Quantifying the Locomotive Features in EEG of Impaired Consciousness and Coma with Distinctive Cerebral Rhythms

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Declaration of Authorship

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List of Acronyms

AASM	American Academy of Sleep Medicine
ADHD	Attention Deficit Hyperactivity Disorder
AF	Atrial Fibrillation/ Alpha Frequency
ASSC	Automatic Sleep Stage Classification
BCI	Brain to Computer Interface
BIS	Bi-spectral Index
CWD	Choi-William Distribution
CWT	Continuous Wavelet Transform
DFA	Detrend Fluctuation Analysis
EDF	European Data Format
EEG	Electro-encephalogram
EMA	Exponential Mean Average
EMG	Electro Myography
EOG	Electro-oculogram
ESPIS	EEG Signal Processing Interpretation during Sleep
FFT	Fast Fourier Transform
GCS	Glasgow Coma Scale
HHT	Hilbert-Huang Transform
HOS	Higher-Order Spectra
HYP	Hypnogram
ICU	Intensive Care Unit
IFCN	International Federation of Clinical Neurophysiology
LOPP	Loss of Paw Pinch
LORR	Loss of Righting Reflex
LOTC	Loss of Tail Clamp
LRTC	Long-Range Temporal Correlation
MCS	Minimally Conscious State
MWT	Morlet Wavelet Transform
NREM	Non-Rapid Eye Movement
PSG	Polysomnography
PVS	Persistent Vegetative State
REM	Rapid Eye Movement
ROPP	Return of Paw Pinch
RORR	Return of Righting Reflex
ROTC	Return of Tail Clamp
SMA	Simple Mean Average
SPIS	Signal Processing Interpretation Sleep
STFT	Short-Time Fourier Transform
WT	Wavelet Transform

Acknowledgments

The research work and the idea to process the brain waves could not be materialized without the open-access database for functional EEG. We acknowledge the contribution of *Sleep EDF Database Extended* for their massive and organized archive of EEG that offers hours of sleep and wake EEG from volunteers of different ages and conditions. The dataset comes in rigorous filtering that allows us to work with the brain waves without worrying about unavoidable noise removal. The EDF format also provides Amplitude Spectrum curves with respect to Frequency and Hypnogram markers at each epoch that helped us verify the pre-hand analysis.

Our utmost gratitude goes to the tutorial endeavor of *Michael & Cohen* who made the fundamentals of wavelet transform in an EEG perspective. To employ a known technique to something new was highly stimulated by their approach and eventually, we have developed our own *Signal Reconstruction* possibilities.

Special thanks go to the honorable head of the Department for supervising us throughout the process with priceless table-turning suggestions and overall support.

2021

Abstract

The classic, easier, and the most practiced way of comprehending the functionalities of the Human Brain is collecting Encephalic Potential Difference – technically known as EEG. As Neuroscience Researchers worldwide are using the time series data of Brain Wave voltage into analyzing, building, and featuring Human Behavioral Traits, Motor Functionalities, Cognitive Cerebral Activities, and BCI, the focus has been shifted on the consciousness factors of the Human Psyche. Meanwhile, the subdued consciousness studies remain highly unattended and untouched. So, with an aspiration to exploit Biomedical Signal Processing into the unknown arena of Unconsciousness, the team has chosen to dig into the features of Impaired Consciousness i.e. Anesthesia and Comatose Patients. The work focuses on the comparative analysis of different consciousness levels along with cerebral signatures with the help of EEG signals. By deploying the known set of parameters for consciousness, the research looks forward to quantifying the EEG data acquired from the patients in Coma and identify the existing rhythms thereafter. With continual progress, the study shed light on the previously unknown Cerebral facts of the patients with subdued consciousness. As the features, identifiers, and parameters are superposed to depict the outcome, the study yielded a new finding – termed Failure Harmonics which deliberately exposes the failure in the transition from one level of consciousness to the other – marking one of the potential reasons for traumatic long-term Unconsciousness. The whole set of findings and extractions will not only usher new comprehensive perceptions of Coma as an addition to neuroscience but also help diagnosing the patients of impaired consciousness to a hopeful recovery.

Chapter 1

Introduction

The field of research in EEG, despite its popularity, lacks insight into the chosen field of study. To bridge the gap between consciousness featuring and unconscious characteristics analyzing, the team approached with the assistance of Sleep Data. The subconscious state reveals a significant cue to understanding how the cortex of the brain manages and renders different levels of awakening and consciousness.

Before diving deep into the research work details, the chapter offers a theoretical and relevant overview of the topics that are inevitably attached to the core of the study. In this chapter, the keynotes of the Human Brain, Cortical Activity & Cerebral Rhythms, Consciousness Types & Levels, Glasgow Coma Scale attributes, and the basics of EEG measurements are surmised.

1.1 Cerebral Activity, Rhythms & Sleep Stages

Brain wave is a result of electric activity due to the cumulative ion discharge from one group of neurons to the other. Since the neural activity is precise, localized, and distributed, the pairs of electrodes probing on different locations of the brain can sense and meter the potential difference. The time series potential data acquired from the localized electrodes render signals of different amplitude, patterns, and frequencies as the patients/volunteers do different conscious activities. As the person being examined starts to dive deep into the levels of subconsciousness, all the cortical activities seem to wrap up – giving space to asleep, confined, involuntary brain activities.

There is no such thing as a uniform state of being when it comes to sleep. Instead, sleep is divided into several stages; each of them can be distinguished by the patterns of brain wave activity that occur during that particular stage. EEG is used to visualize these variations in the brain wave function, which are differentiated from one another by the frequency and intensity of brain waves. In this study, the first approach to deal with the unconscious featuring was initiated with Sleep staging from raw EEG data.

REM (rapid eye movement) and non-REM (non-rapid eye movement) sleep are the two general phases of sleep. Rapid eye movement (REM) sleep is described by darting eye movements under closed eyelids. The brain waves that occur during REM sleep are very close to those that occur during wakefulness. Non-REM (NREM) sleep, on the other hand, is divided into four phases, each of which is separated from the others and wakefulness by distinct patterns of brain waves. NREM sleep is the first four stages of sleep, while REM sleep is the fifth and final stage.

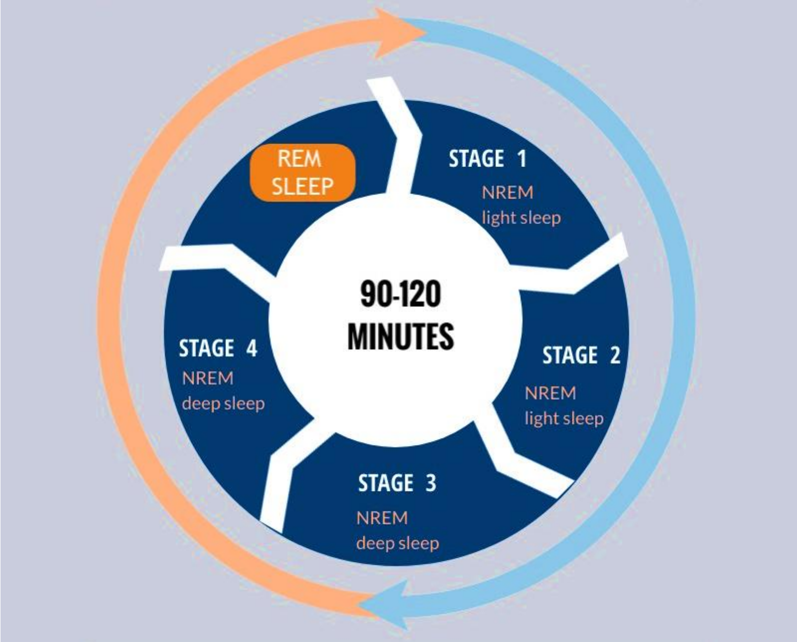


Figure 1.1 (a): REM & N-REM Sleep Cycle [1]

Cerebral rhythm. Different patterns of massed neuronal activity are correlated with different activities, arousal levels, and sleep states, and are referred to as brain rhythms. Electroencephalogram (EEG) and/or neuronal population field recordings are commonly used to measure them. The hippocampus, thalamus, and neocortex have been the most studied areas of the brain. [2]

During sleep, the human brain goes through many physiological phases that are relatively stable. Rapid Eye Movement (REM) sleep and Non-REM (NREM) sleep are the two phases of human sleep. NREM sleep is divided into four phases as seen in Figure 1.1 (a), each of which includes the closing of the eyes as well as the inactivation of many nervous centers, rendering the person partially or fully unconscious and simplifying the brain network. Many biomedical signals, including EEG, ECG, EMG, and EOG, are now used in clinical settings to classify sleep disorders, with the EEG signal serving as the most important signal in sleep stage classification. Table 1.1 gives a precise idea about the cerebral rhythms, associated with the sleep stages.

Table 1.1 Cerebral Rhythms with Distinguished Brain Activity & Consciousness [3]–[5]

Cerebral Rhythm	**Frequency** (Dominant Bandwidth)	**Potential Difference**	**Conscious/ Sleep State**	**Mental State**	**Cerebral Transmission**
Alpha (α)	8–12 Hz	~ 50 uV	Eyes Closed & Aware/ rare at REM	Very Relaxed, Passive Attention	All over the cerebrum but converging
Beta (β)	12-35 Hz	50-100 uV	Eyes Open & Aware	Active, external Attention, Conscious	All over the Cerebral Hemispheres
Theta (θ)	4-8 Hz	50-150 uV	NREM, Stage-1	Drowsy, Inward Focused	Transition Hippocampus
k-Complex	10-15 Hz	100-150 uV	Sleep Spindle, Stage-2, Stage-3, REM	Memory Processing	Transition: Cortex ~ Thalamus
Delta (δ)	0.5-4 Hz	100-200 uV	NREM, Stage-4	Deep Sleep	Thalamus
Gamma (γ)	>35 Hz	~ < 50 uV	Awake/ Disturbed REM	Active, Seizure	All over the cerebrum

As it can be seen from the specific attributes, each stage comes with a particular frequency, voltage, and indicates neural activity at specific regions of the brain. (Figure 1.1 b) To consider Sleep Stage gives us its advantage by confining and localizing cerebral activities. At each stage, the EEG signal renders a dominant bandwidth, often letting the following cerebral rhythms expose.

Alpha. People who are awake but have their eyes closed and are relaxing or meditating usually have alpha waves. The most prominent feature of the entirety of human EEG records is the alpha rhythm, which is historically regarded as the fundamental and definitive EEG rhythm.[6] Multiple studies have found that alpha rhythm obtained from the scalp reflects neurophysiological processes that are directly linked to individual differences in information processing in the human brain. Also, AF is not affected by extracerebral factors like skull thickness or conductance but is affected by the amplitude and power of the alpha rhythm.[6] The frequency spectrum of alpha waves is between Beta and Theta. They assist us in destressing and promoting feelings of deep relaxation when needed. Daydreaming, inability to concentrate, and being very calm are all examples of Alpha waves, suppression of the rhythm can cause anxiety, high stress, and insomnia.[6]

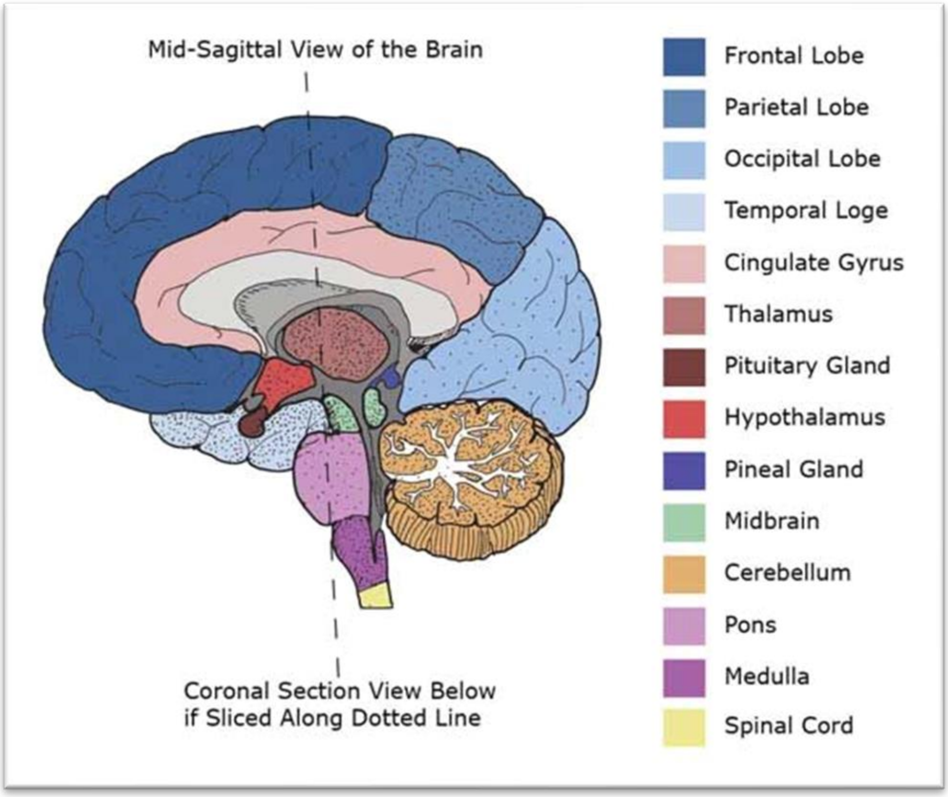


Figure 1.2 (b): A Color-graphic Presentation of Different Lobes of Cortex & Other Parts [7]

Beta. When a subject/patient/volunteer is sober, alert, and effectively analyzing data externally provided or acquired from the environment, beta waves can be identified and recorded on the EEG. Beta waves are low-amplitude, high-frequency brain waves that are common in people who are awake. It is associated with logical thinking. When this wave is prominent, it causes anxiety, high arousal, inability to relax, and stress. And when it is suppressed, it causes ADHD, daydreaming, depression, and poor cognition. Beta waves aid conscious focus, memory, and problem-solving in ideal circumstances. These waves can be classified into three categories.[8]

.

• Low beta waves (12-15 Hz): known as "beta one" waves and associated mostly with quiet, focused, introverted concentration. [8]

• Mid-range beta waves (15-20 Hz): known as "beta two" waves and associated with increases in energy, anxiety, and performance. [8]

• High beta waves (18-35 Hz): known as "beta three" waves and associated with significant stress, anxiety, paranoia, high energy, and high arousal. [8]

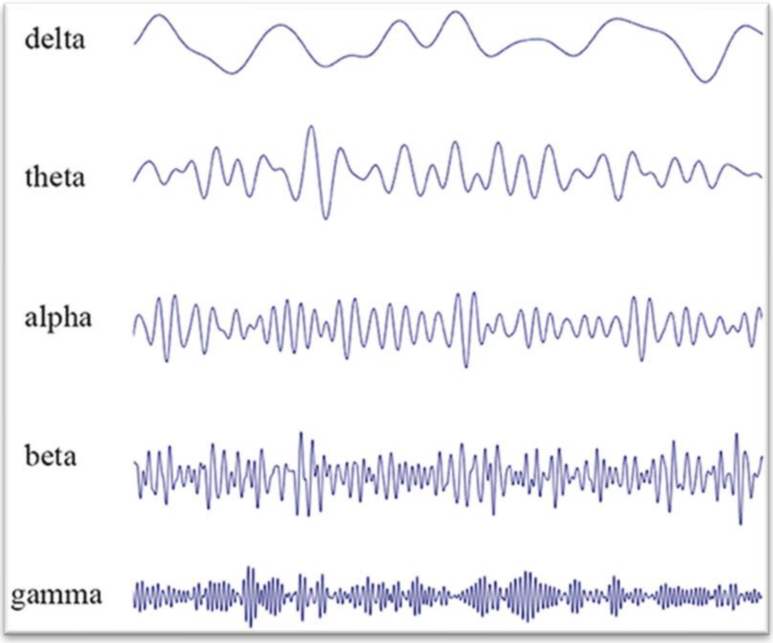


Figure 1.3 (c): Visuals of Raw EEG Time-series Data containing Different Cerebral Rhythms [9]

Delta: When people are sleeping deeply or in a trance, they produce delta waves. Delta waves are the slowest brain waves ever documented in humans. They're most common in infants and small children, and they're linked to deep relaxation and restorative, healing sleep. Brain injuries, learning difficulties, inability to remember, and extreme ADHD are all common symptoms of having Delta wave.[4] If this wave is suppressed, the body and brain will not be able to rejuvenate, and the sleep system will suffer. The immune system, natural healing, deep sleep are all aided by sufficient development of delta waves.

Theta. Memory, thoughts, and limbic system function are all correlated with theta waves. Daydreaming and sleep are also associated with this frequency spectrum. While theta waves are dominant, it is associated with ADHD, depression, hyperactivity, impulsivity, and inattentiveness; when they are blocked, it is associated with anxiety, low emotional awareness, and tension.[4] Theta assists in imagination, personal interaction, intuition, and relaxation when it is in its optimum state. Theta waves make us feel more natural and develop our instincts and imagination. In restful sleep, theta is also active.

1.2 Types of Impaired Consciousness

Consciousness is subdued by traumatic or non-traumatic injuries or forced by using Neuro-Blockers or sedatives. The resultant state ends up in different types of stages, collectively noted as *Impaired Consciousness*. The two cardinal elements of consciousness are *Wakefulness* and *Awareness*.[10] Several stages of impaired consciousness are classified based on the condition of the two elements. It occurs when the normal consciousness level is hampered due to some injury to the brain (traumatic injury) and the patient has an interrupted sense of awareness.[10] Based on this theory, impaired consciousness is divided into 3 types: *Minimally Aware State, Vegetative State*, and *Coma*.[11] Each of the stages is briefly explained with the identifying attributes in the upcoming sub-sections. And the precise identifier attributes are listed in Table 1.2.

