Cognitive Neuroscience

Electroencephalogram (EEG)

Name:	**Hosein Dadras**
Gmail:	Hoseindadras6@gmail.com
University Email:	Hoseindadras@ut.ac.ir

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Introduction

Electroencephalography (EEG) represents one of the most significant advancements in the field of neuroscience and clinical neurology. Over its more than 100-year history, EEG has evolved from a rudimentary observation of electrical activity in animal brains to a sophisticated diagnostic and research tool essential for understanding brain function.

The origins of EEG can be traced back to the 19th century when Richard Caton, an English physician, made the pioneering discovery of electrical currents in the brains of live animals. This groundbreaking work in 1875 laid the groundwork for future explorations into the electrical nature of brain activity. Caton's meticulous experiments with rabbits and monkeys demonstrated that the brain's electrical phenomena could be measured and recorded, providing a new avenue for understanding the brain's functioning.

The real breakthrough in EEG came in the early 20th century with the work of Hans Berger, a German neurologist. In 1924, Berger utilized basic radio equipment to amplify the brain's electrical signals captured from the human scalp. His innovation marked the first time that these weak electrical currents could be recorded non-invasively. Berger's recordings, graphically represented on paper strips, showed distinct variations in brain activity corresponding to different mental states and physiological conditions.

Berger's systematic studies revealed that brain activity is not random but exhibits recognizable patterns that change with the functional status of the brain. For instance, he observed distinct changes in brain waves during sleep, anesthesia, oxygen deprivation, and in the presence of neurological disorders such as epilepsy. These findings were monumental, as they suggested that brain activity could be monitored and interpreted to diagnose and understand various neurological conditions.

Moreover, Berger introduced the term "electroencephalogram" to describe these recordings of brain electrical activity. His work provided the first clear evidence that the brain's electrical activity could be consistently recorded and analyzed, leading to significant advancements in both clinical and research settings. His assertion that brain activity reflects the general status of the subject—from relaxation to alertness—has been foundational in the development of EEG as a tool for neurological diagnosis and cognitive research.

Today, EEG is indispensable in both clinical and research domains. Clinically, it is used to diagnose and monitor conditions such as epilepsy, sleep disorders, encephalopathies, and brain death. In research, EEG provides insights into cognitive processes, brain-computer interfaces, and neurofeedback, making it a versatile tool for neuroscientists and clinicians alike.

Historical Milestones

The development of electroencephalography (EEG) is marked by several key milestones that have significantly advanced our understanding of brain function and the capabilities of this technology. Each milestone represents a leap in both the methodology and application of EEG, contributing to its evolution into a crucial tool in neuroscience and clinical neurology.

1875: Richard Caton's Discovery

The first significant milestone in the history of EEG was achieved by Richard Caton, an English physician, in 1875. Caton's pioneering experiments involved measuring electrical currents from the exposed brains of rabbits and monkeys. Using a galvanometer, Caton was able to detect electrical fluctuations corresponding to brain activity. His findings, published in the British Medical Journal, were the first to demonstrate that the brain generates electrical currents, laying the groundwork for future research in this domain.

1924: Hans Berger's Breakthrough

The next monumental leap in EEG came from the work of Hans Berger, a German neurologist, in 1924. Berger's ingenuity lay in his application of radio technology to amplify the brain's electrical signals, which he recorded from electrodes placed on the human scalp. Berger's equipment, though rudimentary by today's standards, enabled him to capture and document the brain's electrical activity non-invasively. He meticulously recorded these signals, producing the first human electroencephalogram (EEG). His initial studies revealed distinct patterns of brain activity, which he associated with different physiological states and mental conditions.

1929: Publication of Berger's Findings

In 1929, Hans Berger published his landmark findings in the journal *Archiv für Psychiatrie und Nervenkrankheiten*. This publication marked the official introduction of EEG to the scientific community. Berger described the rhythmic oscillations he observed, including the alpha waves (8-13 Hz) associated with relaxed wakefulness and the beta waves (¿13 Hz) linked to active thinking and concentration. His work laid the foundation for the classification of different brain wave patterns and their correlation with various mental states.

1930s-1940s: Technological Advancements

The 1930s and 1940s saw rapid advancements in EEG technology and its clinical applications. Key figures such as Edgar Douglas Adrian and Frederic Gibbs further refined EEG recording techniques. Adrian, who later won the Nobel Prize in Physiology or Medicine, confirmed and expanded upon Berger's findings, solidifying the scientific basis of EEG. Frederic Gibbs, along with William Lennox, used EEG to study epilepsy, leading to the identification of characteristic epileptiform discharges. Their work established EEG as a critical diagnostic tool for epilepsy.

1950s-1970s: Expanding Clinical Applications

During the 1950s to 1970s, EEG technology continued to evolve, with significant improvements in electrode design, signal amplification, and data recording. This period saw the expansion of EEG's clinical applications beyond epilepsy. Researchers and clinicians began using EEG to study sleep disorders, brain tumors, head injuries, and encephalopathies. The development of the International 10-20 system in 1958 standardized electrode placement, enhancing the consistency and reliability of EEG recordings across different studies and clinical settings.

1980s-Present: Digital EEG and Advanced Applications

The advent of digital technology in the 1980s revolutionized EEG. Digital EEG systems allowed for higher precision in signal recording, storage, and analysis. Advanced computational techniques enabled more sophisticated processing of EEG data, including spectral analysis, coherence analysis, and source localization. Modern EEG is integral to brain-computer interface (BCI) research, neurofeedback therapy, and cognitive neuroscience. The continuous improvement of EEG technology and analytical methods has expanded its applications, making it an indispensable tool in both clinical and research environments.

Significance of Berger's Observations

Hans Berger's pioneering work in the early 20th century was a turning point in the study of brain function. His observations and methods not only demonstrated the feasibility of recording electrical activity from the human brain but also revealed the profound implications of these recordings for understanding brain physiology and pathology.

Pioneering the Field of Electroencephalography

Berger's successful recording of electrical activity from the human scalp was revolutionary. He was able to demonstrate that the brain's electrical activity could be monitored non-invasively, providing a window into the functioning of the brain in real time. This non-invasive technique opened new avenues for research and clinical diagnosis, setting the stage for EEG to become an essential tool in both neuroscience and medicine.

Identification of Brain Wave Patterns

One of Berger's most significant contributions was the identification of distinct brain wave patterns, which he termed "alpha waves" and "beta waves." Alpha waves, which oscillate at frequencies between 8 and 13 Hz, were observed when subjects were in a relaxed, awake state with their eyes closed. In contrast, beta waves, with frequencies greater than 13 Hz, were associated with active thinking and concentration. These discoveries provided the first insights into the relationship between brain activity and mental states, forming the basis for later classifications of brain rhythms.

Correlation with Physiological and Pathological States

Berger's observations extended beyond the identification of brain wave patterns. He noticed that these patterns varied with different physiological and pathological conditions. For instance, he observed changes in brain activity during sleep, anesthesia, and hypoxia (lack of oxygen). More importantly, he identified abnormal brain wave patterns in patients with neurological disorders such as epilepsy. This correlation between EEG patterns and various states of brain function and dysfunction established EEG as a critical diagnostic tool in neurology.

Foundation for Modern Clinical Applications

The implications of Berger's work were profound for clinical practice. By establishing that specific EEG patterns could be linked to particular neurological conditions, Berger laid the groundwork for the use of EEG in diagnosing and monitoring disorders such as epilepsy, sleep disorders, and encephalopathies. Today, EEG is a standard diagnostic tool used in hospitals and clinics worldwide, thanks to the foundational work of Hans Berger.

Advancing Neuroscientific Research

Beyond its clinical applications, Berger's work has had a lasting impact on neuroscientific research. EEG has become a key method for studying cognitive processes, brain-computer interfaces (BCIs), and neurofeedback. Researchers use EEG to investigate a wide range of topics, from the neural basis of consciousness to the mechanisms underlying mental disorders. The non-invasive nature of EEG makes it an ideal tool for studying brain activity in both healthy individuals and clinical populations.

Legacy and Continuing Influence

Hans Berger's contributions continue to influence the field of neuroscience and clinical neurology. The basic principles he established for recording and interpreting EEG remain in use, even as technology has advanced. Modern digital EEG systems, with their enhanced precision and analytical capabilities, build upon Berger's pioneering work. His legacy is evident in the widespread use of EEG in research and clinical practice, underscoring the enduring significance of his observations.

Terminology and Impact

Hans Berger's contributions to electroencephalography (EEG) extended beyond his technical innovations; he also introduced key terminology that has become foundational in the field. His work has had a lasting impact on both scientific research and clinical practice, shaping our understanding of brain function and influencing the development of various diagnostic and therapeutic techniques.

Brain Wave Classification

Berger's research led to the identification and classification of various brain wave patterns. He introduced the terms "alpha waves" and "beta waves" to describe different frequency ranges of brain activity. Alpha waves (8-13 Hz) were associated with a state of relaxed wakefulness, while beta waves (greater than 13 Hz) were linked to active cognitive processes and alertness. These terms have since become standard in neuroscience, providing a basis for further research into brain rhythms and their functional significance.

Impact on Clinical Diagnostics

The terminology and concepts introduced by Berger have had a profound impact on clinical diagnostics. The ability to categorize brain wave patterns and correlate them with different physiological and pathological states has made EEG an invaluable tool in clinical neurology. For example, specific EEG patterns are used to diagnose epilepsy, with epileptiform discharges serving as a hallmark of the condition. Similarly, changes in brain wave patterns can indicate sleep disorders, encephalopathies, and other neurological conditions.

Influence on Research Methodology

Berger's work has also influenced research methodology in neuroscience. The standardized terminology and classification of brain waves have enabled researchers to systematically study brain function and dysfunction. This has led to significant advancements in understanding cognitive processes, brain development, and the effects of various interventions on brain activity. Researchers have used EEG to explore topics ranging from sensory processing to higher-order cognitive functions, making it a cornerstone of experimental neuroscience.

Development of Brain-Computer Interfaces

The impact of Berger's contributions extends to the development of brain-computer interfaces (BCIs). BCIs leverage EEG signals to enable direct communication between the brain and external devices. By interpreting specific patterns of brain activity, BCIs can facilitate control of prosthetic limbs, computer cursors, and other assistive technologies. This has profound implications for individuals with disabilities, providing new avenues for interaction and communication.

Advancements in Neurofeedback and Therapeutic Interventions

Berger's pioneering work has also paved the way for advancements in neurofeedback and other therapeutic interventions. Neurofeedback involves training individuals to modulate their brain activity using real-time EEG feedback. This technique has been used to treat conditions such as ADHD, anxiety, and depression. By helping individuals learn to regulate their brain activity, neurofeedback offers a non-invasive approach to improving mental health and cognitive function.

Continuing Influence and Legacy

The terminology and impact of Berger's work continue to resonate in contemporary neuroscience and clinical practice. Modern digital EEG systems, advanced signal processing techniques, and new applications of EEG all build upon the foundations laid by Berger. His contributions have not only enhanced our understanding of the brain but have also driven innovations in diagnosis, treatment, and research methodologies. The enduring relevance of Berger's work underscores the transformative power of his discoveries and their ongoing significance in the field of neuroscience.

Modern Applications

Electroencephalography (EEG) has evolved significantly since its inception, and its applications have expanded far beyond initial clinical diagnostics. Modern advancements in technology and analytical techniques have propelled EEG into a wide array of fields, enhancing our understanding of brain function and enabling innovative applications in both clinical and research settings.

Clinical Diagnostics

EEG remains a cornerstone in the diagnosis and management of neurological disorders. It is widely used to detect abnormalities in brain activity that are indicative of various conditions:

Epilepsy

EEG is essential for diagnosing epilepsy and localizing seizure foci. Specific patterns, such as spike-and-wave discharges, help differentiate between different types of seizures and guide treatment decisions.

Sleep Disorders

EEG is a critical component of polysomnography, the comprehensive recording of physiological changes during sleep. It helps diagnose sleep disorders such as sleep apnea, narcolepsy, and insomnia by identifying abnormal sleep patterns and stages.

Encephalopathies

EEG assists in diagnosing various encephalopathies, including metabolic, infectious, and toxic encephalopathies. Abnormal EEG patterns, such as diffuse slowing or periodic discharges, provide clues to underlying brain dysfunction.

Cognitive Neuroscience

EEG is a fundamental tool in cognitive neuroscience, enabling researchers to investigate the neural underpinnings of cognitive processes. Its high temporal resolution allows for the precise measurement of brain activity related to sensory perception, attention, memory, and decision-making:

Event-Related Potentials (ERPs)

ERPs are time-locked EEG responses to specific sensory, cognitive, or motor events. They are used to study the timing and sequence of neural processes underlying perception, attention, and other cognitive functions.

Neural Oscillations

Researchers study various frequency bands (e.g., theta, alpha, beta, gamma) to understand their roles in different cognitive processes. For example, theta rhythms are associated with memory encoding and retrieval, while gamma oscillations are linked to higher-order cognitive functions and consciousness.

Brain-Computer Interfaces (BCIs)

EEG-based brain-computer interfaces (BCIs) have revolutionized the way we interact with technology, particularly for individuals with severe physical disabilities:

Communication

BCIs enable individuals with conditions such as amyotrophic lateral sclerosis (ALS) to communicate by translating brain signals into text or speech. By detecting specific EEG patterns associated with intended actions, BCIs provide an alternative means of communication.

