regress strongly to its mean or to cluster in a direction noted mathematician Benoit Mandelbrot happened to stumble across Hurst work, recognizing the potential therein, introduced to fractal geometry.

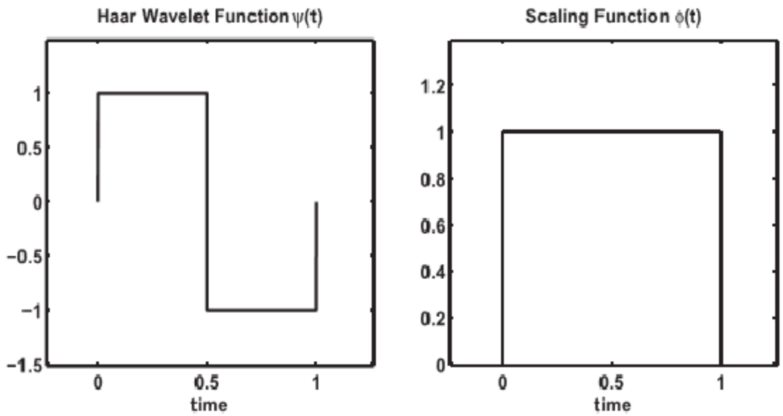


Figure 3.1: Haar wavelet and scaling function

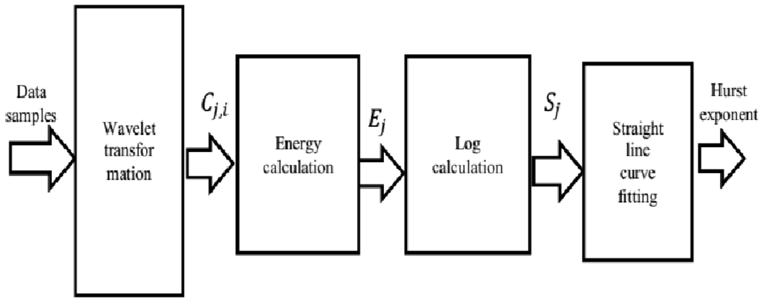


Figure 3.2: Algorithmic flow of Hurst algorithm

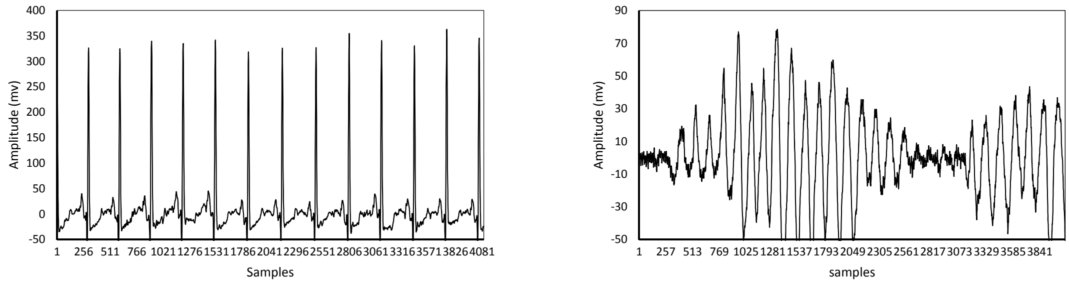
3.3 Formulating Hurst Algorithm

Hurst exponent is basically used for measuring self-similarity of signal. When a signal satisfies scaling property then it is followed in its wavelet domain as well [9]. So if j, m, n, k are integers such that j=m +n, we have

$$D_{j,k} = 2^{-n(1+2H)/2} d_{m,k}, iff(2^{-n}) = 2^{-nH} f(t)$$

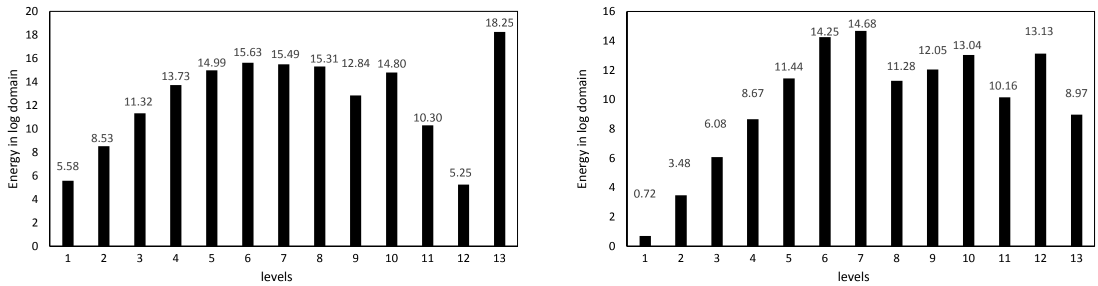
So computing energy at j^{th} scale we can write

$$\begin{aligned} E_j &= \frac{1}{N_j} \Sigma_k |(d_{j,k})^2| \\ &= \frac{2^{-n(1+2H)}}{N_j} \Sigma_k |(d_{j,k})^2| \\ &= 2^{-n(1+2H)} E_m \end{aligned} \tag{3.1}$$



