Pavol Jozef Safarik University in Košice
Faculty of Science

Neural Oscillations and Spatial Auditory Attentional Control

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Master’s Thesis

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Názov SK: Neurálne oscilácie a riadenie priestorovej sluchovej pozornosti
Cieľ:
- set up analytical tools for EEG data preprocessing and ERP analysis using the Fieldtrip Matlab toolbox,
- replicate the behavioral and ERP data analysis of Kopco et al. (2021) and perform analysis of the data of Vargova (2022),
- perform brain oscillation analysis on EEG data of Kopco et al. (2021) and Vargova (2022) to test the hypothesis that oscillatory components in the alpha- band correlate with spatial attentional effects observed behaviorally
- modify the experiment of Vargova (2022) to test the effect of cue type on attention, collect and analyze behavioral and EEG data

Literatúra: Kopco, N., Sebena, R., Ahveninen, J., Best, V., Shinn-Cunningham, B. (2021), "Electrophysiological correlates of auditory and visual attentional cueing in fine-grained auditory spatial discrimination task", DAGA conference 2021, 15.-18.08.2021 in Wien (abstract, video presentation). https://pcl.upjs.sk/wp- content/uploads/2021/08/Norbert_DAGA_2021.mp4
Kopco, N., Sebena, R. (2020). "Evoked responses to auditory vs. visual attentional cues in auditory spatial discrimination" (Abstract, poster) Poster D1, presented at the Cognitive Neuroscience Society 2020 Annual Meeting, Virtual Conference, Boston, MA, May 2-5, 2020. https://pcl.upjs.sk/wp-content/uploads/2020/06/Noro_cns_2020_final.pdf
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Abstract

We live in a complex, multisensory world where the brain constantly processes vast amounts of information. Effective task performance often requires the suppression of irrelevant sensory inputs—a process that relies heavily on attentional mechanisms. One such mechanism is auditory spatial attention, which enables individuals to focus on a specific sound source amid competing stimuli by directing attention toward its spatial location. Research suggests that the interaction between auditory and visual modalities can influence this process.

This thesis explores previously collected experimental EEG data, for which we explore its event-related potential (ERP). We perform an analysis of oscillatory activity recorded while a subject performed an auditory spatial attention task, with a focus on the alpha band, to better understand the temporal dynamics of attention-related processes. Using the FieldTrip toolbox in MATLAB, we conducted spectral decomposition via the Hanning multi-taper method, performed topographical analysis, and applied standard preprocessing pipelines. Statistical significance was assessed using analysis of variance (ANOVA).

Among the six experimental factors, three—cue modality and validity (cue presented at the same target's location or at an opposite location), and response correctness (subject's ability to discriminate the target location)—showed notable modulation of alpha-band activity. Cue validity had no significant effect on alpha power. However, alpha oscillations in the fronto-central region varied systematically with modality, response correctness, and timing. Specifically, pre-target alpha dynamics revealed that higher alpha power predicted correct responses in auditory trials, whereas alpha suppression preceded successful performance in visual tasks. These findings suggest that alpha activity reflects modality-specific preparatory mechanisms that are predictive of behavioral performance.

In conclusion, our results support the hypothesis that alpha oscillations play a functional role in mediating attentional selection processes and reflect both the sensory modality of the cue and task-related outcomes.

Abstrakt (in Slovak)

Žijeme vo zložitom, multisenzorickom svete, v ktorom mozog neustále spracováva obrovské množstvo informácií. Efektívne vykonávanie úloh často vyžaduje potlačenie nerelevantných senzorických vstupov – proces, ktorý do veľkej miery závisí od mechanizmov pozornosti. Jedným z takýchto mechanizmov je sluchová priestorová pozornosť, ktorá umožňuje jednotlivcom sústrediť sa na konkrétny zvukový zdroj medzi rušivými podnetmi tak, že nasmerujú pozornosť na jeho priestorovú polohu. Výskumy naznačujú, že interakcia medzi sluchovými a zrakovými modalitami môže tento proces ovplyvniť.

Táto diplomová práca analyzuje experimentálne EEG dáta zozbierané v predchádzajúcom výskume. Zameriavame sa na analýzu evokovaných potenciálov (EP) a oscilatorickej aktivity zaznamenanej počas úlohy vyžadujúcej sluchovú priestorovú pozornosť, pričom dôraz kladieme najmä na alfa pásmo, aby sme lepšie pochopili časovú dynamiku procesov súvisiacich s pozornosťou. Pomocou nástroja FieldTrip v prostredí MATLAB sme vykonali spektrálnu dekompozíciu pomocou multitaperovej metódy s Hanningovým oknom, topografickú analýzu a štandardné predspracovanie dát. Štatistická významnosť bola hodnotená pomocou analýzy rozptylu (ANOVA).

Zo šiestich experimentálnych faktorov sa ako významné pri modulácii alfa aktivity ukázali tri – modalita návodného podnetu, platnosť návodného podnetu (či bol návodny podnet prezentovaný v rovnakom alebo opačnom priestore ako cieľ), a správnosť reakcie (schopnosť subjektu správne určiť polohu cieľa). Platnosť návodného podnetu nemala významný vplyv na alfa výkon. Alfa oscilácie vo fronto-centrálnom regióne sa však systematicky menili v závislosti od modality, správnosti odpovede a časového okna. Najmä dynamika pred podnetom ukázala, že vyšší výkon v alfa pásme predikoval správne odpovede v sluchových úlohách, zatiaľ čo pokles alfa aktivity predchádzal úspešnej výkonnosti v prípade vizuálnych návodných podnetov. Tieto výsledky naznačujú, že alfa aktivita odráža modality-špecifické prípravné mechanizmy, ktoré sú prediktívne pre správanie.

Záverom možno povedať, že výsledky podporujú hypotézu, že alfa oscilácie zohrávajú funkčnú úlohu v mechanizmoch selekcie pozornosti a odrážajú nielen senzorickú modalitu návodného podnetu, ale aj výkonnostné výsledky úlohy.

Acknowledgement

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Introduction

In the complex world we live in, much information surrounds us on our daily lives. This information varies by its modality, such as visuals, auditions, somatosensory and others. Moreover, every modality varies by intensity, frequency and other parameters. This makes it challenging for our brains to process all this information to produce meaningful understanding of the environment around us. In other words, perception is a challenging and complex neural process which enables us to understand and safely interact with the environment.

Apparently, our brains have their strategy to understand this complex input. For instance, when concentrating on a specific task, our brain would be highly employed to process the task-related input rather than unrelated inputs. This reflects the idea of attention and filtering out unnecessary information.

The brain’s ability to attend a specific task or position can be noticed in auditory scenes. For example, in a crowded restaurant, a person can concentrate on a friend’s speech and neglect all the voice in the background. What happens in such a situation is exactly that the brain directs the attention into a specific position, i.e. the speaker’s position, giving it the most importance and filtering out less-important audio information, i.e. background music. More interestingly, directing our vision into the source of sound, to the speaker in our example, seems to play a crucial role in auditory attention.

This is known as cross-modal interaction, where vision interacts with audition to generate a clearer version of what we hear. The neural processing of these different modalities simultaneously is known as multisensory processing.

Research on multisensory processing and spatial attention reveals a complex interplay between sensory modalities in the nervous system. Contrary to the idea of independent processing, several studies indicate shared attentional resources and interactive processing across modalities. Wahn and Konig (2015) suggests that visual and auditory spatial attentional resources are shared, as performance in a dual-task paradigm was similar regardless of the modality of location cues. Similarly, (Wahn and König 2017) proposes that for spatial attention tasks, attentional processing consistently involves shared attentional resources across sensory modalities. However, some evidence supports modality-specific processing. (Zuanazzi and Noppeney 2019) demonstrates that while the brain controls attentional resources interactively across senses, it encodes spatial expectations independently for each sensory system. (Braga, et al. 2013) provides further support for modality-specific attention networks, showing distinct superior frontoparietal and frontotemporal networks for visuospatial and non-spatial auditory attention, respectively. Therefore, while there is evidence for both shared and independent processing of spatial attention across modalities, the nervous system appears to employ a flexible approach.

The attentional system can allocate resources depending on task demands, optimizing processing of relevant information while minimizing resource expenditure (Wahn and König 2017). This suggests that spatial auditory attention is not processed entirely independently but rather as part of a complex, interconnected multisensory system. This is supported by previous studies that utilized event related potentials (ERP) and behavioral outcomes, like in (Sebena 2017) , where it was shown that subject's performance in auditory spatial attention tended to have no effect with visual cues being used rather than auditory cues. Other studies indicate that visual cues can indeed enhance auditory attention performance. Spatial attention mechanisms may function differently across sensory modalities. For example, some studies suggest that visual spatial cues can enhance performance more reliably than auditory ones

(Roberts, Summerfield and Hall 2006). This aligns with the idea that visual cues may provide perceptual benefits for auditory attention tasks. Additionally, Guan et al. (2023) found differences in the activation level of the frontoparietal network and visual/auditory cortex under different attention conditions, suggesting a potential visual dominance effect in spatial attention tasks. In the context of auditory attention studies, automatic attention may involve the automatic orienting of attention to a sudden loud sound, a distinct change in pitch or timbre, or a biologically relevant auditory cue (e.g., a baby crying). These stimuli can capture attention rapidly and involuntarily, even when individuals are engaged in other tasks or activities.

While previous research has examined various factors influencing alpha waves in auditory attentional control, a comprehensive study integrating multiple modalities remains lacking.

This thesis focuses on oscillatory analysis to study the role of alpha waves in the auditory attention control driven by auditory factors and non-auditory factors, visuals in specific. More precisely, we aim to test the hypothesis that oscillatory components in the alpha frequency band (8–12 Hz) are correlated with behavioral effects of spatial attention. Studying alpha oscillations could reveal important rhythmic modulations that govern spatial auditory processing. Hence, it could help answer the question that oscillatory components in the alpha-band correlate with spatial attentional effects observed behaviorally.

This thesis uses computational analytical tools to analyze the mechanisms of auditory spatial attention controlled by vision or hearing. Such tools include signal analysis to process the recorded data like filtering, noise suppression, and structural organization of data. Moreover, advanced data analysis techniques including spectral decomposition were used to test our hypotheses regarding alpha band.

Understanding the neural substrates of auditory spatial attention can inform the development of rehabilitation strategies for individuals with hearing impairments or visual deficits ((King 2008); (Neher, et al. 2011)). For example, recent cognitive science studies have employed advanced data analysis methods—such as multivariate pattern analysis (MVPA), machine learning classifiers, and regression modeling—to decode neural responses to spatial auditory cues and predict attentional shifts based on EEG or fMRI data (e.g., Kerlin et al., (2010); O'Sullivan et al., (2015)).

Additionally, research in this area has implications for the design of assistive technologies, such as hearing aids and cochlear implants, to improve the abilities of spatial hearing, which is the cognitive process that helps us orient in space by understating the environment's physical characteristics. For instance, interpreting the physical characteristics of sound sources in our environment helps us orient. Foundational work has described how spatial hearing enables listeners to locate, segregate, and focus on relevant auditory stimuli in complex environments, supporting both basic perception and applied technologies (Moore 2013).

Furthermore, insights gained from studying auditory spatial discrimination can be applied to enhance virtual reality experiences, improve sound design in multimedia applications, and optimize acoustic environments in public spaces (Zündorf, Karnath and Lewald 2013).

1. Goals

The goals of the thesis work were to use the previously collected data, used for behavioral and event-related potential (ERP) analysis in (Sebena 2017) and (Kopčo, Modaresnia, et al. 2025), to expand into oscillatory analysis as follows:

1. learn and understand the basics of EEG data preprocessing and ERP analysis in the Fieldtrip Matlab toolbox.
2. learn how to perform brain oscillation analysis on EEG data.
3. analyze EEG data of Kopco et al. (2021) to test the hypothesis that oscillatory components in the alpha-band correlate with spatial attentional effects observed behaviorally.
4. **Optional**: perform source analysis and connection analysis on the data.

The previously mentioned studies by Kopco et al. looked at behavioral outcomes of auditory attentional control experiments. Also, they studied the encephalography alpha waves event-related potential components in a try to understand how audition and vision together formulate brain activity mechanisms in response to improve auditory spatial awareness and attention.

In our work, we investigate oscillatory alpha-band activity rather than traditional event-related potentials (ERPs), with the goal of understanding how alpha oscillations are modulated by experimental factors such as stimulus modality (auditory vs. visual) and cue validity. We analyze data collected by Šebeňa et al., which includes EEG responses to spatial cueing tasks involving both sensory modalities. This enables us to test the hypothesis that alpha oscillatory dynamics are sensitive to spatial attentional mechanisms across modalities — a pattern that has been observed in behavioral performance. By focusing on oscillatory activity, our study contributes to the growing body of work in auditory neuroscience and multisensory spatial attention, and provides a computational approach to understanding attentional modulation in the brain.

2. Theoretical background

This section provides the necessary information the user can read to follow up more to our work. It includes an overview of auditory perception and attention, event-related potential, neural oscillations, and brain activity measurement.

2.1. Auditory perception

The huge amount of information we receive from our different senses of the surrounding environment needs to be correctly processed. Our ability to understand these precepted information is called perception. Auditory perception could be defined as the ability to receive and interpret information that reached the ears through audible frequency waves transmitted through the air or other means (CogniFit). This complex process involves detecting sound waves, transforming them into neural signals, and processing them in various brain regions responsible for decoding features such as pitch, loudness, and timing. A key component of auditory perception is auditory spatial perception, which enables individuals to localize sound sources in the environment. This spatial awareness relies on binaural cues—such as interaural time differences (ITD) and interaural level differences (ILD)—as well as monaural spectral cues shaped by the outer ear. These cues allow the auditory system to estimate the direction and distance of sounds, contributing to critical functions like speech understanding in noisy environments, orienting attention, and navigating through space. Understanding these mechanisms is fundamental to auditory neuroscience and has practical implications in developing assistive technologies and studying multisensory integration.

2.2. Basics of attention

Attention is a fundamental cognitive process that allows individuals to selectively concentrate on specific stimuli while ignoring others. It plays a critical role in perception, learning, memory, and decision-making by prioritizing relevant information in complex sensory environments. Attention can be voluntary (endogenous)—guided by internal goals and expectations—or involuntary (exogenous)—captured automatically by salient external events. It operates across multiple modalities (e.g., visual, auditory) and can be directed toward spatial locations, features, or entire objects. Neuroscientific research has shown that attention modulates neural activity in sensory cortices, enhancing the processing of attended information. Understanding attention is crucial in fields such as cognitive neuroscience, psychology, and artificial intelligence, where models often seek to replicate the brain's ability to allocate processing resources efficiently.