Table 1.2 Different Types of Impaired Consciousness & their Attributes [12]

State	Sleep-Wake Cycles	Awareness	Motor Behavior Characteristics
Coma	None	None	Purposeless
Vegetative	Exists	None	Purposeless
Minimally Aware State	Exists	Partial, Unstable	Inconsistent, reproducible

1.2.1 *Minimally Aware State*

It occurs when the evidence of the consciousness level and awareness is minimum and does not go with the symptoms of the PVC or vegetative state. According to the Aspen neurobehavioral conference, the stage has been declared as 'Minimally Conscious State' or MCS.[12] Comparatively, this type is more common than the other cases of Impaired Consciousness. However, the MCS doesn't depend on conventionally approved data and was not unanimously accepted.[12] Owing to the limitations, a proper diagnosis, recovery course, and treatment for MCS are still unknown.

Criteria for a Patient in Minimally Conscious State [13]:

- Follows simple commands
- Gestural or verbal yes/no responses (regardless of accuracy)
- Intelligible verbalization
- Purposeful behavior, including movements or effective behaviors that occur in contingent relationship to relevant environmental stimuli and are not due to reflexive activity.

1.2.2 *Vegetative State*

It is a complex neurological condition where a patient is awake but has no sense of awareness. This can happen suddenly due to traumatic or non-traumatic brain injury that holds a high chance of misdiagnosis of the patient in a vegetative state. In most cases, the absence of awareness is considered as the absence of wakefulness due to the lack of experience of the doctors.[12] Patients in vegetative states come in a wide internal hierarchy with different levels of response, hence rendering acute or permanent consciousness disability.

1.2.3 *Coma*

The type dealt with in the study is absolute unconsciousness known as Coma. It occurs when the brain injury (trauma) blocks the Neural Network of the Brain and does not let the transmission of a signal through the neurons.[14] The comatose patient faces extreme impedance in the awareness and arousal process of the brain and renders no signs of wakefulness.[10] When this condition remains for a very long time, it is called Persistent Vegetative State (PVS) which is a rare case. Coma can be a result of severe injury to the brain or other infective and non-infective diseases. The stage of unconsciousness, which is the main concern of the study is divided into 8 etiological groups.[15]

- Toxic Coma
- Diabetic coma
- Hepatic coma
- Coma due to hemorrhagic stroke
- Coma due to ischemic stroke
- Coma due to subarachnoid/parenchymal hemorrhage
- Post hypoxic coma &
- Traumatic coma

The patients undergoing Coma face different levels of impedance in conscious interactions. To measure the consciousness accessibilities of a Coma Patient, a conventional scale is being used worldwide. Popularly known as GCS which stands for Glasgow Coma Scale, the score determines the condition of a patient.[16]

The **Glasgow Coma Scale** was first introduced in 1974 by Teasdale and Jennett from the Department of Neurosurgery Institute of Neurologic Sciences, Glasgow University.[17] It was developed as a clinical assessment to compare the comatose patient data and minimize the misunderstanding and ambiguities. Since then, it is widely used to score and grade individual patients, to compare the treatment effectiveness, and as a prognostic indicator. [6] The three major components of GCS are:

i. Motor response: a suitable indicator for a functioning brain
ii. Verbal response: the most common state for a coma recovering patient. It can indicate the end of a coma state
iii. Eye-opening: Spontaneous eye movement can be an indication of an active brainstem movement.

A simple *scoring system* for GCS was proposed in 1976 which has a maximum of 14 points.[18] Eye-opening consists of 4 points, 5 points for the best possible verbal response by the patient being examined, and the other 6 for the best motor response rendered by the patient. All these activities hint toward conscious brain activities. Table 1.2.3 depicts the chart of the accepted scoring system for GCS:

Table 1.2.3 Scoring Chart of Glasgow Coma Scale [19]

Score:	**Eye-opening**	Score:	**Verbal Response**	Score:	**Motor response**
4	Spontaneous	**5**	Oriented	**6**	Obeys commands
3	To speech	**4**	Confused conversation	**5**	Localizes pain
2	To pain	**3**	Inappropriate words	**4**	Withdrawal (normal flexion)
1	None	**2**	Incomprehensible sounds	**3**	Abnormal flexion (decorticate)
		1	None	**2**	Extension (decerebrate)
				1	None

1.2.4 The Artificial Coma – Anesthesia

The remaining close companion of consciousness studies in the EEG acquired from the patients in Anesthesia. The objective of the process is to render conscious activities to the minimum possible conscious level and render a retrievable stage of unconscious state for a calculatingly predicted amount of time.

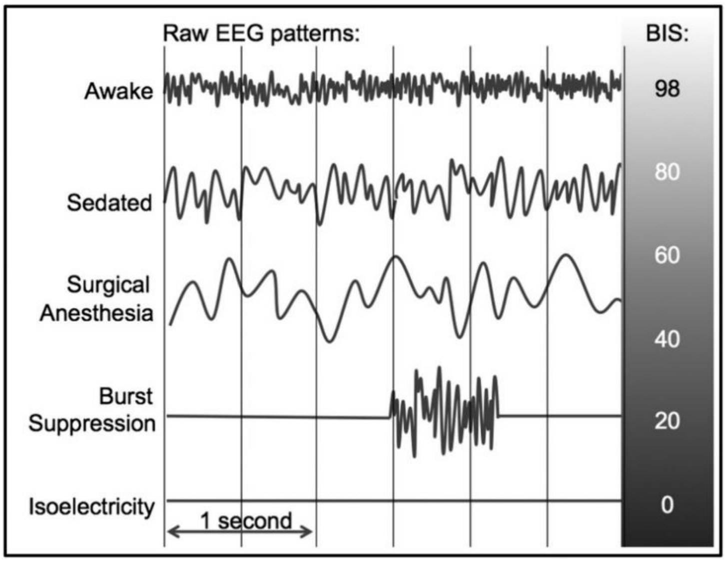


Figure 1.2.4(a): Comparative EEG Visuals of Conscious, Sedated & Anesthetized States [20]

The level of unconsciousness is forced on the nervous system grid of the patient with the use of different chemicals like Propofol, Chloroform, Fentanyl, etc.[21] As the dose of the anesthetic agents is increased, the EEG of the patient shows a radical transition from conscious to the sedated stage as depicted respectively in the diagram of Figure 1.2.4 (b). Soon enough in this chronological progress, the patient dives deep into *Forced Unconsciousness*, rendering almost the exact patterns and behaviors of Coma EEG.

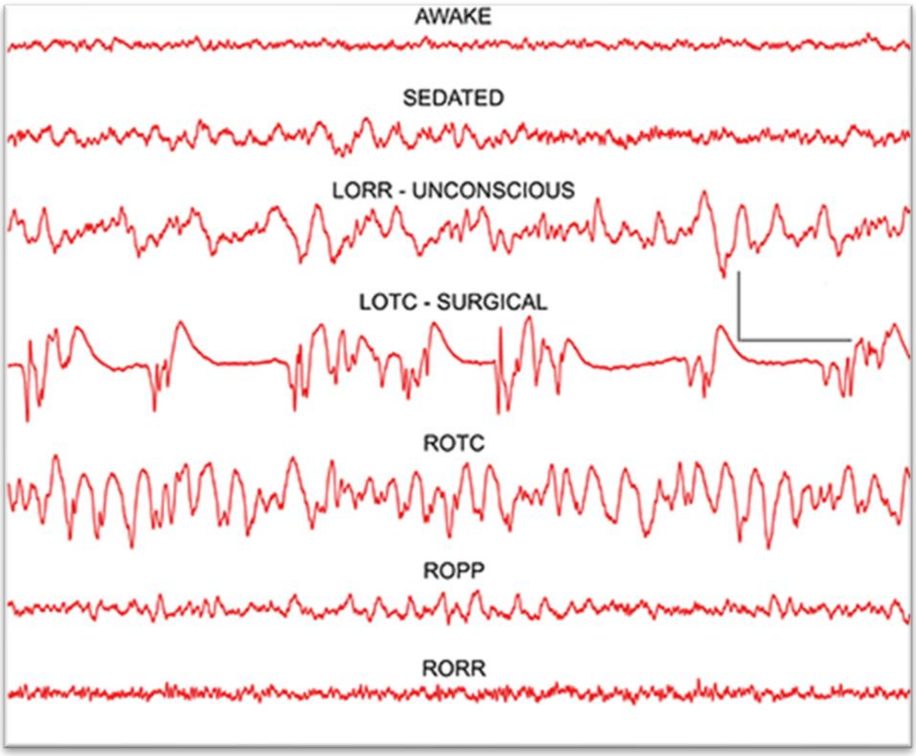
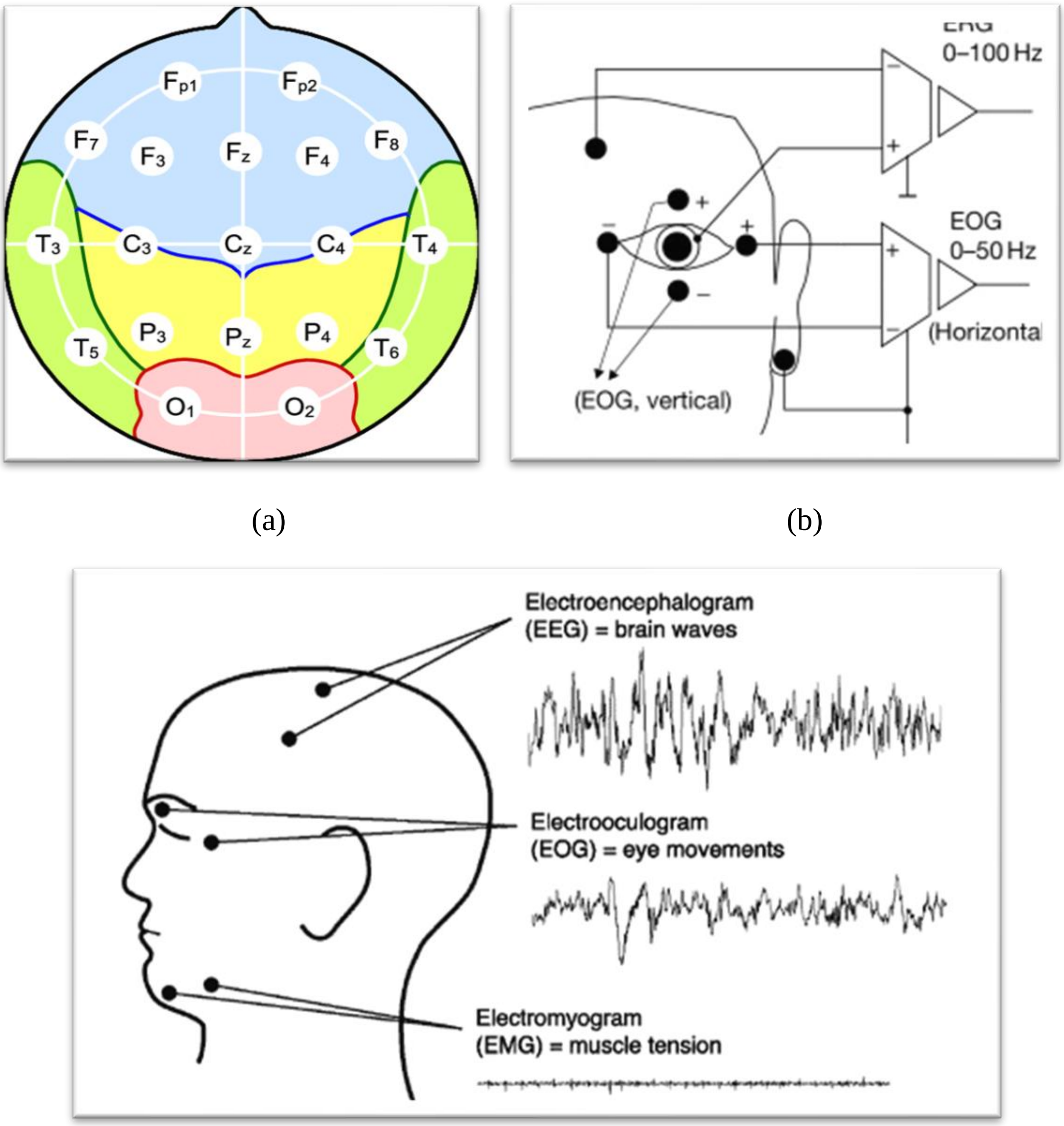


Figure 1.2.4 (b): Gradual Changes in Frontal-cortex EEG at 3 Anesthetic Endpoints [22]

The changes are monitored and scored by the widely accepted convention of BIS, also known as the Bi-spectral Index. As shown in Figure 1.2.4 (a), from a score of 0 ~ 100, a patient's anesthetized state is measured and dosed accordingly.[23] The patterns of EEG in anesthesia show keen insight into the unconscious attribute featuring for patients in Coma – shedding light onto the fact how the brain encounters transition from conscious to unconscious alongside, why a brain might fail to trigger consciousness for an unprecedented amount of time. The study by the team uses the EEG data of anesthesia due to the unavailability of EEG Coma Data for the time being.

1.3 Conventions of EEG Measurement

The non-invasive technique of diagnosing Brain Waves via EEG is one of the most popular and accurate methods. Since billions of neurons in a human brain each create small electrical signals, together they yield a conspicuous potential difference to the connected electrodes placed on the scalp. The EEG machines amplify the signals and render distinguished patterns at specific mental and consciousness stages. [24]



(a) (b)

(c)

Figure 1.3: (a) 10-20 system of EEG Electrode Placement [25] **(b)** Electro-Oculogram Electrode Placement [26] **(c)** EEG, EOG, EMG Electrode Positions [27]

The most common placement pattern of the electrodes which is internationally accepted is the 10-20 system of EEG. The cerebral hemispheres of the brain are divided into lobes as color-coded in the cross-section of Figure 1.1 (b) and the top POV of Figure 1.3 (a) as Frontal (blue), Temporal (green), Central (in between blue and yellow), Parietal (yellow), and Occipital (red). The whole region is covered with a minimum of 19 electrodes following 10-20% distancing of the total front-back and left-right direction of the skull.[28] The electrodes are labeled with the initial of the region or lobe where it is placed – the Pre-frontal electrode as 'Fp', Frontal electrodes as 'F', Temporal, Parietal, and Occipital ones as 'T', 'P', 'O' respectively. Each of the lobe-wise electrodes is incorporated with a number or the shorthand letter 'z' for better precision in placement. Even-numbered electrodes denote their placement on the right half and the Odd-numbered ones indicate placement on the left half of the skull. The suffix 'z' is short for zero refers that the electrode is to be placed on the midline sagittal plane of the skull.[28]

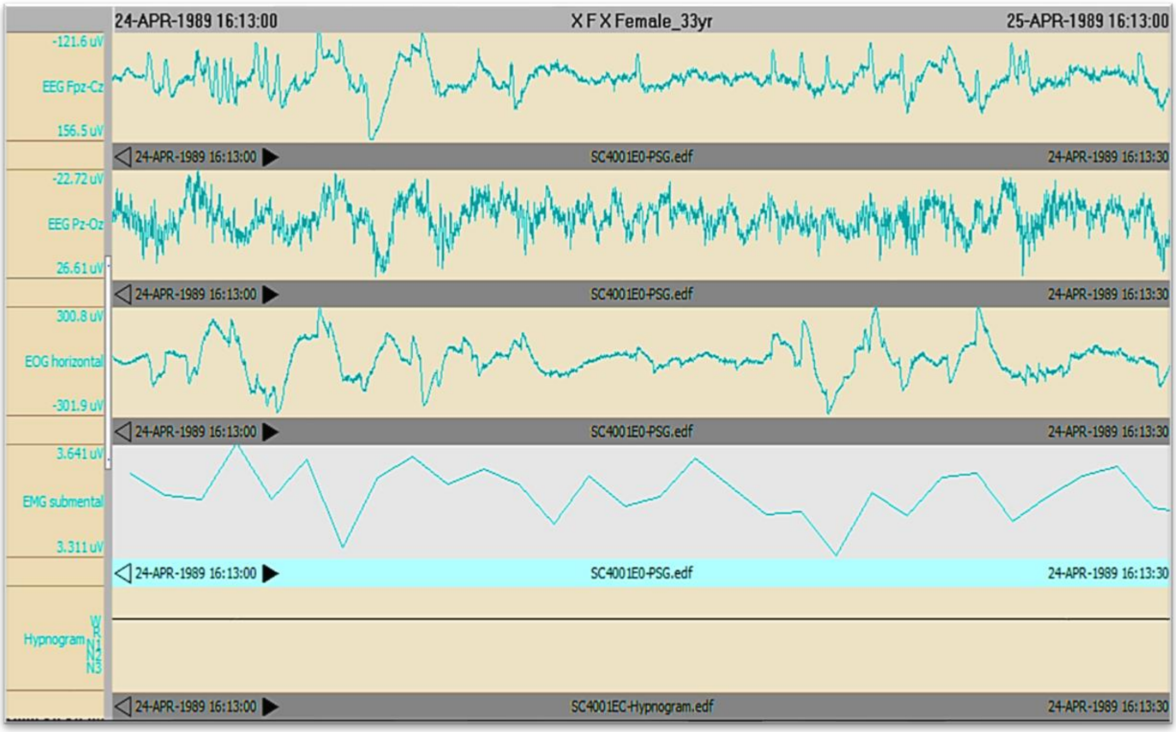


Figure 1.3 (d): Sleep EEG Dataset (time series) of a 33-year-old Healthy Female [29]

Alongside EEG electrodes via multiple channels, other factors like the movement of the eyes (Electro-oculogram), facial muscles (Electromyogram), rate of respiration are monitored while recording the EEG data of a subject. Figure 1.3 (b) and (c) shows the position and placement of Electrodes for EOG and EMG respectively. So, the data set usually comes in a package of EEG (multiple electrodes or selective channels of the specific cerebral lobes), EOG, EMG, and Hypnogram. The dataset initially used in this study was acquired from the public EDF Sleep Database.[29], [30] As extrapolated in Figure 1.3 (d), the dataset contains (row-wise): EEG of Fpz-Cz, EEG of Pz-Oz, EOG, EMG, and a manually referred Hypnogram. The electrode pairs used for the Dataset are marked in Figure 1.3 (e). The first channel is placed on Pre-frontal ~ Central, and the second channel is placed over the Parietal ~ Occipital zone to cover both the anterior and posterior part of the skull.

