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Application of Adaptive Chebyshev and Fast-Fourier Transform to Identify Bradykinesia in Humans from EEG Data Features

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Abstract: Neuroscience is a field that requires utmost meticulousness, and careful dissection of the signals involved. Brain disorders are diverse in nature, and entails one to hold a holistic cognizance of the structure and working of the neurons, along with its signals involved. The Electroencephalogram (EEG) is a data that aids in agnizing the abnormalities, and therefore requires scrupulous analysis through appropriate techniques. Bradykinesia is a neurological disorder which can subsequently lead to Parkinson's disease, and thus requires explicit observation of any small differences at its early stages through the EEG feature signals. While algorithmic approaches from previous studies have entailed the movements and development of sensory organs, this study pivots on recognizing the abnormality of the EEG data signal for an individual through pre-processing and signal processing methods. This paper pivots on utilizing Fast-Fourier Transform (FFT) and Adaptive Chebyshev using Discrete time-direct form filter to segregate the spectrum bands, the Power Spectral Density (PSD), along with the process of side lobe reduction are proposed in order to unambiguously comprehend the inconsistencies of the frequency amplitude between the normal and abnormal signals. The simulations for this study are carried out in MATLAB, and the results are successfully obtained.

Keywords: *Adaptive Chebyshev, Bradykinesia, Discrete Time - Direct Form Filter, Electroencephalogram (EEG), Fast-Fourier Transform, MATLAB, Neuroscience, Signal Processing.*

1. Introduction

A primary cardinal organ for an individual is the brain, which is enclosed within a complex structure called the cranium [4], [1]. While every organ of the human body holds vital importance in the efficient functioning of the individual's quotidian responsibilities, the functional paramount of the brain requires assiduous attention even with minor variations. The spatiotemporal operations [4] and signals from and to the brain have been studied through various domains and technological advancements, nevertheless proving their idiosyncrasy for each individual. A study by the World Health Organization (WHO) estimates the neurological and brain related disorders to be approximately higher than 50 million population [20]. Nonetheless, the advanced technologies and signal tests have helped in yielding augmented results through the recent few years as compared to the earlier decades. The electroencephalogram (EEG) is a sequence of signals passed between the various neurons in the composed structure of the brain, and has been a data of vital importance in recognizing the disparities from the usual in many cases [1]. The EEG data depicts the frequency band amplitude signals that are evident when the brain entails communication from other organs to itself. Nonetheless, the careful processing of this data is ubiquitous for any indagation relevant to the brain disorders. Bradykinesia is a neurological disorder that can be evident through efficiently analysing the EEG signals [6]. While this analysis requires the smallest variations to be monitored with utmost care, the negligence in observing the variance in EEG could lead to Parkinson's disease and other paralytic occurrences. The primary symptoms of Bradykinesia are the loss of motor skills, along with significant detrimental facial expressions [7]. However, the detection of this disorder could be identified when the EEG signals are explicitly solution to render optimal clarity of frequency-amplitude band stratification. The study of brain related disorders have been studied in the past through various mechanisms and processing tools [5], [12], nonetheless this paper pivots toward the scrupulous scrutinization of the EEG signal waves through a series of processing phases in MATLAB, before it delineates the classification variations from the given input. The key aspect of processing the EEG signals through the MATLAB built-in functions is to compare its effective frequency-band comparisons to that of the previous studies that have entailed the identification of the disease through physical movements of fingers and the utilization of sensors [8], [9]. The features of the EEG signal can be

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broadly classified based on the type of disorder that is taken up for study. Statistical anatomization of the signal data entailing mean, standard deviation and other functionalities could be effectuated in order to unsheathe the underlying categories. Nevertheless, the amplitude signal waves and their frequency ranges constitute the global motivating factor of this study. This paper is organized into different sections, with the second section providing a brief overview about the existing methods and processing techniques in correlation with Bradykinesia and EEG signal processing. Section III explicates the methodology of implementation, with section IV illustrating the results obtained, subsequently followed by the conglomerate summary in the form of conclusion and potential future work of indagation.

