EEG Signal Analysis for Movement Imagery Classification

Abstract: In brain-computer interfaces (BCIs), using different neural activities to control the external devices is quite a complicated task. For that, we need to find the distinctive characteristic in the EEG signal associated with motor imagery to use that difference as the control command for external devices. I used average ERP for time-domain analysis, and FFT, spectrogram, and power spectral for the frequency domain analysis. Different power spectral values could be seen in the delta band between left hand, right hand, both feet, and tongue movement imagery and whereas in delta and alpha band it was not discernible. In the spectrogram, power spectral could be seen changing with time within an average ERP between the different tasks. Opposite to my hypothesis that the difference can be seen in all three bands, I concluded that the left hand, right hand, both feet, and tongue movement imagery can be differentiated in delta band but not in the delta and alpha band.

Introduction: Brain-Computer Interfaces (BCIs) provide a direct connection between the human brain and a computer, which captures the neural activities associated with external stimuli or mental tasks without involving nerves or muscles. Then the interpretation of the brain activities recorded can be used to create a command to carry out specific tasks such as controlling robotics arms, wheelchairs, computers, etc. Even though there are methods such as functional magnetic response imaging (fMRI) or electrocorticography (ECoG) or magnetoencephalogram (MEG), electroencephalogram (EEG) is mostly used for BCIs due to its non-invasive procedure, cost feasibility, better time resolution, and ease of use. Event-related potentials (ERP) and sensorimotor rhythms (SMR) are two of the most used potentials to build EEG-based BCI systems. In SMR-based systems, neural activities associated with delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), and beta (13-30 Hz) rhythms are observed. These rhythms are easily readable in both healthy and disabled people with neuromuscular injuries. Also, the event-related potentials are brain response that is the direct result of specific sensory, cognitive, or motor event. I hypothesize that during the motor movement or imagery, neural activity associated with the specific task is differentiable from each other in the delta, theta, and alpha band. Motor imagery is a cognitive process in which a subject imagines that he/she performs a movement without actually performing the movement. From the motor imagery EEG signals, we can extract different features such as statistical, time-domain, frequency-domain, wavelet, etc. Extracting those features is a tedious task that requires removing artifacts from the EEG data. EEG signals contain many types of artifacts[1] such as ocular, muscle, cardiac or instrumentation artifacts due to their non-invasive nature of data acquisition. Extracting EEG signals without noise is, thus, a significant step of preprocessing the data. Once those features from clean EEG signals are extracted, then they can be used to interpret the association between motor imagery and neural activity.

Methods and Analysis: For this project, I used the publicly provided dataset called BCI competition IV 2a dataset[2]. This dataset consisted of EEG data from 9 subjects recorded using 22 Ag/AgCl electrodes with an international 10-20 system electrode placement system. It was a cue-based BCI paradigm of four different motor imagery tasks: the imagination of movement of 1) the left hand 2) right hand, 3) both feet, and 4) tongue. There were two sessions recorded for two different days for each subject with each session consisting of 6 runs separated by short breaks. At the beginning of each session, electrooculography (EOG) was recorded to estimate the effect of EOG in EEG signals. One run consists of 48 trials for each of the four possible tasks, totaling 288 trials per session. Each trial consisted of three phases (figure 1): 1) at time start of a trail (t = 0s), a fixation cross appeared on the black screen, 2) after two seconds (t = 2s), a cue as an arrow pointing either to the left, right, down, or up, corresponding to one the four tasks, appeared and stayed on the screen for 1.25 seconds. This cue guided the subject to person the indicated motor imagery task. The subjects were instructed to carry out the motor imagery task until the fixation cross disappeared from the screen at t = 6s. It is illustrated in Figure 1.