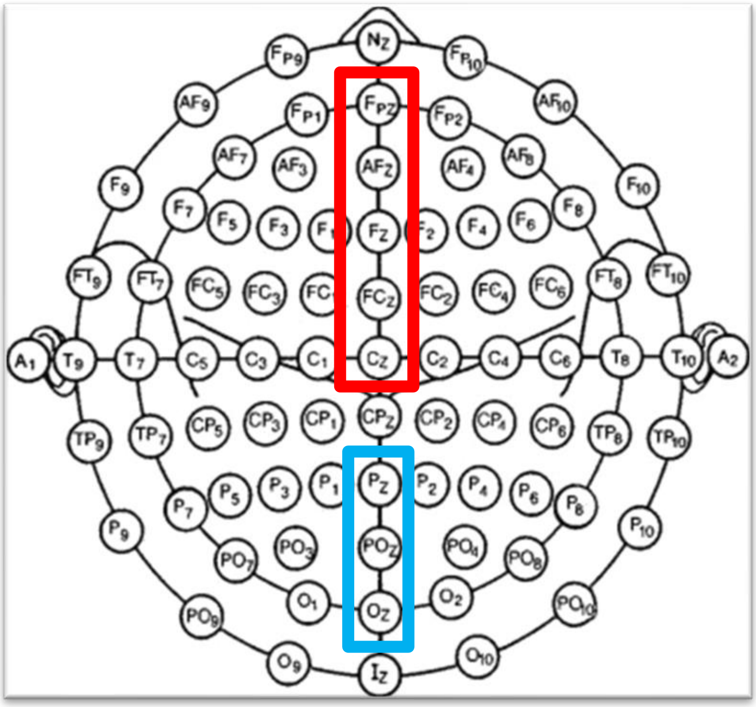


Figure 1.3 (e): The Standard EEG 25-Electrode Array by IFCN [31] The Red-marked zone is the Fpz-Cz channel and the Blue marked region is covered by Pz-Oz Channel.

The selected regions from the midsagittal line of the cerebrum hold significant information in consciousness studies. At each transition from conscious-subconscious to the unconscious, the EEG at those channels can indicate the dominant cerebral rhythms and share insight into the change of the process which is experimented in detail in the upcoming chapters. The hypnogram of the dataset is considered as the reference frame since the sleep specialist observers marked stages of consciousness by manual analysis every 30 seconds.[29]

Chapter 2

Overview of Consciousness Studies

The research has converged multiple perspectives, different parameters, and attributes into collecting features of and understanding the impaired consciousness rendered by the human brain. Despite the variety of characteristics in conscious and unconscious stages, there always remains a subtle hint and inter-connection at their phenomenal occurrence. The objective of the study was to optimally exploit all the possible techniques into building more than one feature that can shed light on the arena of Impaired Consciousness. To carry out the research, the approach was initiated with the rigorous study of Sleep Staging, Anesthesia, and finally Coma.

2.1 Introduction to Unconsciousness Studies

The research arena of EEG is widely dedicated to BCI, Epileptic seizures, Behavioral Strategy and Prediction, and Cognitive analysis. Since the EEG of an unconscious patient could not provide exceptional and conspicuous information, the whole department remained highly neglected and unsupervised. Yet, some of the researches including EEG quantification, Frequency, and Time-series or mixed analysis, Feature building, and predicting the percentage of recovery nailed landmarks in this field of study.

The grouping or classification of Coma on the basis of EEG was first done in 1965. The advancement was made by *Hockaday et al.* who divided anoxic coma into five subgroups.[32] Yet, there was more space to specialize and classify with parameters previously not considered. Some of the EEG coma datasets exhibit specific cerebral rhythms in a dominant frequency range. The Alpha/Spindle/Theta Coma patterns were worked out in several studies [33], [34] that have helped to bridge the gaps between unconsciousness and active cerebral rhythms. The prognostic validity of the previous studies and their scaling/grading conventions were verified and re-validated for the post-anoxic patients and post-traumatic encephalopathies.[35]

The thalamus, cortex, and thalamocortical transmission of neural signal data are not clinically accessible. *Young et al.* however, probed into these regional outputs in EEG and found out the potential of recovery, treatability, or instability.[36] Apart from the automatic trended analysis of Alpha/Theta patterns, and other empirical follow-ups, the study holds promising prognostics for pre-hand determination of the patients in coma.[36] Coma caused by metabolic dysfunction i.e. hypoxia, renal or hepatic failure, drug intoxication can yield abnormal patterns like spindles, Alpha patterns, and burst suppression. [37] The *triphasic waves* in these cases have been reviewed by *Brenner et al.* which provide significant insight into neocortical death, PVS, brainstem death or brain death, and locked-in syndrome differences. An unprecedented cardiac arrest to a coma patient in ICU contributes valuable EEG data for the immediate consecutive 24 hours.[38] The dataset contributes to making a forecast of a better or worse outcome due to the momentary excitation created by cardiac arrest.

The practice of considering Sleep EEG patterns and stages for comatose patients dates back to the last ten decades. The sleep polygraphic patterns rendered by the EEG of patients in coma yielded distinctive prognostic signs for day and night.[39]

2.2 Introduction to Subconscious Studies

The practice of researching with EEG of coma patients is highly dependent on Sleep EEG and Anesthesia studies. In this section, an overview of existing research works in Sleep and Anesthesia is surmised that have directly assisted in the team's research on Coma EEG and Unconscious featuring.

2.2.1 Sleep Stage EEG & Application

Apart from the tedious and time-consuming method of manually sleep-staging, a number of methods, techniques, and strategies have been developed and updated over time. A conventional system of pan overnight laboratory study on multiple subjects has been developed – known as Polysomnography, in short PSG.[40] The Automatic Sleep Stage Classification, known as ASSC has reduced the toil, time, and limitations of manual scoring. *Aboalayon et al.* collected all the existing types in building a wide range of ASSC variety and discussed their advantages along with scopes of further development.[41] The comprehensive survey has brought together all the significant works in all places and eventually helped us to pick the most optimal algorithm to build for the purpose of the study.

The minimization of technical artifacts that interfere with the ASSC has been demonstrated by *Anderer et al.* who corrected EEG Sleep data for automated staging and rendered a "contamination-free" signal to proceed with.[42] The SPIS arena is a dynamic field of research that has intrigued many researchers to work on it and let them comprehend the hidden figures out of EEG signal analysis. *Toussant et al.* developed a workbench to process and interpret multiple-channeled EEG to deal with real-time Sleep Signal (ESPIS).[43] The method has been further exploited through biomedical devices to identify and comprehend other types of medical signals. As time went by, researchers preferred to exploit mixed analyzing approaches rather than only frequency or only time-series processing. *Fraiwan et al.* combined three time-frequency-based analyses (CWT, CWD, HHT) in feature extraction and classification of PSG records according to the new standard by AASM (American Academy of Sleep Medicine).[44] An automated identification technique was demonstrated by *Acharya et al.* using HOS (higher-order spectra).[45]

Other than the typical stochastic and non-linear deterministic systems, *Achermann et al.* compared the computational correlation dimensions of an all-night sleep EEG.[46] In the last decade of the 20th Century with the help of a Super Computer, the study incorporated artificial signal comparison with identical Power Spectrum which helped overcome the limitations of chaos in usual SPIS.[46] Through the comparing process, the study found similar responses in the progressive occurrence of declined correlation at Delta Wave and high correlation at REM, which sheds great insight and similarity with the team's unconsciousness studies. The comparison studies by *Achermann et al.* confirmed the inconsistency of about 7.3% in the real EEG signal that does not comply with the generation through "chaotic attractor." However, our research has shown convincing and profressive declining correlation outcomes in deep sleep which reinforces the concept of "*Failure Harmonics"* and holds bigger possibility to exist in coma EEG.

The traditional sleep staging techniques had an addition with a different concern of EEG by the research of *Imbach et al* that shares unique insight into the variation of EEG around the cortex with time.[47] The study provided an automatic sleep staging, depending on the statistical probability, and identified inter-hemispheric oscillations during the REM stage of sleep.

2.2.2 *Anesthesia – the artificial Coma EEG*

Since anesthesia is a forced unconsciousness as stated earlier, and the fact that it is a gradual occurrence through chemical sedation, the field of study connects all the factors of unconsciousness, sleep, and awareness as well. At every hospital during the overall surgery procedure, the EEG of the operand/patient is observed to measure, demonstrate, and determine the consciousness state; the dose of sedative chemicals is set or applied accordingly. With a wide variety of Anesthesia data, our work was paced as an alternative to real Coma data.

It is a compulsory issue to index and grade the level of unconsciousness to determine the non-lethal dose of anesthetic agents. Several methods have been introduced and deployed in hospitals to grade anesthesia by EEG. The popular methods and measurement conventions in Quantitative Anesthesia have been explained in Chapter 1, Section 1.2.4. By applying a novel energy scattering method, *Zoughi et al.* represented the basics of Anesthetic EEG with sampled wavelet domain.[23] The method can differentiate deep anesthesia from moderately sedated and awake stages.

The changes are monitored and scored by the widely accepted convention of BIS, also known as the Bi-spectral Index. [23] The patterns of EEG in anesthesia show keen insight into the unconscious attribute featuring for patients in Coma – shedding light onto the fact how the brain encounters transition from conscious to unconscious alongside, why a brain might fail to trigger consciousness for an unprecedented amount of time. The study by the team uses the EEG data of anesthesia due to the unavailability of EEG Coma Data for the time being.

Chapter 3

Technical Approach

The study on EEG Sleep and Anesthesia Data has undergone three separate ways to yield different features, parameters, identifiers, and discoveries. Primarily, the whole EEG data were analyzed bases on the frequency components. Alongside, some statistical features have been calculated from the results of frequency analysis that helped us make decisions on the consciousness states. Furthermore, a time series analysis of the two different channels of EEG was demonstrated. The chapter offers a precise and selective discourse on the technical aspects that have been implemented in the overall study of impaired consciousness.

3.1 Frequency Analysis

EEG data in coma, anesthesia, and sleep are highly distinguishable through frequency. To identify the existence of different features and interpret them accordingly, several methods have been deployed. In this section of the chapter, all the approaches to frequency analysis are overviewed.

3.1.1 Fast Fourier Transform FFT

Fourier Transform is a very powerful tool for signal analysis from the 19^{th} century. Though the development of the Fourier Transform by Jean Baptiste Joseph Fourier in 1807, due to the computational constrain it was not used until the fast Fourier transform in 1965 by Cooley and Tukey was developed. The Fourier Transform function represents the complex-valued function of frequency where the magnitude refers to the presence of any frequency. But this complex function calculation needs a huge computation which was quite impossible for the early 19^{th} century. This computational constrain overcomer James W. Cooley and John W. Tukey came with a basic idea to break up the transform of any length N into two transforms of length N/2. This factorization of transform was described earlier by Gauss in 1805. [50]

$$\sum_{n=0}^{N-1} a_n e^{-2\pi ink/N} = \sum_{n=0}^{N/2-1} a_{2n} e^{-2\pi i(2n)k/N} + \sum_{n=0}^{N/2-1} a_{2n+1} e^{-2\pi i(2n+1)k/N}$$

$$= \sum_{n=0}^{N/2-1} a_n^{even} e^{-2\pi ink/(N/2)} + e^{-2\pi ik/N} \sum_{n=0}^{N/2-1} a_n^{odd} e^{-2\pi ink/(N/2)}$$

This discrete Fourier Transform algorithm reduces computation that makes it viable to use Fourier Transform in the real world. Also, this has much impact on real-time signal analysis. [50]

3.1.2 Wavelet Transform

When we conventionally work with a periodic signal, generally it doesn't have any time-bound. So, for analyzing signals when we use these signals it works on a global scale. But when we want to work on a specific and short signal it becomes a major problem which causes computational constrain as well as takes longer time to implement algorithms. For this solution Wavelet which is considered a wave that rises from zero to show the specific wave property and then goes back to zero became a very popular solution for short-term signal analysis. For non-stationary signals, this Wavelet can be very handy to analyze signals in real-time.

Wavelet transform starts with a Wavelet and works like Fourier transform for signals to analyze specific ranges. For a typical Morlet wavelet,

$$\Psi(\tau) = \left[exp\left(-\frac{\tau^2}{2\delta^2}\right) - \sqrt{2}exp - \left(\frac{\tau^2}{\delta^2} + \pi^2\delta^2\right)\right] e^{i2\pi\tau} \qquad [48]$$

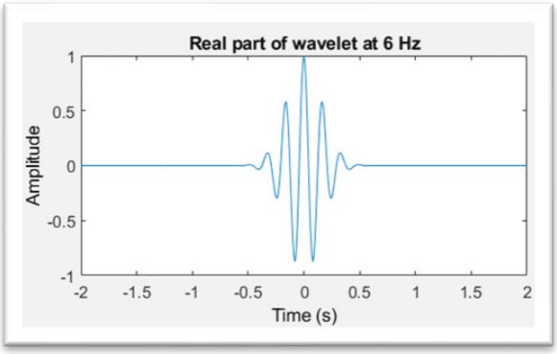
Where δ is the window width factor and it can't be negative. So, δ is a positive constant [48]. For such a complex signal to produce, there is an easy way we can follow. If we produce a Gaussian window and multiply it with a complex sine wave then it can also produce a complex Morlet wavelet:

$$\omega = e^{2i\pi ft} e^{\frac{-t^2}{2\sigma^2}} \qquad [49]$$

In this Gaussian signal, σ is defined as width and very much related to δ. Gaussian with is defined as

$$\sigma = \frac{n}{2\pi f} \qquad [49]$$

The parameter that defines the time-frequency precision trade-off is n, which is often referred to as the “number of cycles.” For neurophysiology data such as EEG, MEG, and LFP, typical values of ‘n’ range from 2 to 15 over frequencies between 2 Hz and 80 Hz. [49]



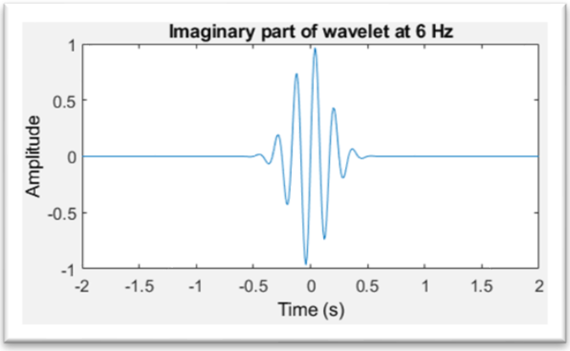


Figure 3.1.1: Real (left) & Imaginary (right) Comprehension of Morlet Wavelet

This Wavelet Transform can be used for frequency analysis. This can also be used for signal reconstruction described in the upcoming section.

3.1.3 Moving Mean

Moving average is a simple statistical tool that is commonly used in technical analysis. For a series of data, a specific subset of data is taken into account and made average from that. This subset can be called a kernel, where it moves throughout the data and smoothen the volatility. Short-term fluctuation and random impact in data can be easily overcome by this technique. In time-series data if we set the kernel size as N and the value of data represented by A then,

$$\text{Moving Average} = \frac{A1 + A2 + A3 \ldots + An}{N}$$

This is a simple moving average (SMA) where every data in a kernel is prioritized equally. There is another type of moving average where more emphasis is placed on the most recent data. That is called exponential moving average (EMA). In SMA all data get equal weight in the kernel but for EMA weight varies depending on the position in the kernel. For N size kernel it is said as N point Moving Average. Sensitivity differs for different values of N.

3.1.4 *Power Spectral Density (PSD)*

Power Spectral Density is a way of visualizing the variation of signal energy in terms of frequency. It is calculated from Discrete Fourier Transform (DFT). For any signal x(t) if we get x(f) after Fourier Transform then the area under $|x(f)|^2$ is the total power. From Plancherel's theorem $|x(f)|^2$gives the energy distribution over frequency for the truncated signal x(t) [51]. The normalized energy spectrum can be written,

$$G(v) = \frac{|x(f)|^2}{T} \qquad [51]$$

Where T is the width in the signal space. This has units of power per unit frequency. So, the power spectral density for x(t) will be,

$$PSD(v) = \lim_{T \to \infty} \frac{|x(v)|^2}{T} \qquad [51]$$

The value of the T defines the frequency bin of PSD. Decreasing T will give smoothen spectral component, thus PSD. The normalization will occur within the bin width and will not have any impact on signal length. So, PSD will be independent of signal duration.

3.1.5 *Median Frequency & Kaiser Window*

Median Frequency (MDF) is the central frequency (fc), centroid, and the spectral center of gravity of the Power Spectral Density. MDF is a frequency at which the EMG power spectrum is divided into two regions with equal amplitude. MDF is also defined as half of the total power, or TTP (dividing the total power area into two equal parts). [52]

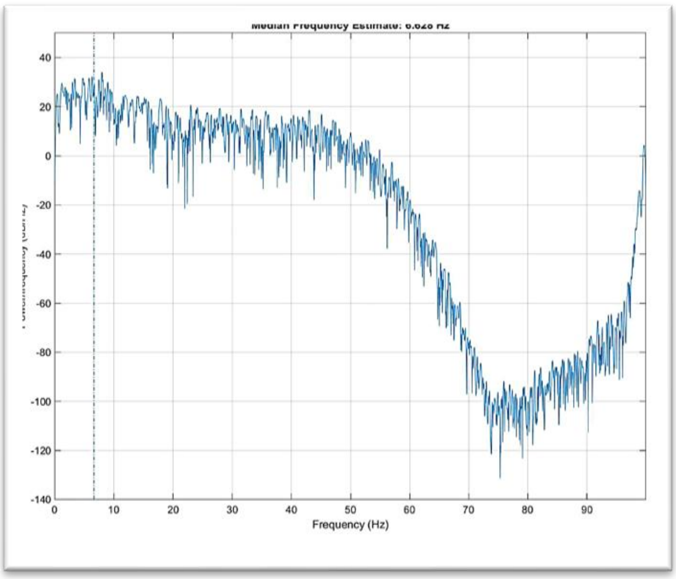


Figure 3.1.5: Extrapolation of Median Frequency from PSD through Kaiser Window.

