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"Relationship between Frontoparietal alpha oscillations and visual working memory task"

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Abstract

Working Memory (WM) is a vital capacity that supports various cognitive activities and is intimately associated with intellectual ability and academic performance. With the aid of 30 participants in the study, we explored the dynamic network architecture underpinning the preservation of visual information in WM using EEG. We found greater and more persistent connections in the alpha frequency region (8 to 14 Hz) throughout the retention interval associated with correct trials vs. wrong trials. Furthermore, our network study demonstrated increased alpha synchronization during WM maintenance. Our findings imply that alpha inter-regional synchronization is an essential mechanism for preserving the memory of visual WM tasks without stimuli. Aside from the spectrum analysis of the chosen electrodes, the PLV analysis was used to investigate the signal connection. Throughout the retention period, the total brain connectivity time series showed a significant difference between correct and erroneous trials for the alpha band only. This influence was significant for most of the retention duration, showing that alpha oscillations play an important role in WM maintenance processes. Reduced alpha connection reported during the delay interval linked with incorrect replies might thus be explained by endogenous changes in attention.

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List of Acronyms

AM Amplitude Modulation

AMF Amplitude Modulation Frequency

CF Carrier Frequency

CFC Cross Frequency Coupling

DQ Direct Quadrature

ECoG Electrocorticography

EEG Electroencephalography

EMD Empirical Mode Decomposition

ERD Event Related Desynchronization

FDR False Discovery Rate

FMRI Functional Magnetic Resonance Imaging

FO Fast Oscillation

FHWM Full Spectral Width Half Maximum

GLM General Linear Model

HHCFPC Holo-Hilbert Cross Frequency Phase Clustering

HHS Holo-Hilbert Spectrum

HHSA Holo-Hilbert Spectral Analysis

IMF Intrinsic Mode Function

LTM Long Term Memory

MF Middle Frontal

PAC Phase Amplitude Coupling

PFC Prefrontal Cortex

PLV Phase Locking Value

SFG Superior Frontal Gyri

SO Slow Oscillation

TMS Transcranial Magnetic Stimulation

WM Working Memory

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Introduction

1.1 BACKGROUND

The brain is undoubtedly the most intricate and interesting thing ever discovered by humans. Thus, it should be no surprise that humans have labored endlessly throughout recorded history to comprehend how the brain generates the variegated fabric of human experience. In recent years, our capacity to mimic the physiological and dynamic characteristics of the mammalian brain has increased significantly, and this has greatly contributed to our advancements in brain knowledge. The spatial-temporal recording of the brain's activity and the mapping of its structural characteristics have been made possible by technical breakthroughs that have been essential to our development.

Recording the dynamic activity of the brain may be roughly categorized as invasive and non-invasive methods. One technique in the former category, electrocardiography (ECoG), usually needs surgical intervention to permit the implantation of an electrode directly onto or into the cortical surface to record the electrical signals produced by the underlying neuronal populations [13].

Invasive procedures give higher spatial and temporal resolution by bypassing the distorting/filtering features of the skin, skull, and meninges, but they are linked with all the hazards of intracranial surgery.

Electroencephalography (EEG) and magnetoencephalography (MEG), which measure brain activity at the scalp level, and functional magnetic resonance imaging (fMRI), which detects susceptibility changes across the entire brain induced by changes in regional cerebral blood flow, belong to the latter category of recording techniques.

EEG is a non-invasive method used to measure the electrical activity of the brain by placing electrodes on the head (Figure 1.1 depicts a typical EEG cap), with the recorded voltage fluctuations being primarily caused by ionic current flows induced by synaptic activity terminating on populations of excitatory neurons in the cerebral cortex [12]. EEG time series recordings reveal a diverse spectrum of dynamic activity that is spatially and temporally spread throughout the scalp, giving a unique window into the inner workings of the human brain. Hans Berger pioneered the use of EEG in human investigations in the early 1920s [10]. Since its invention, the EEG has been extensively used as a sensitive measure of brain status in sickness and health [69]. Due to the non-invasive character of EEG, it is regrettably susceptible to distortions caused by the filtering properties of the different tissues comprising the skull, i.e., volume conduction [51]. Despite these shortcomings, the EEG has shown itself to be a valuable scientific and diagnostic tool with great temporal resolution and is affordable and easier to apply than other techniques [25].

Analysis of EEG time series recordings based on frequency reveals a broad spectrum of behavior, with the dynamic activity presenting a variety of distinctive frequencies. The activity observed in EEG recordings is occasionally divided into rhythmic and arrhythmic processes, with the recorded signals believed to represent a mix of both [5]. Rhythmic processes refer to the well-measured periodic brain rhythms that are typically separated into distinct frequency bands; delta (0-4 Hz), theta (4-8 Hz), alpha (8-14 Hz), beta (14-30 Hz), and gamma (30-100 Hz), which generally, but not always, appear as peaks in the power spectrum in response to a variety of physiological and behavioral states, suggesting that they may play an important role in brain function [12]. The supposed arrhythmic component, which is characterized as the largest contribution to total EEG power, is not well understood at present and is often disregarded and regarded as "$\frac{1}{f}$ noise."

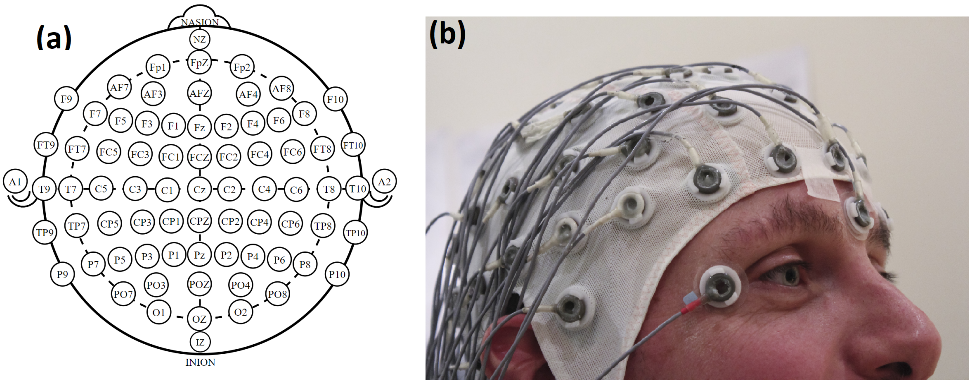

Figure 1.1: Example of human EEG recording electrode configuration

1.2

This research aimed to determine if practicing a change-detection task repeatedly positively affected participants' working memory. We were also curious whether the alpha band's parietal individual oscillatory peak frequency might be linked to these purported enhancements.

1.3 THESIS STRUCTURE

The study involves two main parts. The first part of the study was the EEG data collection which was accomplished using 30 participants doing the working memory task. The collected data was then processed, and the PSD of signals after prepossessing steps was calculated. The peak values of the power spectrum were plotted against the accuracy of each participant during the working memory task. The time-frequency analysis and connectivity of the signals were also calculated to investigate any logical correlation or trend between the accuracy of the participant's behavior and the magnitude of the power spectrum of the alpha band of that subject. The overview of the steps taken is shown in Figure 1.2.