(a) Normal E.C.G (b) Anomalous E.C.G

Figure 3.3: E.C.G signal in time domain



(a) Energy at each level for normal E.C.G (b) Energy at each level for anomalous E.C.G

Figure 3.4: Energy at each level for ECG signal

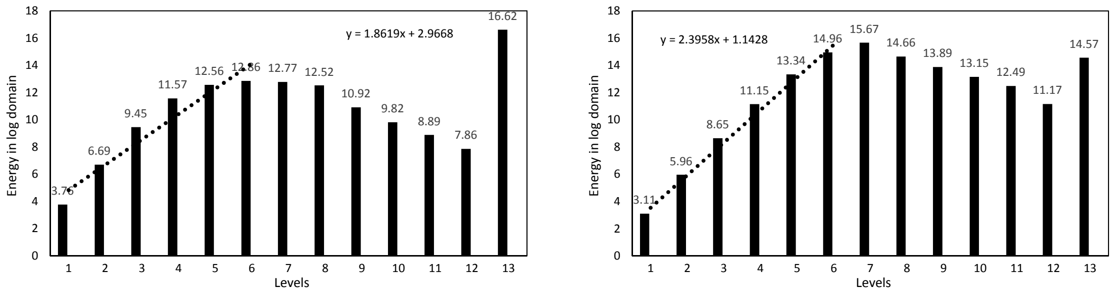
Converting energy at each level to log domain gives

$$log_2(E_j) = -j(2H+1) + log_2(E_m) \tag{3.2}$$

From above equation the H is taken as parameter to compare self-similarity. Fig.3.2 shows the algorithm to calculate Hurst exponent from paper [8]. In this algorithm twelve level of wavelet decomposition is taken assuming E.C.G. signal to be sampled at 500 Hz, so that 5 to 6 complete PQRST complex can be captured. From transformed wavelet component C_{ji} energy at each scale is calculated in log domain, which is used to fit straight line. The Hurst exponent so calculated from slope of fitted line (m) is used as measure of detecting normal and anomalous E.C.G. signal.

3.4 Hurst Algorithm as CVD Classifier

Hurst exponent is measure of long term memory of signal. It quantifies the tendency of signal to regress strongly to mean or to cluster in a particular direction. Hurst exponent value lies in range of 0-1. Hurst exponent of any signal lying between 0-0.5, signifies that it has very high switching tendency of its magnitude between high and low amplitudes. On the other hand if Hurst exponent



(a) Mean of energy levels in log domain for Normal E.C.G

(b) Mean of energy levels in log domain for Anomalous E.C.G

Figure 3.5: Mean of energy at each level in log domain for E.C.G signal

of signal lies between 0.5 to 1 then it has lower switching tendency in future between high and low amplitudes.

Normal ECG is a periodic signal. Usually the Heart beat rate of a normal patient lies between 70-72 beats per minute. In this work we have divided ECG signals in two classes i.e. Normal and Abnormal. Normal class comprises of all the ECG signals collected from normal patients while in abnormal class we have considered all the diseased patient ECG signal. In reference [9] S. Chandra et all have tried to classify the ECG signals between above mentioned two classes. They have taken 4096 samples of ECG signal, sampled at 500 Hz. After suitable signal preprocessing Hurst exponent of ECG signal is calculated. The Hurst exponent calculated so shows a good contrast between normal and abnormal ECG signals. Hurst exponent for Normal signal lies between 0.15to 0.58 and for abnormal signal between 0.58 to 1. It is to be mentioned that in algorithm, conversion of energy in log domain and taking slope of straight line so fitted makes the algorithm robust for any ADC i.e. it is independent of scaling of raw E.C.G signal. The paper [8] doesn't talk about which energy scales to choose and why in context of E.C.G signals. In this paper we have tried to deal with this issue to make the algorithm more perfect in terms of sensitivity and specificity towards E.C.G signals.

3.5 Proposed Hurst Based CVD Classification Method

Previous section describes how Hurst exponent can be used to classify CVD signals in two classes e.g. Normal and Abnormal. This section Introduces to the modification in standard Hurst exponent based method so that its classification efficiency increases. Standard Hurst exponent method uses all the 12 levels of wavelet coefficients to fit the straight line, whose slope ultimately defines the Hurst exponent.

Fig.3.3a show normal and Fig.3.3b abnormal ECG signals. Normal ECG signals are highly periodic in nature and have R peak which has sudden high amplitude. While in abnormal ECG signals there is no sudden change in amplitude as compared to normal signal. Major class of CVD diseases like Ventricular tachycardia, atrial fibrillation etc. deviate from normal signals in terms of strength of amplitude around R peak i.e. they have very less difference between average value of signal and the peak value (R peak) of signal.