The definition of MDF is given by

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$$

MDP is a frequency-domain feature that extracts information as time-domain based on the Power Spectral Density.

Kaiser Window. The spectral analysis function by MATLAB© *'spectrum* works out the Kaiser Window [53] on a small-time frame and there is a compromise between the resolution of the spectra and signal length.[54], [55]

- This function can be used to compute spectrogram for the whole signal also if resources allow it.
- Starting by computing Welch periodogram, using Kaiser window and overlapping segments to determine it.

There are two parameters for the Kaiser window, length, and β. The energy captured by the main lobe depends on the value of β. The length will the length of the 30-sec signal window and β was calibrated manually. [53]

3.2 Time-series Analysis

Alongside the Frequency and Power Spectral parameters and attributes, the time series data are equally significant and insightful. To find the patterns, matches, and transmission identifiers, time-series data are analyzed. Several Methods like Cepstrum Analysis, Envelope detection and Building, High Order Spectrum, STFT, Weigner-Ville distribution, Cyclostattionary Analysis, and many more are exploited to probe into the enormous time data of an EEG and help the researchers find unique and different features of Cerebral activities and Consciousness.[56]

In the study, we approached to analyze the time-series data with correlation technique. Applying the correlation on the same and different EEG channel time-series data, the team succeeded to find cyclic and harmonic matches which help explain the failure in awakening. The section surmises the keynote of the technique which is exploited in the subjective EEG data in the research.

3.2.1 *Correlation*

Correlation is a term that refers to the mutual comparative miss-and-match relationship among two or more signals in consideration. It is a measurement that says how much a signal resembles the other at which point of time along with the lag in shifting. When a signal is correlated on itself, it is termed *Auto-correlation.*[57] It helps the signal processors to find the existence of chronological and periodical development of a single signal. On the other hand, *Cross-correlation* finds the match, relevance, and resemblance of two different signals.[57] From the cross-correlated signal, we find the strength of resemblance that exists between two signals that originate from different sources. If *x(t)* and *y(t)* are different time-series signals, the cross-correlated result out of those can be mathematically expressed as:

$$R_{xy}(\tau) = \int_{-\infty}^{\infty} x(t)y^{*}(t-\tau)\,dt$$

But in most cases, the time-series data are enormous and to deal with every part of it, the researchers discretize them with a convenient sampling frequency which yields lower complexity and less time of execution – expressed as:

$$R_{xy}[m] = \sum_{n=-\infty}^{\infty} x\,[n]y^{*}[n-m]$$

As a simple demonstration, the cross-correlation of two sinusoidal signals who vary not in frequency but phase is demonstrated below:

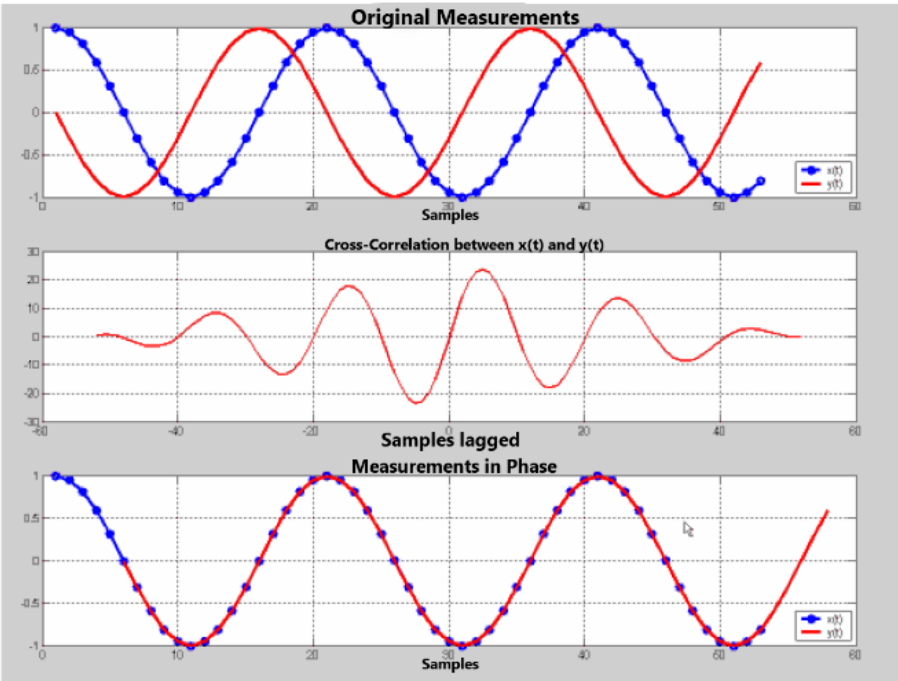


Figure 3.2.1: Cross-correlation results of two sinusoidal signals.[58]

Cross-correlation helps in determining:

- Periodicity of one and more signals
- Signal delays and lags in resemblance

3.2.2 Cross-correlation from EEG Perspective

The correlation techniques have had huge impacts on EEG dynamics analysis over decades. The research by *Meisel et al.* exhibits the application of *Long-Range Temporal Correlations*, in short, LRTCs to assess cerebral activity, specifically memory processing and decision making for a continual sleep-deprivation of 40 hours.[59] the LRTCs have detected false changes in the usual/ predicted brain wave pattern and rhythm as an unprecedented causality of sleep. *Zebende et al.* carried out research on high-density 64-Channel EEG with DFA (Detrended Fluctuation Analysis), Auto-correlation, and RMS (Root Mean Square) function to find the distinguished amount of Fluctuation at Parietal and Frontal Lobes.[60] They developed an auto-correlation coefficient using the DFA method that measures "*Self-affinity"* at pin-pointed times in the time-series EEG data.[60] The DFA method in a two-dimensional feature space has been used to distinguish different stages of sleep and consciousness.[61] As the research yielded high percentages of accuracy at detected each stage of sleep, it affirms the significance of Time-series Data for the thesis research purpose.

The cortical connections inside the brain exist at every stage and type of mental case and stages of consciousness. The track the trails of information dispersing from one neural group to the other, the EEG data can be distorting in Frequency series analysis. However, if the EEG signals from two separate channels or lobes are cross-correlated, and the result shows high matching strengths between those time series data, then we can that information has been transferred from one channel region to the other.[47] Based on the correlation method, the study by *Imbach et al.* reflects upon the variations of interhemispheric oscillations at different sleep cycles.[47]

Although the correlation result may show convincing matching strengths denoting the localized transfer of neural signal, it fails to indicate which way the transfer took place. But if the matches in patterns of the time-series data show delay or lag in the matching strength result, it would indicate the direction of data transfer. The signal which lags in time or sample concerning the other is the receiver of the signal. This lagging phenomenon is known as *Granger Causality* [62] and the pattern shifting movement functionality can be measured to identify neural signal transmission in the cerebrum.[63]

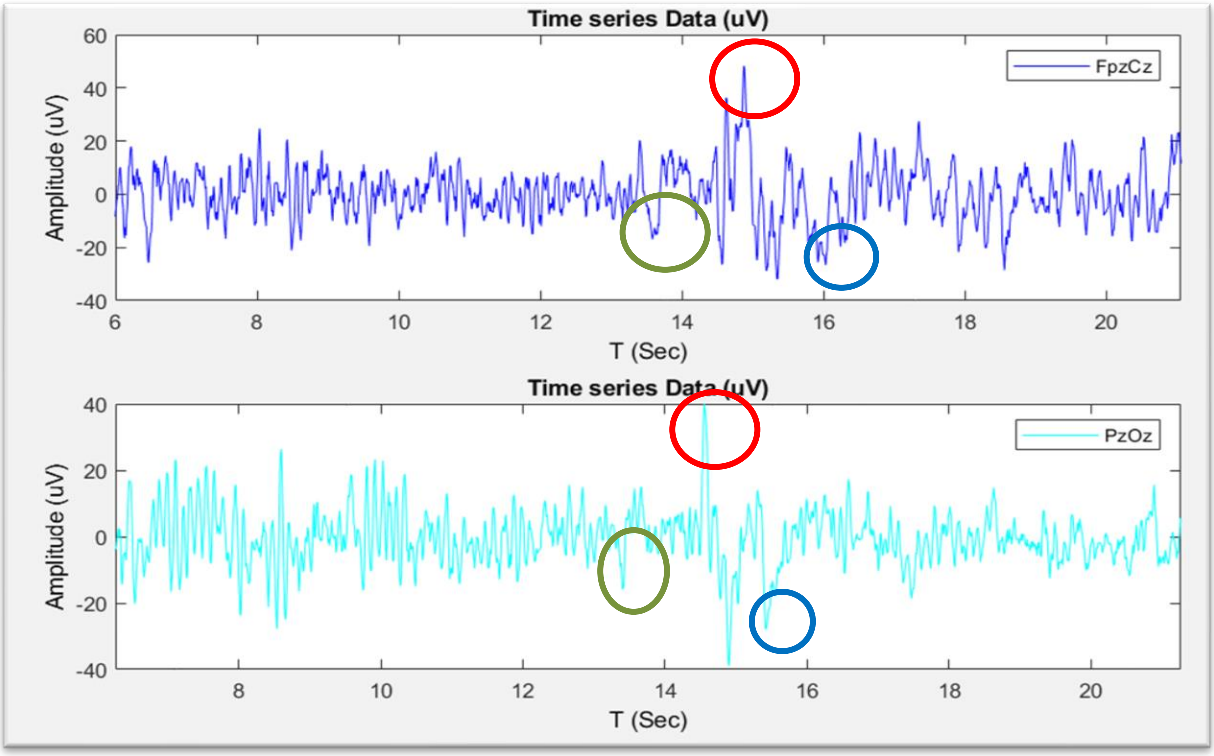


Figure 3.2.2: Potential for Cross-correlation Matching Strength in Multi-channel EEG

To think through the perspective of the study of unconscious featuring and identifying the locomotive incentives, the above-mentioned set of techniques holds high impact. These have been exploited to find which region of the brain is capable of transmitting, processing, and receiving neural signals. Since the team has worked on two separate channels – Fpz-Cz & Pz-Oz, they show matching patterns with a specific time lag as color-marked in Figure 3.2.2. Furthermore, the approach in time-series analysis helped the team to discover 'Failure Harmonics' which indicates futile endeavors of the brain to create an end-to-end neural connection at the deepest stage.

Chapter 4

Methodology

The technical approaches overviewed in the previous chapters are optimally applied in our overall study. The results are processed through the algorithms discussed in the previous chapters. In the upcoming sections, a detailed discourse of all the algorithms is offered.

4.1 Frequency Analysis

4.1.1 Filtering the Time-series Signal

In the sleep-edf-database-extended database, the signal pre-filtered in the transducer. The signals were filtered accordingly,

Table 4.1.1 Pre-Filter information for edf-database of EEG

S/n	Label	Frequency (Hz)	Physical Dimension	Pre-Filter	Transducer Type
1	EEG Fpz-Cz	100	uV	HP: 0.5Hz, LP: 100Hz [enhanced cassette BW]	Ag-AgCl electrodes
2	EEG Pz-Oz	100	uV	HP: 0.5Hz, LP: 100Hz [enhanced cassette BW]	Ag-AgCl electrodes
3	EOG horizontal	100	uV	HP: .5Hz, LP: 100Hz [enhanced cassette BW]	Ag-AgCl electrodes
4	Resp oro-nasal	1		HP: 0.03Hz, LP: 0.9Hz Oral nasal thermistors	
5	EMG submental	1	uV	HP: 16Hz Rectification LP: 0.7Hz Ag-AgCl electrodes	
6	Temp rectal	1	DegC	Rectal thermistor	
7	Event marker	1	Hold during 2 seconds	Marker button	

Through the pre-filter helps in some cases but some low-frequency noise is added to the signal while recording due to internal noise. So, signal reconstruction using a wavelet will come in handy in this situation.

4.1.2 Signal Reconstruction

Today's most commonly used time-frequency analysis methods are short-time fast Fourier transform (STFT), complex wavelet convolution, and filter-Hilbert [49]. These methods have been applied in many fields and acquired some good results. But restriction comes for Heisenberg uncertainty principle and large computational power. On the other hand, these methods work very well on stationary time-series data and give results based on the global range. For our work in EEG signal analysis, we have constrained time-series data which are not stationary. Wavelet transform becomes handier in this situation. More works are going on in this transform including synchro squeezed wavelet transforms (SST) [64], Haar Wavelet Transform [65], the integral Wavelet Transform (IWT) [66], Daubechies Wavelet Transform [67], Morlet Wavelet Transform [68], Gabor wavelet [69] and people are achieving outstanding results.

As non-stationary data, EEE signal from Fpz-Cz and Pz-Oz, wavelet transform became a noble solution. From different discrete Wavelet Transform, Morlet Wavelet was an easy choice for us as it windows the data, computationally efficient, works in real-time, and provides the best trade-off between spatial and frequency resolution. The work is closely related to the consciousness of the patient which needs a range of information from the signal. Wavelet transform allows us to reconstruct signals according to our interests which allows us to process the signal more effectively and efficiently. Moreover, signal reconstruction with this transform can very cleverly diminish the use of a filter to some extent. Our interest in the signal starts with the frequency 0.5 Hz which can be a bit difficult to implement a filter for. Nevertheless, for such kind of sensitive data higher-order filter can be the only way that leads to a much processing time.

For reconstructing the signal there is one constrain that comes from the frequency of the signal we want to extract and the width of the Morlet Wavelet. The relation between the width and the number of cycles poses much impact on the signal information. So, the solution comes with an adaptive cycle selection. Another important parameter was the resolution of frequency selection. These two things combined act as how much information we want to work on. The resolution we choose was 0.01 as our data sample rate was 100Hz and we want the total information. The parameter that defines the time-frequency precision trade-off in n, which ranges from 2 to 15 over the frequency between 2 Hz to 80 Hz. So, a dynamic change of n depending on the value of f_{rex} which differs in range of 78 for a scale of 13 is managed to produce best value of n to reconstruct the signal. An offset of 2 is kept for minimun range and $\frac{1}{3}$ is substructed to match with the frequency shift to produce the calibrated value for n.

$$n = 2 + \frac{13}{78} \times f_{rex} - \frac{1}{3}$$

The ceiling value of the n will be used to reconstruct the signal using Morlet Wavelet because decreasing the value of n will decrease the quality of the reconstructed signal. In this equation f_{rex} is the frequency of complex sine waves to produce the Morlet Wavelet. For the adaptive use of the cycle to reproduce the signal we named it "Cumulative Morlet Wavelet Transform". After the reconstruction of the signal, the comparison with the original signal gives a pure idea of filtering.

4.1.3 Windowing & Overlapping Epoch

As we are working with non-stationary signals working with epoch becomes mandatory. Each of the windows we want to work with must be fast enough to be processed in real-time as well as the quality of the result should be as expected. From the conventional way, a 30-sec window frame is selected for analyzing signals where an abrupt and random change can be identified to figure out the actual result. If we try to make the window smaller, the quality of the result will be degraded. So, we manage to work with 30-sec windows which will further move by 5 sec making 6 Epoch to complete one 30 sec window. In this process, each Epoch will process 30-sec windows which will give our expected result, as well as the 5-sec Epoch, which will make it faster to update the result.

4.1.4 Fast Fourier Transform & Moving Mean

After the reconstruction of the signal which is both filtered and efficiently holding the information for the frequency features the first thing, we will do is FFT. The FFT for such kind of signal containing random impact and short-time fluctuation is a difficult one to estimate the result from it. For this purpose, we use 12 points moving average and the result is visible.

From Figure 4.1.4 (a), we have a clear idea about the benefit rendered by signal-reconstruction incorporated with the application of Moving mean. To begin with, a moving mean formula considering 50 consecutive points was applied which did not yield satisfactory lessening of chaotic representation. Later, a lower approach of 10 points Moving mean was given a try which yielded a more chaotic curve – unable to be precisely comprehended.

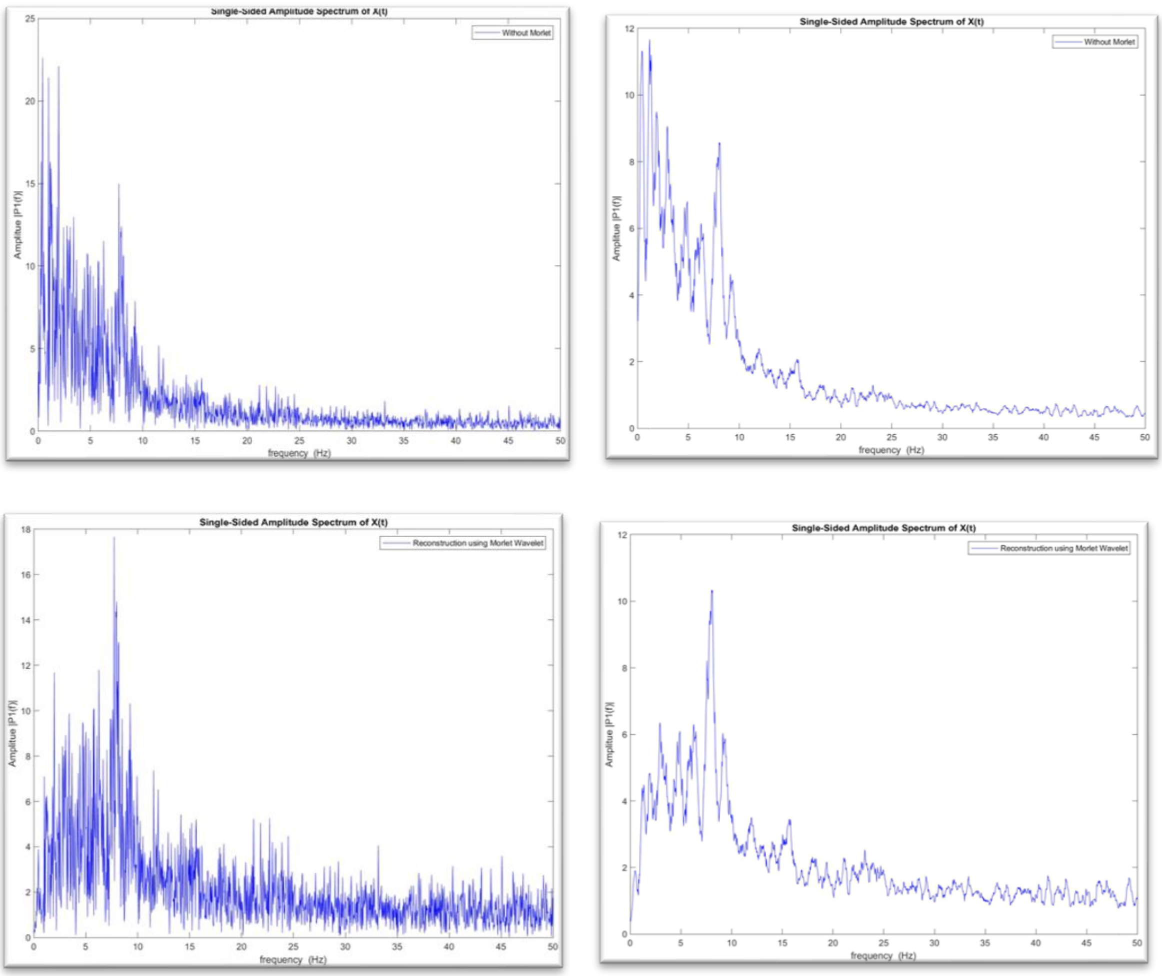


Figure 4.1.4(a): FFT of the original signal (Top left), original signal with 12 points moving average (Top right), reconstructed signal (Bottom left), reconstructed signal with 12 points moving average (Bottom right).