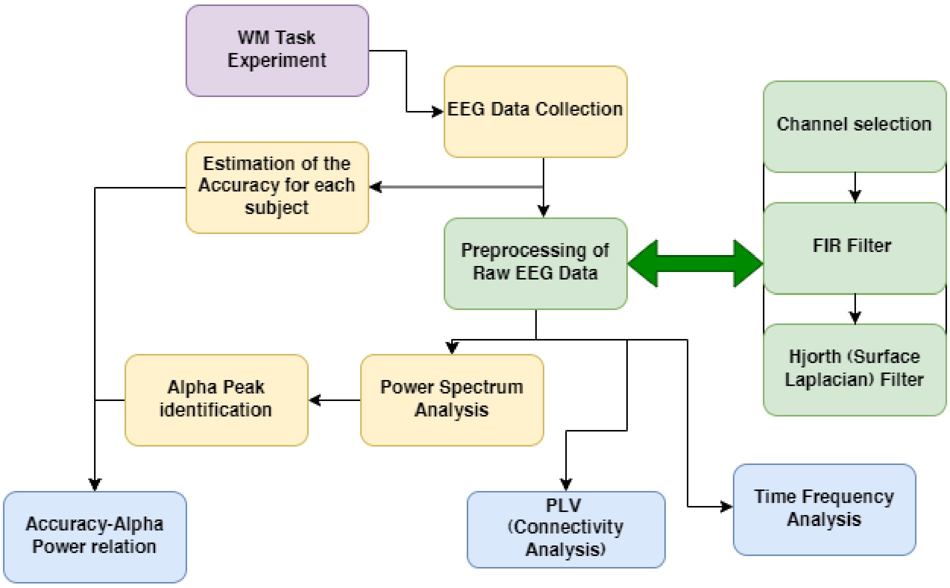

Figure 1.2: The study overview

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Literature Review

2.1 WORKING MEMORY

There are two main components of working memory (WM): the capacity to temporarily store information in a way that makes it easily accessible and the ability to process newly acquired and previously stored data to direct behavior. WM is essential for normal functioning because it allows us to keep mental representations of things in mind while we perform other mental processes [26]. We think that interactions between selective attention processes, perceptual representations, and long-term memory (LTM) representations lead to the limited capacity system assumed by the concept of working memory (WM), which stores information for only a short time [1]. Famous four-part model of working memory (WM) breaks down the theoretical foundations of WM as follows: phonological loop; visuospatial sketchpad; central executive; and, most recently, the episodic buffer [8]. The visual-spatial sketchpad and the phonological loop are passive storage systems that hold and process data in visual-spatial and auditory formats, respectively, for understanding and communicating verbal and written language. The most critical part of this system is the executive, which controls the data flow between the buffers. The central executive is responsible for dividing or switching attention between buffer systems or inhibiting irrelevant information to successfully execute the task [16]. The episodic buffer, on the other hand, is a system that mediates between the executive working memory and the LTM databases. While LTM can store and retrieve vast amounts of information in a short amount of time, WM has a much lower capacity [16]. The ability to keep information active in one's mind for relatively brief amounts of time is known as working memory maintenance (WM maintenance), another fundamental process [9]. In this view, the executive branch directly controls both the WM's ability to store information and its ability to keep itself in good working order.

Our reasoning, learning, and language comprehension are all supported by our working memory (WM) ability, which underpins our capacity for complex thought [7]. Reading comprehension [56], arithmetic performance [47], social ability [59], and overall academic performance are all strongly correlated with WM capacity [48]. Furthermore, it has been reported that WM is a better predictor of learning ability in people with learning difficulties than IQ [38]. Deficits in WM have been linked to a wide range of developmental disorders and learning difficulties, including attention deficit hyperactivity disorder, dyslexia [52], language [30], and reading [57]. As a result, there is a great deal of curiosity about WM's cognitive and neural basis due to the wide range of symptoms associated with WM impairments.

2.1.1 TEMPORAL AND SPECTRAL CHARACTERISTICS OF EEG

Hans Berger(1929)[10] first measured human brain electrical activity at the scalp's surface in the 1920s. Berger pioneered using the EEG as a revolutionary non-invasive method of assessing cerebral electrical activity. All previous recordings of mammalian brain electrical activity were made using invasive methods, with electrodes implanted directly into the exposed cortex [6]. Thus, Berger's innovation laid the groundwork for safely and efficiently measuring brain activity. Surprisingly, Berger's initial motivations for studying brain electrical activity stemmed from superstition in human telepathy, which is said to have originated during his time in the military when he was involved in an accident involving a horse, the details of which his sister coincidentally dreamed of [12]. While Berger could not demonstrate human telepathy, what he uncovered would eventually revolutionize how we examine brain activity. Berger observed continual oscillations when recording the human EEG, the most apparent of which occurred occipitally with frequencies between 8-14 Hz while the person was at rest and with closed eyes.

Because these occipital oscillations were the first oscillations Berger identified, he termed them the "alpha" rhythm [10]. The EEG has now become a very effective diagnostic and research tool, providing a wide variety of electrical activity that is both geographically and temporally variable [45]. Individual neuron action potentials do not create the electrical oscillations captured by the EEG but are generated by postsynaptic potentials of neuron populations located locally (the area underneath the electrode). The synchronized activity of several neurons with comparable spatial alignments provides enough big currents to be detected by the overlying electrode [68].

Cortical pyramidal neurons, which are normally positioned perpendicular to the scalp, contribute the most to the EEG signal. This spatial organization allows synchronous activity to spread over millions of neurons, resulting in summed electrical fields recorded by the EEG [46]. Since the initial recordings of human brain activity, the brain's rhythmic activity has been the principal experimental focus. The periodicity of the brain is manifested in the EEG as oscillations of varying frequencies, which are easily observable in the frequency domain, where brain oscillations appear as distinct peaks in the power spectrum at a range of frequencies, most notably at alpha (8 - 14 Hz) frequencies, but also at other frequency ranges such as delta (0.5-4 Hz), theta (4-8 Hz), and beta (14-30 Hz). The margins between these frequency bands were mostly chosen heuristically and for practical reasons [12].

However, studies have shown frequency-specific behavioral correlations within these precise bands. Delta waves, for example, have been linked to deep sleep phases [44], whereas beta waves have been found to occur when a person is intensively focused [11]. However, the alpha rhythm is undeniably the most easily visible aspect of scalp-recorded EEG and has been the focus of countless medically and behaviorally driven brain investigations. Specifically, conventionally defined alpha refers to an occipitally dominating rhythm fluctuating between 8-14 Hz that is reactive to eye-opening and shutting and was found by Hans Berger. More broadly, alpha band activity or alpha waves are oscillations of 8-14 Hz that occur in but are not limited to, the occipital area of the brain [24]. Even when not spectrally dominating, such alpha band activity may be detected in the EEG signal recorded at channels spread around the scalp [17]. Oscillations in the same frequency range may also be detected in the temporal and somatosensory cortex and have been dubbed the third and mu rhythms [43]. The mu rhythm has been observed to coincide with a state of muscular relaxation and appears to be behaviorally modulated, whereas the third rhythm can only be recorded with the EEG when the subject has an underlying bone defect and has not been consistently associated with a behavioral response [63].

The dynamic properties of alpha band activity (peak frequency, amplitude, and full spectral width half maximum (FHWM) are highly reactive to a variety of stimuli, including eye-opening and closure, mental effort, and acute physical exercise [17] It is also known that the parameters of alpha band activity alter with age [42] and in sickness and mental problems [38]. Peak alpha frequency changes are substantially linked with information processing rates[70]. [73] tested four response time measures in healthy participants using EEG (14 - 9 males, five females). The peak alpha frequency was negatively connected with conflict perception and calculating response times (statistically significant p 0.05), resulting in shorter reaction times when the peak alpha frequency was greater. Alpha band activity is thought to indicate cortical excitability (as measured by transcranial magnetic stimulation), with higher alpha power indicating lower excitability [52].

However, contrary experimental results show that increased cortical excitability in the visual cortex is related to increased alpha band power when the eyes are closed [67]. Furthermore, Samaha et al. [31] tested the frequency-specific correlations of occipital and parietal cortical excitability and visual phosphenes perception using transcranial magnetic stimulation and simultaneously collected EEG. Only occipital phosphene vision was predicted by pre-stimulus alpha-band oscillation strength and phase, not parietal, which was predicted by beta band (14-20 Hz) oscillations, suggesting that alpha frequencies alone are not a valid indicator of excitability.

Despite extensive research into these state-dependent modifications, a thorough understanding of the alpha rhythm's functional significance and physiological origins remains difficult. The apparent suppression or decrease in the amplitude of alpha oscillations in sensory areas presumably engaged in task processing [20] has led to the emerging idea that alpha is an inhibitory rhythm-gating resource required for information processing. On the other hand, theoretical and experimental data support the opposing idea that alpha is a moderately stable rhythm expressing a brain state susceptible to disruption from various inputs. According to this viewpoint, the alpha rhythm is best defined as a readiness rhythm corresponding to a physiologically significant condition to and from which transitions may be made [40].

