Comparative Resting-State EEG Analysis of Alzheimer's Disease

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1 Abstract

This project aims to investigate the differences in electroencephalography (EEG) signals between individuals with Alzheimer's disease (AD) and controls. We used two datapoints from Mitiadous et al. (2023), which contains scalp EEG recordings of AD patients, and healthy controls under eyes-closed rest. In this project, we will first apply signal processing techniques including filtering and artifact rejection remove noise and isolate the frequency range of interest. Our methodology includes the application of the discrete Fourier transform (DFT) to examine spectral components, followed by the computation of power spectral density (PSD) via the Welch method. Through this approach, we aim to quantify the relative band power across different frequency bands, allowing for a detailed comparison of neural activity between the two subjects.

2 Exploratory Data Analysis

Below is the dataset description provided by our TA:

> This dataset provides resting-state EEG recordings from individuals with Alzheimer's disease (AD), frontotemporal dementia (FTD), and healthy controls, collected using a clinical EEG system with 19 scalp electrodes during an eyes-closed resting state. The dataset includes 36 AD patients, 23 FTD patients, and 29 healthy age-matched subjects, with Mini-Mental State Examination (MMSE) scores reported for each. EEG signals were recorded using a monopolar montage, and both raw and preprocessed EEG data are available in BIDS format. Preprocessing involved artifact subspace reconstruction and independent component analysis for denoising. This dataset has high reuse potential for studying EEG-based biomarkers for dementia, brain connectivity alterations, and machine learning applications in neurodegenerative disease diagnosis.
>
> - Two individual EEG data included(Alzheimer's disease - subject_001, Healthy Control - subject_027)
> - The sampling rate was 500 Hz and the resolution was 10 uV/mm
> - Three channel included: Fp1','Fp2','F3'

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.signal import butter, firwin, filtfilt, welch, freqz, lfilter

np.random.seed = 118
```

```
F_s = 500
```

Load in the dataset and transform it into a pandas dataframe.

[2]:
```
Control = np.load("./dataset/Control_EEG_sub_027.npy")
AD = np.load("./dataset/AD_EEG_sub_001.npy")

feature_names = ['Fp1', 'Fp2', 'F3']
df_control = pd.DataFrame(Control.T, columns=feature_names)
df_AD = pd.DataFrame(AD.T, columns=feature_names)

df_AD.head()
```

[2]:

	Fp1	Fp2	F3
0	-0.000190	-0.000142	-0.000107
1	-0.000180	-0.000137	-0.000100
2	-0.000167	-0.000135	-0.000106
3	-0.000160	-0.000133	-0.000105
4	-0.000159	-0.000124	-0.000104

Since the usual measurement for EEG studies is μV, we upscale the entire dataset by 10^6

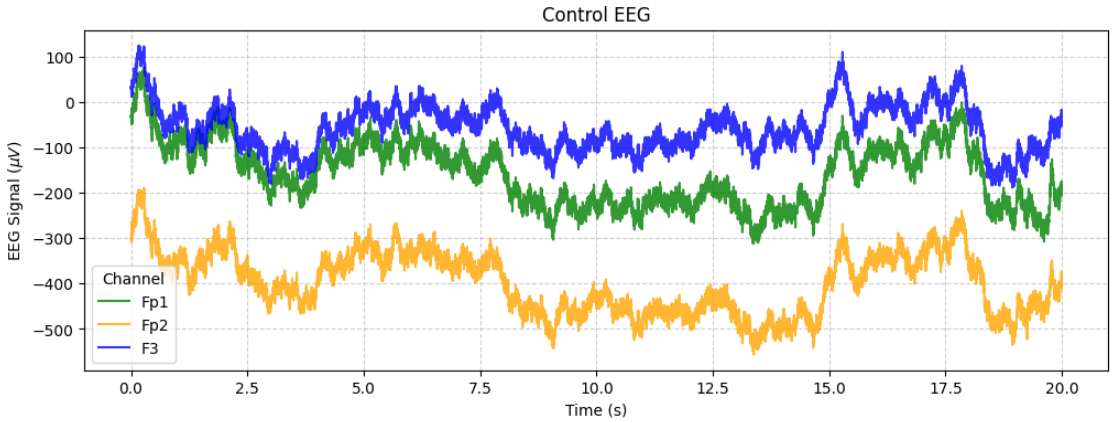
[3]:
```
df_AD *= 1e6
df_control *= 1e6
df_AD.head()
```

[3]:

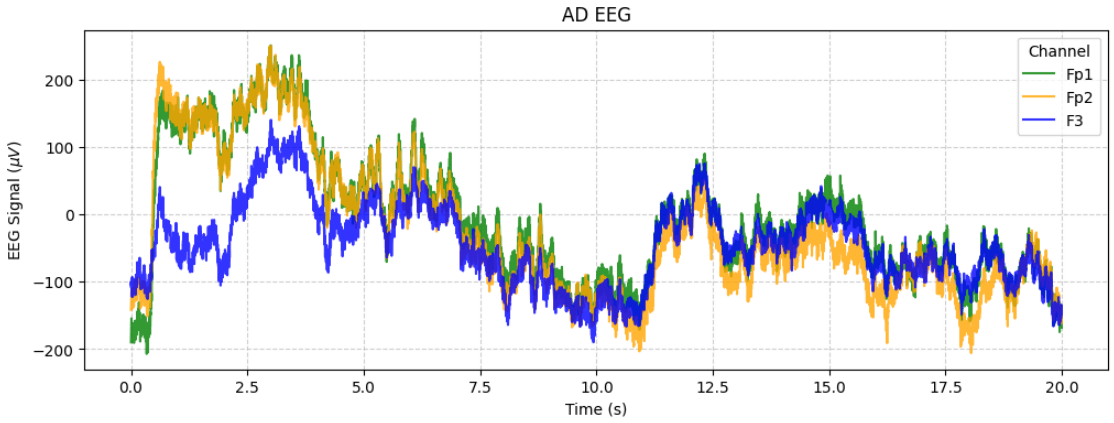
	Fp1	Fp2	F3
0	-189.892563	-141.845688	-107.373039
1	-180.419907	-137.353500	-100.048820
2	-166.992172	-135.058578	-105.761711
3	-160.205063	-132.958969	-105.322258
4	-159.326157	-124.462883	-104.150383

Display the raw EEG data of two subjects.

[4]:
```
def plot_EEG (df,title):
    t = df.index/F_s
    plt.figure(figsize=(12, 4))
    plt.plot(t,df["Fp1"], color = "green", label = "Fp1", alpha = 0.8)
    plt.plot(t,df["Fp2"], color = "orange", label = "Fp2", alpha = 0.8)
    plt.plot(t,df["F3"], color = "blue", label = "F3", alpha = 0.8)
    plt.xlabel('Time (s)')
    plt.ylabel(r'EEG Signal $(\mu V)$')
    plt.title(title)
    plt.legend(title="Channel")
    plt.grid(True, linestyle='--', alpha=0.6)
    plt.show()