Control of Assistive Devices

BCIs allow users to control prosthetic limbs, wheelchairs, and other assistive devices using their brain signals. This application significantly enhances the quality of life for individuals with motor impairments.

Neurorehabilitation

BCIs are used in neurorehabilitation to restore motor functions in stroke and spinal cord injury patients. By engaging neural plasticity, BCIs facilitate the recovery of motor control through brain-directed training.

Neurofeedback

Neurofeedback, a form of biofeedback, involves training individuals to modulate their brain activity consciously. This therapeutic intervention is used to address various psychological and neurological conditions:

Attention Deficit Hyperactivity Disorder (ADHD)

Neurofeedback training helps individuals with ADHD improve attention and reduce hyperactive behaviors by reinforcing desired EEG patterns (e.g., increasing beta waves and reducing theta waves).

Anxiety and Depression

Neurofeedback is used to regulate brain activity associated with anxiety and depression. By training individuals to increase alpha waves or other specific patterns, neurofeedback can alleviate symptoms and enhance emotional regulation.

Peak Performance

Athletes, musicians, and professionals use neurofeedback to optimize brain function and enhance performance. By training specific brain wave patterns, individuals can improve focus, creativity, and overall cognitive performance.

Research and Innovations

Modern EEG applications extend to cutting-edge research and innovative technologies:

Neuroergonomics

This interdisciplinary field combines neuroscience and ergonomics to optimize the design of systems and environments based on human brain function. EEG is used to assess cognitive workload, mental fatigue, and human-computer interaction.

Virtual Reality (VR) and Augmented Reality (AR)

EEG is integrated with VR and AR technologies to study brain responses in immersive environments. This combination is used in research on spatial navigation, presence, and therapeutic interventions for phobias and PTSD.

Neuromarketing

EEG is employed in neuromarketing to understand consumer behavior and preferences. By analyzing brain responses to advertisements and products, marketers can gain insights into decision-making processes and emotional engagement.

TASK PARADIGM

Experiment Design

The experiment utilized a Rapid Serial Visual Presentation (RSVP) task, a well-established paradigm in cognitive neuroscience used to study various aspects of visual perception and attention. This task involved the presentation of a series of images at a high rate, allowing researchers to investigate participants' ability to process and recognize visual stimuli under rapid conditions.

Stimulus Details

The visual stimuli consisted of 155 unique images, categorized into four distinct types: artificial, body, face, and natural images. Each image was presented 10 times, resulting in a total of 1,550 stimulus presentations. This repetition ensured that each type of image was adequately represented and allowed for the assessment of recognition and attention across different categories.

Task Procedure

Participants were required to maintain their gaze on a centrally positioned fixation cross for 500 milliseconds before the presentation of each stimulus. The stimulus was then briefly displayed for 50 milliseconds. This short presentation time was designed to challenge the participants' visual processing capabilities and mimic real-world scenarios where visual information is often fleeting.

To ensure accurate data collection, participants were instructed to maintain fixation on the cross throughout the task. If a participant lost fixation during the stimulus presentation, the trial was interrupted, and the stimulus was re-presented later in the task sequence. This procedure ensured that the data collected reflected true visual processing rather than artifacts caused by eye movements.

Eye Tracking Technology

Eye tracking technology played a crucial role in the experiment. By continuously monitoring participants' eye movements, researchers ensured that fixation was maintained as required. Eye tracking provided precise and objective measurements of where participants were looking, allowing for the identification of any deviations from the fixation point. This technology not only ensured the validity of the task but also provided additional data on participants' visual attention and gaze patterns.

Preprocessing

This report provides a detailed account of preprocessing raw EEG data using the EEGLab toolbox in MATLAB. The preprocessing steps include data loading, filtering, re-referencing, artifact removal, and Independent Component Analysis (ICA). The aim is to enhance the quality of EEG data for subsequent analysis by systematically removing noise and artifacts while preserving neural signals of interest.

Introduction

EEG data preprocessing is a critical step that significantly impacts the quality of analysis results. The raw EEG data is often contaminated by various types of noise such as environmental noise, muscle artifacts, and electrode artifacts. Additionally, variability in data collection across subjects, sessions, and studies necessitates standardization in preprocessing. This report outlines a comprehensive preprocessing pipeline implemented using the EEGLab toolbox in MATLAB.

Initial Setup with EEGLab

First, download the EEGLab toolbox and add its path to MATLAB using the `Set Path` feature. Initialize EEGLab by executing the `eeglab` command in MATLAB.

Data Loading and Inspection

Load the raw EEG data into MATLAB. The sampling frequency of the data is determined to be 1200 Hz, as there are 1200 samples per second. Load the data into EEGLAB and import the events/channel locations from the `location_xyz` file.

Channel Location Plot

After loading the electrode locations, visualize the 2D plot of electrode placements as shown in Figure 1.

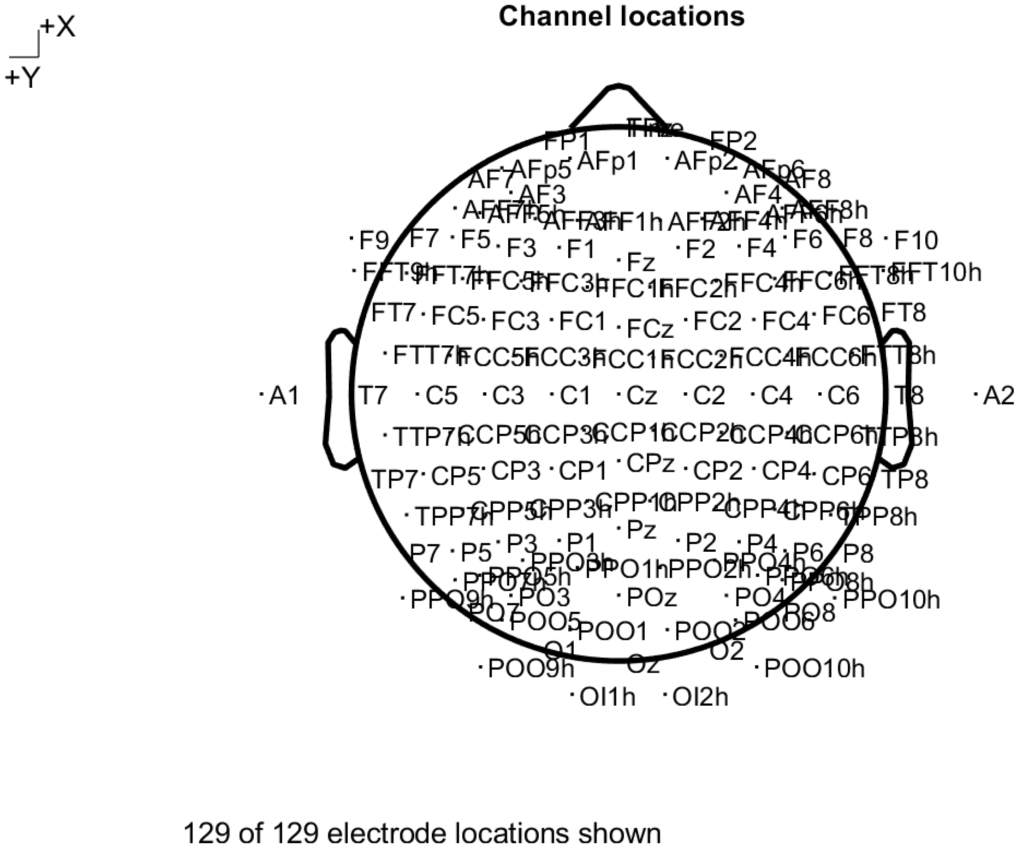


Figure 1: Electrode locations after loading the `location_xyz` file.

High-Pass Filtering

To eliminate DC signals from the data, apply a high-pass filter that allows frequencies above 0.5 Hz to pass through. Figure 2 illustrates the signals from electrodes 0 to 10 after applying this high-pass filter. The initial distortion in the y-axis scale at the beginning of the experiment is evident in these signals.

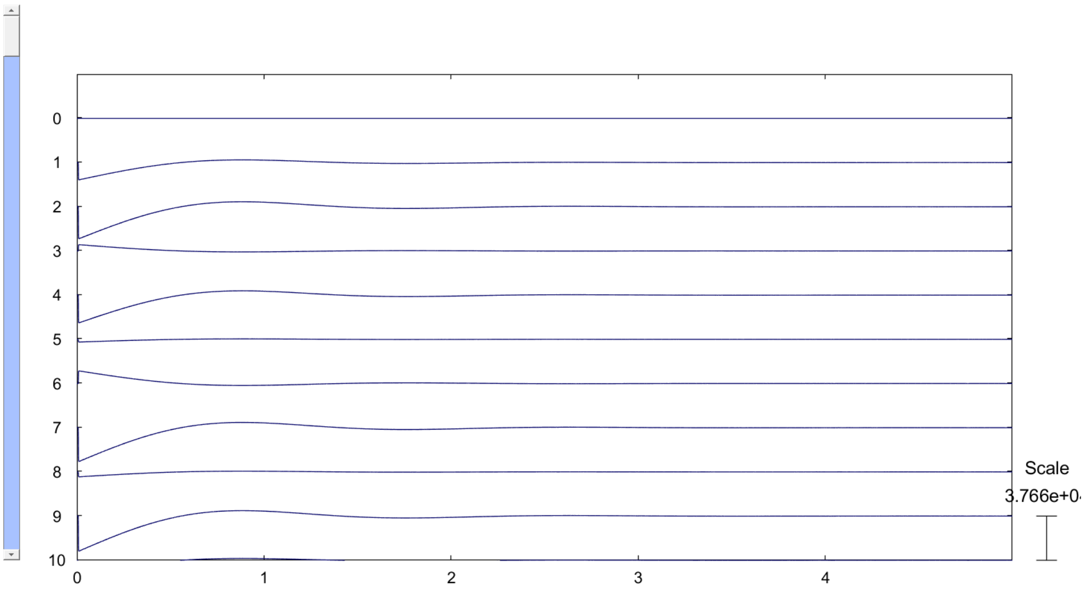


Figure 2: Signals from electrodes 0 to 10 after applying a high-pass filter. The signals from electrodes 0 to 10 (where electrode 0 is the baseline) are shown, revealing significant initial distortion in the y-axis scale of the experiment.

Frequency Response of High-Pass Filter

The frequency response of the high-pass filter, designed to remove the DC component, is depicted in Figure 3.

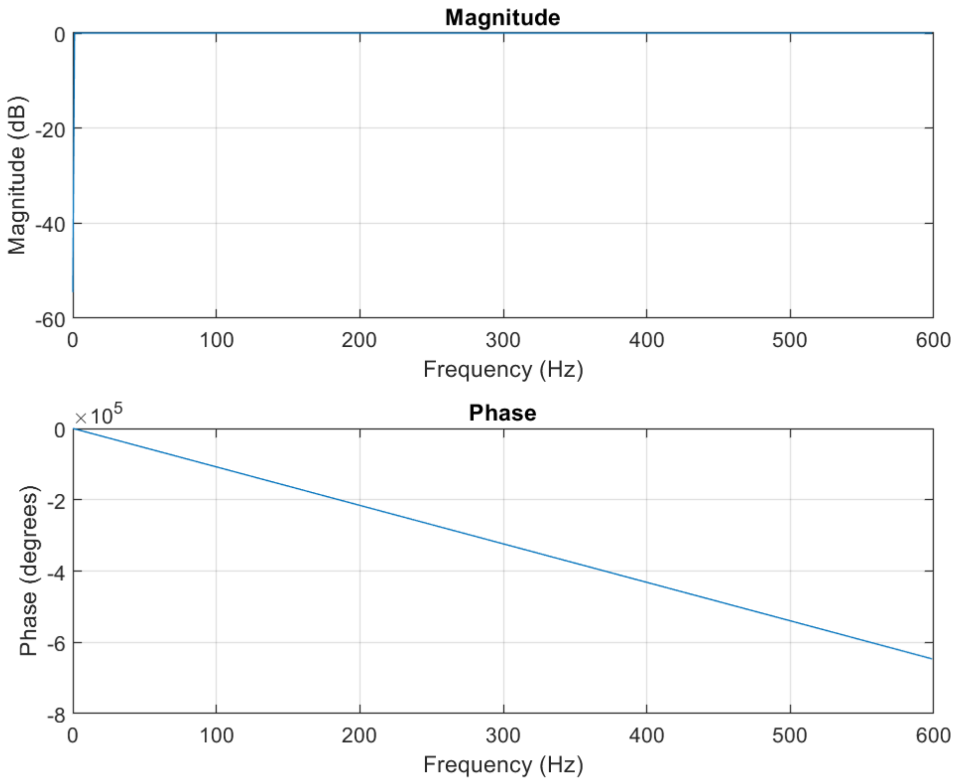


Figure 3: Signals from electrodes 0 to 10 (with electrode 0 representing the time axis). A significant distortion at the beginning of the experiment disrupts the y-axis scaling of the graph, making it evident in the initial part of the recording.

