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DESIGN AND IMPLEMENTATION OF MULTIBAND FILTER FORNOISE CANCELLATION IN ECG SIGNALS

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Abstract: A signal from an electrocardiogram (ECG) carries important data about heart activity. When taking an ECG using electrodes, Power Line Interference (PLI), Baseline Wandering (BW), Motion Artefacts (MA), and High Frequency(HF) noise pollute the data. It is necessary to recover the ECG signal from the noisy environment without losing any of the information. It is suggested to choose and use an effective filterdesign. Separate digital filters, such as Low pass, High pass, andBand stop Filter in cascade, are required for the Finite Impulse Response (FIR)-based multiband. The suggested filter's performance is assessed using data from the Physionet ECG IDdatabase, which contains records of naturally noisy ECG signals. The multiband filter is proposed and executed on MATLAB 2018.b. It removes 90% of the noise. For the furtherreduction of MATLAB Output residue noises are achieved by simulation in Vivado.

Index Terms - **Electrocardiogram, Low pass Filter, High pass Filter, and Band stop Filter, Empirical mode decomposition**

I. INTRODUCTION

The electrocardiography procedure includes recording the cardiac electrical system across numerous cycles to produce anelectrocardiogram. Sensors attached to your skin pick up the electrical signals the heart sends out with each beat. These signals are recorded by a machine, and a doctor reviews them todetermine whether anything seems strange. Using electrodes applied to the skin, a cardiac electro gram graphs the voltage ofthe heart's electrical activity versus time. A typical, non- pathological ECG signal is composed of five distinct waves: P,Q, R, S, and T waves. Each wave corresponds to a certain physiological activation within the atria and ventricles with theheart. The QRS complex is a term used to describe the intersection of the Q, R, and S deflections. Usually, it is the most conspicuous and noticeable part of the trace. Due to its small size, atrial repolarization is often not visibleon an ECG. The P wave is usually smooth and circular, with a height of no more than 2.5 mm and a duration of no more than 0.11 seconds. It is important to realize that complexes other thanP won't include waves at all. It is conventional for the Q wave to always be negative, and the R wave is the complex's first positive wave.

Any type of heart the state is shown by a T wave that is typically facing away from the QRS complex. The functionalityinner heart is fundamentally measured by an ECG signal a clinician can identify arrhythmia, for instance, by looking for irregularities within the ECG signal. A clean signal is essentialbecause even the smallest nuances in an ECG signal may carryimportant information. Electromagnetic interference from the alternating current is what causes power-line interference. PLI can run at 50 or 60 Hz, depending on the power source. With several harmonics, this noise exhibits a sinusoidal structure.

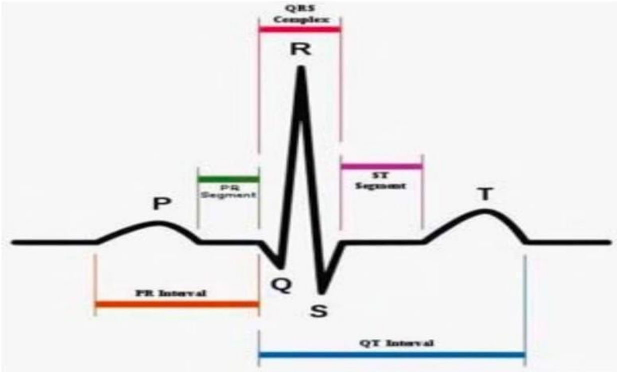


Fig 1 Basic ECG Pattern

PLI noise is one of the factors contributing to the P-wave and T-wave suppression. The fact that these noisy signals reduces the diagnostic' accuracy. It can be removed with a high-pass filter that has a cut off frequency between 0.5 and 0.6 Hz. Power line interference (50 or 60 Hz noise from the mains supply) can be eliminated using a notch filter with a 50 or 60 Hz cut-off frequency.

A patient's ECG signal recorded between 0.5 and 0.6 Hz will exhibit baseline wander, a low-frequency artifact. It can be removed with a high-pass filter that has a cut off frequency between 0.5 and 0.6 Hz. BW reduction is a vital stage in the processing of ECG data as BW makes it difficult to analyse ECG recordings.

