Motor-Imagery Based Brain-Computer Interface for External Device Control

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BME 296 – Brain Computer Interfaces

Introduction

The proposed brain-computer interface (BCI) is intended to utilize electroencephalographic (EEG) data of the motor imagery region of the brain to control external devices. An analysis was conducted using a large EEG motor imagery dataset, where the procedure focused on EEG data associated with hand movement. The dataset contains EEG data from subjects who were asked to focus on the center of an experimental graphical user interface (eGUI) where they were prompted to imagine closing or opening the left or right fist. When no image was displayed, the subjects remained passive and did not engage in mental imagery until the beginning of the next trial[1]

This proposed BCI utilizes the raw EEG data taken from the provided dataset, extracts features, isolates event-related potentials (ERPs), and implements a machine-learning (ML) pipeline for potential use as an assistive technology for locked-in users, where there is no control of voluntary muscles, save vertical eye movements, and blinks[2] Additional applications apply to the approximately 150,000 tetraplegic/quadriplegic patients living in the U.S. who have no upper extremity control[3] By using EEG data, actual muscle activity would not be required to generate signals. The EEG dataset was not targeted for specific end-effector tasks. However, there is a need to use this kind of data and apply machine learning protocols that will produce targeted, useful functions for mobility restricted patients. Current technologies involve dangerous, risky, and invasive surgeries, bulky and expensive equipment, and high costs[4]

In this report, specific information is discussed regarding the methods of coding, debugging, and data collection, interpretation of results with associated figures of merit, discussion of significance in the wider field including applications, and concluding statements with an evaluation of technical challenges, ethical concerns, and how the stated need was met with the proposed BCI application.

Methods

Subjects

13 healthy volunteers, consisting of 8 males and 5 females of ages 20 to 35, participated in the study. All participants were screened for psychiatric conditions, medications, and any possible contraindications to EEG beforehand. All participants were informed of the purpose of the study, and submitted consent to the collection of data, with all identifying information anonymized[1]

Data Collection

Participants were seated in a chair with an EEG cap placed on their head, and a computer screen positioned in front of them. This computer screen displayed a Graphical User Interface (GUI), in which images of the left or right hand were presented, as shown in Figure 1. Participants began by focusing on the gaze-fixation point at the center of the window. At the beginning of the recording session, a 2.5 minute "rest period" was initiated to allow for subjects to adjust to the recording environment. Following this, three separate 15-minute BCI interaction segments were conducted, each separated by 2 minute breaks. At the start of each trial, a 1s action signal was displayed, representing left hand, right hand, or circle (passive). With the display of an action signal, the participants were instructed to imagine closing and opening the respective fist once. For a passive display, participants remained inactive until the next action signal was displayed. Following the display of an action signal, a pause varying between 1.5-2.5s was conducted, signaling the end of the trial. Each trial duration was approximately 3s, with 300 trials performed within each 15-

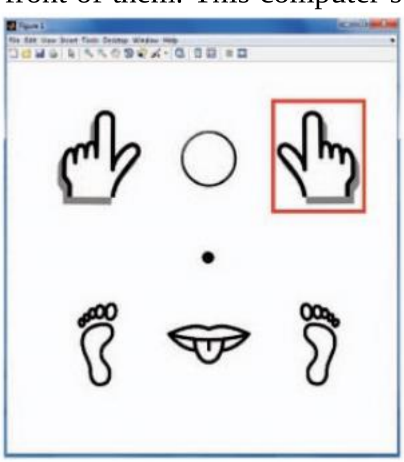

Figure 1:Example of eGUI instructing the user to perform the action signal bounded by the red rectangle

minute interaction segment. Each data recording session lasted between 50 and 55 minutes, with continuous EEG data collection throughout the entire duration.

Data acquisition was conducted using an EEG-1200 system, a standard medical EEG station used in many hospitals. A 10/20 EEG cap with 19 bridge electrodes arranged in the 10/20 international configuration, shown in Figure 2, was placed on the participant's head, after being cleaned with an EEG cleansing solution. Two ground leads, A1 and A2, were placed at the subjects' ears for referencing, and one bipolar lead, X3, was used for data synchronization, for a total of 22 input channels. The EEG signal was recorded at a sampling rate of 200 Hz, and a 0.53-70 Hz band-pass filter was implemented in all EEG data recorded by the Neurofax recording software associated with the EEG-1200 system[1]

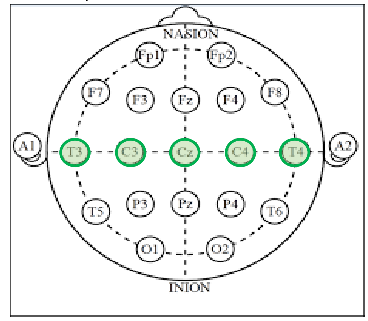

Figure 2. 10-20 EEG electrode configuration with motor imagery electrodes highlighted