2. Existing Methodology – An Empirical Overview

The detriment Bradykinesia has been popularized much lesser in Asian countries, but is widely cognized in the western countries, along with gargantuan research implemented. Maria Camillo et al [2] elaborated unambiguously regarding the processing of EEG signals to diagnose a disease known as Epilepsy which is most commonly discussed and sort solutions for [5]. Their application of the different classification techniques provides an impeccable insight into the performance of these algorithmic approaches. The feature extraction of EEG signals through wavelet transforms and classification techniques through SVM and ANN [3] have been explicated by Nitendra et al. This study provides a scrupulously unambiguous perspective of the various signal waveform processing mechanisms, thus rendering the potential overview on accuracy, precision and classifier extraction parameters. Hang-Cheng Wang et al [10], delved into the impairment of EEG desynchronization prior and post motor skills, and the prominent impact that left with Bradykinesia patients. The paper detailed on the clinical results of the patients taken for observation, thereby classifying them through the statistical measurement methods such as mean and standard deviation. Yet another vital source of literature review on the chosen area of study is the articulation by Hafeez Ullah Amin et al [21], on the classification of EEG signals based on a pattern recognition approach. The accuracy of classification was delineated through a panel of processing methods such as Fisher's discriminant ratio (FDR) and principal component analysis (PCA), along with analysing the recorded signals with techniques such as K-nearest (neighbours KNN), Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and Naïve Bayes (NB) to cognize the precision and accuracy variations amongst them.

3. Methodology of Implementation

The frequency wave amplitude signals from the EEG data are panelled through a process of implementation inorder to obtain precise stratification, and identification of the disparities leading to Bradykinesia. The following figure illustrates the progressive sequence that the EEG input is subjected to.

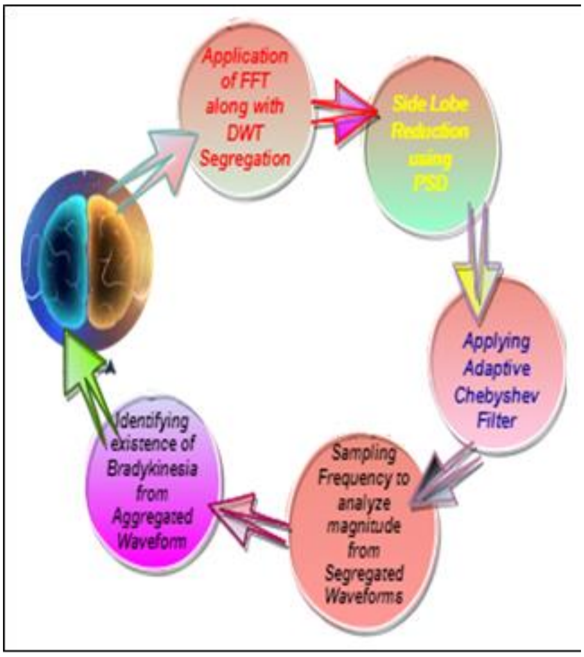


Fig 1. Process flow of the proposed Research

The EEG signal is collected with varying frequency amplitudes for each individual, and thus the segregation of the signals requires the application of discrete wavelet transform to segment the time period and frequency of the amplitude [13]. The segregated signal waves are passed through a Fast-Fourier transform that computes the inverse transform coupling pair for the vector [1]. The EEG signals of the input signal are segregated through DWT and FFT functions into different bandwidths such as [18]:

- The most prominent signal bandwidth with amplitude in the range of 1-3Hz [16], and experienced when an individual is asleep is the delta signal wave.
- The ineptness of the mental order of the individual is observed in this range of signal waves denoted by the theta frequency waves, which holds an amplitude of 4-7Hz [16], and is represented as slow waves indicating a relaxed state.
- The alpha waves are more sluggish, but hold higher range than the former with 8-12Hz [16], and denoting the brain's activity to be more indolent.
- The fastest frequency with an amplitude range of 13-38Hz [16], and thereby holding higher level of focus is proffered by the Beta waves, which most

commonly can indicate the incapacitation of an individual in any form.