plot_EEG(df_control, "Control EEG")
```



[5]:
```
plot_EEG(df_AD, "AD EEG")
```



The unprocessed data shows signs of high-frequency noise as the range of the signal varies from $\pm 200 \mu V$, which is abnormal for calm state EEG. Preprocessing and cleaning is needed before doing further analysis.

3 Preprocessing

In the original dataset paper, a preprocessing pipeline is applied as the following:

> First, a Butterworth band-pass filter 0.5-45 Hz was applied and the signals were re-referenced to A1-A2. Then, the Artifact Subspace Reconstruction routine (ASR) which is an EEG artifact correction method included in the EEGLab Matlab software was applied to the signals, removing bad data periods which exceeded the max acceptable 0.5 second window standard deviation of 17, which is considered a conservative window. Next, the Independent Component Analysis (ICA) method (RunICA algorithm) was performed, transforming the 19 EEG signals to 19 ICA components. ICA components

that were classified as “eye artifacts” or “jaw artifacts” by the automatic classification routine “ICLabel” in the EEGLAB platform were automatically rejected. It should be noted that, even though the recording was performed in a resting state, eyes-closed condition, eye artifacts of eye movement were still found at some EEG recordings.

Since we do not have the whole data set, we will be focusing on the filtering part.

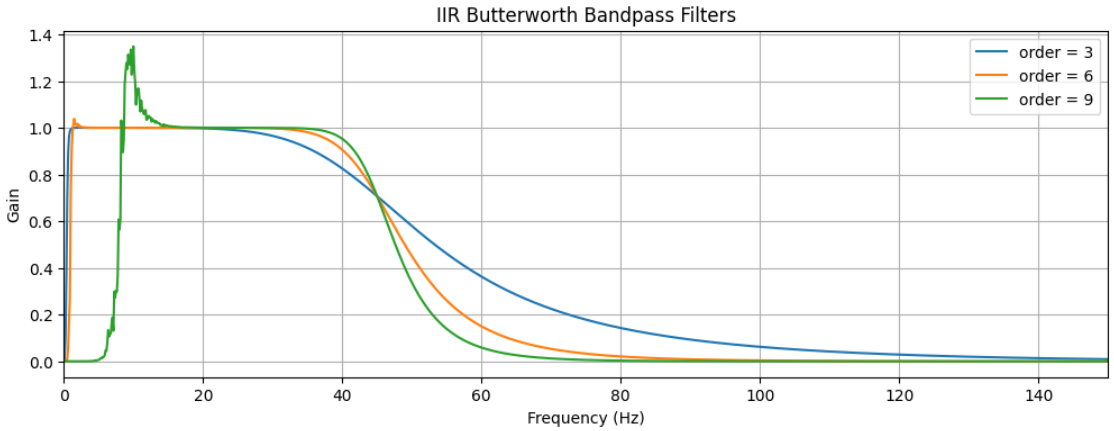
[6]:
```
lowcut = 0.5
highcut = 45
```

3.1 Butterworth Filter

Below is the Butterworth band-pass filter suggested from “scipy-cookbook”. It also included a useful graph displaying how the order of butter reflected to the shape of the filter.

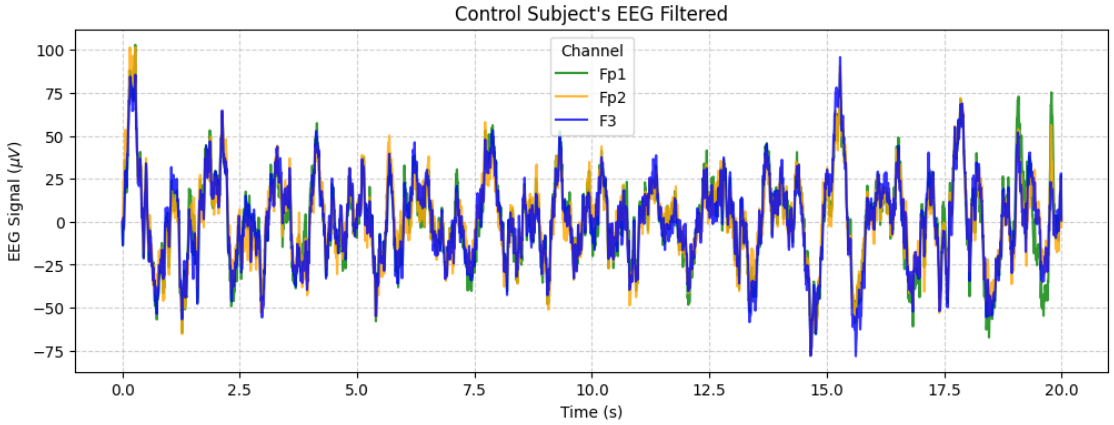
[7]:
```
def butter_bandpass(lowcut, highcut, fs, order):
    nyq = 0.5 * fs
    low = lowcut / nyq
    high = highcut / nyq
    b, a = butter(order, [low, high], btype='band')
    return b, a

