FPGA BASED ECG ANALYSIS SYSTEM

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ABSTRACT

This paper presents a proposed design for analyzing electrocardiography (ECG) signals. This methodology employs adaptive filtering technique to filter out the baseline wander noise embedded in the input ECG signal to the system. Discrete Cosine Transform (DCT) was utilized as a feature extraction methodology to extract the reduced feature set from the input ECG signal. The design uses back propagation neural network classifier to classify the input ECG signal. The system is implemented on Xilinx Spartan 6 Field Programming Gate Array (FPGA) board. We have compared discrete wavelet transform (DWT) with discrete cosine transform (DCT) as feature extraction methodology in simulation. Adaptive filters self learn. As the signal into the filter continues, the adaptive filter coefficients adjust themselves to achieve the desired result, such as identifying an unknown filter or canceling noise in the input signal. Adaptive filter is mainly used for ECG since the signals are very feeble..We have simulated both the systems one using DCT and other using DWT and studied the area occupied in SYSTEM GENERATOR mat lab R2013a. .For the real time analysis we have dumped the DCT system coding done in ISE design suit 14.5.

Keyword : - *Adaptive filter , FIR, Discrete Cosine Transform,Discrete Wavelet Transform,Neural Network*

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1. Introduction

. In recent years, cardiovascular disease, including heart disease and stroke, remains the leading cause of death around the world. Yet most heart attacks and strokes could be prevented if some method of pre-monitoring and pre-diagnosing can be provided. In particular, early detection of abnormalities in the function of the heart can be valuable for clinicians. Studying the electrocardiogram (ECG) signal provides an insight to understand life-threatening cardiac conditions. This typically is centered on the study of arrhythmias, which can be any disturbance in the rate, regularity, and site of origin or conduction of the cardiac electric impulse. Not all arrhythmias are abnormal or dangerous but some do require immediate therapy to prevent further problems.

A subject's ECG information can be recorded using a portable Holter monitor which is worn by the subject. A Holter monitor typically employs a few electrodes and stores a recording of the subject's heart rhythm as they go about their daily activities over a 24–48 h period. The Holter monitor is then returned to a cardiologist who examines the recordings and determines a diagnosis. Examining these recordings is a time-consuming and hence any automated processing of the ECG that assists the cardiologist in determining a diagnosis would be of assistance. The basic problem of automating ECG analysis occurs from the non-linearity in ECG signals and the large variation in ECG morphologies of different patients. And in most cases, ECG signals are contaminated by background noises, such as electrode motion artifact and electromyogram-induced noise, which also add to the difficulty of automatic ECG pattern recognition. Many researches depend on digital signal processing (DSP) techniques as a methodology to design automated ECG signal analysis systems. Most DSP systems use typical main stages for analyzing ECG signals, those main stages include denoising stages, feature extraction stages, and classification stages.

1.1.Literature Survey:

1. Estimation of the ECG Signal Spectrum During Ventricular Fibrillation using the Fast Fourier Transform and Maximum Entropy Methods

The aim of this study was to compare two approaches for estimating the spectrum of the suface ECG during ventricular fibrillation (W): the Fast Fourier Transform (FFT) and Maximum Entropy Spectral Analysis (MESA). lhefirst 10 s of 10 recordings of clinical W sampled at 250 Hz were separated into 1 s epochs for analysis by the FFT, zero padded FFT and Burg algorithm with 5,10, 20 and 50 coeflcients. lhe mean direrence in dominant frequency between the FFT and Burg algorithm with 50 coeflcients was 0.04 Hz (SO 0.56). lhe mean frequency of the dominant peak in the spectrum of VF can be measured accurately using either the FFT, zero padded FFT or MESA with a model order of more than 10.

2. Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network

Cardiac Arrhythmias shows a condition of abnormal electrical activity in the heart which is a threat to humans. This paper presents a method to analyze electrocardiogram (ECG) signal, extract the features, for the classification of heart beats according to different arrhythmias. Data were obtained from 40 records of the MIT-BIH arrhythmia database (only one lead). Cardiac arrhythmias which are found are Tachycardia, Bradycardia, Supraventricular Tachycardia, Incomplete Bundle Branch Block, Bundle Branch Block, Ventricular Tachycardia. A learning dataset for the neural network was obtained from a twenty records set which were manually classified using MIT-BIH Arrhythmia Database Directory and documentation, taking advantage of the professional experience of a cardiologist.

