BCI Project 3

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Introduction

Various studies have shown that electroencephalogram (EEG) based brain computer interfaces (BCIs) can be used to restore normal hand function to people who have lost the ability to move their hand(s) normally due to an event such as a stroke [1]. In *A full upper limb robotic exoskeleton for reaching and grasping rehabilitation triggered by MI-BCI* [2], Barsotti et al. propose an upper-limb exoskeleton that is integrated with a BCI. This device enables people who have experienced a stroke and subsequently lost the ability to perform hand movements normally on their own to perform those hand movements in a normal fashion through detecting the person's desired movement through EEG, then translating that desire into controlled movement of the exoskeleton. This process can aid in re-establishing the person's ability to perform more normal movements independently over time through stimulating impaired sensorimotor brain areas and thus leveraging neural plasticity- the central nervous system's (CNS) ability to adapt and reorganize in response to stimuli.

Our study aims to further improve devices such as the exoskeleton described prior by analyzing EEG signals evoked when a subject lifts their hand or touches an object with their finger. To perform this analysis of EEG data, we utilized a dataset derived from a study by Luciw et al., *Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction* [3]. In this study, EEG and EMG data was collected while each participant reached for an object, grasped the object, held the object for a few seconds, then replaced the object back on a surface.

In the following sections of this paper, we will describe the analysis we performed and the specific methodology used to carry out that analysis including a detailed description of the dataset, the results of our analysis, a discussion of how this work could be used to improve BCIs for movement rehabilitation, and a discussion of challenges that stand in the way of bringing BCIs for movement rehabilitation to market. Lastly, we will outline the contributions that each group member has made to this project.

Methods

Our analysis was performed on a dataset from the study *Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction by Luciw et al.* [3]. In this study, twelve right-handed participants (8 of which were female, the gender of the remaining participants was not specified) were instructed to sit close to a table with their shoulders relaxed and right elbow higher than their right wrist. Participants were instructed to ensure their forearms did not touch the table and to keep their left arm close to their waist during the task. Participants were instructed prior to the experiment that when a red light was displayed, they were to reach out and lift the object, then grasp the object with their thumb and index finger and lift the object approximately 5 cm from the table. Participants were instructed to then hold the object in a designated area until the light turned off, at which point they were to place the object back on the table, place their arm next to their body, and rest their hand on a specific surface. Participants were given earplugs to wear throughout the duration of the task and the object to be grasped and lifted was partially visible to participants during trials. To record the EEG data, an EEG cap was used along with a BrainAmp EEG signal amplifier. BrainAmp sampled at 5kHz and applied a band-pass filter on each channel to restrict EEG data recordings to be within 0.016 to 1000 Hz, then data was downsampled to 500 Hz and a low-pass filter was used to prevent aliasing. No artifact rejection was applied to the EEG signals within the original study, implying that artifacts related to blinks or eye movement could still be present.

To begin our analysis, we separated EEG data into epochs beginning 1.5 seconds prior to the onset of each event and ending .85 seconds after the event onset. Epochs were structured in this way to ensure we capture the Bereitschaftspotential (also referred to as readiness potential) preceding movement and surrounding subtle fluctuations in EEG data as well as the beta rebound following an event. The readiness potential is a negative slow cortical response (SCP) that usually begins .5 to 1 second prior to a self-initiated movement while the beta rebound is an increase in beta range frequency oscillations within the electric field over the sensorimotor cortex after movement. The amplitude and topography of the readiness potential SCP is influenced by the type of movement that is about to occur [4]. We were interested in capturing this important feature of EEG data to see if we can reliably detect when a movement should begin and what type of movement it should be. The readiness potential likely reflects activity in the supplementary motor area and in the primary motor and sensory cortices [4], so we chose to focus our analysis on channels Fz, C3, and Cz as they are positioned over the supplementary motor area, primary motor cortex, and primary somatosensory cortex respectively. C3 is included, but not C4 because each subject utilized their right hand in the dataset that we were working with. Additionally, we included channel Pz in our analysis to explore whether useful insights can be derived through analysis of activity in the parietal region because it relates to sensorimotor integration.

Data Processing

Filtering

In our analysis, since we focus on brain signals representing sensorimotor activities, a Hann band pass filter with a passband of 8-30 Hz is applied to the raw EEG data. was used. This frequency range is selected to include Beta rhythms and Mu rhythms, which are critical for studying these activities.

