SCHOLARLY REVIEW

Periodic and Aperiodic EEG Activity in Cognitive Tasks: A Scalp Topography Study

By Nidhi George

Author Biography

Nidhi George is a senior at Arrowhead High School in Hartland, Wisconsin. She enjoys public speaking, using her voice to promote ideas she cares about, and learning about the brain and mathematics. With a passion for empowering women in STEM, Nidhi hopes to major in Neuroscience and Gender Studies.

Abstract

This study investigates the correlation between electrical activity patterns in various brain regions during an information-integration task using electroencephalography (EEG). EEG recordings were analyzed to find both periodic activity, in this case, Alpha power, and aperiodic activity, which is usually considered background noise. The study found that Alpha power was most prominent in the posterior regions of the brain, while aperiodic activity was most prominent in the anterior regions. Using an open EEG dataset and multiple Python packages, the study includes multiple scalp topography maps and violin plots to visualize the data. The results indicate the importance of considering both aperiodic and periodic activity in the brain during different cognitive functions, supporting previous findings about neural excitation and inhibition.

Keywords: Neuroscience, EEG, Information Integration, Periodic activity, Aperiodic activity, Scalp topography, Alpha power, Occipital lobe, Categorization task

Introduction

Patterns of electrical activity originating from the brain have been associated with cognitive abilities, such as sensory processing (Skrandies, 1995). Furthermore, these patterns of electrical brain activity are shaped by the underlying ratio of different cell types in the brain, together being active in synchrony or not (Gong & Townsend, 2018). There are various ways to measure these associations, primarily through different types of scans and readings. Functional imaging focuses on brain activity rather than structure, allowing us to see relationships between neural activity and processes. Commonly used forms of functional imaging include functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and electroencephalography (EEG) (Horwitz et al., 2000).

In this study, EEG measures brain activity as subjects complete a task. Electrodes, small metal discs that attach to areas across the scalp, record electrical activity between neurons through the different regions of the brain. The signals collected are then processed and analyzed to find patterns in different locations and frequencies (Kirschstein & Köhling, 2009). These signals contain both periodic and aperiodic activity. Periodic activity is characterized by consistent, repetitive oscillations, typically in a clear frequency range (Wilson et al., 2022). This activity is commonly characterized as beta, alpha, theta, delta, and gamma waves and is believed to correlate to brain functions occurring during the reading. Aperiodic activity is sporadic and commonly referred to as background noise, as it is not believed to correlate to the same synchronized neural processes as periodic activity (Koudelková & Strmiska, 2018).

Periodic and aperiodic activity are indicators of various traits of the brain's functions. Alpha waves, as measured with EEGs, are typically observed in the thalamus (Lopes de Silva et al., 1974). They are believed to be associated with sensory processing and attention, and increased Alpha power is associated with relaxation and calmness. Aperiodic waves are common throughout the brain and are believed to reflect non-synchronous neural activity. A higher aperiodic exponent may suggest more inhibition in brain activity, while a lower one may suggest more excitation in brain activity. Analysis of periodic and aperiodic waves gives a holistic view of oscillatory and background activity in the brain.

To measure the periodic and aperiodic activity while subjects complete an information-integration task, EEG signals were analyzed to calculate the mean Alpha power and aperiodic exponent during the task. This data was then used to create topographic views of aperiodic and periodic activity across different brain regions, illustrating the neural activity throughout the task.

Methods

We first leveraged an open EEG dataset (Trujillo, 2020) from individuals as they performed an information-integration categorization task. Subjects had to categorize visual stimuli into two groups. The stimuli were circular sine-wave gratings, which were organized based on the frequency and rotation of the gratings. An EEG with 64 channels measured brain activity through this task. We used the Python package specparam to parameterize the periodic and aperiodic power spectral density components of EEG signals (Ostlund et al., 2022). To preprocess the data, we bandpass filtered the signal and applied a notch filter using these parameters: peak_width_limits=[2, 6], max_n_peaks=3, min_peak_height=0.075, peak_threshold=1, aperiodic_mode='fixed'. These components included the exponent of the aperiodic signal model fit, as well as the relative power difference of periodic activity over the aperiodic signal model fit within canonical frequency bands Alpha (8–14 Hz). This removed noise in the 60 Hz range, focusing on the signals needed for Alpha power. The Power Spectral Density of the data was computed with a focal point of 1-40 Hz frequencies.

```
# Define the lower and upper cutoff frequencies
low_freq = 0.1
high_freq = 100
# Apply bandpass filter to EEG data
filtered_raw_notch = filtered_raw.copy().filter(l_freq=low_freq, h_freq=high_freq, verbose=True)
psd = filtered_raw_notch.compute_psd(method="welch", fmin=1, fmax=40, tmin=0, tmax=200,n_overlap=150, n_fft=300)
## FOOOF SETTINGS specified model parameters
```

```
FIT_RANGE = (2, 30)
FOOOF_SETTINGS = FOOOFSettings(
    peak_width_limits=[2, 6],
    max_n_peaks=3,
    min_peak_height=0.075,
    peak_threshold=1,
    aperiodic_mode='fixed',
)
fg = FOOOFGroup(*FOOOF_SETTINGS) # modeling
fg.fit(freqs, spectra, FIT_RANGE) # fitting
```

Using the Python package MNE-python, we then mapped the mean of each of these components onto scalp topography maps to determine their neuroanatomical spread. We also created violin plots of the mean Alpha power and aperiodic exponent across all 64 channels.