After a number of trial and error, a fixed-point value of Linear Moving Mean has been calibrated where we found 12 points as the optimum one. A comparative graphical representation of the Moving Mean on the FFT is depicted in Figure 4.1.4 (a) and (b).

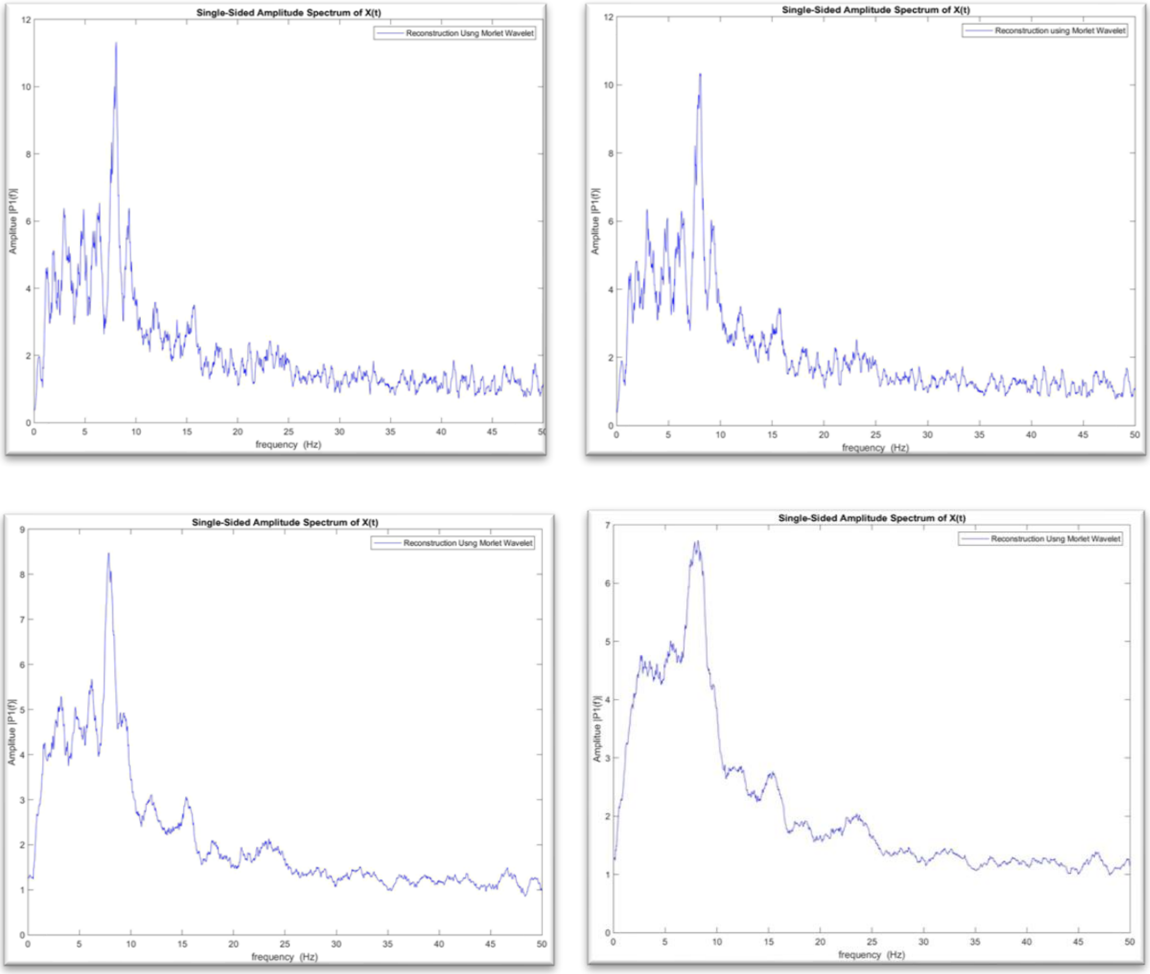


Figure 4.1.4(b): FFT of reconstructed signal with 10 points moving average (Top left), 12 points moving average (Top right), 30 point moving average (Bottom left), 50 points moving average (Bottom right).

For the frequency features extraction, we made four fragments of the frequency band.

- Band 1: 0-4 Hz (relatable to delta wave)
- Band 2: 4-8 Hz (relatable to theta wave)
- Band 3: 8-15 Hz (relatable to alpha wave)
- Band 4: 15-50 Hz (relatable to beta wave)

This fragmentation is very close to Brain rhythms which were discussed before in Section 1.1. We worked on the frequency component as well as the time component to extract features. For the frequency feature extraction, we followed very basic frequency bands (alpha, beta, theta, delta) that are related to human sleep. However, the consciousness of humans will also be connected to these bands. From the analysis of the sleeping stages, we concluded to work on 4 frequency bands. From the EEG data of the wake stage and the sleeping stages, there is a general understanding that in the time of wake period frequency components are randomly occurring but most importantly the average power of the signal is much higher than any of the sleeping stages and averagely distributed after 13 Hz.

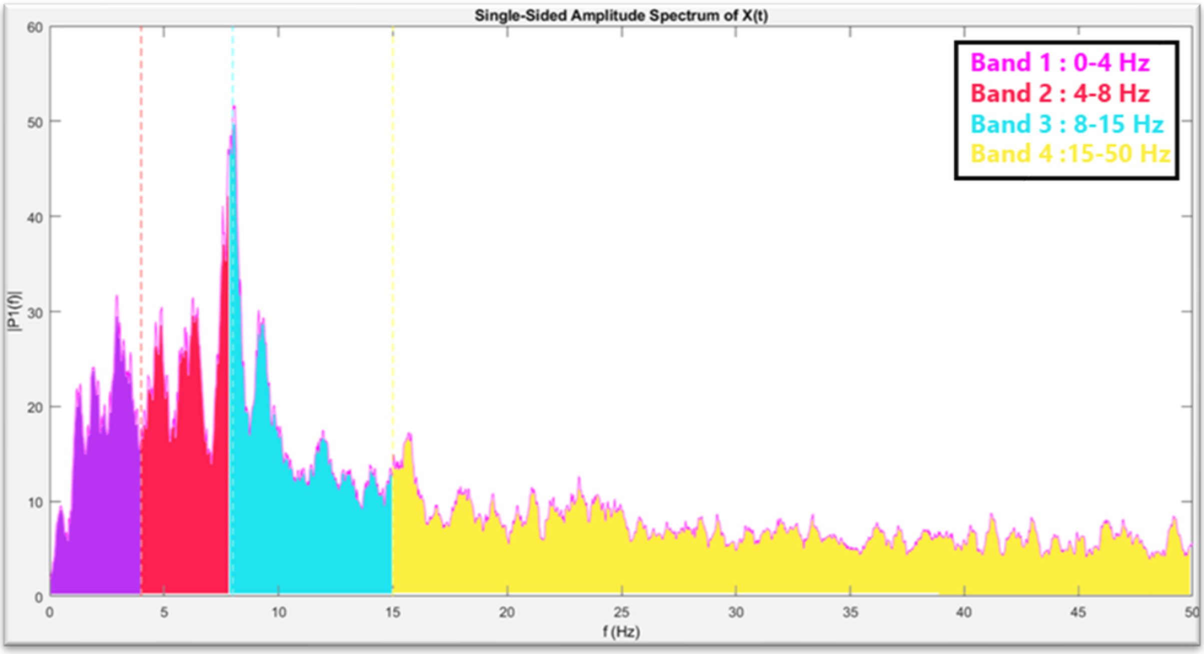


Figure 4.1.4(c): Four frequency band positions are shown in an FFT.

We can see during the sleeping periods, the more one enters into a deep sleep the frequency components of EEG shift towards delta, and the signal strength increases proportionally. So, to find the consciousness sleeping stages study was a must. For these purposes, we agreed to work on these frequency bands. We analyzed the signal for the frequency features in two levels,

- Amplitude spectrum in different frequency bands
- Power Spectral Density in different bands

After reconstructing the signal, we dived into the frequency feature extraction. For that purpose, we first did the fast Fourier transform FFT, a very basic thing to do for frequency analysis.

4.1.5 Statistical approaches & Prime Peak on Amplitude Spectrum

The amplitude varying function of frequency that we got from FFT will be analyzed based on four bands. For amplitude spectrum analysis we analyzed the signal with a basic statistical approach. Finding out the max, mean, median, min for each of the bands. Max will help out to find the highest picks from different bands. These picks are very much important for detecting deep sleep periods when higher peaks will be more available in band 1. For the wake stage, the mean of band 4 can give a clear idea. Light sleeping stages are a bit challenging which needs new features to work on. Moreover, REM can be easily detected by EOG and oral-nasal respiration.

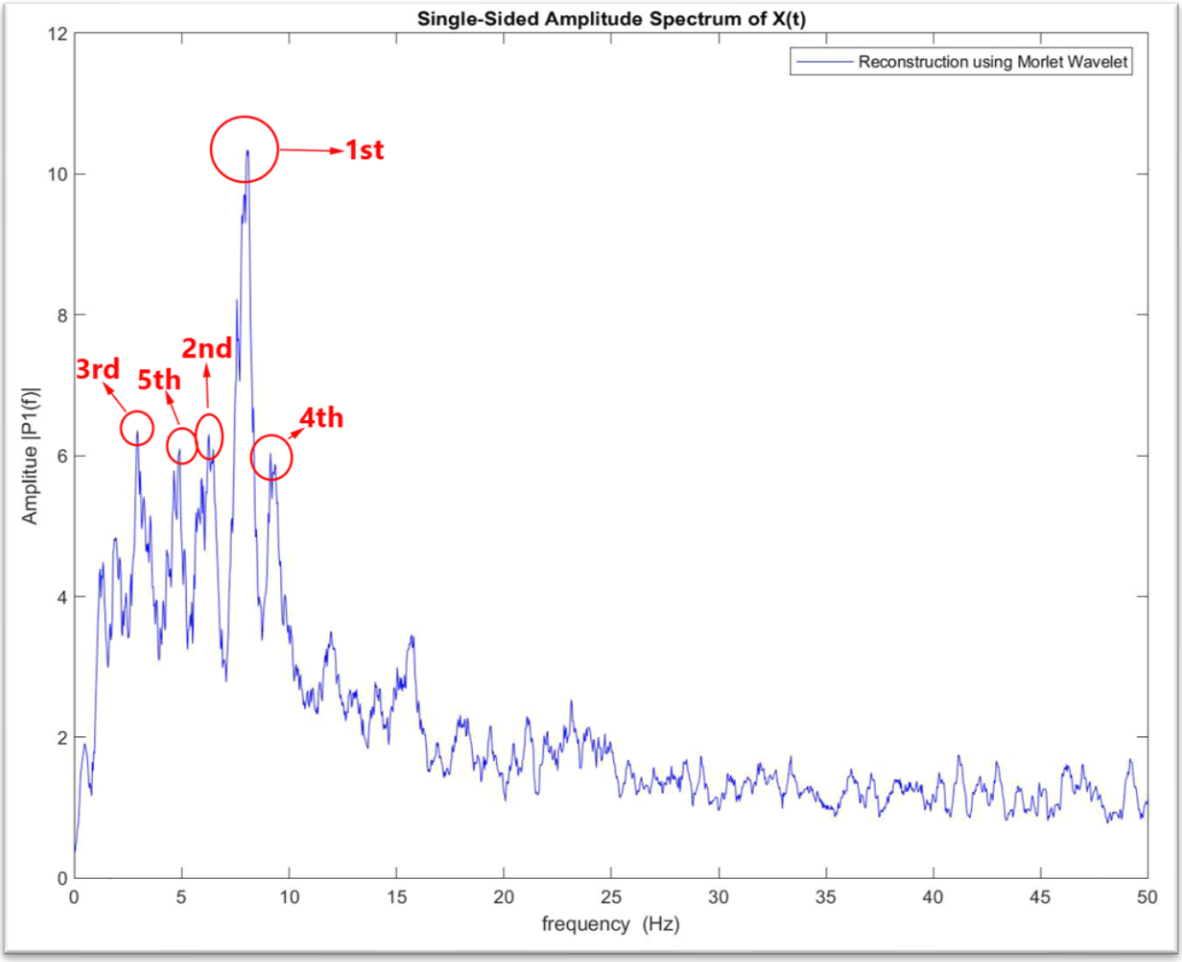


Figure 4.1.5: Prime frequency components are shown with the order in an FFT

Table 4.1.5 Peak order according to strength

Order	Primary	Secondary	Tertiary	Quaternary	Quinary	Senary
Top peaks	7.7333	6.2667	1.9667	9.2667	3.4	4.7

But, the Sequence of the top peaks and the placement of them in the frequency band while maintaining a minimum distance is a nice relation for light sleep. We have seen this working very well for deep sleep also. This feature can be used to predict the depth of the consciousness which is outstanding.

For finding out this peak sequence where the top 100 peaks were taken to compared them and only kept those peaks that maintain that minimum distance. For our case, we took 1 Hz as the minimum distance for making the sequence. In that peak sequence vector, dominant peaks are placed in ascending order.

4.1.6 Power Spectral Density & Band-wise power analysis

Band-wise power from the Power Spectral Density is a valuable feature for determining consciousness level. In Figure 4.1.6(a) the PSD for different stages is shown. The power distribution on different bands for different stages gives an idea of the presence of power in bands. The spectrogram shows the spectrum of frequencies with the variation of time. But persistence plots in Figure 4.1.6(b) all the FFT's for a kernel and also the frequency of the appearing of the signals with a color-coding. For each band, the power can be determined with the help of median frequency which represents the half-power on both sides of that frequency.

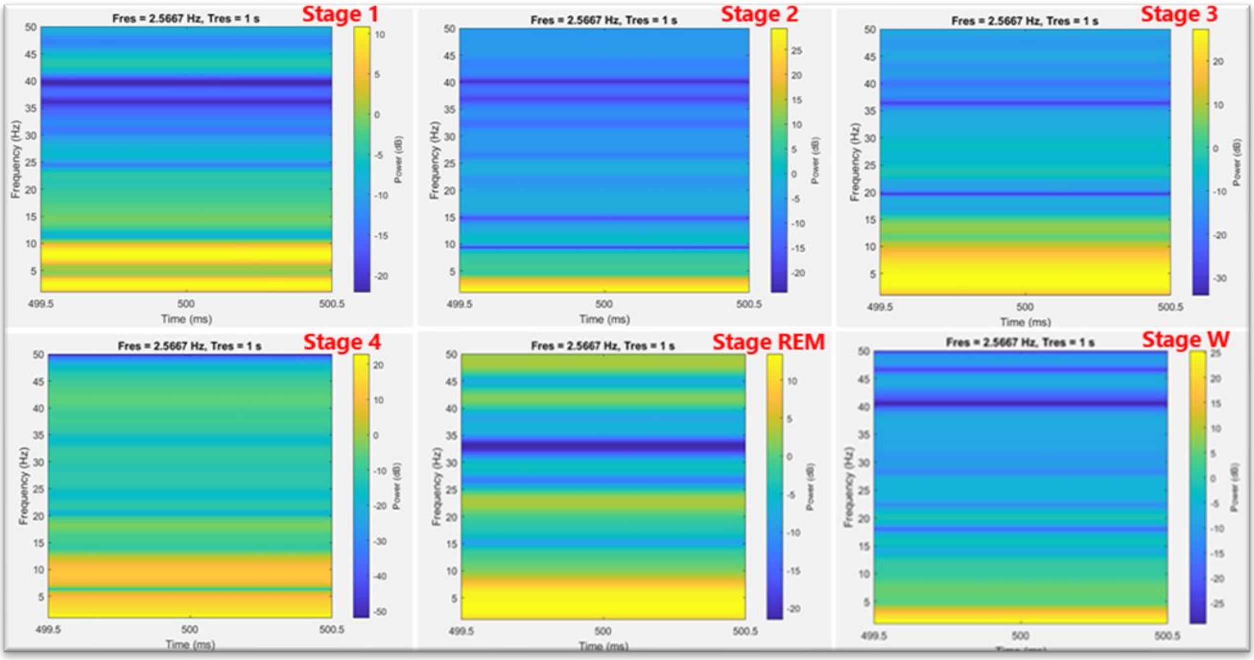


Figure 4.1.6(a): Spectrogram for different sleep stages.

