Exercise #4

Identifying Individual Alpha Frequency

Introduction

Electroencephalography (EEG) is a widely used method for non-invasively measuring brain activity, particularly oscillatory patterns that reflect ongoing neural processes. One prominent oscillation is the alpha rhythm, generally observed in the frequency range of 8–12 Hz. This rhythm is strongly associated with states of relaxation, attentional disengagement, and eye closure. The Individual Alpha Frequency (IAF)—the specific peak frequency within the alpha band for a given individual—can serve as a useful biomarker for cognitive function, arousal levels, and inter-individual differences in neural processing.

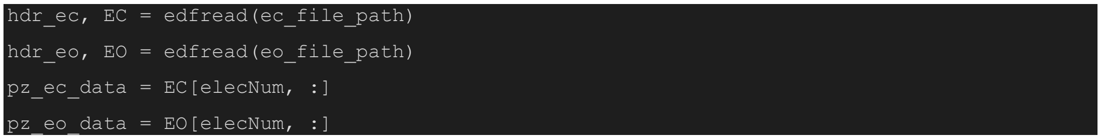
To identify the IAF for each subject, we rely on frequency-domain analysis, specifically through power spectral density (PSD) estimation. The PSD quantifies how signal power is distributed across different frequencies. Two methods were used in this assignment to estimate the PSD:

- Fast Fourier Transform (FFT): This algorithm decomposes a time-domain signal into its frequency components by computing the Discrete Fourier Transform (DFT) efficiently. The EEG signal is assumed to be stationary over the recording window, and all frequency components are extracted in one computation. The power at each frequency is estimated by squaring the magnitude of the FFT output. While FFT is fast and accurate for long, clean signals, it can be sensitive to noise and windowing effects.
- Welch's Method: An improvement on the basic FFT approach, Welch's method splits the signal into overlapping segments, applies a window function, computes the FFT on each segment, and then averages the resulting spectra. This reduces variance and smooths out noise artifacts at the cost of some frequency resolution. It is particularly suitable for analysing noisy or non-stationary EEG signals, making it a common choice in neuroscience.

In this assignment, we used both FFT and Welch's method to estimate the PSD of the EEG signal at the Pz electrode for three subjects under two conditions: eyes open (EO) and eyes closed (EC). By comparing the spectra from EO and EC conditions, we aimed to extract each subject's IAF and assess the effectiveness of each method in revealing stimulus-dependent alpha activity.

Methods

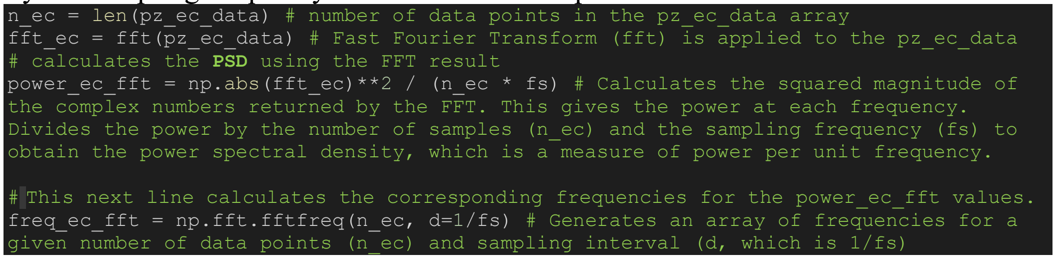
1. **Data organization and loading**: We began by organizing and importing the experimental data files from three subjects, identifying files with subject numbers, 'EO' (eyes open – orange in the plots), or 'EC' (eyes closed – blue in the plots) tags. The edfread function we received was used to parse the EDF file to signal information. The function calculated scaling factors to convert the raw integer values from the analog-to-digital converter into actual EEG voltage measurements (microvolts), and allowed us to select specific electrodes data for analysis. The function returned both header information and the processed signal data in a format ready for our subsequent analysis steps.
   This is how we've used the function and got the Pz electrode data:



```
hdr_ec, EC = edfread(ec_file_path)

hdr_eo, EO = edfread(eo_file_path)

pz_ec_data = EC[elecNum, :]

pz_eo_data = EO[elecNum, :]
```