The segregation of these wave amplitudes is implemented through the Fast-Fourier-Discrete Wavelet Transform that is sequenced with respect to time and bandwidth range [1], [14]. The formula used for the Fast-Fourier transform function is as given below:

$$\mathbf{Input}(\mathbf{g}) = \sum_{n=1}^{M} y(n)\ \omega_M^{(n-1)(g-1)} \quad (1)$$

$$y(n) = \left(\frac{1}{M}\right) \sum_{g=1}^{M} h(k)\ \omega_M \quad (2)$$

Where $\omega_M = e^{(-2\pi b)/M}$ can be considered as the Mth root of unity.

The next process of utilizing short-time Fourier transform to obtain the spectrogram is effectuated through the MATLAB function which returns the vector-matrix composition of the Power Spectral Density (PSD) for each of the segregated segments [17], [18]. The computation of PSD is implemented through the formula as given in equation (3).

$$P(m,n) = h|j(m,n)|^2 \quad \textbf{(3)}$$

Where h is obtained through the real-valued scalar definition utilized in side lobe reductions [19].

$$h = \frac{2}{F_s \sum_{n=1}^{V} |w(o)|^2} \quad \textbf{(4)}$$

Where w (o) depicts the hamming function which extracts the amplitude through the window sampling method. F_s Delineates the sampling through NY Quist frequencies through the factoring method. The primary reason for the use of PSD is to analyze the distributive strength of the frequency waves throughout the bandwidth [18]. The side lobe reduction process initiates the explicit identification of accurately vital data amidst closely-spaced signals [15], thereby circumventing misclassifications through the hamming function. The stop band attenuation is affixed to 0.0001 with the PSD of epochs [18] fixed using equation (5).

$$N(w) = \frac{1}{2\pi m} \left| \sum_{j=1}^{b} k(j)\, e^{-swj} \right|^2 \quad \textbf{(5)}$$

The subsequent process incorporates the adaptive Chebyshev method [11] through the discrete-time, direct-form finite impulse response filter [16] through their format parameters. This method works best with vector-matrix data, and takes into account five types of flow formats:

- Input format deals with input data signals, and processes filtering in the given input signal.
- Number format that elucidates the coefficient and numeric incorporations.
- Accumulator format, utilizes the accumulator to interpret the output signals.
- Product format, performs fraction multiplication on the operational results.
- Output format that procures the filtered output through explicitly analyzing the precision.

Figure 2 given below indicates the flow of signal through the parametric formats of the adaptive Chebyshev