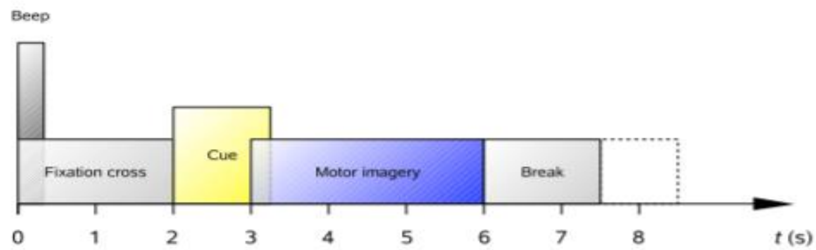

Figure 1: Timing Scheme for each trial

All the signals were recorded with the left mastoid serving as a reference and the right mastoid as the ground. The signals were sampled at 250 Hz, band-pass filtered between 0.5 Hz and 100 Hz, and notch filtered with 50 Hz frequency to remove electrical noise during the recording. But for this project, I will be using only one run from one session for the first subject, which will consist of 48 trials (12 trials for each task) for 4 channels (FCz, C3, Cz, C4). And my primary time of interest would be from 2 seconds to 6 seconds of a trial, the reason being the actual motor imagery happens after the cue starts because of the assumption that the EEG pattern is similar during the fixation cross display (t=0 to t = 2 secs).

For preprocessing of the EEG data, event-related potential (ERP), EEG signal for 2 to 6 seconds of trial, associated with the specific motor imagery task or event was used. After time-domain inspection, Gaussian distributed noise was removed by calculating the average event-related potential for all the classes and all 4 channels; that happens because at each time point there will be noise that will have a normal distribution with mean zero. But practically, it tends to zero but not exactly zero. Any clear difference couldn't be visually inspected in the average ERP. Then, fast Fourier transform (FFT) to see the frequency magnitude distribution in the frequency axis. FFT computes the discrete Fourier transform (DFT) of a sequence which converts the signal (mostly time domain) to a representation in the frequency domain. Since our signal has a sampling frequency of 250 Hz, the highest frequency component that occurs in our EEG signal is 125 without aliasing. Since our number of samples will be 1000 (4 seconds multiply by 250), we would get 1000 DFT points as output for each trial with a frequency resolution equal to 0.25 Hz (250/1000). And the first 501 points would be the positive half of the frequency domain. The first and 501st points will not have symmetry whereas the other 1 to 500th points will have an even symmetry. Infinite impulse response filter (IIR) with the degree of 8 with the cut-off frequency of 12 Hz was used to remove the high-frequency noise and signal which seemed insignificant after visually inspecting the average ERP's FFT. The selection of the IIR filter was based on the two facts: IIR requires less memory and phase response is not primary analysis for our project. Since I don't focus on the phase of the signal, I used *filtfilt* function of MATLAB which performs zero-phase filtering by processing the input data in both forward and backward directions. I specifically chose 12 Hz because I wanted to check the frequency-domain power spectra at delta (1-3 Hz), theta (4-7 Hz), and alpha (8 -12 Hz) bands. I also looked at the spectrogram of the filtered average ERP. Spectrogram gives us the time and frequency domain representation in a single plot which helps us to analyze the variation in the frequency domain changes with time. I used Hamming window of length 125 samples with 100 points overlapping and I used 250 number of points FFT to calculate the frequency-domain power spectral density. I used the *spectrogram* function of MATLAB. Once the spectrogram is visually inspected, I calculated the power spectrum in delta, theta, and alpha frequency band and compared them with each other in terms of classes and for each channel. For delta band, power spectral was calculated using the FFT points from 5th (corresponds to 1 Hz) to 13th (corresponds to 3 Hz) point; for theta band, FFT points from 17th (corresponds to 4 Hz) to 29th (corresponds to 7 Hz) point; and for the alpha band, FFT points from 33rd point (corresponds to 8 Hz) to 49th (corresponds to 12 Hz) point. And the interpretation will mainly focus on the differentiation in the results per class and channel.

Results: In the results, I will try to show as much as possible for all the channels. I will start with the raw EEG signals for 48 trials from 2 seconds to 6 seconds of each trial.