Independent Component Analysis (ICA)

After applying filters, ICA was performed to find and remove artifacts. FastICA is used to create mixing and unmixing matrices of EEG data in each series. A matrix has 32 components (column) and 32 features (row). Total 96 pairs (12 subject x 9 series) of a mixing and an unmixing matrices are created.

For each mixing matrix, spatial topographies of 10 most variance components are plotted to visually inspect. Components exhibiting high magnitude weights and representing abrupt changes or severe asymmetries were identified and removed from the EEG data to minimize artifact influence.

Analysis of Statistical Significance

As part of our analysis, we attempted to determine whether a difference was present between ERPs during two important events – when the subject's hand began to move and when a digit first touched the object. If this difference existed, then it could be used to inform a BCI controlling a mechanical prosthetic on when to perform the appropriate steps to grasp the object. To achieve this, we compared the epoched data for these two events on each channel for each subject and series. For each pair of samples in the two events, we performed a two sample independent t-test. We selected this test because it gives accurate results even when the samples have unequal variance. Since we were interested in either a positive or a negative difference between the two, this was a two-sided test. We performed it at the α=0.05 significance level. Results from this test were plotted along with the ERPs for each subject and series.

Results

Statistical Significance

The results of the statistical significance analysis were ambiguous. In many cases, a statistically significant difference between ERPs appeared between 0 and 0.25 seconds after event onset, as observed in the plot below. This pattern occurred most consistently in the Cz channel, but was observed in the Fz, C3 and Pz channels as well.We noted this trend in many subjects and series. However, the difference did not occur universally. There were observations where this gap was not large enough to be called statistically significant, and in other cases statistically significant differences occurred before the event as well.

Figure 1. ERPs for events "Hand Start" and "First Digit Touch" for subject 5, series 1. Blue dots represent time points where statistically significant differences in ERPs were found.

Discussion

Based on the statistical analysis of ERP differences that we performed, the Cz channel, with potential contributions from the Fz, C3 and Pz channels, could be used to distinguish when a BCI should reach for or touch a finger to an object based on ERP signals. However, due to the inconsistent nature of this trend, other control mechanisms might need to be incorporated to complement this method. In addition, the slight delay between the events and the statistically significant difference would need to be considered, since this would slow down output slightly.

These findings could be used to improve the performance of existing BCI devices for normal movement restoration in terms of accuracy and speed. Through understanding that significant differences in readiness potentials and beta rebounds related to reaching for an object and touching an object with a finger exist, BCI algorithms can be tailored to interpret this activity more effectively and thus make more accurate predictions in less time. Additionally, understanding in which channels those differences are most prominent and which filtering methods are effective for pre-processing data can further improve these algorithms. BCI devices for normal movement restoration can benefit users who have lost normal motor function in a hand, such as those who have experienced a stroke, by guiding the user's hand through the normal motor pattern, stimulating the impaired sensorimotor brain area and thus leveraging neural plasticity to re-train the brain to ultimately allow the user to perform more normal motor patterns with their own hand independently.

To produce predictions, our BCI needs to perform the analysis outlined in the following flowchart in real-time:

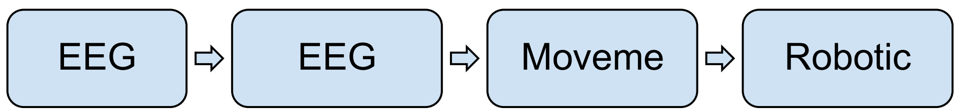

Figure 2. Flowchart of real-time analysis for our BCI.

EEG data acquisition will involve collecting raw EEG signals from electrodes placed on a user's scalp. EEG processing involves the specific methodology discussed in the data processing sub-section of the methods section of this paper as well as feature selection or extraction through selecting to use signals that are important for capturing the user's intention for how to move their hand. This will involve selecting EEG signals corresponding to specific channels such as Fz, C3, C4, Cz, and Pz as they are positioned over the supplementary motor area, primary motor cortex, primary somatosensory cortex, and related to sensorimotor integration respectively. Additionally, it is possible that feature selection could be further refined through performing spectral feature analysis as described in the challenges section below. Next, a machine learning classifier will be implemented to predict the intended action based on the processed EEG data. Lastly, the robotic hand will move in accordance with the predicted action to guide the user's hand in a more normal movement pattern, re-training the brain to ultimately allow the user to perform more normal movements independently.