In addition to the rhythmic brain oscillations, significant background cerebral activity scales roughly as the inverse of frequency and accounts for most of the observed signals. Power-law-like relationships in temporal characteristics of brain activity are found in one form or another across various recording modalities [5], including EEG, MEG, ECoG, and fMRI. Brain activity recorded at these various spatial and temporal scales generally does not follow a perfect $1/f$ profile over the full spectrum but rather 1/f, where the slope exponent may take on a range of 0 3.

2.1.2 Neural Correlated Functions of Working Memory

In recent decades, functional neuroimaging research has discovered unique brain areas and networks supporting WM activities. A dispersed network of areas underlies visual WM mechanisms, comprising frontoparietal regions that regulate attentional and central executive processes and posterior visual regions that preserve representations of stimuli. Other brain regions are engaged depending on stimulus type (e.g., spatial vs. object) and task design, but frontoparietal interactions form the core network underpinning WM maintenance processes. It has been shown that the prefrontal cortex (PFC) underlies various higher cognitive activities, including attention, inhibitory control, planning, and monitoring, which are closely connected to WM executive processes [19].

Middle frontal (MFG) and superior frontal gyri (SFG) regions of the PFC are consistently recruited during various WM processes in multiple studies and have been hypothesized to function as control centers that actively maintain representations by suppressing distracting or interfering information, both external and internal [2]. This area's damage led to reduced performance in delayed-response tasks, especially if the task contained distractions [2]. This was the first association between WM processes and the dlPFC. In keeping with this, early electrophysiological studies in monkeys revealed prolonged activity in individual dlPFC neurons throughout the retention phase of a delayed-response test [29]. This result was subsequently confirmed in human research and understood as the process enabling the preservation and integration of information in WM [61].

Temporal [3]and parietal [2] areas have also shown sustained activity throughout the delay period. Thus, persistent activity throughout the latency period is believed to guide behavior until a response is made and the memory process is ended [29]). It has also been shown that persistent activity in the dlPFC is predictive of WM performance, with more sustained activity throughout the retention phase correlating with better performance accuracy [72]. Feredoes and colleagues (2011) found that non-invasive activation of the dlPFC with transcranial magnetic stimulation (TMS) affected WM performance. Using time-locked TMS on the dlPFC during the retention phase boosted activity in posterior visual brain areas involved in target maintenance. Importantly, they discovered that this activation increase occurred only when distractions were provided during the retention phase, indicating that the dlPFC uses top-down regulation to suppress distracting information during WM maintenance.

Consequently, these and similar data indicate the central involvement of the frontal cortex in WM function. In young people, a more specialized network of areas, including the dlPFC, anterior cingulate, and anterior insula, starts to form [35]. Specifically, higher activation in the lateral prefrontal and superior parietal areas has been linked to enhanced WM performance throughout development [35]. Research examining WM delay activity discovered that individuals use the same brain areas to support fundamental WM activities. These regions include the frontal, parietal, and temporal lobes [14]. Continued functional improvements in WM representations and response accuracy continue to evolve throughout adolescence, with age-related changes particularly prominent during prolonged delay periods as opposed to shorter ones. During prolonged delays, youngsters engaged in a more dispersed network of areas, indicating a less developed brain system that may be more prone to distraction [14]. Given that effective WM processes depend on intact frontoparietal circuits, it is probable that the activation and functional localization of WM networks increases with age.

In addition, structural evidence supports the relationship between enhanced white matter connections between prefrontal, parietal, and temporal areas and

WM performance. Magnetoencephalography may be used to better describe the involvement of the dlPFC in WM processes by examining its connection with other brain areas (MEG). Due to its superior spatiotemporal resolution, MEG is superior to other neuroimaging modalities for identifying functional networks engaged in particular phases of working memory (e.g., encoding, maintenance, retrieval) [62].

2.1.3 NEURAL OSCILLATIONS

Neuronal assemblies have an inherent capacity to oscillate in unison and endure periodic changes in excitability that enable the coordinated flow of information (Fries, 2005). The synchronization of neuronal assemblies across brain areas is the most energy-efficient technique for coordinating dispersed neural activity [12]. Healthy brain growth depends on diverse brain areas' capacity to connect successfully to facilitate the transitory construction of large-scale functional networks. Long-range synchronization of oscillations is believed to enhance functional connectivity across cortical areas and has been connected with cognitive capacity throughout development (Benasich, Gou, Choudhury, & Harris, 2008).

Therefore, the synchronization of oscillatory activity is a significant indicator of the effectiveness and maturity of neural networks [32]. Neural oscillatory activity may be divided into several frequency bands, such as delta (0.5-3.5 Hz), theta (3-7 Hz), alpha (8-14 Hz), beta (15-30 Hz), low gamma (30-55 Hz), and high gamma (55-100 Hz) (60-100 Hz). Due to their functional importance in human cognition, certain frequencies and their limits have been determined. Different frequencies work on separate brain scales and support unique cognitive processes. Lower frequencies (theta and alpha) are believed to mediate large-scale networks, while higher frequencies (gamma) are crucial for local integration. However, the beta frequency seems to function between local and long-range cortical scales [60].

In addition to their frequency, oscillations may be described by their phase and amplitude dynamics, which can be used to evaluate neuronal synchronization. Using time-frequency analysis, signal attributes may be deconstructed to derive phase and amplitude information. The synchronization of oscillations was approximated for this thesis using phase relationships. Thus, synchronization between neural groups may be evaluated based on their phase-locking pattern, a process known as "communication via coherence" (Fries, 2005). Effective communication across distinct brain areas happens when action potentials (or spikes) arrive at the network's peak excitability (Fries, 2005). When this favored window of rhythmic excitability occurs, functional networks become synchronized, enabling neuronal activity across regions with an adequate phase difference (e.g., consistent, non-random) and inhibiting inputs that enter during the inhibitory period [65].

2.2 The relationship between Alpha Oscillations and Working Memory

Hans Berger (1929) was the first to describe neural oscillations, or "brain waves," during a state of wakefulness [10]. Berger (1929) noticed strong alpha rhythms in the posterior brain areas of awake, non-task-focused subjects. This early observation led to the idea that alpha oscillations were not essential for active cognitive processing but indicated cortical idling in the brain [58].

This notion, however, has been strongly refuted, and several recent studies show the essential function of alpha oscillations in brain transmission and cognition [50]. The main idea about the function of alpha oscillations is the ′gating by inhibition′ hypothesis, which states that information is directed to task-relevant areas by inhibiting information flow to task-irrelevant pathways [50]. Event-Related Synchronization (ERS) reflects the active suppression of the relevant cortical region, often due to top-down regulation from another area. In this approach, greater alpha synchronization blocks task-irrelevant pathways and allocates resources to task-relevant areas [50].

Event-Related Desynchronization (ERD) is believed to indicate neural inhibition release and enhanced cortical activity [71]. Jokisch and Jensen (2007) confirmed this idea by demonstrating that alpha power distinguishes between the dorsal and ventral visual stream during a WM task in which face identification or face orientation must be recalled. The ventral visual stream (′what′ route) is generally responsible for object and visual identification, whereas the dorsal visual stream (′where′ pathway) is responsible for identifying the spatial placement of things in space [39]. Around the temporo-occipital and parieto-occipital sulci are the ventral and dorsal visual streams. The authors observed an increase in alpha power in the parieto-occipital sulcus during the maintenance of face identities (which engages the ventral stream) compared to the maintenance of face orientations (which engages the dorsal stream), which they interpreted as the dorsal stream being inhibited [33].

In contrast, they discovered a drop in alpha power in the dorsal stream during face orientation maintenance. This separation in alpha power supports the view that local alpha oscillations reflect the functional regulation of task-irrelevant areas (e.g., suppression of dorsal stream while the ventral stream is engaged in WM maintenance) to perform the task at hand efficiently [53]. In addition, investigations of visuospatial WM reveal a similar impact of power dissociation in posterior alpha. These investigations demonstrated an increase in alpha power ipsilateral to the cued visual hemifield and a reduction in alpha power contralateral to the cued visual hemifield [36].

