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Design and Implementation of Filtering Scheme for Electro Encephalo Gram Segmentation

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ABSTRACT

ElectroEncephaloGraph represents electrical activity of the brain and potential fluctuations derived from neuronal ionic current flow. A unique analytical and computational tool is required to identify various components for driving assistive systems. This paper proposes and implements a segmentation scheme to extract delta, theta, alpha, beta and gamma bands. This scheme perceives time domain filtering nuances and provides a platform for empirical investigations. This scheme exhibits flexibility in responding to the variation in pass band frequencies. The effectiveness of the scheme is substantiated through magnitude response and phase response for various frequency bands.

1. INTRODUCTION

Performing mining operation on a signal contaminated by numerous features forms the foundation of Electro Encephalo Graph (EEG) analysis. This operation yields either current activity or Event Related Potentials (ERPs). This filtering process can be implemented in various schemes. The definition of digital filter points out mathematical schemes applied to analog or digital versions of the waveforms either to localize a specific feature or discarding certain features [1]. Computing a set of weights and multiplying them with all unfiltered data points defines the digital filtering methodology on an EEG waveform. This process is iterative for the entire time duration of the signal and the summation of results represents the filtered waveform.The computation scheme is founded on extracting specific feature from the composite EEG. Theparameters such as degree of perpetuation, removal level and computational speed are performance metrics for the filtering scheme. An existence of abundant methods for weights calculation and selection of data points in the signal to be filtered enable the designer to design a suitable filter for a specific application. The effectiveness of the scheme is determined by the alignment of magnitude, frequency, phase values of the weights and the signal to be filtered. For deriving a sinusoidal waveform, if data point's frequency and phase values are equal with that of the selected weights positive half will occur. The Negative half of the waveform of interest will result by multiplying weights and data points with opposite phase and same frequency and a value nearer to null will result for other operations [2].

Computation of each output value in filtering process involves cross-multiplication of weights and input data points as in Eq. (1).

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$$Y_t = \sum_{i=-j}^{j} W_i X_{i+1} \tag{1}$$

Where "*W*" is the series of "2 *j* + 1" weights, "*X*" is the input time series, "*Y*" is the filtered time series and the subscript "*t*" refers to each time point in the input series. This cross-multiplication and summing procedure executed on a range of values "*t*" is defined as "convolution". The 2 *j* + 1 weights are symmetric about an unpaired center weight W_0. This filter that derives output solely on the basis of input points are referred as Finite Impulse Response (FIR) filters. The perturbation caused in the input will not reflect in the output as the impact of the aberrant confines to the adjacent 2j points [3]. Distinctively, a scheme that derives each filtered point from part on the basis of prior filtered points is referred as Infinite Impulse Response (IIR) filters [3]. The characteristics such as non linear phase response, yielding to finite length arithmetic, slow implementation rate, poor computational capacity limits IIR scheme to be used for EEG analysis [4].

Event Related Potential (ERP) template-matching algorithms uses FIR filtering schemes in profuse way. The structure of the signal of interest defines an unambiguous hypothesis of the template constructed from a set of weights. A P300 component of the ERP on a single-trial basis can be extracted from EEG by cross multiplying a template made up of a positive half cycle of a 2Hz sinusoidal waveform [5].

Smoothing a time series i.e., high frequency components removal is widely used in extracting ERP from composite EEG. It refers to averaging a symmetric set of points before and after each point being filtered. For an average of "*N*" points each point is weighted by 1/N. This function effectively removes swift changes and fails to respond to slow changes. This scheme is referred as moving-average filter [6]. The merits of this scheme lie in simplicity and computational speed and the demerits are poor frequency precision, ability to introduce phase shift.