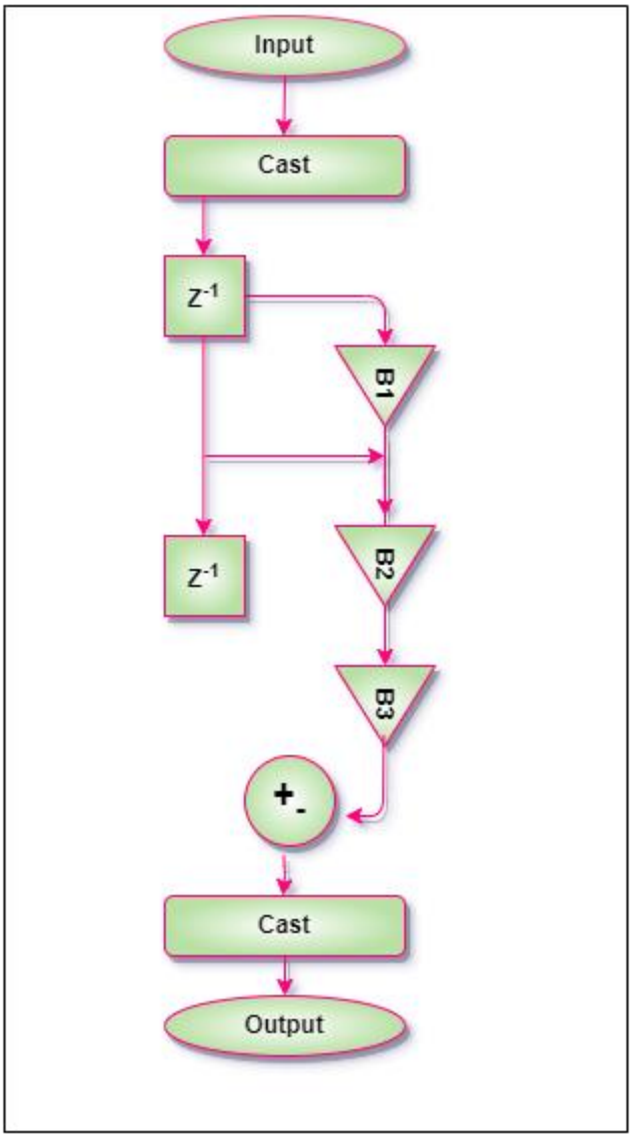


Fig 2. Signal Flow in Adaptive Chebyshev

The input format is used when the data is cast to the filter, and the inverse transform is then used with the product format in B1, B2 and B3 in order to interpret the filtered signals from the accumulator using the accumulator format. The output format unsheathes the signals that can render a rationally filtered data procured from the coefficient transfer function. The results for the above processing methods are unambiguously explicated in the subsequent section.

4. Results

The EEG signal processing outcomes are delineated in a step-wise manner for both normal and abnormal data, where disparities with the signals obtained after filtering, sequencing and segregation are set to a threshold. The segregated bandwidths from alpha, beta, delta and theta are then aggregated to check their relevance to the threshold, and the summated value is analysed to check if variations persist, in order to decide the presence of Bradykinesia symptoms for the individual.

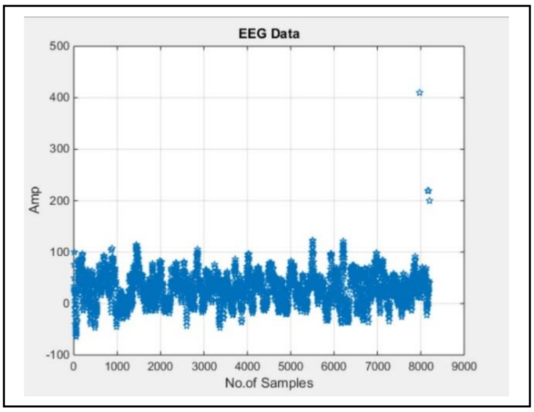


Fig 3. EEG Data for Abnormal Classification

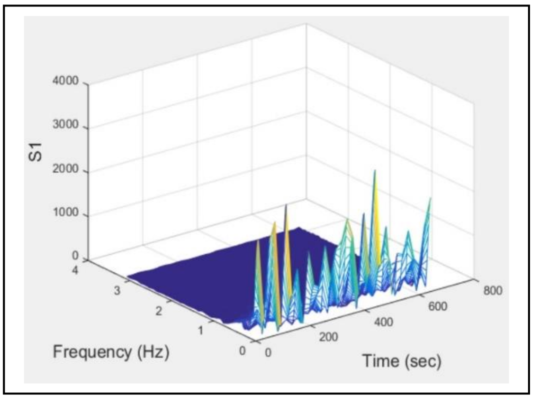


Fig 4. DWT Application

Figure 3 indicates EEG data which has been undertaken for classifying abnormalities. The abnormalities are stated in four different segments and furthermost the data are classified and evaluated as stated above. Finding of abnormalities particularly in brain is tedious task. Hence the differentiation is evaluated and concluded with optimum results. Figure 4 states DWT Application which is used for data compression to represent discrete signal.