Increases in alpha activity in task-irrelevant areas have also been shown to correlate with task performance, providing further support for the ′gating by inhibition′ concept of alpha for good WM performance [64]. Long-range alpha synchronization is assumed to represent the functional connectivity across cortical areas despite the involvement of local alpha suppression [55]. Synchronization between dispersed brain regions results in the large-scale integration of neuronal assemblies and is crucial for the transitory creation of large-scale functional networks in the brain. In addition, the phase lag between synchronised brain regions in the alpha frequency spectrum is commensurate with the pace of neuronal transmission [37]. ADHD and autism spectrum disorders reveal alterations in long-range oscillatory activity [49].

Recent research has shown that oscillatory networks are altered during WM tasks (for a review, see [21] and that these networks are predictive of an individual′s WM ability [54] discovered an increase in interregional synchronization between frontoparietal areas in alpha, beta, and gamma frequency bands as memory demand increased. They discovered that alpha synchronization was most strongly connected with increasing memory load, indicating that alpha rhythms are tightly tied to task demands [54]. Alpha-band networks were also found to be more frontally positioned than beta- or gamma-band networks, indicating that alpha networks may play a role in aiding the top-down attentional procedures required to maintain neuronal representations in WM [54]. This is consistent with previous research linking alpha rhythms to WM processing [66]. As the phase lag index was evaluated, Alpha phase synchronization was also found to promote signal encoding and task performance [66].

In particular, greater phase coherence in the alpha band has been linked to correctly recalled items in a Sternberg-like working memory (WM) paradigm. In contrast, 'not to be recalled' cued items were linked with reduced phase coherence in the alpha frequency domain. In keeping with this, another research has shown that consciously observed items were related to increased alpha phase-locking relative to unperceived stimuli . These results highlight the significance of alpha oscillations in facilitating successful signal encoding and subsequent WM maintenance processes.

3

Methodology

3.1 WORKING MEMORY TASK EXPERIMENT

For the working memory task experiment, 30 healthy men and women participants (22-31 years old) were asked to remember the first scene of five colored squares briefly displayed (200ms). After a short delay period (3000 ms), the second scene of five colored squared appears. After the disappearance of this second scene, participants were asked to indicate if the first scene and second scene were similar or different. They can easily press the button yes if they are similar or no if they are not similar. The responses, either it was correct or incorrect, were recorded as epoch events in the datasets, which used later for the analysis and accuracy estimation.

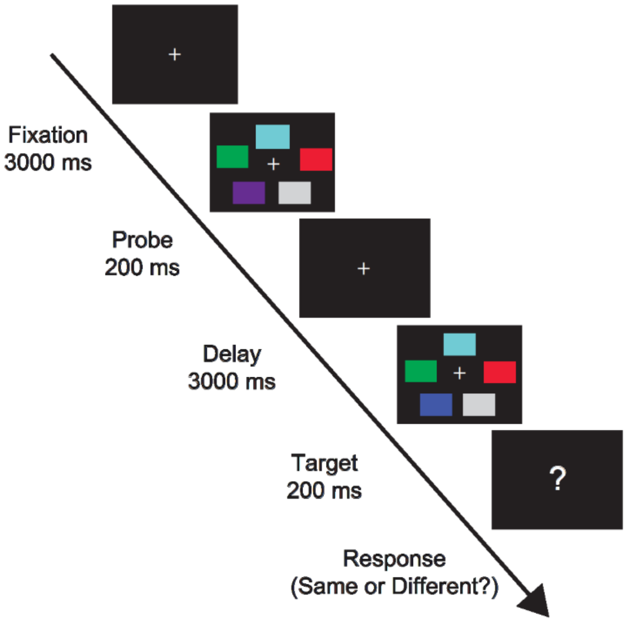

Figure 3.1: Schematic representation of the working memory (WM) change discrimination task

3.2 EEG RECORDING

In order to track the electroencephalogram steadily throughout the entire trial, we used a 64-electrode Ag/AgCl electrode cap placed in a 10-10 international system, and the software suite Brain Vision Recorder was employed to collect and convert the NeurOne 24-bit data format to GDR data. The experiment was conducted with electrode impedance < 10 kW at all times. The EEG trace was viewed visually after the impedance check and before beginning the recording. To rule out big artifacts from non-physiological factors such as power lines, poor electrode connection, and damaged electrodes. This was done before each session, throughout the EEG recording, and after it was finished.

3.3 EEG Data Processing

Brain Vision Analyzer 1.0 was used for the analysis of the EEG data. Each electrode was then manually re-referenced offline to the mean of all electrodes. The sampling rate was reduced to 256 Hz. A total of 3000 ms were extracted from the continuous signals, beginning at 3200 ms before the response recorded on the epochs and continuing for another 3000 ms after the start time. This duration would correspond to the delay time shown in Figure 3.1. To reduce power line noise and motor artifacts, the collected data were filtered with a low-band pass filter of 1 Hz and a high-band pass filter of 40 Hz and then baseline-corrected using a time window extending from 3200 to 200 ms before the epoch commencement.

Following multiple studies and evidence regarding the role of frontoparietal sites in driving WM performance, five electrodes (Fz, F4, F3, AF3, AF4) were chosen to evaluate the frequency peaks recorded from channels on the frontal lobe, and five electrodes placed over the parietal part (Pz, P4, P3, PO7, PO8) were considered for the analysis.

Besides the bandpass filtration of the signals, based on a finite-difference approach, the local Hjorth algorithm (Hjorth, 1975) was applied to evaluate the second derivative of the scalp voltage. This has been done following the equations shown in Figure 3.2.

Subtracting the average activity of neighboring electrodes from each electrode provides a rough estimate of the surface Laplacian [28]. However, this is not the most elegant method, as volume conduction affects many electrodes, not just those immediately next, and the effect of volume conduction varies according to the distance of each electrode from the "source" electrode.

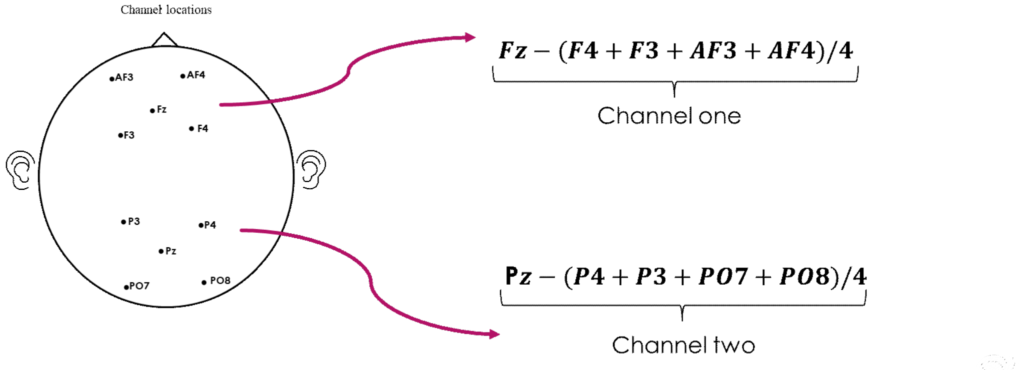

Figure 3.2: Estimations of surface Laplacian following the Hjorth method

The Hjorth method implemented in Python and two filtered channels calculated for the analysis.

3.4 PSD ESTIMATION/ALPHA PEAKS

To carry out spectral decomposition at each frequency between 1 and 40 Hz, a Pweltch Power Spectrum function was employed on the filtered signals obtained in the previous step. The selected signals were taken from $t = 1$ to $t = 430s$, and the total number of fft lines was set to 20×sampling frequency, which resulted in the PSD resolution of 0.05 Hz. We then averaged across the alpha (8–14 Hz) band.