2. RELATED WORKS

Areas such as multirate systems, image processing, communication systems and biological signal processing extensively uses Linear Phase FIR digital filters. The design methods for linear phase FIR filters are regularly refined to improve efficiency. The design methodology of linear phase FIR filter involves, Ideal frequency response selection, FIR filter length, ascertaining righteousness between ideal and practical frequency response, filter coefficients computation scheme. The definition of optimality criterion will fix the filter behavior and tradeoff management of the design procedure [7]. Approximating a discontinuous function chosen as ideal frequency response is by a finite number of smooth functions perceives FIR filter design as approximating problem. Inherently this method possess a tradeoff between upholding the flatness response in pass band, stop band and preserving sharp transitions in ideal frequency response [8].

The requirement of uncomplicated methodology of solving single linear system of equations, minimization of least-square error makes Least-square design as the most favorable methodology [9] [10] [11] [12] [13]. This scheme offers energy minimization which enables high signal to noise ratio provision for signals to be filtered [14]. The disadvantages of least square scheme are high overshoot and high error level facilitates optimal filter design in minimax sense [15] [16] [17]. The minimax filter design offers a computation scheme with less complexity and it can be implemented with minimum number of coefficients. These filters can be implemented by Remez method, an iterative design algorithm [16] [17]. The minimax filters delivers equiripple behavior in pass band, stop band and a transition band of very low narrow value. For a specific length, the maximally flat filters yields a wider transition band and very flat pass band, stop band magnitude response [18].

Segmentation of EEG signal can help to diagnosing brain disorders. Presence of Epileptic seizures can be accomplished by decomposing the EEG signal into delta, theta, alpha and beta subbands [19]. Sub band segmentation enables in assessing human's discrete emotions forms one of the active research areas in

Brain Computer Interface (BCI) development. An effective preprocessing and filtering scheme will provide statistical features from alpha frequency band for emotion classification [20]. Attentive reading can be detected by analyzing EEG signals. Computation of signal power in different frequency bands can be used to build feature vectors. Classification can be performed on selected feature vectors [21].

An adaptive signal segmentation scheme for EEG can be implemented to retrieve the emotion-related information associated with the signal. The frontal brain asymmetry, a vital structure to evoke emotional reaction is used to realize the segmentation process [22]. Band Power extraction scheme can be extremely useful in designing an EEG based Brain Computer Interface (BCI).. This scheme computes spectral power and power difference in 4 bands: delta and theta, beta, alpha and gamma [23].