2.3. Auditory Spatial Attention: Definition and Mechanisms

Auditory spatial attention is the ability to focus on specific sound sources in the environment while ignoring others. This selective attention mechanism allows us to navigate complex auditory scenes, such as following a conversation in a noisy room or locating a ringing phone. Auditory spatial attention represents a complex cognitive function that allows individuals to selectively focus on relevant auditory stimuli while filtering out irrelevant background noise, requiring a sophisticated interplay of neural processes across different levels of the auditory system in addition to other sensory systems like the visual system. This selective process involves both bottom-up and top-down mechanisms, with the former driven by the physical properties of sounds and the latter influenced by cognitive factors such as expectations and task demands. Top-down attention allows us to focus on specific sounds based on our goals and expectations, while bottom-up attention is captured by salient or unexpected sounds (Alho et al. (2015)).

The mechanisms of the bottom-up and top-down are supported by a distributed network of brain regions, including the prefrontal cortex, which is involved in executive control and maintaining task goals, the posterior parietal cortex, which contributes to spatial attention and shifting focus, and the auditory cortex, which processes sound features. In the context of auditory attention, this network works to enhance the processing of relevant auditory input while suppressing distracting information. Importantly, recent research highlights the role of oscillatory dynamics, particularly in the alpha band (8–12 Hz), in mediating attentional selection by regulating cortical excitability and sensory gating. Understanding these foundational theories and neural systems is essential for interpreting how the brain prioritizes auditory information in complex environments.

A previous study, conducted in the university of Pavol Jozef Safarik in Slovakia, tried to answer the question whether directing spatial auditory attention affects the cross-modal, visual to auditory, enhancement of auditory spatial attention, when using realistic spatial simulation (Sebena 2017). According to their findings, visual cues did not improve performance, suggesting that visual information alone may not provide perceptual benefits for guiding selective auditory attention. Instead, they observed that **auditory cues** could either enhance or disrupt attention, depending on the context. This was interpreted as consistent with previous studies indicating that auditory cues can aid target discrimination by enhancing perception when the target is energetically masked or when attentional focus is difficult to maintain. Fig. 1 illustrates the response percentages of both visual-cued and auditory-cued trials, divided into two graphs by cue position in the left, and by cue validity in the right, where valid cue means that the cue location is correspondent to the target location and invalid cue means that the cue location is different than target location. This figure shows overall better visual-cue performance than auditory-cue performance, which is more investigated statistically in the study.

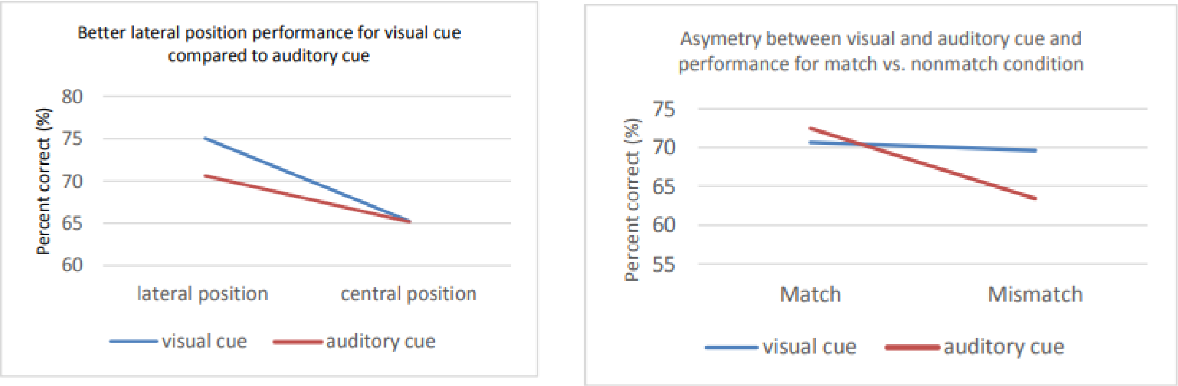


Fig. 1 Response correctness percentage by cue modality, and by cue position (Left) and cue validity (Right). Note: reprinted from (Sebena 2017).

Following preliminary findings showed that the central N1 and N2 components of the ERP response were both generally consistent with behavioral observations (Kopčo, Modaresnia, et al., Cueing vs. Distracting Effects of Attentional Orienting on Auditory Spatial Discrimination 2025). Cue validity had no influence on the sensitivity index for visual cue but a large influence for auditory cue, where the sensitivity index reflects the ability to distinguish between target and non-target signals, independent of response bias. A higher value indicates better perceptual discrimination performance. Fig. 2 shows there is no significant difference between the two cases of validity when the cue is visual, whereas for the auditory cue, a significant difference appears, especially at N1 and N2.

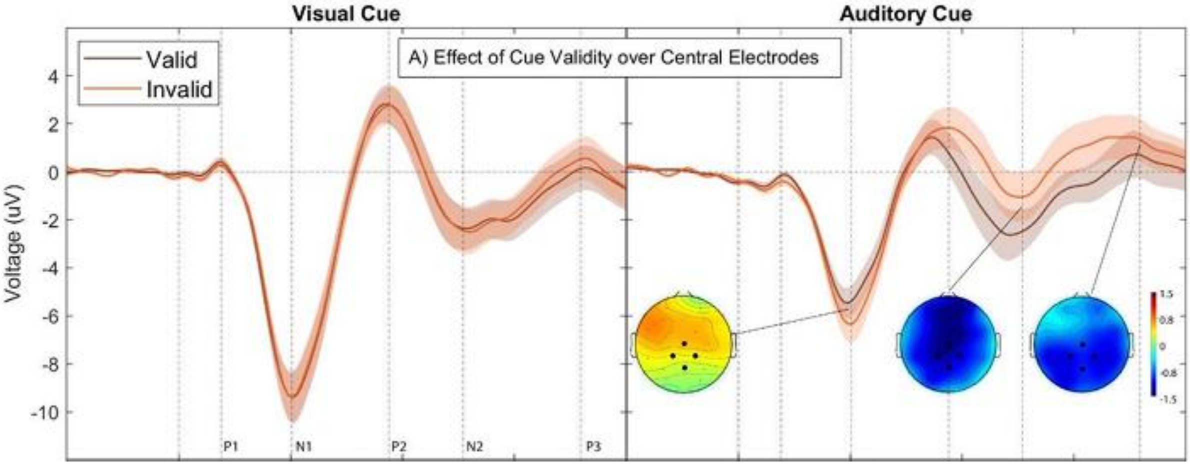


Fig. 2 ERP response of visual vs auditory cue by cue validity and using the front-central electrodes. Note: reprinted from (Sebena 2017).

Our current study extends this by examining which of these findings are reflected in the oscillatory dynamics. Moreover, it examines the hypothesis that alpha oscillations correlate with spatial attentional effects observed behaviorally, as for the ERP study, overall response is easily interpretable but oscillatory components are not, which can vary significantly and can give more overview on the cortical processes.

2.4. Brain activity measurement

Different tools and modalities can be used to capture cortical activity, each offering distinct advantages depending on the nature of the neural signals being measured. Some of these tools depend on the electrical signals generated by the orchestration of neural networks in the brain like Electroencephalography (EEG) devices, which involve placing electrodes on the scalp to measure voltage fluctuations resulting from ionic currents within neurons. Others benefit from the electromagnetic field generated by the electrical charge on the scalp like Magnetoencephalography (MEG) devices, which measures the weak magnetic fields generated by neural electrical currents, allowing for high temporal resolution and a more direct mapping of brain dynamics. Nevertheless, electrical activity is not the sole measure of the brain, however, Structural and functional changes in the brain can also be investigated using imaging modalities that do not directly measure electrical activity, such as magnetic resonance imaging (MRI) which provide detailed anatomical structural images by detecting the response of hydrogen nuclei (protons) in water molecules to strong magnetic fields and radio waves. In cognition studies, a special type of MRI is usually used, which is the functional magnetic resonance imaging (fMRI). Unlike standard MRI, fMRI tracks changes in blood oxygenation and flow that occur in response to neural activity which is measured indirectly through Blood-Oxygen-Level-Dependent (BOLD) signals, offering insight into which brain regions are engaged during specific cognitive tasks (Huettel, Song and McCarthy 2009).

Given that no single modality provides a complete picture of brain function, multimodal measurement approaches have become increasingly important in neuroscience research. These approaches combine complementary techniques to overcome the limitations of individual methods. For example, integrating EEG or MEG with fMRI allows researchers to take advantage of the high temporal resolution of electrophysiological recordings and the high spatial resolution of fMRI. This fusion enables more precise mapping of both when and where neural processes occur during cognitive tasks. Additionally, combining structural MRI with diffusion tensor imaging (DTI) provides insights into both brain anatomy and the connectivity of white matter tracts, enriching our understanding of functional networks.

Multimodal approaches are particularly valuable in studying complex cognitive functions, where capturing different aspects of neural activity—such as timing, location, and connectivity—is essential. Apparently, multimodal signal acquisition, analyzing and interpreting is much more challenging than unimodal approaches.

2.5. Event related potentials (ERPs)

Event-related brain potentials (ERPs) have been instrumental in studying auditory attention discrimination. Generally, brains generate three types of signals, spontaneous, induced, and evoked (Luck 2014). Spontaneous activity is completely uncorrelated with the occurrence of an experimental condition, as it reflects the continuous work of the brain, so it is usually an additional signal when studying the ERPs. Induced activity is correlated with experimental conditions but is not strictly phase-locked to its onset. Therefore, induced activity is neglected when studying the ERPs, as these signals cancel themselves out after averaging as shown in Fig. 3. Evoked activity is strictly phase-locked to the onset of an experimental condition across trials, i.e. it has the same phase in every stimulus repetition, making it the one signal activity considered in ERP studies. Fig. 3 shows the result of an averaging of 10 trials, where induced signals cancel out, whereas evoked signals remain visible due to their nature of time-locking.

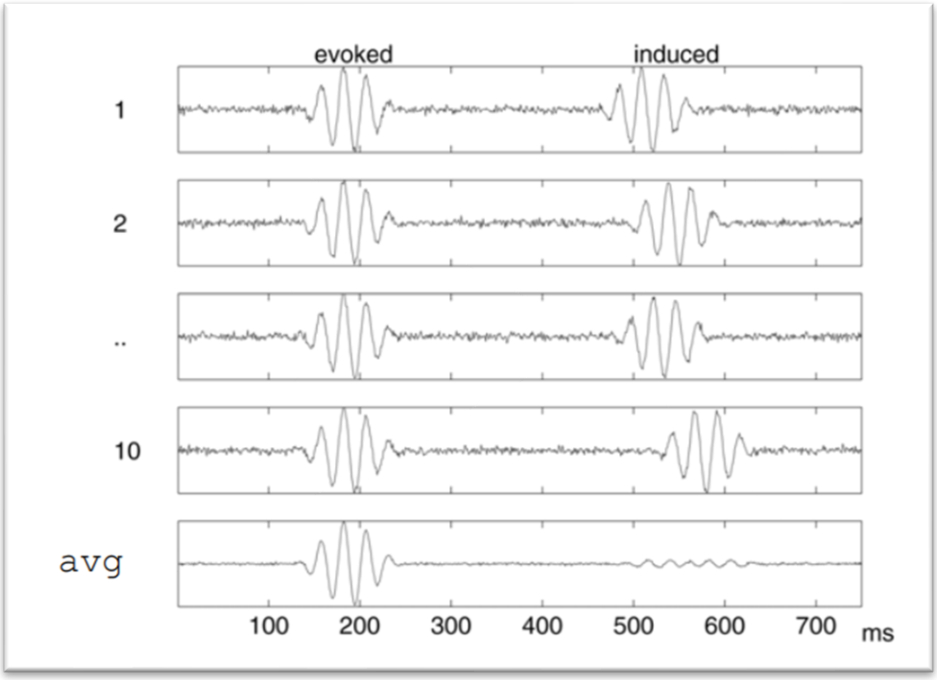


Fig. 3. comparison of time locking property between evoked and induced ERP responses. Note: reprinted from Herrman et al. (2004)

ERP signals consist of several components whose many of them are well-defined in literature. In auditory attention studies, a stimulus preceding negativity is considered a related ERP component (Luck 2014). This negativity grows as the subject anticipates the occurrence of an information-bearing stimulus, such as a feedback tone, irrespective of whether an overt response is required for this stimulus. According to (Luck 2014), the systematic listing of the ERP components could be as follows:

1. Early Sensory Components

These reflect initial sensory processing and are typically modality specific.

- P1 (P100): A positive deflection occurring around 80–130ms post-stimulus, primarily over occipital regions. It is sensitive to low-level visual features and can be modulated by spatial attention.
- N1 (N100): A negative peak around 100–150ms, present in both visual and auditory modalities. It reflects sensory discrimination and is enhanced by attention to stimulus features.
- P2 (P200): A positive component around 150–250ms, associated with stimulus classification and early perceptual evaluation.

2. Cognitive Processing Components

These components are linked to attention, memory, and language comprehension.

- N2 (N200): Appears around 200–350ms; often linked to conflict detection, novelty processing, and cognitive control, especially in go/no-go and oddball tasks.
- P3 (P300): A broad positive wave peaking around 300–600ms. It is often divided into:
    - P3a: Fronto-central, associated with involuntary attention shifts to novel stimuli.
    - P3b: Parietal, reflects conscious evaluation of task-relevant stimuli and memory updating.
- N400: A negative deflection peaking around 400ms, prominent in semantic and language-related tasks. It reflects the ease or difficulty of integrating a word or meaning into a given context.
- LPC (Late Positive Complex): A sustained positivity following P3, associated with memory retrieval and decision-making.

3. Response-Related Components

These are time-locked to the participant's response rather than the stimulus.

- LRP (Lateralized Readiness Potential): Reflects motor preparation and lateralized movement planning, indicating when and which hand will respond, when we are talking about hand responding like clicking two buttons left and right with left and right hands.
- ERN (Error-Related Negativity): A sharp negative deflection occurring approximately 50–100 ms after an incorrect response, typically maximal at fronto-central electrodes. It reflects error monitoring and internal performance evaluation.
- Pe (Error Positivity): A later positive component following the ERN, thought to reflect conscious awareness of an error.