Data Trimming

Observing severe changes in signal amplitude at the start of the experiment, potentially due to pronounced initial oscillations without participant stimulation, we opted to remove the initial 20 seconds of data. The result is illustrated in Figure 4.

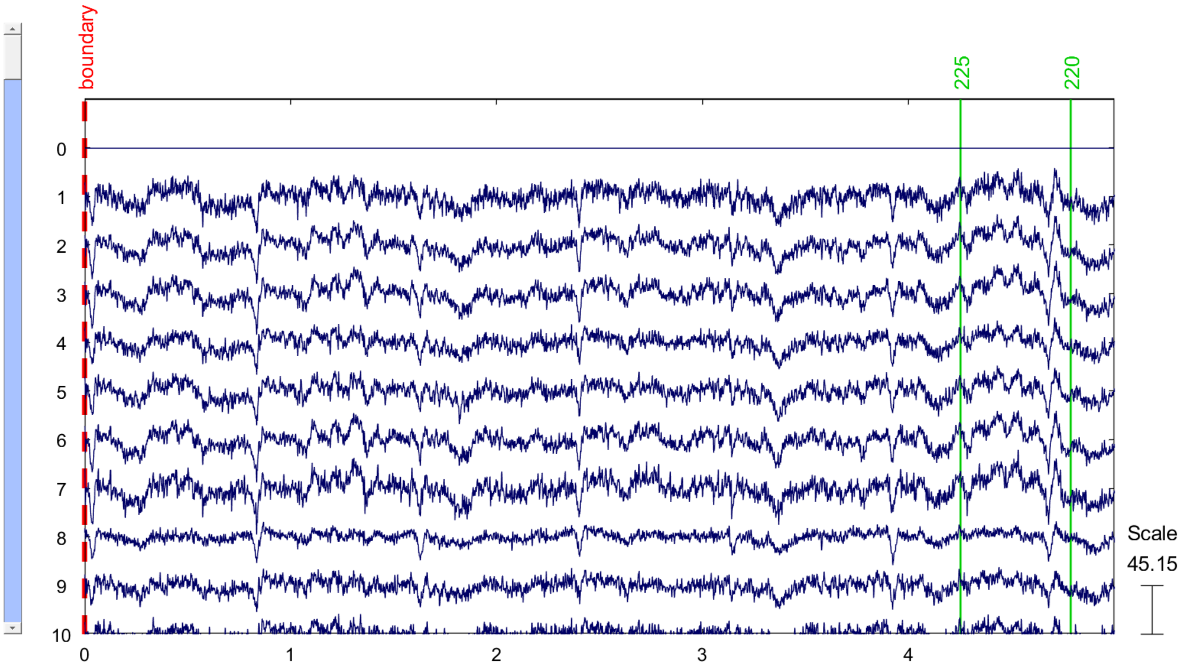


Figure 4: Signal after trimming the first 20 seconds and applying a high-pass filter.

Removing Time Channel

To ensure that the time channel does not affect subsequent analyses, it was removed, leaving 128 channels that represent signals from 128 electrodes.

Spectral Power Analysis

At this stage, we plot the Fourier transform and power spectrum for all channels. Figure 5 displays this spectral power.

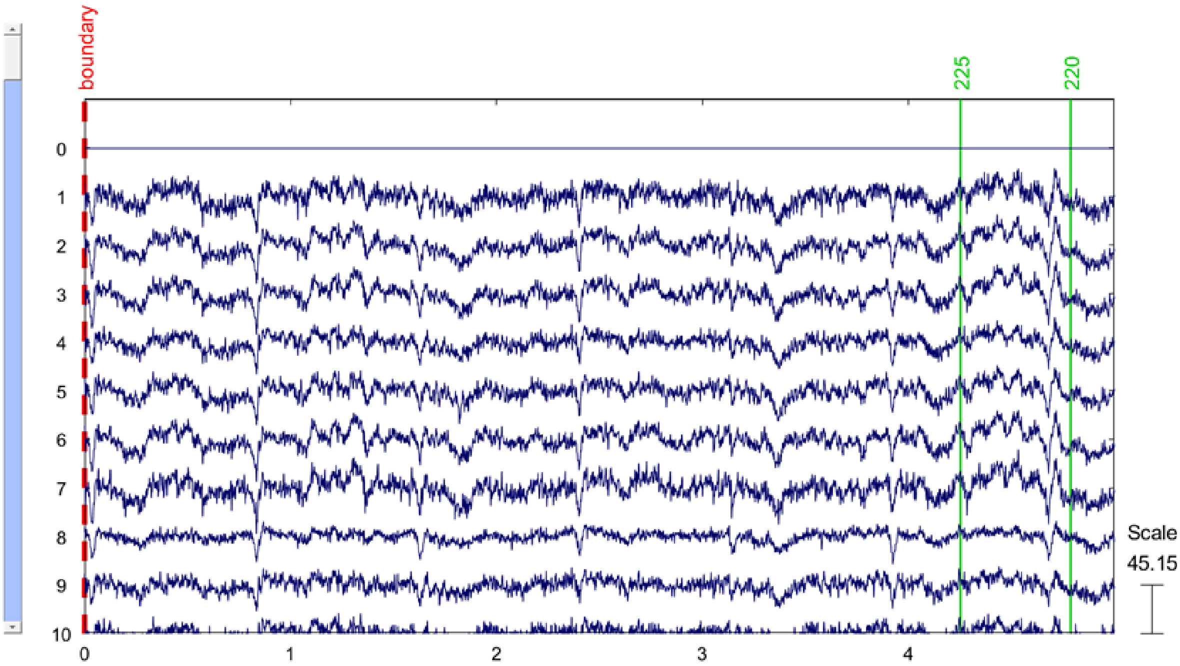


Figure 5: Spectral power of the EEG signals.

As Figure 5 demonstrates, the data contains powerline noise, particularly evident at the 50 Hz peak. We applied two common methods for noise removal and used the more effective one for subsequent data processing.

Re-referencing

We performed re-referencing using the average of all electrodes to mitigate common noise sources, including powerline interference. The results are depicted in Figures 6 and 7.

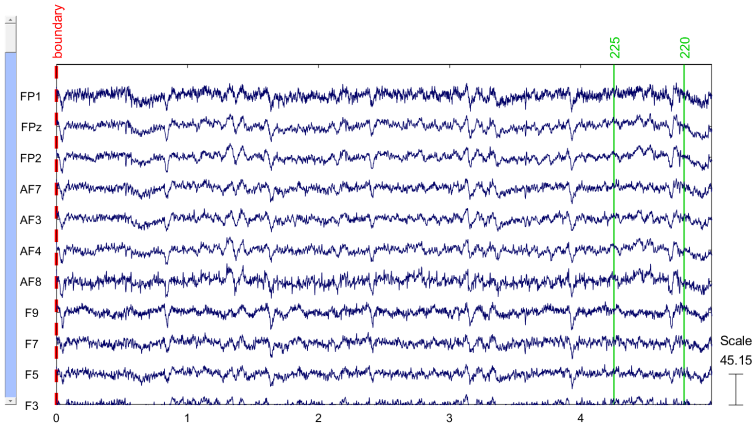


Figure 6: Signals for the first 10 electrodes after re-referencing.

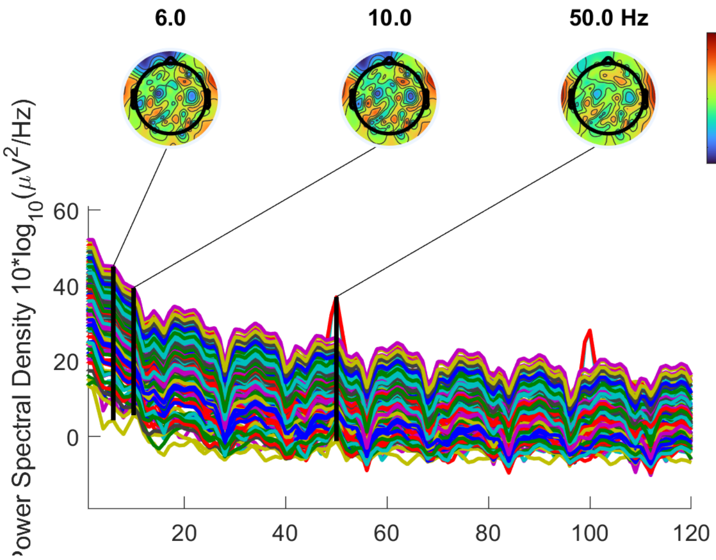


Figure 7: Spectral power of different channels shows improved signal quality, but power line noise is still evident. The red channels, with the most severe power line noise, are channels 64 and 63.

As noted in Figure 7, two channels (64 and 63) show significant power at 50 Hz. These channels correspond to A1 and A2, located on either side of the head in a vertical alignment.

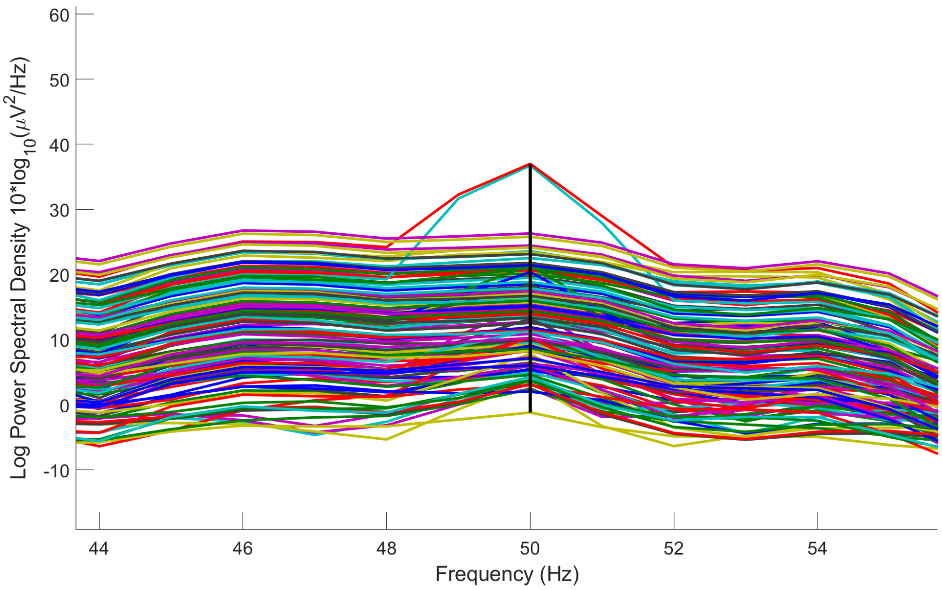


Figure 8: Spectral power of different channels around 50 Hz. As noted in Figure 6, channels 64 and 63 show significant power at 50 Hz. These channels correspond to A1 and A2, located on either side of the head in a vertical alignment.

Notch Filtering

Since re-referencing did not completely eliminate the power line noise, we apply a notch filter specifically targeting 50 Hz.

This approach might attenuate some data at 50 Hz, but it effectively eliminates the severe power line noise. The frequency response of the notch filter is shown in Figure 9.

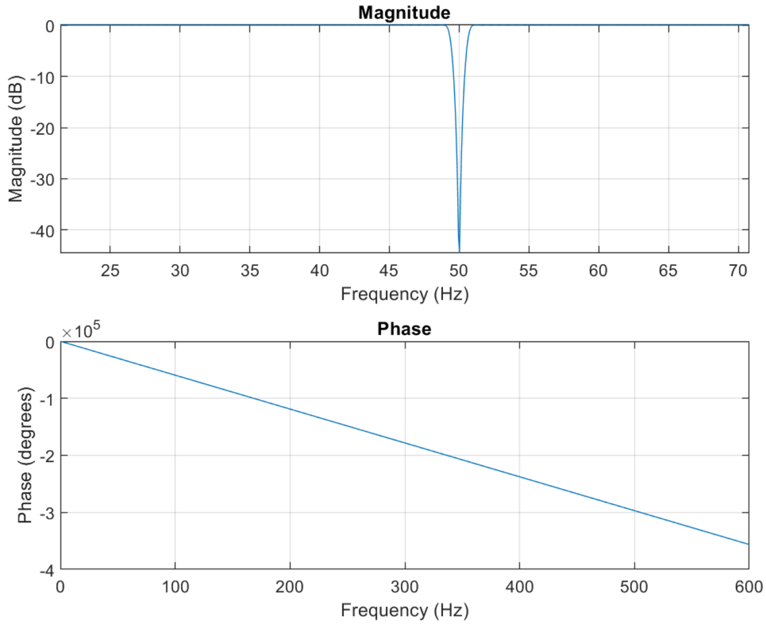


Figure 9: Frequency response of the notch filter applied to remove power line noise.

The filtered signal's spectral power is depicted in Figure 10, demonstrating the complete removal of powerline noise.