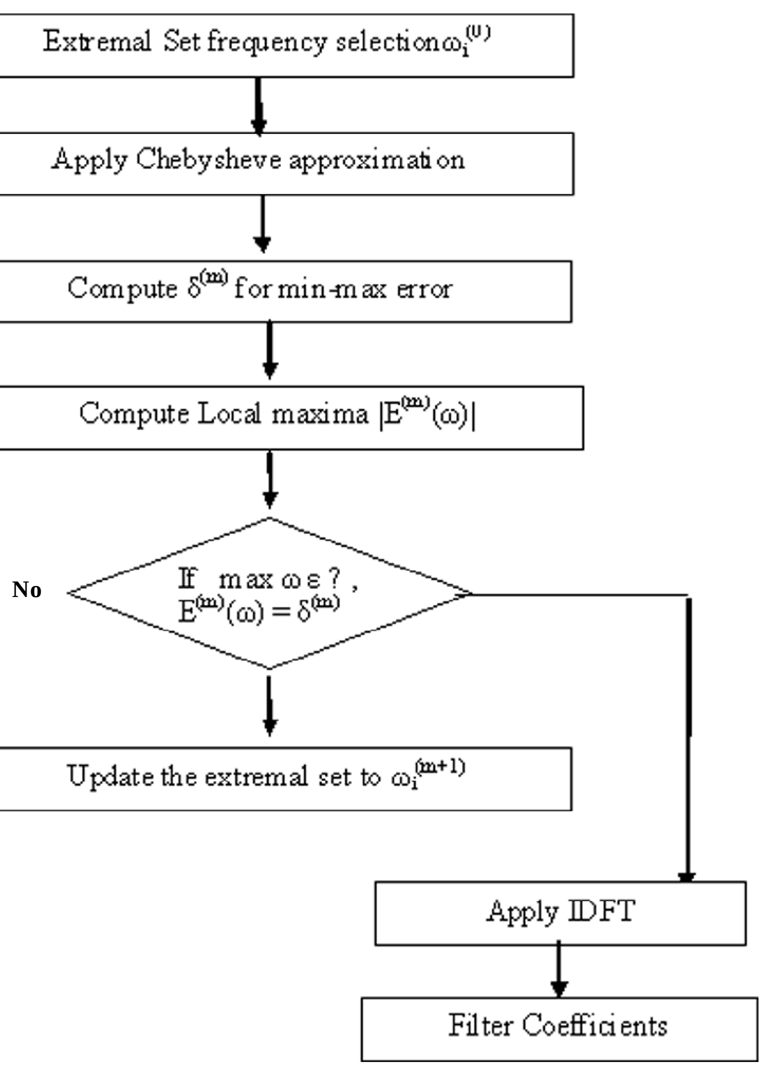
3. PROPOSED ALGORITHM

A Discrete time system can be characterized mathematically by using a mathematical tool defined as “Difference equation”. The expression for a difference equation can be described as in Eq. (2),

$$y(n)+\sum_{k=1}^{M} a(k)\,y(n-k)=\sum_{k=1}^{M} b(k)\,x(n-k) \tag{2}$$

Where sequences $x(n)$ and $y(n)$ represent input and output signals and “M” represents order. The mathematical expression for Infinite Impulse Response (IIR) filter can be stated as in Eq. 3,

$$y(n)=-\sum_{k=1}^{M} a(k)\,y(n-k)+\sum_{k=1}^{M} b(k)\,x(n-k) \tag{3}$$



4. ELECTRO ENCEPHALO GRAPH RECORDING EXPERIMENTAL SET UP

This visual stimuli paradigm proposes a method to present stimulus to evoke potential across the brain.

i. During this selective visual attention experiment, stimuli will appear briefly in any of five squares arrayed horizontally above a central fixation cross.

ii. In each experimental block, one (target) box was differently colored from the rest whenever a square appeared in the target box the subject was asked to respond quickly with a right thumb button press. If the stimulus was a circular disk, the subject was instructed to ignore it.

iii. The resulting potentials were recorded using 10-20 electrode placement scheme. The proposed electrode montage scheme is shown in Fig.1.