3. Time-Frequency Methods for High-Resolution ECG Analysis

Spectro-temporal methods of High Resolution ECG analysis based on fast Fourier transform, a-ve estimation and wavelet transform are discussed. Sensitivity of these mthods were evaluated by analysis of 80 patients after myocardial infimtion - 40 with sustained ventricular tachycardia and 40 without arrhythmia To compare the results of alI three methods quantitative parameters were calculated The avezaged values of these parameters were significantly different for patients with ventricular tachycardia compared to patients without arrhythmia Sensitivity obtained in our study by wavelet transfarm (61%) was lower than for Fourier transform (81%) and autoregressive (73%) methods.

2.DESINGING OF THE EXISTING AND PROPOSED SYSTEM

2.1. FIR FILTER

An FIR with constant coefficient is an Linear Time-Invariant (LTI) filter.–The output of an FIR of order (or length) L, to an input time-series x[n], is given by a finite version of the convolution sum: $y[n]= f[n]*x[n]= \Sigma f[k]\ x[n-k]$ where $f[0] \neq 0$through$f[L-1] \neq 0$ are the filter's L coefficients.They also correspond to the FIR's impulse response.

Where $f[0] \neq 0$through$f[L-1] \neq 0$ are the filter's L coefficients. They also correspond to the FIR's impulse response.LTI system expressed in the z-domain: Y(z) = F(z) X(z) Where F(z) is the FIR's transfer function defined in z-domain by F(z) = Σf[k]zk.The roots of polynomial F(z) define the zeros of the filter. FIRs are also called all zero filters.

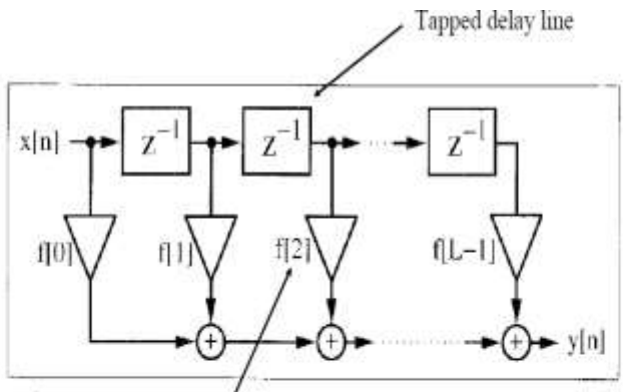
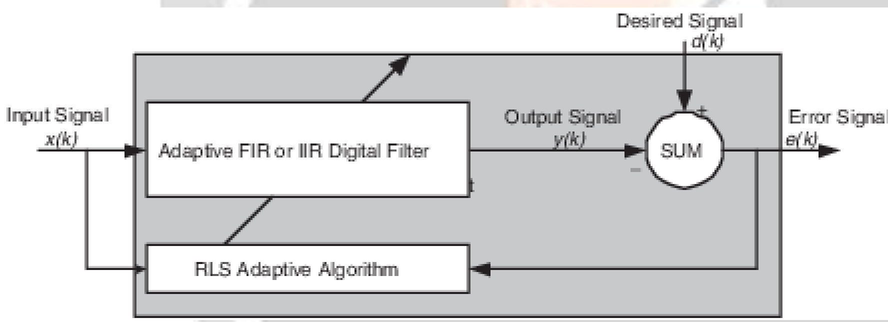


Fig. 3.1.

2.2.ADAPTIVE FILTER

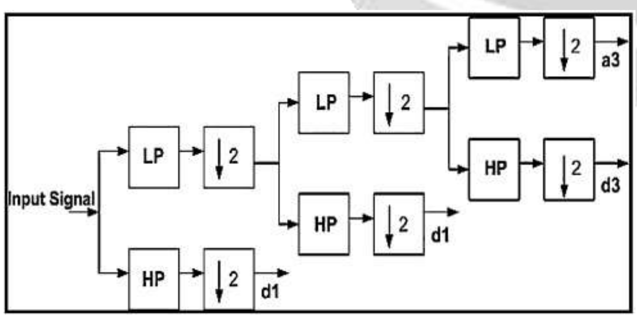
Introduction

Adaptive filtering involves the changing of filter parameters (coefficients) over time, to adapt to changing signal characteristics. Over the past three decades, digital signal processors have made great advances in increasing speed and complexity, and reducing power consumption. As a result, real-time adaptive filtering algorithms are quickly becoming practical and essential for the future of communications, both wired and wireless.