Mobility artifacts are short-lived base line changes caused by fluctuations in the electrode-skin impedance caused by electrode mobility. It is possible to alter the impedance betweenthe electrode and the skin by moving the electrode away from the skin's contact point, which can alter the ECG. These alterations frequently manifest as brief, sustained baseline jumps or total saturation lasting up to 0.5 seconds.

ECG signal distortion is frequently caused by high frequency noise, the bulk of which is electromyography noise. It may be constant or only occur sometimes, like when a fast body movement happens. The frequency elements of the EMG expands into higher frequencies and show a large degree of cross-over with the frequency items that make up the QRS complex.

II. LITERATURE REVIEW

B. Chen, et al. "Removal of Power Line Interference from ECG Signals Using Adaptive Notch Filters of Sharp Resolution". Digital notch filters can be used to suppress PLI in ECG signals [1]. However, problems with ringing and transient interferences do occur, especially when PLI digitization does not follow the rule of full periodsampling.

J. Huang et al. "ECG Arrhythmia Classification Using STFT-Based Spectrogram and Convolutional Neural Network" recommends using a two-dimensional (2D) deep convolutional neural network (CNN) to categorize ECGarrhythmias [2]. Using the spectrograms of the five differenttypes of arrhythmia as input to the 2D-CNN, the ECGarrhythmia types were identified and categorized.

Rishi Raj Sharma et al. [3] created "Baseline wander and power line interference removal from ECGsignals using Eigen value decomposition" These transmissions commonly encounter two problems: baseline drift and power line interference.

R. Rajni et al [4] used "ECG Signal Analysis and Arrhythmia Detection Using Wavelet Transform". With theuse of a powerful technique like the discrete wavelet transform (DWT), it is essential to accurately assess the ECG signal. The first stage of denoising is carried out in DWT using the thresholding approach.

S. Mishra et al [5] described "A Power-Line Interference Canceler based on Sliding DFT Phase Locking Scheme for ECG Signals". The electrocardiogram (ECG) signal is separated from the non-stationary sinusoids using the sliding discrete Fourier transform (SDFT) phase lockingtechnique (PLL), and a method is presented for removing power-line interference (PLI).

L. Smital et al "Adaptive Wavelet Wiener Filtering of ECG Signals". ECG signals' wideband myopotentials (EMG) can be reduced by using wavelet Wiener filtering with noise- free signal estimation [6]. The dyadic stationary wavelet transform (SWT) was used by both of us to estimate the noise- free signal and apply the Wiener filter.

"Efficient and Simplified Adaptive Noise Cancelers for ECG Sensor Based Remote Health Monitoring" R. A. Shaik,et al. [7] explains the contaminated ECG signal by motion artifactsis fed into the adaptive filter. When discussing the concept of artifact reduction in the context of non-stationary noise, one must take electrode motion artifact (EM) into account.

S. Sanei et al. presented "A New Adaptive Line Enhancer based on Singular Spectrum Analysis". White noise and periodic signals may be divided using an adaptive line enhancer (ALE) [8]. When the SSA was rebuilt phase, the Eigentriples are chosen in an adaptive way (filtered) utilizing the data's delayed version.

M. A. Kabir et al. [9] devised "Denoising of ECG Signals based on Noise Reduction Algorithms in EMD and Wavelet Domains". ECG denoising technique due to empiricalmode decomposition (EMD) and discrete wavelet transform (DWT) domain noise reduction techniques.

III. PROPOSED METHODOLOGY

A. MULTIBAND FILTER

Since a multiband filter may reject various frequency bands from the signal's frequency spectrum, it is more suited tosimultaneously remove multiple disturbances the ECG signal provides. The suggested technique uses of Multiband Filter, a collection of independent digital filters that includes Low Pass,High Pass, and Band Stop Filter. We take into account a low frequency ECG signal BW, MA, PLI, and other HF disturbances.