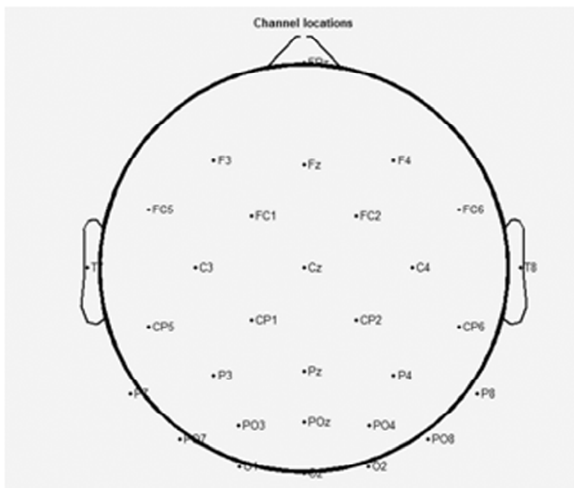


Figure 1: Electrode Montage Scheme

1. GRAPHICAL REPRESENTATION OF RECORDED EEG

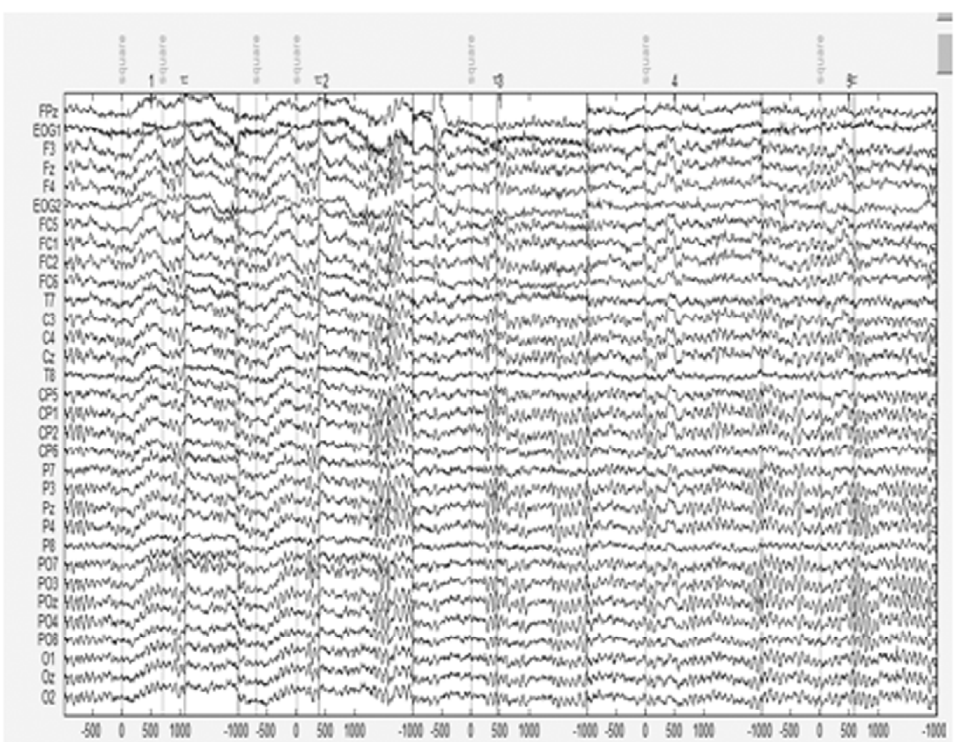


Figure 2: Graphical representation of EEG

2. FINITE IMPULSE RESPONSE FILTER DESIGN TO EXTRACT DIFFERENT BANDS OF FREQUENCIES

