Electroencephalogram

When the system theorists join the neuroscience team!

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1. Electroencephalogram

During more than 100 years of its history, encephalography has undergone massive progress. The existence of electrical currents in the brain was discovered in 1875 by an English physician, Richard Caton. Caton observed the EEG from the exposed brains of rabbits and monkeys. In 1924 Hans Berger, a German neurologist, used his ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. He announced that weak electric currents generated in the brain can be recorded without opening the skull, and depicted graphically on a strip of paper. The activity that he observed changed according to the functional status of the brain, such as in sleep, anesthesia, lack of oxygen and in certain neural diseases, such as in epilepsy. Berger laid the foundations for many of the present applications of electroencephalography. He also used the word electroencephalogram as the first for describing brain electric potentials in humans. He was right with his suggestion, that brain activity changes in a consistent and recognizable way when the general status of the subject changes, as from relaxation to alertness [1].

1.1. What is EEG?

EEG (Electroencephalography) is one of the most widely-used noninvasive brain imaging tools in neuroscience and in the clinic. EEG reflects mainly the summation of excitatory and inhibitory postsynaptic potentials at the dendrites of ensembles of neurons with parallel geometric orientation. As neurotransmitters activate

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ion channels on the cell membrane, ions flow into and out of the neuron from and to the extracellular space. This change in potential generates electrical fields that surround the neuron.
The electrical field generated by one neuron is too weak to be measured from an EEG electrode several centimeters away, but as neural activity becomes synchronous across hundreds, thousands, or tens of thousands of neurons, the electrical fields generated by individual neurons sum, and the resulting field becomes powerful enough to be measured from outside the head [3]. Encephalographic measurements employ a recording system that consists of electrodes with conductive media, amplifiers with filters, an A/D converter, and a recording device. Electrodes read the signal from the head surface, amplifiers bring the microvolt signals into the range where they can be digitized accurately, the converter changes signals from analog to digital form, and the personal computer (or other relevant device) stores and displays obtained data.

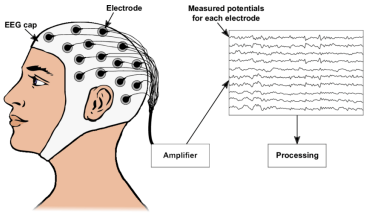

Figure 1: Sketch of how to record an Electroencephalogram. An EEG allows measuring the electrical activity on the scalp using electrodes which are often fixated on an EEG cap. For each electrode, the signals are amplified and can be used in the following for a desired processing [2].

1.2. Why EEG?

EEG has several advantages over other brain imaging techniques such as fMRI or PET, that make it a valuable tool for studying the brain. EEG is a non-invasive technique, which makes it a safer and more practical option for many applications, especially in research studies involving human subjects. Compared to other brain imaging techniques, EEG is relatively low cost, and its equipment is typically smaller and more portable than other brain imaging technologies. EEG measures electrical activity directly from the scalp, providing a direct measure of neural activity. In contrast, fMRI measures changes in blood flow in the brain, which is an indirect measure of neural activity. While EEG has relatively poor spatial resolution compared to other imaging techniques, it can still provide good temporal localization of neural activity. This means that researchers can track the timing of neural events with high precision, even if they cannot pinpoint the exact location in the brain where those events are occurring. EEG has several advantages that make it a valuable tool for studying the brain, particularly when high temporal resolution and non-invasiveness are important [3].

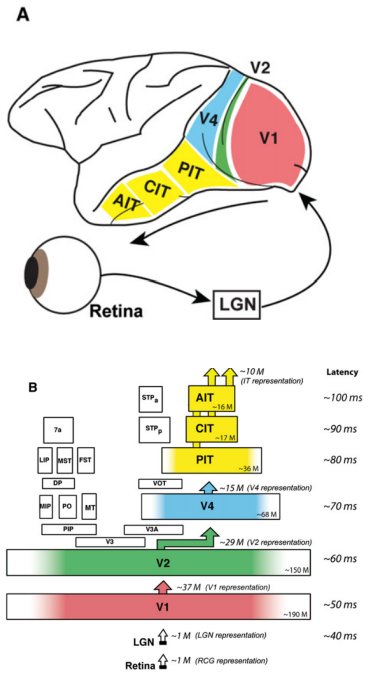

Figure 2: The Ventral Visual Pathway. From V1, the visual processing pathways split into two streams: the ventral stream and the dorsal stream. The ventral stream, which is shown in the figure, also known as the "what" pathway, is involved in object recognition and identification. It continues through a series of visual areas, including V2, V4, and the inferior temporal cortex, where increasingly complex features of objects such as shape, texture, and color are processed. [4].