Mapping the time domain properties of Normal and Abnormal ECG signals to frequency domain, we can expect a high amplitude around the 20-30 Hz band as R peak lies in it. Fig shows energy plot of signal at each level of time frequency analysis. To reduce the computational complexity we have used Haar wavelet as mother wavelet for our analysis. Fig.3.4a shows that enrgy level of ECG signal increases monotonically from level 1 to level 6 and there onward it starts decreasing monotonically. In modification we have tried to exploit the frequency component analysis of normal E.C.G signal to choose the best energy levels which follow scaling property for straight line curve fitting. Fig.3.4a and fig.3.4b shows normal and anomalous E.C.G signals respectively. Looking at the morphology of E.C.G. signal's energy we can say that normal E.C.G. signal has more power at high frequency components compared to anomalous since R peaks are inherent component of normal E.C.G. and they contribute to high frequency terms because of high transition in time domain. While anomalous signals, they miss the usual E.C.G. pattern i.e. R peaks are missing, so the power in high frequency components are less than the normal one. This has tremendous effect on Hurst parameter because it depends on the slope of fitted line on selected energy levels.

Fig.3.4a and fig.3.4b shows energies in log domain at various scale of normal and anomalous E.C.G. signals respectively. Note that the energy first level in normal E.C.G is more than of corresponding case in anomalous E.C.G. This supports the above arguments. Also the energies from level 1 to level 6 decreases faster in anomalous E.C.G than in normal E.C.G. This sets the basis for choosing correct energy levels for straight line fitting, so that more contrast in Hurst exponent can be obtained.

Fig.3.5b shows plot of mean energy at each level for 300 anomalous and Fig.3.5a for normal E.C.G. Observing at the figures we can say that level 1 to level 6 of energy show the straight line feature compared to rest. Recall that for Hurst exponent to measure self-similarity we have to choose energy level which follow scaling property (i.e. straight line feature in log domain). So we can conclude that energy level 1 to energy level 6 are best for straight line curve fitting. The dotted line Fig.3.5b and Fig. 3.5a is straight line fit to first 6 energy levels. Observe that the slope (fitted equation is on the figure) for anomalous E.C.G is greater than normal E.C.G.

3.6 Theoretical Threshold Calculation

The slope for normal E.C.G. is $m_{normal} = 1.8619$ (refer fig.) while for anomalous E.C.G is $m_{anomalous} = 2.3958$. The Hurst value can be calculated by following equation

$$H = abs(m - 1)/2 \tag{3.3}$$

However here the energies are plotted from high to low, so we can modify above equation as

$$H = abs(m + 1)/2 \tag{3.4}$$

So using above we can calculate H^{mean}_{normal} as

$$\begin{aligned} H^{mean}_{normal} &= abs(1.8619 + 1)/2 \\ &= 1.43095 \end{aligned} \tag{3.5}$$

Similarly $H^{mean}_{anamalous}$ can be calculated as

$$\begin{aligned} H^{mean}_{anamalous} &= abs(2.3958 + 1)/2 \\ &= 1.6979 \end{aligned} \tag{3.6}$$

Taking average of anomalous and normal Hurst values to decide the Theoretical value of threshold for classification

$$\begin{aligned} H^{theoritical}_{threshold} &= (1.43095 + 1.6979)/2 \\ &= 1.5644 \end{aligned} \tag{3.7}$$

3.7 Robustness of Proposed Algorithm Towards Scaling Issues of ADCs

ADCs (Analog to Digital converters) take analog values of physical signal and then convert them to digital values. However the input voltage range for ECG signals and Resolutions of ADCs is not standardized. So because of this arbitrary input range, the signal which is produced from different

ADC may be scaled version of each other. In this scenario when classification system migrates from one ADC to others it has to recalibrate as per the input range and Resolution of ADC. The proposed algorithm is robust towards the scaling effect in input signals Fig. shows the flow of estimation of Hurst exponent from ECG signal. The ECG signals coming from leads is captured by analog front end. Analog front filters the physical signals to ECG signals input frequency range, removes 50 Hz power line interference, adjusts the gain according to need of ADC and then forwards the signal to ADC block for digitization. ADC samples the analog signals, quantizes them and send to classification unit. The classification unit does the time frequency analysis of ECG using HAAR wavelet. Energy calculation of first six level of HAAR wavelet is done. Energies of the each level is converted to log domain. Now a straight line is fitted to $log_2(energies)$ and slope of that line is calculated. The calculated slope directly corresponds to Hurst value of ECG signals.

The calculated energy is susceptible to scaling effect when the ADC of system is changed, because we are directly calculating energy from amplitudes of ECG signals. This effect of scaling in Energies can easily propagate to Hurst exponent and can deteriorate the classification efficiency. So to stop the propagation of scaling effect in ADC, energies of each level is passed through logarithmic block. Output of logarithmic block is used for straight line curve fitting. This step checks the propagation of scaling factor to the slope of fitted line. Thus the proposed methodology is robust against the scaling effect in ADC and can be used across all kind of ADC.

