Introduction to Cognitive Science

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EEG Processing

Electroencephalogram

Over the past century, electroencephalography (EEG) has evolved significantly. The discovery of electrical activity in the brain dates back to 1875, when English physician Richard Caton observed electrical signals from the exposed brains of rabbits and monkeys. In 1924, German neurologist Hans Berger recorded similar activity from the human scalp using modified radio equipment. Berger's recordings revealed that brain activity varies depending on mental state — for instance, during sleep, anesthesia, or neurological disorders such as epilepsy. He coined the term electroencephalogram (EEG) and established foundational principles for its modern-day use.

(1) What is EEG? EEG is a noninvasive method widely used in both clinical and cognitive neuroscience to measure electrical activity of the brain. It primarily reflects the summed excitatory and inhibitory postsynaptic potentials at the dendrites of large populations of neurons that are aligned in parallel. When neurotransmitters open ion channels, the resulting ionic fluxes generate electric fields. Though the field from an individual neuron is too weak to be detected on the scalp, the synchronous activity of thousands of neurons can produce signals measurable by EEG electrodes.

A typical EEG setup includes electrodes (usually embedded in a cap), amplifiers, analog-to-digital converters, and a recording system. The electrodes capture scalp potentials, amplifiers boost the microvolt-level signals, the converters digitize them, and the data is stored and visualized for analysis.

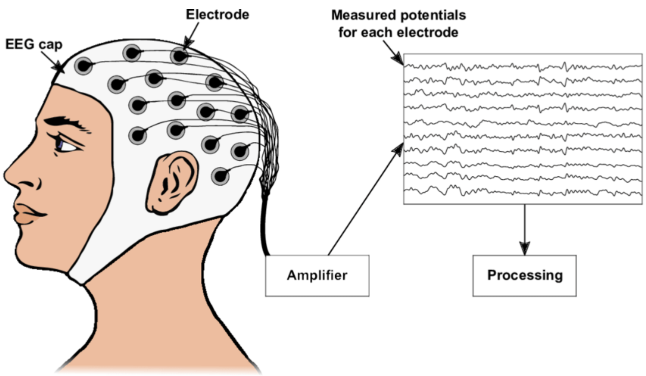

Figure 1: Sketch of how to record an Electroencephalogram. An EEG allows measuring the electrical activity on the scalp using electrodes which are often fixated on an EEG cap. For each electrode, the signals are amplified and can be used in the following for a desired processing [?].

High-level vision

Vision is a complex process involving multiple interacting systems in the brain. It is often conceptualized hierarchically, ranging from low-level to high-level visual processing. The retina receives complex, dynamic light patterns which are processed through this visual hierarchy.

- Low-level vision extracts basic features such as brightness, contrast, and edges.
- Intermediate-level vision identifies visual primitives like contours, motion, and surfaces.
- High-level vision integrates information to form object representations and support conscious perception.

Neural processing of vision is also hierarchical. The retina and lateral geniculate nucleus (LGN) of the thalamus handle initial signal transmission. Primary visual cortex (V1) processes simple visual features like orientation and edges. Regions such as V2 and V3 handle more complex properties like motion and depth. High-level regions, such as V4 and the inferior temporal cortex, process object features like shape and color.

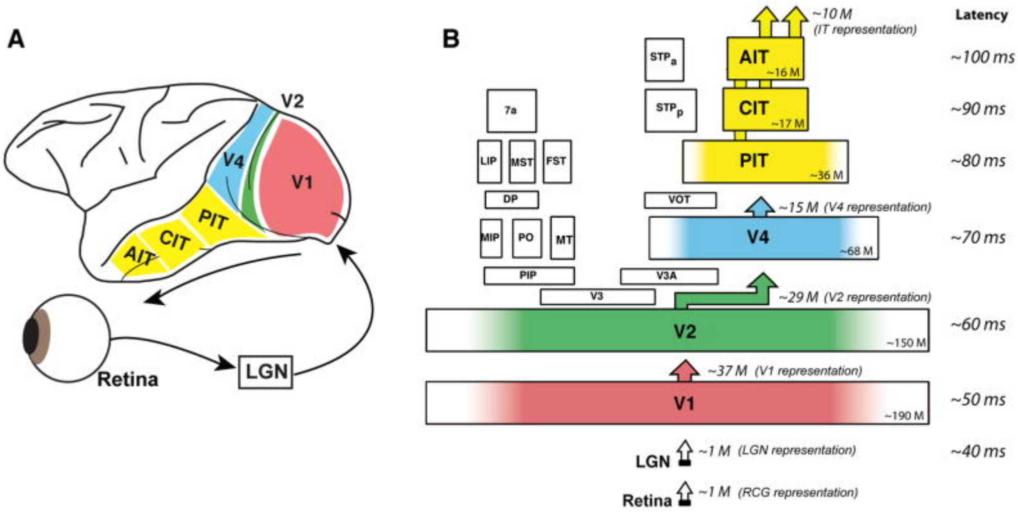

Figure 2: The Ventral Visual Pathway. From V1, the visual processing pathways split into two streams: the ventral stream and the dorsal stream. The ventral stream, which is shown in the figure, also known as the "what" pathway, is involved in object recognition and identification. It continues through 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 [?].

Multivariate Pattern Analysis (MVPA)

Multivariate Pattern Analysis (MVPA) is a powerful analytical approach used to decode information from patterns of brain activity. Unlike traditional univariate analyses that focus on each channel or voxel independently, MVPA considers the spatial and/or temporal patterns of activity across multiple sensors or brain regions simultaneously. This allows researchers to detect subtle, distributed representations that may not be evident when examining individual signals in isolation.

