A REPORT

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REAL TIME ANALYSIS OF EEG SIGNAL USING FPGA

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A REPORT ON

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PROF. YENUGANTI SUJAN

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EEE F246

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1. Introduction

Electroencephalography (EEG) has been serving the healthcare industry for over a decade since its introduction in 1924. The current application comprises a broad domain from diseases' diagnosis to the current trend in developing assistive devices for rehabilitation. EEG is the physiological approach of choice to record the brain's electrical activity via electrodes placed on the scalp surface. Through improved technology over the course, EEG has become one of the quickest imaging-techniques available as it often has a high sampling rate.

The current approach utilizes an FPGA based system for EEG implementation. The field-programmable gate array (FPGA) is an integrated circuit consisting of internal hardware blocks with user-programmable interconnects to customize operation for a specific application. The Main Advantage of using an FPGA is the availability of multiple hardware running parallel for computation.FPGAs are particularly useful for prototyping application-specific integrated circuits (ASICs) or processors.

Moreover, FPGA based implementation of EEG is predominantly used as it allows to optimize its workflow. It enables making any possible iteration at the chip level throughout experimentation and portraying a more economical option.

In this project we are majorly focusing on implementing filters using FPGA for extracting alpha, beta and gamma signals from the given EEG signal. Also we have done a literature survey on feature extraction and classification of EEG signals.

1.1. <u>DECIPHERING THE EEG SIGNAL</u>

I] Recording of EEG Signal:

The recordings of the EEG signal are obtained by connecting cup electrodes or scalp discs on the scalp. The scalp is prepared beforehand by light abrasion to decrease the resistance caused due to light skin cells. Then the conducting gel is applied to the scalp, followed by attaching the electrodes to the head. The sampling occurs between 256- 512 Hz for Analog to digital conversion.

II] Preprocessing the Data

The feature extraction method followed in this analysis is based in the time domain and is explained properly in the following topic. The wavelets have to be further processed to extract the particular frequency bands found in the EEG signal. The three EEG sub-bands fall within 8 - 64 Hz, so the frequency signals above 64 Hz and below 8 Hz are dismissed as noise. Therefore, to obtain more quickly the frequency sub-bands of the EEG during the wavelet analysis, the EEG is band-limited to 8–64Hz range by convolving with a low-pass finite impulse response (FIR) filter.

FIR filter is one of the best choices for processing EEG signals because of its linear phase property. Moreover, an FIR filter will always give a stable output because it is non-recursive and has a constant delay overall frequencies; phase shifts will not influence the signal shape.

In order to further differentiate these three sub-bands, Discrete Wavelet Transformation (DWT) is used. In this method, using db4 wavelet transform, first the signal is differentiated into two groups using High pass filters and low pass filters, into 0-30 Hz and 30-60 Hz, where the latter frequency corresponds to gamma signal and the former frequency is again differentiated further using the same method. The method is repeated three times, as shown in the figure, which result in the final sub-bands as:

1. alpha (8-15 Hz)
2. beta (15-30 Hz)
3. gamma (30 – 60 Hz)

Note that theta and delta are usually neglected while preprocessing EEG signal, thus frequencies falling in the range (0-8 Hz) are neglected.

III] Feature Extraction

A feature essentially means a unique property, an identifiable measurement, obtained from the given set of data. And feature extractions are used to minimize the loss of important information by identifying them from the embedded set of data. They are important so as to unravel the complexity of the signal, to further compress the data and reduce the cost of maintaining the information.

For EEG signals, the techniques used are in the time domain, frequency domain or the wavelet domain. There are several varieties of methods known for feature extraction. The Fast Fourier Transform (FFT) method, which is a time domain method and uses mathematical means and tool for EEG analysis, usually get about 91% accuracy. The DWT method, which is being used in this study gives an accuracy of 93.3% for epilepsy detection. The highest rated model comes under wavelet domain and develops an artificial neural network. The accuracy obtained for this model is 97%.

IV] Classification

In our daily life, classification essentially means making decisions developed on the information currently available. Once feature extraction is completed and we are left with the important information, we require efficient classification techniques to properly distinguish the EEG segments based on the acquired data and help in the making the decisions on the person's health. A productive classification system is important for diagnosing the brain disease and results in a more appropriate perspective of the cognitive processes.

There are four different types of classifiers.First, the linear classifiers use linear functions to classify signals. Linear Discriminant Analysis and Support Vector Methods are the popular methods coming under linear classifiers which use hyperplanes to classify and separate the data. The main issue with linear classifiers is that they give poor outcomes to nonlinear complex data.