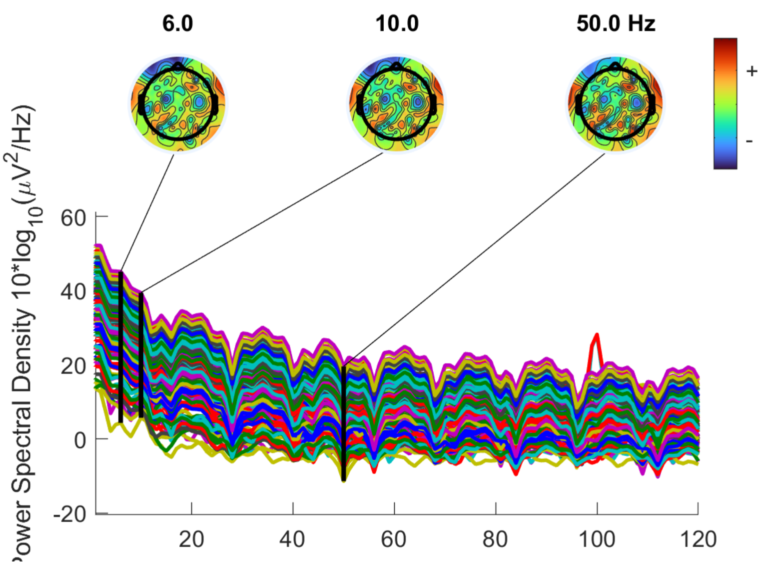


Figure 10: Spectral power of the filtered signal after applying the notch filter, showing the complete removal of powerline noise.

Bandpass Filtering

To remove any remaining noise, we apply a bandpass filter with a passband of 0.5 Hz to 110 Hz. The frequency response of this filter is shown in Figure 11.

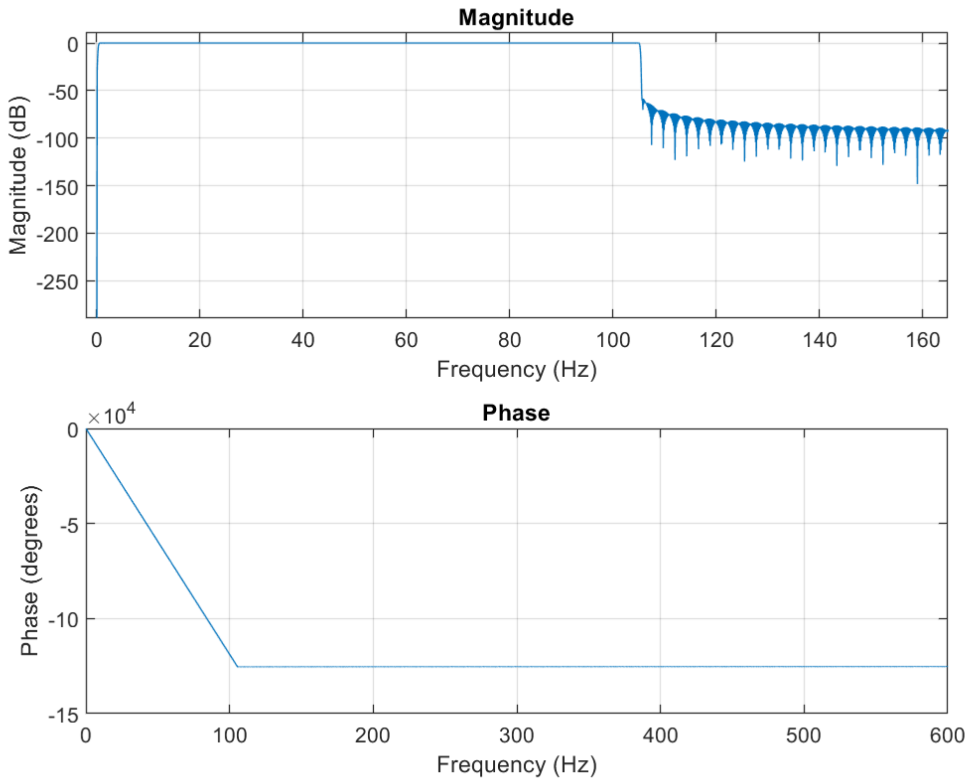


Figure 11: Frequency response of the bandpass filter for removing noise outside the 0.5-110 Hz range.

Applying this filter does not affect the brain signals because neural activity typically occurs within the 2-100 Hz frequency range.

Epoch Extraction and Baseline Removal

To extract epochs, we segment the data based on trigger 222, using a time window from -100 to 700 ms.

Baseline removal is then performed to eliminate offsets and drifts, normalizing the data around zero.

Bad Channel Removal

In the process of EEG data preprocessing, it is crucial to ensure the quality of the recorded signals.

During visual inspection of the data, channels A1 and A2 were identified to have significant noise artifacts.

These channels are positioned near the ears, which could be a plausible reason for the observed noise, likely stemming from muscular activity or other external interferences.

The spectral power analysis, depicted in Figure 12, clearly indicates abnormally high power at 50 Hz and its harmonics, specifically at 100 Hz.

These peaks are symptomatic of power line interference, which severely compromises the integrity of the recorded EEG signals.

Additionally, the time-domain signals of channels A1 and A2, shown in Figure 13, exhibit large amplitude fluctuations, further affirming the presence of significant noise.

Given these observations, it is advisable to exclude channels A1 and A2 from further analysis.

This step is essential to prevent the propagation of noise into subsequent stages of data processing, which could distort the outcomes and lead to erroneous interpretations.

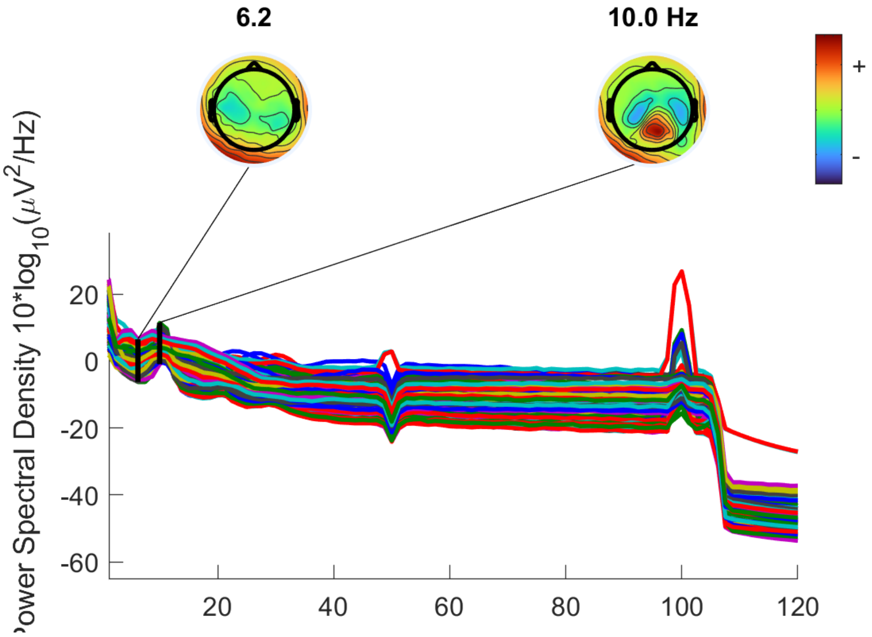


Figure 12: Spectral power of channels after preprocessing, indicating persistent noise in channels A1 and A2. These channels show prominent peaks at 50 Hz and 100 Hz, typical of power line interference.

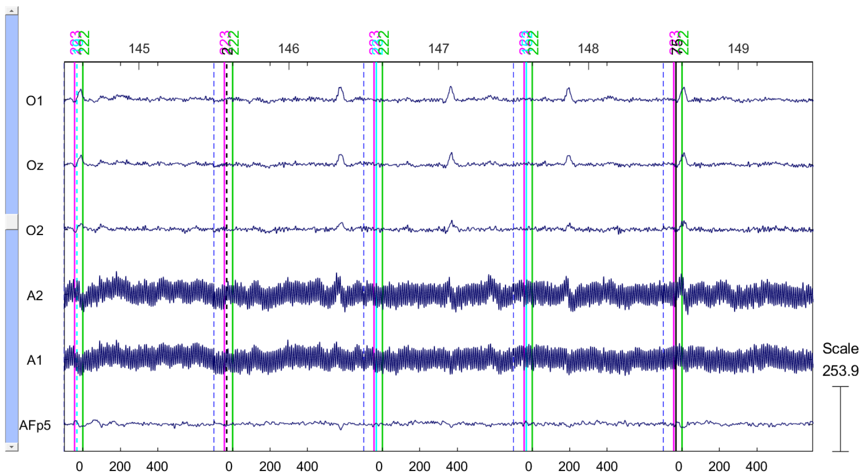


Figure 13: Time-domain signal of channels A1 and A2, displaying large amplitude fluctuations indicative of severe noise contamination.

After removing these two channels, it is imperative to re-reference the data to maintain the integrity of the spatial information captured by the EEG.

Re-referencing helps in redistributing the voltage potentials across the remaining channels, thereby reducing the impact of the removed noisy channels.

Manual Trial Rejection

Subsequent to the removal of bad channels, the next critical step involves the identification and exclusion of noisy trials.

These noisy trials often result from participant movements or electrode displacements, which introduce substantial artifacts into the EEG recordings.

Visual inspection of the data is conducted to identify such trials.

Trials exhibiting significant deviations from the expected EEG patterns, characterized by abrupt, high-amplitude artifacts, are marked for removal.

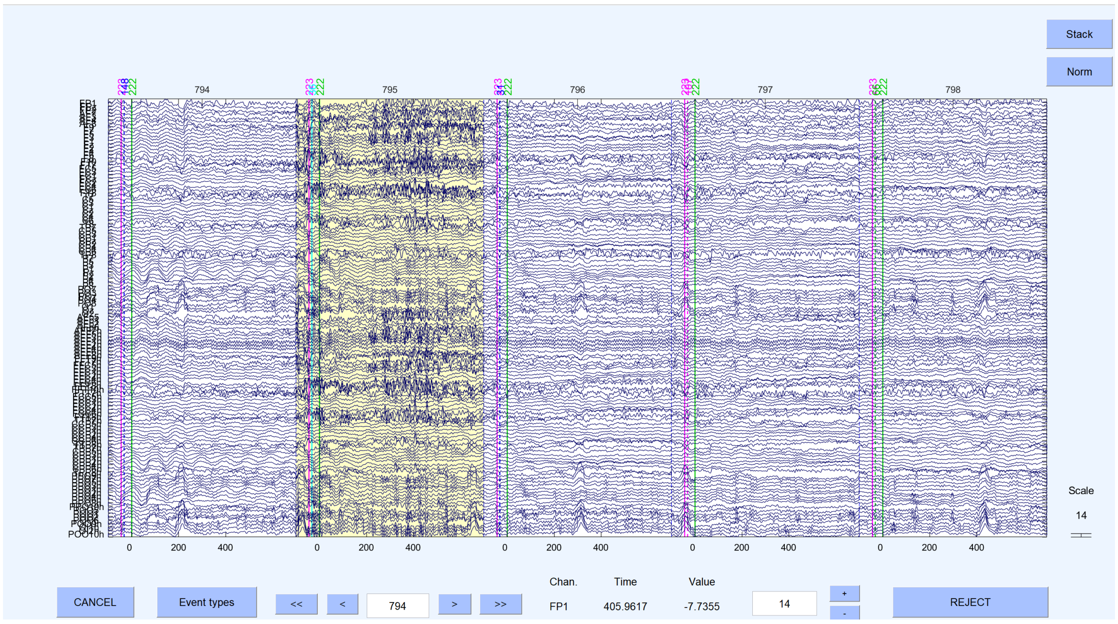
In this study, a total of 34 trials were identified and excluded based on these criteria.

The process ensures that only clean and reliable data is subjected to further analysis, thereby enhancing the robustness and validity of the results.

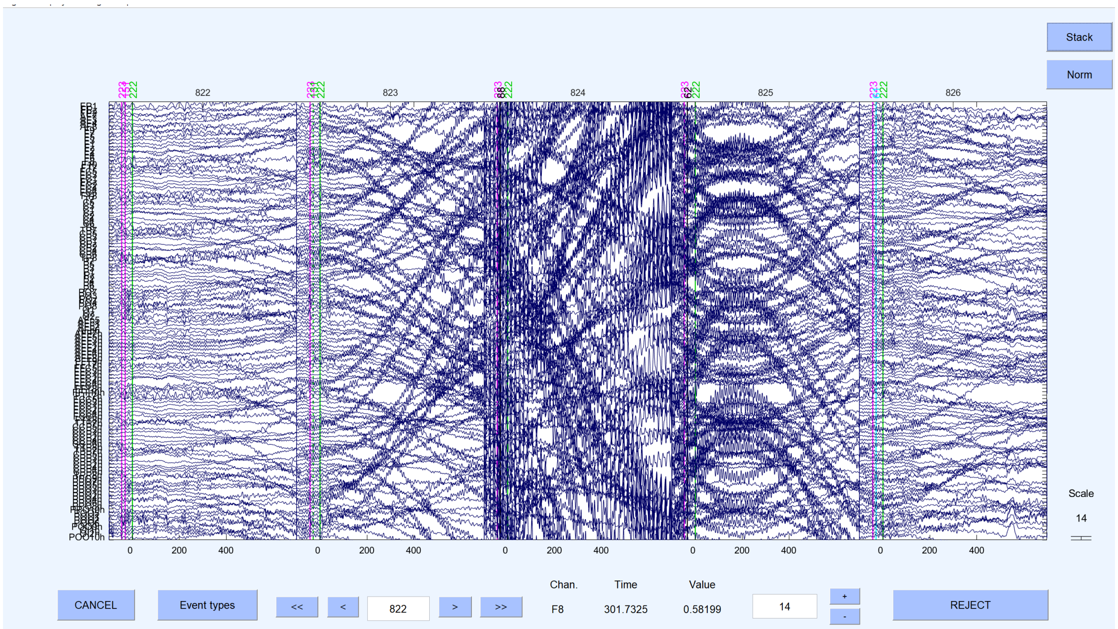
Figures 14a and 14b illustrate several examples of the identified noisy trials.These examples highlight the extent of the artifacts, which render the affected trials unsuitable for accurate analysis.