Data Processing, Analysis, and Statistical Testing

In the initial analysis and training of the ML classifier, data was extracted for one recording session from one subject. From the raw data file, information such as EEG data (in µV), channel data, frequency data (in Hz), event sample info, and event type info were extracted and placed into a Python dictionary. The data was then re-referenced to improve performance using a common average reference. This averages the raw EEG data across electrodes and subtracts that average from each electrode. The re-referenced data was then epoched into a 3D array of size (epochs x samples x channels), whose length was determined by the duration of the event, or action signal. The epoch duration for this dataset was 1.5 seconds from the event onset time. This event onset time was identified as the transition period in the array of event labels, e.g. 0 to 1, indicating a transition from a "rest" state to an "action" state.

To account for the poor spatial resolution of EEG data, the ERP was calculated and plotted to average the signals across all trials and identify the response to the action signal. This process helped eliminate noisy signals, while summing signals evoked by the action signal to better identify the response to the stimulus. After calculating the mean, a Gaussian distribution was assumed and the standard deviation across trials was calculated. 95% confidence intervals were generated on the plots to establish bounds within two standard deviations of the mean in which the ERP lies.

Prior to the creation of a machine-learning classifier, features had to be extracted in order to train the classifier. The data was epoched from 0s to 0.85s after the action signal onset time. Then a Fourier transform was computed for each epoch, and corresponding frequencies calculated. A low-pass filter was then applied to the data, filtering out all frequencies above 5 Hz. According to Mischenko et al., frequency ranges from 2-10 Hz are pronounced in mental imagery-responses, with ranges from 2-4 Hz specifically related to imagery of hand movements[2] The corresponding real and imaginary components of the Fourier transform were then extracted and populated into a blank array to then feed into the machine learning classifier.

Following feature extraction, a machine learning pipeline was created to train and validate a classifier using functions from the scikit-learn machine learning package. The dataset was downsampled in order to create classes of equal size to account for the rest period between trials, while EEG data was continuously being recorded. The data was then split into training and testing sets, and used to optimize the regularization parameter, C, and gamma, the effect the influence of one training example has on the rest of the data. A cross-validated grid-search was performed over a range of C and gamma values to determine the optimal parameters for the model. These parameters were then selected and implemented into a C-support vector classifier, using the default 'RBF' kernel and default 'one-vs-rest' decision function shape. The model was then trained on the split training data and tested to generate the predicted labels. The accuracy and information transfer rate of the model were then generated to evaluate performance and a confusion matrix was plotted to display the classification results of the model.

The classifier was trained and tested on various subjects and trials, with results reported in the following section.

Results

Our goal was to use motor imagery EEG to implement the BCI application for locked-in users, therefore we expected to see significantly different ERP's evoked when participants imagined opening and closing their hands. Plots for the left and right-hand mean motor imagery ERP's across epochs along with 95% confidence intervals for subject B and C on electrode C3 are shown in Figure 3. Though these ERP's from subject B highly overlap, ERP's from subject C displayed an observable difference between left and right-hand motor imagery during the time interval of [0.2, 0.4] seconds, where the left-hand ERP reached a positive peak around 2 µV and the right-hand ERP reached a negative peak about -4.5 µV.

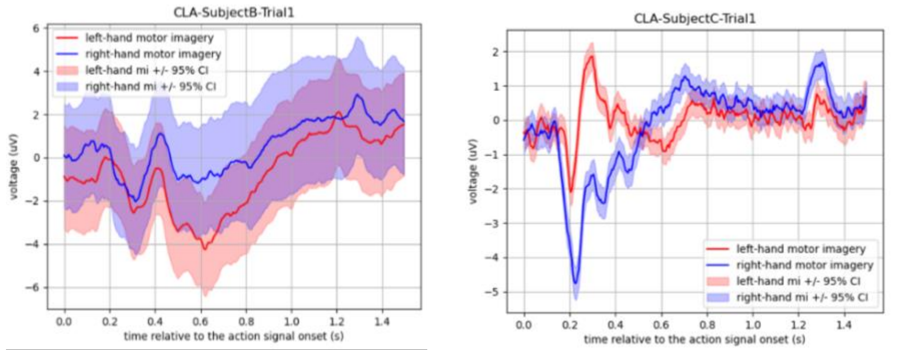

Figure 3: ERP curves of hand motor imagery recorded from both subjects on electrode C3. The x-axis is the time relative to the action signal onset in seconds up to 1.5s and the y-axis is the voltage of ERPs in microvolts. The red and blue lines are the left- and right-hand motor imagery average ERPs. The color areas represent the 95% confidence interval of average ERPs.

