I.J. Intelligent Systems and Applications, **2024, 2, 40-52**
Published Online on April 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijisa.2024.02.04

Quantification of EEG Characteristics for Epileptic Seizure Detection and Monitoring of Anaesthesia Using Spectral Analysis

Anand Ghuli*
Department of Computer Applications, B.L.D.E.A's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur-586103, Karnataka, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India
E-mail: mca.anand@bldeacet.ac.in
ORCID iD: https://orcid.org/0000-0002-4173-0283
*Corresponding Author

Anil Kannur
Department of Computer Science & Engineering, B.L.D.E.A's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur-586103, Karnataka, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India
E-mail: anilkannur1978@gmail.com
ORCID iD: https://orcid.org/0000-0003-2492-1683

Abhishek Mali
Department of Computer Applications, B.L.D.E.A's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur-586103, Karnataka, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India
E-mail: maliabhishek168@gmail.com

Aishwarya Mangasuli
Department of Computer Applications, B.L.D.E.A's V.P. Dr. P.G. Halakatti College of Engineering and Technology, Vijayapur-586103, Karnataka, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India
E-mail: aishwaryam302001@gmail.com

Received: 26 December 2023; Revised: 14 January 2024; Accepted: 23 February 2024; Published: 08 April 2024

Abstract: Epilepsy is considered one of the primary neurological disorders, and its treatment requires abundant technological assistance. General Anaesthesia induces distinct patterns in brain activity, with the most common being a gradual increase in low-frequency signals as the level of Anaesthesia deepens. In this instance, a method of validating epileptic seizures and Anaesthesia through the utilization of electroencephalogram (EEG) data, acquired non-invasively, is introduced. Epileptic seizures and detection of the presence of Anaesthesia approaches make use of discrete Laplace Transformation (LT), Discrete Cosine Transformation (DCT), and Fast Fourier Transform (FFT). Here, it is discussed how power spectral analysis (PSA) helps study EEG characteristics in detecting epileptic behavior and the presence of Anaesthesia. A dataset of EEG (Epileptic and Anaesthesia), which is available publicly [1,2], has been used in the propounded technique using FIR filters and LT, DCT, and FFT are used to store and process 16 channel data. Power Spectrum Density (PSD) and its average were contrasted against a specific spectrum and frequency range of a typical EEG signal to obtain the results. This work uses a technique to determine whether the patient being studied is epileptic and awake or anesthetized.

Index Terms: EEG, Epileptic, Anaesthesia, Seizure, Wake.

1. Introduction

A common neurological condition known as epileptic seizure and Anaesthesia is characterized by aberrant electrical brain activity. Numerous researchers have worked on EEG signal processing to accomplish accurate categorization and interpretation of EEG data and are actively doing so today. Accurate seizure detection and forecasting are essential for epilepsy management and treatment. To support the recognition and diagnosis of epileptic seizures and detecting the presence of Anaesthesia, numerous signal processing and analysis techniques have been created. Many academics are increasingly becoming interested in EEG signal processing to help in the precise analysis and categorization of epilepsy [3,4]. The clinical symptoms, including the EEG patterns associated with unconsciousness induced by general Anaesthesia can be categorized based on their occurrence at three different time points: induction, maintenance, and emergence.

Epilepsy's clinical symptoms and EEG patterns vary depending on the person's response. Epileptogenesis refers to conditions such as tumors in the brain, strokes, head injuries, and neurological disorders. Such situations may potentially be related to hereditary alterations. One method for capturing the brain's activity, which is electrical, from the upper part of the scalp, is using an EEG. The recorded waveforms depict the electrical behavior of the outer layer of the cerebral cortex. The quantity of collected signals indicates the lowest level of EEG activity and is commonly measured in microvolts (μV). EEG is the technical term. It is used for capturing and assessing electrical activity of the brain. The electrical potentials that neurons (brain cells) produce as EEG measures brain waves. These brain waves result from synchronized electrical activity among several different neuronal populations.

Tiny metal electrodes are positioned on the scalp in certain places throughout the EEG recording to identify and gauge the electrical impulses generated by the brain. An EEG amplifier linked with the electrodes amplifies and digitizes the data for additional analysis. With negligible input from glial cells, the EEG comprises the collective electric impulses of groups of neurons because neurons are cells that can be stimulated easily with specific intrinsic features. When neurons display their distinct electrical characteristics while in an active state, they generate both electrical and magnetic fields. These fields can be identified by utilizing electrodes positioned in proximity to the sources (referred to as local EEG or local field potentials, LFPs), located above the outer layer of the cortex (known as electrocorticogram, or ECoG), or even from a greater distance through the scalp (specifically, the EEG, in the most direct sense). Sensors close to each other around the scalp and fragile neuronal electromagnetic fields are usually employed to record the accompanying MEG [5].

Human EEG wave frequencies are categorized into four main groups: delta wave, theta wave, alpha wave, and beta wave. A delta wave exhibits a frequency of 3 Hz or lower and displays the highest amplitude. This dominant rhythm is observed in infants up to one year of age and during sleep stages 3 and 4 [6]. Focal instances of this wave can be observed in conditions such as "subcortical lesions," while more widespread distribution with diffuse lesions, metabolic encephalopathy, hydrocephalus, or deep midline lesions may also lead to this pattern. Notably, this wave is more pronounced in the posterior region of children and in the frontal region of adults [6]. Regarding theta waves, the sluggish activity range of frequencies is between 3.5 Hz and 7.5 Hz [6]. This would be deemed weird for adults who are awake, but for children under 13, it's perfectly natural. Typically, this would be regarded as a symptom stemming from isolated subcortical lesions. Additionally, it could also be interpreted as a widespread dispersion seen in diffuse conditions like metabolic encephalopathy or occasional instances of hydrocephalus [6]. Alpha waves encompass frequencies ranging from 7.5 Hz to 13 Hz; they are located on the backs of the heads on opposite sides and are more readily accepted on the dominant side. Contrarily, beta waves denote "quick" behavior, extends a range of frequencies of a minimum of 14 Hz, and is often distributed evenly between both sides of the brain, with the frontal region showing the most significant sign of it [5]. Narcotic sleep aids, in particular, "Benzodiazepines and barbiturates," emphasize this. It is often thought of as a regular rhythm, may be not present or reduced in regions of cortical impairment and in favor of those who awake, restless, or with their eyes open, is the predominant beat [6]. Medicative treatment for those with mental disorders frequently considers the EEG waves emphasizing properties. Because human EEG waves have specific characteristics, medical professionals can effectively treat epilepsy, a mental condition. A synergistic addition will be made of technical help for epileptic seizure endorsement and detecting the presence of anaesthesia for medical practitioners.

