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'

[9]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.signal import butter, filtfilt

np.random.seed = 118
```

```
F_s = 500
```

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

[10]:
```
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()
```

[10]:

	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

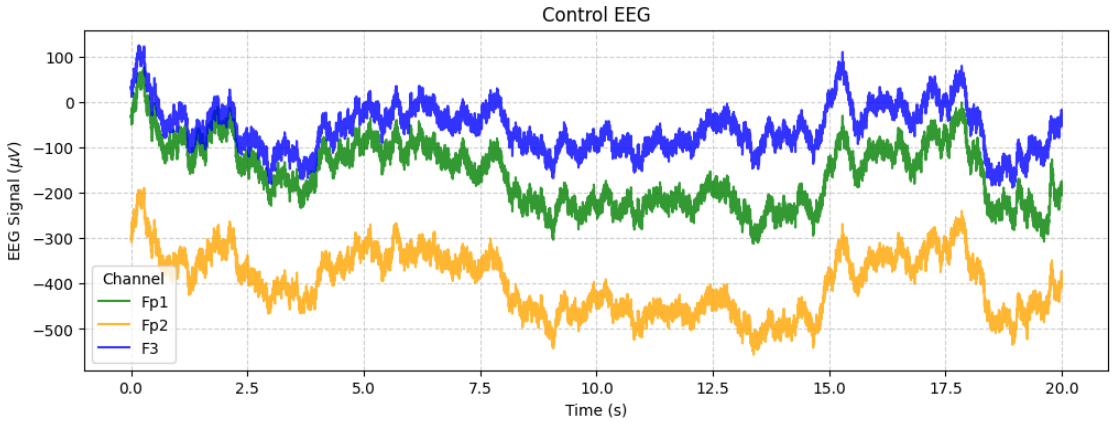
[11]:
```
df_AD *= 1e6
df_control *= 1e6
df_AD.head()
```

[11]:

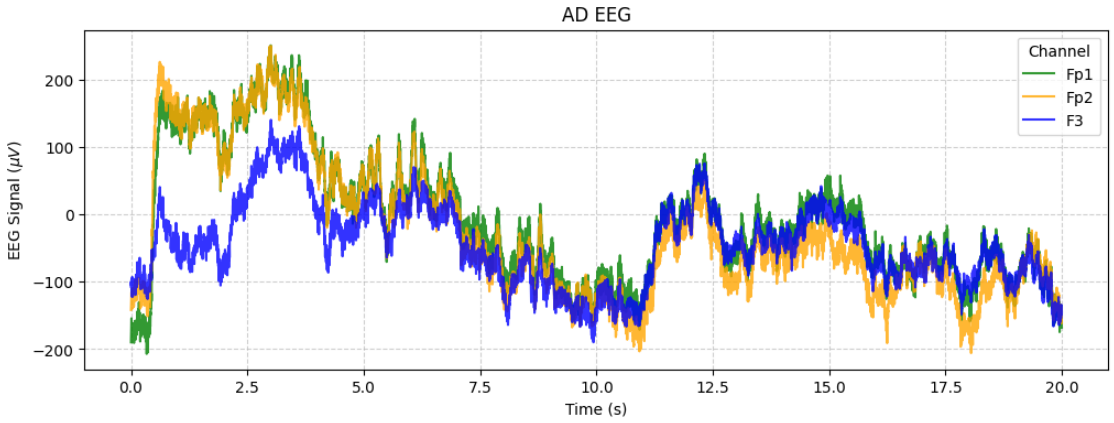
	Fp1	Fp2	F3
0	-189.892563	-141.845688	-107.373039
1	-180.419907	-137.353500	-100.048820
2	-166.992172	-135.058578	-105.761711
3	-160.205063	-132.958969	-105.322258
4	-159.326157	-124.462883	-104.150383

Display the raw EEG data of two subjects.

[12]:
```
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")
```



[13]:
```
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:

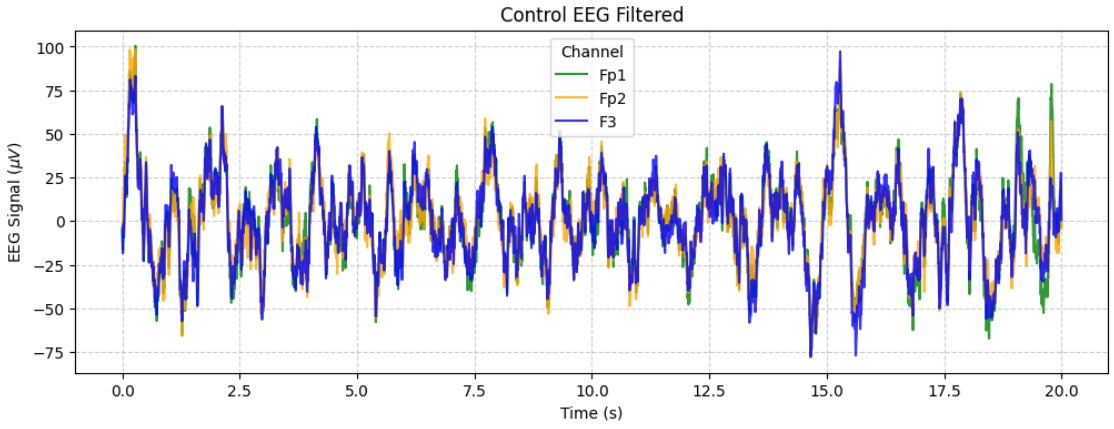
> First, a Butterworth band-pass filter 0.5-45 Hz was applied and the signals were re-referenced to A1-A2. Then, the Artifact Subspace Reconstruction routine (ASR) which is an EEG artifact correction method included in the EEGLab Matlab software was applied to the signals, removing bad data periods which 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 were only given 20-second data of 2 subjects with 3 channels, we are unable to perform complex cleaning methods like ICA. Luckily we can still construct a butter band-pass filter, which will effectively remove slow drifts and high-frequency noise.

[14]:
```
import numpy as np
import pandas as pd

def butter_bandpass_filter(data, lowcut, highcut, fs, order=4):
    nyquist = 0.5 * fs
    low = lowcut / nyquist
    high = highcut / nyquist
    b, a = butter(order, [low, high], btype='band', analog=False)
    return filtfilt(b, a, data)


lowcut = 0.5
highcut = 45

for col in df_control.columns:
    df_control[col] = butter_bandpass_filter(df_control[col], lowcut, highcut,␣
 ↪F_s)

for col in df_AD.columns:
    df_AD[col] = butter_bandpass_filter(df_AD[col], lowcut, highcut, F_s)
```

[15]:
```
plot_EEG(df_control, "Control EEG Filtered")
```



[16]:
```
plot_EEG(df_AD, "AD EEG Filtered")
```