1.3. High-level vision

Vision is a complex process that includes many interacting components involved. The collection of processes involved in visual perception are often perceived as a hierarchy spanning the range from "low" via "intermediate" to "high-level" vision. The images projected onto the retina are generally complex dynamic patterns of light of varying intensity and color. low-level visual processing is responsible for detection of various types of contrast in these

images, whereas intermediate-level processing is involved in the identification of so-called visual primitives, such as contours and fields of motion, and the representation of surfaces. High-level visual processing integrates information from a variety of sources and is the final stage in the visual pathway leading to conscious visual experience [5].

Visual processing in the brain is organized hierarchically, with different stages processing increasingly complex features of the visual stimulus. At the lowest level of the hierarchy, the retina and the lateral geniculate nucleus (LGN) of the thalamus process basic visual features such as brightness, contrast, and spatial frequency. These low-level visual features are then transmitted to the primary visual cortex (V1), which extracts simple features such as edges and lines. As information flows through the visual hierarchy, increasingly complex features are processed at intermediate and high-levels. In the intermediate stages, visual information is processed in regions such as V2 and V3, where information about motion, depth, and spatial location is processed. At the high-levels, visual information is processed in regions such as V4 and the inferior temporal cortex, where complex features of objects such as shape, texture, and color are processed [4].

2. Task paradigm

The experiment consisted of a rapid serial visual presentation (RSVP) task that included 155 images from 4 different categories: artificial, body, face, and natural images. Each image was repeated 10 times, for a total of 1,550 stimulus presentations. Participants were instructed to maintain fixation on a centered cross for 500 milliseconds, followed by a brief (50 ms) presentation of the stimulus. If participants lost fixation during the visual presentation, the trial was interrupted, and the stimulus was shown again later in the task. In order to ensure that participants maintained fixation throughout the task, eye tracking technology was employed to monitor participants' eye movements during each trial.

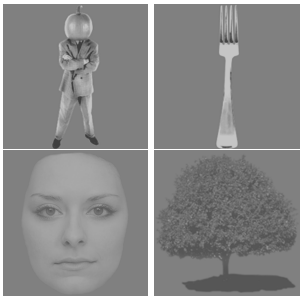

Figure 3: Stimuli types

3. Preprocessing

The preprocessing of EEG data is a crucial step in EEG analysis, as it has a significant impact on the quality of the results. EEG data is often contaminated by various types of noise, including environmental noise, muscle artifacts, and electrode artifacts. Furthermore, differences in data collection and recording across subjects, sessions, and studies can lead to variability in the raw EEG data, making standardization an essential aspect of EEG preprocessing. The preprocessing step involves cleaning, filtering, and transforming raw EEG data into a format that can be analyzed efficiently. The benefits of preprocessing EEG data include reducing noise, standardizing the data, extracting relevant features, and improving interpretability, which ultimately leads to more accurate and reliable results. Preprocessing EEG data can be a tedious and time-consuming process, often requiring a significant amount of expertise and attention to detail. Manual preprocessing of EEG data is often subjective and can be prone to errors, making it challenging to standardize and reproduce across studies. As a result, several open-source toolboxes have been developed to streamline the EEG preprocessing pipeline, automate tedious tasks, and improve the reproducibility of results. Some of the most widely used EEG preprocessing toolboxes include EEGLAB, FieldTrip, MNE, and the PREP pipeline. These toolboxes provide users with a range of preprocessing options, including artifact removal, filtering, event-related potential extraction, and source reconstruction, among others. Furthermore, they offer user-friendly interfaces that facilitate the application of these preprocessing techniques to large-scale EEG datasets. A general preprocessing pipeline for EEG data is as below:

1. Import the raw EEG data: Load the raw EEG data into the EEG analysis software or toolbox of your choice (e.g., EEGLAB,

MNE-Python, or FieldTrip). Also, import events/channel locations file if it is not included in the EEG data.