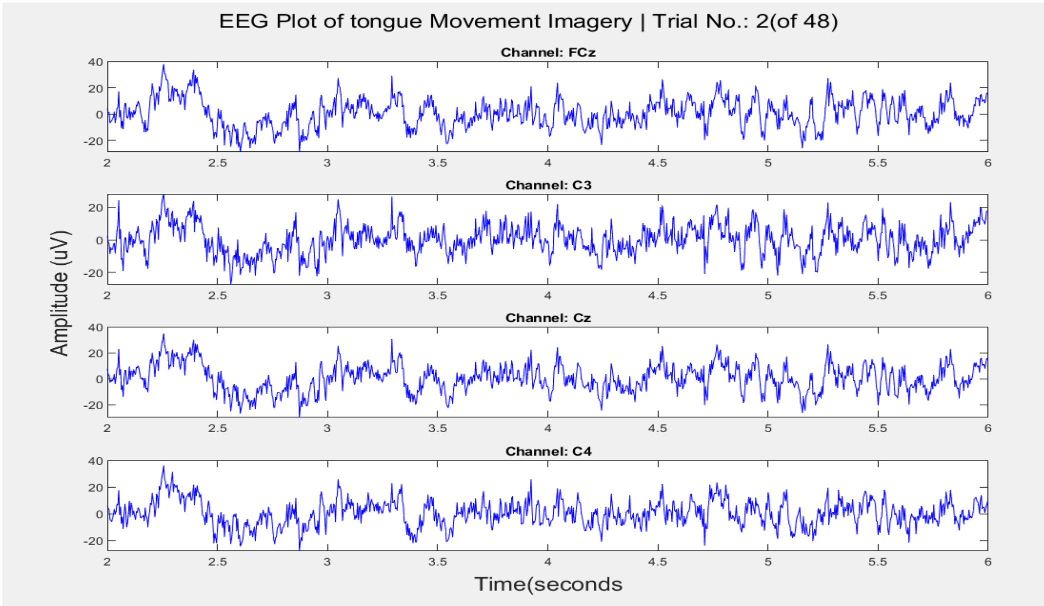

Figure 2: EEG Signals of 4 channels for first 'tongue' movement imagery task

Figure 2 shows the EEG plots of 4 different channels from 2 seconds to 6 seconds of the 2nd trial which is a tongue movement imagery task. There were 48 of these images to visually inspect for 48 different trials. We can see that the EEG looks quite the same for all the channels. The same kind of pattern for the first 1 second could be seen in all the trials, which will be more clear in the average ERP. Then I average all the 12 trials of each task for each channel.