This paper is structured as follows: section 2 presents a review of the state of the art methods. Afterwards, section 3 presents a little description of the EEG data preprocessing and processing. We then present our detailed architecture for classification. We analyze the experimental results in section 4. In final, section 5 presents a conclusion of the paper.

2. Related Works

Brain-computer interface (BCI) research is currently captivating a lot of attention. BCI functions as a conduit between the brain and other devices. The BCI considers the outside equipment a body part and aids in thorough brain mapping. In the BCI, research is done along with the augmentation, mapping, correction, and restoration of sensory, experimental, and cognitive processes. A Brain-Computer Interface (BCI) acts as a communication bridge, translating brain signals into commands for electronic devices. It enables users to interact with computers and other devices solely through their brain activity, bypassing the need for peripheral nerves and muscles. BCI research focuses on empowering individuals with impairments, allowing them to connect with others, control mechanical limbs, and manage their surroundings. Beyond assistive technology, BCIs also show potential in multimedia communication. Researchers explore invasive and non-invasive technologies, analyze control signals, develop algorithms for translating brain signals, and innovate new BCI applications [7].

In the investigation of mental illnesses, EEG signals are essential. Among primary mental disorders, epilepsy requires much technological help to be treated. An endorsement strategy for epileptic seizures via EEG data recorded using a non-invasive technique is suggested. Discrete wavelet transformation (DWT) and the PSD are utilized in the procedure. Here, it is discussed how PSA affects the use of EEG characteristics to support the methodology. FIR filters and DWT are employed to analyze an openly accessible EEG dataset of epileptic activity. In order to acquire the outcomes, the PSD and its mean were correlated with a particular spectrum and the range of frequency of typical EEG signal [7].

The study's main emphasis focuses on the BCI and the difficulties that come with it. The study also seeks to achieve the classification of left- and right-hand movements by tackling signal artifacts present in the signals collected during different hand motions [8]. Around 70 million people worldwide experience epileptic seizures. This study utilizes EEG, a non-invasive method for monitoring brain activity, to create an efficient algorithm for automated seizure detection. The method distinguishes between regular and seizure-related EEG data by analyzing fundamental dynamics. Parameters like Shannon entropy, collision and transfer entropies, conditional probability, and Hjorth parameters are extracted from sub-bands using adaptable Q wavelet transform for robust classification. Kruskal-Walli's test determines the optimal decomposition level for each feature vector, ensuring reliable performance. Many features are combined into a single fused feature vector using a fusion approach known as discriminant correlation analysis. Transfer entropy is also discovered to be very important in differentiating between distinct class combinations. The suggested method for distinguishing healthy-seizure EEG signals uses hidden Markov models with faster calculation times and simple yet effective features to attain 100% accuracy[9].

The discrete wavelet transform (DWT) is utilized alongside the EA technique to extract crucial features from EEG signals. Furthermore, a specialized neural network model (NNE) is developed specifically for detecting epilepsy. To thoroughly gauge the effectiveness of this approach, the study examined various classifiers and feature extraction methods. The test results demonstrate that the introduced method achieved a remarkable recognition accuracy exceeding 98%. This high accuracy renders it a valuable and practical solution for real-world applications related to individuals with epilepsy [10].

The rapid prototyping platform, coupled with the design and development framework, facilitates swift exploration of innovative human-in-the-loop applications, fostering research opportunitiesin technologies that improve how humans interact with the physical environment [11]. Machine Learning (ML) has progressed into various domains or disciplines, the cutting-edge approach for numerous challenges. However, given the specific constraints offered by ML, adding user expertise integrating this into the system could prove beneficial. The objective of including human domain knowledge is to bolster the automation of machine learning. Given that machine learning cannot rival human domain expertise, the concept of human in-the -loop is becoming more pertinent in forthcoming research endeavors[12].

The study aims to create an automated system that reliably and correctly categorizes seizure patterns in complex EEG data. Automated solutions are required since visual analysis of EEGs for seizure identification is challenging, time-consuming, and prone to error. The suggested method uses little supervised training to analyze EEG data from two separate repositories[13]. Among the foremost essential approaches for curing or controlling drug-resistant epilepsyis surgical treatment, and preoperative localization of epileptic lesions is critical to surgical success. Given the time and effort required for manual diagnosis, a self-operating identification system to facilitate medical assessment required. As a result, a new automatic focal EEG identification technique was proposed by adding flexible analytic wavelet transform (FAWT). The suggested methodology was evaluated using theBern Barcelona data repository with accuracy rate of 94.80% in discriminating F and NFEEG recording were acquired using the LS-SVM classifier [14].

Unexpected deaths kill about 0.1 percent of epileptic patients. Broadly speaking, in cases of stubborn seizures, possessing an algorithm capable of seizure detection correctly and automatically and notify carers so that patients can receive assistance is very crucial. EEG signals are used to create a conclusive diagnosis of seizure occurrences. The suggested data embedding technique efficiently addresses the difficulties associated with high-dimensional data classification, including time complexityand memory needs, and enables data visualization in two or three dimensions. Additionally, to distinguish between epileptic and non-epileptic occurrences, KNN classifier was used. The results show that, with an F-measure of morethan 87%, our nonlinear strategy outperforms conventional dimension reduction techniques in visualization and classification effectiveness [15].

The EEG provide information about the brain, are read to identify epileptic seizures. The sudden aberrant activity of many neurons that causes a brain electric surge is an epileptic seizure. To classify data and extract the characteristic used in the detection of epileptic seizures, a mixture of DWT and power spectral density is suggested. Deep Learning (DL) has been utilized to acquire a high seizure detection rate and analyze pertinent informationfrom the EEG-analyzed dataset[16].

The BCI-equipped robotic arm has been designed and tested to trigger each joint in every possible direction. Amputees who have lost appendages but yet have normal brain function can utilize this device [17]. By appropriately collecting and analyzing the brain waves, the prosthetic arm may be programmed to bend in any direction the user desires [17]. Developing a system with decreased noise sensitivity is possible by using more efficient signal processing techniques. The execution of device commands and feature extraction can be made less unpredictable by a comparable algorithm [17]. The frontoparietal and parieto-occipital networks primarily encode data related to target and cursor locations as well as velocities in the low-frequency EEG [18].

Among individuals who have experienced spinal cord injuries (SCI), attempts at movement of the arms and hands are maintained as decodable neural correlates. The open hand, the palmar part comprehends lateral grasp, pronation, and supination of ten patients with cervical SCI have all been evaluated. Low-frequency EEG signals' time domain offered discriminative movement information. Regarding the 5 investigated classes, a maximum average classification accuracy of 45% has been attained based on these signals (chance level was 20%). When applied to an individual with cervical SCI, the proof of concept demonstrated the ability to classify movements for online closed-loop attempts. The system achieved a modest classification performance of 68.4% for distinguishing palmar grasp from hand open (compared to a chance level of 50%) [19].