In the power spectrum of EEG/MEG recordings, the alpha band (8-14 Hz) often generates the most consistent and conspicuous peak. During movement or cognitive tasks like tapping your fingers, driving a car, doing math, or understanding what you read, the strength of these oscillations changes, usually attenuating, in the areas of the brain that are important for such activities. It has also been shown that group activity and task difficulty correlate with a decrease in alpha band power attenuation. Although it has been shown at the individual level that alpha power at rest or just before the task corresponds with, evidence for such a link for the task-related power attenuation during task execution is scant. In light of this, it is unclear if attenuation is a generic phenomenon, like concentration or vigilance, that may also be evident during rest intervals in the same study or if it is directly tied to maintaining or restoring the fundamental cognitive processes.

```

rho, pvalue = scipy.stats.spearmanr(listACC_new, alphas_list_new)
pearsoncorr = f_cd.corr(method='pearson')
spearman = f_cd.corr(method='spearman')
```

Code 3.1: Connectivity Analysis in Python

3.5 PHASE-LOCKING VALUES ANALYSIS

A method suggested by Lachau x, Rodriguez, Martinerie, and Varela (1999), termed phase-locking value (PLV), was used to investigate alpha phase synchrony. PLVs represent the phase covariance between two signals that are close in time. Unlike the more traditional method of spectral coherence, PLVs separate the phase and amplitude components, making PLV far less susceptible to the amplitude of the signal amplitude, and can be directly interpreted in the framework of neural integration [47]. Using wavelet analysis, using wavelet analysis phase-locking between two signals (s_i^a and s_i^b) was quantified from the unaveraged signals [47]. A complex representation of the phase for trial i at time t and frequency f_0 is given by the convolution of a Morelet wavelet centered at

11 Hz (i.e., the center of the alpha range),

$$w(t, f_0) = A \exp(-t^2/2\sigma_t^2) exp(j2\pi f_0 t) \tag{3.1}$$

and the signal s_i^a normalized by the amplitude

$$\phi_i^a(t, f_0) = \frac{w(t, f_0)^* s_i^a(t)}{\left|w(t, f_0)^* s_i^a(t)\right|} \tag{3.2}$$

The width of the wavelet ($m = f_0/\sigma_f$) was chosen to be 7 [18]; where $\sigma_f = 1/2\pi\sigma_t$ The PLVs over N trials between signals s_i^a and s_i^b are defined as:

$$PLV(t, f_0) = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{\phi_i^a}{\phi_i^b} \right) \tag{3.3}$$

Normalized PLVs range from 0 to 1, which estimates the variability of phase differences between two signals across trials. If the phase difference varies little across trials, PLV is close to 1; with large variability in the phase difference, it is close to zero. To stabilize the variance of the PLV data, an inverse hyperbolic tangent transformation was used [63]. For all PLV calculations, we selected one (i.e., a posterior electrode site) as the seed electrode. We examined average alpha power (8–14 Hz) for each trial type and selected the electrode that showed the greatest power modulation during the delay period for Location and Relation separately.

The PLV statistic can be argued to be a proxy for connectivity. Intuitively, if the EEG signal in two channels (electrodes) during an experimental condition rises and falls together more than a baseline value, then there is more synchronization or enhanced connectivity between these two electrodes. If it is less than the baseline value, there is desynchronization or, loosely speaking, decreased connectivity between the two electrodes. Note that this metric does not care about the co-variation in the power of the EEG signal between two electrodes.

The schematic below illustrates how PLV is computed in this implementation. The explanation for each step follows.

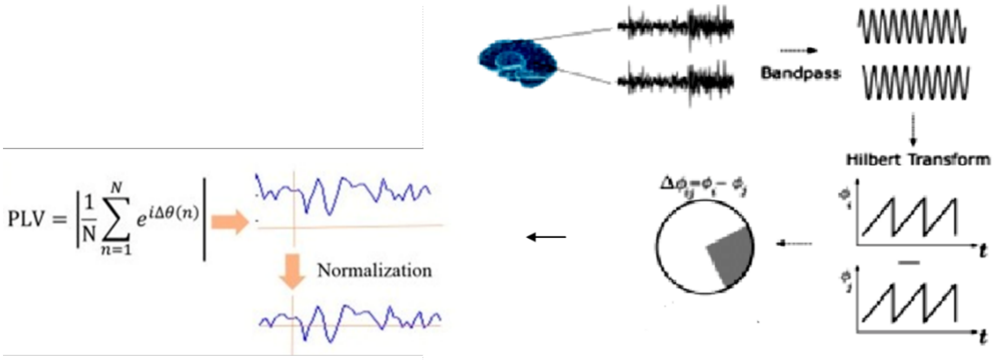

Figure 3.3: Connectivity analysis steps

The EEG data is first filtered in the desired frequency band of interest, the alpha band, 8-14 Hz. It is best to use an FIR (finite impulse response) filter to filter such data compared to IIR (infinite impulse response) filters. Loosely speaking, FIR filters filter the signal in the time domain, and IIR filters operate in the frequency domain. An FIR filter computes the value of the filtered signal at a time point from the values of the previous and future points. How far the FIR filter looks is known as the order of the FIR filter. A helpful rule of thumb for EEG signals is to ′look at about 4 to 5 cycles of the desired EEG rhythm. As an example, consider alpha rhythm (8-14 Hz). Here, one cycle is about 25 ms, and I would set the order of the filter to 100 ms. If the sampling rate is 500 Hz, the filter order would be 50 data points.

Hilbert transform: This step is used to quantify the rising and falling of EEG data. Hilbert transform of a signal can be used to compute the instantaneous amplitude and the instantaneous phase. We ignore the former and use the phase (φ) for PLV computation. φ is a value between $-\pi$ and π. Think of the filtered EEG signal as a series of crests and troughs. A value of π indicates the peak of a crest, and a $-\pi$ indicates the bottom of a trough.

It should be noted that there is a phase time course φ for every EEG electrode. Now consider the phase time courses of two electrodes. The difference between these two-time courses ($\Delta\varphi$) quantifies locking between the phases of these two electrodes. If an experimental stimulus influences the signal in two electrodes to rise and fall together or with a certain lag, then $\Delta\varphi$ will be consistent between trials. If there is no relationship between when the signal in these two electrodes will rise and fall, then $\Delta\varphi$ will be random. All we need to do now is to quantify the randomness in $\Delta\varphi$.

```python

 iter_freqs = [('theta', 3, 8),('Alpha', 8, 14),('beta', 14, 30)]
 signal1 = filteredchannel_fz
 signal2 = filteredchannel_Pz
# filter signals and extract instantaneous phases
 lfp_df = extracthilbertphase(signal1, signal2, fs, iter_freqs)
# calculate Phase-Locking Value (PLV)
 plv_df = phase_locking_value(lfp_df, iter_freqs)
 plvlist=plv_df.loc[1,["PLV"]]
 plv_list[ii]=plvlist
```

Code 3.2: Conectivity Analysis in Python

3.5.1 NORMALIZATION

This step is performed to make the PLV a valuable metric in practice. Due to its definition, PLV is always a value between 0 and 1; 0 signifies unexpected rise and fall, whereas a value of 1 indicates that one signal perfectly follows the other. In practice, the value of a PLV obtained will vary very little over time, and the absolute PLV is not what we are interested in. We are interested in knowing whether an experimental stimulus induced a change in PLV. We are interested in answering questions such as "was there increased connectivity between the frontal and parietal electrodes when the subject performed a task?". To find this, we should test if PLV after the stimulus is significantly greater than the PLV before. To simplify things, we can use the pre-stimulus period as a baseline and perform a z-transform normalization.

3.5.2 Whole trial spectral and PLV plots

The period of interest here was Delay 2, so the statistical analyses only test for differences between Relation and Location trials. However, for completeness, we also provide plots of alpha power and PLV for the entire trial duration. Using the Fixation period as a baseline, we calculated corrected [(signal – baseline)/baseline] alpha power (8–14H z) for every 100 ms time bin for each participant and plotted the average across participants and electrodes of interest. To plot out PLVs for the entire trial duration, we calculated PLV between the seed electrode and those frontal electrodes that showed significant differences between Relation and Location trials for every 100-ms time bin for each participant. No statistical analyses were tested on the entire trial duration data; these plots show the fluctuation of spectral alpha power and phase synchrony throughout the entire trial for Relation and Location trials separately.