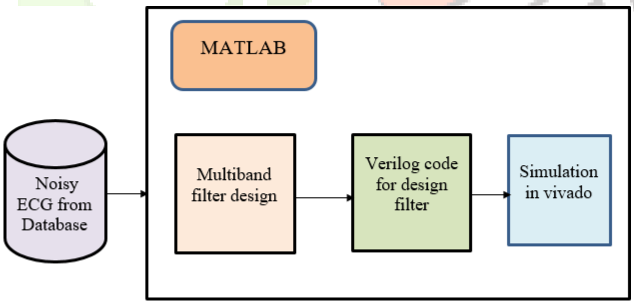


Figure 2: Multiband Filter Design Overview

B. LOW PASS FILTER

A circuit known being a low pass filter only permits signals below its cut off frequency to pass while attenuating all signalsabove it. The two sections of the low pass filter is referred to asPass band area and the Stop band area, respectively. The filter'spass band the variety of frequencies within which it should passinput to output with a particular gain. A low-pass filter's pass band spans zero hertz (Hz) to a specific frequency. Low pass filters can be used to filter circuit noise. A signal with a high frequency is noise. The majority of noise is reduced by the result of a low pass filter, which a clean signal. Numerous audio applications use low pass filters, often known as high-cut or treble cut filters.

C. HIGH PASS FILTER

A high pass filter is a circuit that weakens signals that have a frequency below a particular cut off frequency while passing signals that are higher frequency the cut off frequency. The stop band is a range of lower frequencies, and the ideal pass band isa high frequency range that goes on forever. High-pass filters simultaneously increase low-frequency interference signals like those brought on by breathing. These oscillate between 0.05 and1 Hz. A high-pass filter was used to reduce noise in the ECG data; its cut off frequency ranged from 0.01 Hz to 0.05 H.

D. BAND PASS FILTER

The bulk of frequencies are passed through a band stop filter, also known as a notch or band reject filter, while the frequencies in a specific range are weakened. The band stop filter can be made with little interaction if the bandwidth is wide enough to combine the low pass and high pass filters.

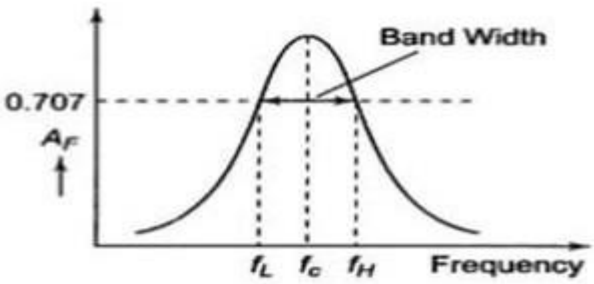


Figure 3: Band stop Filter Design

E. EMPIRICAL MODE DECOMPOSITION

Empirical mode decomposition, a data-adaptive multi- resolution approach, can split a signal up into physically meaningful parts. EMD perhaps utilized to investigate signals that are non-stationary and non-linear by separating them into their component parts at different resolutions. Empirical modedecomposition is frequently employed in the study of seismic signals, biological data, power signals, and bearing fault diagnosis. As opposed to standard multi resolution analysis (MRA) methods like wavelet analysis, empirical mode decomposition recursively extracts various resolutions from the data itself without the requirement for specified functions or filters. Once the fast oscillation has been recovered, the remaining slower component is processed as the new signal bythe EMD algorithm, and it is once again displayed as a fast oscillation superimposed on a slower one. The elements of EMD are known as intrinsic mode functions (IMFs). The foundation of the EMD method is the idea that any non-stationary, non-linear time series is made up of a variety of simple intrinsic oscillations. The main goal of the approach is to deconstruct the data in a way that allows for the empirical identification of these fundamental oscillatory modes by the data's distinctive time scales. EMD is a method of signal processing that doesn't need leaving the time domain. It is similar to other analysis methods like wavelet decomposition and Fourier Transforms. Since natural signals are typically non-stationary and non-linear, the approach is useful for understanding them. Using EMD filters, the complete andalmost orthogonal basis the initial signal is eliminated.