Second, the most used classifiers are the neural networks. In this paper, the AntMiner+ classification algorithm is used which comes under Ant Colony Optimization (ACO), which works on swarm intelligence. Ants communicate through pheromones while searching for shorter paths between their food source and destination, which is the inspiration for this model. This algorithm also keeps working on improving the levels classification from the classified data.

Third, the non-linear Bayer classifiers are efficient in rejecting uncertain samples than other classifiers. There are two types of such classifiers, Hidden Markov Model and Bayes Quadratic. Fourth, there are Nearest Neighbour classifiers, which perform accurately even with low dimensional Feature Vectors. The prominent two models under this classifier are Mahalanobis Distance and K Nearest Neighbour (kNN).

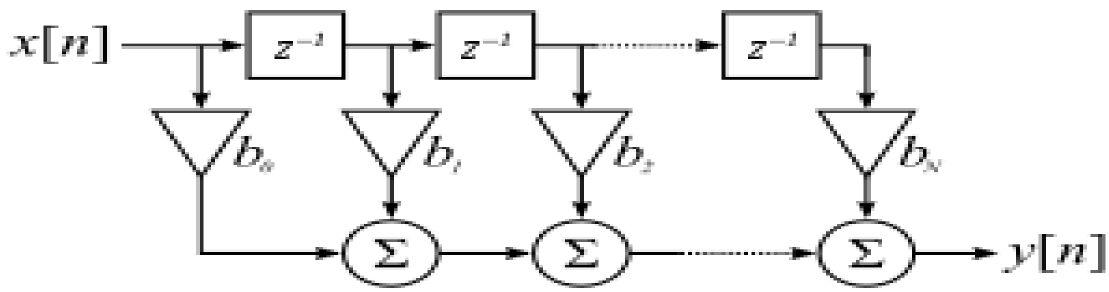
2. LITERATURE REVIEW

Ozpolat, E., Karakaya, B., Kaya, T., & Gulten, A. (2016, April) highlights FPGA-based digital Filter Design for Biomedical Signal. This paper presents a Field Programmable Gate Array (FPGA)-based Fir Filter Design for Biomedical signal processing. Electroencephalography (EEG) has been the most dependable tool used for biomedical signal processing. The digital filter is used to filter discrete-time signals with the ability to modify the frequency response of the filter at any time, and it is used in many applications such as data compression, biomedical signal processing, communication receivers, etc. The Finite Impulse Response (FIR) filter has many advantages in signal processing, such that it has a simple structure, stationary response, and adaptivity with embedded microprocessors. FIR filter is proposed due to facilitate structural characteristics and design properties on filtering EEG signal. The system has a computer where the design can be programmed and simulated on the Xilinx FPGA ISE editor. The focus of this paper is to compute FIR filter coefficients on MATLAB Filter Design Toolbox and then transfer them to embedded design on FPGA to filter EEG signal. **Sundaram, K. (2016, March)** talks about FPGA-based filters for EEG pre-processing. The EEG preprocessing steps involve removing noise and artifacts from EEG. The noise from the main source like electrooculogram, electrocardiogram, electromyogram, and other sources should be eliminated to increase accuracy in classification. As these artifacts may be misinterpreted as originating from the brain, there is a need to minimize or remove them from recorded EEG signals. The artifacts are undesirable potentials of non cerebral origin and eye blinking that contaminate the EEG signal. EEG artifacts originate from two sources, namely, physiological and technical. Technical artifacts are mainly due to equipment malfunction; result from poor electrode contact or line interference. Offset, filter settings or incorrect gain of the amplifier will cause distortion clipping or saturation of the recorded signals. Technical artifacts can be avoided through consistent monitoring, a meticulous inspection of equipment, and proper apparatus setup. Physiological artifacts arise from a variety of body activities that are either due to movements, skin resistance fluctuations, or other bioelectrical potentials. Proper filters need to be designed to filter these artifacts. Moving average filter and Median filters are easy to implement, and these filters act as the best pre-processing stage for noise removal. In this paper, filters such as Moving average and Median filter are implemented in FPGA (Virtex-5) and compared in terms of area, power, and delay. Though Moving average is fast when compared to Median filters. Median filter is the best for pre-processing since it occupies less area and power. **Subha, D. P., Joseph, P. K., Acharya, R., & Lim, C. M. (2010)** gives details about EEG signal analysis. The EEG (Electroencephalogram) signal indicates the electrical activity of the brain. They are highly random in nature and may contain useful information about the brain state. However, it isn't easy to get useful information from these signals directly in the time domain just by observing them. They are basically non-linear and non-stationary in nature. Hence, important features can be extracted for the diagnosis of different diseases using advanced signal processing techniques. In this paper, the effect of different events on the EEG signal and different signal processing methods used to extract the hidden information from the signal are discussed in detail. Linear, Frequency domain, time-frequency, and non-linear techniques like correlation dimension (CD), largest Lyapunov exponent (LLE), Hurst exponent (H), different entropies, fractal dimension(FD), Higher-Order Spectra (HOS), phase space plots, and recurrence plots are discussed in detail using a typical normal EEG signal. **Yarahuaman, J. C. R., & Huamaní-Navarrete, P. F. (2020, October)** mentions about Design and Simulation of a Digital Filter in Hardware for EEG Signals Based on FPGA. This paper presents a Design and Simulation of a Digital Filter with Finite Impulse Response in Hardware for electroencephalographic