3.6 TIME-FREQUENCY ANALYSIS

Morlet Wavelet Convolution is similar to a time-varying Fourier transform. Rather than taking a sinusoid the length of our data, we zero out everything save the center of the sinusoid and then move this shortened sinusoid along our data. The end effect is similar to a series of tiny time-localized overlapping Fourier transformations focused on each sample in our data. Understanding the Frequency-Temporal Resolution Tradeoff Before we go into the specifics of how MNE performs wavelet convolution, let's get a sense of how significant factors impact the nature of our wavelets. Three primary parameters influence wavelets:

The wavelet's frequency: This indicates the frequency activity that is being investigated.

The wavelet's cycle count defines the number of cycles of the selected frequency that the Gaussian taper will NOT wipe out.

Our data's sample frequency determines the number of samples in our wavelet for a particular cycle.

What matters most is understanding how these factors govern your wavelet and the tradeoff between temporal and frequency resolution. Most significantly, having more cycles implies having better frequency resolution but inferior temporal resolution. The greater the number of cycles, the less spread out the frequency content of the wavelet is, and hence the higher the frequency resolution. We can more correctly resolve the activity predicted by that wavelet to the frequency of the underlying sinusoidal with higher frequency resolution. Greater frequency resolution, however, comes at the expense of worse temporal precision. With more cycles, the length of your wavelet's non-zero component must rise, meaning that the estimate of frequency content is smeared over a longer time.

The frequency of the wavelet influences the tradeoff between frequency and temporal resolution. This is because various frequencies take varying periods to complete the same number of cycles. For example, five cycles of a 5 Hz sinusoidal take 1 second, whereas five cycles of a 20 Hz sinusoidal take only 25 seconds! As a result, five cycles at a lower frequency will result in a considerably lower

Although the sampling frequency does not directly affect the time/frequency resolution tradeoff, ensuring that the oscillations in your wavelet match the right frequency is critical. The wavelet's length will thus be scaled depending on the actual sampling rate (since a wavelet of length 1000 is 1 second for a 1000 Hz sampling rate but 2 seconds for a 500 Hz sampling rate).

It should be noted that the sample rate is set at 2000 hertz. This is convenient and obvious since each sample can be interpreted as 0.5 milliseconds. $\left(\frac{number of cycles}{frequency}\right) \times 2000$ is the temporal resolution. This is the amount of non-zero time in the wavelet. The lower this number, the higher the resolution.

The full width, half maximum (FWHM) metric summarises frequency resolution. Because each wavelet's spectra are roughly Gaussian, the resolution is estimated by normalizing the spectra and then taking the breadth of the Gaussian at the spots closest to 0.5 on either side of the peak. It should be noted that a larger FWHM signifies a higher resolution.

```
picks = mne.pick_types(raw_p1.info, meg='mag', eeg=True, eog=False,
    stim=False)
event_id, tmin, tmax = 10, -1.5, 3.4
```

```python
baseline = (0.7, 2.1)
epochs = mne.Epochs(raw_p1, events, event_id, tmin, tmax, picks=picks
    ,baseline=baseline,preload=True)
psds, freqs = psd_multitaper(epochs, fmin=0.5, fmax=40, n_jobs=None)
psds = 10 * np.log10(psds)  # convert to dB
kwargs = dict(fmin=0.5, fmax=40, n_jobs=None)
psds_welch_mean, freqs_mean = psd_welch(epochs, average='mean', **
    kwargs)
ch_idx = epochs.info['ch_names'].index(ch_name)
epo_idx = 0
psds_welch_unagg, freqs_unagg = psd_welch(epochs, average=None, **
    kwargs)
# define frequencies of interest (log-spaced)
freqs = np.logspace(*np.log10([0.5, 40]), num=500)
n_cycles = freqs / 2.  # different number of cycle per frequency
power, itc = tfr_morlet(epochs, freqs=freqs, n_cycles=n_cycles,
    use_fft=True,return_itc=True, decim=2, n_jobs=None)
```

Code 3.3: Time Frequency Analysis in Python

4

Results and Analysis

In this research, we sought to determine if the simple repeating of a change-detection task improved WM performance. Additionally, we were curious to know how much these alleged enhancements would be related to the frontal and parietal individual oscillation peak frequency in the alpha bands. To achieve this, we enlisted the help of 30 healthy volunteers who completed a change-detection task for approximately 10 minutes. Individual alpha frequency band peaks were then extracted from the power spectra concerning the retention period during baseline and subsequent sessions.

4.1 STATISTICAL ANALYSIS

There is no substantial correlation between alpha frequency and accuracy or alpha power and accuracy, according to this analysis and p-value and r. The statistical analysis of the events saved in the raw data channels shows that the average time between two consecutive epoches is 5.48 seconds.

Interestingly, band-specific Spearman analysis on oscillatory peaks to look for practice-induced alterations didn't provide conclusive findings. In other words, regardless of the hemisphere or the cortical region from which they were recorded, the individual frequency peaks of alpha did not seem to be influenced by the amount of practice. The research comparing frequency peaks to an individual attribute with a high degree of stability is consistent with this data. Furthermore, our results add to the body of knowledge by indicating that such stability is also resistant to practice-related short-term impacts.

The individual alpha peak could then be understood as the neurophysiological parameter ensuring sufficient cognitive flexibility to benefit from the amount of practice since performance estimates obtained via IES account for the degree of efficiency by which a system draws upon its internal resources. Recent research suggests that these skills may relate to how quickly people absorb information and how much they learn, as a task proceeds, how to successfully cope with distracting stimuli. Surprisingly, the alpha peaks at baseline and retest predicted participant flexibility in adapting to task demands (i.e., as a practice function). This finding further supports previous findings regarding such an electrophysiological index's trait-like properties (e.g., stability).

The efficiency gain (relative to the entire visual field) over the course of the experiment appears to be causally determined by only individual alpha peaks over the parietal lobe, resembling many functional and topographical characteristics ascribed to the attentional vector claimed by proponents of the hemispatial theory. The data points to a psychophysiological scenario in which the parietal alpha oscillation's speed functions as a trustworthy biomarker of short-term practice results. The translational significance of such effects must be considered, even if it is unclear whether this link extends to cognitive domains other than those related to working memory. Clinicians may be able to anticipate the efficacy of short-term training procedures to be given to patients with attentional or cognitive problems by using early screens to measure parietal alpha frequency. Consequently, more individualized treatment plans that consider each patient's electrophysiological characteristics would be possible. Data regarding individual theta peak frequency, however, seem to be equivocal. It has been hypothesized that oscillatory activity in the theta band supports the online preservation of the elements that need to be recalled during WM tasks.

Indeed, it has been shown that oscillatory activity in the theta band rises during WM tasks in direct proportion to the challenge or cognitive load concerning the utilized paradigms. Rhythmic activity between 3 and 7 Hz has also been linked to top-down regulation and cognitive monitoring. These pieces of data imply that our paradigm was not difficult enough to elicit a significant amount of theta activity (as shown by frequency peaks across frontal and parietal locations) to support the cognitive load and general structure performance. This is probably due to the number of items that must be remembered (which corresponds to the average storage capacity, which was not increased throughout the experiment) and the fact that the retest session took place. During this session, the task may have been easier to complete (due to practice) than during the baseline session, necessitating less monitoring of the processes. To sum up, WM performance measured by IES was shown to benefit by simply repeating a change-detection test. Individual alpha frequency measurements taken across the parietal lobe at baseline and retest indicate that this improvement is expected. These patterns suggest that parietal alpha peaks have a functional role in promoting the use of novel and more effective cognitive strategies established during the experiment due to experience.