def butter_bandpass_filter(data, lowcut, highcut, fs, order):
    b, a = butter_bandpass(lowcut, highcut, fs, order)
    y = filtfilt(b, a, data)
    return y
```

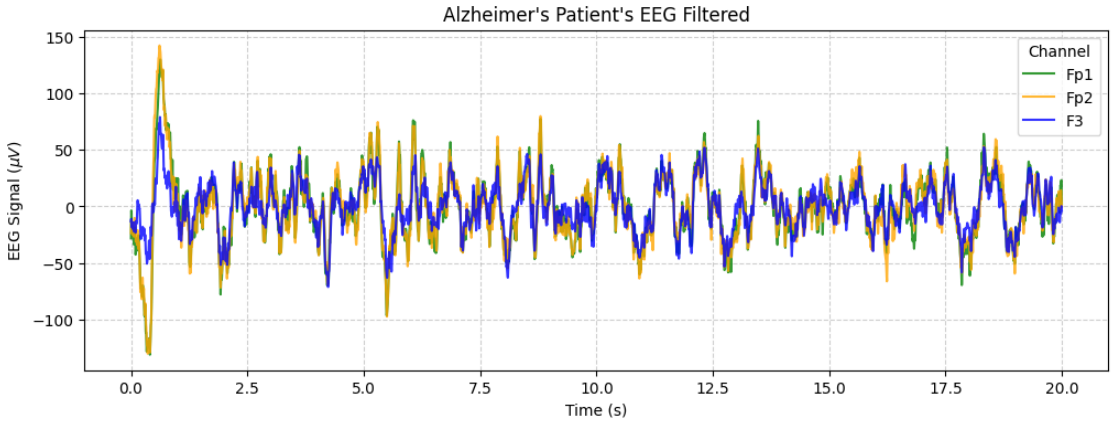
[8]:
```
plt.figure(figsize=(12, 4))

for order in [3, 6, 9]:
    b, a = butter_bandpass(lowcut, highcut, F_s, order=order)
    w, h = freqz(b, a, worN=2000)
    plt.plot((F_s * 0.5 / np.pi) * w, abs(h), label="order = %d" % order)

plt.title('IIR Butterworth Bandpass Filters')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Gain')
plt.xlim(0,150)
plt.grid(True)
plt.legend(loc='best')
plt.show()
```



Notice that when `order = 9`, there is a strange spike in the filter. This is likely because of the recursive calculation of the IIR filter. So in our actual filter, we used `order = 5` to prevent this from happening.

[9]:
```
df_control_IIRfiltered = df_control.copy()
df_AD_IIRfiltered = df_AD.copy()