The survey emphasizes addressing the gap between the endorsement of epilepsy and anaesthesia manual and the usage of technology, leading to a conclusory remark as "Scope in contributing towards 100% accuracy in endorsement and correlative analysis of epileptic seizure and anaesthesia".

3. Proposed Approach

Applications across both medical and non-medical domains demonstrate the usefulness of EEG signal processing. The methodology presented here consists of several vital steps significantly affecting the outcome. The steps in this process are dataset acquisition, filtration, feature extraction, categorization, and recognition. Filtering is done to extract signals of interest, DCT is applied to extract features. Recognition and classification are performed for the power spectrum. The block diagram of EEG signal processing and classification of the brain is illustrated in Fig. 1. The patient being studied was verified using the 16 - channel EEG cap, which was utilized to acquire the dataset for the suggested method (epilepsy and anaesthesia). For epileptic seizure detection, EEG signal capture is first completed on ten subjects, followed by channel selection to obtain the desired data. The attributes used in the categorization are extracted as features using Laplacian. The attributes for categorizing epileptic seizure detection and the presence of Anaesthesia are extracted as features using Laplacian and DCT. Raw EEG power spectral examination revealed the properties of the hypnotic agent, which are correlated with the agent's mechanism, and these properties illustrate the power spectrum's potency.

Fig.1. EEG signal processing and analysis of brain

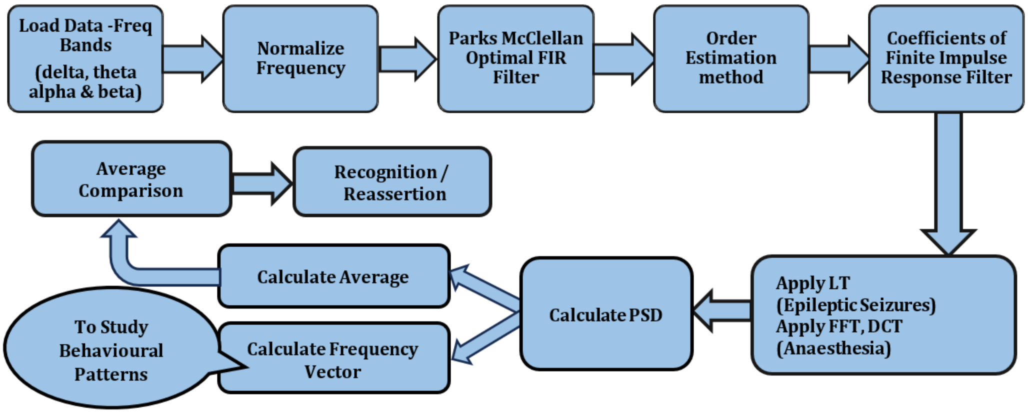

Fig.2. Detailed Methodology of EEG signal processing and analysis for brain

Beta oscillation occurs commonly when propofol is used to sedate a patient, and slow-delta oscillation happens when the patient loses consciousness. Midazolam's EEG pattern and method of action are comparable to propofol, and it frequently induces beta oscillation, which is a common sign of drowsiness. The 25–32 Hz band exhibits the oscillations of beta, gamma, and ketamine. A slow oscillation within the spindles characterizes dexmedetomidine.

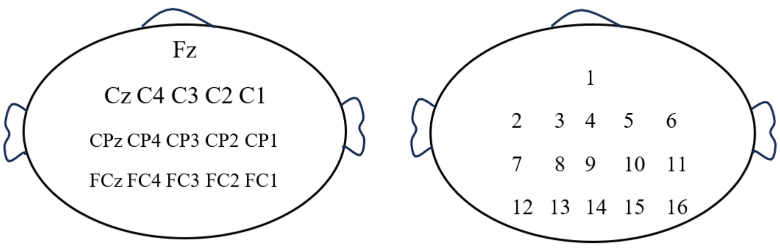

Fig.3. 16 channels cap layout

The proposed approach of Fig. 1 depicts the processing and classification of brain EEG signals. Fig. 2 illustrates the processing and interpretation of the signal obtained from the EEG recordings and the patient's epilepsy and Anaesthesia reassertion process. The methodology followed here needs some initial setup. The EEG data collected utilizing a 16-channel EEG cap is displayed in Fig. 3 using settings such as sampling frequency (SF), passband frequency (PBF), passband ripples (PBR) for both initializing and stop band frequency (SBF) pertaining to the frequencies of waveforms (delta, alpha, beta, and theta), a publicly accessible EEG dataset is used [20,21]. The signal is measured using the fixed, straightforward range of [PBF. SBF] / Half of SF after PBF and SBF normalization. Using frequency sampling, the frequency $'f'$ is normalized to yield $'fn'$ within the range of [0 to 1]:

$$fn = {}^{f}/_{fs} \tag{1}$$

According to the Nyquist-Shannon theorem, the SF is typically at least twice as frequent as f. As a result, Eq. (1) cannot be greater than 1/2. Eq. (1) is multiplied by 2 in order to obtain fn between the range [0, 1]:

$$fn = 2 \times {}^{f}/_{fs} \tag{2}$$

This algorithm produced the highest filter coefficients, with the most effective FIR filters being produced by a more indirect method. Using the Chebyshev approximation, the algorithm's primary goal is to decrease inaccuracy within pass bands and stop bands. Digital FIR filters are constructed using the Parks-McClellan algorithm, commonly called the Remez exchange algorithm. It bears the names of James H. McClellan and Thomas W. Parks, the project's creators. The approach is frequently employed to create linear-phase FIR filters with predetermined frequency response properties. It seeks to identify the ideal filter coefficients that reduce the discrepancy within the anticipated frequency response and the actual filter response. The Parks-McClellan technique uses an iterative method that alternates extremal positions to update the filter coefficients iteratively. It begins with a preliminary estimate of the coefficients of filters and iteratively improves them until convergence is reached, often based on predetermined fault tolerance.

Parks-McClellan Algorithm [22]

- Set the filter's desired frequency response. This includes the required magnitude response, including any filter limitations, such as the highest passband ripple or the minimal stopband attenuation.
- Create a starting collection of filtering coefficients. A windowing function, such as the Kaiser or Hamming window, can do this.
- Utilize the Remez exchange method to update the filter coefficients iteratively. The algorithm alternates between estimating the required frequency response and adjusting the filtering coefficients based on the current estimation.
- Calculate the filter's frequency response using the revised coefficients, then match it with the desired response. The method ends if the most significant deviation satisfies the intended standards. If not, it moves on to the next iteration.
- Till the appropriate frequency response is obtained within the designated tolerance or the allotted number of iterations has been reached, repeat steps 3 and 4 as necessary.

The Parks-McClellan algorithm represents a complex filter design subject, and the implementation specifics can be complex.