F. WAVELET TRANSFORMS

Mathematicians can analyse data containing features thatchange over a variety of scales by using wavelet transforms. Tobe able to address the inadequacies regarding the Fouriertransform, wavelet transforms were developed. Differentwavelets can be used, depending on the application. Time-series financial data, biomedical signals, and audio signals allregularly exhibit piecewise smooth behaviour that is disruptedby transients. The illustration of in the frequency domain a non-stationary signal changes over time. With the use of discretewavelet transforms, multi-resolution analysis can be carried outon signals by decomposing them into physically relevant and intelligible pieces. Signals and images can both have smooth zones and transients that can be sparsely represented using wavelet transforms. Wavelet transformations can be classified into two main groups: Continuous Wavelet Transforms (CWT)and Discrete Wavelet Transforms (DWT). Analysis of non- stationary signals benefits greatly from the continuous wavelettransform, a time-frequency transformation. The CWT and theshort-time Fourier transform (STFT) are equivalent. WhileSTFT generates a local frequency analysis using a fixed window, CWT tiles the time-frequency plane using windows ofvarying sizes. A discrete wavelet transform (DWT) separates an input signal into several sets, of which each consists of a sequence of coefficients that characterize the signal's temporal evolution in the corresponding frequency band.

G. MULTIBAND FILTER ALGORITHM

Step1: Gathering the ECG ID Dataset.

Step2: Analyse both the train and test sets in the dataset**.**

Step3: Digital filters such as Band stop, High pass, and that arespecific to multiband are required in cascade.

Step4: All of these filters have MATLAB code that is createdand run in MATLABR2018b.

Step5: The noise has been reduced by 90%.

Step6: To get rid of the noise's leftovers, Verilog code is produced.

Step7: VIVADO 2018.2 runs code.

Step8: There are no noises made during output generation

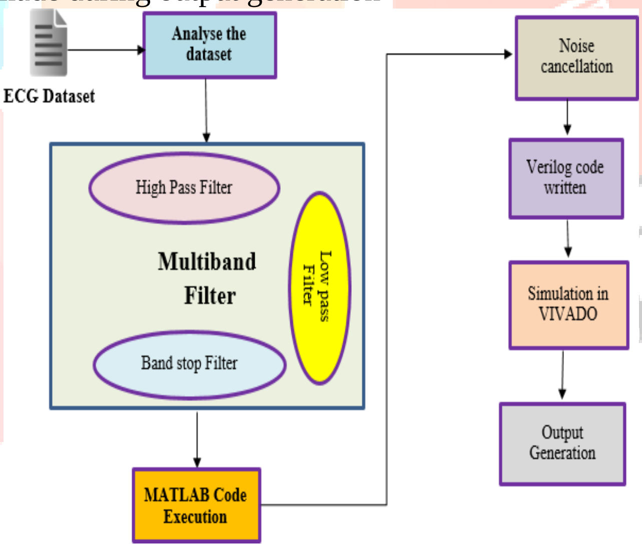


Figure 4: Proposed Methodology Design Overview

IV. RESULTS AND DISCUSSION

Output waveform from a low pass filter that is noise-free. Thereis just a low frequency allowed by this. Both the low frequencyand high frequency components are preserved.