2. **Power spectrum calculation**: For each subject, we loaded both EC and EO data files and extracted signals specifically from the Pz electrode (index 18) for our analysis. We calculated the power spectrum using two different methods: Fast Fourier Transform (FFT) where we squared the absolute FFT values and normalized by data points and sampling frequency, and Welch's method which segments the data and averages multiple power spectra for better frequency resolution. For visualization, we created 2x2 subplot figures for each subject's 4-14 Hz range comparisons between EC and EO conditions using both FFT and Welch methods. Also, we normalized the data by dividing it by the peak measurements (between 4 and 14 Hz) of each subject; this way we can see all the plots on the same y-axis scale.

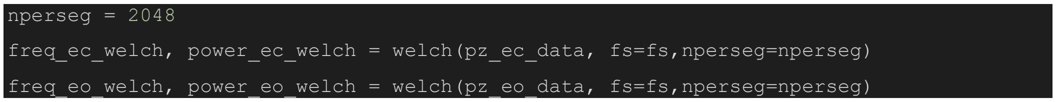
a. Fast Fourier Transform (FFT) - We applied FFT to each condition and computed the power spectrum by squaring the absolute FFT coefficients and normalizing them by the sampling frequency and number of data points.



```
n_ec = len(pz_ec_data) # number of data points in the pz_ec_data array
fft_ec = fft(pz_ec_data) # Fast Fourier Transform (fft) is applied to the pz_ec_data
# calculates the PSD using the FFT result
power_ec_fft = np.abs(fft_ec)**2 / (n_ec * fs) # Calculates the squared magnitude of
the complex numbers returned by the FFT. This gives the power at each frequency.
Divides the power by the number of samples (n_ec) and the sampling frequency (fs) to
obtain the power spectral density, which is a measure of power per unit frequency.

# This next line calculates the corresponding frequencies for the power_ec_fft values.
freq_ec_fft = np.fft.fftfreq(n_ec, d=1/fs) # Generates an array of frequencies for a
given number of data points (n_ec) and sampling interval (d, which is 1/fs)
```

Only the positive half of the spectrum was retained. We repeated this for the EO condition.

b. Welch's Method - Welch's method divides the signal into overlapping segments, computes the FFT on each, and averages them to reduce noise and variance.



```
nperseg = 2048

freq_ec_welch, power_ec_welch = welch(pz_ec_data, fs=fs,nperseg=nperseg)

freq_eo_welch, power_eo_welch = welch(pz_eo_data, fs=fs,nperseg=nperseg)
```

We chose nperseg of 2048 as it gave us the best results; it looked the best middle ground between resolution and smoothness.

3. **Normalization:** To make spectra comparable across subjects and conditions, we normalized power values within the 4–14 Hz band by dividing each spectrum by its peak value in that range.

```
max_power_ec_fft_range = np.max(power_ec_fft[freq_range_indices_fft_norm])

max_power_fft= np.maximum(max_power_ec_fft_range,max_power_eo_fft_range)

normalized_power_ec_fft_range = power_ec_fft[freq_range_indices_fft_norm] / max_power_fft
```

And then we did the same to the Welch method:

```
max_power_ec_welch_range = np.max(power_ec_welch[freq_range_indices_welch_norm])

max_power_welch= np.maximum(max_power_ec_welch_range,max_power_eo_welch_range)

normalized_power_ec_welch_range = power_ec_welch[freq_range_indices_welch_norm] / max_power_welch
```