2.6. Neural oscillations and alpha band

Neural oscillations are rhythmic patterns of electrical activity in the brain, arising from the synchronized firing of large groups of neurons. These oscillations emerge from synchronized synaptic activity, resulting in periodic collective shifts between higher and lower intracellular voltage or excitability states. It was proposed that different rhythms cooperate to change the dynamics of neuronal populations, thereby preparing the system for the task. Oscillations in different frequency bands may serve distinct functions. Slow (<8 Hz) oscillations -theta band- seem to provide the temporal framework for sensory selection and encoding (Ibarra-Lecue, Haegens and Harris 2022). Other frequencies seem to play distinct roles. Among these oscillations, the alpha band, typically defined as frequencies between 8-12 Hz, plays a crucial role in cognitive processes. Alpha oscillations are particularly prominent in the posterior regions of the brain and are often associated with states of relaxed wakefulness (Klimesch 1999). Research has shown that alpha activity is involved in various cognitive functions, including attention, memory, and sensory processing. For instance, increased alpha power has been linked to improved performance in working memory tasks and enhanced top-down control of attention. Conversely, a decrease in alpha activity is often observed during active cognitive processing or when attention is directed towards external stimuli. Understanding the dynamics of alpha oscillations provides valuable insights into brain function and has potential applications in neurofeedback, brain-computer interfaces, and the diagnosis of neurological disorders.

Increasing evidence suggests that alpha oscillations are not simply markers of idling, but are dynamically involved in processes such as attention, working memory, and sensory gating. Alpha power, in particular, has been interpreted as reflecting a mechanism of functional inhibition—suppressing the processing of task-irrelevant or distracting information to enable selective attention (Jensen and Mazaheri 2010). For instance, in attention tasks, increased alpha power in task-irrelevant sensory regions (such as visual cortex during auditory tasks) may help to filter out interference. Conversely, alpha desynchronization is typically associated with increased sensory engagement and cognitive effort.

Beyond alpha, higher-frequency oscillations also contribute to cognitive functioning. The beta band (13–30 Hz) is often associated with the maintenance of the current cognitive state and sensorimotor integration. Beta activity is typically observed during tasks requiring sustained attention or motor planning and has been linked to top-down predictive processes. Meanwhile, gamma oscillations (>30 Hz) are implicated in higher-level functions such as perceptual binding, memory encoding, and conscious awareness. Gamma synchronization is thought to support the integration of information across distributed neural populations, particularly during tasks involving complex sensory processing or active decision-making.

Together, these rhythmic activities across frequency bands form a coordinated framework through which the brain regulates attention, perception, and behavior. Studying their dynamics enables a richer understanding of the neural basis of cognition and how it may differ across individuals or clinical populations.

2.7. Time-Frequency decomposition in EEG signals

Time–frequency analysis is based on variants of the Fourier transformation. The Fourier transformation decomposes a signal into a sum of sinusoidal components, each characterized by a specific frequency, amplitude, and phase. This allows us to analyze how different frequency components contribute to the overall signal, which is particularly useful in EEG analysis for identifying neural oscillations. For example, if we were to apply the Fourier transform to a 1-s EEG epoch, we would be able to determine the amount of activity at 10 Hz, 15 Hz, 20 Hz, or almost at any frequency. However, the standard Fourier transformation is not suitable in EEG oscillatory analysis case because it does not provide any information about the timing of oscillations. Instead, it yields a single value per frequency, representing the overall power (squared amplitude) of that frequency across the entire epoch. Instead, we require a method that gives us the power of a given frequency at each time point in the waveform. More precisely, power is not defined at a single time point. However, we can approximate it by calculating the power of a specific frequency over a short window (e.g., 200ms) and assigning this value to the midpoint of that window. This is also beneficial because it reduces the effect of non-stationarity nature of EEG signals, as Fourier transformation considers the transformed signal as a stationary signal which yields many problems, such as spectral leakage that occurs due to the finite duration of EEG epochs, which introduces discontinuities at the boundaries of the analyzed signal. These discontinuities result in energy spreading across neighboring frequency bins, obscuring true spectral features and reducing frequency resolution. This phenomenon can lead to challenges in accurately identifying and interpreting oscillatory activity, particularly when signals contain closely spaced frequency components.

There are many basic approaches to decompose an EEG signal into time-frequency representation, like a moving window version of Fourier analysis and a wavelet analysis (Luck, 2014). In the next subsections, we will present three important decomposition methods, where the first subsection explains the idea of moving window approach. The second subsection delves more into the multi-tapering approach and why it is preferable for us, as we used it in our analysis. The last subsection presents the wavelet approach, which we used partially in our analysis.

2.7.1. Spectral decomposition by moving window approach

Unlike the Fourier transform, which yields a single amplitude value per frequency, representing the aggregate power across the entire epoch, time-frequency methods aim to resolve the power spectral density at each time point. This requires a departure from the global perspective of the Fourier transform and an embrace of localized analysis, where the signal is examined within short, overlapping time windows. This principle, known as windowing or tapering, acknowledges the inherent trade-off between temporal and spectral resolution, as power cannot be precisely defined at a single time point (Bârzan, et al. 2022). This principle relies on a moving window, or taper, that shifts across the signal's time points, as illustrated in Fig. 4, which shows four single trials in which a 10-Hz oscillation occurred, but starting at different time points on each trial. The gray rectangle represents the time window that is being used in the analysis. A Fourier analysis is done in this time window, and the power at each frequency is then assigned to the midpoint of that window. The window is then slid over to the right by one sample period (e.g., 4 ms), and a new Fourier analysis is done in the new time window. Thus, the taper is centered at each time point, and the Fourier transform is applied to the windowed signal. This gives us an estimate of the power at each frequency at each sample point in the waveform. Note, however, that we have lost some temporal resolution because the power at a given time point really reflects the entire time window centered at that time point. Notably, when averaging across trials, the reversed components cancel each other out, whereas the average power estimate remains unaffected, which we also benefit from when decomposing EEG trials signals into time-frequency decomposition.

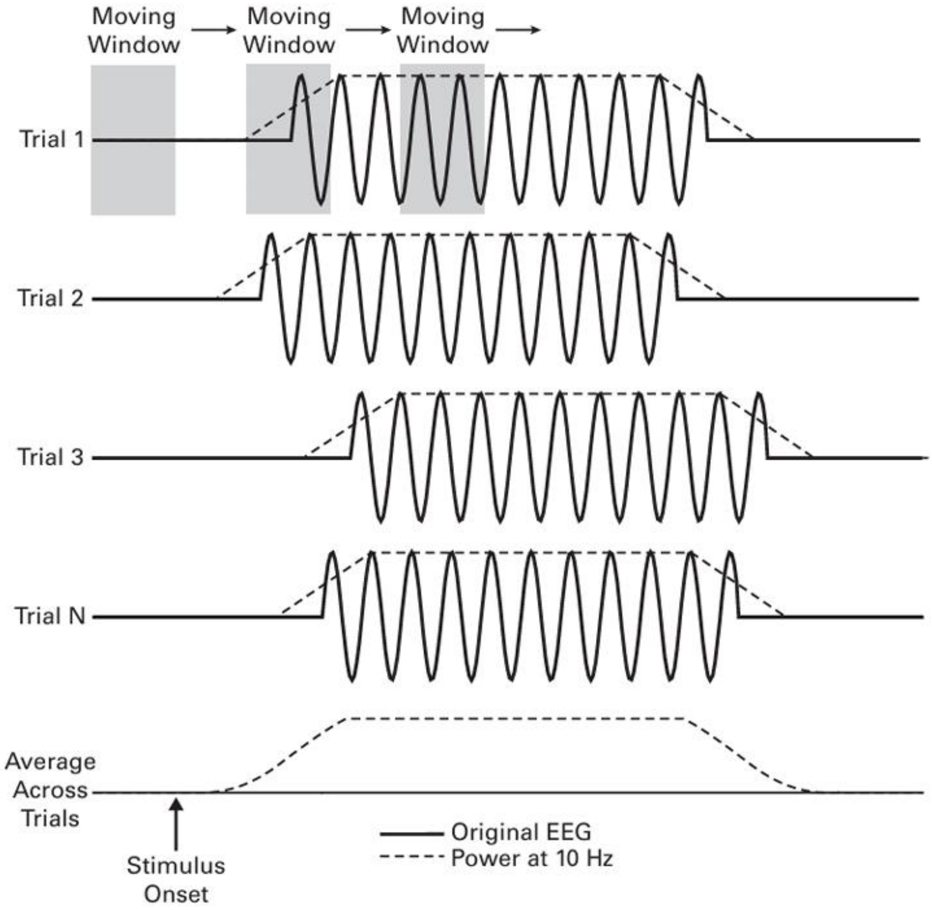


Fig. 4 A simplified example of N trials signals of the same frequency with a moving window and the power estimate as dashed lines. (Reprinted from (J.Luck, 2014))

The nature of this taper or window plays a crucial role. More precisely, this operation, which can be called Short Time Fourier Transform (STFT), consists of two steps, multiplying a taper on the signal as in signal filtering, then applying a Fast Fourier Transform (FFT) to the multiplied signal. While rectangular windows are simple, they can introduce more spectral leakage. Gaussian windows, on the other hand, offer better frequency resolution but at the cost of temporal precision. Therefore, the selection of an appropriate window size and type is crucial, especially when dealing with signals of unknown characteristics.

2.7.2. Spectral decomposition by multi-tapering approach (Kim et al. (2018))

One of the most common issues encountered in EEG spectral analysis is the spectral leakage, which is explained in 2.7. Multi-taper method reduces this leakage outside the desired band, as multi-taper methods use a set of orthogonal tapers, often Slepian sequences, that are designed to optimally concentrate the signal's energy within a specified bandwidth. By calculating the power spectrum using multiple tapers and then averaging the results, multi-taper methods mitigate random noise and leakage effects, leading to a cleaner and more accurate spectral estimate (Kim, Ba and Brown, A Multitaper Frequency-Domain Bootstrap Method 2018). Mathematically, a signal is multiplied by each taper to produce a taperd version of the signal. This tapering ensures that the spectral energy is concentrated in the desired bandwidth, reducing the effect of spectral leakage. The orthonormal nature of the tapers ensures that each tapered version of the signal contributes uniquely and non-redundantly to the final multi-tapered spectrum. This improves the robustness and accuracy of the spectral estimate. Let’s take a signal $x_k; k = 0,1, \dots, N-1$, of N observations, and let’s take M orthonormal tapers, discrete prolate spheroidal sequences, $h_k^1, h_k^2, h_k^3, \dots, h_k^M$ such as:

$$\sum_{k=0}^{N-1} \boldsymbol{h_k^i} \,.\, \boldsymbol{h_k^j} = \boldsymbol{\delta_{i,j}} \qquad \textit{Equation 1}$$

Taking the discrete Fourier transform for the mth tapered signal, we can have:

$$\boldsymbol{X^{(m)}(w_j) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} h_k^m \ x_k \, e^{-iw_j k}}$$ *Equation 2*

For $w_j = 2\pi j/N$ for j = 0, 1, ..., N-1. From this we can write the mth spectral estimate as:

$$\boldsymbol{\widehat{S}^m(w_j) = \left\|X^{(m)}(w_j)\right\|^2}$$ *Equation 3*

And the multi-tapered spectrum estimate:

$$\boldsymbol{\widehat{S}\,(w_j) = \frac{1}{M} \sum_{m=1}^{M} \widehat{S}^m(w_j)}$$ *Equation 4*

The multi-taper method can be regarded as the decomposition of the spectral representation of the time signal over a set of orthogonal basis functions. In this regard, $X^m(\omega j)$ and $\hat{S}^m(\omega j)$ for m =1, 2, …, M are called the eigencoefficients and eigenspectra, respectively. The multi-taper estimate is approximately unbiased if only the number of tapers is significantly less than $\lfloor 2\alpha \rfloor - 1$. where α is the time-bandwidth product (Kim, Ba and Brown 2018). Additionally, if the true power spectral density is uniformly continuous, the variance can be upper bounded and is reduced by a factor of M compared to the periodogram estimate. A graphical representation of 4-slepian function is shown in Fig. 5. with a sequence length= 512, and half bandwidth= 2. The time-bandwidth product is defined as α=N·W

- N: Length (duration) of the signal in time.
- W: Half-bandwidth, indicating the frequency range over which spectral energy is concentrated.

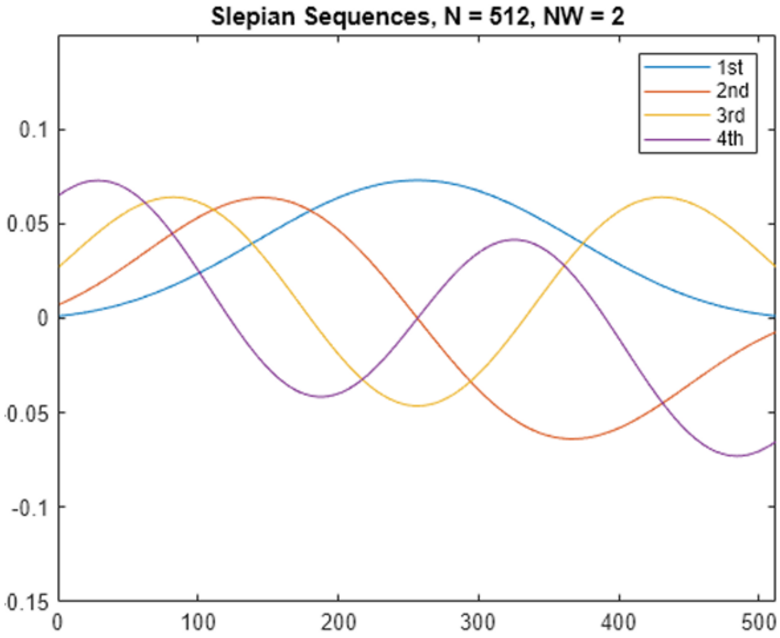


Fig. 5 An example of a DPSS set function

2.7.3. Spectral decomposition by wavelet approach (C. S. Burrus 1988)

Wavelets represent another valid approach for EEG time-frequency decomposition as it resolves two main problems occurring while transforming a signal from time domain into frequency domain. The first problem is that when using a tapered version of a signal and then transforming it into the frequency domain, we consider that the entire window power is concentrated in the center of the taper, while it is not correct in real, as the entire window participates equally into this power estimate. Secondly, when a uniform window size is employed to calculate power across all frequencies, it results in reduced precision for low frequencies compared to high frequencies. While the second issue can be mitigated by adjusting the window length according to frequency—using a wider window for lower frequencies—the first issue remains challenging to resolve. Fortunately, the wavelet approach can address both limitations. Mathematically, a signal or function f(t) can often be better analyzed, described, or processed if expressed as a linear decomposition (C. C. Burrus 1998), by

$$f(t) = \sum_l a_l \ \psi_l(t) \qquad \textit{Equation 5}$$

where l is an integer index for the finite or infinite sum, a_l are the real-valued expansion coefficients, and $\psi_l(t)$ are a set of real-valued functions of t called the expansion set. If the expansion is unique, the set is called a basis for the class of functions that can be so expressed. If the basis is orthogonal, meaning:

$$< \psi_k(t) \, , \psi_l(t) > = \int \psi_k(t) \ \psi_l(t) \ dt = 0 \, ; k \neq l \qquad \textit{Equation 6}$$

then the coefficients can be calculated by the inner product

$$a_k = < f(t), \psi_k(t) > = \int f(t) \psi_k(t) dt \qquad \textit{Equation 7}$$

One can notice that substituting Equation 5 into Equation 7 and by using Equation 6 will give the a_K single coefficient. However, If the basis set is not orthogonal, then a dual basis set $\psi^{'}$ exists such that using Equation 7 with the dual basis gives the desired coefficients. Therefore Equation 5 for wavelet expansion with two parameters becomes

$$f(t) = \sum_k \ \sum_j a_{j,k} \ \psi_{j,k}(t) \qquad \textit{Equation 8}$$

where both j and k are integer indices and the ψ are the wavelet expansion functions that usually form an orthogonal basis. The set of expansion coefficients $a_{j,k}$ is called the discrete wavelet transform (DWT) of f(t) and Equation 8 is the inverse transform.