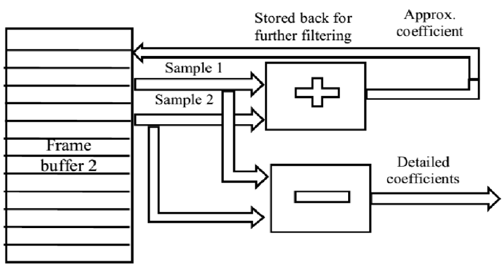
Chapter 4

Proposed Architecture for CVD Classification

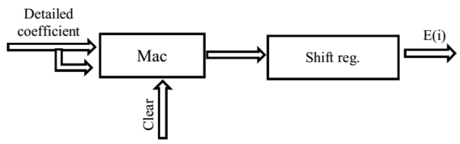
4.1 Introduction and Architectural Constraints

State of the art ECG classification algorithm run on highly complex computer system in form of software. These kind of systems are power consuming and bulky in nature. They require the patient to be admitted for long term monitoring. One major drawback of these kind of system is that they require bulk investment and can only be installed in big hospitals.

This work proposes a low complex design methodology for on body classification of ECG signals using the algorithm proposed in chapter 3. On body ECG classification puts many challenges apart from usual challenges to a classifier e.g. low power, low cost, high efficiency etc. On body systems are battery dependent. Any system which is battery run needs to be extremely low power in nature. Size and weight also puts a constraint on "On body devices". This chapter focuses on architectural development for algorithm proposed in chapter 3 using algorithm architecture holistic design view. Complete Design can be broken down into six sections. 1. Wavelet transformation 2. Energy calculation 3. Log calculation 4. Straight line curve fitting 5. Decision making block 6. Control unit. Fig.4.3 gives the complete architectural view of the design in block diagram format. Explanation of each block has been given in the following sections.



(a) Wavelet transformation



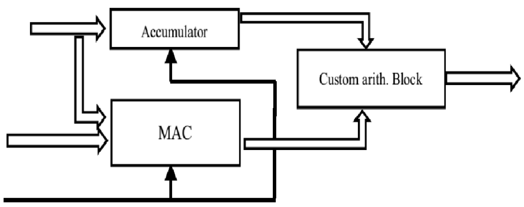
(b) Energy calculation

Figure 4.1: Building Blocks

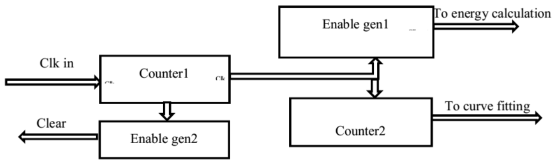
4.2 Wavelet Transformation

First step for Hurst exponent calculation is wavelet transformation of ECG samples coming from ADC (Analog to Digital converter). Haar wavelet has been chosen as mother wavelet for time frequency analysis because of computational simplicity and fairly informative nature [9]. Fig.3.1 from paper [24], shows the Haar wavelet and its scaling function. Haar wavelet beaks the spectrum in two levels of high and low frequency. For realization of haar wavelet we have chosen mallat's algorithm. Mallat's algorithm is low complex way of realizing haar wavelet. Fig.4.1a shows implementation of haar wavelet using mallats algorithm. ECG samples are passed through series of high and low pass filters. The high frequency components (coming from high pass filters) are called detailed components and low frequency components (coming from low pass filters) are called approximate components. Approximate components are again passed through next level of high and low pass filter to obtain detailed components. The analysis of ecg signals is done using 4096 samples taken at a time. So at max twelve levels of decomposition is possible. Although for analysis we will use only six levels as proved in algorithm that they correspond to hurst exponent more strongly than all levels taken together.

Fig.4.1a shows the architecture for implementation of haar wavelet. Two 8kB memory banks are used to store digitized ECG samples coming out from ADC. The output of ADC feeds memory banks via demux. Demux selects the memory bank alternatively by the control unit. The output of memory bank is connected to one adder and subtractor via mux which is controlled by control unit. At any given time one memory bank is used for storing ECG inputs, while other is used for processing i.e. calculating discrete wavelet transform. Two samples from memory bank are taken and fed to adder and subtracter. The adder produces approximate results while subtracter produces detailed results. Detailed results are sent to energy calculation block for further processing. Approximate results are stored back to the same memory as they will be used to calculate more



(a) Straight line curve fitting



(b) Control unit

Figure 4.2: Building Blocks

detailed coefficients in next levels. However direct implementation of equation 4.1 and equation 4.2 needs complex architecture with divider. So to avoid the divider we can ignore $\frac{1}{\sqrt{2}}$ factor. This modification transforms equation 4.1 and equation 4.2 to equation 4.3 and equation 4.3. The compensation of $\frac{1}{\sqrt{2}}$ factor is done in energy calculation stage because while calculating energy we do squaring of coefficients, so $\frac{1}{\sqrt{2}}$ is converted to 1/2 which can be easily implemented by shifting operation.

$$C_D = \frac{X[n] - X[n-1]}{\sqrt{2}} \tag{4.1}$$

$$C_A = \frac{X[n] + X[n-1]}{\sqrt{2}} \tag{4.2}$$

$$C_D = X[n] - X[n-1] \tag{4.3}$$

$$C_A = X[n] + X[n-1] \tag{4.4}$$

The detailed coefficients are used for further calculation while approximate coefficients are refined again to obtain detailed coefficients. To save space we can make refinement process serial i.e. approximate coefficients are again saved in frame buffer for processing.