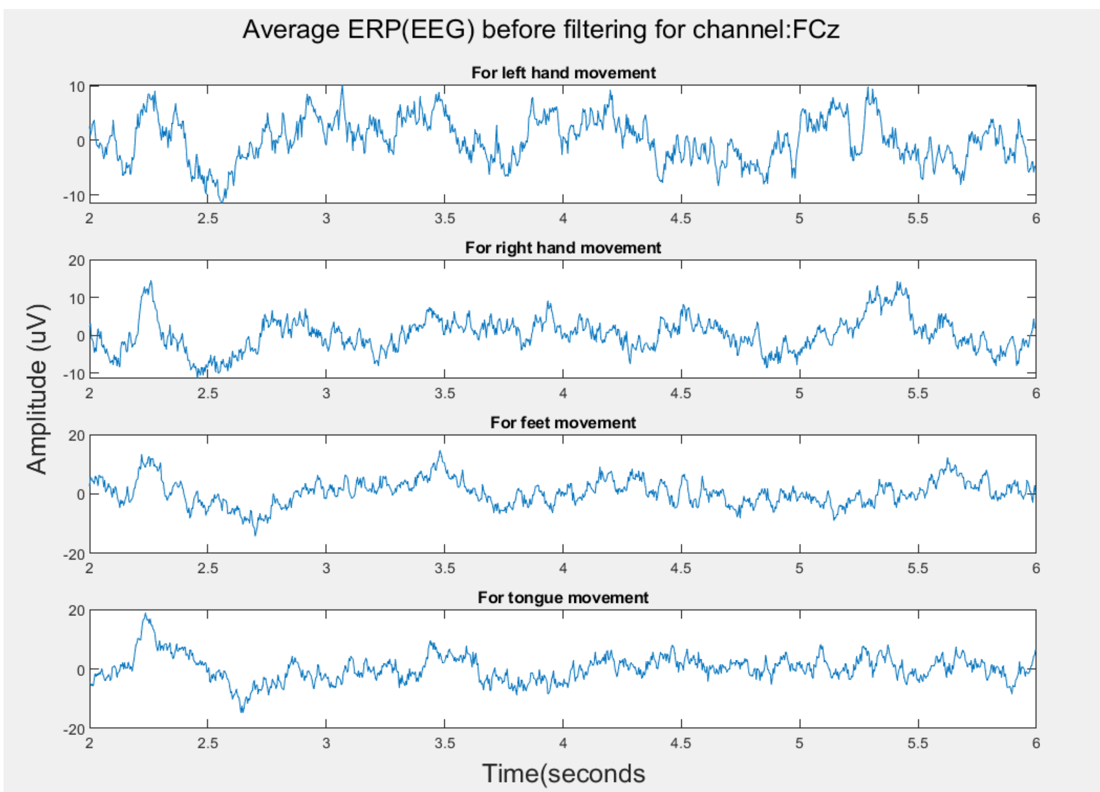

Figure 3: Average ERP of channel FCz for all 4 different tasks.

Figure 3 shows the average ERP of the channel FCz of different imagery tasks. In the first 0.5 seconds after the cue starts, same kind of EEG can be seen which tells us that the cue has the same kind of effect on the EEG for almost every trial. There were 4 of these plots to analyze for all 4 channels.