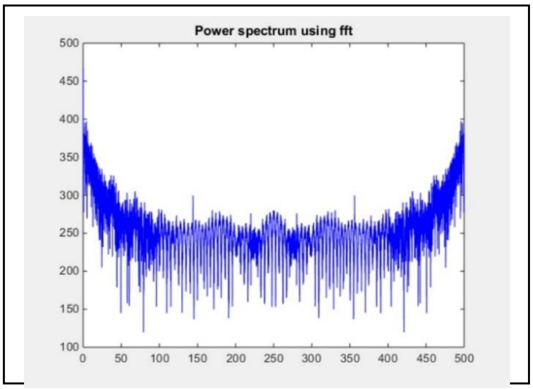


Fig 5. Power Spectrum using FFT

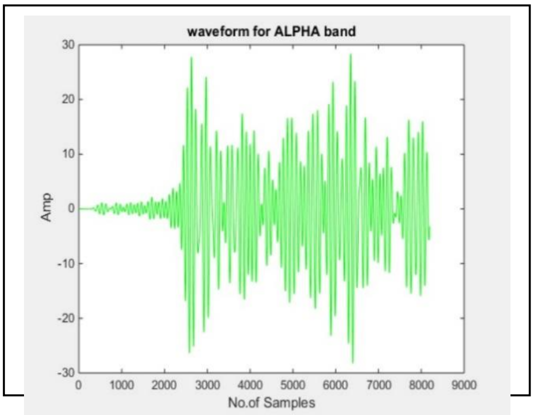


Fig 6. Alpha Waveform

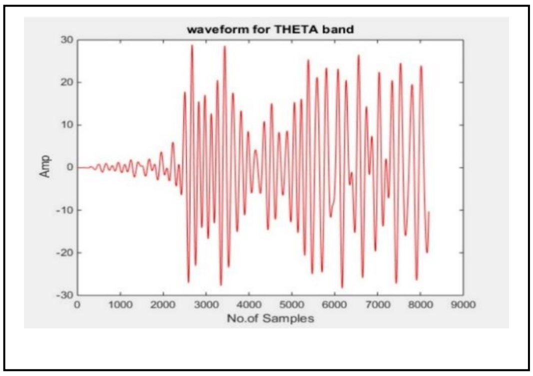


Fig 7. Theta Waveforms

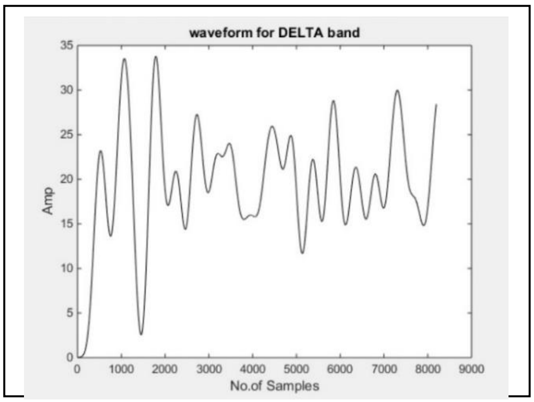


Fig 8. Delta Waveforms

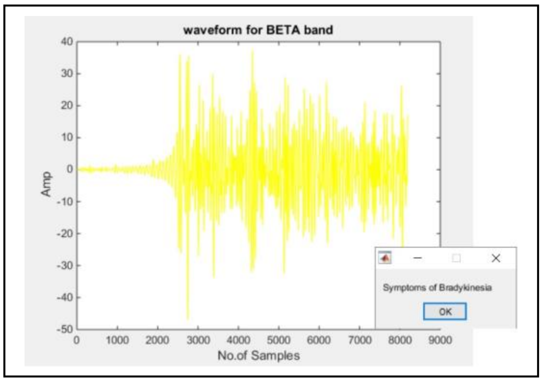


Fig 9. Beta Waveforms

The above results from figures 5 to 9 indicate the signals being processed from an abnormal EEG data, filtered through time and segregated based on the bandwidth to explicitly analyze the differences from the threshold value in the amplitude ranges.