2. **Downsampling:** Reduce the sample rate of the EEG data to a lower frequency if computational resources or analysis requirements demand it.
3. **Filtering:** Apply appropriate filters to remove unwanted noise and artifacts while preserving the frequency range of interest. Commonly used filters include:
   - High-pass filter: Remove low-frequency drifts and baseline fluctuations (e.g., 0.5 - 1 Hz).
   - Low-pass filter: Eliminate high-frequency noise (e.g., 100 Hz).
   - Notch filter: Remove powerline interference (e.g., 50 Hz in Europe and Iran).

   Note: Ensure the filter settings are suitable for your specific research question and data characteristics.
4. **Re-referencing:** Choose an appropriate reference electrode based on your experimental design and analysis requirements. Common options include:
   - Common average reference (CAR): Calculate the average of all electrode signals and use it as the reference for each channel.
   - Linked mastoids: Use the average of the mastoid electrodes (M1 and M2) as the reference.
   - Bipolar referencing: Compute the difference between neighboring electrodes to create bipolar channels.
5. **Epoching:** Segment the continuous EEG data into shorter epochs or time windows of interest. This can be based on experimental events, stimuli, or specific time intervals. Typical epoch lengths can range from a few hundred milliseconds to several seconds.
6. **Baseline normalization:** A pre-stimulus or pre-task interval, often referred to as the baseline period, is chosen within each epoch. Adjust the baseline of each epoch by subtracting the mean amplitude of a pre-stimulus.
7. **Bad channel interpolation:** Identify electrodes with poor signal quality or significant artifacts. Use interpolation techniques (e.g., spherical spline interpolation) to estimate the missing or bad channels based on neighboring electrodes.
8. **Manual trial rejection:** Visually investigate the possible artifacts (e.g., EOG and EMG) in retrieved trials. By considering the occurred time and channels of these artifacts, remove the trial with excessive noise or artifacts.
9. **Independent Component Analysis (ICA):** Perform ICA decomposition on the EEG data and identify independent components related to non-brain regions. Remove or correct

the artifact-related components from the data.

It's worth noting that the specific steps and parameters in the preprocessing pipeline can vary depending on your research question, experimental design, and the software/toolbox you are using. It's important to adapt the pipeline to your specific needs and consult relevant literature or experts in the field to ensure appropriate preprocessing for your EEG data. For instance, detailed explanations of Makoto's preprocessing pipeline in the EEGLAB toolbox can be found in [6].

Question

Import the data to the EEGLAB toolbox, preprocess data based on the previous section. Set the high-pass and low-pass filter frequency to 0.5 and 100 Hz, respectively. Re-reference the data using a common average reference (CAR). Define epoch ranges from -100 to 1000 ms relative to the stimulus onset.

(a) Describe the effect of the high-pass filter and notch filter on the data. Also, mention the reason why these phenomena happened.
(b) Explain the logic of noise removal steps (referencing and baseline normalization).
(c) Explain the rationale behind removing components in independent component analysis (ICA) by plotting their time and frequency domain signals.

4. Event-Related Potential

The logic underlying the computation of an ERP is straightforward: each trial contains signal and noise; the signal is similar on each trial, whereas the noise fluctuates across trials. Because the noise fluctuations are randomly distributed around zero, noise cancels out when many trials are averaged, thus leaving the signal (the ERP). To create an ERP, simply align the time domain EEG to the time = 0 event (this was probably already done during preprocessing) and average across trials at each time point.

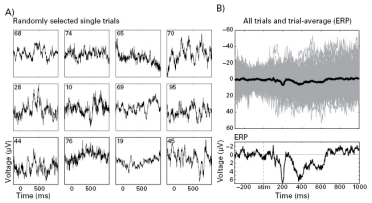

Figure 4: A: a few randomly selected trials from one electrode. B: all trials from this electrode and the average of all trials superimposed. The average is considerably smaller in magnitude than the individual trials. This is because all non-phase-locked activity, which tends to have larger amplitude, is subtracted out during averaging.