(EEG) signals based on Field Programmable Gate Array (FPGA). The EEG signals were obtained from the database of Graz University of Technology, which is a database of EEG signals based on multi-class motor imaginations paradigms. The purpose of this research was to filter the noise of the EEG signals due to different factors and electronic components that contaminate them during the digitization stage. The Modelsim and Matlab software were used for the design and simulation stage of digital filter and the Hamming and Blackman windows for the design of the filter with an order of 81 and the development board DE0-Nano-SoC for the hardware description of the digital filter. Finally, it was obtained a high performance of combinational logic resources occupying 98% and low latency in processing time.

3. Implementation of FIR Filter in FPGA for processing EEG signals

3.1. Architecture Implemented :



Here

- X[n] is the input EEG signal . EEG signals are usually measured in Microvolts. Arithmetic operations with floating point values in FPGA is time consuming and also highly complicated. So therefore we convert the signal to a fixed point notation of 12bits. Further we normalize it by only taking 12 bits without the decimal point and finally we take the decimal point into account in the end result.

  Note:In our case we have taken the total no.of samples = 32.
  Each Sample point is made up of 12 bits.
  Sampling Frequency of input sample is 128 Hz.

- b0, b1, b2……..bn are the coefficients of the FIR Filter. We used matlab for finding the coefficients of FIR Filter. Command used - fir1 which implements Hamming window for the desired range of frequency.

  These Hamming window coefficients can be used for either implementing a low pass filter or bandpass or high pass filter.
  We have implemented a bandpass filter with having generated the coefficients for hamming windows.
  Note: Filtering is done in time-domain and not in Frequency domain .We have used the FIR filter in segregation of EEG signal components into Alpha , Beta and Gamma rays.
  In our case we have taken the order of the filter to be 16.
  So we get N+1 Coefficients.
  These coefficients in decimals are converted to fixed point notation as done for X[n]. The hamming window coefficients are converted to 12 bit binary values and these values without the decimal point are taken and multiplied with X[n] and finally the powers are added along with the multiplied result to get the final result.

The converted binary values after quantization are given below.

Binary conversion for implementing in FPGA

X[n]- Input sample in microvolts	Binary representation (decimal point is assumed to be at 4 places from the left)
-3.0525	110011110011
-2.9548	110100001100
-2.0269	110111111010
-0.2442	111110000011
4.0048	010000000001
3.9316	001111101110
-1.221	111011001000
-1.1965	111011001110
-0.4151	111110010110
2.271062271	001001000101
3.833943834	001111010101
1.05006105	000100001100
-2.8815	110100011111
-4.4688	101110001000
-4.0781	101111101100
-1.978	111000000110
-3.6141	110001100011
-3.9804	110000000110
-3.028	110011111001
-3.2234	110011000111
-1.0989	111011100111
-0.757	111100111111
0.6105	000010011100
0.2686	000001000100
1.3675	000101011110
1.978	000111111010
-2.6617	110101010111
-6.8131	100100110000
-7.9365	100000010010
-7.2039	100011001100
-1.7338	111001000101
1.8803	000111100001

Coefficients for alpha waves (8 -15Hz)	Coefficients in binary(decimal is assumed to one place from left)
-0.0027	111111111011
-0.015	111111100010
-0.0422	111110101010
-0.0742	111101101001
-0.077	111101100011
-0.0204	111111010111
0.0883	000000101101
0.1975	000110010100
0.2435	000011111001