Parks-McClellan FIR filter [23]

Filtering the data with a discrete-time (DT), direct-form FIR filter determined by a numerator coefficient vector results from computing the numerator coefficients. The LT of the filtered EEG signals is calculated which determines the second-order discrete difference along each input data dimension. For discrete signals, it is often utilized to approximate the Laplacian operator. In signal processing and image processing, the Laplacian operator is used to improve features and find edges or discontinuities in the data. The discrete Laplacian method can be used in EEG analysis to learn more about the signal's spatial distribution and to spot abnormalities or localized alterations.

When applied to U using the standard point spacing of h = 1, L = LT(U) gives a discrete approximation of Laplace's differential operator. A consistent scalar distance, h, between points in all of U's dimensions is defined by the formula L = LT(U, h) [23].

$$l = \frac{\Delta^2 u}{4} = \frac{1}{4}\left[\frac{d^2u}{dx^2} + \frac{d^2u}{dy^2}\right] \tag{3}$$

The spacing hx, hy, hN between points in each dimension of U is defined by L = LT(U, hx, hy, hN). Indicate whether each input for spacing is a scalar or a vector of coordinates. There must be an equal number of inputs for spacing for each U-dimensional element [23]. The initial spacing value, hx, provides details regarding the x-spacing or x-coordinates of the points. If it is a vector, its length must match the size(U,2). The second spacing value, hy, describes the points' y-coordinates or y-spacing as a vector. If input U is a matrix, the interior points of L can be determined by comparing each point in U to the average of its four adjacent points.

As with any Fourier-related transform, DCTs combine sinusoids with different frequencies and amplitudes for expressing a function or a signal. Functions at discrete data points having a finite number of points each are subjected to a DFT and DCT. A DFT uses cosines and sines (in the format of complex exponentials), but a DCT only uses cosine functions, this is an obvious distinction between the two. A DCT implies distinct boundary factors from a DFT or any analogous transformations, which is the cause of this apparent mismatch[24,25]

$$X_{K=} \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right] \qquad \text{for k=0, …N-1} \tag{4}$$

Up to a scale factor of 2, this transform is precisely equal to a DFT with 4N factual inputs exhibiting even symmetry and zero even-indexed elements.

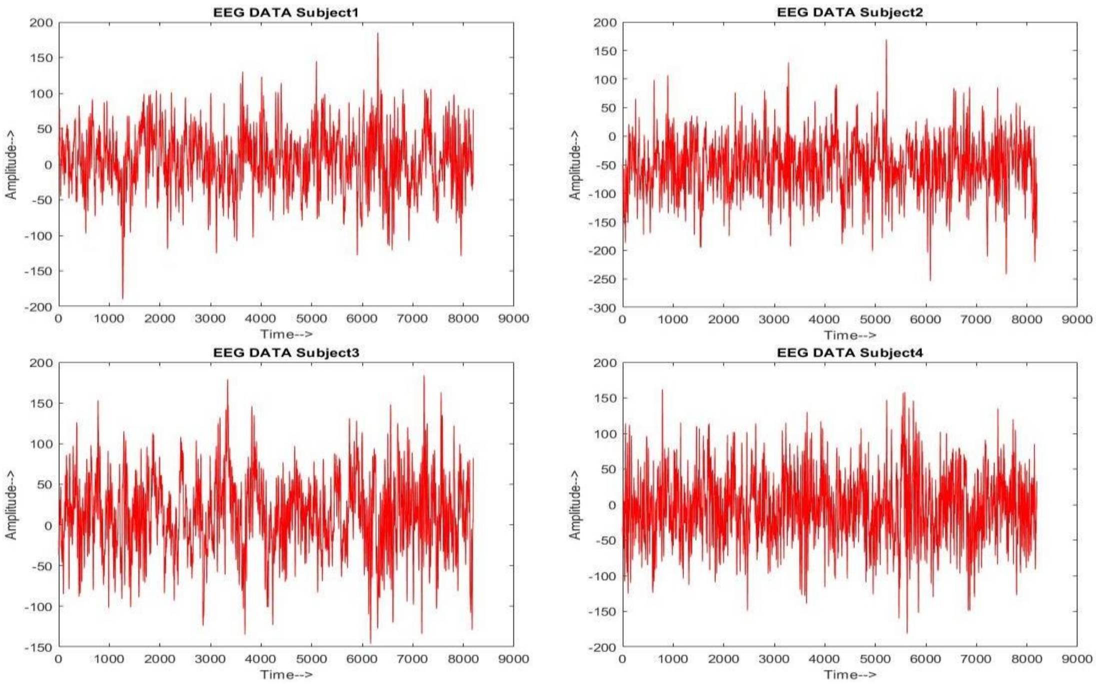

Fig.4. Few samples of EEG data collected from the subjects

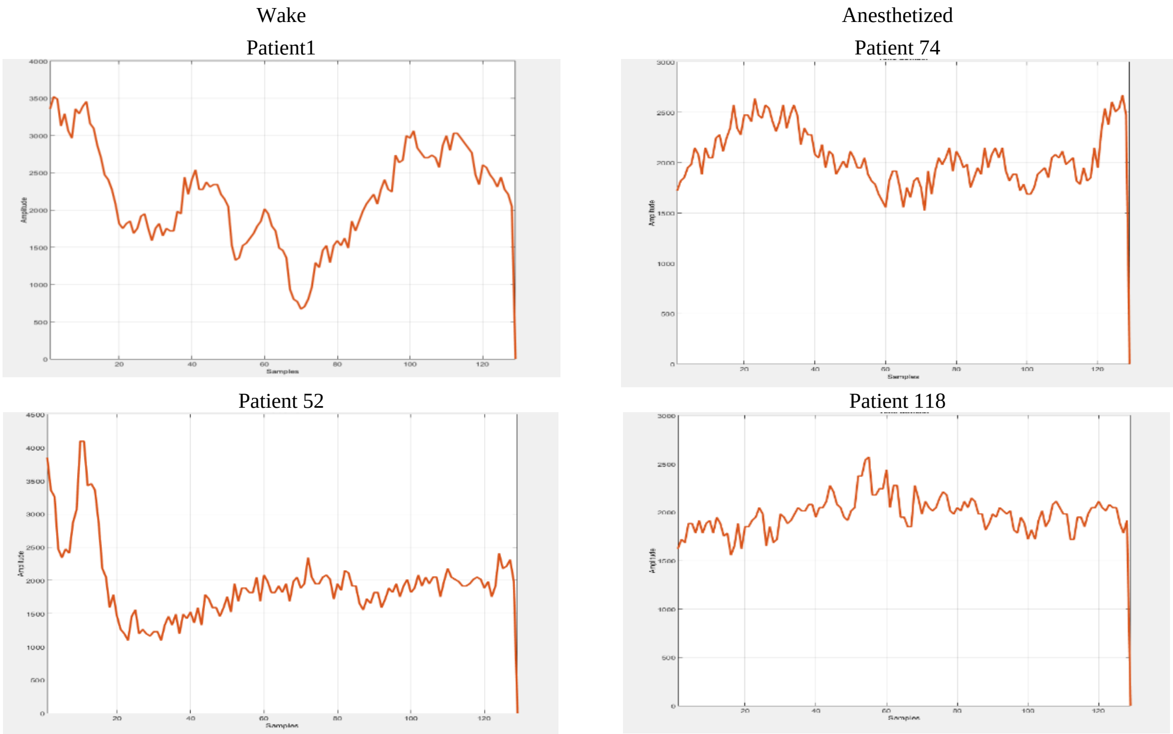

Fig.5. Few samples of EEG data acquired from dataset (Anaesthesia)