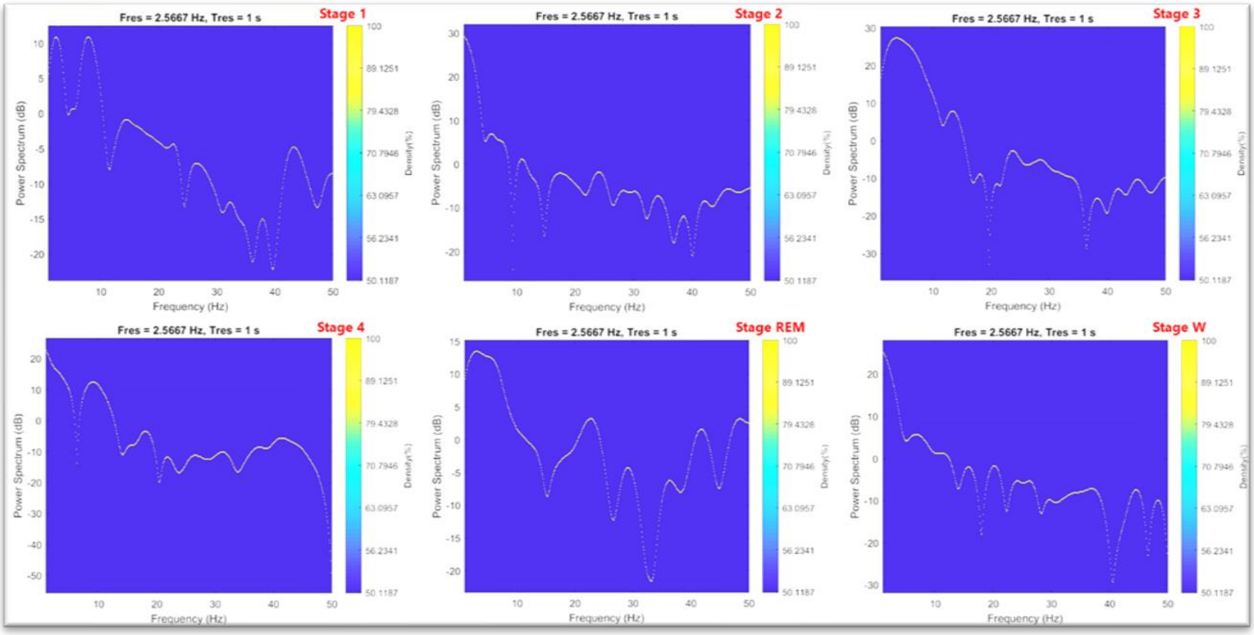


Figure 4.1.6(b): Persistence plot for different sleep stages.

The median frequency placed in any band will justify the most power available in that band. Determination of median frequency will give a concrete idea about the power holding on a band. So, a simple approach determined the median frequency for each band can be done by eliminating each band power after getting the median frequency. Repetition of this process will give the idea of band-wise power domination.

4.2 Time Series Analysis

As explained in the first chapter and Section 1.3, the study was carried out with two separate channels of EEG data – Fpz-Cz & Pz-Oz. With the help of MATLAB©'s built-in function for cross-correlation and additional attributes to calculate lags and delays, the matching strength of the two separate signals from Frontal-to-Central and Parietal-to-Occipital was measured.

As seen from the Figure 4.2, high matching strengths are conspicuous in the form of peaks. Along with the correlation matching strengths, the peaks are cross-verified with the pre-defined sleeping and subconscious states.

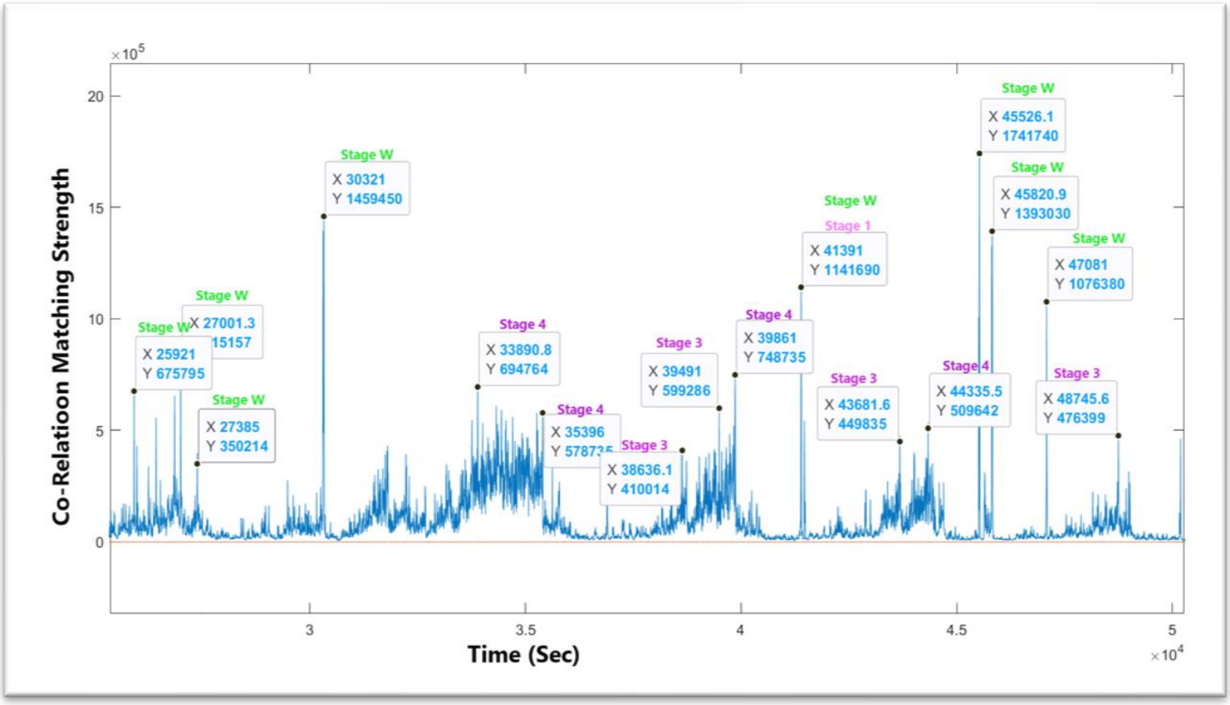


Figure 4.2: The Cross-correlation Result between Channels Fpz-Cz & Pz-Oz

The peaks have a tendency to score up highly at the wake stages and immediately after the moment of transition to awakening. Stage 4 which is known as the slowest wave with the lowest possible frequency shows lower matching strength as well. But the point that should be carefully noted is the repetitive occurrence of the low matching strength at almost every time Stage 4 hits subconsciousness. The minimal rise and fall at each occurrence of Stage 4 fail to awaken the subject up until it peaks at Stage Wake. This behavior in time-series analysis holds previously unnoticed insight that contains useful cues for the patients with impaired consciousness and coma.

Chapter 5

Result

The technical approaches overviewed in the previous chapters are optimally applied in our overall study. The results are processed through the algorithms discussed in the previous chapters. In the upcoming sections, a detailed discourse of all the algorithms is offered.

5.1 Parameters

From our collected data we are presenting out analysis on SC4001E0-PSG.edf which is acquired from a 33-year-old female. We mainly focused on the unconscious state and selected some sleeping stages time frame. Which are the processed. From the hypnogram we acquire with the data, we can locate the state of the patient and compare our result with the patient's consciousness.

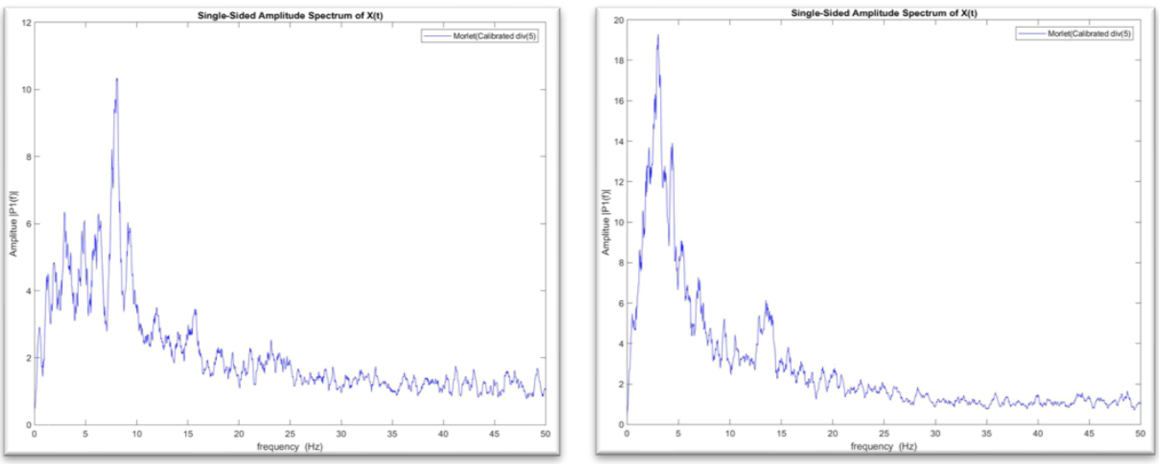


Figure 5.1: FFT of sleep Stage 1 (left) & Stage 2(right).

5.1.1 Stage 1

In sleeping stage 1 the consciousness of humans decreases with time and larger amplitude values are available on a higher frequency. In this stage theta wave with high amplitude is produced by the human brain and it tries to rest forcefully and immediately works in theta rhythm. In this stage, one sometimes doesn't feel he or she is sleeping [70]. In this stage, one is preparing oneself for sleeping by relaxing their mind and thus this stage can be considered as the transition from consciousness to unconsciousness. In this state, people are somewhat aware of their surroundings and can wake themselves up easily [71].

Table 5.1.1 Extracted features of consciousness from sleeping stage 1

SC4001E0-PSG.edf					Data time: 30630 Sec
Patient Age: **33**					Hypnogram: **Stage 1**
Patient gender: **Female**					
Features	0-50 Hz	0.5-4 Hz	4-8 Hz	8-15 Hz	15-50 Hz
Mean	10.891	21.535	25.615	17.003	7.1876
Median	7.9382	21.917	180	14.581	6.5308
Max	88.335	58.309	88.335	74.086	26.302
Min	0.16707	1.0572	0.62347	0.80686	0.16707
Median Frequency	**Primary**	**Secondary**	**Tertiary**	**Quaternary**	**Quinary**
	6.628	8.4863	3.399	23.913	35.657
Relative power	1.0897e+05	68458	42887	16875	6899.8

Top peaks	7.7333	6.2667	1.9667	9.2667	3.4	4.7

The primary median frequency of 6.628 determines the theta wave domination and the sequence of the top peaks can give a clear idea about the presence of the other frequencies as well. The early portion of this stage produces alpha wave which higher than theta and indicates more consciousness. So, a transition occurs from alpha wave to theta wave in this cycle.

5.1.2 Stage 2

During this stage, a person becomes less aware of his surroundings. Deep stimuli are needed to awaken the person. Theta wave dominates this time but sleep spindles and k-complex occurs in this stage. K-complex represents a response to external stimuli and sleep spindles are thought to be important for memory and learning [71], [72]. So, a theta dominant signal with random spindle and k-complex made this stage pretty complex to detect. Time series signal is also needed for detecting k-complex which is the largest event in EEG. From frequency analysis, it is very much frequent that sleeping stage 2 is detected as sleeping stage 1 with theta dominant. Nevertheless, frequency analysis can predict stage 2 sometimes.

Table 5.1.2 Extracted features of consciousness from sleeping Stage 2

SC4001E0-PSG.edf					Data time: 30850 Sec
Patient Age: **33**					Hypnogram: **Stage 2**
Patient gender: **Female**					
Features	0-50 Hz	0.5-4 Hz	4-8 Hz	8-15 Hz	15-50 Hz
Mean	14.688	62.283	35.431	19.233	7.2057
Median	8.1092	59.258	180	17.325	6.3239
Max	178.36	178.36	122.76	58.492	39.659
Min	0.17888	3.7716	3.7518	1.044	0.17888
Median Frequency	**Primary**	**Secondary**	**Tertiary**	**Quaternary**	**Quinary**
	3.1428	5.3974	14.389	20.904	39.169
Relative power	3.6396e+05	1.4623e+05	46960	22215	6575.8
Top peaks	1.7	3.0667	0.3	4.5667	

5.1.3 Stage 3

This stage is referred to as slow-wave because of the high amplitude delta wave. Delta wave is characterized by low frequency (0.5-4 Hz). In this stage, it is difficult to awake one. Sometimes alpha wave can be found in this stage for some individuals[73].

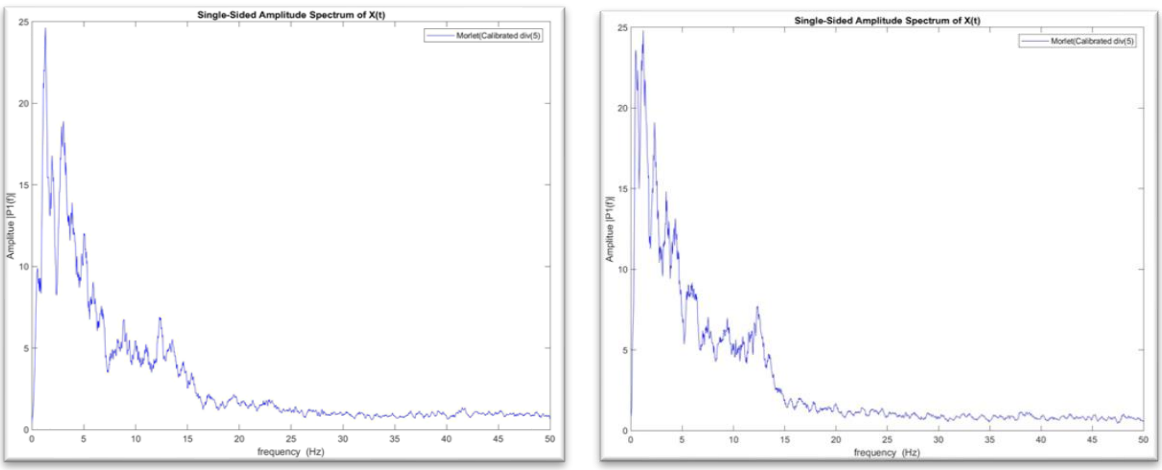


Figure 5.1.2: FFT of sleep stage 3 (left) & stage 4(right).

The presence of the alpha wave in this stage can be a cause of sleep disturbance. In stage 4 deep relaxation is expected but having alpha wave present in this stage hamper this and causes a feeling of not having good sleep.

In this stage, the Max value of band 1 is comparatively higher and the top peaks move towards 0.5 to 1 Hz which represents the deep relaxation with slow-wave. Power in band 1 also verifies the slow-wave dominant stage and the consciousness is relatively low.

Table 5.1.1 Extracted features of consciousness from sleeping stage 3

<table>
<tr><td colspan="4">SC4001E0-PSG.edf
Patient Age: 33
Patient gender: Female</td><td colspan="2">Data time: 31225 Sec
Hypnogram: Stage 3</td></tr>
<tr><td>Features</td><td>0-50 Hz</td><td>0.5-4 Hz</td><td>4-8 Hz</td><td>8-15 Hz</td><td>15-50 Hz</td></tr>
<tr><td>Mean</td><td>15.682</td><td>76.593</td><td>38.359</td><td>23.34</td><td>5.8108</td></tr>
<tr><td>Median</td><td>6.7098</td><td>71.702</td><td>180</td><td>20.759</td><td>5.1217</td></tr>
<tr><td>Max</td><td>214.72</td><td>214.72</td><td>111.14</td><td>66.67</td><td>31.053</td></tr>
<tr><td>Min</td><td>0.34639</td><td>7.9447</td><td>1.6223</td><td>3.1866</td><td>0.34639</td></tr>
<tr><td rowspan="2">Median Frequency</td><td>Primary</td><td>Secondary</td><td>Tertiary</td><td>Quaternary</td><td>Quinary</td></tr>
<tr><td>3.0981</td><td>8.2181</td><td>5.9756</td><td>19.389</td><td>34.902</td></tr>
<tr><td>Relative power</td><td>2.7848e+05</td><td>1.0198e+05</td><td>61607</td><td>12278</td><td>3403</td></tr>
<tr><td>Top peaks</td><td>1.1</td><td>2.6333</td><td>3.7333</td><td colspan="2">5.1333</td></tr>
</table>

From band 1 maximum value and top peak sequence, this stage can easily be separated. Moreover, the Median frequency and the higher ratio of the band 1 power compared to the whole spectrum also reconfirms the presence of this stage.

5.1.4 Stage 4

This stage is pretty much the same as stage 4 and both are considered as the deep sleep period. The median frequency shifts more towards the lower frequency and the amplitude is higher than Stage 3. This stage is often misclassified as Stage 3 but as for consciousness concern, both are considered to be the deep sleep state having the lowest consciousness during sleep.

Table 5.1.4 Extracted features of consciousness from sleeping Stage 4

SC4001E0-PSG.edf				Data time: 33525 Sec	
Patient Age: **33**				Hypnogram: **Stage 4**	
Patient gender: **Female**					
Features	0-50 Hz	0.5-4 Hz	4-8 Hz	8-15 Hz	15-50 Hz
Mean	15.898	74.193	39.514	24.501	4.8789
Median	5.8955	71.857	180	22.872	4.501
Max	284.38	236.52	123.71	64.952	19.984
Min	0.16599	7.9029	3.2293	2.8002	0.16599
Median Frequency	**Primary**	**Secondary**	**Tertiary**	**Quaternary**	**Quinary**
	2.635	7.2038	12.475	23.878	37.151
Relative power	2.4501e+05	88585	37913	7187.2	2461.4
Top peaks	0.56667	2.1667	3.6	4.9	5.9667

5.1.5 Stage W

Depending on the basis of different work in this stage there can be variation in the frequency analysis. Various works are being done in this regard where Brain-computer Interface (BCI) is mentionable. The very common fact is that the higher frequencies are dominant here. The power of the signal, as well as the top peaks, describes it best. If we look at band 4 the mean power is considerably higher than any other stage where the consciousness is minimized.