Coefficentsfor Beta waves (15Hz-30Hz)	Coefficients in binary(decimal is assumed to one place from left)
-0.0013	111111111110
0	0
0.0212	000000101011
0.0397	000001010001
-0.0305	111111000010
-0.1643	111010110000
-0.1353	111011101011
0.1221	000001111101
0.2879	001001001101

Coefficentsfor Beta waves (15Hz-30Hz)	Coefficients in binary(decimal is assumed to one place from left)
0	0
0.0091	000000010010
-0.0168	111111011110
-0.0012	111111111110
-0.0139	111111100100
0.1146	000001110101
-0.0794	111101011110
-0.2451	111000001011
0.4675	001110111101

3.2. <u>Simulation results (With explanation)</u>

The simulations were conducted in Xilinx Vivado and MATLAB.

Since each sample is of 12 bits and coefficients is also of 12 bits, the resulting computation requires 24 bits .

Since the order is 16 (requires 5 bits), each resulting value is added with the partial product from other coefficients . resulting in 29 bits(24 + 5).

From This resulting 29 bits the decimal point is kept at 5 places from left.

Note: 5 because we have assumed the decimal point in binary conversion for input signal to be from 4 places from the left and 1 place for the coefficients(5 = 1+4).

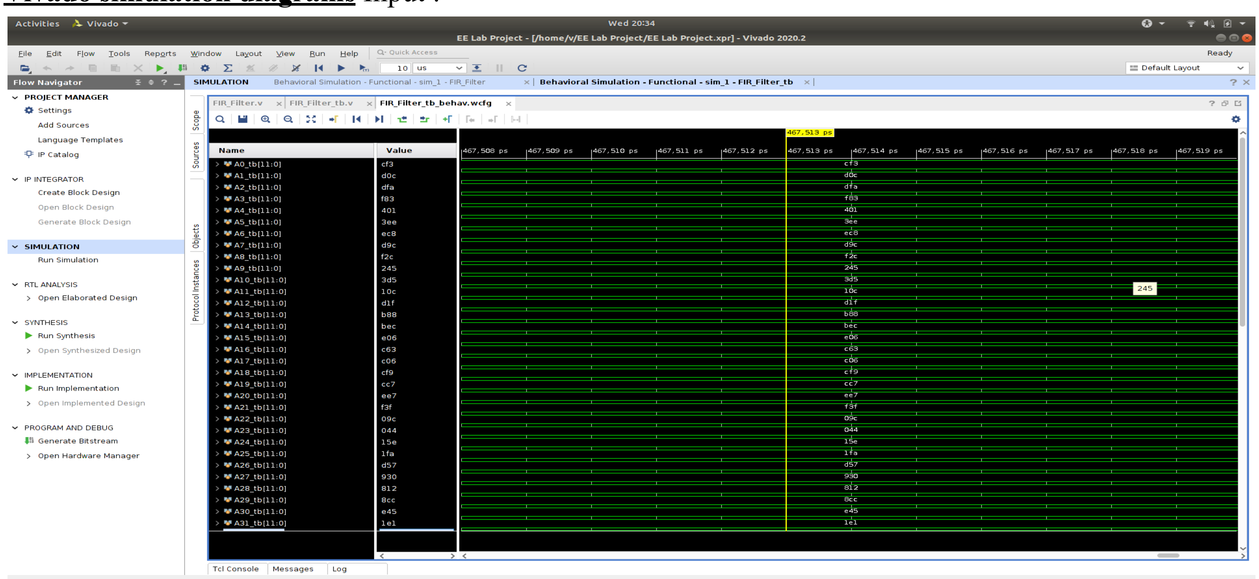
In each clock cycle computation is done (multiplication and addition as shown in the architecture) to find Y[n] at that clock cycle.

As the clock count increases, the input values move from left to right .