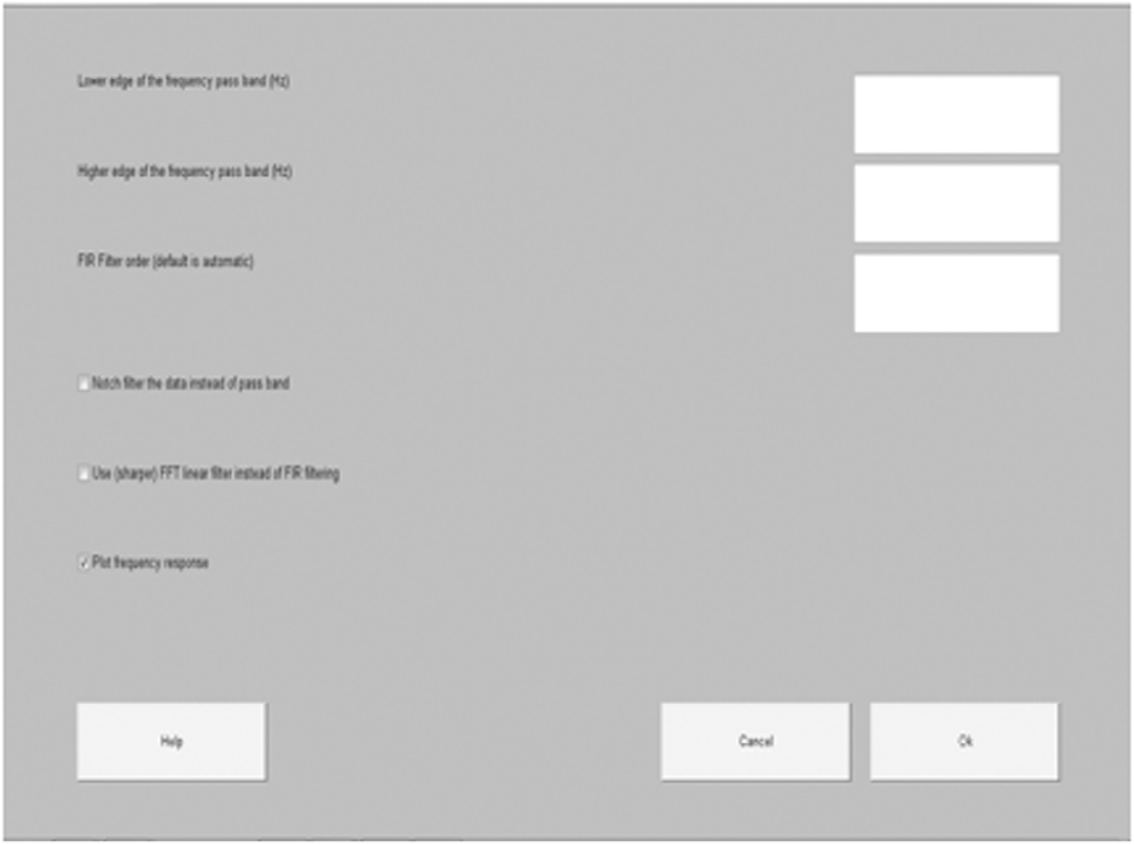


Figure 3: FIR filter input parameter feeding window

3. GRAPHICAL REPRESANTATION OF EEG IN DELTA FREQUENCY RANGE [1 Hz – 3 Hz]

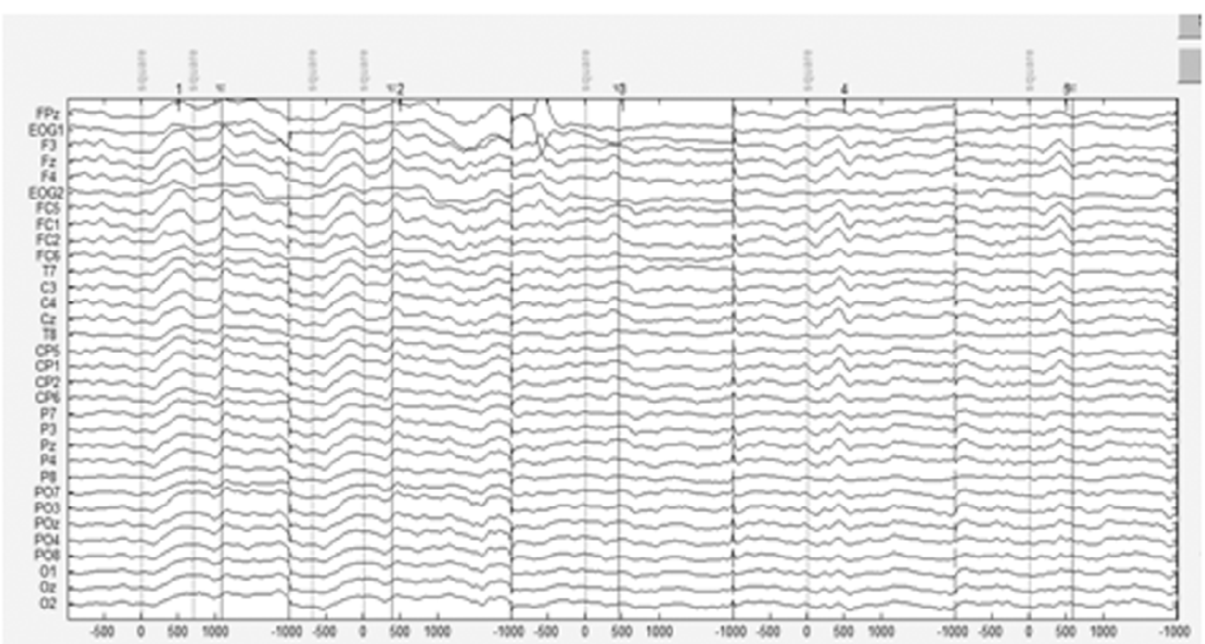