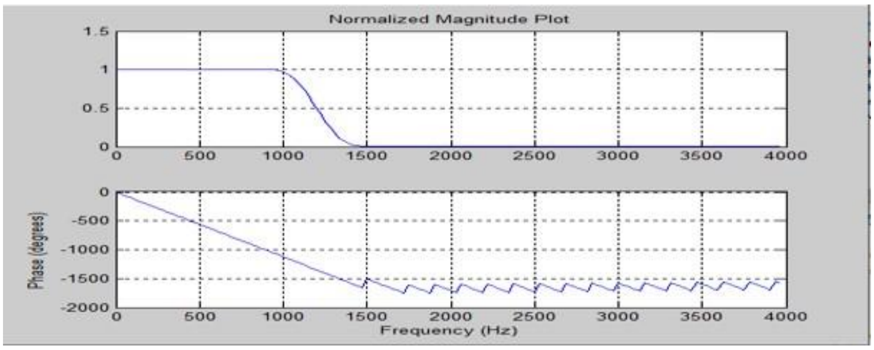


Figure 5: Low Pass Filter waveform without any noise

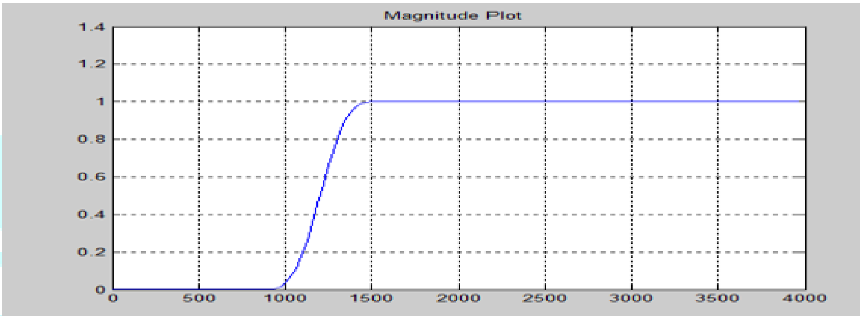


Figure 6: High Pass Filter waveform without any noise

This waveform represents the output of a high pass filter and isnoise-free. This only permits high frequency. Slow frequenciescan be removed using a high pass filter.

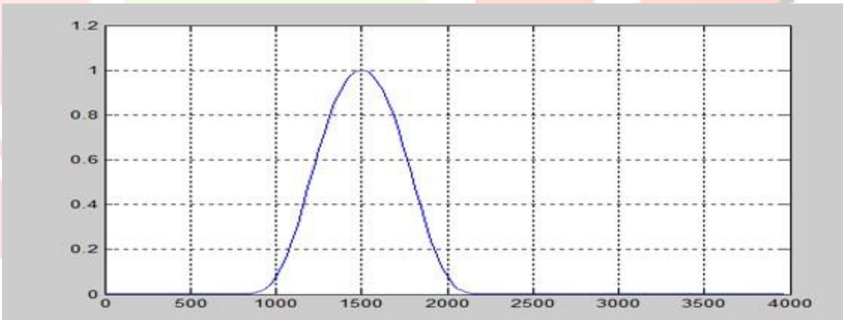


Figure 7: Band stop Filter waveform without any noise

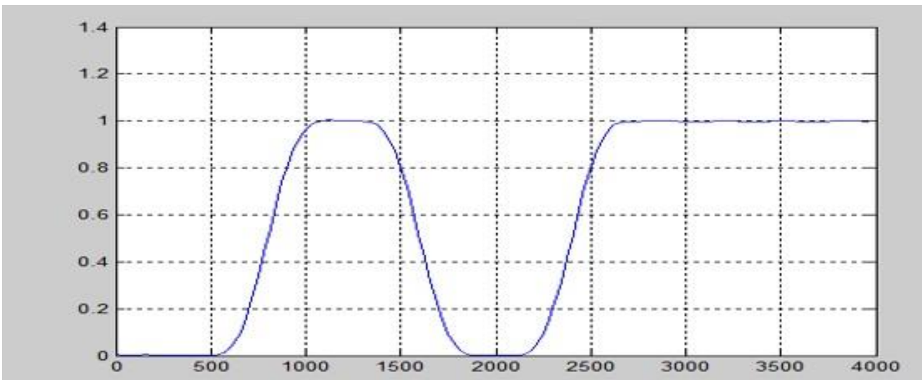


Figure 8: Multiband Filter waveform without any noise

The output waveforms of all the filters are shown here, and theyare all noise-free. Code in MATLAB incorporates the noises from the ID Dataset. This is the waveform produced by MATLAB after the noise has been eliminated. However, only 90% of the noise is removed, not all of it.