It is our hope that our work can ultimately be used to enhance the speed and accuracy of BCIs for movement rehabilitation. In the study performed by Barsotti et al. [2] mentioned in the introduction of this paper, it was found that the robotic exoskeleton had a mean correct classification rate of 82.51% and an average delay of 3.45 seconds between task presentation and device movement across three subjects. Accurately identifying the user's intention and executing that desired movement more quickly would be desirable as more accurate and immediate feedback would be more akin to the user initiating the movement on their own. Producing more accurate movements closer to when the user desired to initiate the movement could help to evoke neural plasticity more strongly, which in turn could result in more effective rehabilitation.

Conclusion & Challenges

Broadly, we found that statistically significant differences in ERPs related to a subject reaching for or touching a finger to an object do exist and that these differences are often found during the beta rebound following an event instead of within the readiness potential leading up to the event. However, these results were not consistent across all subjects and series. As motor activity tends to be spectral, further spectral feature analysis is warranted in order to optimize the BCI further. Statistically significant differences were most often found in the Cz channel. This channel, along with channels Fz, C3, C4 and Pz, requires further investigation to verify that the trend of statistical significance observed is not spurious, since it was not universally consistent.

Technical Challenges

Spectral Feature Analysis

In addition to ERPs analysis, potential solutions could be developed based on spectral feature analysis. For example, from a few visual observations, it was noted certain differences in power level from Fast Fourier Transform (FFT) around 15 Hz in epochs of two event types: 'HandStart' and 'FirstDigitTouch'. Further statistical analysis is required to confirm these differences. The process includes experimenting with various ranges of epochs. Success on further analysis could enhance identification of features of specific events.

Classifier

Utilizing ERPs and Spectral analysis, features of our data could be extracted and these features can be important data to build a machine learning classifier (ML) classifier which can complement a classifying method entirely depending on the difference in signal of ERPs or Frequencies. Since raw EEG data and processed data have spatial features, a Convolutional Neural Network (CNN) model would be a good choice. If there is not a great amount of data, a simple linear regression model can be used as well. This ML classifier can increase the accuracy significantly.

By addressing these significant challenges, we will be able to develop a more precise and robust event classifier for use in brain-computer interface (BCI) devices.

Ethical challenges

Responsibility

Regardless of accuracy of our BCI, an unexpected behavior could be caused by a prosthesis utilizing our BCI and it raises ownership and responsibility issues. If a life or a property was damaged by this prosthesis. In many cases, to determine how much the user's intention was reflected, and responsibility of this incident is at the user or a flaw of the device would be extremely tricky. A technique that can track all information about the device and bio-neural information of user, relieve this issue, but this could arise another ethical issue such as how close a BCI device can access to user's bio information

Efficacy

It remains unknown whether BCIs for movement rehabilitation such as the device we have described are more effective than traditional therapeutic rehabilitation methods [4]. This presents an ethical challenge for bringing this BCI to market; selling a device that is less effective or equally effective when compared to traditional methods could present financial and emotional harm. This is because users would need to spend money purchasing the device and would expect that investment to lead to significant improvements in their condition. If traditional therapeutic rehabilitation methods were just as effective or more effective, there would be little incentive for a user to purchase the device and if it were purchased without knowing this, the buyer could feel a sense of disappointment or that they have wasted resources. Therefore, additional research comparing the efficacy of BCIs for movement rehabilitation with the efficacy of traditional therapeutic methods is warranted and necessary before bringing this BCI to market.

Contributions

Alaina found the dataset and did preliminary research, Alaina and Yoonki worked together to develop the process for loading data, Alaina separated data into epochs, calculated ERPs, and chose which EEG channels to focus on for analysis, Yoonki did all filtering, component removal, and work with frequency and power spectra, and Ashley performed the analysis of statistically significant differences in ERPs between event types of interest. Initially we had stated that Ashley would develop a machine learning model to classify the subject's desired event based on their EEG data and Alaina would perform the analysis of statistically significant differences in ERPs between event types of interest, but we found that creating the machine learning model was beyond the scope of this project and subsequently reorganized our distribution of work.