4.1. ERP component

P100 and N170 are two commonly used components in event-related potential (ERP) studies of EEG data. P100 refers to a positive voltage deflection that occurs 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, and is thought to reflect early visual processing in the occipital cortex. N170, on the other hand, is a negative voltage deflection that occurs approximately 170 milliseconds after the onset of a visual stimulus. It is typically elicited by more complex visual stimuli, such as faces and objects, and is thought to reflect the processing of facial and object recognition in the temporal cortex. Both P100 and N170 are considered to be reliable and robust markers of visual processing in EEG studies, and are widely used in research on visual perception, attention, and cognition [3].

Question

1. Provide Event-Related Potentials (ERPs) for all channels.
2. Compare ERPs of the face vs. nonface stimulus. Ensure that your plots include confidence intervals.
3. Compare the timing and amplitude of the N170 component between face and non-face stimuli. Plot the signals with confidence intervals alongside the searchlight. Determine if there is a statistically significant difference between the two sets of results.

5. Spectral Analysis

Spectral analysis in EEG signals refers to the process of examining the frequency content of the electrical activity recorded from the brain. It involves analyzing the power distribution across different frequency bands to understand the underlying neural processes and to extract meaningful information from the EEG data.

The spectral analysis of EEG signals provides valuable insights into brain oscillations and their dynamics. By decomposing the EEG signal into its frequency components, researchers can identify and analyze various frequency bands that are associated with different cognitive and neural processes.

Here are a few key aspects of spectral analysis in EEG signals:

Power spectral density (PSD): The power spectral density represents the distribution of power across different frequencies in the EEG signal. It quantifies the relative contribution or strength of each frequency component to the overall EEG activity. There are several common methods for estimating the power spectral density (PSD) of signals, including EEG signals:

- Periodogram: A simple method that involves taking the squared magnitude of the Fourier transform of the signal. It can suffer from high variance and spectral leakage.
- Welch's Method: Divides the signal into overlapping segments and averages their periodograms to reduce variance and spectral leakage.
- Multitaper Method: Uses multiple overlapping tapers to obtain multiple estimates of the PSD, which are then averaged. It provides improved frequency resolution and reduced spectral leakage.
- Wavelet Transform: Provides time-frequency analysis and adaptive estimation of the PSD at different scales or frequencies. Useful for transient or non-stationary phenomena.

Frequency bands: EEG signals exhibit characteristic frequency bands that are linked to specific cognitive and physiological processes. Commonly studied frequency bands include delta (0.5 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 13 Hz), beta (13 - 30 Hz), and gamma (30 - 100 Hz or higher) bands. Each frequency band is associated with different cognitive functions and may vary depending on the task or brain state being studied.

Power changes and oscillatory activity: Spectral analysis allows researchers to identify and quantify power changes or modulations within specific frequency bands. These changes in power, often referred to as event-related desynchronization (ERD) or event-related synchronization (ERS), reflect the activation or suppression of neural activity in response to stimuli or cognitive tasks. Oscillatory activity refers to the rhythmic patterns of power fluctuations

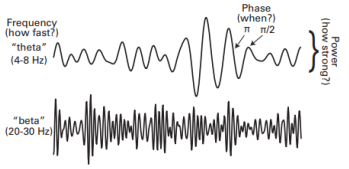

Figure 5: The three dimensions that define oscillations: frequency, power, and phase [3].

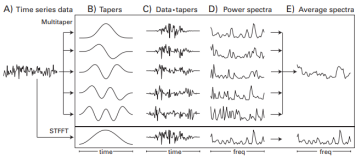

Figure 6: Overview of the multitaper method and comparison with the short-time FFT approach. The y-axes were arbitrary scaled to facilitate visual comparison. Note that the x-axes show time in columns A, B, and C and frequency in columns D and E. The dot between data and tapers in the label of panel C indicates the pointwise multiplication [3].

within specific frequency bands.

Question

1. Use the Multitaper method to estimate the power spectral density (PSD) of EEG signals and visualize them with confidence intervals.
2. Perform baseline normalization prior to applying the Multitaper method and compare your results with those obtained in the previous question.
3. Re-evaluate the power spectral density (PSD) within the frequency bands. Compare the results with previous questions and explain the differences observed.