4.3 Energy Calculation

$$E_j = \frac{1}{N_j} \Sigma_k |d_{j,k}|^2 \tag{4.5}$$

$$E_j = \frac{1}{2N_j} \Sigma_k |d_{j,k}|^2 \tag{4.6}$$

The energy in frequency domain can be expressed by equation 4.5 where $C_{i,j}$ represents i^{th} energy component of j^{th}level and $E_j$is energy at j^{th} level. For compensating $1/\sqrt{2}$ scaling factor it is to

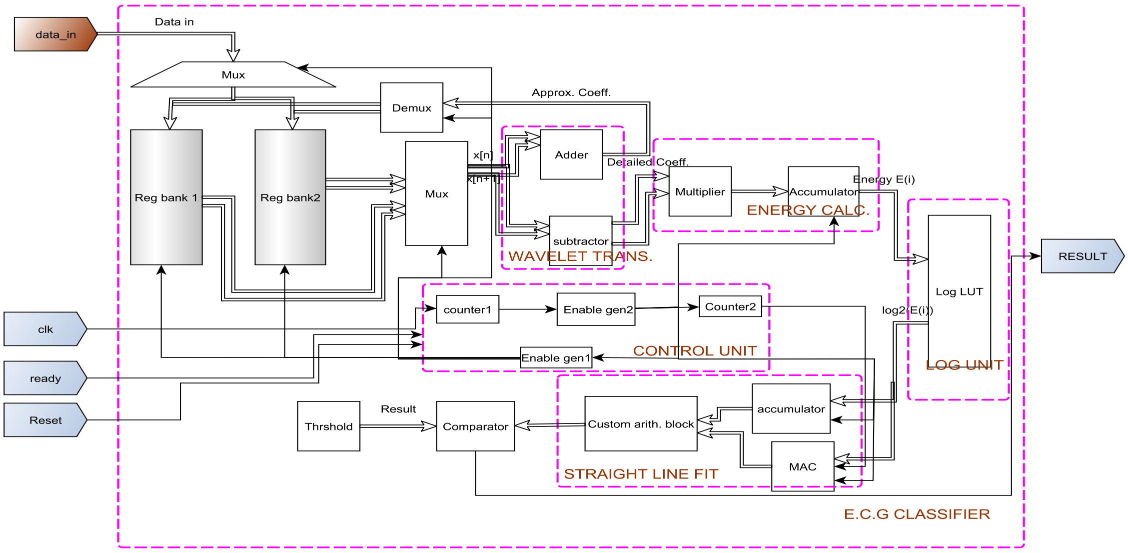


Figure 4.3: Complete architectural view of modified Hurst

be expressed in form of equation 4.6. The equation 4.6 can be implemented with the help of mac and shift register. The mac squares and accumulates coefficients till the tick of enable signal. The enable signal is fired by control unit according to the number of elements in each level. Since the no. of elements in each stage is in dyadic space we can use shift register for averaging the energy in each stage. Later on the shift register has to be shifted one more bit for compensation of the factor $\frac{1}{\sqrt{2}}$ (ignored in wavelet transformation), which will become 1/2 in energy domain.

4.4 Log Calculation

$$S_j = log_2 E_j \tag{4.7}$$

To reduce the complexity, log is implemented with the help of look up table. For a 16 bit word length implementation 256 MB of memory is needed.

4.5 Straight Line Curve Fitiing

The slope (m) to any one dimensional data points can be fitted by following equation where x_i are indices and y_i is energy level in log domain.

$$m = \frac{n\Sigma_i x_i y_i - \Sigma_i x_i \Sigma_i yi}{n\Sigma_i x_i^2 - (\Sigma_i x_i)^2} \tag{4.8}$$

Here we are considering 6 levels of decomposition only (explained in section III) so, $i = [1, 6]$ and equation can be modified as following

$$m = \frac{6\Sigma_i i y_i - 21\Sigma_i i \Sigma_i yi}{105} \tag{4.9}$$

To remove divider (division by 105) we can replace m as

$$m = 6\Sigma_i i y_i - 21\Sigma_i i \Sigma_i yi \tag{4.10}$$

The ignorance of factor 1/105 again needs compensation in next step. The first term in equation 4.10 can be implemented using mac and second using accumulator and finally one custom arithmetic block computes m of equation 4.10. Fig.4.2a shows the straight line curve fitting block. Equation 4.11 gives the relation between slope of line m and H (Hurst exponent)

$$H = abs((m - 1)/2) \tag{4.11}$$

In previous steps we have ignored division by 105 so H can be modified as

$$H = abs(\frac{m - 1 * 105}{2 * 105}) \tag{4.12}$$

Now in above equation still division by $210(2 * 105)$ is left. We will carry this factor to next step and modify equation as

$$H = abs(m - 105) \tag{4.13}$$

4.6 Decision Making Block

The decision making block compares the computed Hurst exponent with a threshold to make decision between normal and anomalous E.C.G. signal. Following is the governing equation for comparison.

$$result = \begin{cases} 0 & \text{if } H < threshold \\ 1 & \text{otherwise} \end{cases}$$

However for compensation of division ignored in previous step above equation needs modification which can be written as

$$result = \begin{cases} 0 & \text{if } H < threshold * 392 \\ 1 & \text{otherwise} \end{cases}$$

The decision making block is implemented using standard comparator block. The comparator output is high whenever the Hurst exponent crosses the threshold otherwise it is in low state.