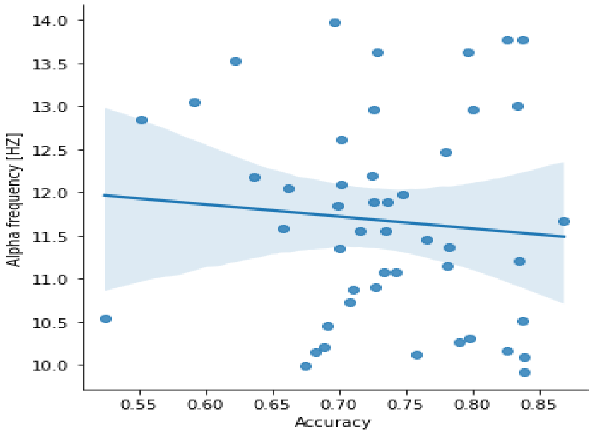

Figure 4.1: Frequency of the alpha range peaks V.s Accuracy of the responses

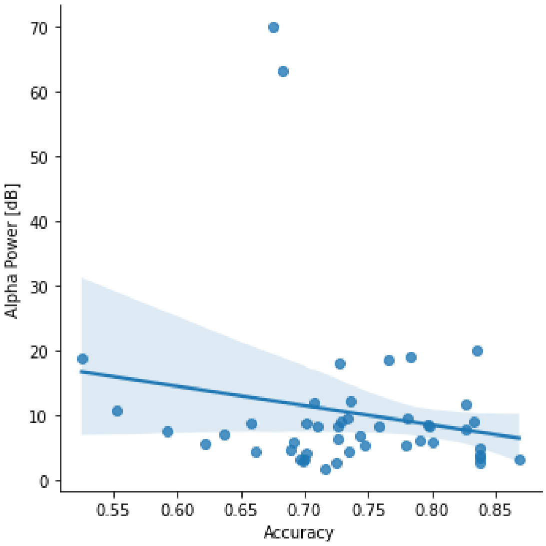

Figure 4.2: PSD of the alpha range peaks V.s Accuracy of the responses

4.2 Time-frequency Analysis

The statistical analysis of the events saved in the raw data channels shows that the average time between two consecutive events is calculated at 5.48 s. Therefore, the timing diagram demonstrated in the previous chapter has been slightly modified for defining the event baseline. Thus, each trial was epoched from -1500 to 3400 msec, with 0 msec marking the start of the probe and -1500 to 0 msec denoting the time ranging from the precue and the cue inside the fixation time. Data from the retention period (700-2100 msec), selected as the time period under consideration, were evaluated for each memory load. The 200-700 msec section was eliminated to avoid the negative influence of cue-offset elicited activities on the spectrum analysis of current brain oscillations, and the 2100-3200 msec portion was excluded to avoid the adverse impact of probe processing preparation on alpha oscillations. The diagram shown below, demonstrated the selected period with the highlighted cubes, noting that each cube represents 0.5 seconds.

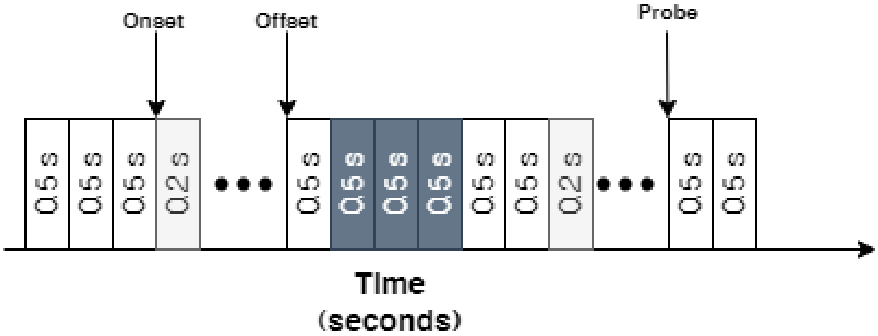

Figure 4.3: Events analysis and baseline definition

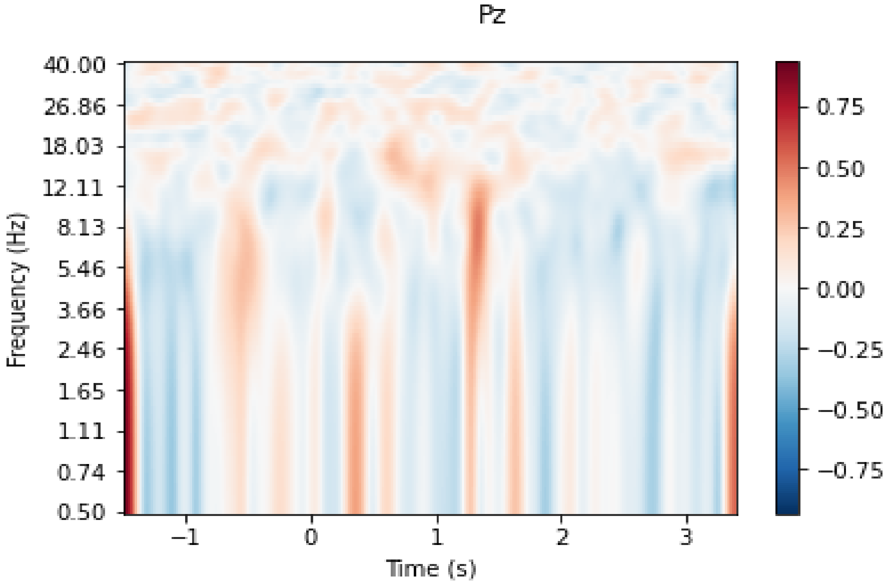

Figure 4.4: Averaged Time-frequency representations for incorrect responses

Time-frequency representations (TFRs) reflecting the proportion change in power were computed for the retention interval relative to the baseline period (1.2s -2.7). Time-frequency plots are shown for a subject's incorrect (Figure 4.) and correct Figure 3.10, response using Morlet Wavelet.

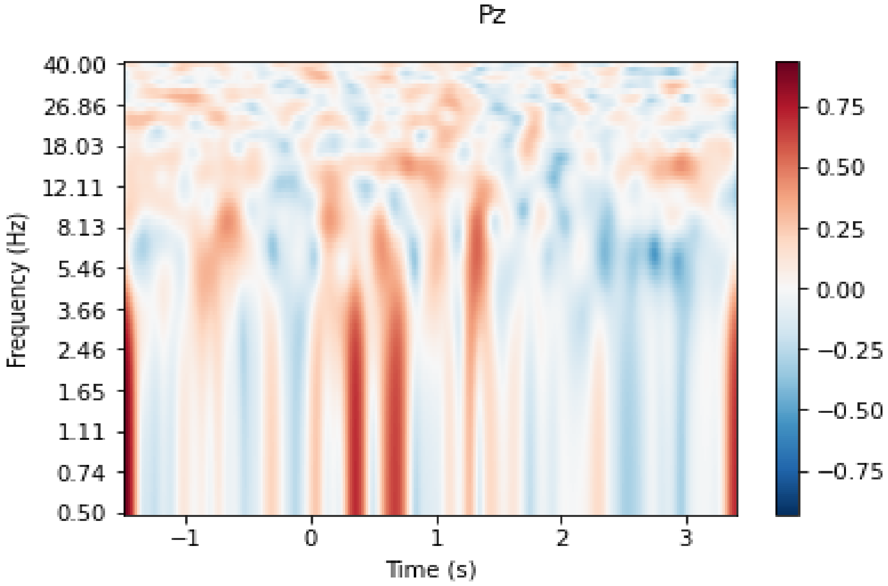

Figure 4.5: Averaged Time-frequency representations for the correct responses

The spatiotemporal plots shown in Figure 4. and Figure 4. demonstrated a higher brain activity in the alpha band (8 to 14 Hz) for the correct responses. The results are based on each subject's average correct or incorrect responses. The Multi-taper method was also implemented to create several orthogonal tapering windows in the TFR estimation to reduce the variance.

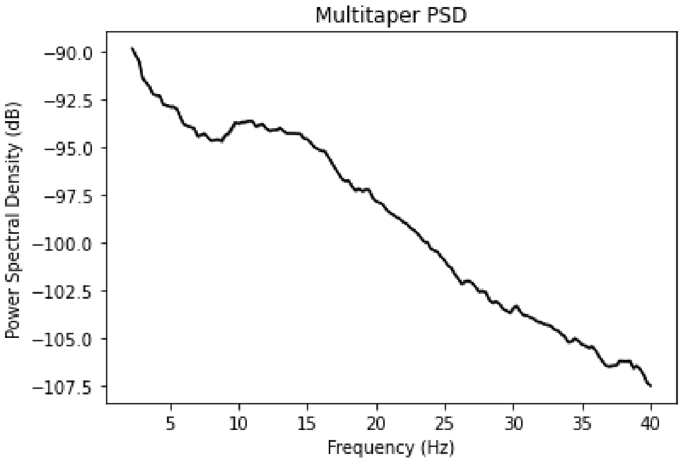

Figure 4.6: Multitaper PSD plot

4.3 Connectivity Analysis

Whole-brain connection in the alpha band peaked shortly after probing demonstration commencement and remained rather steady throughout the retention or delay interval and reaction time. This impact was evident for both correct and incorrect answers. However, connectivity for incorrect epochs decreased significantly over the retention period. Only the alpha frequency band exhibited significant variations in connectivity between correct and incorrect epochs, indicating that this impact was frequency-specific.