2.3.FEATURE EXTRACTION METHODOLOGY -DISCRETE WAVELET TRANSFORM

In numerical analysis and functional analysis, a **discrete wavelet transform** (**DWT**) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency *and* location information (location in time).



It has a filter structure as shown in Fig. 2. The input signal is filtered by the low-pass (LP) and the high-pass (HP) filters. The outputs from the low-pass filter are called the approximation coefficients while the outputs from the high-pass filter are called the detail coefficients. The output of each filter is then down sampled by a factor of 2. The LP output is further filtered and this process goes on until enough steps of decomposition are reached. In LLFE the input signal is passed through three levels of filtering results in four signals (d1, d2, d3 and a3).

The feature extraction is done by wavelet transform decomposition. In this step, the continuous ECG signals are transformed into individual ECG beats. The width of individual beats is approximated to 300 sample data, and the extracted beat is centered around the R peak. For each R-peak, the continuous signal for each beat start at R − 150 position is cutoff until R + 149 position therefore a beat with 300 sample data in width is achieved (Jatmiko et al., 2011).
In this decomposition, Daubechies order 3 is used as a mother wavelet. In this method the input signal is decomposed into 3 levels as shown in Fig. 2. The input signal with 300 samples will be down sampled by a factor of 2 in each stage, reaching only 38 samples in the 3rd stage (d3, a3). The detail d1 is usually noise signal and has to be eliminated.
On the other hand, d2 and d3 represent the high frequency coefficients of the signal. Since a3, represented by 38 samples, represents the approximation of the signal, and contains the main features of the signal, thus a3 is considered as the reduced feature vector that is used in the subsequent stage for the classifier.

The filter bank is implemented using Xilinx System Generator FIR complier blocks to implement both lowpass and highpass filters.