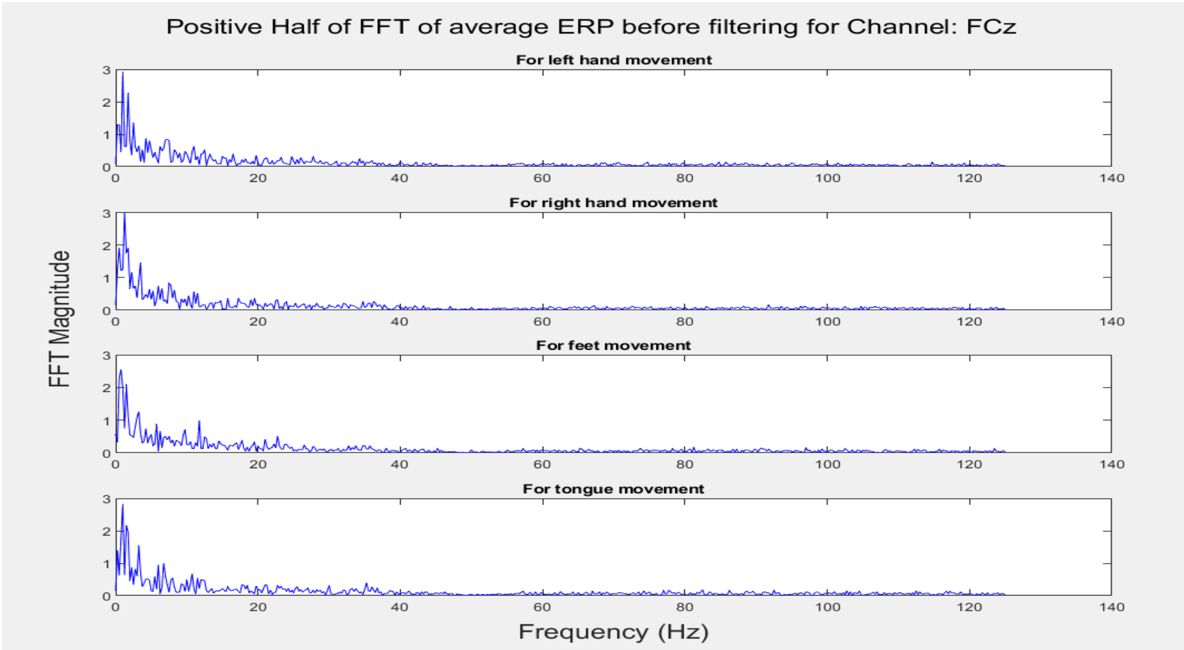

Figure 4: FFT Plot of Average ERP before filtering for Channel FCz

Figure 4 shows the amplitude spectrum for different frequency components of average ERP before filtering for channel FCz. We can see that FFT for different imagery tasks is evidently different in the higher frequencies but there are some variations in the lower frequency components. The plot has the highest component at 125 Hz since our sampling frequency is 250 Hz. When calculating positive half FFT, I doubled the 2^{nd} to 500^{th} points out of 501 points because of the even symmetry.

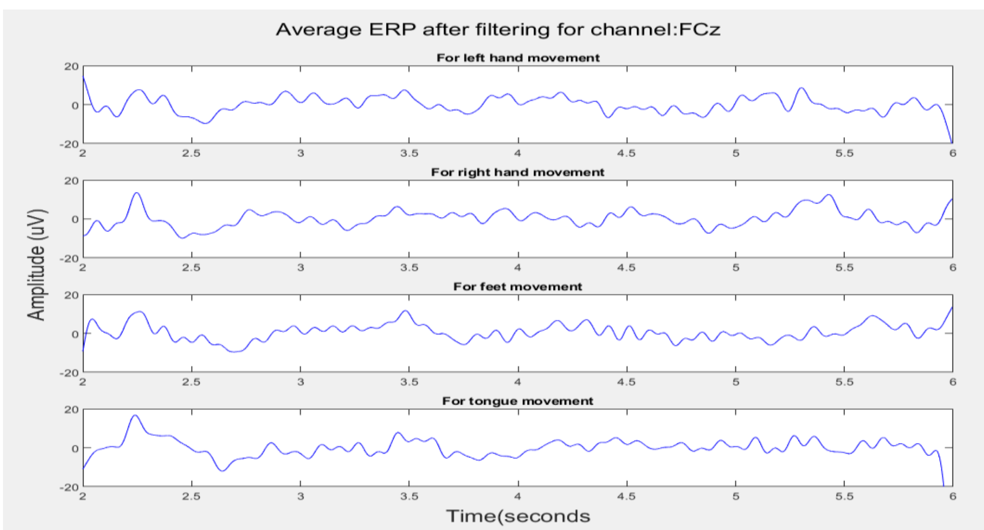

Figure 5: Average ERP After Filtering for channel FCz for all 4 different tasks.

Figure 5 shows the average ERP, after low-pass filtering with cut-off frequency 12 Hz, for channel FCz (figure 3) for 4 different movement imagery tasks. Once the average ERP is low pass filtered we can see the smoother signal and can also see some of the differences after 3 seconds of trial. I had 4 of these plots for 4 different channels. Their results were not so much different for all the channels. Figure 6 shows the spectrogram plot of filtered average ERP for channel FCz. The spectrogram gives the value of power spectral density (PSD). We can see that the PSD is changing with time and then settles down in the later phase of the trial. Then I calculated the power spectral in the three frequency bands for all the channels.