The DFT of the 4N inputs, y_n, where y_{2n}=0, y_{2n+1} = x_n for 0≤ $n < N$, y_{2N}=0, and y_{4N-n} = y_n for 0< $n < 2N$. Using a 2N signal next to multiplication by half shift and DCT transformation is also an option. Accordingly, the rest of the matrix is multiplied by a total scale factor of $\sqrt{2/N}$. the X_0 term is further multiplied by $1/\sqrt{N}$. This eliminates the immediate correlation with a real-even DFT of a half-shifted input but makes the DCT matrix orthogonal.

Scaling can be selected to compute DCT with fewer multiplications in many applications, such as JPEG, where scale factors are capable of being paired with computing stages (such as the quantization step). The DCT entails the boundary conditions: x_n is even around n = - $^1/_2$ and n=N= - $^1/_2$, X_k is centred around k=0 and exhibits odd symmetry around k=N. The periodogram is the Fourier transformed of the biased estimate of the autocorrelation sequence. For a signal x_n sampled at fs samples per unit time, the periodogram is expressed as

$$\hat{P}(\omega) = \frac{\Delta t}{N}\left|\sum_{n=0}^{n-1} x_n e^{j2\pi f \Delta t n}\right|^2, -^1/_2\,\Delta t < f < {}^1/_2\,\Delta t \qquad (5)$$

4. Experiments

Algorithm

Input:

EEG Data: It comprises the raw EEG data, displayed as a matrix with a time point for each row and an electrode channel for each column. The program believes that the variable "data" has this EEG information[26-30].

Output:

The result of the provided code snippet is a determination of whether the EEG data is categorized as "Epileptic" as well as “Anesthetized or Awake” based on the calculated average power values and the highest power value in each frequency band (delta, theta, alpha, and beta).

Step.1: START: Set up any necessary hardware, libraries, or variables.
Step.2: LOAD THE EEG DATA: Load the processing environment with the EEG data.
Step.3: Define the sampling frequency (SF): Describe how frequently the data were recorded.
Step.4: Set the PBF data to 0 at initialization.
Step.5: Set the delta, alpha, beta, and theta waves SBF.
Step.6: Adjust the PBR for the delta, alpha, beta, and theta waves.
Step.7: Define stop band ripples (SBR) of the waves(alpha, beta, delta, theta).
Step.8: NF = [PBF SBF] / (SF/2) to calculate the normalized frequency.
Step.9: Implement the Parks-McClellan algorithm-based linear-phase FIR filter.
Step.10: Get the FIR filter coefficients.
Step.11: Produce FIR filter with numerator coefficients in discrete time.
Step.12: Apply the numerator coefficient vector-described filter to the data.
Step.13: Apply the Discrete Laplacian function (Epileptic Seizure) and FFT, DCT (Anaesthesia)
Step.14: Take samples.
Step.15: Use the periodogram method to calculate the samples' power spectrum densities (PSD).
Step.16: Calculate the average power.
Step.17: Compare the average power of the delta, alpha, beta, and theta waves with the maximum PSD (Anaesthesia, Wake, Epileptic)
Step.18: STOP

Overall, this technique describes the steps involved in filtering the EEG data, computing power spectrum densities, and finally utilizing those calculations to examine the patient's brain activity to detect epileptic seizures along with being anesthetized or awake. The flow diagram in the suggested technique recognizes that the patient being tested is experiencing epileptic symptoms along with being anesthetized or awake[30-36].

Result And Discussion

In this section, the importance and accuracy of the outcomes are discussed. Power spectral density (PSD) EEG data analysis is implemented within the provided code to identify seizures, including anesthetized ones. To identify whether an individual is in both the proposed cases, the PSD is computed for a variety of frequency bands. A minor divergence in LT indicates that the brain is experiencing epilepsy rather than being in a coma or unconscious. Epileptic seizures vary from hardly discernible, shortbursts to prolonged, vigorous shaking[37-42]. Fig. 7 shows that epileptic seizures are marked by high and erratic cerebral cortex neuronal activity. These seizures frequently recur and lack a clear-cut, immediate explanation.

Data visualization can be done loads and displays the Subject's EEG data. It allows for visual data analysis by plotting time-domain EEG signals for various channels. This stage of visualizing the raw EEG signals aids in recognizing any patterns or anomalies that could be present. The method proposed concentrates on the frequency ranges of delta, theta, alpha, and beta.

Nature of Power Spectrum (Epileptic Seizures)

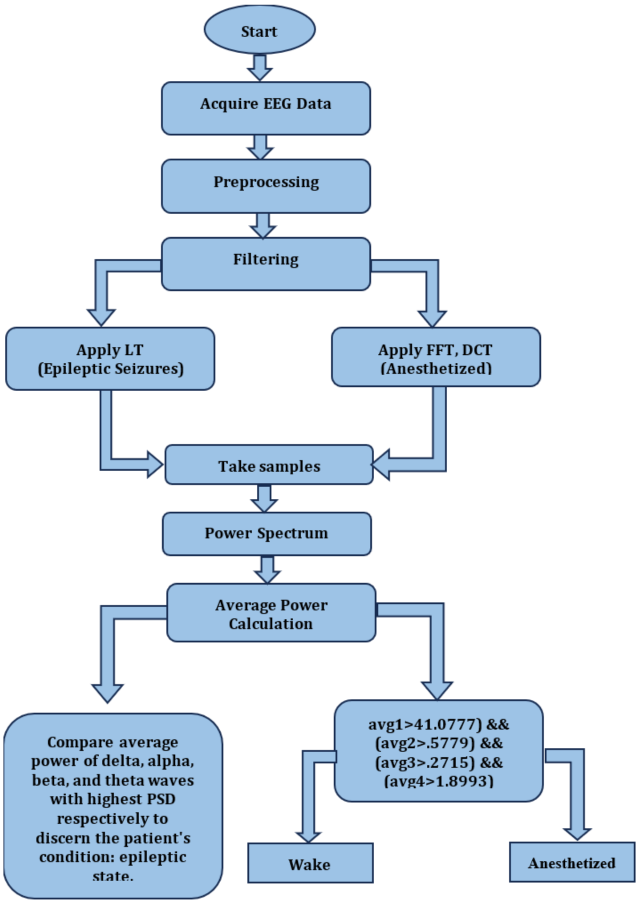

Fig.6. Flow diagram for analysis and detection of epileptic seizure and Anaesthesia