In another representation, we can represent the wavelet transformation coefficients as the following

$$\psi(b \, , a) = A_\psi \, . \int \psi^* \left(\frac{t-b}{a}\right) . \, x(t). \, dt \qquad \textit{Equation 9}$$

where Ψ^* denotes the complex conjugation of the wavelet function, b is the translation parameter, a is the wavelet's scaling parameter, and A_Ψ denotes a (wavelet specific) normalization parameter. The wavelet coefficients quantify the similarity between the original signal and the wavelet function at a specific scale a, and target latency b. Hence, the wavelet coefficients depend on the choice of the mother wavelet function (Herrmann, Grigutsch and Busch 2004).

An example of a wavelet is shown in Fig. 6, the Gabor function, which can be represented by the equation:

$$\boldsymbol{\Psi(t) = e^{jw_0 t}.e^{-t^2/2}} \qquad \textit{Equation 10}$$

Fig. 6 Gabor function. An example of a wavelet

where j denotes the imaginary unit, $(-1)^{1/2}$, and ω_0 is 2π times the frequency of the unshifted and uncompressed mother wavelet.

This particular wavelet, Gabor function, was created by taking a 10-Hz sine wave and multiplying it by a Gaussian function. Whereas the original sine wave was infinite in duration, the multiplication by the Gaussian function causes the oscillations to taper down over time. This solves the first of the two problems that arise from moving window Fourier transforms. Rather than treating every point within a time period equally, a wavelet gives the greatest weight to the center of the time period. We still have lost some temporal resolution, because the power at a given time point is influenced by a range of surrounding time points, but this problem has been reduced somewhat because more distant time points receive lower weights.

The second problem — different precision for different frequencies — is solved by using Gabor functions with different widths for different frequencies. For example, in Fig. 6, the Gabor function to the right has the same number of cycles as the function to the left, but with a duration half as great. When multiple wavelets are created that are all identical but are squeezed or expanded horizontally to represent different frequencies, these wavelets are called a wavelet family. When each wavelet is a Gabor function, the family is called a Morlet wavelet family (Luck 2014).

3. Research Objectives

The overarching goal of this thesis is to expand the analysis of EEG data originally collected and used for behavioral and ERP studies (Kopčo, Modaresnia, et al. 2025), by focusing on oscillatory brain dynamics, particularly in the alpha band. While earlier analyses investigated event-related potential components, this study shifts the emphasis to induced neural oscillations, which may provide complementary insight into cortical processes underlying spatial attention.

Specifically, the objectives of the thesis are:

1. To learn and apply EEG preprocessing techniques in the FieldTrip MATLAB toolbox, including filtering, artifact rejection, and trial segmentation, as a foundation for both ERP and oscillatory analysis.

2. To understand and perform spectral decomposition methods (e.g., multitaper and wavelet analysis) for analyzing brain oscillations.

3. To analyze oscillatory alpha-band activity in the dataset of Šebeňa et al., with a focus on how it is modulated by cue modality (auditory vs. visual) and cue validity (valid vs. invalid).

4. To test the hypothesis that alpha-band dynamics correlate with spatial attentional effects observed in behavioral responses, particularly in pre-target time windows.
5. *(Optional)* To explore advanced analyses such as source localization or connectivity analysis, if time and data quality permit.

By analyzing EEG oscillations instead of ERP components, we aim to capture neural mechanisms that are not strictly phase-locked to stimulus onset and thus may reflect sustained or preparatory attentional states. This approach allows us to test whether alpha power modulations in the fronto-central region are associated with attentional orienting and behavioral performance.

Our work builds upon the findings of Kopčo et al., who demonstrated cross-modal attentional effects in spatial cueing paradigms. By focusing on the oscillatory components, we contribute to the growing field of auditory neuroscience and multisensory attention, providing further insight into the computational and neurophysiological basis of attentional control mechanisms.

4. Experimental design, analysis and results

Our research is focused on analyzing a previously collected dataset of EEG recordings (Sebena 2017), and is mainly focusing on oscillatory analysis rather than ERP or behavioral analysis. In this section, we present a description of the data of research along with the experiment description. Also, we present the analysis methods we used to achieve our goal of exploring alpha oscillations and whether they match the behavioral results produced previously. Finally, we present the results of our work.

4.1. Description of data

4.1.1. Experiment of Sebena et al. (2025)

The EEG dataset used in this study was obtained from a previous study conducted in the university of Pavol Jozef Safarik (Šebeňa, et al. 2025). The study included 14 subjects (9 male, aged 20-38 years). All participants were with normal hearing by self-report. Participants performed auditory spatial discrimination tasks. During the experiment, the subject was seated in a chair, in a double-walled sound-proof booth with electromagnetic shielding, facing an LCD monitor with a keyboard. The subject's position was adjusted so that the eyes were vertically and horizontally aligned with the center of the screen at a constant distance of 42 cm. Subjects followed on-screen instructions and entered their responses using the keyboard. Subjects wore a 32-electrode BioSemi EEG cap with additional electrodes at the temples to monitor eye-gaze direction. For extended information about data acquisition see (Šebeňa, et al. 2025).

4.1.2. Stimuli

Two stimuli were presented, auditory and visual. The auditory stimuli were presented as 100ms buzzing sound with a 5ms cosine wave ramping up and down to avoid a clicking sound. These sounds had a repetition rate of 170Hz. One of these sounds was a cue. The other two were the target sounds (click trains). These two click trains were presented consecutively from two different locations but with no gap in time between them. This presentation was used as the auditory target; sounds shifting to the left or to the right. One of the visual stimuli was the white fixation point that keeps showing during the whole trial on the black screen. This visual is placed on the screen at ±12.5°. The second visual stimulus is the visual cue, which is a flash dot light showing on the screen in the visual cued trials. Both cues were presented at ±12.5° relative to the fixation point, i.e. cues were presented at ±25° or at 0°. The listener's task was to discriminate the direction of the target location change. The first click train (T1) was presented at 0 or ±25 degrees, and the second train (T2) was at a slightly shifted location (4.2° for the central position and 8.4° for the lateral position).

4.1.3. Experimental procedure

During the experiment, subjects were asked to keep their eyes on the fixation point. 100ms after the beginning of the trial, a visual or auditory cue was presented. Then the target was presented after a delay of 700±100ms, the two target trains had no gap in between. The first click train was presented at ±12.5° relative to the fixation point, and the second train was presented at ±4.2° if the first target (T1) was at 0°, and at ±8.4° if (T1) was at ±25°. The location of the first click train target (T1) determines whether the cue was valid or invalid, from the same side OF WHAT? or from the opposite side respectively. The subject's task was to indicate whether the target shifted left or right (i.e., whether T2 was to the left or right of T1) using the keys “1” or “2” on the computer numeric keypad. The structure of the experimental trial is shown in Fig. 7. A more detailed presentation of the timing indices during the trial can be shown in Fig. 8. The experiment consists of 2 sessions done in 2 separate days. Every session consists of 20 blocks, each with 40 trials. Within each block, fixation and cue modality were fixed, while target position, target shift direction, and cue validity varied randomly from trial to trial with equal probability (thus, the cue was valid on 50% of trials). Subjects were instructed to perform trials within a block without any break, but they were free to take breaks after each block. The order of blocks was fixed within sessions and counterbalanced across sessions. Each session lasted approximately 40 minutes.

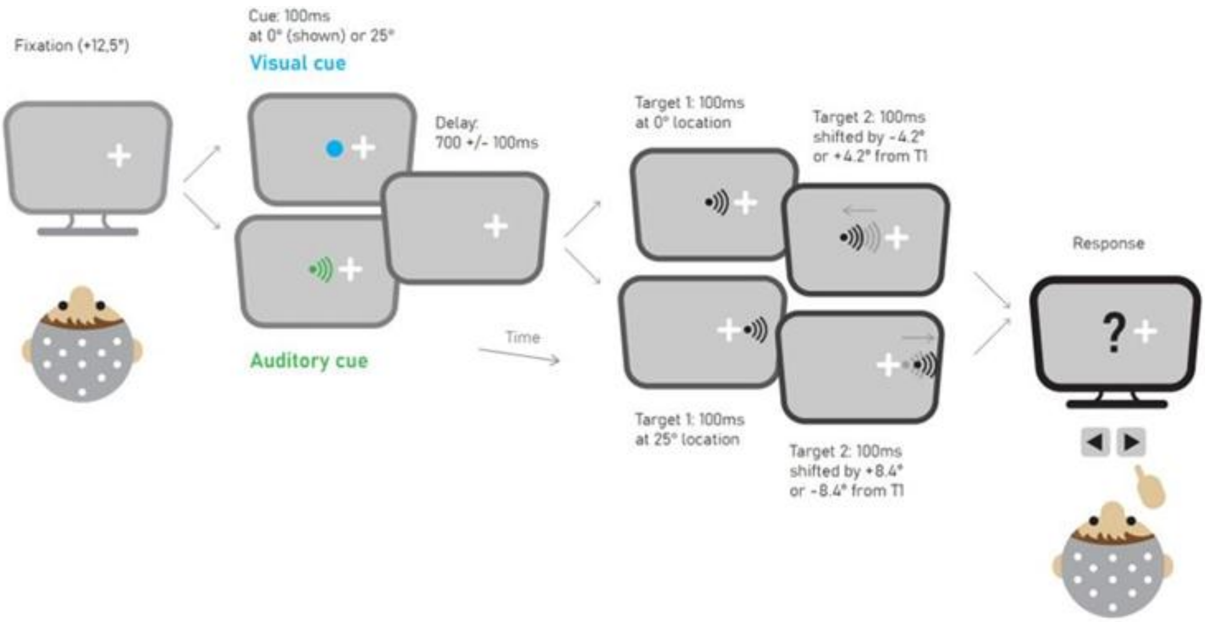


Fig. 7 Experiment Illustrative graph of the structure of a subset of trials, with fixation point at 12.5°, cue to the left of fixation point (at 0°), and with valid (T1 at 0°) and invalid (T1 at 25°) cues.

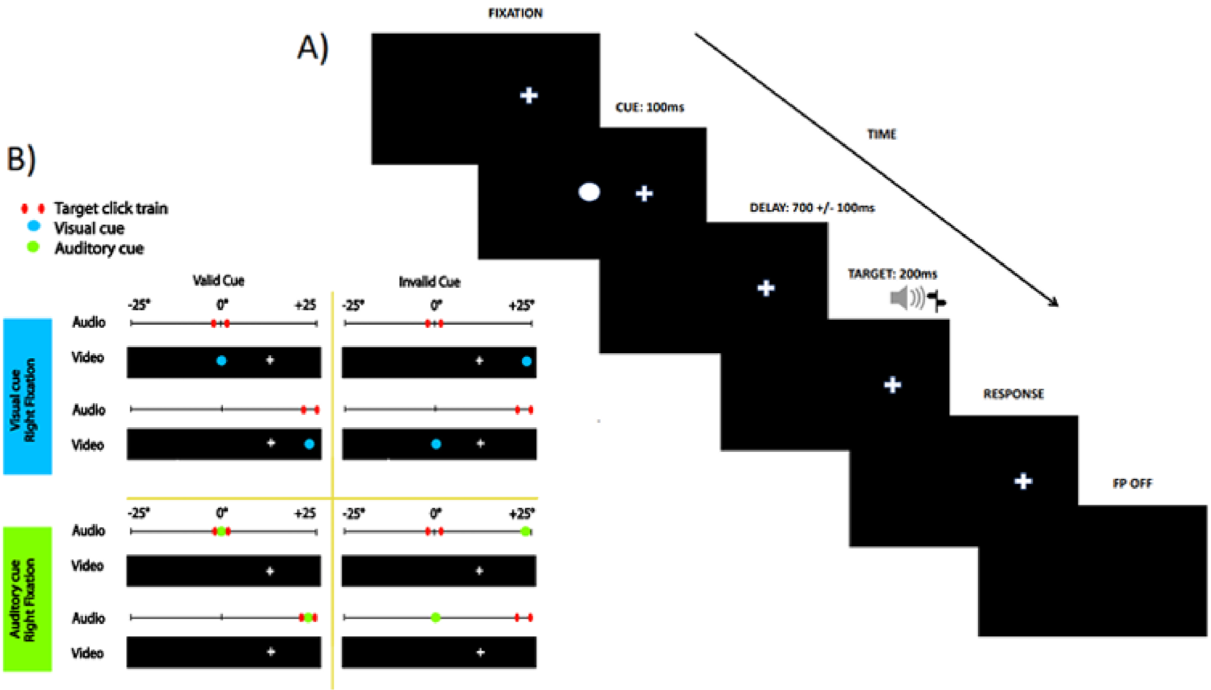


Fig. 8 Experimental timing setup. A) temporal structure of a single trial. B) Spatial arrangement of stimuli in different experimental conditions with fixation point to the right.