Figure 4: Graphical representation of DELTA band in EEG

4. MAGNITUDE RESPONSE AND PHASE RESPONSE OF 10-tap FIR FILTER TO EXTRACT DELTA RANGE

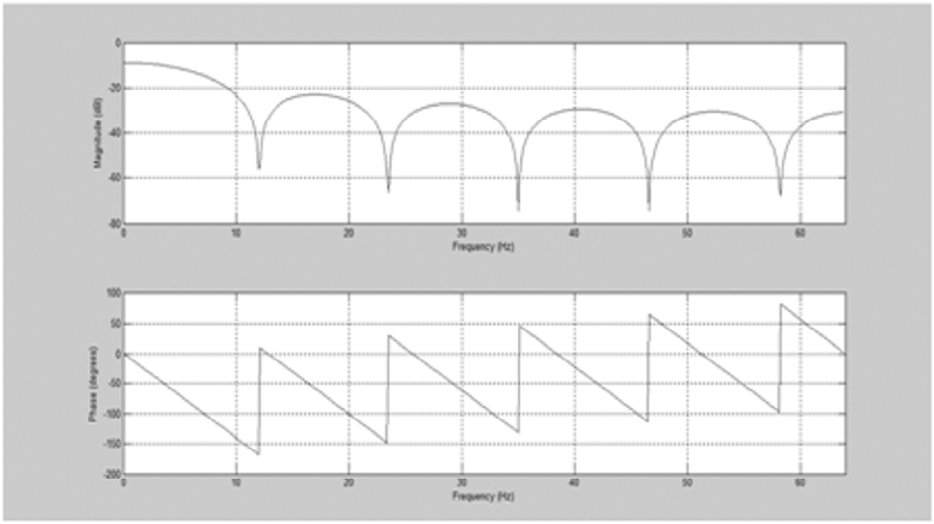


Figure 5: 10-tap FIR filter's magnitude and phase response for DELTA band extraction in EEG