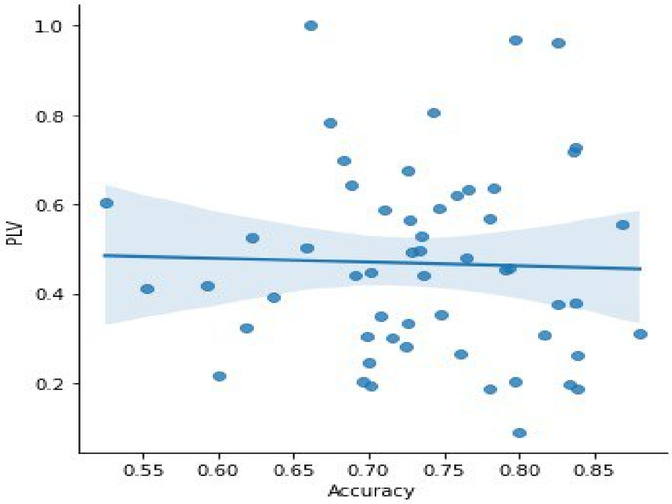

Figure 4.7: PLV connectivity V.s Accuracy of the subject's answers

We were also curious about the relationship between whole-brain connectivity and WM performance. Pearson's one-tailed correlations were calculated between the retention interval and the median of the chosen electrodes' alpha connectivity (normalised to baseline). This connection showed a positive but non-significant relationship (r=0.309, p=0.1).

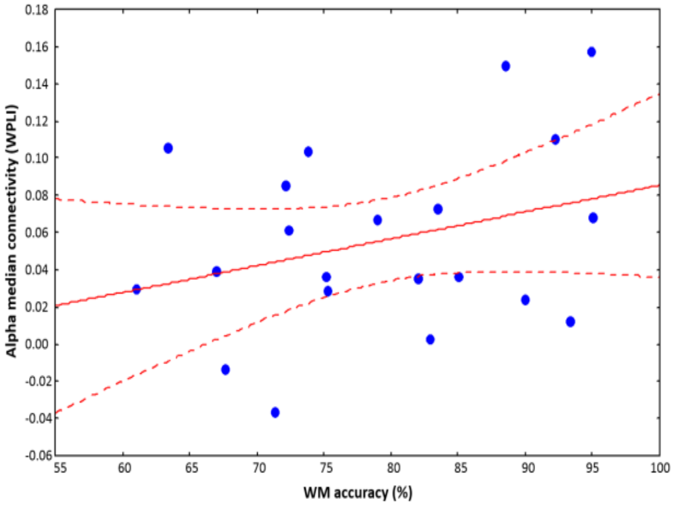

Figure 4.8: Correlation of Alpha connectivity and Working Memory Accuracy

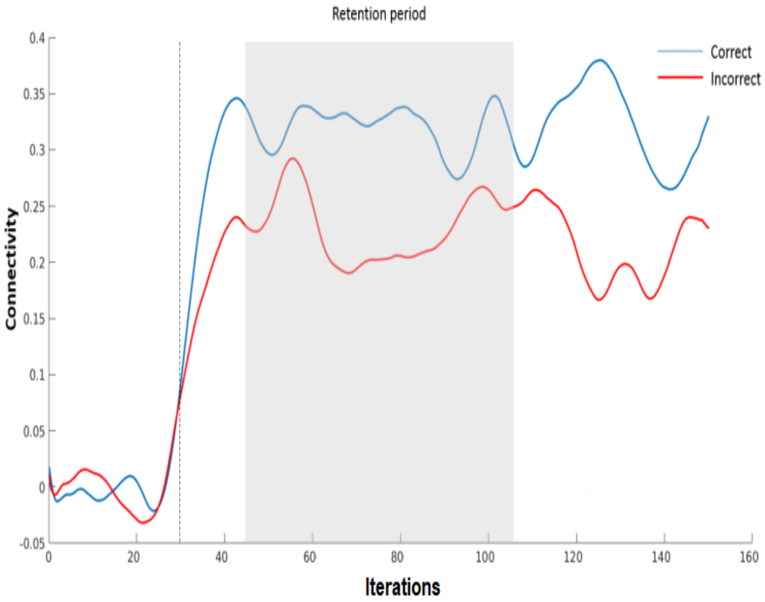

Figure 4.9: Connectivity of the selected electrodes for correct and incorrect responses

5

Conclusions and Future Works

This research uses EEG to investigate the rhythmic processes behind WM maintenance. We discovered substantial changes in whole-brain connectivity in the alpha band (8 to 14 Hz) between correct and erroneous trials throughout both the retention and retrieval phases. This impact was, importantly, limited to the alpha frequency spectrum. During the retention period associated with successful trials, alpha connectivity was greater and more stable than during the retention period associated with wrong trials. According to our network analysis, subjects had higher alpha synchronization during the retention interval than during the baseline ISI period. This network had considerable frontal, parietal, and temporal connections, which have been extensively described in prior research on WM cognition.

Strong alpha phase locking may support the binding of information in WM maintenance. Non-significant association between the overall accuracy rate and the alpha band spectrum based on Spearman's r and P value for all subject's oscillations in the alpha band and accuracy in the visual WM task.

For the alpha band, the whole brain connectivity time series demonstrated a substantial difference between correct and erroneous trials throughout the retention period. This impact was substantial for a considerable chunk of the retention time, indicating that alpha oscillations play a major role in WM maintenance processes. Furthermore, we discovered that the connection time series for the correct trials was stronger and more constant during the retention phase. Sustained brain activity during the delay period is thought to underpin maintenance mechanisms important for visual representations without sensory input [23]. While our current findings reflect a whole-brain response in connectivity over time, previous research has found sustained delay activity in the prefrontal [15], temporal [4], and parietal [41].

Thus, if continuous activity throughout the delay is required for representation maintenance, then proper WM performance should rely on sustained signals covering the delay's whole duration to guide a response. This was replicated in research by [41], who adjusted the delay interval duration between 18 and 24 s and showed persistent MFG activity during the delay period relative to other prefrontal regions. Neurophysiological data from fMRI and EEG research has also demonstrated that task performance suffers when brain activity is not maintained throughout the delay period [34]. Our findings support the premise that continuous engagement throughout the delay is required to enable proper performance.

Prior literature has also shown that alpha oscillations promote task performance. According to the findings of our investigation, the alpha frequency band exhibited substantial disparities between correct and erroneous trials throughout the retention period and retrieval phase [27] discovered higher phase locking in the alpha frequency band in excellent vs. poor performers in a perceptual discriminating test, which is similar to our results. These data strongly suggest that alpha phase synchronization is a sign of superior perceptual discrimination, which may underpin successful WM maintenance mechanisms [27]. In another investigation, Freudenberger et al. [22] discovered that alpha coherence is greater for well-remembered items. In this research, individuals were given cues to recall or forget the following material. As a result, participants likely had to use top-down control mechanisms to recall specific information while ignoring others. These and other WM studies imply that high alpha phase locking may aid information binding in WM maintenance.

Furthermore, forgetting during an episodic memory test has decreased alpha-phase coupling. This shows that alpha plays a role in the focused attention to external and internal representations necessary for retaining important information in WM. On the other hand, subjects in our research were not asked to forget or disregard specific objects but to recall the color of the squares shown in the sample and reply if the colors in the test matched those in the original sample. Endogenous changes in attention might explain reduced alpha connectivity found during the latency period associated with wrong answers.

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