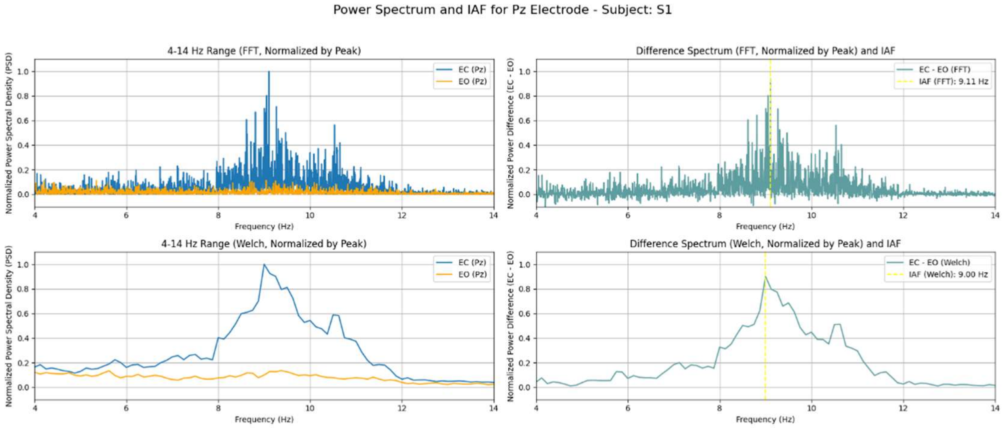
First, we found the maximum measured alpha value for every subject; and then divided the all the data by that value. We did so for both EC and EO, in both methods.

4. **Individual Alpha Frequency Extraction**: We identified each subject's specific IAF by creating difference spectra by subtracting the EO power spectrum from the EC power spectrum for both FFT and Welch methods. Within the 4-14 Hz frequency range, we located the frequency where the power difference (EC - EO) reached its maximum value, defining this peak as each subject's IAF for both calculation methods. We documented our results by printing the calculated IAF values and creating visualizations of the difference spectra with vertical lines marking the identified IAF positions for both FFT and Welch approaches.

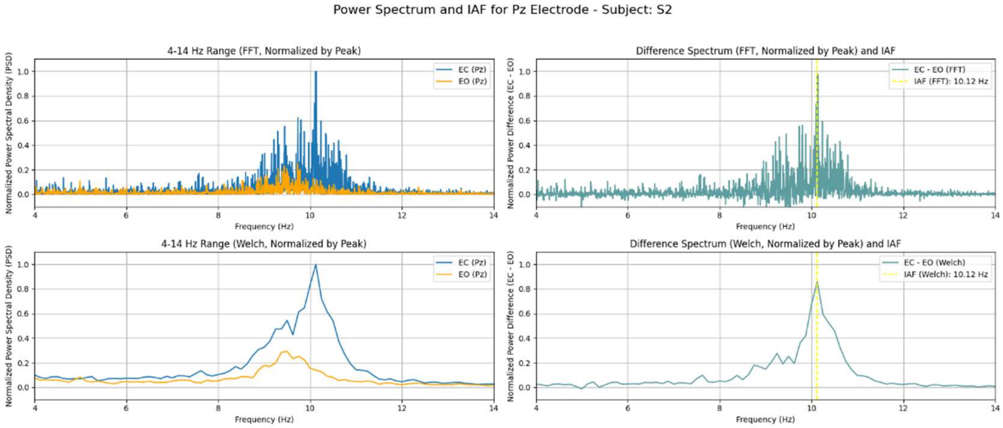
This is how we calculated the difference between the methods:

```
normalized_diff_spectrum_fft_range = normalized_power_ec_fft_range - normalized_power_eo_fft_range

normalized_diff_spectrum_welch_range = normalized_power_ec_welch_range - normalized_power_eo_welch_range
```