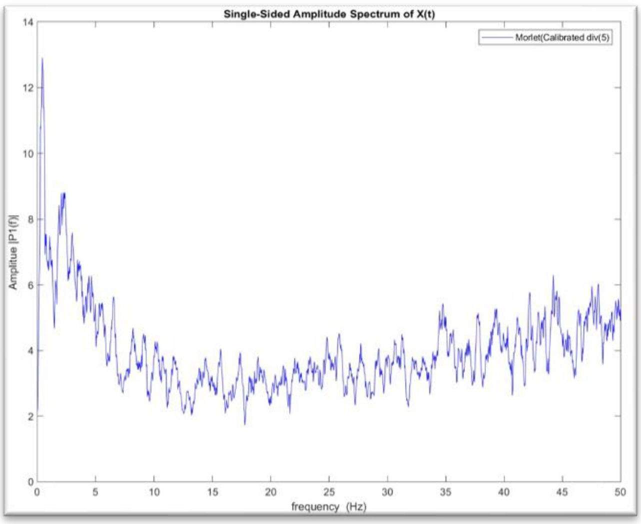


Figure 5.1.4: FFT of wake stage.

Table 5.1.5 Extracted features of consciousness from sleeping stage w

SC4001E0-PSG.edf — Data time: 1000 Sec

Patient Age: **33** — Hypnogram: **Stage W**

Patient gender: **Female**

Features	0-50 Hz	0.5-4 Hz	4-8 Hz	8-15 Hz	15-50 Hz
Mean	20.06	34.159	22.13	16.187	18.801
Median	17.796	32.632	180	15.325	17.116
Max	191.65	76.997	72.78	54.666	67.999
Min	0.39336	1.8911	1.1968	0.47872	0.39336
Median Frequency	**Primary**	**Secondary**	**Tertiary**	**Quaternary**	**Quinary**
	23.95	30.476	3.7011	8.2555	5.6053
Relative power	97089	73973	37391	17608	10266

Top peaks	0.43333	1.6667	3.6	4.8	6.5	9.1667

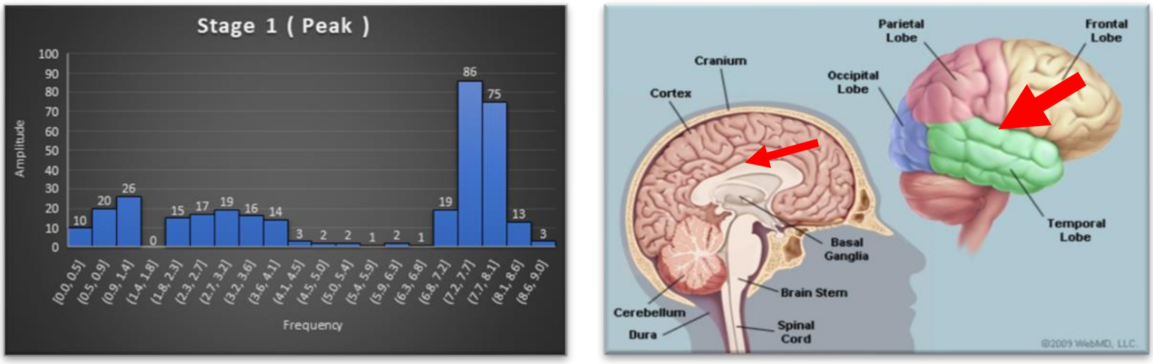
All of the features we have discussed so far are represented as a table here for each of the bands we were talking about. From these different sleeping stages features, we can have a good idea of how the features change while one moves from the conscious stage to the unconscious. From the interpolation of the feature value, we can score the consciousness of a patient. With the help of this prediction through interpolation, we can predict the consciousness level of the patient's data. From these tables, we can clearly state consciousness and unconsciousness state. As the Mean power of band 4 is much higher than any other state. So, we can see that the more unconscious the patient the lower the value of the Mean and Median of the band 4.

The next significant part is that Max's value of band 1 becomes higher if one is in a deeper unconscious state. From the top peaks, the more unconscious the patient is the more peaks shift to the lower frequency. From the media frequency, most of the power is accumulate in band 1 for the highest unconscious level, sleeping stage 4. With the same way of relating these feature values, the state of consciousness can be evaluated.

5.2 Interpretation

5.2.1 Neural transmission

If the EEG acquired from different lobes i.e. brain localities are cross-correlated, a set of information about the existence and direction of neural activity can be extracted. If any information passes from one lobe of the brain to the other, they are bound to show significant matches in patterns with the same frequency. Cross-correlated results give valuable insight into interpreting not only the state of a patient but also the active status of a specific region of the brain. This interaction among different brain lobes can be used to comprehend the consciousness status of the patient, help to diagnose precisely, and predict the chance of recovery.

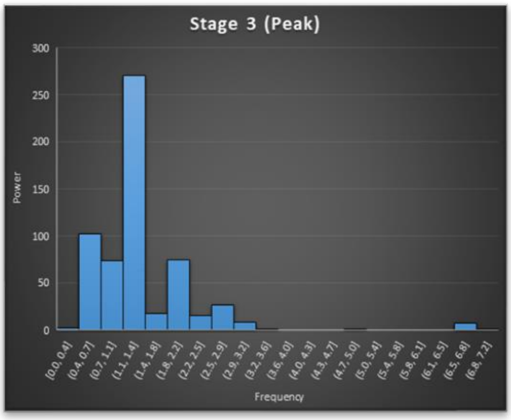


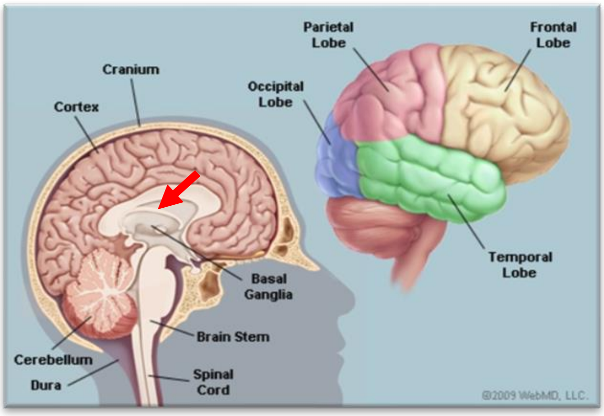
(a) (b)

Figure 5.2.1 (i): **(a)** Distinguished Peak Properties at Stage 1 of Subconscious State
(b) Neurotransmission from Frontal to the Middle Brain

As processed and analyzed in our current study, some of the sleeping or unconscious state can pinpoint the transmitting and receiving station of specific brain lobes. In Figure 5.2.1 (i-a), Stage 1 shows conspicuous peaks right at the expected band of 4-8 Hz. This stage as marked in arrows in Figure 5.2.1 (i-b) determines transmission and reception portal/zones. The existence of the peaks at that certain frequency band validates that the concerning part/lobe of the brain is active.

In a similar manner, the Stage 3 state i.e. Theta Wave at its designated frequency band confirms the transition from cortex to the thalamus (as marked in Figure 5.2.1 i-b). this is the stage where a human brain undergoes *Sleep Spindle* and holds strong evidence of the critical transitioning from drowsiness to deep sleep. As the analysis goes deeper into subconsciousness, the peaks shift to the lower possible frequency bands known as Delta Wave.

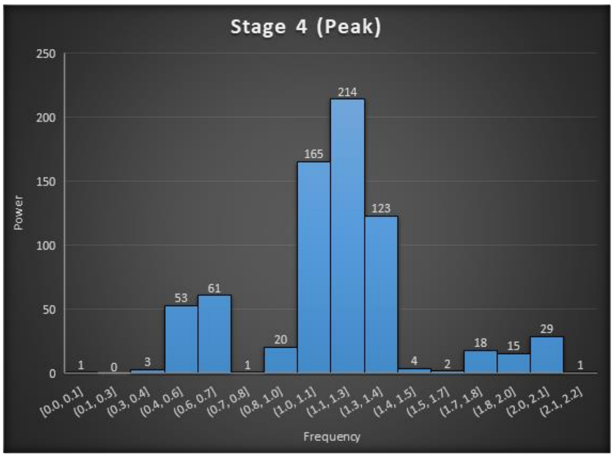


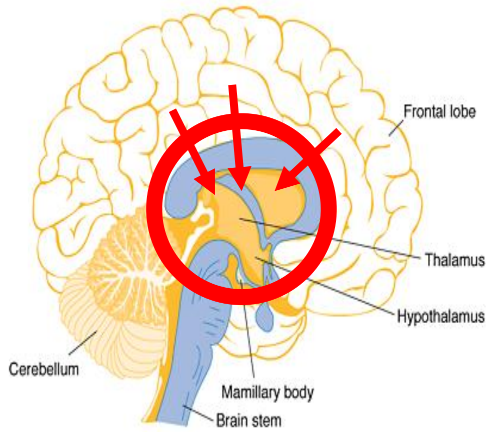


(a) (b)

Figure 5.2.1 (ii): **(a)** Distinguished Peak Properties at Stage 3 of Subconscious State **(b)** Neurotransmission from Frontal to the Middle Brain

When a subject shows this type of brain wave and peaks as shown in Figure 5.2.1 (iii), it means that the brain activity has been confined in the middle brain zone and all the conscious activities are seized for the time being. For the patients in Anesthesia and Coma, the Delta Wave seems to remain consistent over a long (or, forced) period of time. Their brain waves seem to get confined to the middle region of the brain, closing the conscious activities.

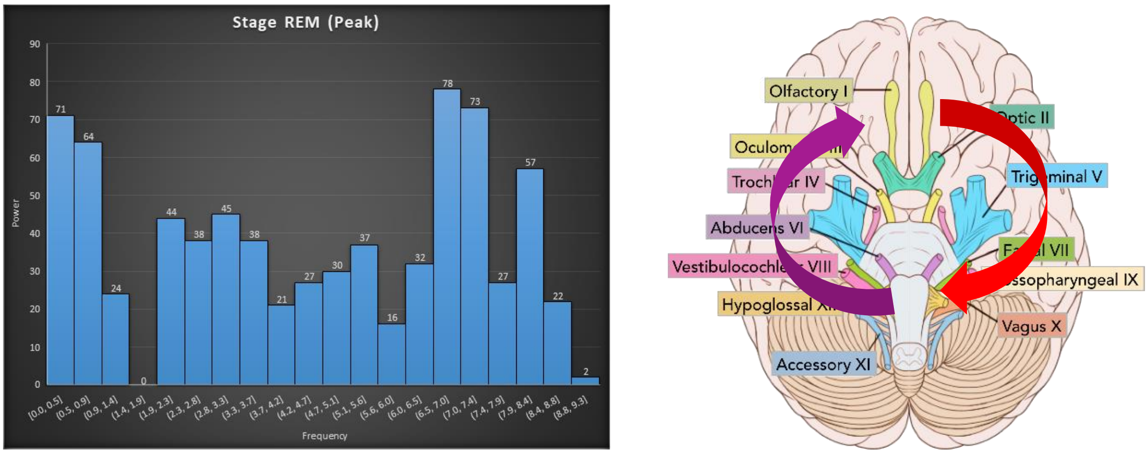




(a) (b)

Figure 5.2.1 (iii): **(a)** Distinguished Peak Properties at Stage 4 of Subconscious State **(b)** Neurotransmission confined in the Middle Brain

It can also determine the active nodes and can predict the recoverable coma state. In the awake and REM stage, however, a many-to-many transmission takes place. Figure 5.2.1 (iv) shows how no specific frequency can dominate and thus different part of the brain gets activated.



(a) (b)

Figure 5.2.1 (iv): **(a)** Distributed Peak Properties at Stage REM of Subconscious State **(b)** Neurotransmission Overall Distributed throughout several Brain Lobes

The phenomenal swinging that occurs after Stage 4 of the subconscious state is the key stimulus that brings a subject to awakening. In the correlation measurements, apart from the visible peaks of matching strengths, a consecutively repetitive harmonic was noticed. The interpretation of *Failure Harmonics* is discussed in the upcoming sub-section.

5.2.2 Failure Harmonics

By deploying the cross-correlation analysis method as detailed in the earlier chapters, we got a new finding related to the sleeping cycle. The generalized sleeping stages come in repetition; each cycle counts from REM to Non-REM and this cycle is found several times during the whole sleeping period. At each transition to awakening, the matching strength peaks in high correlation values. But the fact that is not comparatively conspicuous or negligible as shown in Figure 4.2 is: during the deep sleep period i.e. Delta Wave, the matching strengths seem to rise to a little extent but failing every time to peak up. This is the phase where the brain waves seem to confine themselves within the middle brain locality. To comprehend deeply, when the Parietal-Occipital EEG did not quite match with the Frontal-Central EEG, it could be deliberately assumed that the process of transferring information through neural transmission in between those regions remained somehow barricaded at Stage 4 or Delta Wave. With every occurrence of Stage 4 at each sleeping cycle, the lowering matching strengths kept decreasing. The lag of correlation rendered a harmonious output as pointed in Figure 5.2.2.

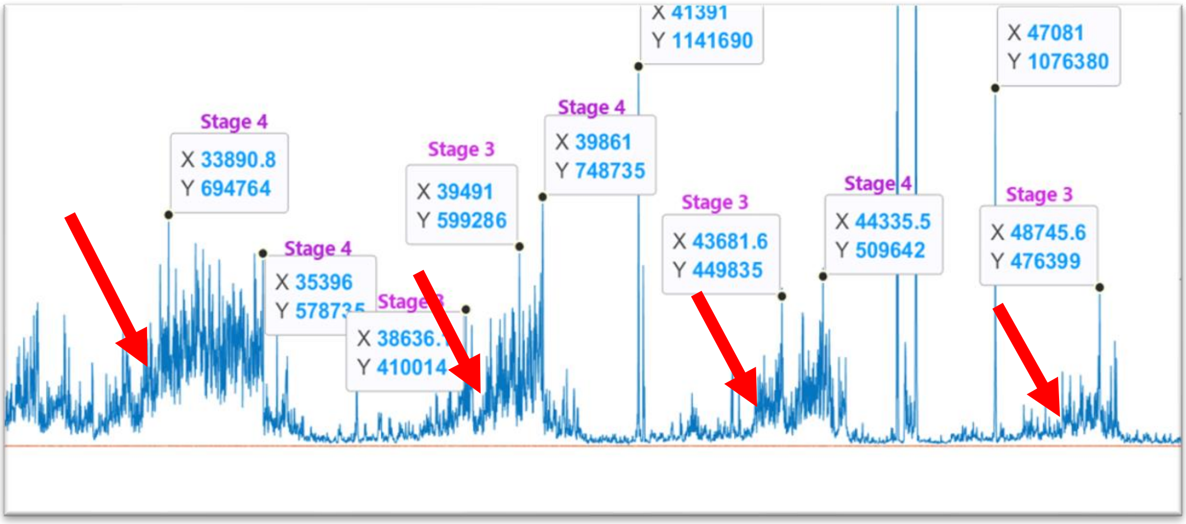


Figure 5.2.2: Repetitive low and decreasing matching strengths in Cross-correlation.

The harmonics for each cycle and the intensity were decreasing as a subject tended to pass by the whole subconscious period. The longer the sleep, the delta wave becomes less prominent. And after each harmonic, there is an abrupt rise to awakening as the brain seems to transfer information to the other regions unlike being deep into subconsciousness, or anesthesia, or coma. It is probable that the harmonics never give in to the abrupt rise at all in non-recovery cases of Coma. As long as they appear, they mark the failure to want to connect other parts of the brain that could inevitably lead to consciousness. This is why the harmonics are termed as *Failure Harmonics* that remain consistent in the unconscious EEG locality-specific cross-correlations. There is a distinct possibility that these harmonics can give us new findings in the depth of non-recoverable coma or impaired consciousness. Moreover, if a one-to-one comparison by cross-correlation is considered among every two different lobes/regions of the brain, and if the cross-correlation results show Failure Harmonics alongside, the diagnosis can help in detecting the inactive region of the brain and positive potential for deploying electromagnetic stimuli for possible recovery.

Chapter 6

Conclusion

Brain wave analysis utilizing EEG Signal Processing has become a very necessary tool of diagnosis in medical, cognitive, and neuroscience. With the help of these tools, different diseases are being diagnosed and the quickest possible recovery is strategized. The currently existing algorithms and datasets give a promising contribution to conscious activity analyzing and BCI, however, as the consciousness decreases, the frequency of the EEG signal decreases as well and becomes difficult to work with. Again, without any major and sturdy feedback from patients, it becomes more challenging. So, the number of works related and researches carried out to understand unconscious state including coma is highly unsatisfactory. With our study on non-conscious analytical attributes, a new addition to unconscious featuring is being made. As our approach is related to both frequency and time analysis to find out the features related to unconsciousness, the research finds a way of extracting valuable features from the signal. With a view to collecting Comatose patient EEG from Bangladesh perspective (after the Covid-19 constraints are over), a detailed study on unconsciousness based on the new finding can pace the comprehension of the mysterious layers of unconsciousness and usher into new ways to promote recovery.

6.1 Future Work

As this work is mostly focused on the consciousness state of a patient, we mostly extracted features to determine that. Edf data, which are used here represents only Fpz-Cz and Pz-Oz with normal EEG convention while using probes. But a high density with individual placement could give a better result with the same feature. Neural transmission can be detected with high precision.

6.1.1 Power Correction

The reconstructed signal using the Morlet wavelet is not calibrated with a power spectrum. Most of our work is based on the ratio and the comparison which doesn't need real power. But a calibration in the signal would be helpful for detecting an individual's feature more accurately.

6.1.2 Applying Machine Learning

The features we have extracted so far can be used to predict the consciousness of the patient. With the help of these features, an Artificial Neural network can be developed to predict the patient consciousness state which will be fast and accurate. As we have labeled data, supervised learning can be applied with a regression model. Neural Network would be much helpful in this regard as the feature vector is pretty much large and we can feed the feature vector as a time sequence of features because the consciousness features depend on the previous state also. With this logical approach, a model can be trained to predict the consciousness of a patient.

6.1.3 Acquiring Real Coma Data from Bangladesh

We worked with the sleeping data for finding out the consciousness of a patient. If we get the chance to work with the coma people data which would greatly help to co-relate the result with unconscious people. A recoverable unconscious state for a coma patient could be separated using these features. Moreover, applying the external stimuli for coma people can be determined and examined the results.

References

[1] MariaConleyMD, "Aging and Sleep Quality: What You Should Know," *Medium*, Jun. 28, 2019. https://medium.com/@mariaannconley/aging-and-sleep-quality-what-you-should-know-c7f7d269e67b (accessed Mar. 09, 2021).