The performance measurements for machine learning classification on different datasets are shown as confusion matrices in Figure 4. The horizontal and vertical direction of the confusion matrix show real targets and prediction results from four classes, respectively. The classifier trained on subject C's dataset outperformed subject B's classifier with almost double the accuracy score, which corresponds to the fact that subject B had indistinguishable ERPs for both hands. In an attempt to make this BCI generically applicable, we trained and validated the classifier on datasets across subjects. However, the accuracy for this classifier was only 0.587 which equates to near random chance. However, when we tested the subjective classifier trained across trials, we attained a more relevant 0.817 accuracy with 1.2 ITR bits per second.

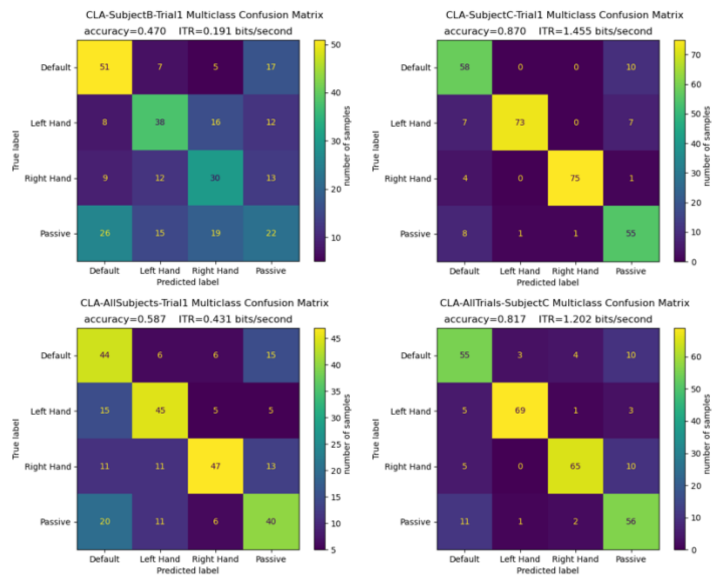

Figure 4a-d (from left to right, top to bottom): Confusion matrices for all classes generated by classifiers trained on different datasets. *The trained and tested datasets are specified in title. The statistics of accuracy and information transfer rate given in bits per trial is in the subtitle.*

Discussion

The intended application of this BCI is in the operation of smart home devices by movement impaired individuals. This device would allow the user to remotely operate smart light-switches, smart door, and navigate simple entertainment systems using visualized motor imagery (Figure 6). The reason we chose this application for our BCI is that the ramifications from incorrect prediction do not threaten the wellbeing of the user. The worst outcome from an incorrect prediction, like turning on a light or changing a channel, is that the user will have to retry their intended action if the desired outcome was not reached the first time. This is not as severe as other potential applications we considered like the control of a powered wheelchair, operation of a robotic prosthetic, or the electrical stimulation of the bladder sphincter, each of which could be harmful to the user due to an incorrect prediction. In order for our BCI to be considered for any of those applications it would require an accuracy of at least 0.90 while maintaining an ITR over 1 bit/second[5].

To enable a user to utilize these control mechanisms using our BCI, they must undergo an intensive data collection session described in the data collection portion of the methods which will be used to train the machine learning classifier. After enough data is collected to yield a satisfactory prediction accuracy, the classifier can be committed to the BCI for everyday use for real time prediction of imagined hand movements.

The ERPs from subject B showed high overlap which resulted in substantially lower prediction accuracies than subject C, which showed significantly less overlap (Figure 3). This also negatively affected the ITR for subject B which was 46% lower than that of subject C making it undesirable for our application (Figure 4b,d). These promising results from subject C suggest that a classifier trained on a subject whose ERPs do not overlap can reliably differentiate between left and right hand squeezes, regardless of the size of the training set. Figure 4b, trained on one trial from subject C, had the most desirable accuracy and ITR values, but was only slightly better than the results of Figure 4d which shows the results of a classifier trained on all 3 trials from subject C. This slight difference suggests that we may be overfitting our classifier when only using one trial and should pursue a larger and more diverse training set when creating our classifier.

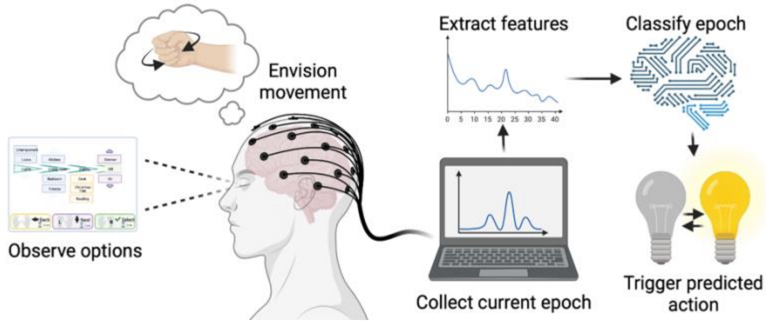

Figure 5: Flow chart of real time analysis.