5. GRAPHICAL REPRESANTATION OF EEG IN THETA FREQUENCY RANGE [3.5 Hz – 7.5 Hz]

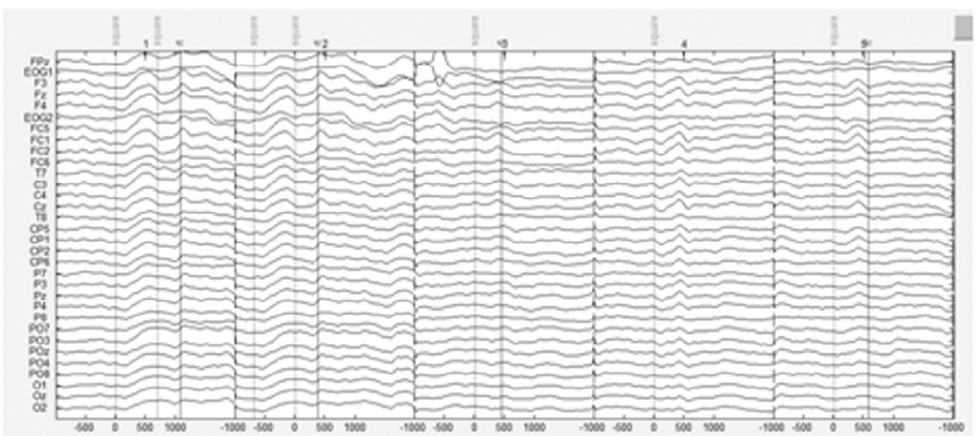


Figure 6: Graphical representation of THETA band in EEG

6. MAGNITUDE RESPONSE AND PHASE RESPONSE OF 10-tap FIR FILTER TO EXTRACT THETA RANGE

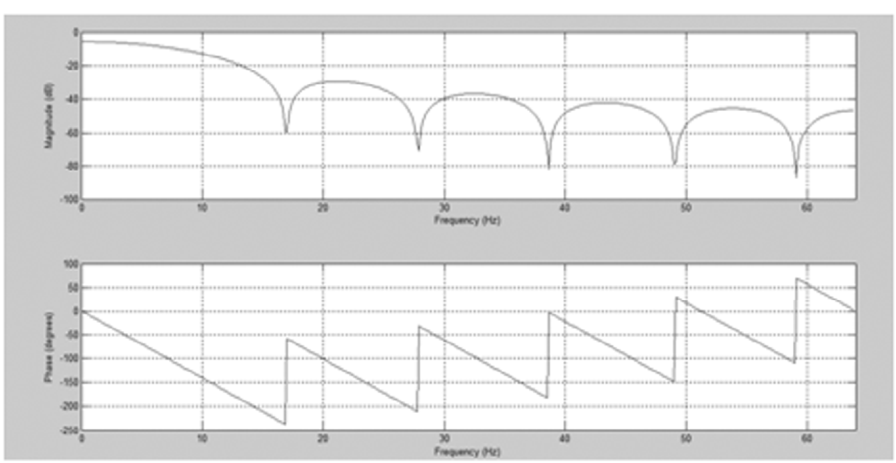


Figure 7: 10-tap FIR filter's magnitude and phase response for THETA band extraction in EEG

7. GRAPHICAL REPRESANTATION OF EEG IN ALPHA FREQUENCY RANGE [8 Hz – 13 Hz]

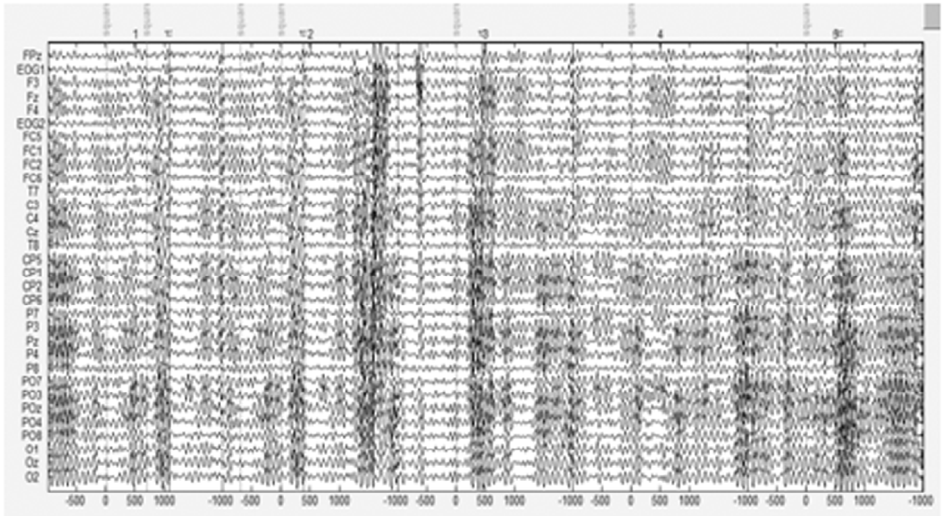


Figure 8: Graphical representation of ALPHA band in EEG

8. MAGNITUDE RESPONSE AND PHASE RESPONSE OF 10-tap FIR FILTER TO EXTRACT ALPHA RANGE

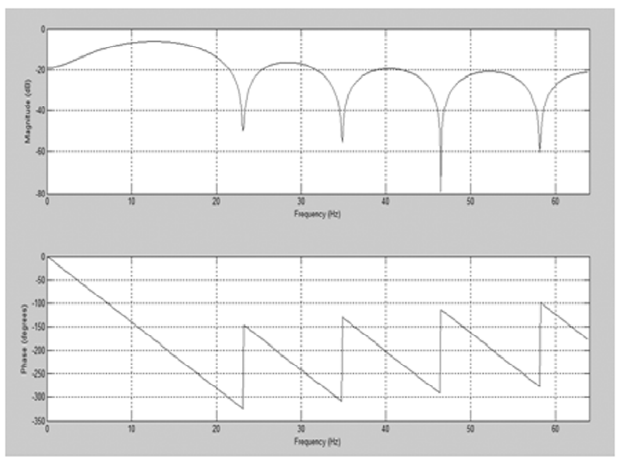


Figure 9: 10-tap FIR filter's magnitude and phase response for ALPHA band extraction in EEG