Following the removal of these noisy trials,14the dataset is rendered cleaner and more suitable for subsequent processing steps, including Independent Component Analysis (ICA).

ICA will further help in isolating and removing remaining artifacts, thus ensuring high-quality EEG data for final analysis.



(a)



(b)

Figure 14: Several noisy trials due to participant movement or electrode displacement. These artifacts introduce significant noise, making the trials unreliable for accurate analysis.

Further Steps and Considerations

It is important to note that visual inspection and manual removal of noisy channels and trials are foundational steps in EEG data preprocessing.

These steps significantly reduce the noise level in the data, thereby enhancing the reliability of the results obtained from subsequent analyses.

However, they should be complemented with automated methods for a more comprehensive cleaning process.

Additionally, maintaining a detailed log of the removed channels and trials is crucial.

This log provides transparency and reproducibility in the data processing pipeline, allowing for better understanding and validation of the findings.

The systematic removal of bad channels and noisy trials is an essential practice in EEG data preprocessing.

It ensures the integrity and quality of the data, facilitating more accurate and meaningful interpretations in neurophysiological research.

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a computational technique used to separate a multivariate signal into additive, independent components. In the context of EEG data analysis, ICA is applied to decompose the EEG signal into spatially independent components, which can then be analyzed to identify and remove artifacts or non-brain-related sources of signal.

Application of ICA

We performed ICA on the EEG data to isolate and analyze individual components. Each component represents a spatial pattern of activity across the electrodes. The ICLabel plugin was employed to categorize these components based on their characteristics, such as whether they correspond to brain activity or various types of artifacts.

Component Labeling and Artifact Removal

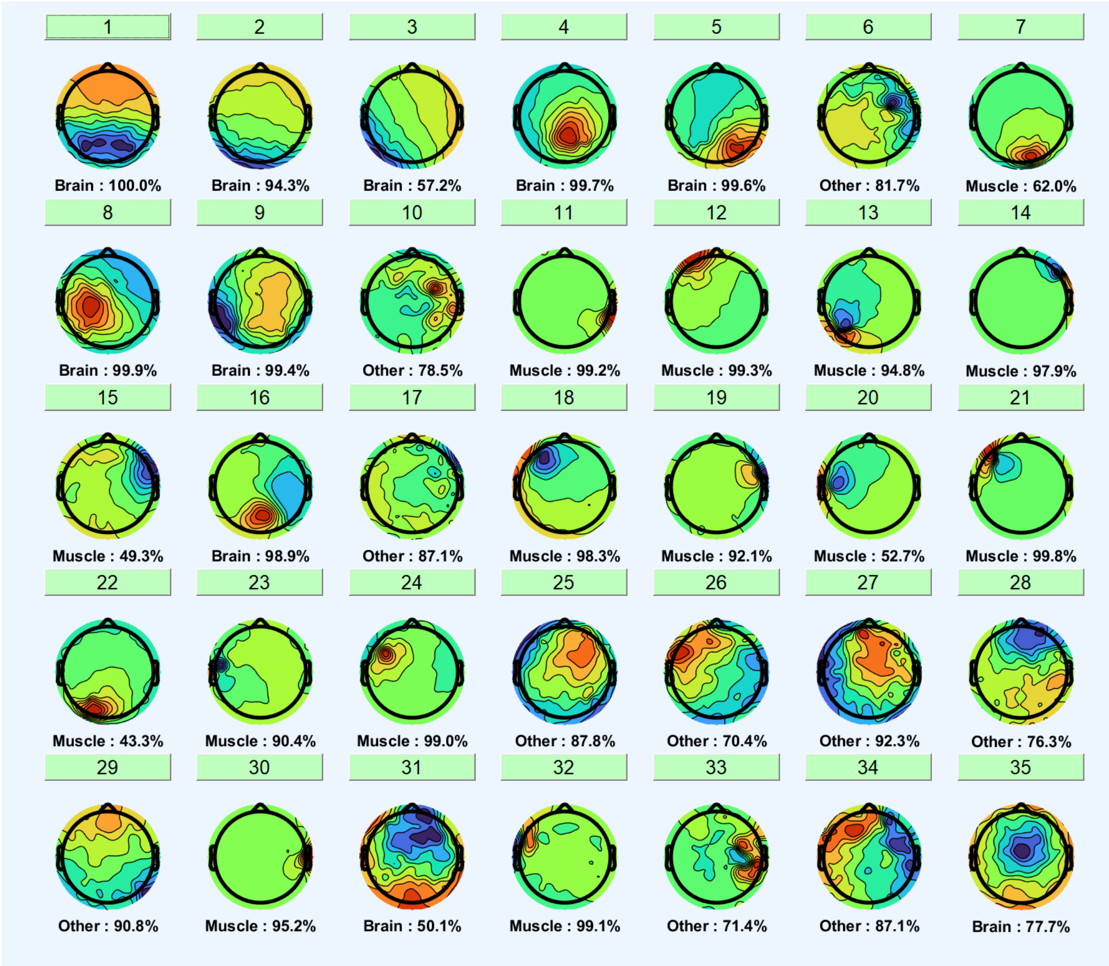
The components identified by ICLabel were reviewed and classified. Components with a probability higher than 0.9 of being noise or other artifacts were removed from the analysis. This step is crucial for ensuring that only relevant brain activity is included in subsequent analyses. The following list enumerates the components that were identified as artifacts and removed:

- Components identified as noise or artifacts:
  `11, 12, 13, 14, 18, 19, 21, 23, 24, 30, 32, 39, 42, 44, 46, 47, 50, 53, 57, 61, 62, 63, 65, 66, 68, 72, 98, 99, 100, 101, 112, 113, 114, 115, 116, 122, 123`

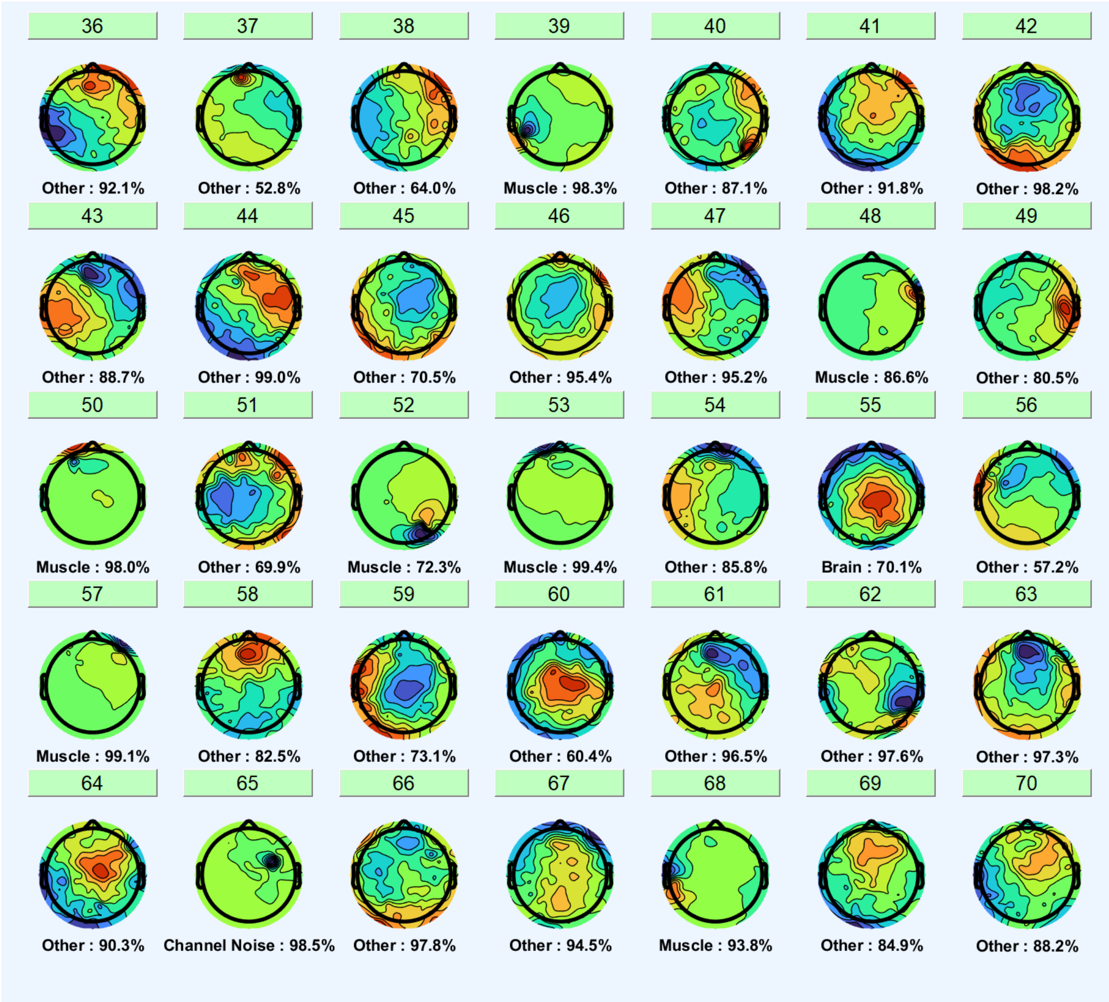
In total, 37 components were removed from the dataset.

Visual Representation

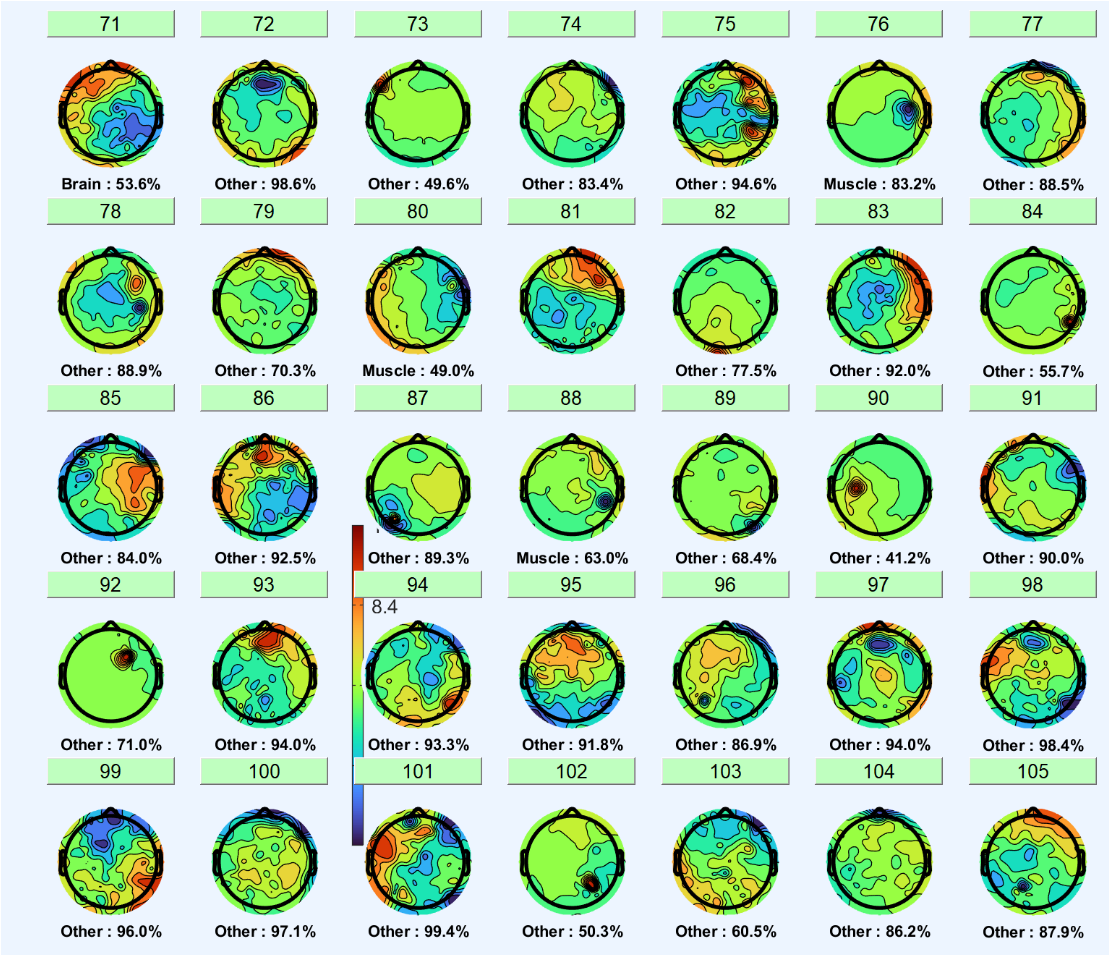
The figures below present all the ICA components along with their respective labels, illustrating both the components retained for further analysis and those that were excluded. The visualization aids in understanding the spatial distribution and characteristics of the components, providing clarity on the decision-making process for artifact removal.