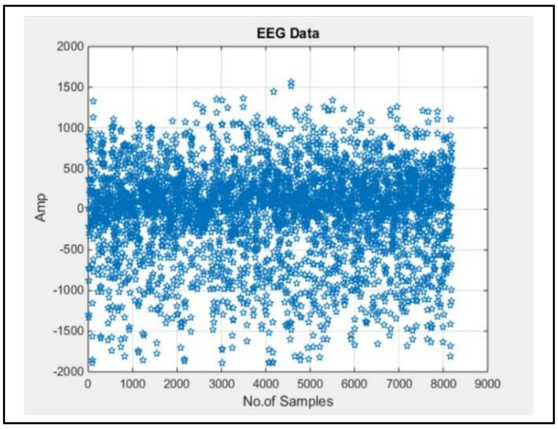


Fig 10. EEG Data for Normal Classification

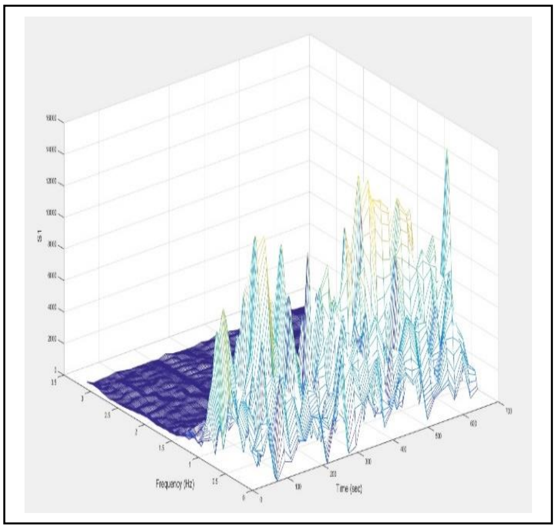


Fig 11. DWT Application

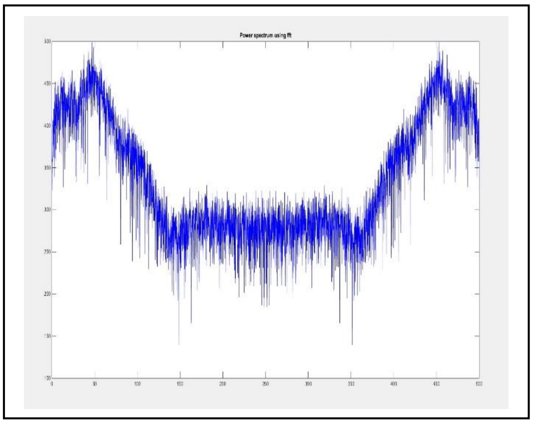


Fig 12. Power Spectrum using FFT

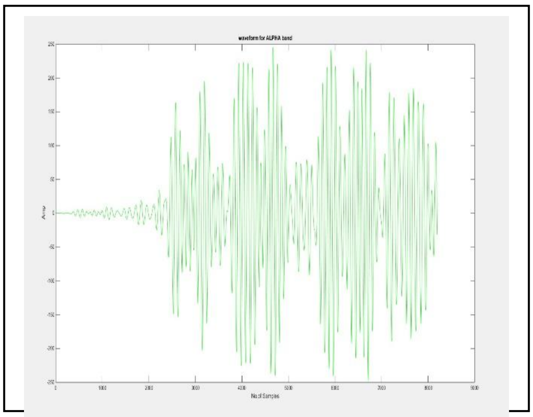


Fig 13. Alpha Waveform

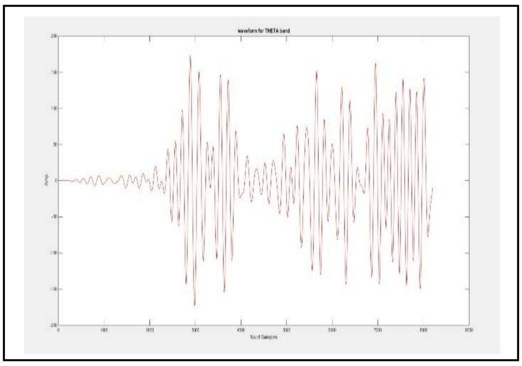
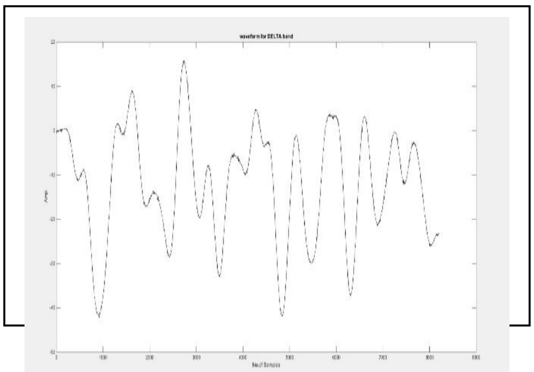


Fig 14. Theta Waveform



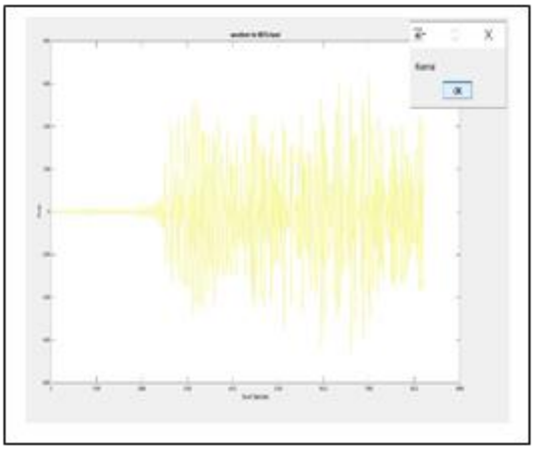


Fig 16. Beta Waveform

Figures 10 to 16 indicate the normality of EEG signals through the various phases of filtering, segregation of amplitude waves, and identifying if there is any disparity with the frequency bands in comparison to the set threshold. However, with no symptoms of Bradykinesia, the individual's data signal indicates the good brain health.

5. Conclusion

The EEG signal processing is a rudimentary methodology for identifying any neurological gremlins associated in the human brain. Nonetheless, this study emphasizes on the requisite for appropriate filtering and segmentation methods in order to explicitly identify the aberrations in the frequency amplitude that may help a neurosurgeon to detect and confirm the presence of Parkinson's at an early stage through the identifies symptoms of Bradykinesia. This study highlights the processing of EEG signals that can be potential detectors of volatility in the frequency amplitude bandwidth of the filtered waveforms. Nonetheless, factors such as side lobe reduction and accurate segmentation of bandwidth based on the amplitude frequency has remained to be a challenge in the past. This indagation successfully deciphers to disentangle the above problems through the use of Fast-Fourier Discrete filtering techniques, and prepares the signal for better stratification by utilizing the Adaptive Chebyshev method. The threshold value distinguishes the normal and abnormal waveforms from the aggregated value obtained from the different frequency bandwidths, thereby delivering accurate stratification results for identifying Bradykinesia. The future enhancements relate to optimizing the accuracy of classification through other classifiers, and in augmenting the EEG feature extraction through algorithmic techniques for establishing juxtapose observations.

Conflicts of Interest

The authors declare no conflicts of interest

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