for col in df_control.columns:
    df_control_IIRfiltered[col] = butter_bandpass_filter(df_control[col],␣
 ↪lowcut, highcut,F_s, order = 5)
for col in df_AD.columns:
    df_AD_IIRfiltered[col] = butter_bandpass_filter(df_AD[col], lowcut,␣
 ↪highcut, F_s, order = 5)


plot_EEG(df_control_IIRfiltered, "Control Subject's EEG Filtered")
plot_EEG(df_AD_IIRfiltered, "Alzheimer's Patient's EEG Filtered")
```



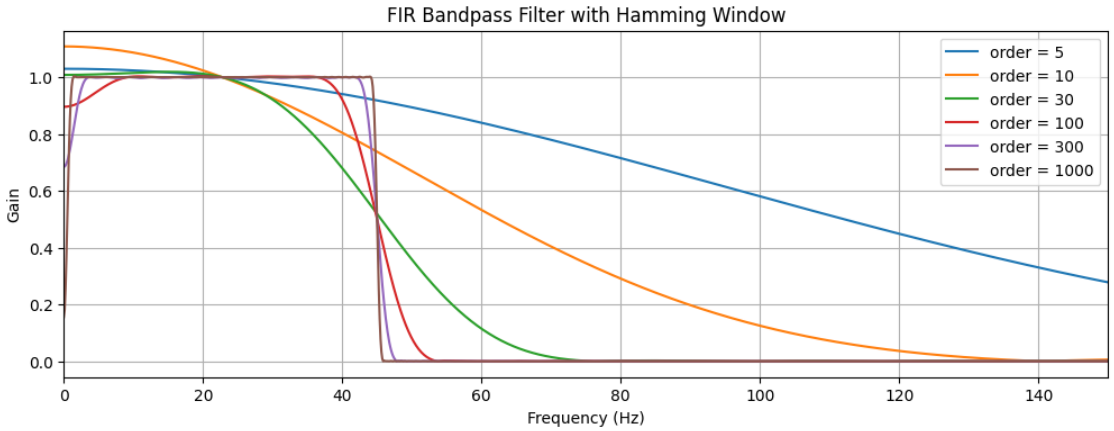


3.2 Why Not an IIR Filter

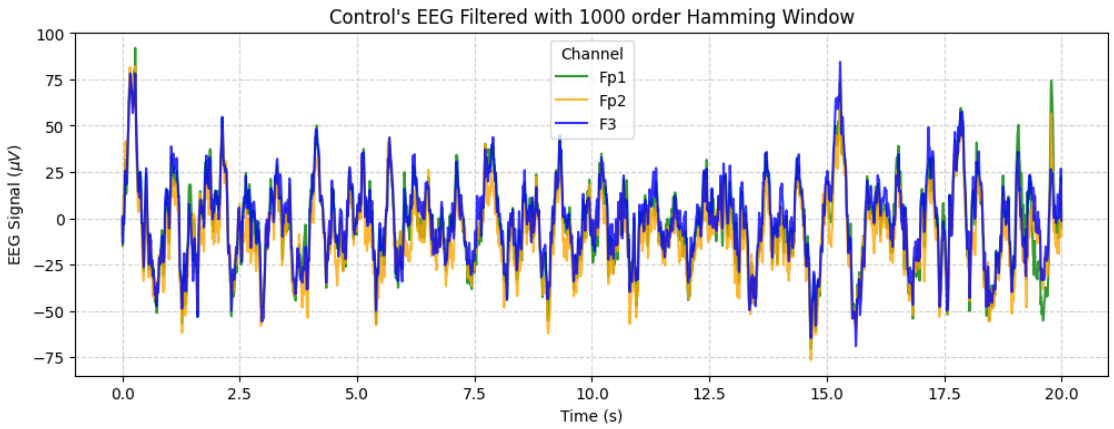
In class we learned a lot a bout finite **impulse response filters** (FIR), but the paper used a **infinite response filter** (IIR). One major reason is because FIR filters need a very high order to achieve the same cutoff as a IIR filter. The original study has 88 subjects with datapoints millions of datapoints, using a high order FIR filter is very inefficient.

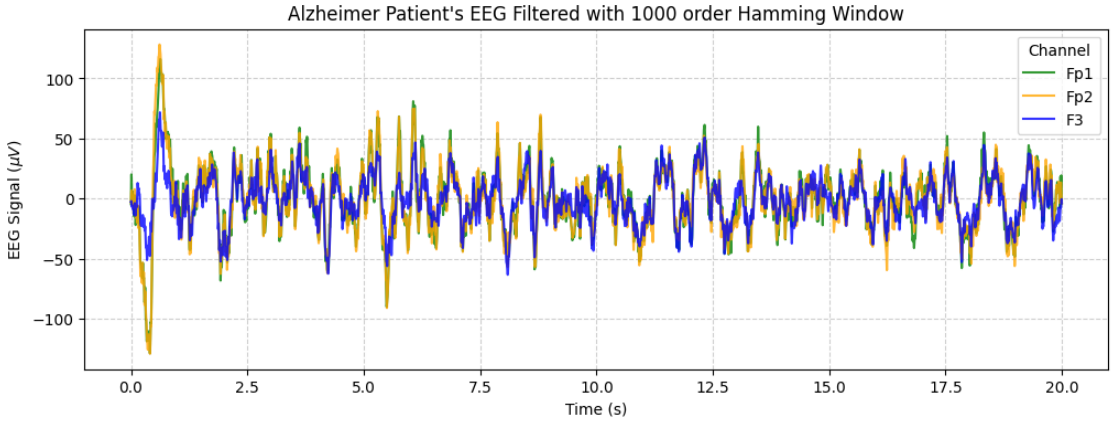
But in our study, we only have 2 subjects with 20 seconds of data. This makes it easy for us to use FIR filters without worrying about computation cost. IIR also has a potential disadvantage: since it utilizes feedback loop, without caution one can create significant artifact after applying them. FIR filters only use original data which is safe.

[10]:
```
nyquist = F_s / 2
low = lowcut / nyquist
high = highcut / nyquist