(a) ICA Component Visualization 1



(b) ICA Component Visualization 2



(c) ICA Component Visualization 3

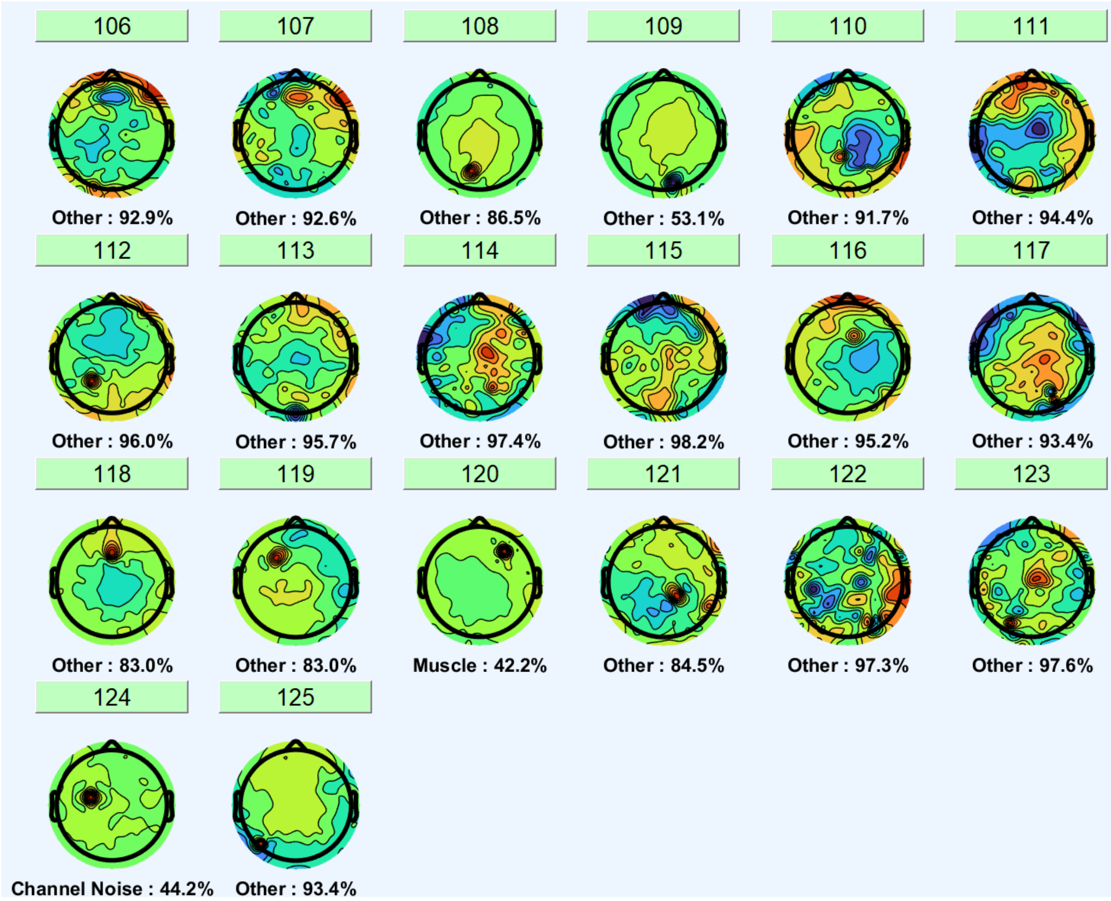


Figure 15: (d) All 125 components labeled by the ICLabel plugin. Components to be removed are also visible.

The preprocessing steps described have significantly improved the quality of the EEG data by removing various types of noise and artifacts. The data is now ready for subsequent analysis, ensuring more accurate and reliable results.

A: Data Processing and Analysis

A-1: Effects of Filters

High-Pass Filter Effects and Reasons

High-pass filters are critical in EEG data preprocessing, primarily serving to remove low-frequency drifts and slow trends that can obscure the neural signals of interest. These drifts and trends can originate from various sources:

- **Physiological Artifacts:** Slow movements, sweating, and gradual changes in temperature can alter the electrode-skin impedance, introducing low-frequency noise into the data.
- **Environmental Changes:** Variations in the environment, such as temperature fluctuations, can also affect the impedance and contribute to slow drifts in the signal.

By applying a high-pass filter with a cut-off frequency of 0.5 Hz, we can effectively attenuate these low-frequency components. The filter works by allowing frequencies above the cut-off point to pass through while attenuating those below it. This process results in a cleaner EEG signal, making it less susceptible to low-frequency noise and more reliable for analysis.
The primary benefits of using a high-pass filter in EEG preprocessing include:

- **Removal of Drifts:** Eliminates slow drifts and trends caused by physiological and environmental factors.
- **Enhanced Signal Clarity:** Increases the signal-to-noise ratio by reducing low-frequency noise.
- **Preservation of Neural Oscillations:** Properly designed high-pass filters ensure that high-frequency neural oscillations remain intact, retaining the critical features necessary for precise analysis.

Notch Filter Effects and Reasons

Notch filters, also known as band-stop filters, are designed to remove a narrow band of frequencies, typically around 50 Hz or 60 Hz. This frequency range corresponds to the electrical interference from power lines and equipment, known as line noise.

The effects and rationale for using a notch filter in EEG preprocessing are as follows:

- **Targeted Noise Removal:** The primary function of a notch filter is to attenuate the power line frequency, thereby eliminating the line noise from the EEG data. This leads to a cleaner signal, free from the periodic artifacts introduced by electrical interference.
- **Minimal Impact on Adjacent Frequencies:** A well-designed notch filter has minimal impact on frequencies outside the targeted range. This ensures that the overall structure of the EEG signal is preserved while removing the unwanted noise.
- **Preservation of Signal Integrity:** Despite its effectiveness, it is important to acknowledge that a notch filter will inevitably affect any neural activity occurring at the targeted frequency. For instance, neural oscillations at 50 Hz or 60 Hz will also be attenuated, potentially impacting the analysis of these frequencies.

To mitigate the potential drawbacks of notch filtering, careful design and implementation are crucial. This includes selecting the appropriate bandwidth and ensuring that the filter's effects on adjacent frequencies are minimized. Advanced techniques, such as adaptive notch filtering, can dynamically adjust to changing noise conditions, providing a more robust solution.

Combining notch filtering with other preprocessing steps, such as Independent Component Analysis (ICA), can further enhance the cleaning process. ICA helps in isolating and removing specific noise sources, thereby complementing the notch filter's role in eliminating line noise.

Both high-pass and notch filters are indispensable in the preprocessing of EEG data, each serving a distinct purpose:

- **High-Pass Filters:** Essential for removing low-frequency drifts and trends, enhancing the clarity and reliability of the EEG signals.
- **Notch Filters:** Crucial for targeting and removing specific narrow frequency bands associated with line noise, ensuring a cleaner and more accurate EEG recording.

While both filters have their limitations, careful design and implementation can minimize their impact on the neural signals. This meticulous approach to preprocessing is vital for obtaining accurate and reliable EEG data, which forms the foundation for meaningful neurophysiological research.

A-2: Noise Removal Logic

Noise removal is a critical step in EEG preprocessing, essential for isolating neural signals from various interferences. Two fundamental techniques for noise removal are re-referencing and baseline normalization. Here, we provide a detailed explanation of the logic behind these steps.

Re-referencing

Re-referencing involves changing the reference electrode against which all EEG signals are measured. The primary goal is to reduce common noise and improve the quality of the EEG signal. Signals recorded with a single reference may contain noise common to all electrodes, such as power line interference or other environmental noise. Re-referencing helps mitigate this common noise by averaging it out. There are three common methods for re-referencing:

1. **Average Reference:**
   - This method uses the average of all electrode signals as the new reference.
   - Assumption: Noise is equally distributed across all electrodes.
   - Benefit: It helps in reducing noise that is common across all electrodes, providing a more stable and uniform reference.
2. **Earlobe Reference:**
   - The average signal from electrodes placed on both earlobes or mastoids is used as the reference.
   - Benefit: This method is useful for reducing noise because earlobes or mastoids are less likely to pick up brain activity and are relatively stable positions.
3. **Single Electrode Reference:**
   - A specific electrode, considered relatively quiet, is used as the reference.
   - Benefit: This approach can be effective if a single electrode is known to be less affected by noise and artifacts.

Baseline Normalization

Baseline normalization involves adjusting the EEG signals to remove slow drifts and other non-neural signals. The objective is to ensure that the signal oscillates around zero without any offset, making it easier to interpret and analyze the data. The steps and logic behind baseline normalization include:

- **Drift Removal:** Slow drifts in the EEG signal can be caused by factors such as changes in electrode impedance, sweating, or gradual shifts in position. By normalizing the baseline, these drifts are effectively removed, ensuring that the signal is centered around zero.
- **Improved Signal Clarity:** Baseline normalization helps in reducing the influence of slow-varying artifacts, making the neural signals more distinct and easier to analyze.
- **Offset Elimination:** Ensures that the signal does not have a constant offset, which can obscure the true neural activity. This is achieved by adjusting the signal so that its mean value over a baseline period (usually a pre-stimulus interval) is zero.

Detailed Steps in Re-referencing and Baseline Normalization

- **Re-referencing:**
  - Collect raw EEG data with the initial reference electrode.
  - Choose the re-referencing method based on the study requirements and noise characteristics.
  - Apply the chosen re-referencing technique (average reference, earlobe reference, or single electrode reference).
  - Verify the quality of the re-referenced signals to ensure that common noise has been reduced.
- **Baseline Normalization:**
  - Identify a baseline period, typically a pre-stimulus interval.
  - Calculate the mean value of the EEG signal during this baseline period for each channel.
  - Subtract the baseline mean from the entire signal for each channel to center it around zero.
  - Check the normalized signals to ensure that drifts and offsets have been effectively removed.

The steps of re-referencing and baseline normalization are essential in EEG preprocessing for noise removal. Re-referencing helps in reducing common noise by averaging out the noise components across electrodes, while baseline normalization ensures that the signal is centered around zero, removing slow drifts and offsets. Together, these techniques enhance the clarity and reliability of the EEG signals, providing a cleaner dataset for subsequent analysis.

By carefully implementing these preprocessing steps, researchers can significantly improve the quality of their EEG data, leading to more accurate and meaningful neurophysiological insights.

A-3: ICA Component Removal

Independent Component Analysis (ICA) is a powerful technique used in EEG data preprocessing to separate mixed signals into their underlying independent components. This technique is particularly useful for identifying and removing artifacts such as eye blinks, muscle movements, and line noise. The rationale behind removing components using ICA involves analyzing their characteristics in both the time and frequency domains to identify and remove components that represent artifacts rather than neural signals.

Logic Behind ICA

ICA works by assuming that the observed EEG signals are linear mixtures of statistically independent source signals. The goal is to decompose these observed signals into their independent sources. This can be thought of as a process of identifying the true sources of the recorded signals, where each source is statistically independent from the others. By doing so, ICA allows us to isolate and remove unwanted artifacts, thereby improving the quality of the EEG data.

Identifying Artifacts

Artifacts have distinctive characteristics in both the time and frequency domains, which set them apart from neural signals. For example:

- **Eye Blinks:** Often appear as large, brief deviations in the time domain.
- **Muscle Activity:** May show high-frequency noise in the frequency domain.
- **Line Noise:** Appears as a narrowband frequency component, typically at 50 Hz or 60 Hz, depending on the local power grid.

By plotting the time and frequency domain signals of the components identified by ICA, we can visually inspect and identify those that correspond to artifacts.

Steps in ICA Decomposition and Artifact Removal

1. **Data Collection:** Record EEG signals using multiple electrodes.
2. **ICA Decomposition:** Apply ICA to decompose the recorded signals into independent components.
3. **Component Analysis:** Plot the time-domain and frequency-domain signals of each component.
4. **Artifact Identification:** Identify components that represent artifacts based on their distinctive features.
5. **Component Removal:** Remove the identified artifact components.
6. **Signal Reconstruction:** Reconstruct the EEG signals using the remaining components.

Example for Better Understanding

Consider a scenario where we have EEG signals recorded from multiple electrodes. Applying ICA allows us to separate these signals into independent components. Each component can then be analyzed:

- A component representing eye blinks might show up as large, brief spikes in the time domain plot.
- A component representing muscle activity might exhibit high-frequency oscillations in the frequency domain plot.
- A component representing line noise might show a narrow peak at 50 Hz or 60 Hz in the frequency domain.

By removing these identified artifact components, we can significantly improve the signal quality, enhancing the clarity and reliability of the neural signals for further analysis.

ICA is an essential tool in EEG preprocessing for artifact removal. By analyzing the time and frequency domain characteristics of the components, we can effectively identify and remove unwanted artifacts. This process results in cleaner EEG data, which is crucial for accurate and meaningful neurophysiological research.

B: Event-Related Potential (ERPs)

Event-Related Potentials (ERPs) are a fundamental tool in cognitive neuroscience, used to study the brain's electrical response to specific stimuli or events. The computation of ERPs relies on the principle of averaging EEG data across multiple trials to isolate the consistent signal from transient noise.