4.7 Control Unit

Control unit comprise of 3 enable generator circuit to synchronize various processing blocks. Enable gen2 ticks at dyadic count of counter1 and makes trigger to counter2. Counter1 is used to control the address of buffer frame1. Enable gen1 is used to switch between process buffer and storage buffer. So, it is fired after every 4096 clock. All the registers are reset after 4096 clock ticks to accept the next frame for operation. Fig.4.2b gives the implementation of control unit.

Chapter 5

Results and Discussion

5.1 Database Selection and Preprocessing

We have selected MIT-BIH Normal sinus Rhythm database (NSTDB), Creighton University Ventricular Tachycardia Databases (CuVT), MIT-BIH Malignant Ventricular Arrhythmia, MIT-BIH Atrial Fibrillation database for evaluation of our classifier. All these databases are corrupted by contact noise, motion artefacts, baseline wandering, so we have used median filter to remove all these noise. For real time evaluation we have also collected database in our institute (IITH db) to test our classifier. To maintain the uniformity among all databases we have chosen 500 Hz as sampling frequency. All the databases were re sampled using suitable multi rate sampling method to obtain effective sampling frequency of 500Hz. For analysis we taken 4096 samples so that 5 to 6 complete PQRST waves can be captured.

5.2 Threshold Selection

For making decision between normal and anomalous signal a threshold is required. The threshold mentioned in chapter 3 is theoretical threshold which don't give optimum performance for classifier. So we chose a learning based threshold selection method. We have chosen threshold by running algorithm on 560 frames such that the false results are minimum. An alternative self-learning based approach can be chosen to decide best threshold by running on more patients. We have chosen 560 frames for selection of threshold and it was found to be 1.5520. The same process was followed for standard Hurst exponent method, so that comparison can be done. The threshold for standard method was 0.71.

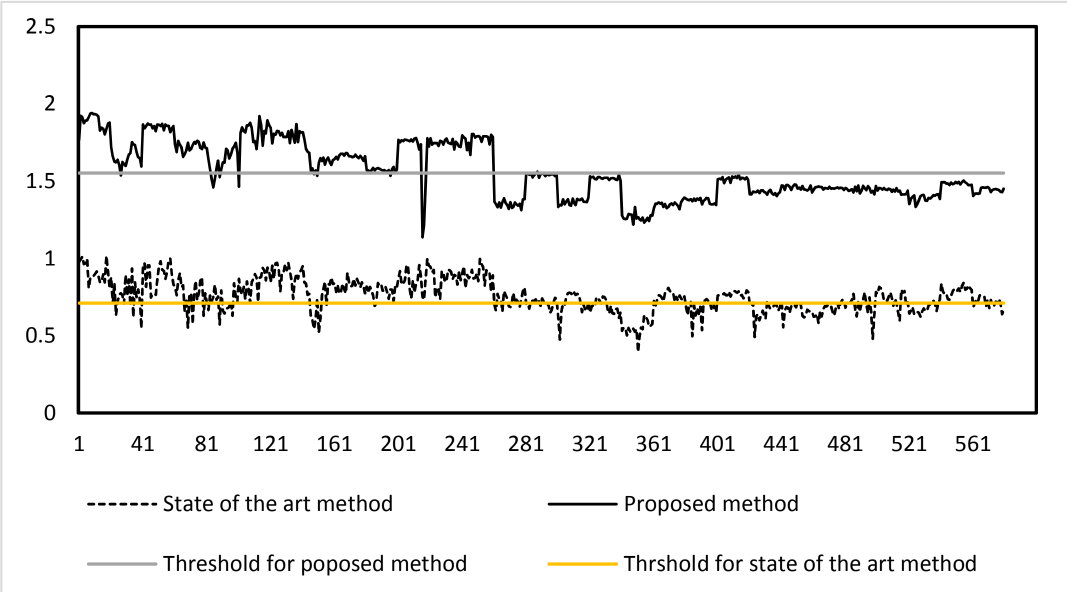


Figure 5.1: Comparison of conventional Hurst method versus Modified Hurst method

5.3 Experimental Results

5.3.1 Algorithm

MIT-BIH Normal sinus Rhythm database (NSTDB), Creighton University Ventricular Tachycardia Databases (CuVT), MIT-BIH Malignant Ventricular Arrhythmia, MIT-BIH Atrial Fibrillation database)are chosen to evaluate the performance of classifier. All the database were re-sampled at sampling frequency of 500 Hz to bring uniformity. Choosing 1.5520 as threshold for modified Hurst and 0.771 for standard Hurst, we have generated all the results. Table 5.2 shows modified Hurst exponent for various cases. Fig. 5.1 shows the plot for normal and modified hurst exponent for 560 cases. First 260 cases are taken from anomalous database while next 300 are taken from normal (NSR) database. From Fig.5.1 it is clear that modified algorithm gives high contrast Hurst exponent for normal and anomalous signal than the standard one proposed in [8] [9].