2.4. FEATURE EXTRACTION METHODOLOGY –DISCRETE COSINE TRANSFORM

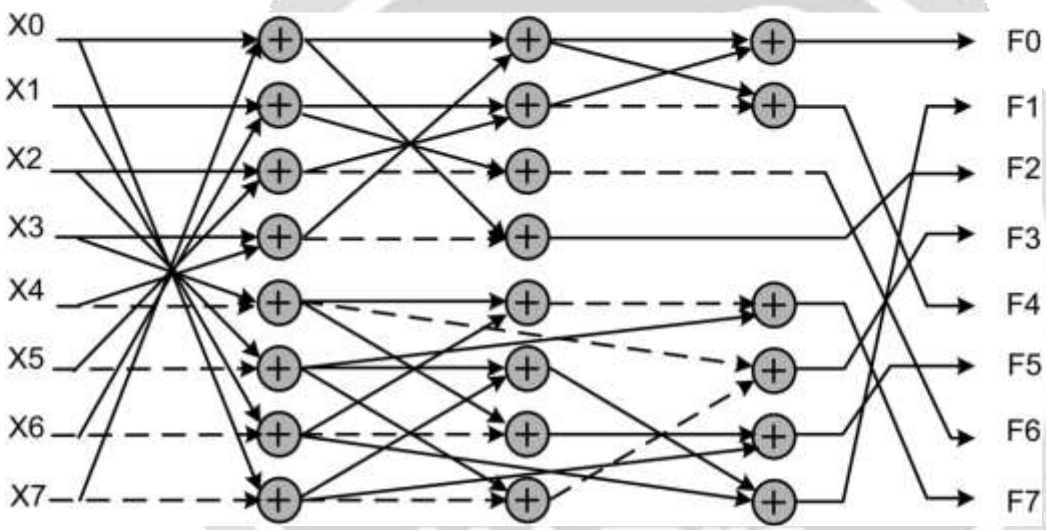


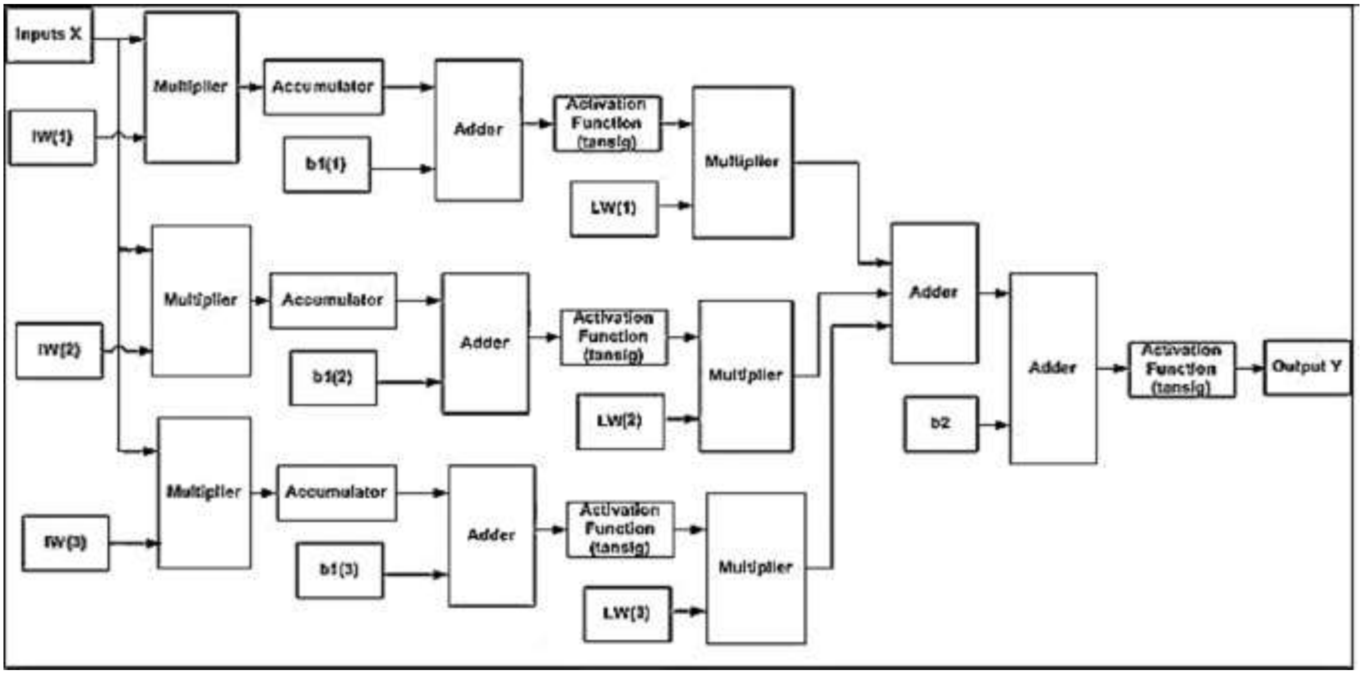
FIGURE 7: 8 POINT DCT STRUCTURE

The above figure represents 8-point Discrete cosine transform (DCT) architecture.The bold line represents addition of terms and the dashed line represents subtraction of terms.This is done in the matrix form and executed.

2.5.CLASSIFICATION BLOCK

The classifier which is implemented in LFEE is based on feed forward back-propagation neural network; the neural network output indicates whether the sample provided in the input of the design represents a normal ECG beat or abnormal ECG beat. The output *y* of each neuron of the neural network according to the input *x*, neurons weights *w*, bias *b*, and activation function *g* is shown below as in:
equation(1)
$y=g(x_i w_i+b)$