6. Phase of eeg

Time-frequency analysis is a method used to investigate how the frequency content of a signal changes over time. It provides a way to examine both temporal and spectral characteristics of a signal simultaneously. Time-frequency analysis is particularly useful for analyzing non-stationary signals, where the frequency content varies dynamically over different time intervals.

There are various techniques for time-frequency analysis, including the Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), spectrogram and Hilbert transform. These methods allow researchers to observe how the power or amplitude of different frequency components evolves over time, providing insights into transient events, oscillatory patterns, and their temporal dynamics.

Functional connectivity refers to the statistical dependencies or correlations between the neural activity of distinct brain regions. It provides insights into how different brain regions interact and work together as functional networks. Functional connectivity analysis aims to identify and quantify the patterns of communication and information flow between brain regions during specific tasks or states.

On the other hand, synchrony in EEG data refers to the temporal coordination or synchronization of neural activity between different electrode sites or brain regions. It indicates the degree to which the oscillatory patterns or phases of EEG signals from different locations coincide or align with each other. Synchrony analysis focuses on identifying and characterizing the coordinated activity between brain regions, which can reveal functional relationships and interactions within the brain.

Various measures and techniques are used to assess functional connectivity and synchrony in EEG data. These include coherence, phase-locking value (PLV), imaginary coherence, mutual information, and Granger causality, among others. These measures quantify the degree of statistical dependence, synchronization, or information flow between EEG signals from different electrode sites and communication pathways in the brain.

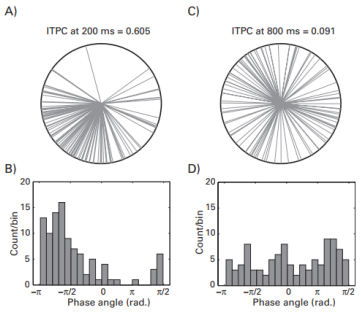

Figure 7: Phase-angle distributions at two time-frequency points. Each line in panels A and C corresponds to one trial, and the histograms in panels B and D show counts of trials per phase bin. It is clear that the phase angles are more clustered at 200 ms (panels A and B) compared to 800 ms (panels C and D) [3].

6.1. Intertrial phase clustering (ITPC)

Intertrial phase clustering (ITPC) is a measure that quantifies the uniformity of the distribution of phase angles at each time-frequency-electrode point across multiple trials. It provides insights into the consistency of phase relationships in EEG signals.

To assess the uniformity of the distribution of phase angles, the average vector is computed rather than the individual phase angles in radians. The average vector represents the average direction of

the phase angles across trials. The length of this average vector indicates the closeness or dispersion of the phase angles.

If the phase angles are tightly clustered or similar across trials, the average vector will have a longer length. Conversely, if the phase angles are widely dispersed or dissimilar, the average vector will be shorter. In essence, the length of the average vector serves as a measure of how closely aligned the unit-length vectors are.

ITPC is derived from the length of the average vector and is bounded between zero and one. A value of zero indicates a completely uniform distribution of phase angles, suggesting no consistent phase relationship across trials. On the other hand, a value of one indicates completely identical phase angles, indicating a strong and consistent phase relationship across trials.

It is important to note that the number of trials used to compute ITPC can influence its value. Since ITPC cannot be below zero, factors such as noise and sampling errors tend to increase ITPC rather than decrease it, particularly when the number of trials is small [3].

Question

1. Utilize the Hilbert transform to extract the phase information from different frequency bands, and generate plots displaying the extracted phases.
2. Inter-trial phase clustering (ITPC) is a measure used to assess the consistency of phase values across multiple trials or repetitions of a stimulus or task. It quantifies the degree to which the phase angles of oscillatory activity align or cluster across trials at specific time points and frequency bands. Calculate ITPC for each group (i.e. face, non-face). Compare the results between the groups by reporting the mean ITPC values along with confidence intervals. Evaluate the statistical difference between two groups using the bootstrap method.
3. Apply shuffle correction to the data and evaluate ITPC one more time. Shuffle correction is determined by randomly reassigning the trial labels while preserving the original spectral characteristics of the data. Compare the results with the previous question and explain whether the observed clustering is genuinely related to the stimulus set.