MVPA works by training a machine learning classifier to distinguish between different experimental conditions based on the multivariate neural activity patterns. For example, in an EEG experiment, MVPA might be used to determine whether the pattern of activity evoked by a "face" stimulus is reliably different from that evoked by a "house" stimulus. The classifier is typically trained on a subset of the data and tested on held-out data to assess generalization performance (e.g., using cross-validation).

There are two major types of MVPA in EEG analysis:

- Temporal MVPA: Decoding is performed at each time point separately across all channels, allowing for a fine-grained temporal resolution of how information unfolds over time.

- Spatial MVPA: Decoding is done across the spatial pattern of all EEG channels, often aggregating information across a temporal window.
- Time-time generalization: A more advanced method that trains the classifier at one time point and tests at all others, revealing when information is encoded and how it evolves or reappears over time.

MVPA is especially useful in EEG and MEG studies due to the high temporal resolution of these signals, enabling precise insights into the dynamics of cognitive processes. Through MVPA, we can examine not only whether brain activity differs between conditions but also when and where these differences arise. For a comprehensive overview, see the tutorial article A Beginner's Guide to Multivariate Decoding for Time-Resolved M/EEG Data.

Representational Dissimilarity Matrices (RDM)

The Representational Dissimilarity Matrix (RDM) is a tool that captures the similarity (or dissimilarity) between activation patterns elicited by different stimuli. For each stimulus pair, a dissimilarity metric (often 1 minus the correlation coefficient) is computed based on the brain's activation patterns. This produces a symmetric matrix where each cell reflects the dissimilarity between a pair of stimuli.

In EEG, the activation pattern is typically defined over time or sensors. The RDM can be used to compare neural data across time, brain regions, participants, or with computational models. Representational Similarity Analysis (RSA) goes one step further by comparing RDMs across modalities (e.g., brain and model representations).

For an in-depth introduction, see the paper: "Representational similarity analysis – connecting the branches of systems neuroscience".

Task paradigm

The experiment uses a Rapid Serial Visual Presentation (RSVP) paradigm with 18 images from two categories: faces and dollhouses. Each image is repeated 4 times, totaling 80 stimulus presentations. Each stimulus appears for 100 ms with a 200 ms inter-stimulus interval. Participants are instructed to maintain fixation.

- EEG acquisition: 64-channel EEG (10-10 system), sampled at 100 Hz. Online filters: 0.1 Hz high-pass and 100 Hz low-pass. The Fz electrode is used as reference.
- Stimulus triggers are recorded in the last channel: 496# marks face images and 436# marks dollhouse images. The number following the # corresponds to the image ID.

Note: For ease of analysis, we extracted epochs around stimulus onset from -500 ms to +1500 ms. Sharp edges at the beginning and end are expected and should not be mistaken for noise.

Instructions and Questions

(2) Preprocessing Preprocess the EEG data so that it can be used for the following analyses.

- Describe each preprocessing step (e.g., filtering, epoching, baseline correction, ICA).
- Justify your choices. What did you include or exclude? Why?
- Use any software toolbox you prefer, but ensure you understand and can explain each step.

(3) ERP Plot the ERP for face vs. dollhouse stimuli.

- Use appropriate time-locking and baseline correction.
- Conduct statistical comparisons (e.g., permutation tests or cluster-based statistics).
- Highlight and interpret significant differences.

(4) Time-Frequency Analysis Analyze the EEG signal in the frequency domain.

- You may use wavelet or short-time Fourier transforms.
- Compare time-frequency maps across categories.
- Discuss neural oscillations (e.g., alpha, beta, gamma) and their role in perception.

(5) MVPA Apply both temporal and spatial MVPA to the EEG data.

- Temporal MVPA: Train classifiers at each time point to distinguish face vs. dollhouse trials.
- Spatial MVPA: Use patterns across electrodes to decode the stimulus category.
- Optionally, use cross-temporal generalization (train on one time, test on others).

Questions to consider:

- Can face and dollhouse stimuli be reliably distinguished using EEG patterns?
- Are some time periods or scalp regions more informative?
- What does the MVPA reveal about the dynamics of object processing in the brain?

(6) RDM and RSA Plot the Representational Dissimilarity Matrix (RDM) for the categorical data.

- Use EEG activation patterns to compute RDMs across time and/or channels.
- Compute the Representational Similarity Analysis (RSA) between your EEG RDMs and those derived from deep neural networks (e.g., CORnet-S).
- Use CORnet-S model features from early to late visual layers (e.g., V1, V2, V4, IT).

You can use the CORnet-S model from this repo: GitHub Corresponding paper: Kubilius et al., 2019

Explain:

- Do some visual layers of CORnet-S correlate more with EEG activity than others?
- Can you identify temporal dynamics that resemble ventral stream processing?
- Discuss any hypotheses and provide supporting evidence.

Final Notes

- Clearly labeled and well-explained figures (ERPs, Time-Frequency plots, MVPA results, and RDMs) are essential and will significantly enhance your submission.
- We understand EEG analysis is a new and challenging area—obtaining exact or perfect results might be difficult. What matters most is your thoughtful reasoning and how clearly your explanations align with **your own findings**. Use your valuable brain (not an artificial one) to uncover meaningful insights from the data!

- Carefully reviewing and following the provided guidelines in the course page will directly benefit your performance on this assignment.
- Above all, enjoy the exploration! EEG analysis is a fascinating window into cognitive neuroscience; embrace this assignment as an opportunity to deepen your understanding.

"If the human brain were so simple that we could understand it, we would be so simple that we couldn't."
— Emerson M. Pugh