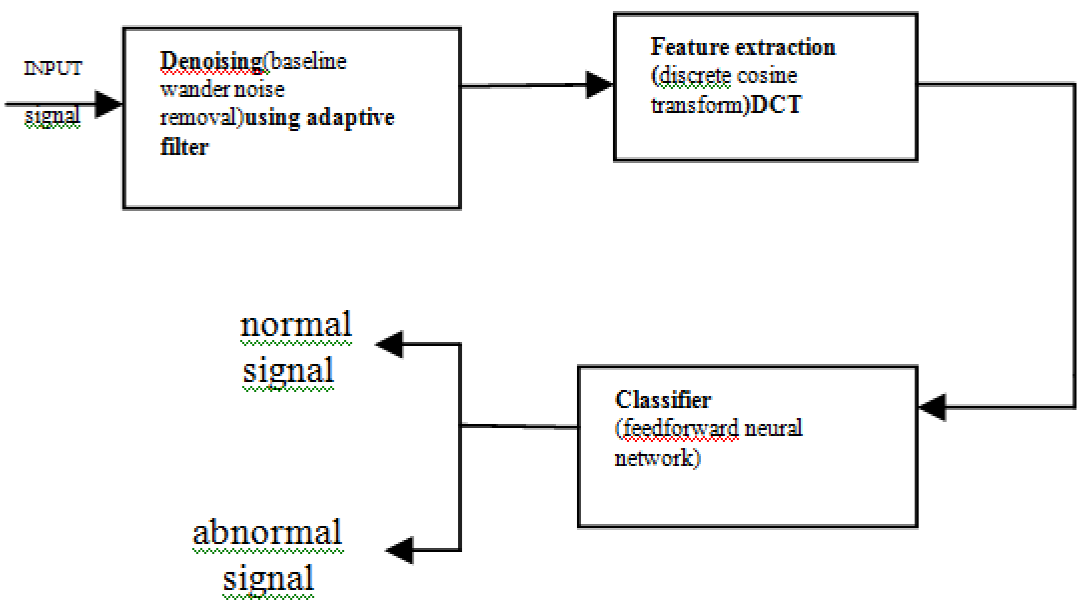
The basic blocks of the neural network are: multiplier blocks, adder blocks and the activation function blocks. The neural network in the proposed LLFE design has one hidden layer with 3 hidden neurons and 1 output layer. A block diagram for the neural network is shown in Fig. 3, the neural network is implemented using Matlab Simulink in terms of Xilinx System Generator blocks.



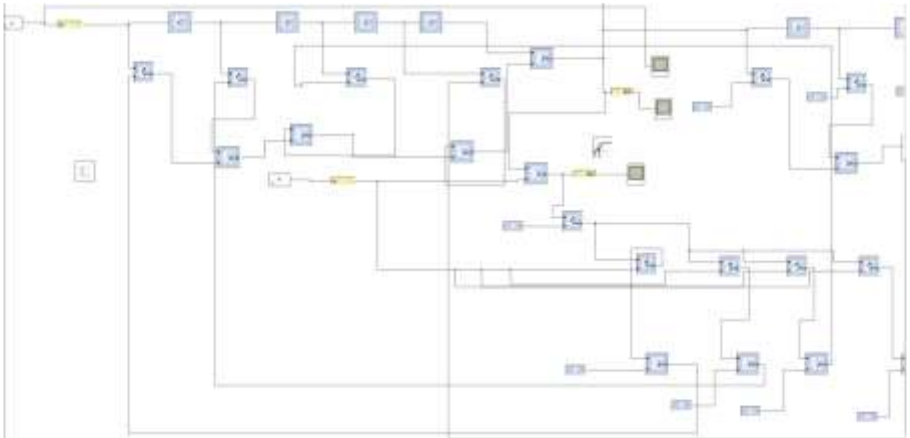
The input to the neural network the approximated signal (a3) (Inputs X) output from the feature extraction block, along with the weight vectors IW and LW, along with the bias values b1 and b2, while the output of the neural network classifier is the diagnosed ECG signal (Output Y) which represents the diagnosed ECG signal. The proposed neural network classifier is created using newff Matlab function to create a feed-forward backpropagation network.

The neural network is trained using a supervised learning algorithm by using traingd Matlab function, traingd is a network training function that updates weights and bias values according to gradient descent, with number of epochs of 100,000 used during the training phase. After the training is done the associated weights are calculated, along with the calculated bias values, those values are fed to the Xilinx System Generator blocks in Matlab Simulink to implement the neural network model.