7. Submission

Each of the students shall submit a typed `pdf` report by which the gist of their analysis is explained. The figures described in the problem description should be included and discussed within the report. For each of the figures, a separate script should be included, in either MATLAB (`.m`), python3 (`.py`, `.py3`), R (`.r`) or Julia (`.jl`). Do not submit your scripts in MATLAB live script, python notebook or r markdown. The submitted codes should run on the grader's system as well. Don't forget to attach all of your functions and non-standard libraries.

The report is considered to be an academic writing, rather than a technical one, so it should not include any codes, neither it should explain the coding logic. It should contain the author's insights about the results and reflect their dominance over the reference article. Academic writings usually are compact and use extremely formal tone.

Each section briefly explains the hypothesis that is going to be tested. The design of test and its implementation is considered as the students duty, as well as the explanations of each of the results. Interpretations shall be comprehensive, while avoiding unnecessary prolixity.

The language in which the report is written in should be either Persian or English, with no preference towards any of them. But if the report is written in Persian, it should use B Nazanin with size 14 as text body font and B Titr 18 for titles. English reports shall use Times New Roman 12 for body and Time New Roman 16 for titles. Sentences should be in passive tense. In persian reports, correct use of zero-width non-joiner is mandatory. In all reports, all equations, figures and tables should be labeled with unique numbers and referenced accordingly. Referencing to a figure with sentences like "the following figure", "the figure above" and etc. is incorrect. All Figures should have descriptive captions below them, while tables have the caption above them. Feel free to use footnotes and citations as needed.

A. Time-Frequency Analysis

The time-frequency domain refers to a representation or analysis of a signal that simultaneously captures information about both its time and frequency characteristics. In traditional signal processing, the time and frequency domains are considered separate and distinct. By examining the time-frequency representation of a signal, we can gain insights into its spectral characteristics over time. This can help identify specific frequency bands or patterns that are relevant to the phenomenon under investigation.

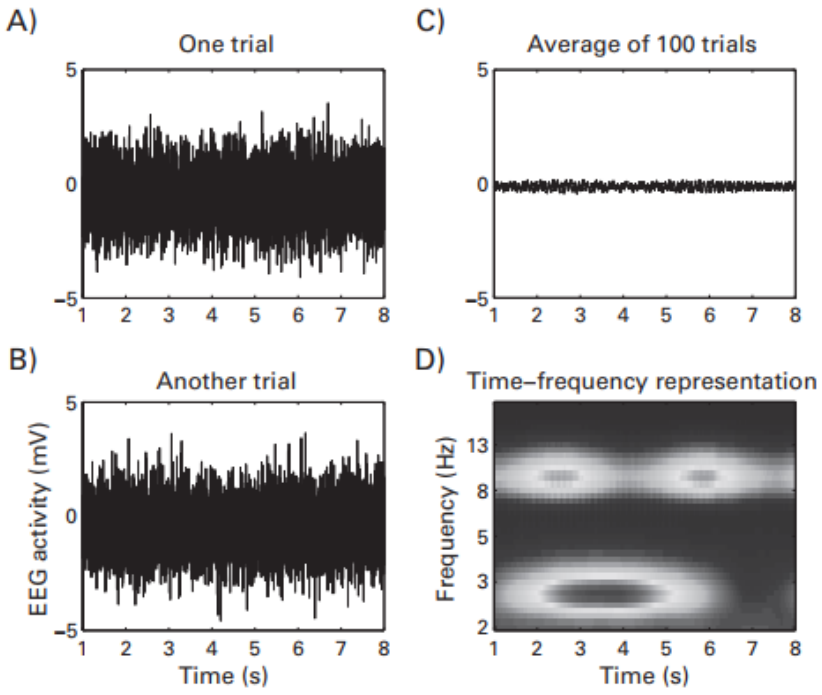

Figure 8: Simulated data showing that complex and multifrequency information contained in EEG data may have no representation in the ERP, if that information is non-phase-locked. One hundred trials were simulated; panels A and B show example trials. Panel C shows the ERP of those 100 trials, and panel D shows the time-frequency power [3].

short-time Fourier transform (STFT)

The Fourier transform is a mathematical technique used to analyze the frequency content of a signal. In the context of EEG signals, the Fourier transform is employed to examine the different frequency components present in the recorded brain activity.