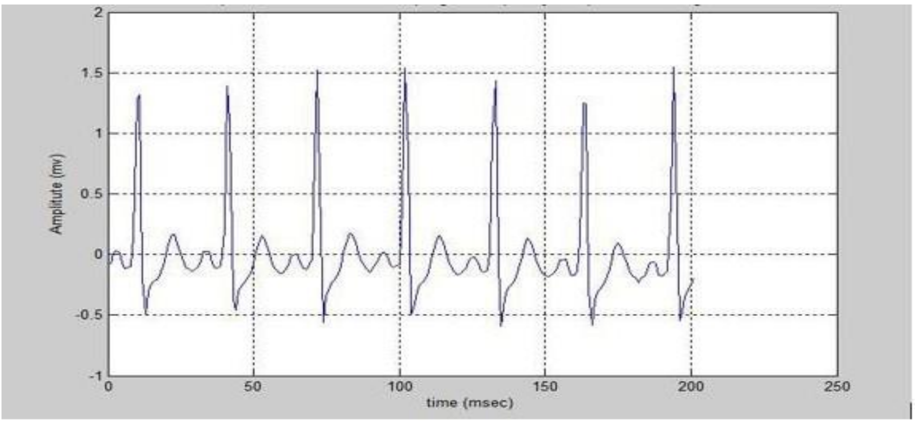


Figure 9: ECG signal in MATLAB

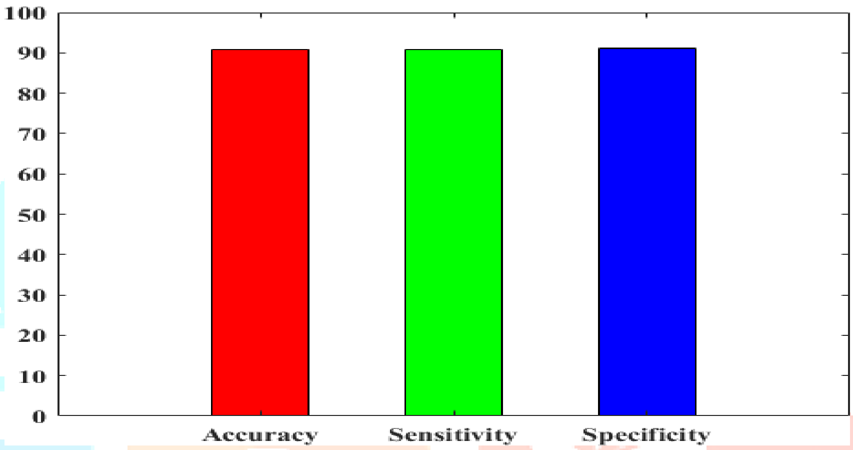
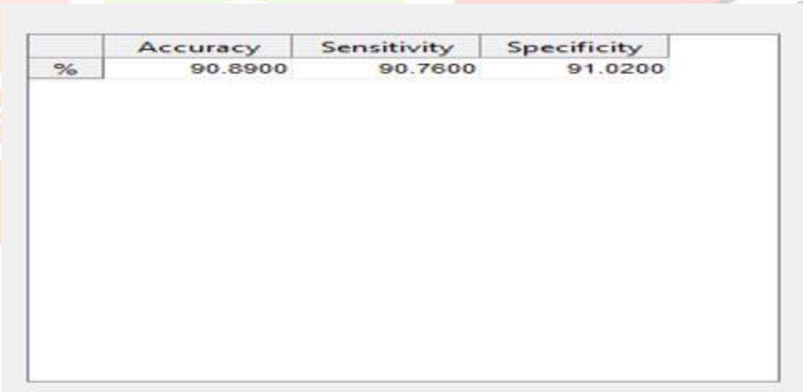


Figure 10: Parameters Report



	Accuracy	Sensitivity	Specificity
%	90.8900	90.7600	91.0200

Figure 11: Report in Percentage

```
[TRAIN]: kappa 0.818, accu: 0.909
[TEST ]: kappa 0.768, accu: 0.884

h1 =
  Histogram with properties:

              Data: [10000×1 categorical]
            Values: [5013 4987]
    NumDisplayBins: 2
        Categories: {'Attention'  'Not Attention'}
      DisplayOrder: 'data'
     Normalization: 'count'
      DisplayStyle: 'bar'
         FaceColor: [0 0 1]
         EdgeColor: [0 0 0]

  Show all properties
  ECG Signal Classification
Non Attention
```