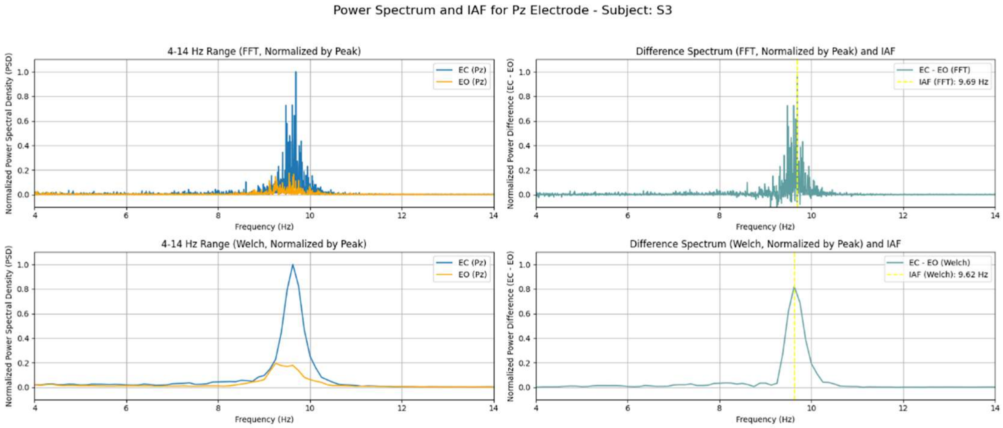
Results



Subject: S1
IAF (FFT method): 9.11 Hz
IAF (Welch method): 9.00 Hz



Subject: S2
IAF (FFT method): 10.12 Hz
IAF (Welch method): 10.12 Hz



Subject: S3
IAF (FFT method): 9.69 Hz
IAF (Welch method): 9.62 Hz

Discussion

FFT vs. Welch Method Comparison

Both methods show similar patterns across all subjects. However, there are some clear differences between the two approaches:

- **Detail vs. Noise:** FFT shows more detailed frequency information but also picks up more random noise, resulting in graphs appearing rough and jagged. Welch's method creates smoother, cleaner graphs by averaging multiple data segments together, which reduces background noise
- **Power Levels:** The Welch method typically shows lower power numbers than FFT. This is due to the windowing process that reduces the overall signal amplitude. This is why we normalized the spectrums.

Individual Subject Analysis:

Subject S1

- **Dominant Peak**: Clear and strong alpha activity on EC, with dominant peak around 9Hz in both methods.
- **Big Power Difference**: The spectral power differences between EC and EO is the highest compared to other subjects.

Subject S2

- **Dominant Peak**: Clear and strong alpha activity on EC, with dominant peak a little above 10Hz in both methods.
- **Less Power Difference**: The spectral power differences between EC and EO is smaller compared to other subjects.

Subject S3

- **Dominant Peak**: Clear and strong alpha activity on EC, with dominant peak around 9-10Hz in both methods.
- **Thin Alpha Band**: Alpha activity appears less distributed- the frequency range is short compared to the others.
- **Clean Spectrum**: Less noise and clearer spectral peak in Welch analysis.

The visible differences between subjects in brain wave power and frequencies show why it's important to analyse each person individually in EEG studies. These differences between subjects might be caused by different levels of alertness or sleepiness during recording (Barry et al., 2004), how well each person was paying attention during the test (Clayton et al., 2015), or even genetic differences that affect brain wave patterns (Smit et al., 2006; Posthuma et al., 2001). All of these are important confounds to take into account when planning the tests. Moreover, it has been shown that higher IAF is associated with greater memory performance, and decreases in IAF relate to performance drops (Klimesch et al., 1993) which highlights it further as an important marker in the EEG measurement.

References

Barry, R. J., Clarke, A. R., McCarthy, R., Selikowitz, M., Rushby, J. A., & Ploskova, E. (2004). EEG differences in children as a function of resting-state arousal level. Clinical Neurophysiology, 15(2), 402-408.

Clayton, M. S., Yeung, N., & Kadosh, R. C. (2015). The roles of cortical oscillations in sustained attention. Trends in cognitive sciences, 19(4), 188-195.

Klimesch, W., Schimke, H., & Pfurtscheller, G. (1993). Alpha frequency, cognitive load and memory performance. Brain topography, 5(3), 241–251. https://doi.org/10.1007/BF01128991

Posthuma, D., Neale, M. C., Boomsma, D. I., & De Geus, E. J. C. (2001). Are smarter brains running faster? Heritability of alpha peak frequency, IQ, and their interrelation. Behavior genetics, 31, 567-579.

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & De Geus, E. J. C. (2005). Heritability of background EEG across the power spectrum. Psychophysiology, 42(6), 691-697.