**CMPS Capstone Milestone 1**

Optimizing EEG-Based Control: A Machine Learning Approach

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**Abstract**

1 in 50 Americans live with paralysis. Computers can interpret electroencephalogram (EEG) data in real-time to allow users to control devices in real-time. EEG data interpretation provides a new way for patients to practice autonomy and increases the accessibility of daily activities. However, current methods using EEG data require multiple, long training sessions, and once trained, they only work for a specific user. In this project, we seek to optimize the training process using new machine learning algorithms and techniques to decrease overall training time and increase the number of people a trained program will work on.

**Motivation**

Current solutions for paralysis patients focus primarily on using movements the person can still perform and translating those movements into directions for the wheelchair. These solutions exclude patient populations where movement cannot be performed or cannot be performed consistently, such as in cases of extreme paralysis, late-stage amyotrophic lateral sclerosis (ALS), or locked-in syndrome. Solutions for these are often limited, with current solutions mostly limited to trials using implanted devices. Another solution for this problem currently being developed is using eeg-controlled wheelchairs in order to allow people with these conditions to regain mobility and independence. The current state of the art is that while it can be done, the amount of training required to use the EEG takes a long time, and the algorithms for training do not transfer well between people once trained. Our approach will be to develop our model using a wide range of data and then use that baseline in order to speed up the process of training and to be able to transfer the EEG much better between people.

**Prior Art**

Prior work with EEG-based BCI control is sparse, but many applications involve solutions for those with mobility disabilities. For those with disabilities, tools like wheelchairs, mechanical arms, and prosthetic limbs are very important. BCI grants control over these devices to those who cannot utilize joysticks or controllers. Essentially BCI helps solve computer-human interaction problems. EEG is one of the most commonly used types of BCI because it does not require invasive techniques and can provide high temporal resolution.

A study by Huang, Zhang, Yu, He, and Li( 2019) found it possible to use EEG (motor imagery [MI] and electrooculography [EOG]) signals to control an assisted device. The study aimed to integrate a wheelchair and mechanical arm into an integrated system. Using this system, they planned for users to steer the wheelchair left and right using imagined hand motions and forward and backward using eye blinks and eyebrow movements. The mechanical arm would also utilize eye blinks and eyebrow movements, along with two cameras. For EEG signal processing, a supervised machine learning algorithm was implemented. This algorithm consisted of offline model training and an online classification process. “During MI offline training, participants performed random L or R hand movements as prompted on a screen. The recorded data was used to build a classifier and to calculate offline classification data,” Huang, Zhang, Yu, He, and Li( 2019). During the offline training, subjects completed a similar task with visual feedback. The subjects were asked to move a GUI bar on the screen during this task by performing the L/R hand MI task. The subjects who performed well during training were then used to hold a mobile movement experiment in which they were required to navigate obstacles, grasp bottles, and pass through doors. Their results found that utilizing EEG and EOG signals, a wheelchair and mechanical arm could be used together in an integrated system with high accuracy.

Another study by Jeong, Shim, Kim, and Lee (2020) aimed to control a robotic arm using EEG signals, but they took a deep learning approach in an attempt to recognize user intention better. The deep learning framework was a multi-directional CNN-BiLSTM network. “This approach was used to train multi-directional information per axis as pretraining and used the BiLSTM network for training relationships in the 3D space. They took an intra-subject approach in combination with this MDCBN, which led to dramatic BCI performance improvement for each subject,” Jeong, Shim, Kim, and Lee (2020). This study found that a deep learning approach to decoding EEG signals was practical. This study suggests that future studies improve the training environment so that there is less cognitive workload on subjects. “They also suggest using pre-trained decoding models to reduce the calibration time when using large amounts of EEG data or to design the training model using a few data samples." Jeong, Shim, Kim, and Lee (2020).

A study by Song, Cai, Yang, Li, Wu, and Xie (2020) aimed to employ a newer, more efficient control method utilizing the P300, which is an EEG component. The ultimate objective would be to create a control method for online use. They used raw EEG data for preliminary processing. They hoped to test their technique on an assistive robot to test the new method against their hypotheses. The new method had an accuracy of 94.43% across 8 participants, with the potential for generalization to other more complicated applications. Furthermore, these results indicate that the new method has the potential to help paralyzed people control mechanical devices.

A study by Bousseta, Ouakouak, Gharbi, and Regragui presents a novel EEG-based brain-computer interface (BCI) system for controlling a robot arm movement through thought. The system uses a noninvasive technique that records EEG signals from the user's scalp using a specialized cap fitted with 64 electrodes. The signals are then processed and analyzed using advanced signal processing and machine learning methods. The system allows the user to perform four mental motor tasks, such as imagining the movement of the right hand, the left hand, both hands or the feet. These tasks are translated into commands to control the robot arm in four directions: right, left, up, and down. The system was tested with eight healthy human subjects who gradually learned to control the robot arm by imagining the movements. The system achieved an average accuracy of 85.45% across all subjects and tasks. This prior research helps reach our solution, including previous works using EEG-based BCI to control robotic platforms for patient assistance or rehabilitation, such as hand prostheses, wheelchairs, or robot arms. Previous works have used different feature extraction and classification methods for EEG signals, such as the wavelet transform, power spectral density, adaptive auto-regressive, linear discriminant analysis, support vector machine, and hidden Markov model. Previous works have used different mental tasks for BCI, such as motor imagery, concentration tasks, visual evoked potentials, and event-related potentials.