References

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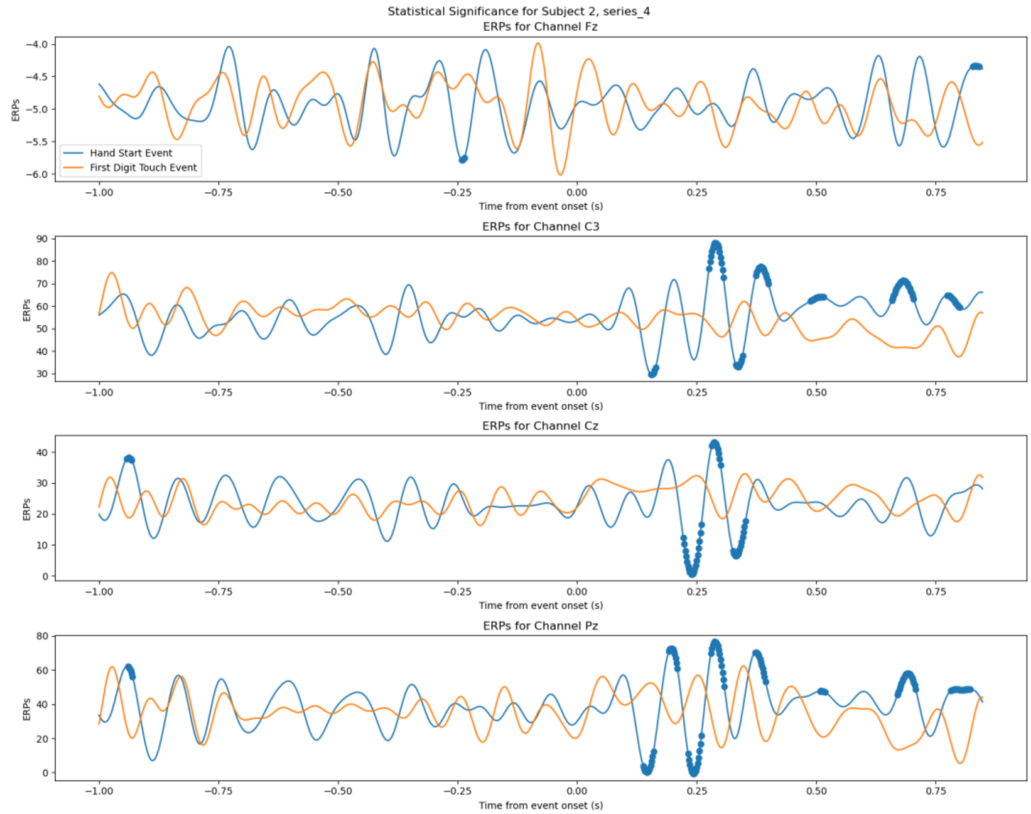
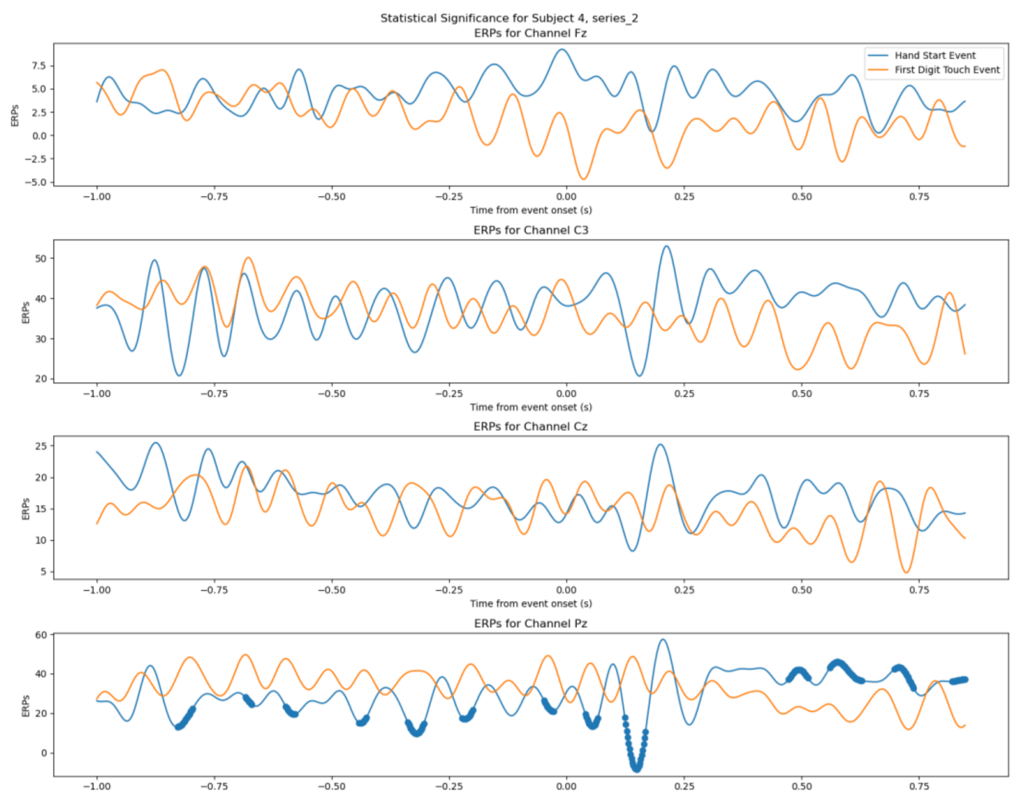
[2] Barsotti, Michele & Leonardis, Daniele & Loconsole, Claudio & Solazzi, M. & Sotgiu, Edoardo & Procopio, Caterina & Chisari, Carmelo & Bergamasco, M. & Frisoli, Antonio. (2015). A full upper limb robotic exoskeleton for reaching and grasping rehabilitation triggered by MI-BCI. 10.1109/ICORR.2015.7281174.
[3] Luciw, M., Jarocka, E. & Edin, B. Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction. Sci Data 1, 140047 (2014). https://doi.org/10.1038/sdata.2014.47
[4] Wolpaw, J., & Wolpaw, E. W. (2012). Brain-Computer Interfaces. Oxford University Press Academic US. https://bookshelf-activate.vitalsource.com/books/9780199921485