Figure 12: Report of ECG signal in MATLAB

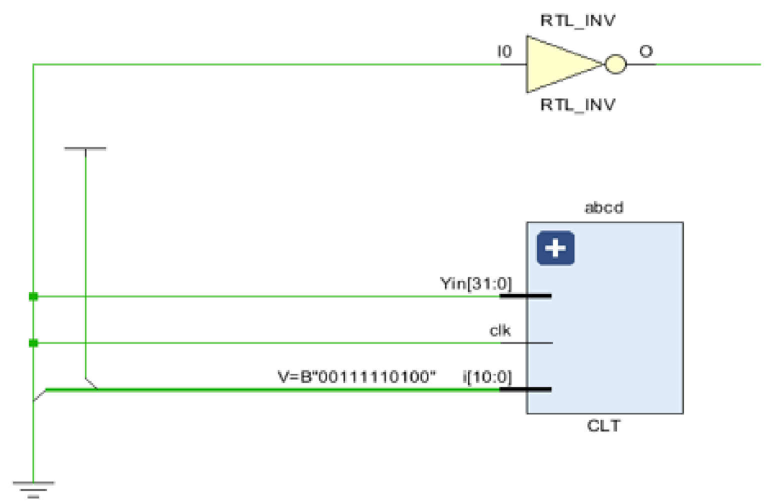


Figure 13: Schematic Design in VIVADO

Here, it stands for the input ECG signal, and yin is a 32-bit sample of the ECG signal. Clock (clk) is present.