Principle of ERP Computation

The core idea behind ERP computation is to differentiate between the stimulus-related signal and the background noise in EEG recordings. Each trial in an EEG experiment contains both a signal, which is consistent across trials, and noise, which fluctuates randomly. By averaging the EEG data from multiple trials, the noise—due to its random distribution around zero—tends to cancel out. This averaging process enhances the signal, revealing the ERP.

The process of ERP creation involves aligning the EEG data to a specific event time, typically denoted as time = 0. This alignment ensures that the data from different trials is synchronized relative to the event of interest. After this alignment, the EEG signals are averaged across all trials at each time point to obtain the ERP waveform.

Historical Context

The use of ERPs dates back to the 1960s when researchers first began to investigate the brain's electrical responses to stimuli. The technique has evolved significantly over the decades, with advancements in technology and analytical methods enhancing its precision and applicability. Early studies established the basic principles of ERP measurement, while subsequent research has expanded the range of components and their associations with various cognitive processes.

ERP Components: P100 and N170

Among the various ERP components, the P100 and N170 are particularly notable for their roles in visual processing.

P100 Component The P100, or P1, is a positive voltage deflection observed approximately 100 milliseconds after the onset of a visual stimulus. It is typically elicited by simple visual stimuli such as a flash of light or a checkerboard pattern. The P100 is associated with early visual processing and is primarily recorded from electrodes over the occipital cortex. This component reflects the brain's initial response to visual input and is crucial for understanding the early stages of visual perception.

N170 Component The N170 is a negative voltage deflection occurring around 170 milliseconds after the onset of a visual stimulus. It is often observed in response to more complex visual stimuli, including faces and objects. The N170 is recorded from electrodes over the temporal cortex and is linked to the processing of facial and object recognition. This component is particularly valuable in research on visual cognition and social perception, as it provides insights into how the brain processes and recognizes complex visual patterns.

Significance and Applications

Both P100 and N170 are considered reliable markers of visual processing in EEG studies. Their robust nature makes them valuable in research on visual perception, attention, and cognitive processing. Understanding these components allows researchers to investigate how the brain responds to visual stimuli and how different cognitive processes are reflected in EEG data.

The study of ERPs has broad implications, including applications in clinical settings, such as diagnosing and monitoring neurological disorders, and in cognitive research, where it contributes to our understanding of sensory and cognitive functions.

B-1: ERPs for All Channels

In this section, we calculate the ERP for each electrode individually. The trials are categorized based on the type of stimulus: face, non-face, or inverse-face. The following figures show the ERPs for these three categories.

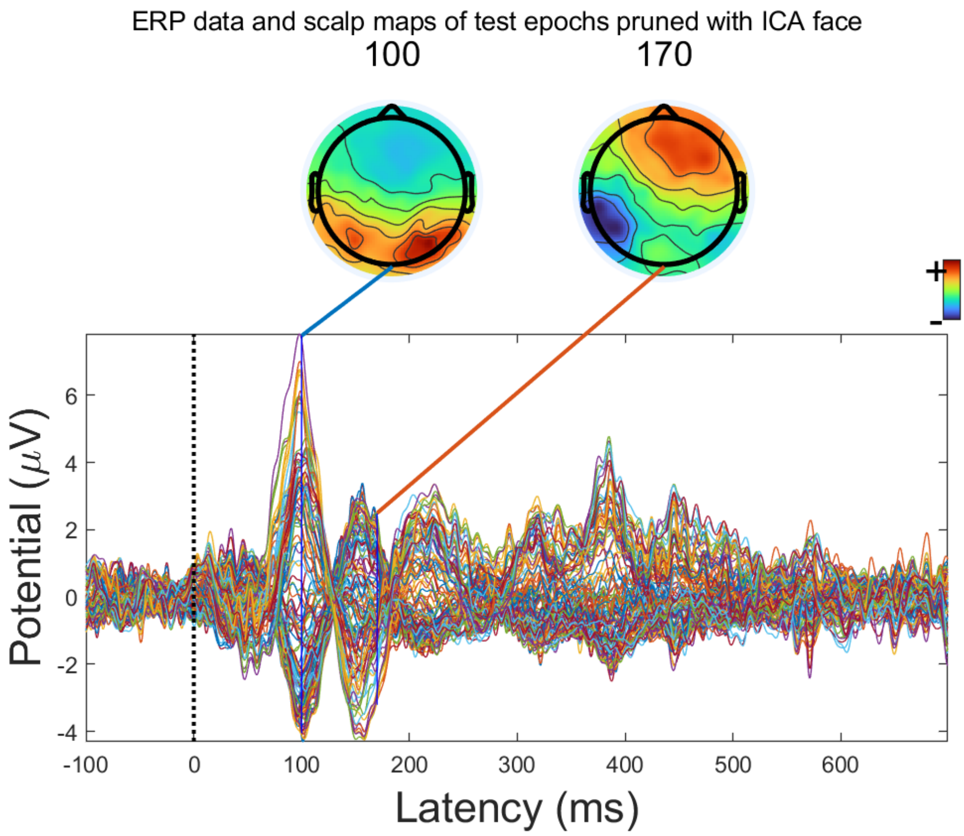


Figure 16: ERP plot for face stimulus and topoplots for N170 and P100 across various channels. The topoplots indicate a reduction in activity in the occipital and temporal regions for N170 and an increase for P100.

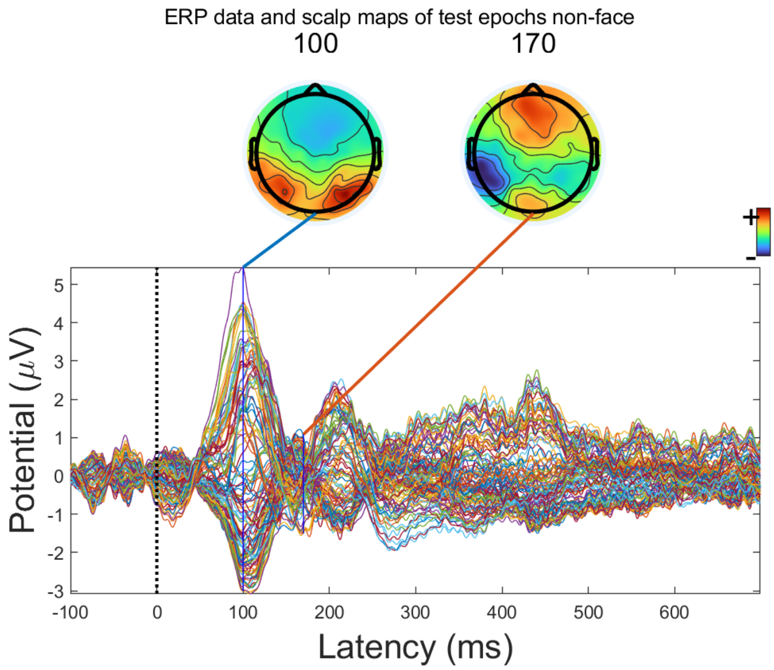


Figure 17: ERP plot for non-face stimulus and topoplots for N170 and P100 across various channels.

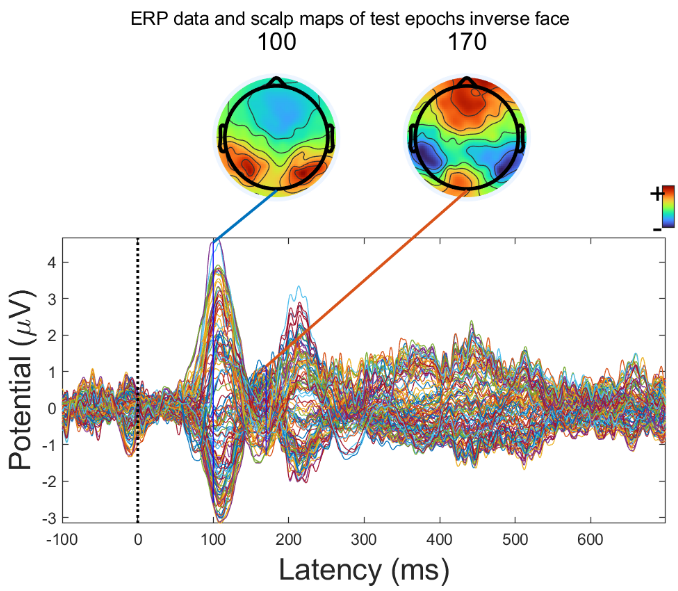


Figure 18: ERP plot for inverse-face stimulus and topoplots for N170 and P100 across various channels.

As shown in the figures above, the P100 component is present in all three stimuli, although it appears slightly delayed for the inverse-face stimulus. Additionally, the N170 component is significantly more negative in response to the face stimulus, reaching -4 µV, while it only reaches -2 µV for the other two stimuli.

It's important to note that the face stimulus differs significantly from the other two. The main difference is a relatively intense activity around 170 ms for the face stimulus, while for the other two stimuli, the signal amplitudes remain below 2 µV up to 200 ms.

For the non-face and inverse-face stimuli, a notable difference is the intense activity around 220 ms for the inverse-face stimulus, which is less pronounced for the non-face stimulus.

B-2: Face vs. Non-Face ERPs

The following figures illustrate the ERP plots for face and non-face stimuli combined for electrodes 118, 119, 120, 121, 122, 123, 124, 125, and 126.

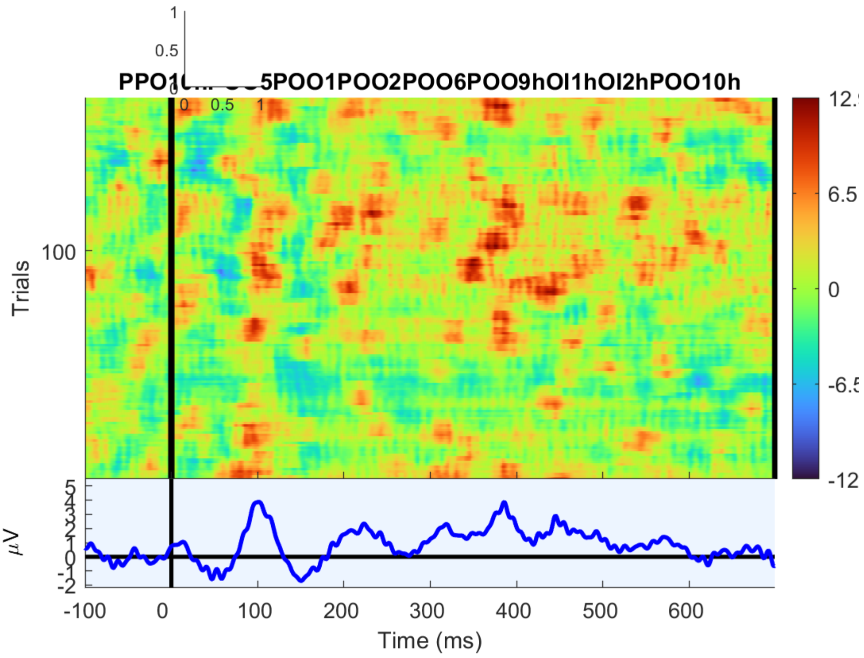


Figure 19: ERP plot for face stimulus across posterior channels including POO10h, OI2h, OI1h, POO9h, POO6, POO2, POO1, POO5, and PPO10h.

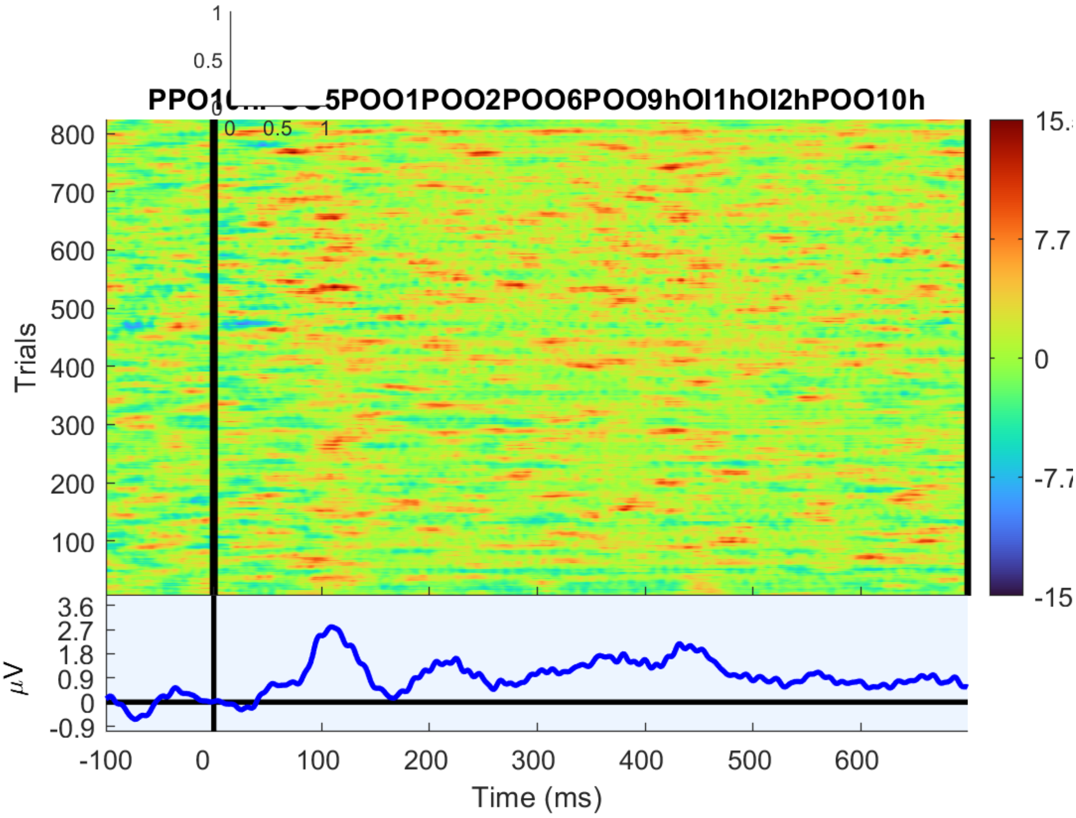


Figure 20: ERP plot for non-face stimulus across posterior channels including POO10h, OI2h, OI1h, POO9h, POO6, POO2, POO1, POO5, and PPO10h.