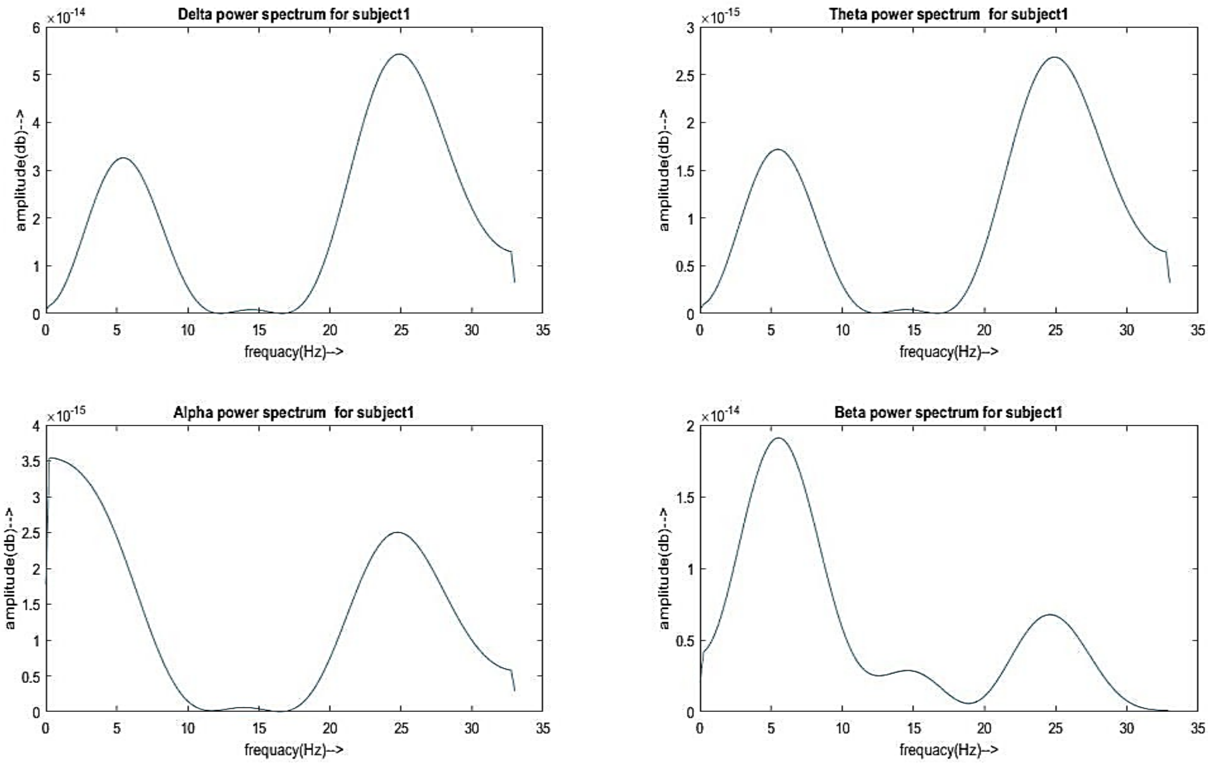

Fig.7. Few samples showing Power spectrum of a subject

These bands are frequently employed in EEG evaluations and have been linked to various patterns of brain activity. Deep sleep is characterized by delta waves (0–4 Hz), aberrant during specific seizure types. When drowsy or in the beginning phases of sleep, theta waves (4–8 Hz) are seen. When the individual is alert or relaxed, with closed eyes, alpha waves from 8 to 13 Hz predominate. Beta waves ranges from 13 to 30 Hz) are connected to attentiveness and active cognitive processing. Depending on the study's unique needs or therapeutic settings the unique needs of the study or therapeutic setting, different frequency bands may be selected. Applying digital filters to isolate the desired frequency ranges allows for filtering and signal processing. The accuracy of the analysis that follows is improved by filtering out undesired frequency components and background noise. For precise results, choosing the proper filter parameters, including ripple, stopband attenuation, and cutoff frequencies, is essential. PSD calculations can be done on separate frequency bands of interest (delta, theta, alpha, and beta); the algorithm applies several digital filters on the EEG data.

The implemented system calculates the PSD by applying the periodogram approach within every frequency band. The PSD represents the power distribution across various frequencies in the corresponding bands. The average power for each band is calculated by adding the PSD values, then dividing the result by the total number of samples. Subsequently, the PSD and average power are plotted for every frequency band. Each frequency band's maximum PSD value is compared to the average power in that band by the code. A possible seizure and the presence of dataset's features if the average power is higher than the maximum PSD value. Based on the feature anesthetization set and particular clinical requirements, the cutoff value for seizure detection and anesthetization might require additional adjusting and fine-tuning. It is critical to assess the algorithm's effectiveness using a variety of datasets that include epileptic in addition to the appearance of Anaesthesia instances. The receiver operating characteristic (ROC) curves, particularity, sensibility, and correctness can all be used to assess how well the algorithm performs. The algorithm's dependability must be assessed by validation tests including several subjects, expert assessment, and comparison with recognized seizure detection techniques.

Seizures come in a variety of forms, such as rigidity of the muscles, decrease in muscular control, jerky motions of the neck, face, and arms, uncontrolled rapid shaking of your legs as well arms, solidifying parts of the body, lack of bladder or inner control, remaining silent, reduction of cognition, and others. When the findings were checked against the techniques of collecting data, along with existing literature, they were found to be different. Therefore, Data that is static and consistent is needed for the comparison, such as the type of epilepsy, the patients' characteristics, their age, etc.