plt.figure(figsize=(12, 4))

for order in [5,10,30,100,300,1000]:
    fir_coeffs = firwin(order, [low,high], pass_zero=False, window="hamming")

    w, h = freqz(fir_coeffs, worN=2000)
    freq = w * F_s / (2 * np.pi)

    plt.plot(freq, abs(h), label=f'order = {order}')

plt.title('FIR Bandpass Filter with Hamming Window')
plt.xlabel('Frequency (Hz)')
plt.xlim(0,150)
plt.ylabel('Gain')
plt.grid()
plt.legend()
plt.show()
```



[11]:
```
order = 1000

fir_coef = firwin(order, [low, high], pass_zero=False, window="hamming")

df_control_FIRfiltered = df_control.copy()
df_AD_FIRfiltered = df_AD.copy()

for col in df_control.columns:
    df_control_FIRfiltered[col] = filtfilt(fir_coef, 1.0, df_control[col])

for col in df_AD.columns:
    df_AD_FIRfiltered[col] = filtfilt(fir_coef, 1.0, df_AD[col])

plot_EEG(df_control_FIRfiltered, "Control's EEG Filtered with 1000 order␣
 ↪Hamming Window")
plot_EEG(df_AD_FIRfiltered, "Alzheimer Patient's EEG Filtered with 1000 order␣
 ↪Hamming Window")
```





Another problem arise when we have extremely high order: transient effect. Since we only have 20 seconds of data, if we use a FIR response, then for the first few seconds, the filter is still "warming up" and we lost 10% of our data just to initialize the filter itself.

4 PSD Analysis

4.1 Fourier Transform

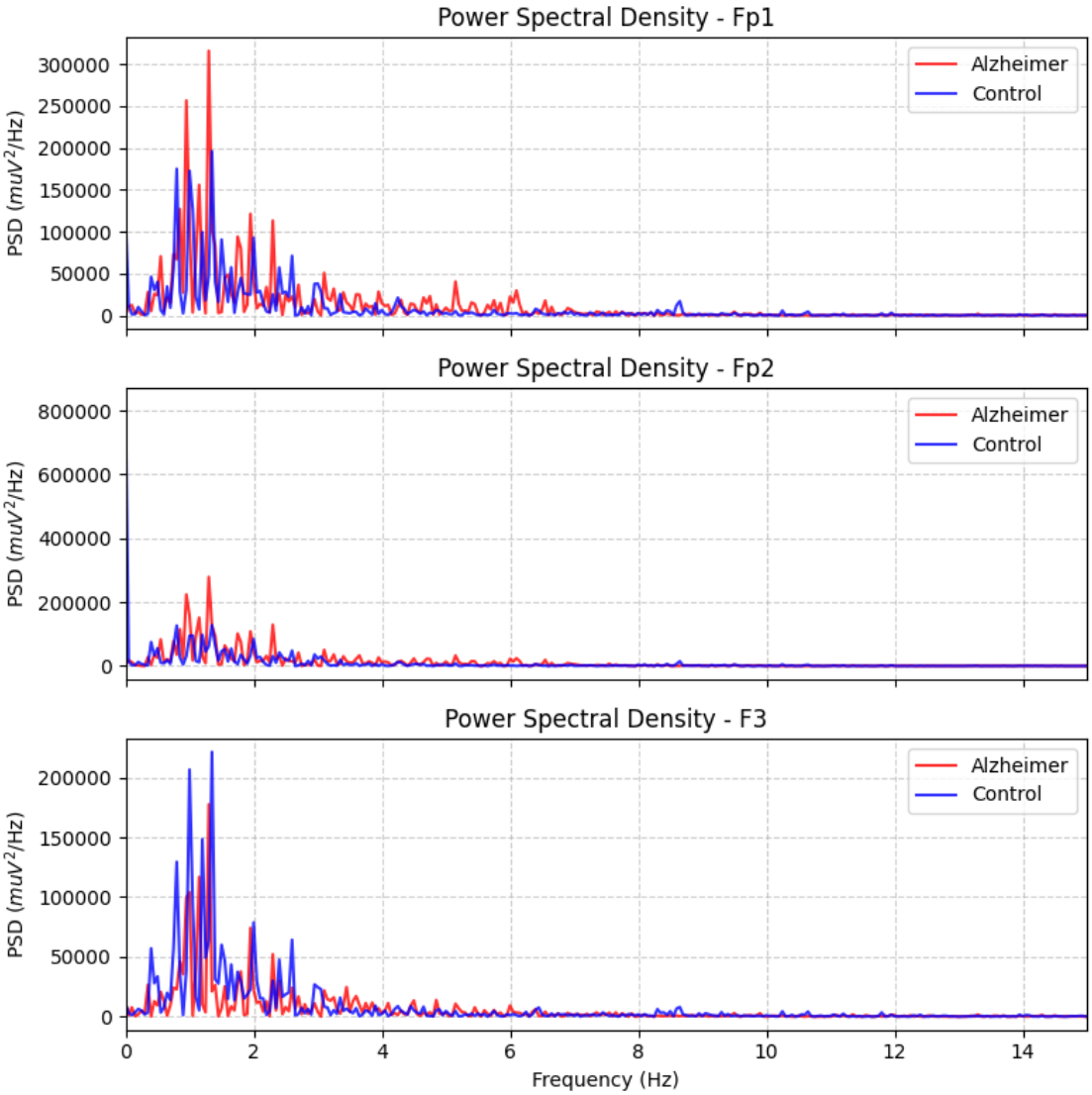
To complement Welch's method, we use the Fast **Fourier Transform (FFT)** which converts time-domain EEG signals into the frequency domain, allowing us to estimate the **Power Spectral Density (PSD)**. Unlike Welch's method, which averages overlapping segments of the signal to reduce noise, FFT-based PSD provides a direct computation with higher frequency resolution which may introduce more variability due to the lack of averaging. Both methods use the same spectral characteristics, which confirms the validity of our results and ensures that the observed EEG slowing in Alzheimer's patients is a strong finding.

