Cognitive Neuroscience Group Project

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Introduction

Electroencephalography (EEG) is an electrophysiological neuromonitoring method that measures the weak electromagnetic signals generated by neural activity in the brain. EEG is used to understand different cognitive processes and functions of the brain such as language processing and sensory perception. While more common neuromonitoring methods such as functional magnetic resonance imaging (fMRI) monitors the blood flow to certain areas of the brain thus giving an insight to activities of the neurons in the brain, EEG has a high temporal resolution which captures the changing dynamics of the brain activations at a millisecond time resolution. This is helpful when examining neuronal activity across a wide range of frequencies that can be used for studying contemporary insights into how the brain works as a large system

The EEG data analysis that was conducted used the second language study done by Dr. Roncaglia-Denisses on the impact of L2 speech rhythm on syntactic ambiguity resolution. This research investigated the role of the age of acquisition in second language rhythmic properties during syntactic ambiguity resolution. Participants in this experiment received syntactically ambiguous and syntactically non-ambiguous sentences embedded in rhythmically regular and irregular contexts.

The dataset used in the EEG data analysis consisted of 85 participants from this study. The participants were divided into three groups:

1. RM - Native German monolinguists.
2. RB - Turkish, early learners of German from birth.
3. RL - Turkish, late learner of German.

As Turkish is a syllable-timed stress language and German is stressed-timed, the Turkish early adopters and late adopters had to utilize rhythm during the processing of syntactic ambiguity in L2. In the study, there were in total 352 sentences with 176 sentences being rhythmically regular pattern sentences and 176 rhythmically irregular pattern sentences. Both types of sentences had two conditions - subject first or object first sentences. Half of the sentences are experimental (ambiguous) sentences and the other half are the control (non-ambiguous) conditional sentences.

The experimental triggers that were analyzed in this data analysis were the onset of the critical item in each sentence (the auxiliary verb). The phenomena that our group was interested in is how participants respond to syntactic ambiguity in regards to the critical item if the participants received regular rhythmic use sentence in comparison with an ambiguous rhythmically use sentence to examine if there is any type of processing of syntactic ambiguity in L2.

Firstly our group loaded and prepared the dataset in the Jupyter environment by setting up the data structure of the EEG data. After that, we explored the data by deep diving into one participant's event-related potential and plotting the baseline, and evoked mean of the subject's voltage. In addition to this, we plotted the subjects'' standard deviation to examine the average deviation between the trials.

Furthermore, after exploring the data, we normalized the data by implementing standard scaling for all participants to reduce the variance of results, eliminate possible outliers. After standardizing the data, we performed a time-resolved frequency analysis on all the participants and trials by conducting a Fourier transformation that allows us to measure and monitor oscillatory activity in the brain with regards to the critical item. Finally, we plotted graphs to investigate the baseline and evoked power-spectrum for all participants and examined the Fz brain channel for all participants.

Furthermore, the group our data analysis focused on were the Early learners of German. In addition to this, the condition that the data analysis investigated was the object first regular rhythm triggers.

Interpretation and Discussion

In this section, four separate graphs are displayed to present the essence of this EEG data analysis.

Figure 1: Mean of the raw and the normalized EEG traces.