4.1.4. Data acquisition and preprocessing

EEG data were recorded during the experiment at a sampling rate of 4096 Hz from 32 scalp electrodes positioned in the standard 10/20 configuration using a Biosemi ActiveTwo system. Flat-type electrodes with individual leads/connectors were placed on the earlobes for reference. Two electrodes were placed above and below the left eye and two additional ones at the outside corners of each eye to measure the electrooculography signal EOG. The processing of the EEG data involved epoching the trials between -2 to 2.98 seconds relative to the onset of the target stimulus. Data were filtered using a [1,40] Hz band-pass filter, the signals were referenced against the two external electrodes placed on the subject's earlobes. Trials were rejected for suprathreshold EEG (< 100 μV) signals. Recordings of electrodes around eyes were epoched between -0.8 to 0.3 sec relative to the onset of the target T1. This epoch interval allows an evaluation of the eye gaze direction during the presentation of fixation point FP, cue and target stimulus. EEG trials contaminated with eye blink artifacts (determined by the vertical eye recordings data analysis) were rejected. Trials where the subject did not hold their gaze steady at the fixation point correctly were also rejected. Moreover, data was prepared to be compatible with the FieldTrip toolbox structures (Oostenveld, Fries, et al. 2011). Specifically, the continuous recordings were segmented into trials based on trigger events, resulting in a trial-based structure containing fields such as .trial, .time, and .label. This format is required for subsequent time-frequency and statistical analyses within the FieldTrip framework.

Four electrodes' recordings were used in our analysis. These electrodes cover part of the fronto-central region and are Cz, FC1, FC2, and Fz as in the standard 10/20 configuration which is illustrated in Fig. 9. The same electrode set was used in a previous related study conducted at our laboratory, allowing for better comparability of results.

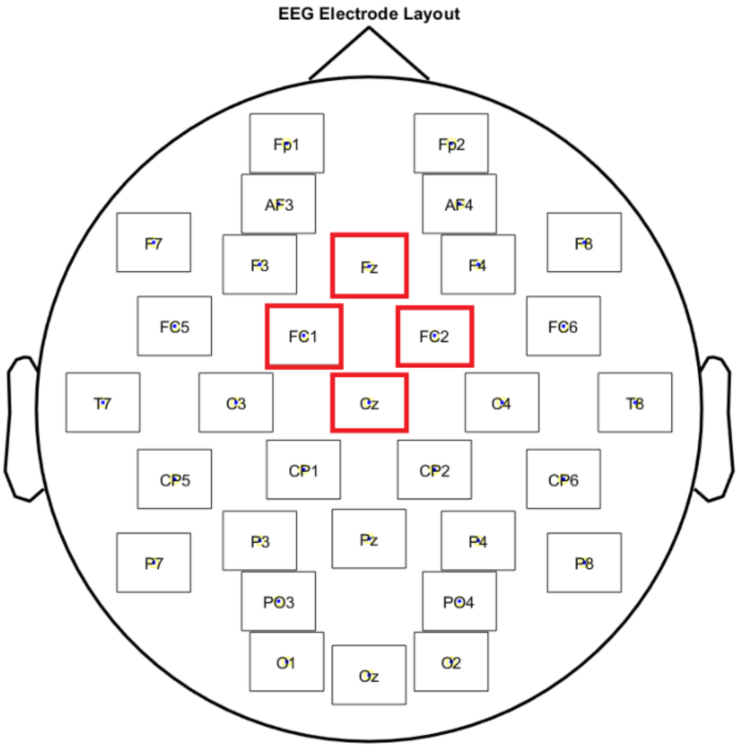


Fig. 9 Schematic representation of the 10/20 standard EEG system layout used in Biosemi 32 electrodes devices. The 4 labeld electrodes are used in our research.

As mentioned in the Description of Data section, fourteen subjects undertook the experiment. However, for our analysis, two subjects were excluded, keeping up only 12 subjects' responses to analyze. The reason behind the exclusion was that some of these subjects' trials indices had missing values making it impossible to link each trial with its starting point and ending point, subsequently misalignment with time vector could occur.

For the analysis, we used MATLAB Fieldtrip toolbox (Oostenveld, Fries, et al. 2011), version released in 2015. Continuous data were filtered by high pass filter at 1Hz and low pass filter at 40Hz.

4.2. Analysis methods

4.2.1. Event-related potential analysis

As part of data validation steps, we tried to replicate the ERP signals reported in (Šebeňa, et al. 2025). Target-evoked ERP analysis focused on one topographical region, which is the fronto-central region, specifically at the set area of the four electrodes Fz,Cz,FC1, and FC2 according to the 10/20 system. Our data was referenced to the onset of the target, i.e. first target train T1 locked. The analysis was done on the averaged signal across all subjects, trials and the 4 electrodes. This averaging leads to cancelling out the induced responses, which leave us with the evoked responses we are interested in. Baseline correction was also done on this averaged signal with the baseline over the time period of -0.1 to 0 sec.

4.2.2. Spectral analysis

To guide our analysis design, we examined preliminarily spectral decompositions for all five task-related factors plus the correctness of response as an additional factor, where the five factors are: cue modality (auditory / visual), cue validity (valid / invalid), fixation point location (left side / right side), target location (center / lateral) and target shift direction (left / right). Analysis started by averaging over subjects and trials. We computed time-frequency representations using Hanning multi-tapering and wavelet methods, where both are useful to suppress spectral leakage. Hanning tapers are a special type of windowing that has a bell-alike shape and reduces the leakage significantly as shown in Fig. 10. These were used to explore whether any spectral differences emerged between conditions of modality, validity and target location.

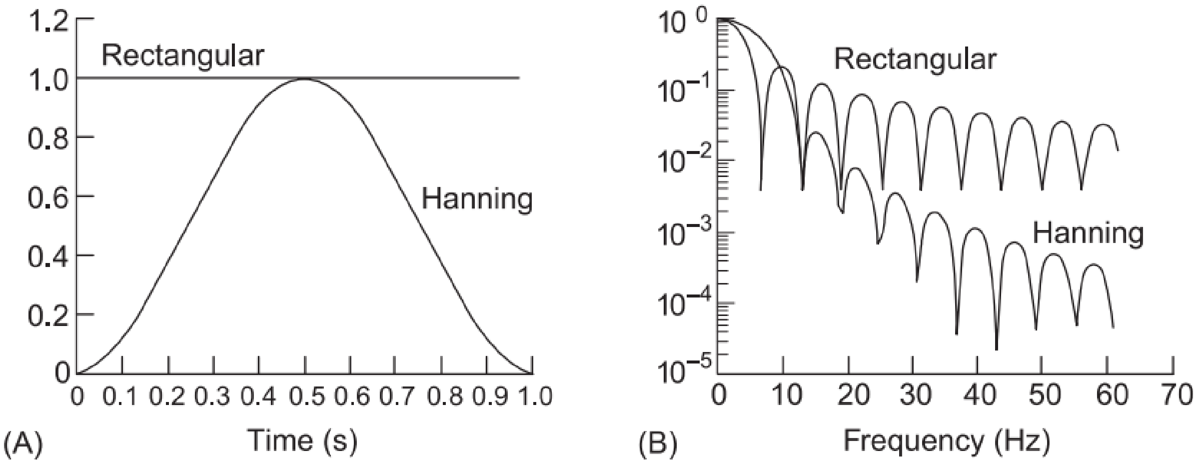


Fig. 10 Rectangular and Hanning windows: (A) time domain windows; (B) magnitude in frequency domain. Reprinted from (Braun 2001)

Specifically, one goal of using both methods was to investigate whether the target location was a prominent factor in power spectrum. Another goal was to show the difference between multi-taper Hanning decomposition and wavelet transformation, to help us determine which one our study shall adopt.

We used a Hanning window of length 250ms running in time -500ms to 500ms relative to target onset with a shift size of 25ms. For the wavelet analysis, we used a 5-cycle Morlet signal with shift size of 25ms as well. This configuration was chosen to balance temporal and spectral resolution: 5-cycle wavelets are commonly used in cognitive EEG studies as they provide adequate frequency precision for analyzing alpha-band dynamics, while still preserving reasonable time resolution. A shift size of 25ms was selected to ensure sufficiently fine temporal sampling of oscillatory activity without overly increasing computational load.

One more important step in our analysis was to normalize subjects' spectra as the raw EEG response among subjects can differ substantially due to physiological and anatomical factors as shown in where it is noticeable that different subjects have different intensity in their brain recordings over the fronto-central region, where the top subplot represents the overall event-related potential responses averaged across trials for every subject and for the exemplary event with the factors: Right side fixation point, valid, visual cueing, centered target, target's shift to the left. The second subplot at the bottom represents the time frequency spectrum of the 10Hz component of the same recording of the upper subplot.

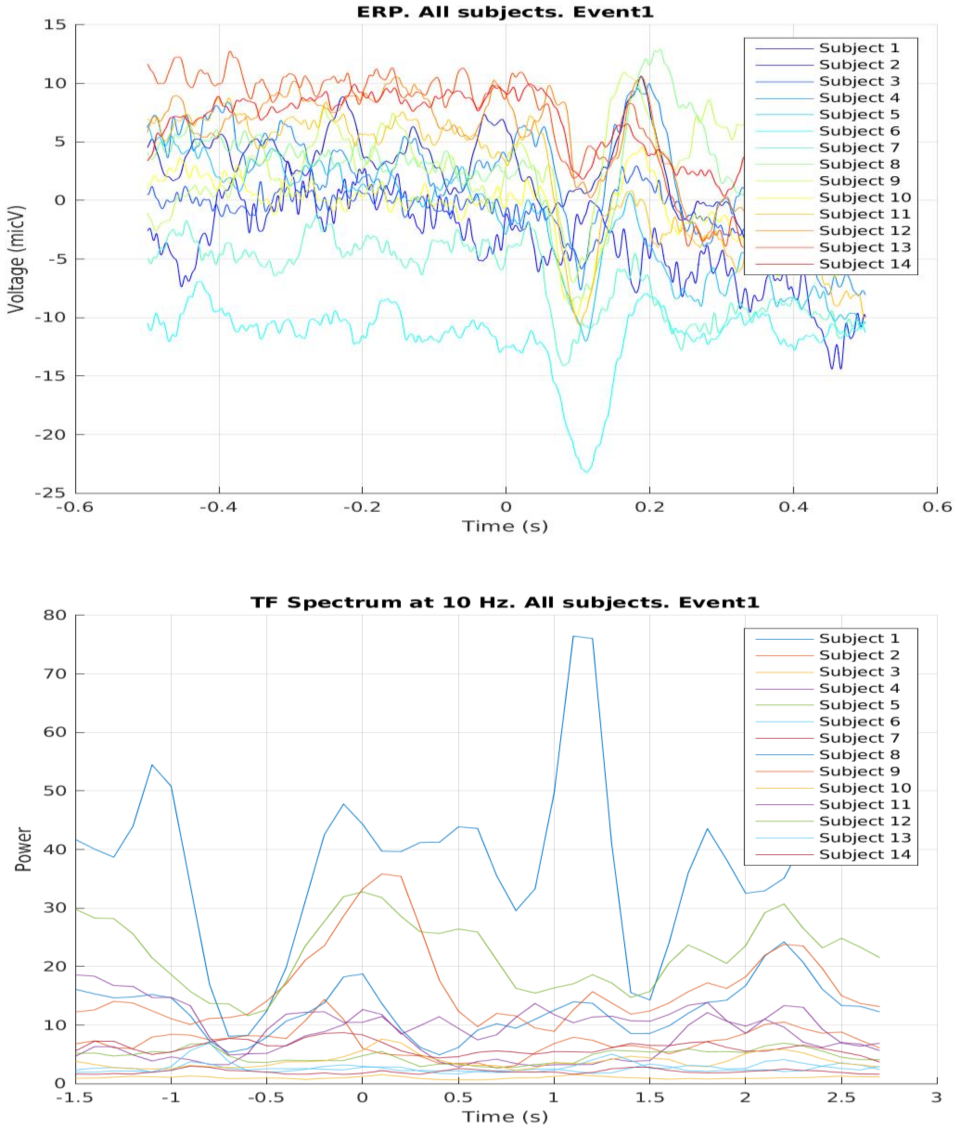


Fig. 11 All subjects recordings for an exemplary event (event #1). Top: All subject raw EEG ERP recordings. Bottom: Time Frequency (TF) spectrum at 10Hz.

Therefore, normalizing each subject's power time course to their own pre-stimulus baseline enables clearer comparisons across participants and conditions. Due to this high inter-subject variability, shown in supplementary figures and , and to isolate task-evoked modulation and to highlight relative modulations and then to better interpret data, we chose a time window of [-1.5, -0.8] sec to be our baseline. Our choice depends on the somewhat stable horizontal alpha response in this time window – look at , which represents alpha (9-10Hz) power distribution over the time window (-1.5,1.5)sec relative to target onset, of the 8 different events that vary by validity, modality and response correctness, averaged across all of the 12 subjects.

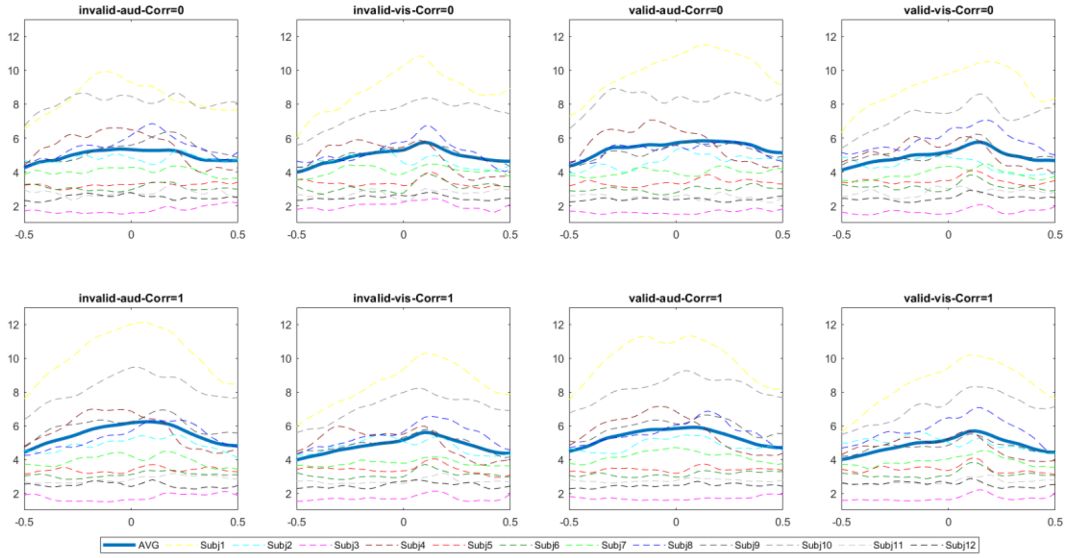


Fig. 12 Alpha (9-10hz) power distribution over time interval (-0.5,0.5) sec across all 12 subjects and over three factors of validity, modality and target location. Continuous blue line represents the average power distribution

Following spectral decomposition of alpha-band power, we focused on the target-locked time window from −0.5 to 0.5 seconds to examine how auditory target processing modulates alpha activity. For more fine-grained temporal analysis, this window was subdivided into four subintervals: −0.35 to −0.15 s, −0.15 to 0.05 s, 0.05 to 0.2 s, and 0.2 to 0.4 s. These intervals were selected a priori and used in subsequent repeated-measures ANOVA to assess time-specific effects on alpha power.