[2] "Wartung / Maintenance." https://www.thieme-connect.com/products/ejournals/abstract/10.1055/s-0028-1094611 (accessed Mar. 09, 2021).

[3] R. Boostani, F. Karimzadeh, and M. Nami, "A comparative review on sleep stage classification methods in patients and healthy individuals," *Computer Methods and Programs in Biomedicine*, vol. 140, pp. 77–91, Mar. 2017, doi: 10.1016/j.cmpb.2016.12.004.

[4] B. Şen, M. Peker, A. Çavuşoğlu, and F. V. Çelebi, "A Comparative Study on Classification of Sleep Stage Based on EEG Signals Using Feature Selection and Classification Algorithms," *J Med Syst*, vol. 38, no. 3, p. 18, Mar. 2014, doi: 10.1007/s10916-014-0018-0.

[5] "Efficient sleep stage classification based on EEG signals." https://ieeexplore.ieee.org/abstract/document/6845193/ (accessed Mar. 10, 2021).

[6] A. Anokhin and F. Vogel, "EEG Alpha rhythm frequency and intelligence in normal adults," *Intelligence*, vol. 23, no. 1, pp. 1–14, Jul. 1996, doi: 10.1016/S0160-2896(96)80002-X.

[7] "Mid-Sagittal Cross Section of Brain | Brain anatomy, Brain anatomy and function, Medical anatomy." https://www.pinterest.com/pin/281123201711807180/ (accessed Mar. 10, 2021).

[8] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, "Chapter 3 - Technical Aspects of Brain Rhythms and Speech Parameters," in *Introduction to EEG- and Speech-Based Emotion Recognition*, P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, Eds. Academic Press, 2016, pp. 51–79.

[9] "Frontiers | Electroencephalography: Clinical Applications During the Perioperative Period | Medicine." https://www.frontiersin.org/articles/10.3389/fmed.2020.00251/full (accessed Mar. 10, 2021).

[10] E. F. M. Wijdicks and R. E. Cranford, "Clinical Diagnosis of Prolonged States of Impaired Consciousness in Adults," *Mayo Clinic Proceedings*, vol. 80, no. 8, pp. 1037–1046, Aug. 2005, doi: 10.4065/80.8.1037.

[11] "Disorders of consciousness," *nhs.uk*, May 09, 2018. https://www.nhs.uk/conditions/disorders-of-consciousness/ (accessed Mar. 11, 2021).

[12] "The vegetative state | The BMJ." https://www.bmj.com/content/341/bmj.c3765.short (accessed Mar. 09, 2021).

[13] J. T. Giacino *et al.*, "The minimally conscious state: Definition and diagnostic criteria," *Neurology*, vol. 58, no. 3, pp. 349–353, Feb. 2002, doi: 10.1212/WNL.58.3.349.

[14] "Coma," *nhs.uk*, Oct. 18, 2017. https://www.nhs.uk/conditions/coma/ (accessed Mar. 11, 2021).

[15] "Georgian Medical News," *ResearchGate*. https://www.researchgate.net/journal/Georgian-Medical-News-1512-0112 (accessed Mar. 09, 2021).

[16] MEDIAmaker, "Glasgow Coma Scale." https://www.headway.org.uk/about-brain-injury/individuals/effects-of-brain-injury/coma-and-reduced-awareness-states/glasgow-coma-scale/ (accessed Mar. 11, 2021).

[17] "ASSESSMENT OF COMA AND IMPAIRED CONSCIOUSNESS: A Practical Scale - ScienceDirect." https://www.sciencedirect.com/science/article/abs/pii/S0140673674916390 (accessed Mar. 09, 2021).

[18] G. Teasdale and B. Jennett, "Assessment and prognosis of coma after head injury," *Acta neurochir*, vol. 34, no. 1, pp. 45–55, Mar. 1976, doi: 10.1007/BF01405862.

[19] B. Jennett, G. Teasdale, R. Braakman, J. Minderhoud, J. Heiden, and T. Kurze, "Prognosis of Patients with Severe Head Injury," *Neurosurgery*, vol. 4, no. 4, pp. 283–289, Apr. 1979, doi: 10.1227/00006123-197904000-00001.

[20] "Protocol for the Electroencephalography Guidance of Anesthesia to Alleviate Geriatric Syndromes (ENGAGES) study: a pragmatic, randomised clinical trial | BMJ Open." https://bmjopen.bmj.com/content/6/6/e011505 (accessed Mar. 10, 2021).

[21] T. Ph, "3 Anesthesia Techniques and Monitors," p. 2.

[22] "Figure 2: Frontal cortex EEG recordings showing changes seen at the...," *ResearchGate*. https://www.researchgate.net/figure/Frontal-cortex-EEG-recordings-showing-changes-seen-at-the-three-anesthetic-endpoints_fig5_267746431 (accessed Mar. 10, 2021).

[23] T. Zoughi and R. Boostani, "Analyzing autocorrelation fluctuation of EEG signal for estimating depth of anesthesia," in *2010 18th Iranian Conference on Electrical Engineering*, May 2010, pp. 24–29, doi: 10.1109/IRANIANCEE.2010.5507110.

[24] M. B. & Spine, "EEG Electroencephalogram | Mayfield Brain & Spine." https://mayfieldclinic.com/pe-eeg.htm (accessed Mar. 10, 2021).

[25] "Figure 3: 10-20 system of electrode placement.," *ResearchGate*. https://www.researchgate.net/figure/10-20-system-of-electrode-placement_fig3_237777779 (accessed Mar. 10, 2021).

[26] "Electrooculogram - an overview | ScienceDirect Topics." https://www.sciencedirect.com/topics/nursing-and-health-professions/electrooculogram (accessed Mar. 10, 2021).

[27] http://science.education.nih.gov/supplements/nih3/sleep/guide/info-sleep.htm, *English: Placement of electrodes to determine EEG, EOG, and EMG*. 2014.

[28] "10–20 system (EEG)," *Wikipedia*. Jan. 29, 2021, Accessed: Mar. 10, 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=10%E2%80%9320_system_(EEG)&oldid=1003622197.

[29] B. Kemp, A. Zwinderman, B. Tuk, H. Kamphuisen, and J. Oberyé, "The Sleep-EDF Database [Expanded]." physionet.org, 2018, doi: 10.13026/C2X676.

[30] B. Kemp, A. H. Zwinderman, B. Tuk, H. A. C. Kamphuisen, and J. J. L. Oberye, "Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 9, pp. 1185–1194, Sep. 2000, doi: 10.1109/10.867928.

[31] M. Seeck *et al.*, "The standardized EEG electrode array of the IFCN," *Clinical Neurophysiology*, vol. 128, no. 10, pp. 2070–2077, Oct. 2017, doi: 10.1016/j.clinph.2017.06.254.

[32] J. M. Hockaday, F. Potts, E. Epstein, A. Bonazzi, and R. S. Schwab, "Electroencephalographic changes in acute cerebral anoxia from cardiac or respiratory arrest," *Electroencephalography and Clinical Neurophysiology*, vol. 18, no. 6, pp. 575–586, May 1965, doi: 10.1016/0013-4694(65)90075-1.

[33] S. Vm, "Prognostically important EEG coma patterns in diffuse anoxic and traumatic encephalopathies in adults.," *J Clin Neurophysiol*, vol. 5, no. 2, pp. 161–174, Apr. 1988, doi: 10.1097/00004691-198804000-00003.

[34] "EEG Abnormality Grades and Subdivisions of Prognostic Importance in Traumatic and Anoxic Coma in Adults - V. M. Synek, 1988." https://journals.sagepub.com/doi/abs/10.1177/155005948801900310?journalCode=eega (accessed Mar. 11, 2021).

[35] V. M. Synek, "Value of a Revised EEG Coma Scale for Prognosis after Cerebral Anoxia and Diffuse Head Injury," *Clinical Electroencephalography*, vol. 21, no. 1, pp. 25–30, Jan. 1990, doi: 10.1177/155005949002100111.

[36] G. B. Young, "The EEG in Coma," *Journal of Clinical Neurophysiology*, vol. 17, no. 5, pp. 473–485, Sep. 2000.

[37] R. P. Brenner, "The Interpretation of the EEG in Stupor and Coma," *The Neurologist*, vol. 11, no. 5, pp. 271–284, Sep. 2005, doi: 10.1097/01.nrl.0000178756.44055.f6.

[38] J. Hofmeijer, T. M. J. Beernink, F. H. Bosch, A. Beishuizen, M. C. Tjepkema-Cloostermans, and M. J. A. M. van Putten, "Early EEG contributes to multimodal outcome prediction of postanoxic coma," *Neurology*, vol. 85, no. 2, pp. 137–143, Jul. 2015, doi: 10.1212/WNL.0000000000001742.

[39] B. Bergamasco, L. Bergamini, T. Doriguzzi, and D. Fabiani, "EEG sleep patterns as a prognostic criterion in post-traumatic coma," *Electroencephalography and Clinical Neurophysiology*, vol. 24, no. 4, pp. 374–377, Apr. 1968, doi: 10.1016/0013-4694(68)90198-3.

[40] C. IBER, "The AASM Manual for the Scoring of Sleep and Associated Events : Rules," *Terminology and Technical Specification*, 2007, Accessed: Mar. 12, 2021. [Online]. Available: https://ci.nii.ac.jp/naid/10024500923/.

[41] K. Aboalayon, M. Faezipour, W. Almuhammadi, and S. Moslehpour, "Sleep Stage Classification Using EEG Signal Analysis: A Comprehensive Survey and New Investigation," *Entropy*, vol. 18, no. 9, p. 272, Aug. 2016, doi: 10.3390/e18090272.

[42] P. Anderer *et al.*, "Artifact Processing in Computerized Analysis of Sleep EEG – A Review," *Neuropsychobiology*, vol. 40, no. 3, pp. 150–157, 1999, doi: 10.1159/000026613.

[43] M. Toussaint *et al.*, "An architecture for EEG signal processing and interpretation during sleep (ESPIS)," *Computer Methods and Programs in Biomedicine*, vol. 45, no. 1–2, pp. 55–60, Oct. 1994, doi: 10.1016/0169-2607(94)90016-7.

[44] L. Fraiwan, K. Lweesy, N. Khasawneh, H. Wenz, and H. Dickhaus, "Automated sleep stage identification system based on time–frequency analysis of a single EEG channel and random forest classifier," *Computer Methods and Programs in Biomedicine*, vol. 108, no. 1, pp. 10–19, Oct. 2012, doi: 10.1016/j.cmpb.2011.11.005.

[45] U. R. Acharya, E. C.-P. Chua, K. C. Chua, L. C. Min, and T. Tamura, "ANALYSIS AND AUTOMATIC IDENTIFICATION OF SLEEP STAGES USING HIGHER ORDER SPECTRA," *Int. J. Neur. Syst.*, vol. 20, no. 06, pp. 509–521, Dec. 2010, doi: 10.1142/S0129065710002589.

[46] P. Achermann, R. Hartmann, A. Gunzinger, W. Guggenbühl, and A. A. Borbély, "All-night sleep EEG and artificial stochastic control signals have similar correlation dimensions," *Electroencephalography and Clinical Neurophysiology*, vol. 90, no. 5, pp. 384–387, May 1994, doi: 10.1016/0013-4694(94)90054-X.

[47] L. L. Imbach, E. Werth, U. Kallweit, J. Sarnthein, T. E. Scammell, and C. R. Baumann, "Inter-Hemispheric Oscillations in Human Sleep," *PLoS ONE*, vol. 7, no. 11, p. e48660, Nov. 2012, doi: 10.1371/journal.pone.0048660.

[48] L. Liu, H. Hsu, and E. W. Grafarend, "Normal Morlet wavelet transform and its application to the Earth's polar motion," *Journal of Geophysical Research: Solid Earth*, vol. 112, no. B8, 2007, doi: https://doi.org/10.1029/2006JB004895.

[49] M. X. Cohen, "A better way to define and describe Morlet wavelets for time-frequency analysis," *NeuroImage*, vol. 199, pp. 81–86, Oct. 2019, doi: 10.1016/j.neuroimage.2019.05.048.

[50] E. W. Weisstein, "Fast Fourier Transform." https://mathworld.wolfram.com/FastFourierTransform.html (accessed Mar. 11, 2021).

[51] R. N. Youngworth, B. B. Gallagher, and B. L. Stamper, "An overview of power spectral density (PSD) calculations," in *Optical Manufacturing and Testing VI*, Aug. 2005, vol. 5869, p. 58690U, doi: 10.1117/12.618478.

[52] A. Phinyomark, S. Thongpanja, H. Hu, P. Phukpattaranont, and C. Limsakul, "The Usefulness of Mean and Median Frequencies in Electromyography Analysis," *Computational Intelligence in Electromyography Analysis - A Perspective on Current Applications and Future Challenges*, Oct. 2012, doi: 10.5772/50639.

[53] "Kaiser window - MATLAB kaiser." https://www.mathworks.com/help/signal/ref/kaiser.html (accessed Mar. 14, 2021).

[54] F. J. Harris, "On the use of windows for harmonic analysis with the discrete Fourier transform," *Proceedings of the IEEE*, vol. 66, no. 1, pp. 51–83, Jan. 1978, doi: 10.1109/PROC.1978.10837.

[55] P. Welch, "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Transactions on Audio and Electroacoustics*, vol. 15, no. 2, pp. 70–73, Jun. 1967, doi: 10.1109/TAU.1967.1161901.

[56] “EEG analysis,” *Wikipedia*. Mar. 01, 2021, Accessed: Mar. 11, 2021. [Online]. Available: https://en.wikipedia.org/w/index.php?title=EEG_analysis&oldid=1009688265.

[57] “Understanding Correlation - Technical Articles.” https://www.allaboutcircuits.com/technical-articles/understanding-correlation/ (accessed Mar. 11, 2021).

[58] J. Tadeu *et al.*, “INTELLIGENT WHILE-DRILLING SYSTEMS,” Mar. 2021.

[59] C. Meisel, K. Bailey, P. Achermann, and D. Plenz, “Decline of long-range temporal correlations in the human brain during sustained wakefulness,” *Scientific Reports*, vol. 7, no. 1, Art. no. 1, Sep. 2017, doi: 10.1038/s41598-017-12140-w.

[60] G. F. Zebende, F. M. O. Filho, and J. A. L. Cruz, “Auto-correlation in the motor/imaginary human EEG signals: A vision about the FDFA fluctuations,” *PLOS ONE*, vol. 12, no. 9, p. e0183121, Sep. 2017, doi: 10.1371/journal.pone.0183121.

[61] A. F. Farag, S. M. El-Metwally, and A. A. A. Morsy, “Automated Sleep Staging Using Detrended Fluctuation Analysis of Sleep EEG,” in *Soft Computing Applications*, Berlin, Heidelberg, 2013, pp. 501–510, doi: 10.1007/978-3-642-33941-7_44.

[62] S. Cekic, D. Grandjean, and O. Renaud, “Time, Frequency & Time-Varying Causality Measures in Neuroscience,” *arXiv:1704.03177 [stat]*, Apr. 2017, Accessed: Mar. 11, 2021. [Online]. Available: http://arxiv.org/abs/1704.03177.

[63] V. J. López-Madrona, F. S. Matias, C. R. Mirasso, S. Canals, and E. Pereda, “Inferring correlations associated to causal interactions in brain signals using autoregressive models,” *Scientific Reports*, vol. 9, no. 1, Art. no. 1, Nov. 2019, doi: 10.1038/s41598-019-53453-2.

[64] R. R. Johnson, D. P. Popovic, R. E. Olmstead, M. Stikic, D. J. Levendowski, and C. Berka, “Drowsiness/alertness algorithm development and validation using synchronized EEG and cognitive performance to individualize a generalized model,” *Biological Psychology*, vol. 87, no. 2, pp. 241–250, May 2011, doi: 10.1016/j.biopsycho.2011.03.003.

[65] A. Haar, “Zur Theorie der orthogonalen Funktionensysteme,” *Math. Ann.*, vol. 69, no. 3, pp. 331–371, Sep. 1910, doi: 10.1007/BF01456326.

[66] C. K. Chui, Ed., “3 - Wavelet Transforms and Time-Frequency Analysis,” in *Wavelet Analysis and Its Applications*, vol. 1, Academic Press, 1992, pp. 49–80.

[67] M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies, “Image coding using vector quantization in the wavelet transform domain,” in *International Conference on Acoustics, Speech, and Signal Processing*, Apr. 1990, pp. 2297–2300 vol.4, doi: 10.1109/ICASSP.1990.116036.

[68] J. Morlet, G. Arens, E. Fourgeau, and D. Giard, “Wave propagation and sampling theory—Part II: Sampling theory and complex waves,” *GEOPHYSICS*, vol. 47, no. 2, pp. 222–236, Feb. 1982, doi: 10.1190/1.1441329.

[69] D. Gabor, “Theory of communication. Part 1: The analysis of information,” *Journal of the Institution of Electrical Engineers - Part III: Radio and Communication Engineering*, vol. 93, no. 26, pp. 429–441, Nov. 1946, doi: 10.1049/ji-3-2.1946.0074.

[70] Facebook and Twitter, “The 4 Stages of Sleep (NREM and REM Sleep Cycles),” *Verywell Health*. https://www.verywellhealth.com/the-four-stages-of-sleep-2795920 (accessed Mar. 19, 2021).
[71] J. E. Brinkman, V. Reddy, and S. Sharma, “Physiology, Sleep,” in *StatPearls*, Treasure Island (FL): StatPearls Publishing, 2021.
[72] “Stages of Sleep | Introduction to Psychology.” https://courses.lumenlearning.com/wsu-sandbox/chapter/stages-of-sleep/ (accessed Mar. 20, 2021).
[73] L. Creti, E. Libman, M. Baltzan, D. Rizzo, S. Bailes, and C. S. Fichten, “Impaired Sleep in Chronic Fatigue Syndrome: How Is It Best Measured?,” *J Health Psychol*, vol. 15, no. 4, pp. 596–607, May 2010, doi: 10.1177/1359105309355336.