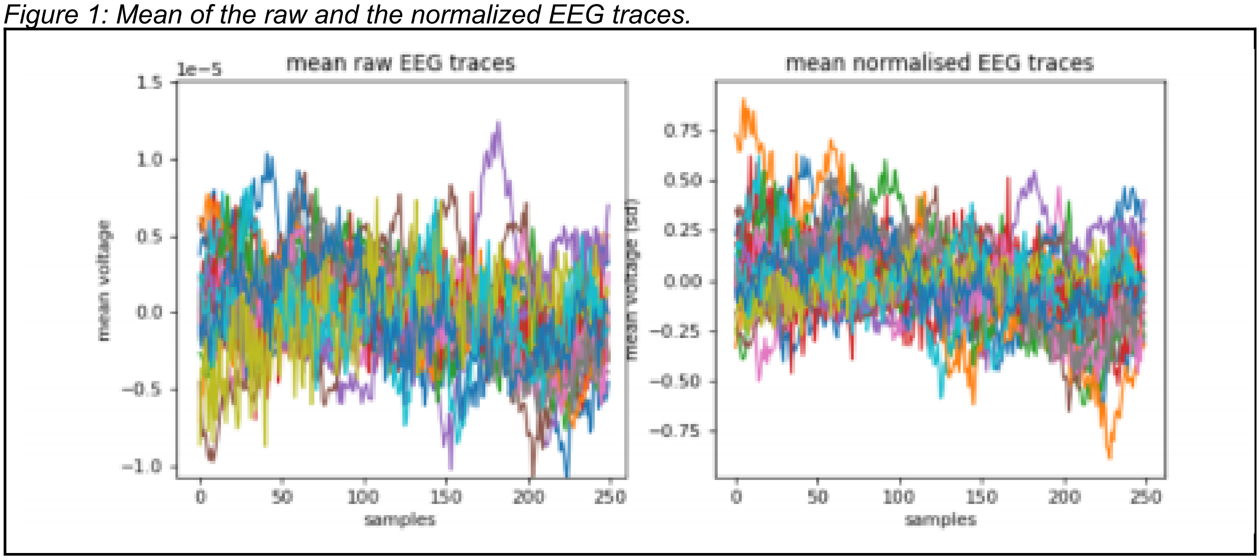


Figure 1 depicts a graph that shows the raw EEG traces before it was normalized and after it was normalized. Normalization was implemented by dividing each participant's data by the grand standard deviation per participant. This was done to eliminate variance and reduce outliers amongst the data that can be caused by recording on different days, with different gel or electrodes.

Normalizing and standardizing EEG data has great relevance to make experiments comparable between participants and also to remove the noise and artifacts that were recorded with the EEG data. This ensures that we have consistent results when performing scientific experiments that involve the brain, and cognitive processes of the brain. By comparing the mean of the raw and the mean of the normalized EEG traces, we eliminated the potential outliers that would have compromised the reliability of our results.

Figure 2: The Baseline power spectrum for participant 12 compared to the average baseline power spectrum for all participants for the Fz channel.