First we define the function `compute_psd_fft()`, which calcluates the PSD by applying the FFT to the EEG signal, and then use `plot_PSD_fft()` to visualize the FFT-based PSD for each EEG channel (Fp1, Fp2, F3). This provides a frequency-domain representation of brain activity and allows us to compare spectral differences between Alzheimer's patients and control subjects.

[12]:
```
def compute_psd_fft(signal, fs):
    N = len(signal)
    fft_vals = np.fft.rfft(signal)
    fft_freqs = np.fft.rfftfreq(N, d=1/fs)
    psd = (np.abs(fft_vals) ** 2) / N
    return fft_freqs, psd
```

[13]:
```
freqs_Fp1_AD, psd_Fp1_AD = compute_psd_fft(df_AD_FIRfiltered["Fp1"].values, F_s)
freqs_Fp1_control, psd_Fp1_control =␣
 ↪compute_psd_fft(df_control_FIRfiltered["Fp1"].values, F_s)
```

```
freqs_Fp2_AD, psd_Fp2_AD = compute_psd_fft(df_AD_FIRfiltered["Fp2"].values, F_s)
freqs_Fp2_control, psd_Fp2_control =␣
 ↪compute_psd_fft(df_control_FIRfiltered["Fp2"].values, F_s)

freqs_F3_AD, psd_F3_AD = compute_psd_fft(df_AD_FIRfiltered["F3"].values, F_s)
freqs_F3_control, psd_F3_control = compute_psd_fft(df_control_FIRfiltered["F3"].
 ↪values, F_s)

fig, axes = plt.subplots(3, 1, figsize=(8, 8), sharex=True)

# Fp1
axes[0].plot(freqs_Fp1_AD, psd_Fp1_AD, label="Alzheimer", color="red", alpha=0.
 ↪8)
axes[0].plot(freqs_Fp1_control, psd_Fp1_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[0].set_ylabel(r"PSD ($muV^2$/Hz)")
axes[0].set_title("Power Spectral Density - Fp1")
axes[0].legend()
axes[0].grid(linestyle="--", alpha=0.6)

# Fp2
axes[1].plot(freqs_Fp2_AD, psd_Fp2_AD, label="Alzheimer", color="red", alpha=0.
 ↪8)
axes[1].plot(freqs_Fp2_control, psd_Fp2_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[1].set_ylabel(r"PSD ($muV^2$/Hz)")
axes[1].set_title("Power Spectral Density - Fp2")
axes[1].legend()
axes[1].grid(linestyle="--", alpha=0.6)