**Challenges & Proposed Solution**

EEG brain-computer interfaces have faced some challenges over the years. The most frequent is that EEGs tend to have a low SNR (signal-to-noise ratio). As a result, it is hard to deduce patterns in EEG data due to noise, and a solution requires lots of preprocessing and data cleaning. It's also difficult to distinguish the patterns you want from other patterns occurring within the data. Another problem is that EEG data has high intersubject variability, making it hard to generalize one dataset to multiple subjects. Large training times are another issue within the space of BCIs that can lead to training fatigue.

In our capstone project, our primary objective is to design and develop an integrated control system and accompanying software tailored specifically for EEG applications. Our aim is to enhance the accessibility and usability of EEG technology, particularly for individuals with disabilities. We have outlined several key components and goals for our project to achieve this. First and foremost, we will create a streamlined control system that serves as the foundation for our software, ensuring efficient data acquisition and management. The software itself will offer a user-friendly interface for training on EEG data and visualizing said training, while conducting analyses. It will prioritize accessibility by being compatible with assistive technologies, and this novel training module will expedite user learning. We will conduct usability testing throughout development, provide comprehensive documentation and support, and prioritize data security and privacy. Our software will be designed for scalability and compatibility, accommodating future advancements in EEG technology and multiple platforms. An interdisciplinary approach involving experts in EEG technology, user experience design, accessibility, and software development will enrich our project's outcomes. Finally, we will evaluate our project's success through performance metrics, user satisfaction surveys, and validation against accessibility standards, guiding refinements and improvements as needed. Through these efforts, we aim to create an inclusive and effective solution that empowers a wide range of users to harness the potential of EEG technology.

**Feasibility**

We believe this project is feasible to complete within the time frame as we can find EEG data online, significantly reducing the amount of time and resources necessary for this project. The project will be divided into two phases, with the first phase being creating the algorithm, training it, and improving it, and the second phase being the integration of the software to be able to move a wheelchair. We hope to be able to complete the first phase of our project by the end of January 2024, using the rest of the second semester to create the wheelchair and test our program. Our meeting plan is to meet on Tuesdays each week at 3:15 to discuss what is necessary to complete that week, divide up the tasks, and check in on our progress from the previous week. If it becomes necessary to meet again, we plan on meeting during class on Monday and/or Friday. We also plan on meeting with Professor Hassan every other week on Friday at 2 p.m. to show our progress on the project and discuss issues that may have come up during that time.

**Member Contributions (Together)**

Member Specialties and Interests:

* Justin Haybert: Machine/deep learning and neural networks, Brain computer interfaces, Data collection, and accessibility/ease of use
* Gabriel Sagrera: Data processing, machine learning, robotics, device fabrication
* Shayne Shelton: Robotics, accessibility, machine learning, prototyping
* Ryan Stevens: Data collection/cleanup/processing, machine/deep learning and neural networks, robotics and 3d printing

Capstone Outline:

1. Understand the problem and proposed solution
2. Learn the EEG, how to use it and understand what it does and tells us
3. How do we collect the data
4. Understanding the data
5. Picking a model
6. Building a model
7. Data collection
8. Data processing
9. Training
10. Testing
11. Create user training application
12. Create device (robotic arm, wheelchair) for EEG integration
13. Link application (Robotic arm, robot wheelchair model) to the user training and EEG models
14. Put everything together into one cohesive EEG control and user training platform

Work Allocation

* Evenly divided agile scrum framework

**Sources**

*Bousseta, R., El Ouakouak, I., Gharbi, M., & Regragui, F. (2018)1. EEG based brain computer interface for controlling a robot arm movement through thought2. IRBM, 39(2), 129-135. https://doi.org/10.1016/j.irbm.2018.02.001*

*Huang Q, Zhang Z, Yu T, He S and Li Y (2019) An EEG-/EOG-Based Hybrid Brain-Computer Interface: Application on Controlling an Integrated Wheelchair Robotic Arm System. Front. Neurosci.13:1243. doi: 10.3389/fnins.2019.01243*

*J. -H. Jeong, K. -H. Shim, D. -J. Kim and S. -W. Lee, "Brain-Controlled Robotic Arm System Based on Multi-Directional CNN-BiLSTM Network Using EEG Signals," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 28, no. 5, pp. 1226-1238, May 2020, doi: 10.1109/TNSRE.2020.2981659.*

*Song Y, Cai S, Yang L, Li G, Wu W, Xie L. A Practical EEG-Based Human-Machine Interface to Online Control an Upper-Limb Assist Robot. Front Neurorobot. 2020 Jul 10;14:32. doi: 10.3389/fnbot.2020.00032. PMID: 32754025; PMCID: PMC7366778.*