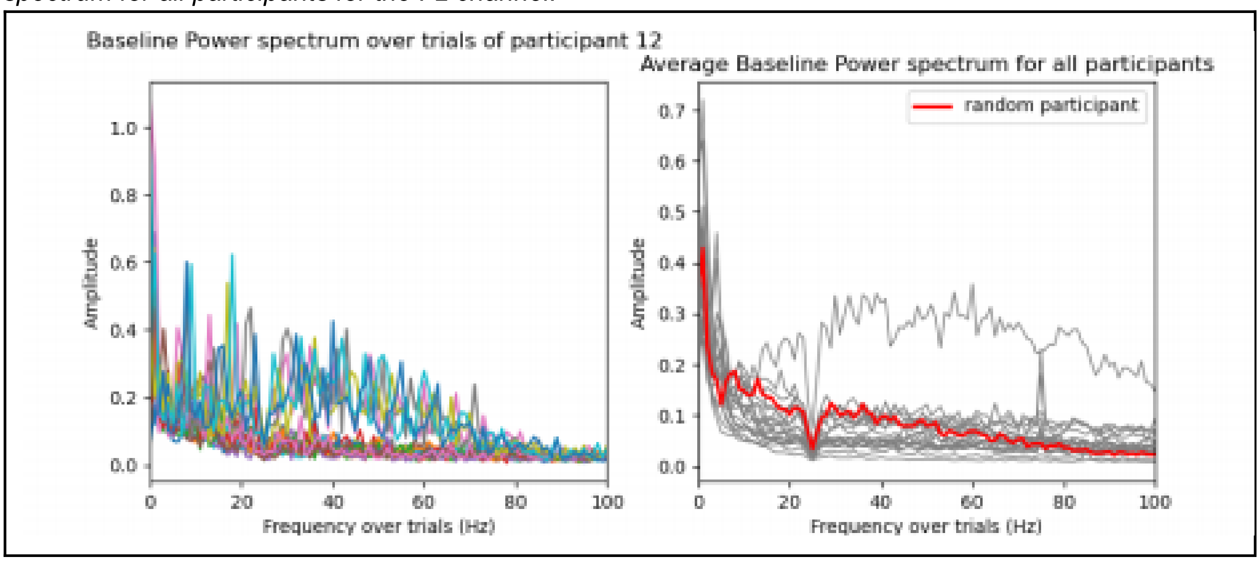
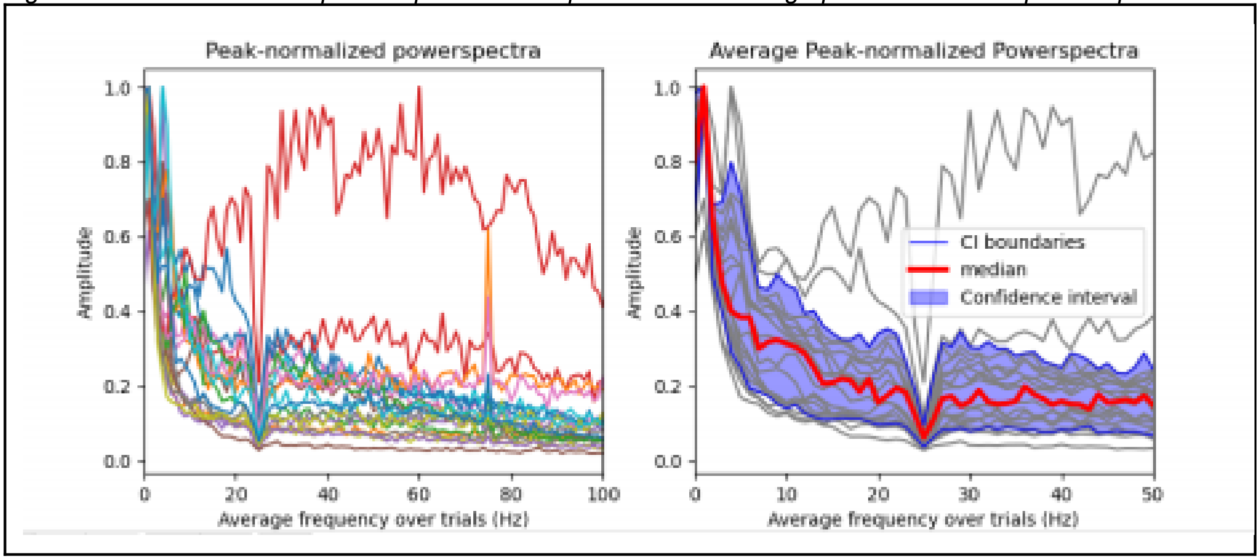


Figure 2 illustrates the baseline power spectrum over trials for participant 12 and the average baseline spectrum for all participants for the Fz- channel. The Fz channel is the frontal mid-sagittal and acts as a reference electrode. A Fourier transformation was implemented to decomposes a single into a complex spectrum for each frequency that can be used to - measure and monitor oscillatory activity in the brain that changes with different cognitive and behavioral states. In the figure above, we can observe that most of the participants are in the Beta (15-25 Hz)frequency range(4 Hz -8 Hz) suggesting that the participants are in an alert and focused state of mind which can suggest syntactic processing of the sentences given in the experiment.