# F3
axes[2].plot(freqs_F3_AD, psd_F3_AD, label="Alzheimer", color="red", alpha=0.8)
axes[2].plot(freqs_F3_control, psd_F3_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[2].set_xlabel("Frequency (Hz)")
axes[2].set_ylabel(r"PSD ($muV^2$/Hz)")
axes[2].set_title("Power Spectral Density - F3")
axes[2].legend()
axes[2].grid(linestyle="--", alpha=0.6)


plt.xlim(0, 15)
plt.tight_layout()
plt.show()
```



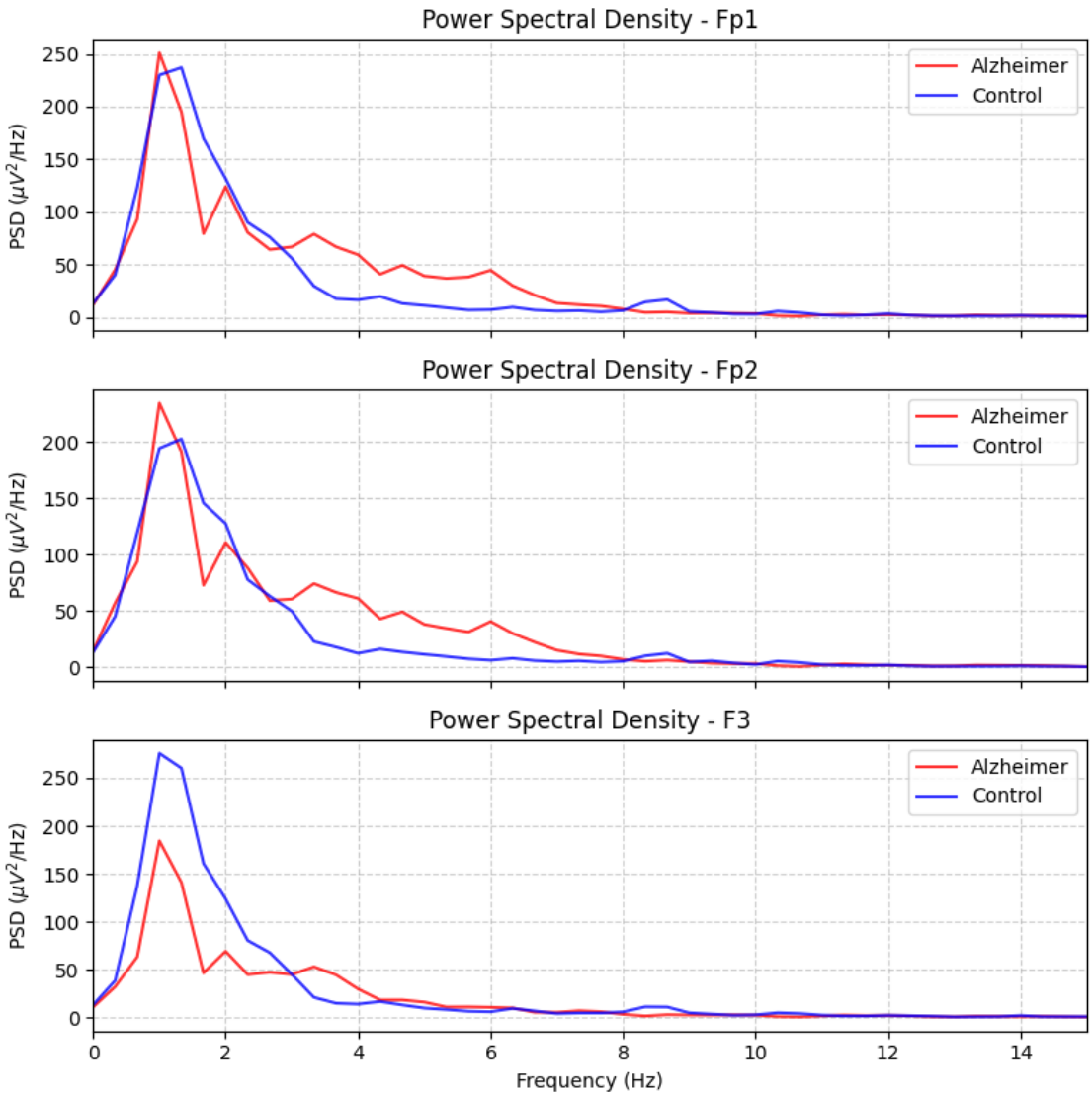
4.2 Welch's Method

To analyze the and compare the EEG signals from Alzheimer's patients and control subjects, we do a Power Spectral Density (PSD) analysis. This will show us how power is distributed across different frequencies, revealing key features related to brain activity. To estimate the PSD, we use **Welch's Method**, which reduces noise and provides a smoother estimate by averaging multiple segments of the signal. This allows us to compare the power across different frequency bands while minimizing variability.

We'll first create a function to calculate the PSD and plot the PSD for all 3 EEG channels (`Fp1`, `Fp2`, `F3`).

[14]:
```
nperseg = 1500