Alpha power topographies were computed using baseline-corrected values, with the baseline defined as the interval from −1.5 to −0.8 seconds relative to target onset (0 sec). All power values reflect relative changes from this baseline, allowing the visualization of task-evoked modulations in the alpha band.

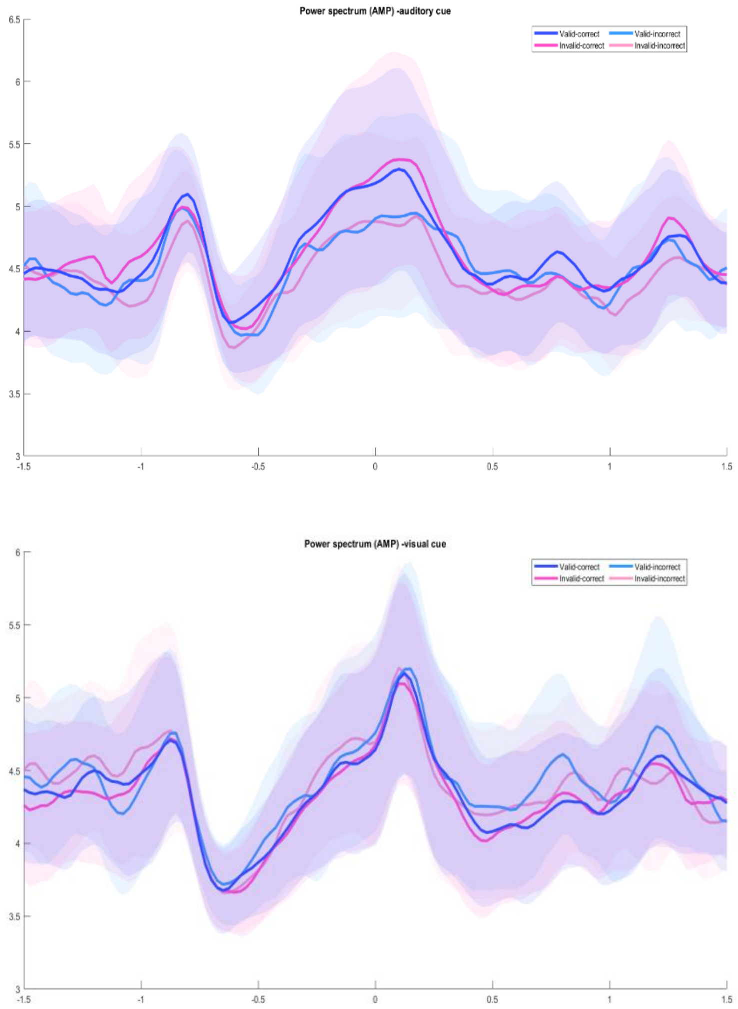


Fig. 13 Power amplitude across-subjects averaged alpha response (9-10hz), target-locked: (TOP: Auditory cue, Bottom: Visual cue)

Because the fixation point was positioned either to the left or right of the fixation across trials, and auditory targets were also shifted from right to left or vice versa, we chose not to include these spatial factors in our spectral analysis. This decision was based on the symmetrical distribution of these conditions, which ensures that any lateralized effects would cancel out when averaging across trials and subjects. Our aim was to examine general patterns of alpha oscillatory modulation related to auditory attention, independent of specific spatial configurations. Including spatial factors that are not expected to systematically affect the spectral distribution would risk overfitting or diluting the overall attention-related effects.

4.3. Results

In this section, we present the work's results, starting with the ERP replication results where we try to replicate these ERP responses found in (Šebeňa, et al. 2025), and following by the alpha oscillations results which are our main goal in this thesis.

Behaviorally, Sebena et al. has stated that validity played a role over auditory cueing but not over visual cueing. Pairwise comparisons to a reference response estimated by the averaging of valid and invalid visual cues responses, showed that invalid auditory cues had the main significance effect rather than the valid auditory cues. In other words, they stated that auditory spatial discrimination is more affected by automatic orientation of within-modal auditory cueing than cross-modal visual cueing. They also found that the target location was a significant factor as performance was better when the target location was peripheral than central.

In our results, we aimed to expand on the previous behavioral results and to show whether alpha band oscillations correspond to their results, so testing the hypothesis of our work that alpha band oscillations over the fronto-central region correlates with their findings.

4.3.1. Event-related potentials

The obtained ERP waveform is shown in Fig. 14. These ERPs were obtained by averaging across trials, subjects and the four fronto-central electrodes of interest: Cz, FC1, FC2 and Fz. While we noticed a similarity between our outcome and the previous study (shown in Fig. 2), we have also observed serious differences. While the general shape and early components of the ERPs were similar, notable differences were observed toward the end of the time interval. Specifically, in our analysis, the ERP waveforms exhibited a declining trend, whereas the original study reported kinds of steadiness around zero in auditory cue ERP, and around -1 μv in visual cue ERP.

One possible source of this discrepancy may be related to differences in preprocessing steps, particularly downsampling. The original study downsampled the data prior to ERP extraction, whereas we maintained the original sampling rate. Downsampling can affect the temporal resolution and potentially influence low-frequency trends, which may partially explain the divergence in the latter ERP components.

In both studies, the N1 component showed a nice time-locking at 0.1s for both auditory and visual cue ERPs. The P2 component also showed similarity particularly in auditory cue ERP, as it is shifted backward and not centered at 0.2s as the previous study shows. The most serious differences are in late components at the end of the epoch. We noticed that N2 and P3 diminished in our study. In both studies, we can notice that visual cues do not modulate N1, suggesting limited early sensory processing effects in this modality. In contrast, auditory cues do, where we notice smaller N1 for valid auditory cues, indicating early attention facilitation. For later components, auditory cues seem to play a crucial role in ERP modulation, while visual cues seem to be of no effect, which also matches the previous study results despite the differences reported here.

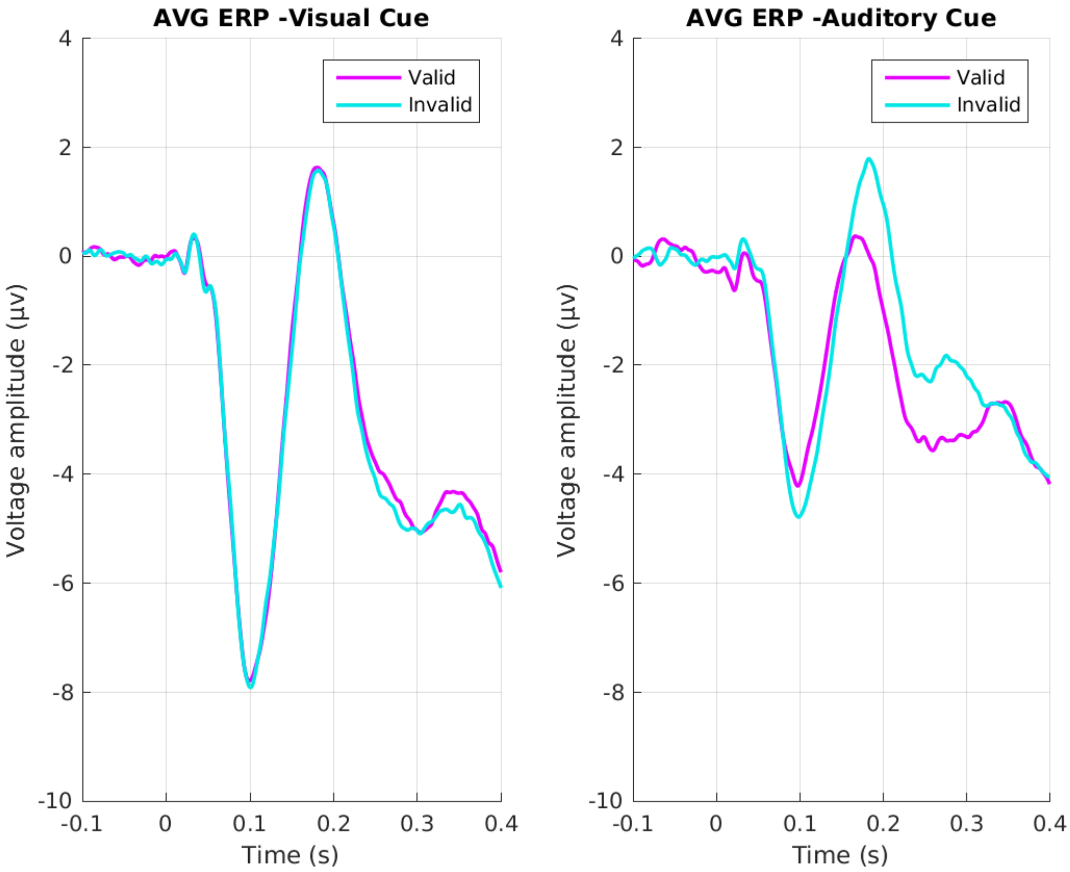


Fig. 14 Cue modality and validity specific averaged ERPs over fronto-central electrodes Cz, FC1, FC2, and Fz and averaged across subjects and trials.

4.3.2. Oscillatory preliminary results

Out of the five factors of the experiment, target location was studied separately as shown in figures and , where both figures are divided into eight subplots, four rows and two columns. The first column represents the spectra of the centered target location case, while the second column represents the spectra of the lateral target location case. The first two panels, A and B, represent the invalid responses, while the last two rows, C and D, represent the valid responses. Modality alternates between auditory and visual panel by panel, starting with auditory. Both figures show the time-frequency spectra but using Hanning multi-tapering in the first figure and wavelet decomposition in the second figure. For each subplot, the x-axis represents the time in seconds, the y-axis represents the frequency (Hz) and the color bar represents the power (μv^2).

Although wavelet analysis showed similar results to Hanning transformation, as shown in , the Hanning multitaper method was preferred for the main analysis due to its smoother time-frequency estimates and reduced spectral leakage. This approach allowed for more stable visualization of alpha dynamics across conditions, as illustrated in Fig. 15.

Looking at these two figures illustrate how the target location does not really modulate the response. More precisely, for visual stimuli (B and D), alpha responses over the fronto-central lobe - electrodes Fz, Cz, FC1, and FC2- do not have big differences by target location variations, as alpha power enhancements are happening after ~100ms of the target onset; look at the panels B and D, and notice that yellow peaks after ~100ms from the target onset in all the four visual cases. This might mean that alpha reduction prior to visual stimulation correlates with more task-engagement since visuals might distract auditory attention less than audition. On the other hand, auditory stimulation causes alpha power enhancement to extend backward in time prior to target onset (panels A and C), as we can notice that alpha power enhances much more earlier than in visual cases, as in panel A, it starts at ~200ms prior the target onset, and in panel C, it starts enhancing ~400ms prior the target onset for the centered target case.

Target location seems not to modulate the alpha response in the region of interest, but it appears interesting in panel C, where it shows some distinction between the two cases.

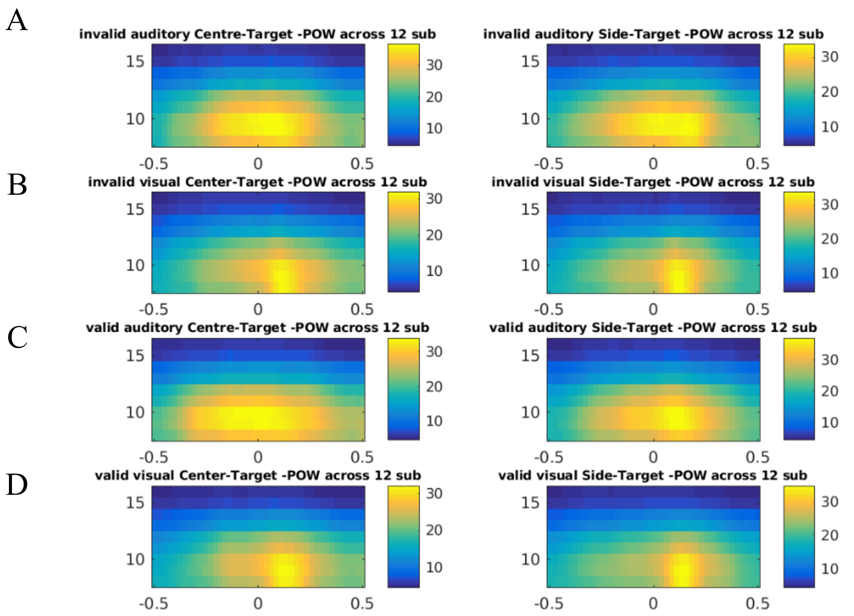


Fig. 15 Averaged power spectra by subjects, and three factors: Modality, Validity, and Target Location, using multi-taper Hanning transformation.