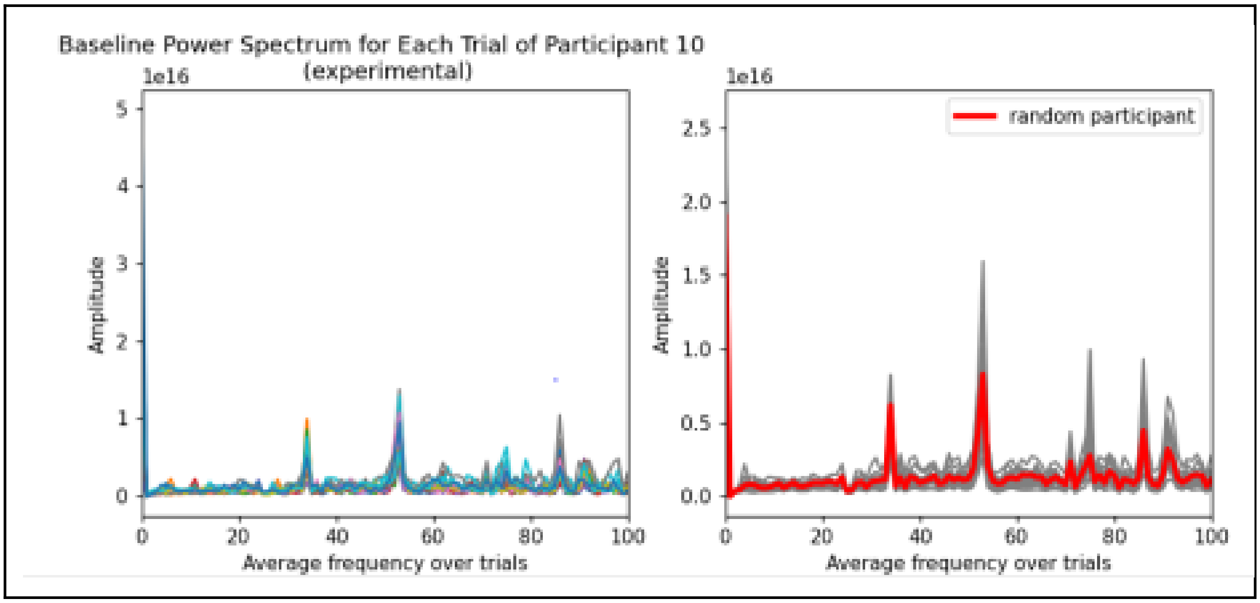
The graph can give us insight into the syntactic processing of non-ambiguous (control condition) language and can be compared to the experimental condition to detect whether the certain brain channel has a difference in frequency concerning the onset of a critical item (auxiliary verb). The difference in frequency will indicate that a certain brain region is more active concerning the critical item.

Figure 3: Peak normalized power spectrum compared to the average peak normalized power spectrum.



By looking at the power spectrum of a signal of all the participants we understand that the average peak normalized frequency is around 5-15Hz. In addition to this, we can see the confidence intervals of the participants that had higher strength of frequencies and lower strength of frequencies. The power spectrum detects the frequency changes of the signal over time. This is to understand the cognitive processes of a certain region of interest in the brain as the power spectrum gives us the durations and the energy of the different components.

Figure 6: Baseline power spectrum for each trial of participant 10 compared to the average participant.



The graph compares two different channels (Fz and F4) with each other. Our group choose these channels as they both appear in the frontal lobe and we wanted to compare the F4 channel to the reference channel Fz. On the left, in figure 6 we can see the experimental data gathered from participant 10 for the F4 channel, on the right, there is an average across the participants for the same channel with the red line representing our random participant; this figure is relevant if compared to the control graph because comparing two brain regions to understand the cognitive processes in both of them remains an important aim in cognitive physiology.

All the graphs have great relevance in the understanding and implementation of brain-computer interfaces which allows the decoding of our intentions using our brain signals to external devices The purpose of brain-computer interfaces is to have a direct/indirect pathway from our brains to our external devices as we interact with devices with the computational capabilities of our brains. The advancements in neurotechnology utilize EEG brain activity to decode the user's input. An example of this is Steady-state visual evoked potential (SSVEP) which can allow users to choose between multiple choices just from electrical activity in the brain. Furthermore, brain-computer interfaces are implementing machine learning algorithms such as deep learning classifiers to allow brain-computer interfaces to read the intentions of the users better and for the BCI systems to be more robust.