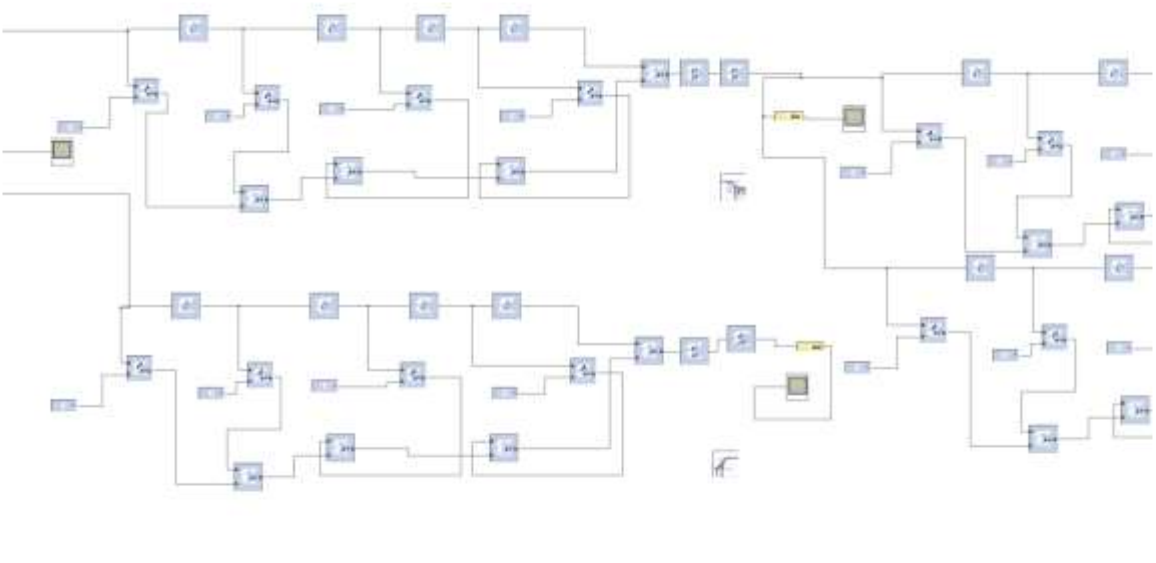
BLOCK DIAGRAM:



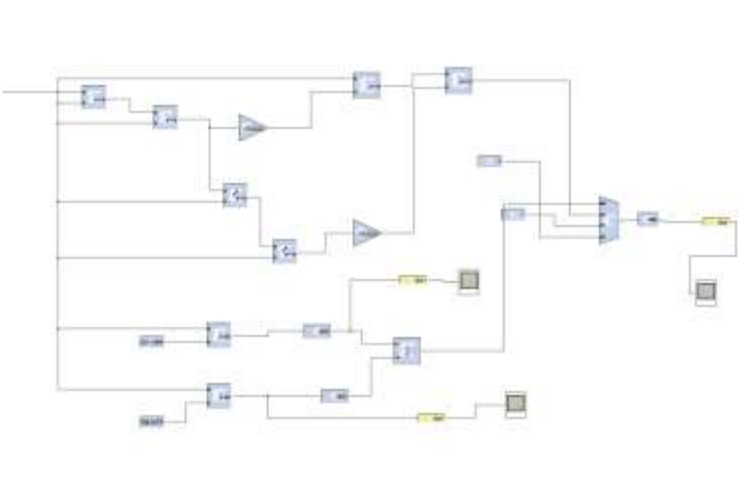
SIMULATED OUTPUT:



ADAPTIVE FILTER OUTPUT



DCT SIMULATION



NEURAL NETWORK OUTPUT

4. FUTURE ENHANCEMENTS:

The system can be enhanced by sending the signal to doctor 's mobile through a zigbee transmitter ,incase of any emergency .Large number of patients signal can be stored by high compression using dwt.

5. CONCLUSIONS

We have thus implemented the entire system in the FPGA kit for real time analysis.This is exactly similar to the simulation of the entire system in MAT LAB.This helps in continuous monitoring of the patient in the absence of the doctor.A real time analysis help in enhancing the system for recording and analyzing the large number of patients simultaneously.

6. ACKNOWLEDGEMENT

We would like to thank our internal guide R.Then Mozhi,assistant professor in directing us with proper guidelines and making the project a success.

7. REFERENCES

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