Machine Learning and Brain Computer Interfaces:
Classifying Brain Signals for Upper Limb Prosthetics

A Technical Report submitted to the Department of Computer Science

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

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Fall, 2024

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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CS4991 Capstone Report, 2024

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ABSTRACT

Brain computer interfaces (BCIs) currently require extensive user training to effectively isolate and translate the desired brain signal characteristics into desired control signals for external devices. To simplify this process, I propose utilizing machine learning to decrease the amount of training time and improve recognition, classification, and prediction of the desired movement. Brain signals of upper limb movement can be detected and captured by an electroencephalogram (EEG). This data can be fed into machine learning (ML) algorithms to develop a model that can categorize and predict the desired action. By creating this model, neuroprosthetics will become more viable due to increased accuracy. Following the creation of an ML model fit to a singular patient, comparing multiple models will determine whether the models can be applied to multiple patients.

1. INTRODUCTION

Computers have evolved the ability to read minds. BCIs are a category of device that captures and decodes brain signals into computer recognizable information. These devices are further split into two categories: invasive and non-invasive. For invasive BCIs, electrodes are implanted either directly on the brain or in the membrane surrounding the brain. For non-invasive BCIs, electrodes are instead attached to the scalp. Brain signals captured by these electrodes are then fed into decoding processes, which are often lengthy and complicated. Once processed, decoded brain signals can be used for various applications, including controlling machines and performing computer tasks.

Brain signals are typically detected using electrocorticography (ECoG) or electroencephalography (EEG) for invasive and non-invasive BCIs, respectively. Both these methods produce a chart of electrical readings from the electrodes over time. By recording these readings while a patient performs specific movements, it is possible to identify characteristic features. These features can then be combined into a patient specific dictionary to speed up future recognition. Manually completing this task requires a large amount of work, including preprocessing, signal amplification and filtering for noise.

2. RELATED WORKS

According to Biddiss and Chau (2007), upper body prosthetics typically have higher abandonment rates and body-powered hands are typically associated with rejection rates as high as 80%. Furthermore, measured rejection rates are likely to be lower than the actual rates since patients who no longer use their prosthetic are less likely to participate in studies regarding its use. Prosthetic abandonment and rejection are caused by a variety of reasons, including weight, difficulty of use, discomfort, slowness in movement, appearance, and lack of functionality, predictability and feedback. My proposed approach targets one of the primary reasons for prosthetic abandonment, lack of functionality, predictability, and feedback. By creating an ML model that can classify the patient's brain signals into their desired limb motion, their prosthetic becomes more closely an extension of their body, as opposed to an attachment.

Chaudhary, et al. (2016) discussed the use of BCIs for communication in paralysis due to ALS and the restoration of motor impairment in stroke patients. For both these applications, there have been successes, though not enough to allow for widespread adoption. My approach builds specifically off the work done to restore motor impairment by applying the same capture and decoding methods but transmitting them to a prosthetic instead of attempting to rebuild degraded or blocked neural pathways.

In 2011, Gert-Jan Oskam, was involved in an accident that paralyzed him from the waist down. He has been fitted with implants in his head and spinal cord that transmit brain signals and send instructions to Oskam's paralyzed legs, returning control of his legs to him (Ghosh, 2023). My proposal builds off this development by applying it to upper limb prosthetics instead of biological legs, with the primary challenge being classifying the many degrees of movement upper body limbs have compared to lower body limbs.

3. PROPOSAL DESIGN

This approach consists of three components: gathering data, training an ML model, and applying the results.

This proposal requires ECoG or EEG data captured while a subject performs specific limb motions. A large amount of data is necessary to provide the most accurate results, so each subject should repeat each motion more than one hundred times. This step has significant time requirements due to the need for a large library of training data. Subjects will likely need to spend multiple sessions having data recorded. For simplicity, the total number of limb motions should be limited to a single appendage, such as an arm or leg, and the most basic movements (up, down, left, right, and rotation).

