An Introduction to Cognitive Neuroscience

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Deadline: 21 Tir

I. Introduction

A. 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]

B. 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 activation 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.

C. 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.[2]

D. 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.[3] 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]

II. 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.

III. 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 rawEEGdata: Load the rawEEGdata into theEEG analysis software or toolbox of your choice (We would recommend EEGLab for this task). 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

IV. Problems

A. Data Processing and Analysis

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.

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

B. *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.

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

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.

C. *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. Figure 5: The three dimensions that define oscillations: frequency, power, and phase [3]. 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 within specific frequency bands.

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.

V. Submission

For the programming section, each student is required to submit a well-structured, typed PDF report that presents a concise summary of their analysis. The report should include the figures mentioned in the problem description and offer a detailed discussion of each. Please avoid uploading theoritical problem in .jpg format and upload them in a single .pdf file. For each section of the report, a separate script is expected, which can be written in MATLAB (.m), Python 3 (.py or .py3), or R (.r). Avoid submitting scripts in formats like MATLAB live scripts, Python notebooks, or R Markdown. It is crucial that the submitted code is compatible with the grader's system. Be sure to include all relevant functions and any non-standard libraries used in your code. The report should be treated as an academic piece of writing, and it should not contain any code snippets or expla- nations of coding logic. Instead, it should provide the author's insights about the results and demonstrate a strong grasp of the reference article. Academic reports typically maintain a concise and highly formal tone. Each section of the report should briefly outline the hypoth- esis being tested. The responsibility for designing and imple- menting the tests lies with the students, as does explaining the results. Interpretations should be comprehensive without unnecessary verbosity. The report can be written in either Persian or English, with no preference for either. In Persian reports, use B Nazanin with a font size of 14 for the text body and B Titr with a font size of 18 for titles. English reports should use Times New Roman 12 for the body text and Times New Roman 16 for titles. Sentences should be written in the passive tense. In Persian reports, the correct usage of the zero-width non- joiner is mandatory. In all reports, equations, figures, and tables must be labeled with unique numbers and referenced accordingly. Referring to figures as "the following figure," "the figure above," and similar expressions is considered incorrect. Every figure in the report should be accompanied by a descriptive caption below it, while tables should have captions above them. Feel free to use footnotes and citations as necessary for clarity and proper attribution.

References

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