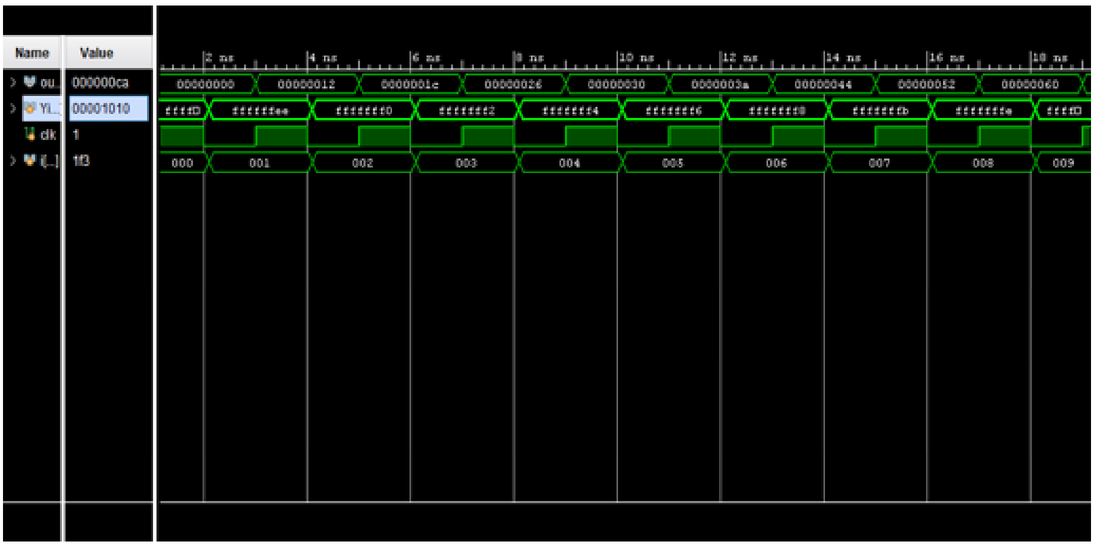


Figure 14: Multiband filter waveform in Hexadecimal from 0 to 9

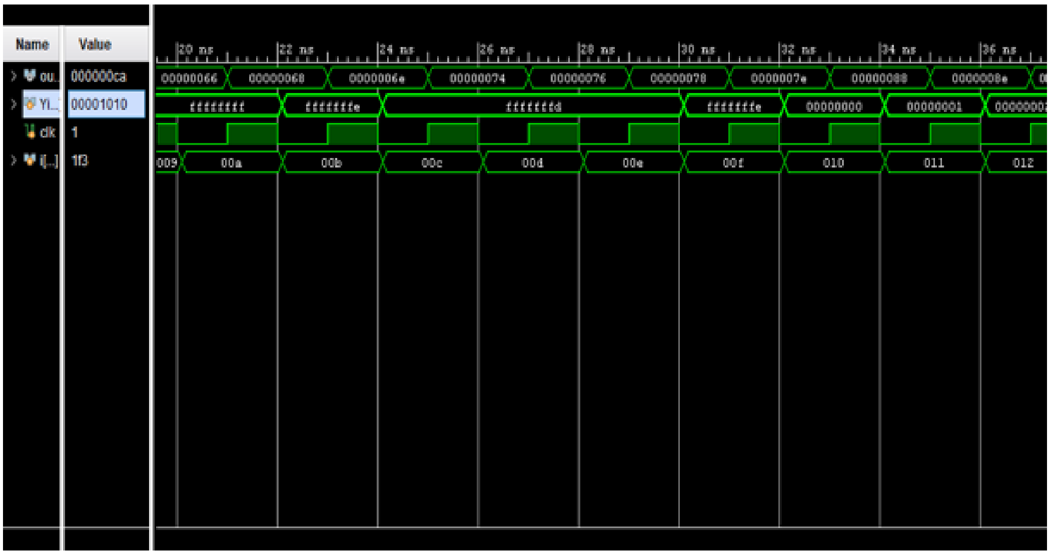


Figure 15: Multiband filter waveform in Hexadecimal from 9 to 12

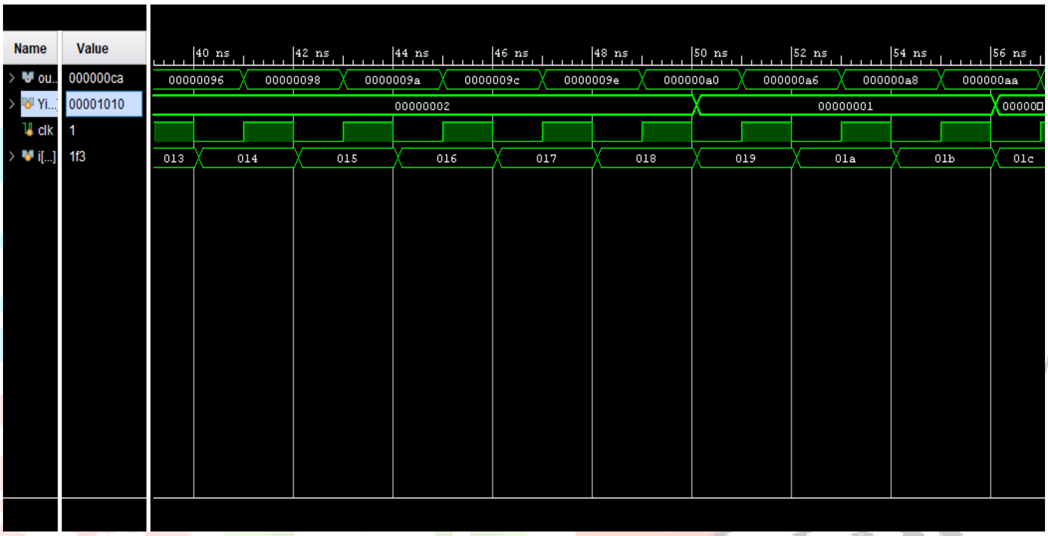


Figure 16: Multiband filter waveform in Hexadecimal from 013 to 01c

Table 1: Report of different samples of ECG

Sample Number	Input ECG		Output	
	Hex	Dec	Hex	Dec
1	e	14	00000012	18
2	0	0	0000001c	28
3	2	2	00000026	38
4	4	4	00000030	48
5	6	6	0000003a	58
6	8	8	00000044	68
7	b	11	00000052	82
8	e	14	00000060	96
9	f	15	00000066	102
a	f	15	00000068	104
b	e	14	0000006e	110
c	d	13	00000074	116
d	d	13	00000076	118

V. CONCLUSION

For the noise-containing ECG database entries, a multiband filter scheme is suggested. PLI, BW, MA, and HF sounds are all simultaneously eliminated by the proposed multiband filter. The multiband filter is designed employing two different approaches that Empirical mode decomposition and Wavelet transform. The suggested multiband filter design has a low order, straightforward construction, the capacity to handle a wide range of noise levels, and good noise attenuation levels. The different ECG signal samples are taken which contain noises. The ECG inputs are also given to the multiband filter which is simulated in MATLAB Tool. To increase resource efficiency and execution speed, the filter coefficients and input sample data were quantized by 32 bits. By using MATLAB, 90% of noises are removed. The accuracy, sensitivity and specificity is calculated. Still complete noises are not removed. So MATLAB output noises is incorporated into the VIVADO tool for the better performance. The output obtained in the VIVADO doesn't contain any noises.

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