The Fourier transform decomposes a time-domain signal into its constituent frequency components. It represents the signal as a sum of sinusoidal waves with different frequencies, amplitudes, and phases. By applying the Fourier transform to an EEG signal, we can obtain information about the power or amplitude of specific frequency bands within the signal. Once you have a solid understanding of how the Fourier transform operates and how to extract power from a complex analytic signal, the implementation of the short-time FFT method becomes relatively straightforward. Instead of analyzing the entire time series, this method involves using the FFT to examine the frequency structure of brief segments of data known as time windows. From this two-dimensional (2-D) result, which represents time and frequency, it is possible to extract either the time course of power at a specific frequency or the power spectrum at a particular time point. Prior to computing

the Fourier transform for each time segment, it is advisable to taper the data within that segment. Tapering serves to attenuate the amplitude of the data at the beginning and end of the segment, which is crucial in preventing edge artifacts from contaminating the time-frequency outcomes. Consequently, it is unnecessary to incorporate large buffer zones at the start and end of each trial for the short-time FFT method. While tapering does attenuate valid EEG signals, this effect can be mitigated by utilizing temporally overlapping segments.There are various taper options available, including the Hann window (sometimes referred to as Hanning), the Hamming window (named after Hamming), and the Gaussian window (named after Gauss). The Hann window is advantageous because it fully tapers the data to zero at the start and end of the time segment, thereby eliminating the possibility of even minor edge artifacts. On the other hand, the Gaussian window can be adjusted to taper to zero, but it results in a relatively narrow window, which may excessively attenuate the data. The Hamming window, meanwhile, does not fully taper the data to zero [3].

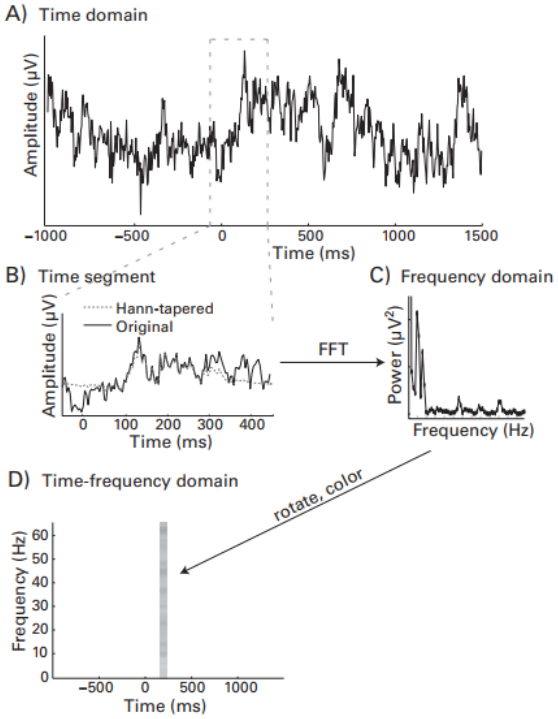

Figure 9: Overview of the short-time FFT method. From the time series data (panel A), a small segment of the data, comprising a few hundred milliseconds, is taken (panel B). A windowing taper is applied to that segment to minimize the possibility of edge artifacts, and then the Fourier transform of the tapered time series is taken (panel C). The power spectrum of that segment is then placed into a time-frequency space with the frequencies corresponding to that of the FFT and the time point corresponding to the center time point of the time segment from panel B. For resting-state data, the same procedure could be applied, but the FFT results would be averaged over time in panel D [3].

Wavelet transform

The reason why the Fourier transform alone is insufficient for capturing changes in frequency characteristics over time is due to the lack of temporal localization in its kernel, which is a sine wave. The amplitude of the sine wave extends infinitely over its entire time series, from negative to positive infinity. However, by applying a Gaussian taper to window the sine wave, it becomes possible to temporally localize the dynamic patterns of frequency structure in a time series.

Gaussian windows offer several advantages for this purpose. Firstly, they lack sharp edges that

would introduce artifacts, ensuring a smooth transition. Additionally, they attenuate the influence of surrounding time points on the estimation of frequency characteristics at each specific time point. Moreover, Gaussian windows allow for a trade-off between temporal precision and frequency precision, providing control over the level of detail captured in the analysis.