Once the data is complete, it must then be fed into an ML process. This involves data cleaning, model selection and training, and fine tuning. Data will undergo a standard cleaning process, called a Data Pipeline. This dictates a series of steps that will prepare the data for the ML algorithm. Most importantly, the Pipeline will remove as much noise as possible from the electrode readings and isolate the signals that produce the movement. Additionally, data from different subjects must be scaled so no single person's data is considered more important. Finally, the dataset must be split into training, validation, and test sets. Adhering to common practice, the training, validation, and test sets will consist of 64%, 16%, and 20% of the total dataset, respectively, with each set containing a random selection. This division is important so that the model is evaluated on data it has never seen before to achieve accurate error metrics. Otherwise, the model may be able to "remember" the correct result for a given input it was trained on.

Once the data is cleaned and prepared, a classification algorithm can be trained on the training set. To determine the best ML model for this dataset, the data will be trained using a selection of classifiers. This will include the Random Forest Classifier, Naïve Bayes Classifier, Logistic Regression, and Kernel Support Vector Machine. Once these models are trained, the error scores from predicting labels in the validation set will be compared and the best model selected for further analysis. This comparison will be done using the one-versus-one strategy, which scores the classification of a new instance into every possible class and compares it individually against every other option. The final assignment for the new instance is the class that wins the most matchups. Although this strategy is computationally expensive, it is designed to provide the highest accuracy.

The remaining model can then be further tuned by adjusting its hyperparameters, or the internal model variables. These can be adjusted, and the model retrained to search for lower error scores. Specifically, the primary error score that will be minimized is the precision score. The precision score prioritizes the ratio of true positives (correct classifications) to all positives. This means that the best models will keep the number of false positives (incorrect classifications) low. The tradeoff to precision is that the number of false negatives will not be given as much importance, however it is better for the machine to not select an action than to select an incorrect action.

With a trained and validated model, final evaluation will be done using the test set, to ensure that the model is able to be generalized to new and unseen data. It is important to ensure the model does not overfit the training data so much that it is unable to correctly classify new information. If needed, further tuning of hyperparameters will be completed to achieve a low error score.

Finally, the model will be evaluated on real time inputs from test subjects. As the subject thinks about their desired action, the signal will be classified by the trained model and compared to the true action.

4. ANTICIPATED RESULTS

The result of my proposal is a classifier that can take an unknown brain signal as input and output a limb motion with a high degree of accuracy. This brain signal classifier can be continuously updated with new data to further improve its classification error. It can then be applied to various applications such as for prosthetics and paralysis patients.

In the realm of neuroprosthetics, this classifier would allow for further advancements, specifically for upper limb prosthetics. The model can be focused to limit selection of signals to only upper limb movements and classify desired actions in real time. Being able to recognize desired limb movements from brain signals would allow for the transmission of the limb movement to a robotic arm such that an amputee patient could control a robotic limb using only their thoughts. This means that the prosthetic limb reacts just as a biologic limb would, thereby vastly reducing the patient's lost functionality.

5. CONCLUSION

Current prosthetics fail to fully replace the functionality of lost limbs. To narrow this gap, my proposal will build a classifier that is able to decode brain signals for the goal of controlling a prosthetic arm. By reacting to the user’s thoughts, the neuroprosthetic will act as if it were a biological arm, thereby greatly increasing regained functionality. This classifier, although trained for use in upper body prosthetics, can then be adapted to other uses such as lower limb prosthetics or other brain-controlled devices. By utilizing ML algorithms, the training time for a user to adapt to the neuroprosthetic will decrease, increasing access and viability.

6. FUTURE WORK

The first step is gathering the resources to complete this proposal in its original form. This includes gathering users to undergo brain signal capturing to build up the initial library of data to train the ML algorithm on. If this proposal is successful, future work can be completed on adapting the upper limb classification to other parts of the body, such as lower limb movement classification. If unsuccessful, future work should be directed at expanding the data used to train the ML algorithm and further training the model to improve accuracy.

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