freqs_Fp1_AD, psd_Fp1_AD = welch(df_AD_FIRfiltered["Fp1"].values, fs=F_s,␣
 ↪nperseg=nperseg)
freqs_Fp1_control, psd_Fp1_control = welch(df_control_FIRfiltered["Fp1"].
 ↪values, fs=F_s, nperseg=nperseg)

freqs_Fp2_AD, psd_Fp2_AD = welch(df_AD_FIRfiltered["Fp2"].values, fs=F_s,␣
 ↪nperseg=nperseg)
freqs_Fp2_control, psd_Fp2_control = welch(df_control_FIRfiltered["Fp2"].
 ↪values, fs=F_s, nperseg=nperseg)

freqs_F3_AD, psd_F3_AD = welch(df_AD_FIRfiltered["F3"].values, fs=F_s,␣
 ↪nperseg=nperseg)
freqs_F3_control, psd_F3_control = welch(df_control_FIRfiltered["F3"].values,␣
 ↪fs=F_s, nperseg=nperseg)

# Create subplots for each channel
fig, axes = plt.subplots(3, 1, figsize=(8, 8), sharex=True)

# Plot Fp1
axes[0].plot(freqs_Fp1_AD, psd_Fp1_AD, label="Alzheimer", color="red", alpha=0.
 ↪8)
axes[0].plot(freqs_Fp1_control, psd_Fp1_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[0].set_ylabel(r"PSD ($\mu V^2$/Hz)")
axes[0].set_title("Power Spectral Density - Fp1")
axes[0].legend()
axes[0].grid(linestyle="--", alpha=0.6)

# Plot Fp2
axes[1].plot(freqs_Fp2_AD, psd_Fp2_AD, label="Alzheimer", color="red", alpha=0.
 ↪8)
axes[1].plot(freqs_Fp2_control, psd_Fp2_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[1].set_ylabel(r"PSD ($\mu V^2$/Hz)")
axes[1].set_title("Power Spectral Density - Fp2")
axes[1].legend()
axes[1].grid(linestyle="--", alpha=0.6)

# Plot F3
axes[2].plot(freqs_F3_AD, psd_F3_AD, label="Alzheimer", color="red", alpha=0.8)
axes[2].plot(freqs_F3_control, psd_F3_control, label="Control", color="blue",␣
 ↪alpha=0.8)
axes[2].set_xlabel("Frequency (Hz)")
axes[2].set_ylabel(r"PSD ($\mu V^2$/Hz)")
```

```
axes[2].set_title("Power Spectral Density - F3")
axes[2].legend()
axes[2].grid(linestyle="--", alpha=0.6)

# Adjust layout
plt.xlim(0, 15)
plt.tight_layout()
plt.show()
```



5 Conclusion

Our preliminary analysis of representative EEG recordings from the Miltiadous et al. (2023) dataset reveals that the healthy control's EEG consistently exhibits a prominent alpha peak in the 8–12 Hz range, whereas the EEG from an Alzheimer's disease (AD) patient shows a significantly attenuated alpha-band component with a relative shift toward lower frequencies. When compared with the group-level analyses presented in the Miltiadous et al. paper—derived from a large dataset of 88 subjects—there is a clear convergence of findings. The paper demonstrates that AD patients have reduced relative alpha power compared to healthy controls; after rigorous preprocessing and spectral estimation (using techniques such as Welch's method to compute the power spectral density), AD patients consistently show a decrease in alpha-band power and, in some cases, an increase in slower rhythms (e.g., theta power), reflecting diminished neural synchrony.

In our analysis, the healthy control's spectrum shows a well-defined alpha peak that aligns with the typical EEG signature of healthy resting-state activity, while the AD subject's spectrum lacks a robust alpha peak, suggesting that the neural networks responsible for generating these oscillations may be compromised. These observations mirror the global pattern seen in the paper, where the relative alpha power is consistently lower in the AD group across the entire dataset—a phenomenon widely documented in the literature as a hallmark of Alzheimer's disease, reinforcing this association.

Furthermore, the similarity between our representative analysis and the paper's group-level results indicates that the frequency band differences are not isolated occurrences but reflect a robust, global alteration in the EEG dynamics of AD patients. This supports the potential of alpha-band power as a reliable non-invasive biomarker for Alzheimer's disease. Extending our analysis to the full dataset would likely reveal statistically significant differences in alpha power between AD patients and healthy controls, as demonstrated by the comprehensive heatmaps and classification benchmarks in the paper. Overall, our initial findings, together with the published results, support the hypothesis that reduced alpha-band power is a global feature of the resting-state EEG in Alzheimer's disease.