9. GRAPHICAL REPRESANTATION OF EEG IN BETA FREQUENCY RANGE [14 Hz – 30 Hz]

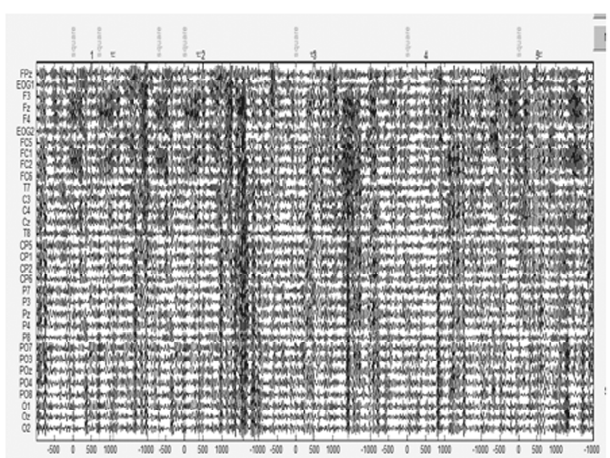


Figure 10: Graphical representation of BETA band in EEG

10. MAGNITUDE RESPONSE AND PHASE RESPONSE OF 10-tap FIR FILTER TO EXTRACT BETA RANGE

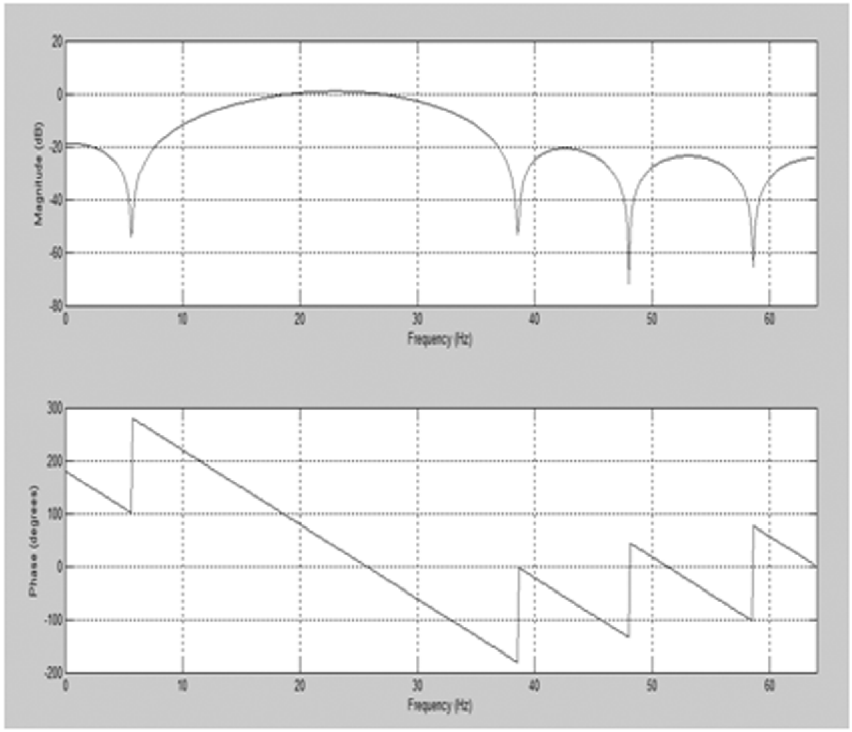


Figure 11: 10-tap FIR filter's magnitude and phase response for BETA band extraction in EEG

5. CONCLUSION

The proposed scheme presents a filtering scheme for segmentation of EEG signal into various bands. The resulting various segments or frequency bands can be mapped to specific features generated by brain in response to the applied stimuli. An experimental setup consists of unique visual stimulation paradigm was presented to record EEG signal was presented in this paper. The proposed filtering scheme demonstrates an improvement of gain function slope at the cut off frequency and reduction in degree of ripples in pass band. Future developments may address the tuning of the segmentation scheme to secondary level segmentation within a specific band.

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