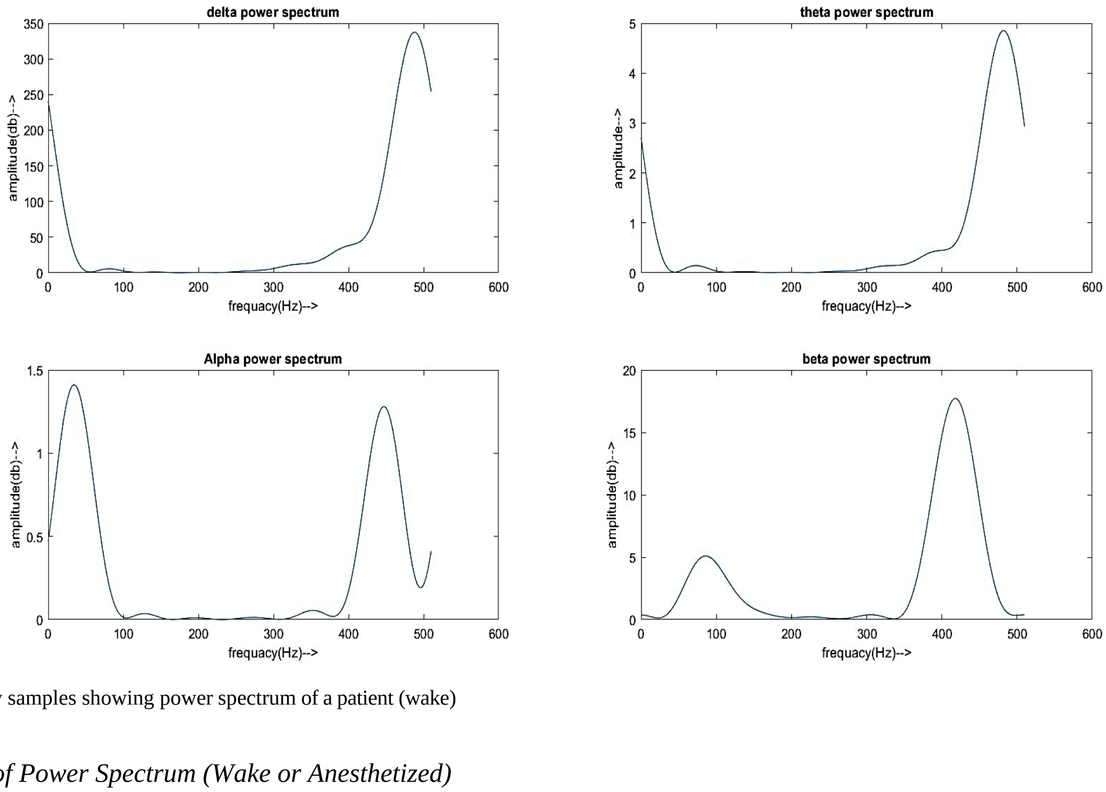

Fig.8. Few samples showing power spectrum of a patient (wake)

Nature of Power Spectrum (Wake or Anesthetized)

The findings, for instance, sub-1 from Fig. 7, reveal that pertaining to the range of frequency from 1 to 35 Hz, the waveform is dropping between 1 to 35 Hz, indicating a likelihood of slow action within the instance of LT of delta and theta waves. Conversely, the beta and alpha waves demonstrate relatively minor amplitude variations, implying an insufficiency in higher-level cognition and actions characterized by swift decision-making. Unlike Sub-1, Sub-2 exhibits a few fast action motions. During epileptic seizures, numerous kinds of bodily movements might be seen. Additionally, the fundamental aim of the present investigation is to ascertain the different correlations between theta, delta, alpha, and beta waves, as well as their influences, among a group of subjects.

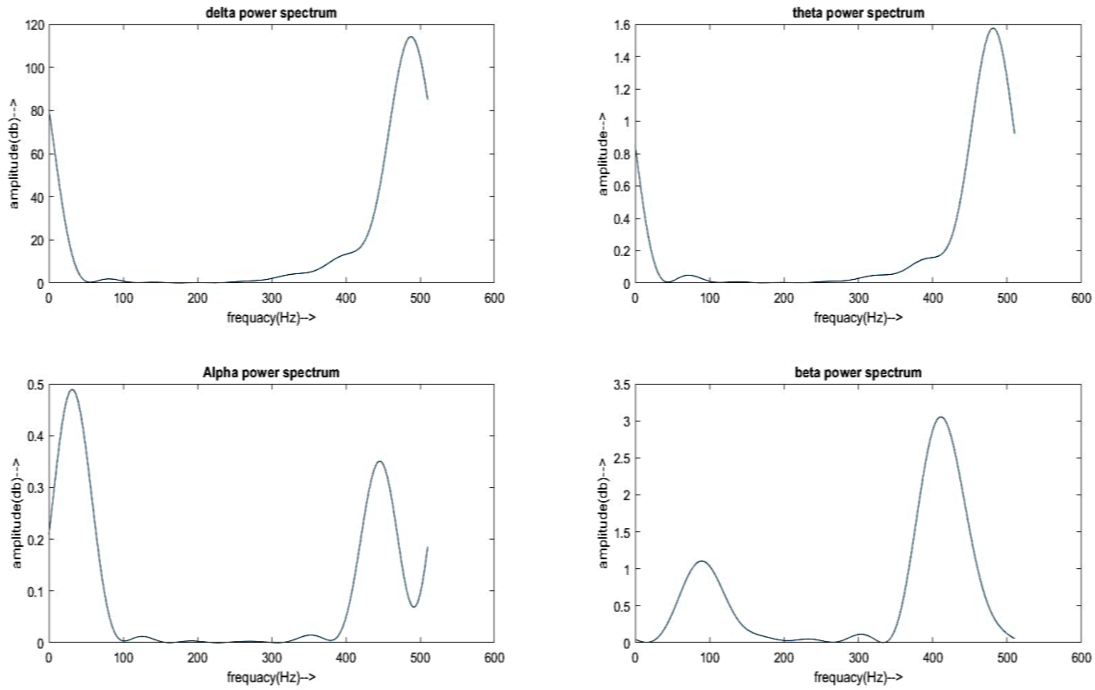

Fig.9. Few samples showing power spectrum of patient 74 (Anesthetized)

Also, as illustrated through the graphical representations, The power spectrum for 1 Hz and its harmonics at 35 Hz showed indentations, which were discovered. Analogous to the outcomes depicted in Fig. 8 within the context of LT show the epileptic activity for the few participants considered in this study. Given that the EEG activity is more significant in alertness and smaller in unresponsiveness, the components with higher frequencies imply that muscular activity may have dominated or negatively impacted the outcomes. The delta, beta, theta, and alpha bands—i.e., frequency bands below 30 Hz—are where traditional EEG analysis is typically carried out.