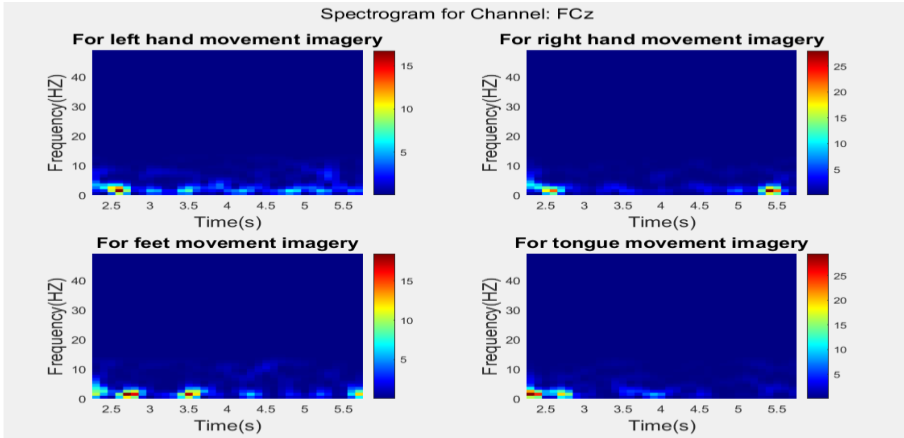

Figure 6: Spectrogram plots for 4 different tasks for FCz Channel

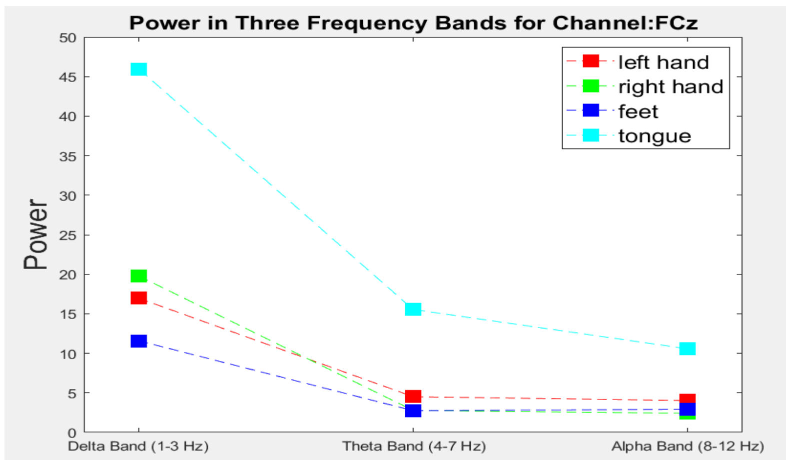

Figure 7: Power Spectral in delta, theta, and the alpha band for channel FCz

Figure 7 shows the power spectral in three frequency bands for channel FCz. Figure 7 is one of the 4 images for 4 different channels. We can see the difference in the delta band for different movement imagery tasks; whereas in theta and alpha, the only tongue is quite different from the other but the other 3 are quite close to each other. Similar results could be seen for the other 3 channels as well.

Interpretation of Results and Conclusion: From the above result, we could see that the EEG signal contained a lot of high-frequency components which include EEG and the noises. To remove that, I used averaging methods to suppress those noises which helped me to get a clearer EEG signal but still that was not clear enough; that is because the Gaussian distributed noise does not only happen in high frequency but also low frequency. Then low pass filter was used in the average ERP to remove the high-frequency components, and with that, it also removed the high-frequency noise as well. From that, we could see better ERP. In the spectrogram after low pass filtering, we could see the changes in the PSD with time, which describes the motor imagery task around 3.5 to 4 second period for each trial. With the help of power spectral in three bands, what I concluded is that there is a significant difference in the delta band in terms of power spectral but not differentiable in the theta and alpha between the 4 motor imagery tasks.

References:

1 Jiang, X., Bian, G.-B. & Tian, Z. Removal of Artifacts from EEG Signals: A Review. *Sensors (Basel)* **19**, 987, doi:10.3390/s19050987 (2019).

2 C. Brunner, R. L., G. R. Muller-Putz, A. Schlogl, and G. Pfurtscheller. (ed Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces)) (http://www.bbci.de/competition/iv/, 2008).