Results

The distribution of Alpha power throughout the various regions of the brain (Figure 1). The highest levels of aperiodic adjusted Alpha power are displayed in the posterior parts of the brain as the subjects completed the information-integration task, with the mean Alpha power averaging around 0.5, as shown in Figure 1B. The error of the goodness of fit model for each channel had an average of 0.4 and ranged from 0.02 to 0.12, and the R^2 value ranged from 0.9 to 1 for all channels except for one outlier at 0.5. The center frequency has a mode of 11 and a mean of 15.

Figure 2 shows the highest levels of aperiodic exponent in the anterior parts of the brain as the subjects completed the information-integration task, with the yellow parts representing the highest exponent. The mean aperiodic exponent averages around 1.55, as shown in Figure 2B. The lowest value of aperiodic exponent in a channel was approximately 0.2, while the highest was approximately 3.5.

A. B.

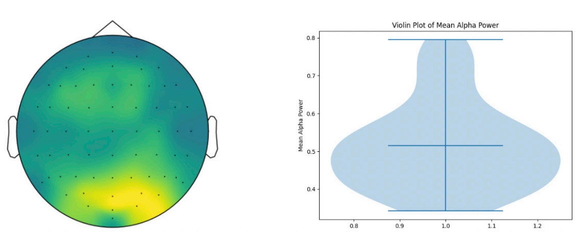

Figure 1. **Distribution of aperiodic adjusted Alpha power across electrode channels.** (A) Alpha power is spatially distributed across 64 scalp EEG electrodes, with posterior parts of the brain displaying the highest relative levels of Alpha power across all subjects. (B) The violin plot demonstrates an average of aperiodic adjusted Alpha power across all subjects.

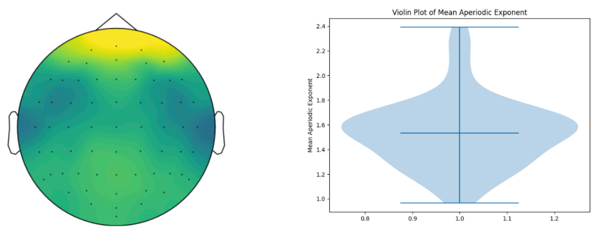

Figure 2. **Distribution of aperiodic exponent across electrode channels.** (A) Aperiodic exponent is spatially distributed across 64 scalp EEG electrodes such that anterior parts of the brain display the highest relative levels of aperiodic activity across all subjects. (B) The violin plot demonstrates an average of aperiodic exponent across all subjects.

Discussion

Our analysis supports the hypothesis that periodic features, such as Alpha power, are prominent in posterior regions of the brain. In contrast, aperiodic features, such as the exponent of the power spectrum fit, are prominent in the anterior areas of the brain. The highest levels of adjusted Alpha power were concentrated in the back half of the brain, near the occipital lobe, suggesting a high level of involved activity from this region. This is likely connected to the amount of sensory activity taking place through the information-integration task (Başar, 2012). The highest levels of aperiodic exponent were concentrated in the front half of the brain, indicating more neural inhibition in this region.

Prior research suggests that aperiodic exponent is a measure of neural excitation and inhibition, while alpha power is related to creative thinking during tasks (Pani et al., 2022; Fink & Benedek, 2012). This aligns with the findings of this study, as inhibition was high in the less active parts of the brain, and alpha power was high in the visual cortex, which is highly involved in an information-integration task (Helbig & Ernst, 2007). High levels of alpha power are also linked to intelligence, so as individuals are categorizing the stimuli, they are using intelligence skills to do so (Doppelmayr, 2002). Both may help predict the task results and other individual skills, such as creativity.

Considering both aperiodic and periodic activity helps give a cumulative perspective of the different functions the brain goes through, with this specific study focusing on the novel ideas of information-integration tasks. Limitations of the study include using a singular data set and EEG data collection errors. The study could be improved by looking at a larger variety of ages and gender in the data set. Nevertheless, our results contribute to the evidence that aperiodic activity is inhibitory, while periodic Alpha power is a measure of functional activity. Alpha power was defined for this study as 1-40 Hz frequencies, and the data was notch-filtered, removing unnecessary noise and increasing validity.

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