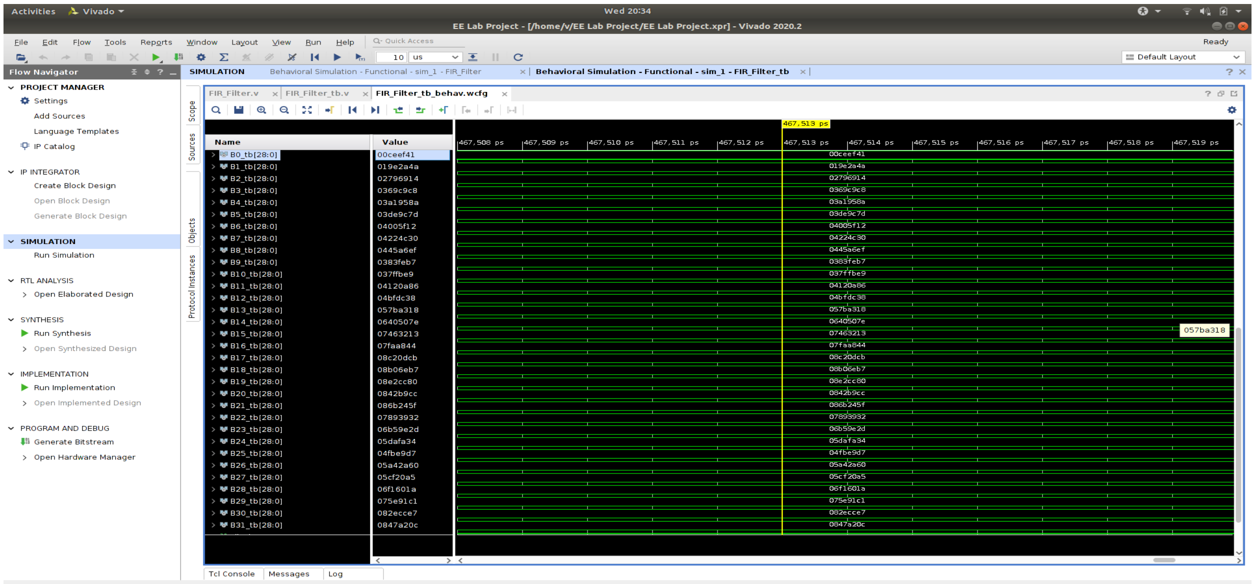
The Architecture shown before introduces the Z^-1 block which introduces the delay.

So therefore the convolution of input signal with the Filter coefficients is done effectively.

<u>Vivado simulation diagrams</u> Input :



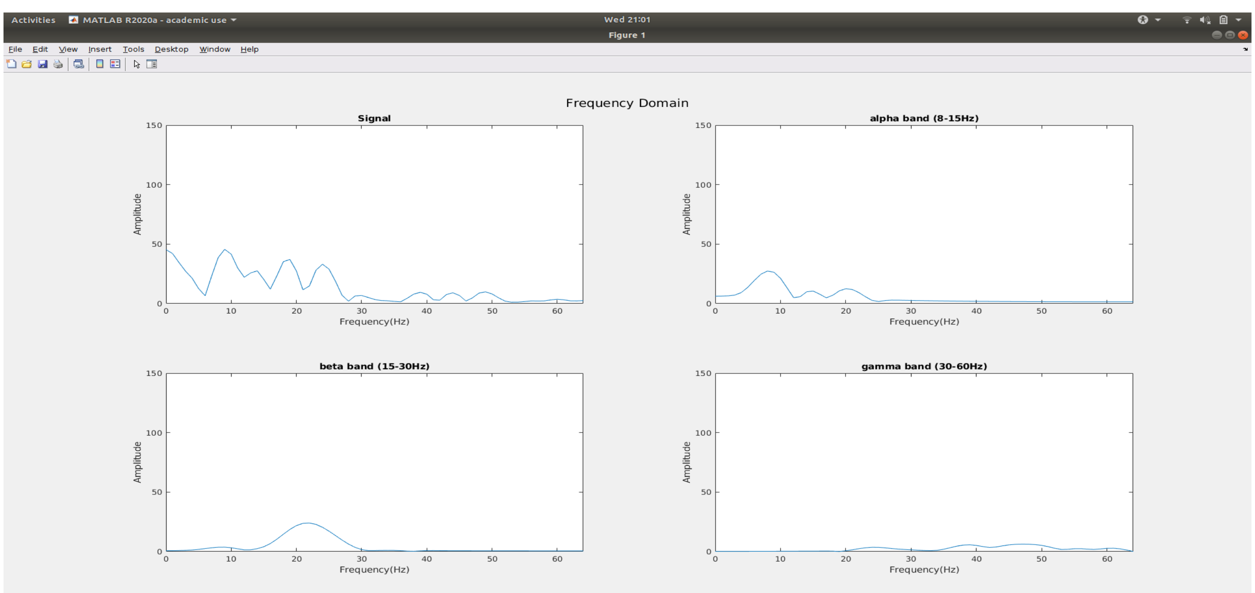
Output :



As stated in the previous page, the output is 28 bit value-With the decimal point assumed to be at 5 places to the right of 28th bit.

These y[n] from each filter (for alpha , beta, gamma) were imported into matlab and Frequency components of each output were analysed.

The results are shown below-



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