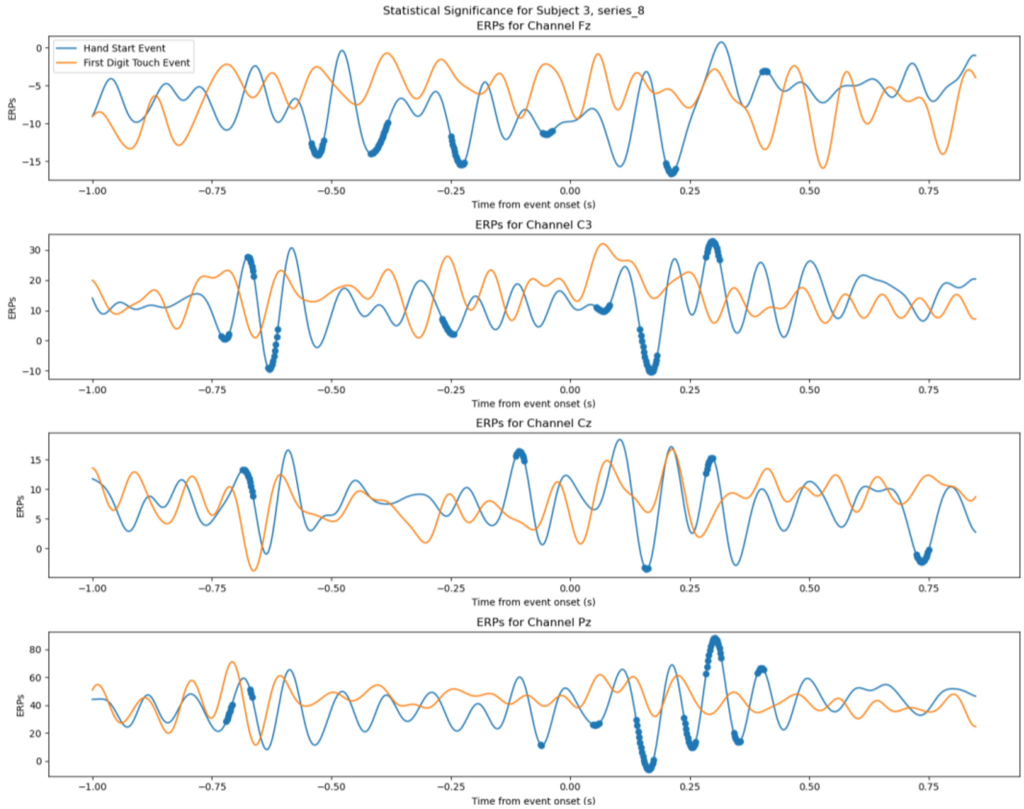
Appendix

Additional Statistical Significance Plot Supporting a Difference in ERPs



Statistical Significance Plots Contradicting a Difference in ERP





Statistical Significance for Subject 3, series_8
ERPs for Channel Fz
Hand Start Event
First Digit Touch Event
ERPs
Time from event onset (s)
ERPs for Channel C3
ERPs
Time from event onset (s)
ERPs for Channel Cz
ERPs
Time from event onset (s)
ERPs for Channel Pz
ERPs
Time from event onset (s)