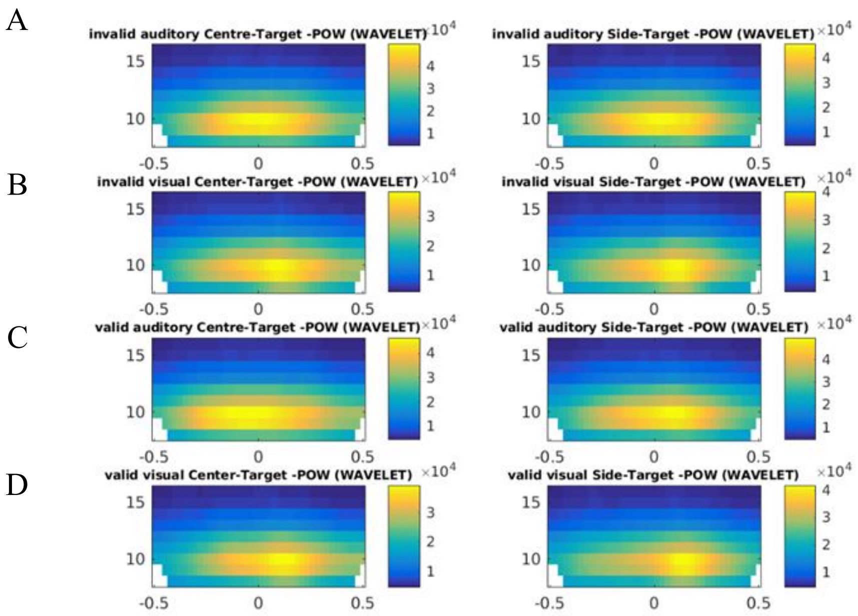


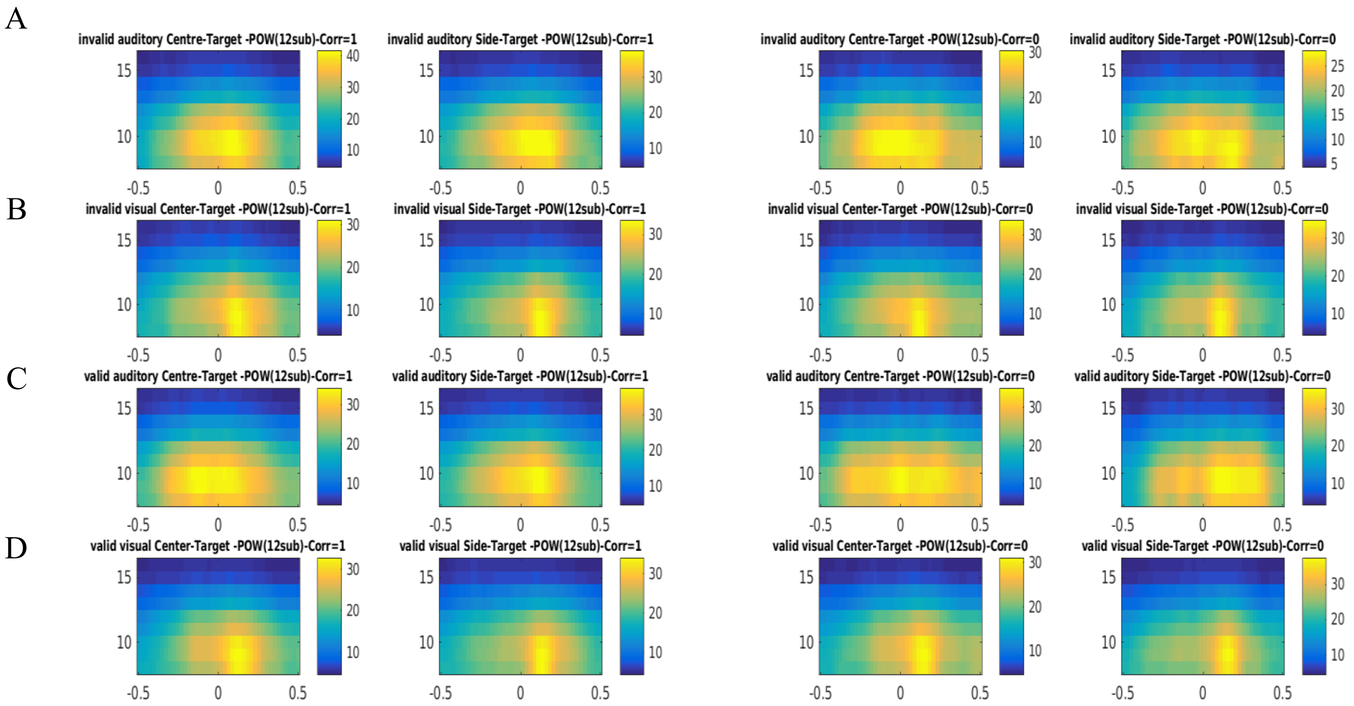
Fig. 16 Averaged power spectra by subjects, and three factors: Modality, Validity, and Target Location, using wavelet transformation.

However, this needs to be analyzed with other factors like correctness. The extension of alpha power is more backward in auditory cueing case than in visual cues could be translated into more distraction by the auditory cues than visual cues.

We extended this analysis to one more level as we added correctness as a 4th factor to distinguish the reason for the slight difference in auditory trials by target location, especially for the valid auditory trials as shown in Fig. 17, which represents time-frequency spectra of different cases of validity and modality, where it is divided into four panels. Each panel represents four variations of target location and correctness. shows that for valid auditory trials (Panel C), alpha power extends in time more when subjects' responses are incorrect than when they are correct. For the correct responses, we notice that alpha power stays maximal until ~250ms after the target onset, but for the incorrect responses, it extends up to ~450ms after the target onset. This could explain the distraction of subjects after stimulus onset, so they were not strongly attended and that in turn affected their decision.

Looking at the invalid auditory cueing case (Panel A), illustrates that alpha power extends slightly more backward in the incorrect responses than in correct responses. It might be the case that extended alpha power enhancement over the fronto-central scalp distracts subject's auditory attention.

For the visual cueing cases, in panels B and D of Fig. 17, we notice that both target location and correctness have minimal modulation on the alpha power over the fronto-central region, as we can see that it is always centered around ~140ms after target onset despite the target location and the correctness. Therefore, it might be that visual cues do not affect the response a lot or at least they do not modulate alpha around the fronto-central region.



invalid auditory Centre-Target -POW(12sub)-Corr=1
invalid auditory Side-Target -POW(12sub)-Corr=1
invalid auditory Centre-Target -POW(12sub)-Corr=0
invalid auditory Side-Target -POW(12sub)-Corr=0
invalid visual Center-Target -POW(12sub)-Corr=1
invalid visual Side-Target -POW(12sub)-Corr=1
invalid visual Center-Target -POW(12sub)-Corr=0
invalid visual Side-Target -POW(12sub)-Corr=0
valid auditory Centre-Target -POW(12sub)-Corr=1
valid auditory Side-Target -POW(12sub)-Corr=1
valid auditory Centre-Target -POW(12sub)-Corr=0
valid auditory Side-Target -POW(12sub)-Corr=0
valid visual Center-Target -POW(12sub)-Corr=1
valid visual Side-Target -POW(12sub)-Corr=1
valid visual Center-Target -POW(12sub)-Corr=0
valid visual Side-Target -POW(12sub)-Corr=0

Fig. 17 Averaged power spectra by subjects, and four factors: Modality, Validity, Target Location and correctness (correct to the left, incorrect to the right), using multi-taper Hanning transformation.

These findings supported us with our decision that correctness is more robust than target location, so we neglected target location and considered correctness along with modality and validity, the two main factors of research’s interest.

4.3.3. Alpha oscillations

As discussed before, we have 6 different factors in our experiment: cue modality, cue validity, target location, shift direction, fixation point position, and correctness of subject’s responses. As we discussed earlier, fixation point position and target shift direction were not considered as main factors due to their symmetrical nature which leaves their effects cancelling out after averaging.

4.3.3.1. Modality but not validity modulates alpha

The computed topographies of the combination of the three factors of modality, validity and correctness are illustrated in Fig. 18, which shows alpha power distribution relative to a baseline (-1.5,-0.8)sec during the time window around the target onset (-0.15, 0.2)sec.

We observed that auditory cues (panels C and D) elicited higher overall relative alpha power compared to visual cues (panels A and B), particularly over bilateral parietotemporal regions.

Although the largest scalp differences in alpha power were not consistently located over the fronto-central electrodes used in our main analyses, these electrodes were selected a priori based on their proximity to sources implicated in auditory attentional processing and early event-related components. This region has been frequently analyzed in prior auditory attention studies (e.g., N1/P2 analyses in Sebena et al.) and in some related oscillatory analysis studies like in Mehraei et al. (2018). This region was maintained for consistency across all conditions and analyses.

Therefore, while the topographic distribution revealed broader or lateralized effects, our statistical focus remains on the fronto-central ROI to align with our original hypotheses and analytical pipeline.

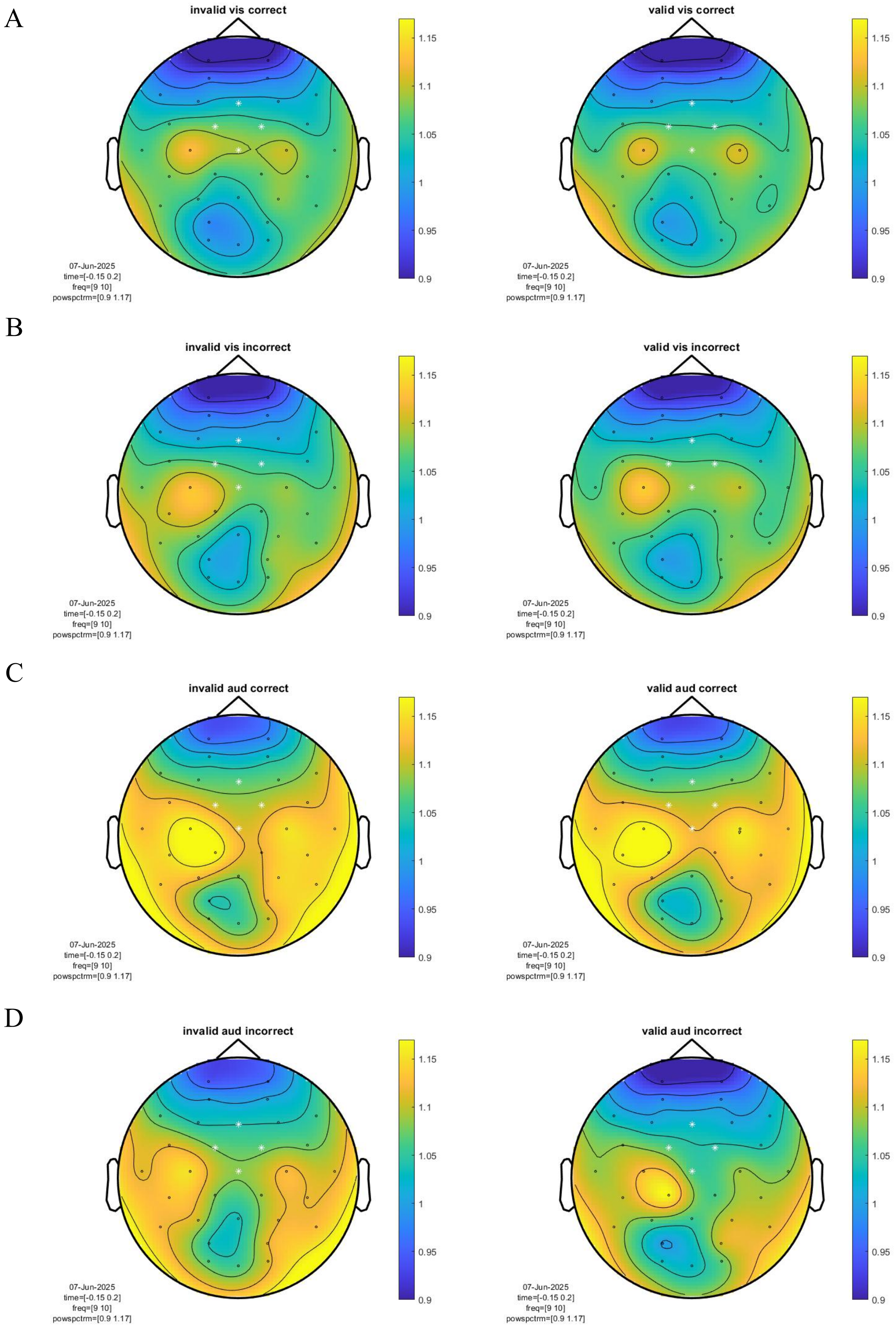


Fig. 18 Topographies of relative Alpha power between -0.15sec before target onset and 0.2sec after target onset and relative to the baseline (-1.5, -0.8) sec. Panels A and B represent visual cued responses, and Panels C and D represent auditory-cued responses. White star symbols represent electrodes of interest Cz, Fz, FC1 and FC2.

Repeated measures analysis of variance ANOVA compared relative-to-baseline alpha power in the fronto-central region during four target-locked time intervals: -0.35 to -0.15 seconds, -0.15 to 0.05 seconds, 0.05 to 0.2 seconds, and 0.2 to 0.4 seconds in all eight conditions of the main three factors of modality, validity and correctness as shown in Fig. 19, which represents alpha power (9-10)Hz relative to a baseline (-1.5,-0.8)sec of visual case to the left and auditory case to the right. The highlighted regions around the plots represent the standard error of the mean SEM.

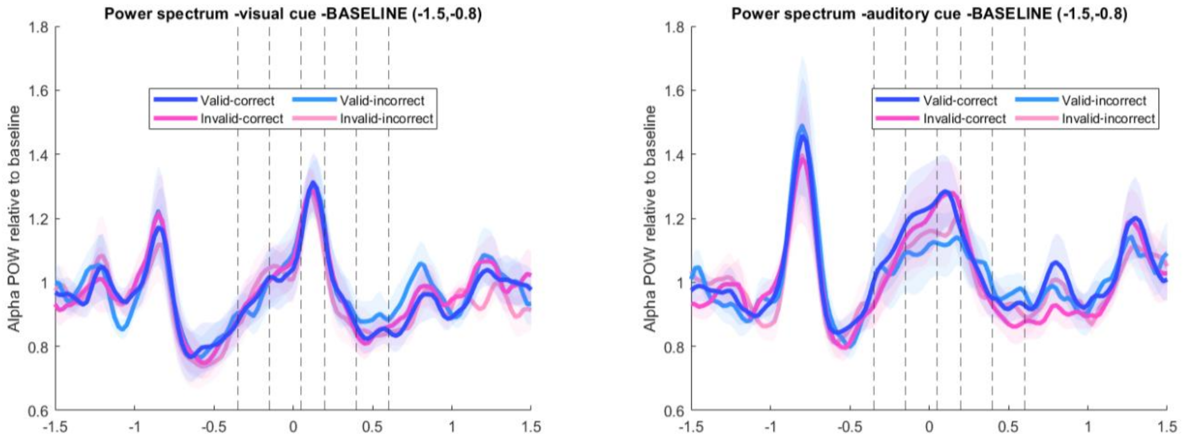


Fig. 19 Alpha power over fronto-central 4 electrodes, relative to the baseline (-1.5, -0.8) sec, divided by modality (Left: Visual, Right: Auditory), validity and correctness. Dashed lines represent time intervals. Highlighted areas around line plots represent SEM regions.

These measures revealed a significant main effect of time interval (F (3,33) = 7.89, p<0.0004), indicating that alpha power varied across time. This could be shown in the third interval in the visual cueing case, as it represents a jump in the relative power compared to neighboring intervals, and also in the last two intervals in the auditory cueing case, compared to first three intervals. The interaction Modality × Interval (F (3,33) = 4.54, p<0.009) suggests that the effect of cue modality on alpha power was time-dependent. Additionally, a significant three-way interaction of Modality × Correctness × Interval (F (3,33) = 4.03, p<0.015) revealed that the temporal dynamics of alpha power were influenced jointly by cue modality and behavioral performance, indicating that correct and incorrect trials followed different alpha time courses depending on modality.