Table 5.1: Confusion matrix for Normal Hurst Algorithm

[!hbt] **Th=0.71**	**Normal Hurst Algorithm**	
label/classifier	*Anomalous*	*Normal*
Anomalous	170	90
Normal	59	241

Table 5.2. Shows confusion matrix for standard algorithm. The standard algorithm gives sensitivity and specificity of 65.38%, 71.33% respectively. The threshold for standard Hurst is.0.71. After modification (choosing effective energy levels for straight line curve fitting mentioned in chapter 3

Table 5.2: Confusion matrix for Modified Hurst Algorithm

[!hbt] **Th=1.5520**	**Modified Hurst Algorithm**	
label/classifier	*Anomalous*	*Normal*
Anomalous	248	12
Normal	1	299

to standard algorithm we got sensitivity of 95.384% and specificity of 99.66%. The threshold for modified Hurst is 1.5520. The confusion matrix shows the superiority of modified algorithm over standard Hurst algorithm. Later the architecture was tested on real data captured in our lab. The classifier was successful for all 20 real data.

5.3.2 Architecture

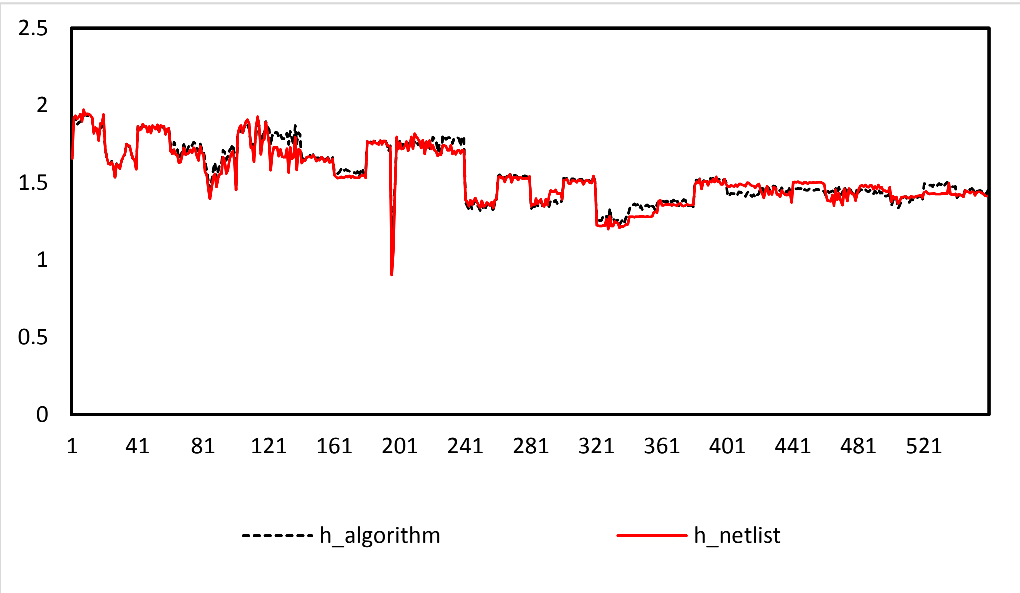


Figure 5.2: Comparison of Hurt exponents obtained from algorithm and architecture(synthesized netlist)

Table 5.3: Confusion matrix for synthesized netlist

th=1.5520	**Synthesized Netlist**	
Label/Classified Output	**Normal**	**Abnormal**
Normal	TN	FP
Abnormal	FN	TP

The proposed architecture in chapter 4 has been synthesized using $UMC130nm$ technology. The synthesized netlist occupies $0.14mm^2$ of area and $26nW$ of power when processing is done at $1kHz$. Comparison of proposed design and the state of the art technique [26] has been presented in table

5.4. The proposed design takes much less area(almost 6 times less) and low power(almost 6 times) compared to state of the art technique. This makes it suitable for resource constrained environment like IoT and Remote Health Care, where low power and less area of utmost need. Fig.5.2 shows

Table 5.4: comparison of synthesized designs

Parameters/Design	**State of the art**	**Proposed**
Area (mm sq.)	*0.7*	*0.14*
Power (nW @ 1khz)	182.94	26

the plot of hurst exponent obtained for different cases through algorithm and proposed architecture. First 280 frames in Fig. 5.2 correspond to various abnormalities and the next 300 correspond to normal sinus rhythm. Table 5.3. Shows confusion matrix for synthesized netlist. The sensitivity 94.61% and specificity 99.66%of synthesized netlist are respectively. The sensitivity obtained by architecture is slightly less than the algorithm. The reason behind this loss is the finite word length effect. Algorithm is designed and tested in floating point environment using Matlab as a tool, while architecture has been designed by converting floating point number to 16 bit fixed point representation. The reason of using fixed point representation is its low complex, low power and ease of implementation. The loss in accuracy using 16 bit fixed point representation is very less which can be ignored with respect to benefit of low power and ease of implementation.