Table 1. Comparing the outcomes with respect to the typical frequency range

	Average PSD										
	Laplace Transformation				FFT, DCT						
	Epileptic Seizures				Wake or Anesthetized						
	Delta	Theta	Alpha	Beta			Patient	Delta	Theta	Alpha	Beta
	<4 Hz	4-7Hz	7-13 Hz	13-39 Hz				<4 Hz	4-7Hz	7-13 Hz	13-39 Hz
Sub 1	1.9793×10^{-14}	9.9922×10^{-16}	1.3154×10^{-15}	5.7654×10^{-15}	Dataset (470)	Wake	1	107.5240	1.4648	0.6343	6.4284
Sub 2	9.0268×10^{-14}	4.4360×10^{-15}	5.5210×10^{-15}	2.0208×10^{-14}			52	95.5618	1.1927	0.5696	8.4916
Sub 3	1.543×10^{-14}	7.7039×10^{-16}	8.5990×10^{-16}	4.9147×10^{-13}			233	51.2489	0.6913	0.2769	2.5736
Sub 4	1.0713×10^{-13}	5.3760×10^{-15}	4.4873×10^{-15}	6.2947×10^{-15}			315	47.9312	0.6314	0.1942	3.8084
Sub 5	7.0702×10^{-15}	3.5738×10^{-16}	3.5660×10^{-16}	1.9375×10^{-15}			444	56.4391	0.8383	0.5243	2.9882
Sub 6	7.8615×10^{-14}	4.0517×10^{-15}	3.0217×10^{-15}	2.1803×10^{-14}		Anesthetized	74	36.5914	0.4809	0.1975	1.2667
Sub 7	8.2266×10^{-14}	3.8125×10^{-15}	5.0033×10^{-15}	3.7111×10^{-15}			118	30.9748	0.4178	0.1736	1.1370
Sub 8	5.6647×10^{-14}	2.6285×10^{-15}	3.063×10^{-15}	3.5188×10^{-15}			288	48.3103	0.7099	0.3154	1.8536
Sub 9	1.1426×10^{-14}	5.7742×10^{-16}	5.6997×10^{-16}	3.3862×10^{-15}			324	27.5649	0.3708	0.1713	0.4660
Sub 10	1.8440×10^{-14}	9.1089×10^{-16}	9.2510×10^{-16}	6.2686×10^{-15}			399	43.2906	0.5775	0.2951	2.8715

“Beta waves”	“Active, busy thinking, active processing, active concentration, arousal and cognition”
“Alpha waves”	“Calm, relaxed yet alert state."
“Theta waves”	“Deep meditation /relaxation, REM sleep”
“Delta waves”	“Deep, dreamless sleep, loss of body awareness."

The PSD plot exhibits a substantial power distribution in the delta frequency region (0 to 3Hz), demonstrating low-frequency activity in the EEG data. This denotes a condition of unconsciousness or deep sleep. The PSD plot shows a rise in power in the theta frequency (4 to 7) band, which is connected to tiredness or light sleep. Alpha Band (7 to 13Hz), the PSD plot shows a noticeable peak in the alpha frequency band, which denotes a calm and awake condition. Beta band (13 to 39 Hz), the PSD plot reveals an intense power concentration in the beta frequency region, which denotes an alert and active condition. When the average values are compared to the PSD values, throughout this research, all ten instances have been verified as epileptic using data gathered from ten participants diagnosed with epilepsy. When compared to the PSD values, all ten instances are confirmed to be epileptic in this study based on the records assembled from ten epileptic participants. In the case of results obtained choosing EEG data of anesthetized patients, the methodology adopted has given perfect results.

The technique of frequency sampling, pass band, pause band, and waves of theta, alpha, beta, and delta signals with a normalization process is adopted. The Parks-McClellan algorithm obtains the linear phase FIR filter's coefficients. Beta, alpha, theta, and gamma average powers should all be analyzed to recognize the patient's status. Applying DCT yields the above observation and result. Here, using EEG wave patterns, an approach for epileptic seizure endorsement and detecting the presence of Anaesthesia is provided. The four EEG wave patterns investigated were Theta, Delta, Beta and Alpha waves. For the objective mentioned above of epileptic seizure detection, the publicly accessible EEG data, which was evaluated by recording it at a SF of 128 Hz. However, a spectral bandwidth of 0.5 Hz to 85 Hz was selected for the acquisition system. The outcome is that the 40 Hz low pass filtering technique is introduced initially. Ten epileptic participants were recorded using EEG to confirm each subject's epilepsy. LT in combination with a FIR filter achieved effective classification and recognition.

For Anaesthesia, the structure designates a person as "wake" if, the mean power readings in the alpha, theta, beta, and delta bands are higher than predetermined thresholds. If not, the person is labeled as "anesthetized." The proposed method is effective and can be considered one of the better algorithms to endorse the patient status as wake and anesthetized. The two sets of data with 470 and 699 patients were classified and tested. High accuracy and acceptable results were obtained.

5. Conclusions

The methodologies adopted present credible outcomes in distinct domains of EEG data analysis. In identifying epileptic seizures, the first methodology employs the LT with power spectrum analysis technique. This approach involves loading EEG data, plotting channel signals, filtering through a linear impulse FIR filter across frequency bands (delta, theta, alpha, beta), and applying the LT to enhance specific components. The PSD is computed for each frequency band, and potential seizures are identified by comparing the average power within bands to PSD's maximum power. This technique enhances EEG data accuracy through combined analysis with the LT operator and power spectrum. However, further study is needed for efficiency validation on larger datasets and parameter optimization. Future work includes evaluating the visual effects of epilepsy via EEG recordings from the occipital lobe region.

In a different context, the second method distinguish between states of wakefulness and anaesthesia. By examining power by examining power spectra across frequency bands, the method differentiates individuals' conditions based on average power values. If average power values exceed predetermined thresholds in delta, theta, alpha, and beta bands, a person is labelled "wake"; otherwise, they are labelled "anesthetized." This technique effectively accurately categorizes individuals' states using two data sets of 470 and 699 patients. These methodologies showcase how EEG data analysis techniques involving power spectrum analysis, LT operator, FFT, and DCT, can be applied to distinct medical scenarios. The first technique focuses on epilepsy detection, exploiting the synergy between LT and power spectrum analysis to enhance EEG data analysis accuracy, with the potential for further optimization and expanded evaluation. The second technique adeptly classifies wakefulness and anaesthesia states through power spectrum examination, demonstrating its proficiency with high accuracy across sizable datasets. Both methodologies offer promising avenues for medical analysis and future development.

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Authors' Profiles

Anand Ghuli has 20 years of experience in teaching and 10 years in research. He has published many research articles in journals and conferences of repute. His areas of interest include BCI, Digital image watermarking.

Dr. Anil Kannur has 21 years of experience in teaching and 9 years in research. He has published many research articles in journals and conferences of repute. His areas of interest include Digital Forensics, BCI and Image Processing

Mr. Abhishek Mali has completed bachelor's degree in computer applications (2021) and pursuing his master's in computer applications. His research interests include Brain computer interfacing.

Ms. Aishwarya Mangasuli has completed bachelor's degree in computer applications (2021) and pursuing her master's in computer applications. Her research interests include Brain computer interfacing.

How to cite this paper: Anand Ghuli, Anil Kannur, Abhishek Mali, Aishwarya Mangasuli, "Quantification of EEG Characteristics for Epileptic Seizure Detection and Monitoring of Anaesthesia Using Spectral Analysis", International Journal of Intelligent Systems and Applications(IJISA), Vol.16, No.2, pp.40-52, 2024. DOI:10.5815/ijisa.2024.02.04