While for the earliest time interval no significant effects were observed individually, modality effects over intervals were observed previously, suggesting early dynamics may still play a role in setting up attentional state.

During the late pre-target interval (-0.15 to 0.05 sec), alpha power was modulated by the interaction between modality and trial correctness (F (1,11) = 4.96, $p<0.047$), as we can see in Fig. 19 in the right panel where the dark lines (Correct responses) start at this interval to differ from the light lines (incorrect responses). This is also shown in the topographies in Fig. 18, where for auditory cases (panels D and C) alpha power over the four highlighted electrodes is stronger in the correct responses cases (panel C) than in incorrect responses (panel D). This might reflect preparatory process that predicts behavioral success depending on cue modality.

Early post-target alpha responses (0.05 to 0.2 sec) showed continued modulation by both modality and correctness (F (1,11) = 4.99, $p<0.047$), which represents a continuation of the previous time window response, which in turn affects the decision the subject takes, then the correctness of the response. This also could be seen in both Fig. 18 and Fig. 19.

In the fourth interval (0.2 to 0.4 sec), alpha power differed by modality independent of the other two factors, possibly reflecting cue-modality-dependent sensory processing interfering with auditory processing. This is shown in Fig. 19 where the averaged relative alpha power of visual cueing cases seems to be higher than in auditory cueing cases. Table 1 presents the detailed ANOVA measurement significant results. Table 1. illustrates the detailed results of ANOVA repeated measurements.

Table 1. ANOVA repeated measurements over four temporal intervals (-0.35, -0.15, 0.05, 0.2) sec. M: Modality, C: Correctness, I: Interval.

Interval	Effect	df	F	p-value	Partial η^2
2	MC	1,11	4.96	0.0478	0.3106
3	MC	1,11	4.99	0.0473	0.3119
4	M	1,11	9.58	0.0102	0.4656
1 & 2	Interval	1,11	18.69	0.0012	0.6295
1 & 3	Interval	1,11	22.75	0.0006	0.6741
	MI	1,11	9.18	0.0114	0.4550
1 to 4	Interval	3,33	7.89	0.0004	0.4177
	MI	3,33	4.54	0.0090	0.2923
	MCI	3,33	4.03	0.0152	0.2679

4.3.3.2. Correctness modulates alpha

As validity variations did not show any significant effects and to examine how alpha power relates to behavioral performance, we computed topographical maps of the difference between correct and incorrect trials (correct – incorrect) separately for auditory and visual cue modalities averaged by validity in both cases, across three intervals relative to target onset: pre-target (-0.30 to -0.15 sec), cue-to-early-target (-0.15 to 0.20 sec), and post-target (0.20 to 0.40 sec). In the visual modality, correct trials consistently showed reduced alpha power compared to incorrect trials at the right occipital region across all three windows (Fig. 20, top row). This widespread alpha suppression was also prominent over frontal region around the target onset and likely reflects enhanced preparatory attention and greater sensory engagement in successful visual trials. The effect was strongest during the anticipatory and early target window (-0.15 to 0.20 sec), suggesting that alpha desynchronization supports attentional readiness and perceptual processing in the visual task. In contrast, the auditory modality showed an opposite pattern during the pre-target and anticipatory windows (Fig. 20, bottom row). Correct auditory trials exhibited higher alpha power, especially over fronto-central and parietal regions, suggesting that alpha synchronization supports top-down attentional control in auditory tasks. This alpha enhancement persisted from the pre-target interval into the early post-target phase (-0.15 to 0.20 sec). However, in the later window (0.20 to 0.40 sec), the difference diminished or reversed slightly, indicating that post-target stimulus processing may require alpha desynchronization for accurate responses.

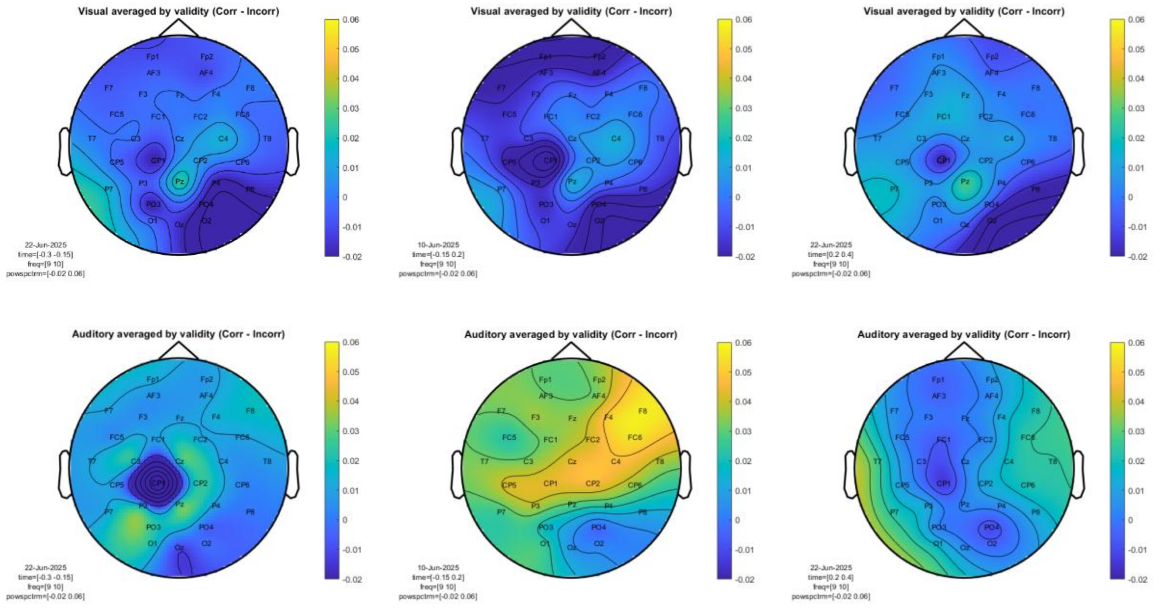


Fig. 20 Topographical alpha power differences between correct and incorrect trials relative to a baseline (-1.5, -0.8) sec over three windows: (-0.3, -0.15), (-0.15,0.2) and (0.2,0.4) sec from left to right. Top: Visual, Bottom: Auditory.

5. Discussion

The main goal of the thesis was to perform oscillatory analysis on EEG data to test the hypothesis that alpha band correlates with spatial attentional effects observed previously in (Sebena 2017) and (Šebeňa, et al. 2025), where they found that auditory cue modulates the ERP component N1 where valid auditory N1 was smaller than invalid auditory N1. At the same time, they found that visual cues do not modulate N1 although it follows a much more negative N1 than in auditory cues but still does not modulate it over validity as auditory cue does. One more interesting behavioral outcome of theirs was that auditory cues affect discrimination more than visual cues, and they justified that by the fact that audition can be more distracting when the cue is invalid than vision.

Several variables were excluded from the main analysis due to their symmetrical nature (e.g., fixation side and target shift direction), under the assumption that their effects would cancel out across balanced trials. Similarly, target location was analyzed separately and found not to modulate fronto-central alpha responses significantly, reinforcing our decision to prioritize correctness as a behavioral marker.

5.1. Comparisons of ERPs

The replicated ERPs exhibited similar early signal behavior compared to the original findings by Šebeňa et al., particularly in the presence of a consistent N1 component approximately 100ms after target onset. This replication of early components supports the validity of the EEG dataset and the preprocessing pipeline used in our study. However, our ERPs did not clearly show the later N2 or P3 components as observed in Šebeňa et al.

One potential explanation for this discrepancy lies in the different preprocessing strategies employed. For instance, the original study involved downsampling, which, if not preceded by appropriate low-pass filtering, could distort high-frequency or late ERP components. In contrast, our preprocessing prioritized maintaining the integrity of the signal for subsequent time-frequency (induced activity) analysis rather than evoked responses.

It is important to note that ERP replication was not the primary goal of this thesis, but rather a methodological validation step before conducting oscillatory analyses. Therefore, we did not attempt to exactly replicate all preprocessing details from the original study. Still, the ERP comparison provided valuable insight into the consistency of early sensory components across both studies.

When comparing validity-related effects, both studies showed similar trends: visual ERPs were largely unaffected by cue validity, while auditory ERPs exhibited notable modulation—particularly in the N1 and later time windows. These findings align with prior literature indicating that auditory spatial cues can elicit stronger attentional ERP components, potentially due to their superior temporal resolution and spatial informativeness (McDonald, et al. 2001).

Despite the differences in the late components as described previously, both studies showed that invalid auditory cues provided a more positive ERP than valid auditory cues which reflect the behavioral results that auditory valid cues do not have big effect while invalid auditory cues seem to play a distractor role.

5.2. Alpha response compared to ERPs

The primary objective of this analysis was to evaluate whether alpha-band activity over the fronto-central region reflects the attentional mechanisms observed in the ERP and behavioral findings reported by (Sebena 2017). To this end, we systematically examined the modulation of alpha power across multiple experimental factors, ultimately focusing on three key variables: cue modality, cue validity, and response correctness.

Consistent with previous findings, ERP responses revealed clear modulation by cue validity for auditory stimuli. Specifically, invalid auditory cues elicited a more negative N1 component and more positive later components compared to valid auditory cues (Fig. 14).

This pattern supports the idea that the brain differentiates between valid and invalid auditory cues during early and late stages of processing.

In contrast, alpha power over the fronto-central region did not reflect cue validity effects. Instead, alpha oscillations were modulated by response correctness, particularly in the auditory modality. Correct trials were associated with greater alpha power around target onset compared to incorrect trials (Fig. 19), suggesting a potential preparatory or inhibitory role of alpha activity in successful auditory attention performance.

Interestingly, visual cues showed weak or no significant modulation in either ERP or alpha-band activity, reinforcing the conclusion that auditory modality plays a more dominant role in engaging spatial attentional mechanisms in this experimental design.

Taken together, these findings suggest a dissociation between ERP and alpha-band responses: while ERPs track validity-related attentional shifts (especially in auditory tasks), alpha activity appears to be more closely linked to behavioral performance, potentially reflecting a neural correlation of attentional success rather than cue processing. This supports the growing view that alpha oscillations encode preparatory mechanisms that facilitate correct responses in attentionally demanding tasks.

5.3. Topographical alpha

Our results showed that auditory cues are associated with higher relative alpha power than visual cues, particularly over bilateral parietotemporal regions, and that this modulation varies with task performance and timing. This pattern may reflect enhanced inhibitory control or reduced anticipatory activation of sensory cortices, consistent with the modality-specific demands of auditory attention. Unlike visual cues, which typically evoke posterior alpha suppression linked to spatial orienting, auditory cues may promote a more sustained or distributed attentional state, preserving alpha synchronization. This interpretation aligns with findings that auditory attention often modulates alpha power in less focal but broader temporal-parietal regions (Weisz, Kraft and Demarchi 2020).

Moreover, modality modulates attention basically by auditory cues and not by visual cues which matches the mentioned previous research, that audition is of more strong cueing or distracting effects than visual cues in spatial auditory tasks.

Moreover, Consistent with previous findings (e.g.(Banerjee, et al. 2011)), we found that auditory spatial attention elicits more sustained and spatially distributed alpha synchronization, whereas visual cues typically induce localized alpha suppression. This supports the hypothesis that auditory attention recruits broader networks, possibly reflecting increased demands on temporal processing and sensory gating. The observed differences in alpha topography between modalities further confirm the modality-specific nature of preparatory attentional mechanisms.

Importantly, alpha power dynamics in the fronto-central region varied not only by modality but also by trial correctness and timing. The interaction between modality and correctness in the late pre-target window suggests that preparatory alpha activity plays a role in predicting behavioral success. This aligns with the idea that alpha power serves a functional inhibitory role in gating task-relevant processing (Jensen & Mazaheri, 2010).

While the strongest alpha effects were topographically located outside the fronto-central electrodes, our decision to focus on these electrodes was guided by previous literature on auditory attention and ERP components. This consistency ensures alignment with established research practices and allows for comparison with earlier work.

In our final results of topographies, and while averaging by validity which proved that it had no significant effects on attention modulation, we observed that the spectral distribution was almost right to left lateralized for correct versus incorrect responses, having the right hemisphere of higher alpha power when the response is correct. Thus, although alpha lateralization in auditory attention is typically direction-dependent (Wöstmann, Maess and Obleser 2021), our results revealed greater right-hemisphere alpha power in correct trials. While the task did not involve overt reorienting, this pattern may reflect the contribution of the right-lateralized ventral attention network, known to support stimulus-driven attentional control, particularly in response to unexpected or behaviorally relevant events (Corbetta and Shulman 2002). This suggests that even in predominantly top-down tasks, reactive control mechanisms in the right hemisphere may contribute to successful auditory attention performance.

These findings confirm that alpha power dynamics are modality-specific and interact with behavioral performance. While alpha suppression facilitates correct responses in visual attention, alpha enhancement prior to target onset appears to benefit auditory task performance.

6. Conclusion

Our study shows that alpha band oscillations over the fronto-central scalp region are basically modulated by cue modality (auditory vs visual). Whether the cue is located at the same location or at a different location from the target's location, i.e. valid vs invalid cues, has no effect on alpha modulation on this scalp region. However, correctness modulates alpha around and after the target onset.

Compared to behavioral and ERP results, our study confirms that modality has a significant effect on the neural response, supporting that automatic attention is more affected by the within-modality rather than cross-modality. However, alpha oscillations are not modulated by cue validity as behavioral and ERP results show, and that could be explained as it might be other frequencies contribute to the formation of the ERP response, rather than alpha alone.

Moreover, alpha oscillations seem to modulate behavioral correctness, as it shows a reduction in its power in occipital regions for correct responses compared to incorrect responses in the visual cuing case, while shows alpha power enhancement for the correct versus incorrect responses when audition is used as a cue. This provided further evidence that alpha dynamics are modulated by modality and interact with correctness.

Our future research directions are suggested to be using other sets of electrodes, like investigating the lateralization of alpha response depending on the target location and/or fixation position. Furthermore, to look at different oscillations like theta, beta and gamma bands which might reflect some kind of auditory attentional modulation. Furthermore, further data analyses could also be conducted like investigating inter-subject alpha band, as alpha waves could differ in its frequency range in addition to its power values among different subjects.

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