Hardware Validation

The proposed Hardware design methodology has been synthesized on FPGA xilinx spartan 6 platform for Hardware validation. Raw ECG samples downloaded from MIT-BIH database were processed as mentioned in section 1 of this chapter and then stored in ROM of FPGA. The design was configured to take samples automatically from ROM. The output ports of the design were diverted to output leds of the board. To take full picture of IO's activity we utilized chipscope functionality of xilinx FPGA. Chipscope puts extra monitoring hardware on the FPGA along with Design so that IO's activity can be properly captured and displayed on the PC.

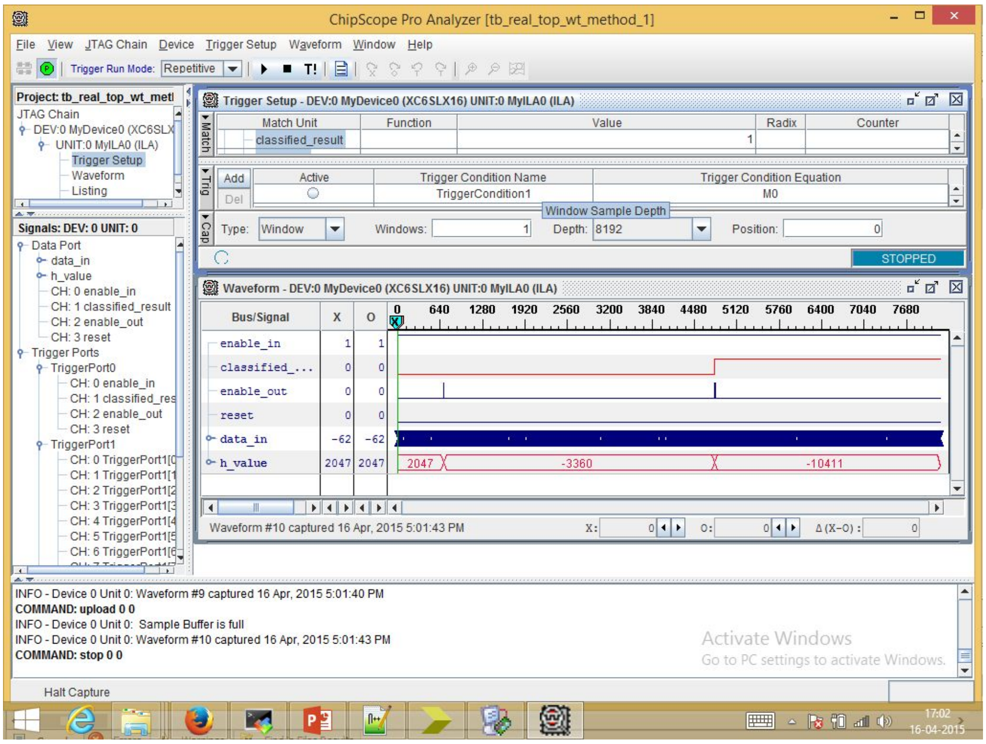


Figure 5.3: Hardware Validation of Classifier

Fig.5.3 shows the snapshot of IO's activity of classifier. Classifier has three input ports reset,enable_in and data_in."reset" acts as active high signal for resetting the design . "enable" is active high signal for enabling the design. "data_in" is feed input ECG samples in the design. Classifier has three output ports e.g. enable_out, h_value and classified_result. "h_value" gives the hurst value of samples in reduced format for debugging purpose. "enable_out" is handshaking signal for interfacing classifiers with other blocks. "classified_result" gives classified result i.e. zero for normal signals and one for abnormal signals. In Fig.5.3 we can see the toggling of "classified_result" pin when abnormal samples are fed.

Chapter 6

Conclusion and Future Work

The presented works attempts to use Hurst exponent for implementation of low complex and low power architecture for E.C.G classification. Although there are many ECG classification algorithms available in literature discussed in chapter 1, but as per our our literature survey we found very few to be implementable in resource constrained environment. The primary reason for this lagging is the use of complex DSP and artificial intelligence based algorithm.

Here in this work we have tried to use the simplicity of Hurst exponent and Haar wavelet to present the binary classification of ECG signal. Standard Hurst exponent method has been fine-tuned for ECG classification such that its accuracy increases. Not only this the modification also reduces the Haar wavelet decomposition of signal to 6 levels only which increases the speed of operation and decreases power consumption which is a positive sign and is very useful for modern day IOT and body sensor network technology. The presented method do not need any scale adjustment for different ADC environment, so its versatile in nature. Although here we have targeted four MITBIH database but since this approach depends on morphology of signal and not on absolute value of collected signal, so it can be targeted for other heart anomalies as well.

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