Comparing the ERPs for face and non-face stimuli reveals significant differences in the timing and amplitude of the N170 component. The N170 is more pronounced and occurs earlier for the face stimulus compared to the non-face stimulus. Additionally, the P100 component is present in both but shows a more consistent and higher amplitude for the face stimulus.

B-3: N170 Component Analysis

To analyze the N170 component in detail, we compare its timing and amplitude between face and non-face stimuli. We plot the signals with confidence intervals and perform a statistical analysis to determine significant differences.

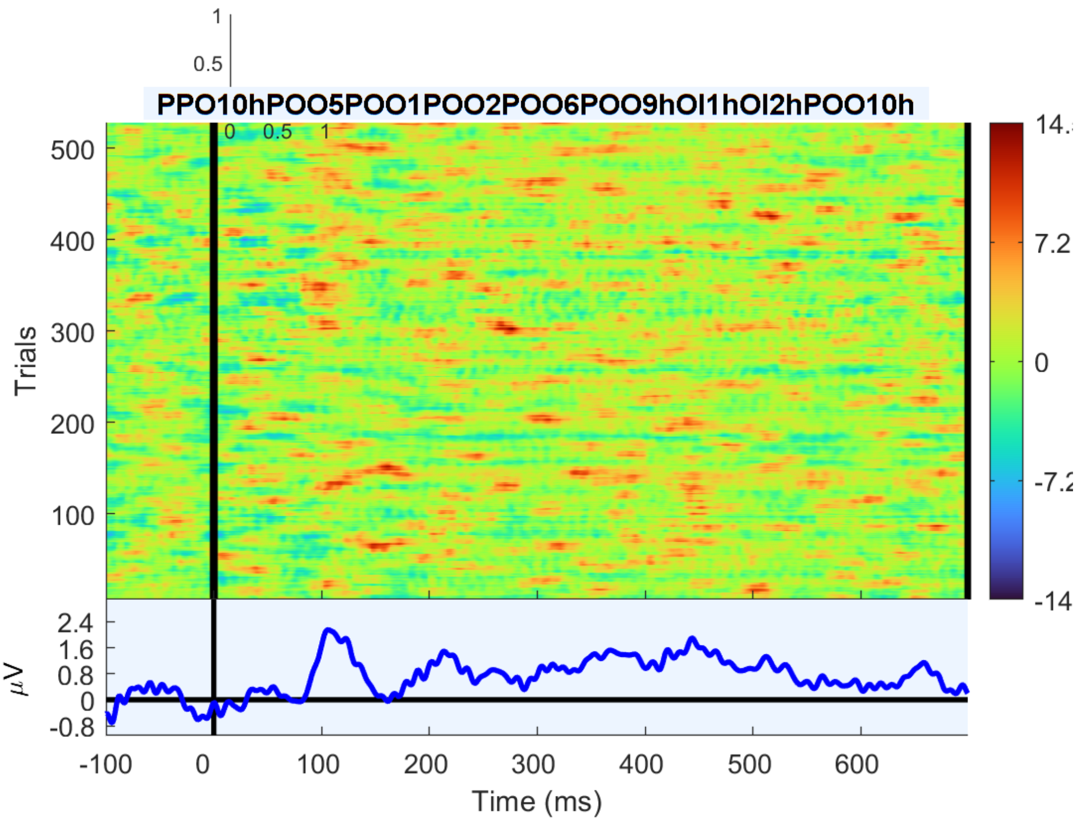


Figure 21: Comparison of the N170 component for face and non-face stimuli with confidence intervals.

Figure 22: ERP plot for inverse-face stimulus across posterior channels including POO10h, OI2h, OI1h, POO9h, POO6, POO2, POO1, POO5, and PPO10h.

Our analysis indicates that the N170 component for the face stimulus is significantly larger in amplitude and occurs earlier than for the non-face stimulus. The searchlight analysis confirms that this effect is most pronounced in the temporal and occipital regions, consistent with the known neural substrates of face processing.

Discussion

The findings from our ERP analysis demonstrate distinct neural responses to face, non-face, and inverse-face stimuli. The P100 component is consistently observed across all stimulus types, with some variability in timing for the inverse-face stimulus. The N170 component shows a significant differentiation between face and non-face stimuli, highlighting its role in face recognition processes.

These results provide valuable insights into the temporal dynamics and spatial localization of visual processing in the brain. The pronounced N170 response to face stimuli underscores its utility as a biomarker for face-specific neural activity, with potential applications in both cognitive neuroscience research and clinical diagnostics.

Our comprehensive ERP analysis reveals critical aspects of visual perception and the brain's differential response to various stimuli, contributing to a deeper understanding of the underlying neural mechanisms.

C: Spectral Analysis

Spectral analysis of EEG signals is a pivotal method for understanding the frequency content of brain activity. It provides insights into the neural oscillations that underpin cognitive and physiological processes. By examining how power is distributed across different frequency bands, researchers can decode the complex electrical activity recorded from the brain and interpret various aspects of neural function.

Fundamentals of Spectral Analysis

Spectral analysis involves breaking down the EEG signal into its frequency components to investigate the power distribution across these frequencies. This technique reveals valuable information about brain oscillations, including their frequency, power, and phase characteristics. By analyzing these components, researchers can study how different frequency bands are associated with cognitive states and brain functions.

The primary objective of spectral analysis is to quantify the power spectral density (PSD) of the EEG signal. PSD represents how power is distributed across different frequencies and helps in identifying specific oscillatory patterns linked to various cognitive and neural processes. Several methods are employed to estimate the PSD:

- **Periodogram:** A straightforward method involving the squared magnitude of the Fourier transform of the signal. Although simple, it can be affected by high variance and spectral leakage.
- **Welch's Method:** This approach mitigates variance and spectral leakage by dividing the signal into overlapping segments, computing periodograms for each, and averaging the results.
- **Multitaper Method:** Utilizes multiple tapers to obtain several estimates of the PSD, which are averaged to improve frequency resolution and reduce spectral leakage.
- **Wavelet Transform:** Offers time-frequency analysis and adaptive PSD estimation at different scales or frequencies, which is beneficial for analyzing transient or non-stationary phenomena.

Frequency Bands in EEG Signals

EEG signals exhibit oscillatory activity in distinct frequency bands, each associated with different cognitive and physiological processes:

- **Delta (0.5 - 4 Hz):** Linked to deep sleep and restorative processes.
- **Theta (4 - 8 Hz):** Associated with memory, learning, and drowsiness.
- **Alpha (8 - 13 Hz):** Reflects relaxed wakefulness and meditation.
- **Beta (13 - 30 Hz):** Related to active thinking, concentration, and motor control.
- **Gamma (30 - 100 Hz or higher):** Connected to higher cognitive functions, sensory processing, and perception.

Power Changes and Oscillatory Activity

Spectral analysis enables the identification and quantification of power changes within specific frequency bands. These changes, referred to as event-related desynchronization (ERD) or event-related synchronization (ERS), indicate neural activation or suppression in response to stimuli or cognitive tasks. Oscillatory activity, characterized by rhythmic power fluctuations, provides insights into the temporal dynamics of neural processes.

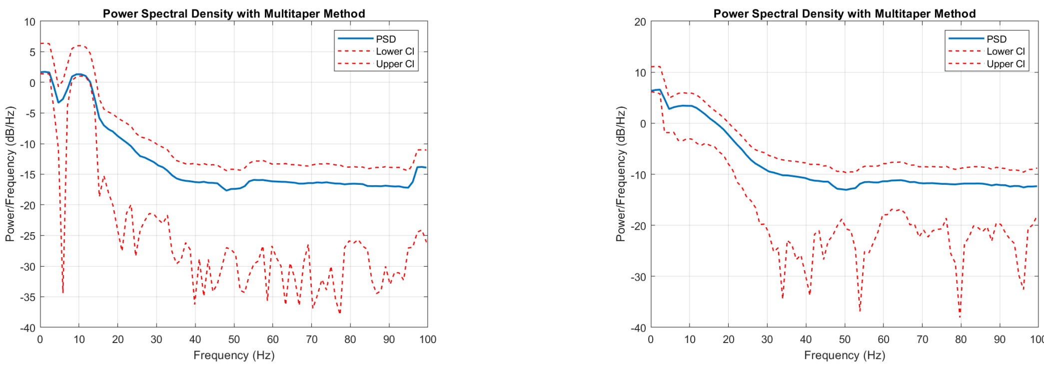
Historical Context

The application of spectral analysis to EEG signals has evolved significantly over the past few decades. Early research laid the foundation for understanding brain oscillations, with initial studies focusing on basic spectral properties. Advances in signal processing techniques and computational methods have since enhanced the precision of spectral analysis, allowing for more detailed investigation of brain activity. Spectral analysis has become a cornerstone of cognitive neuroscience, neurophysiology, and clinical diagnostics, providing crucial insights into the frequency-based activity of the brain and its relationship to various cognitive and physiological states.

C-1: Multitaper PSD Estimation

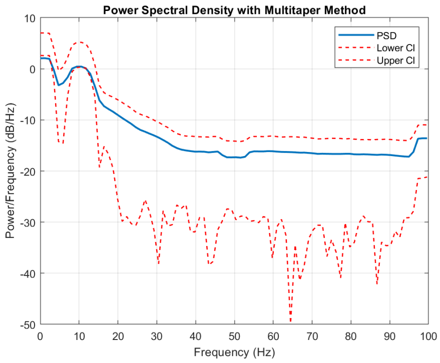
By executing the Matlab code Qc.m, the PSD for each of the three different stimuli was calculated using the multitaper method. The resulting plots with confidence intervals are shown below.

These plots were generated for specific channels.

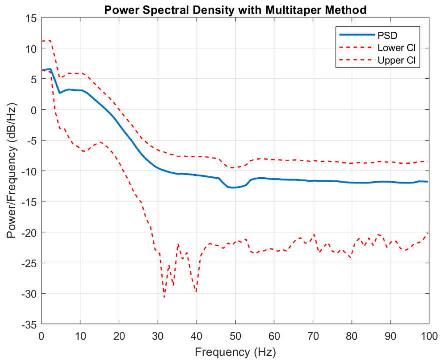


(a) (b)

Figure 23: Figure 3-1: PSD plot with Confidence Interval for face stimulus. The right figure shows the occipital electrodes, and the left figure shows the prefrontal electrodes.

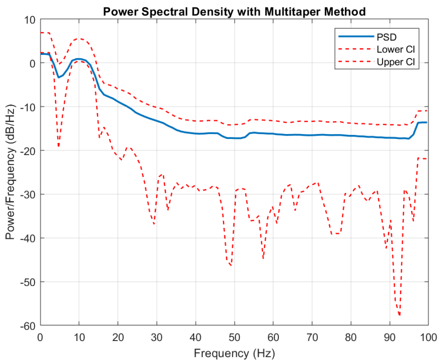


(a)

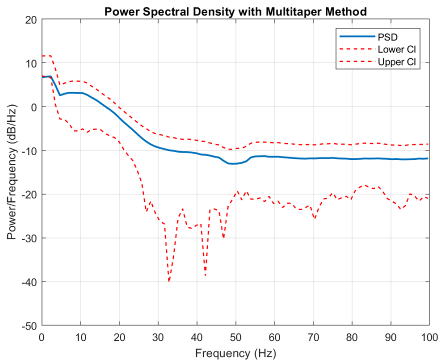


(b)

Figure 24: Figure 3-2: PSD plot with Confidence Interval for non-face stimulus. The right figure shows the occipital electrodes, and the left figure shows the prefrontal electrodes.



(a)



(b)

Figure 25: Figure 3-3: PSD plot with Confidence Interval for inverse-face stimulus. The right figure shows the occipital electrodes, and the left figure shows the prefrontal electrodes.

As illustrated above, differences in the PSD for face and other stimuli are evident, particularly in theta waves, but no significant difference is observed between the two other stimuli.

C-2: Baseline Normalization and Comparison

For these data, baseline normalization was performed as mentioned in the preprocessing section, which improved and reduced noise and drift. This preprocessing step also resulted in smaller confidence intervals.