To achieve temporal localization in the Fourier transform, a sine wave windowed with a Gaussian is used, commonly referred to as a Morlet wavelet. The Morlet wavelet satisfies two key properties: it has values at or very close to zero at both ends, and its mean value is zero. These properties ensure that the wavelet captures relevant information without introducing bias.

In contrast to the Fourier transform, which assumes stationarity of the signal, the wavelet convolution approach acknowledges that the frequency structure of EEG data changes over time. It recognizes that the stationarity assumption holds only during the time period when the wavelet resembles a sine wave. This assumption is more reasonable and likely to be valid, as EEG data often exhibit stationary characteristics for extended durations, typically spanning hundreds of milliseconds [3].

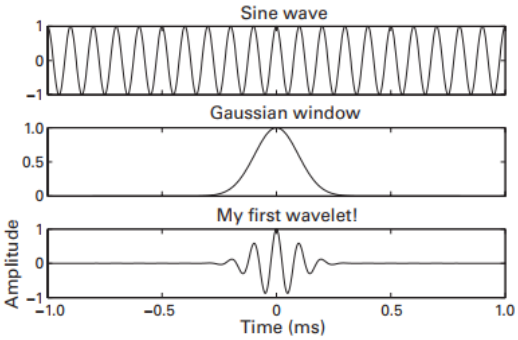

Figure 10: A Morlet wavelet (bottom) is a sine wave (top) windowed by a Gaussian (middle). This is called a realvalued Morlet wavelet because it comprises all real numbers [3].

Hilbert transform

The Hilbert transform is a mathematical operation that is applied to a signal in order to extract its analytic representation. It allows us to convert a real-valued signal into a complex signal by adding an imaginary part to the original signal. The main purpose of the Hilbert transform is to obtain the instantaneous amplitude and phase of a signal at every point in time. By applying the Hilbert transform to a real-valued signal, we obtain a complex signal that consists of the original signal as the real part and the Hilbert transform of the original signal as the imaginary part.

The complex signal obtained from the Hilbert transform can be represented in the form of a complex analytic signal. This representation enables the extraction of various properties, such as the envelope of the signal (instantaneous amplitude) and the instantaneous phase. The envelope of the complex analytic signal represents the magnitude of the signal at each point in time, providing information about the amplitude variations of the signal over time. This can be particularly useful for analyzing oscillatory activity in EEG, where the envelope can indicate the presence and strength of specific frequency components.

The instantaneous phase of the complex analytic signal represents the phase angle of the oscillatory components at each time point. This phase information is valuable for studying phase synchrony or phase relationships between different EEG channels or frequency bands.

When comparing the filter-Hilbert method, which involves applying a bandpass filter before the Hilbert transform, to complex wavelets, an advantage of the former becomes apparent. The

filter-Hilbert method provides greater control over the characteristics of the filter itself, in contrast to the limited control over the characteristics of Morlet wavelets. In fact, the shape of the Morlet wavelet is fixed and Gaussian-shaped in the frequency domain, leaving little room for customization [3].

References

[1] Michal Teplan et al. 'Fundamentals of EEG measurement'. In: *Measurement science review* 2.2 (2002), pp. 1–11 (cited on page 1).

[2] Sebastian Nagel. 'Towards a home-use BCI: fast asynchronous control and robust non-control state detection'. PhD thesis. Universität Tübingen, 2019 (cited on page 2).

[3] Mike X Cohen. *Analyzing neural time series data: theory and practice*. MIT press, 2014 (cited on pages 2, 7, 8, 10, 11, 13–16).

[4] James J DiCarlo, Davide Zoccolan, and Nicole C Rust. 'How does the brain solve visual object recognition?' In: *Neuron* 73.3 (2012), pp. 415–434 (cited on pages 2, 3).

[5] Eric R Kandel et al. *Principles of neural science*. Vol. 4. McGraw-hill New York, 2000 (cited on page 3).

[6] Arnaud Delorme and Miyakoshi Makoto. *Makoto's preprocessing pipeline*. Accessed on April 6, 2023. 2023. URL: https://sccn.ucsd.edu/wiki/Makoto's_preprocessing_pipeline (cited on page 6).

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