Conclusions and Challenges

In conclusion, the first most outstanding result was that the ERPs from subject C displayed an easily distinguishable difference between left and right-hand motor imagery, where the left-hand ERP reached a positive peak, and the right-hand ERP reached a negative peak. Given this, the subjective classifier tested and trained across subject C's trials attained an accuracy of 0.817 and an ITR of 1.2 bits per second (Figure 4d). A high accuracy of 0.817 implies that the BCI obtains good test outcomes when it is trained on a large array of trials from the same subject for which it is tested on. Although the classifier performed better when tested and trained on 1 trial from subject C (Figure 4b), the data could be overfit and the results across all trials represent a more realistic result. These results support that this BCI is suitable to apply to an assistive technology for users who are locked-in or tetraplegic/quadriplegic. A potential application such as a smart home assistive device could benefit a smaller population of users but have a large impact on their quality of life.

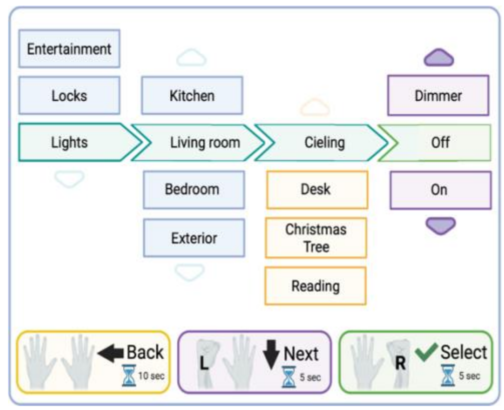

Figure 6: User interface. BCI controlled interface with smart home options allows the user to cycle through options, select, and back out of menus. Users can set selection time thresholds.

With any BCI that turns EEG signals into binary decisions, technical challenges arise when the accuracy is below a certain threshold which deems it unsafe for the user depending on the product it is being applied. For a BCI making low-stakes decisions, such as turning a light or television on or off, does not endanger the user and a lower accuracy will suffice. On the other hand, for a BCI making higher-stakes decisions such as unlocking a door, a low accuracy may endanger the user by creating a risk of their house being intruded. For this BCI to be brought to market in applications in which it is making high-stakes decisions, it would be necessary to improve the performance.

We believe our smart home device BCI is ethically sound. However, the user would have to be able to learn how to visualize squeezing their hand, so the BCI receives a clear differentiation between left-hand and right-hand brain signals. We believe that subject B had a harder time with this visualization because the peaks look very similar to each other. This may deter potential customers if it makes the product seem too complicated to use. Additionally, it is important that our BCI does not require the assistance of a caregiver or technician. Without the assistance of someone else nearby, our BCI could be improved by an "on call" button with immediate technical support or an effective backup solution.

Appendix

Contributions

For many of the tasks, team members who preferred coding to writing or vice versa worked on more of their preferred section. We met as a team to do most of the coding before training the ML classifier. We switched tasks for the final write-up to accommodate individual preferences as we got closer to finishing the project.

Section	Task Description	Task Distribution
Coding	Data collection and README file	Connor Harrigan;
	Data mining and cleaning	Haorui Sun; Nicole Donahue, Connor Harrigan; Max Farrington; Dustin Pereslete
	Epoch and plot ERP	Nicole Donahue; Connor Harrigan
	Abstract machine learning features	Haorui Sun; Max Farrington; Nicole Donahue; Connor Harrigan; Dustin Pereslete
	Train ml classifier	Haorui Sun; Max Farrington
	Validate trained classifier	Haorui Sun; Connor Harrigan
	Figure of merit	Haorui Sun;
Writing	Proposal	Nicole Donahue; Haorui Sun; Dustin Pereslete; Connor Harrigan
Final Write up	Introduction	Dustin Pereslete; Connor Harrigan
	Methods	Connor Harrigan
	Results	Haorui Sun;
	Discussion	Max Farrington; Nicole Donahue
	Conclusions and challenges	Nicole Donahue

References:

[1] Kaya, M., Binli, M.,Ozbay, E. et al. A large electroencephalographic motor imagery dataset for electroencephalographic brain computer interfaces. Sci Data 5, 180211 (2018). https://doi-org.ezproxy.uvm.edu/10.1038/sdata.2018.211

[2] E. Smith and M. Delargy, “Locked-in syndrome,” *BMJ*, vol. 330, no. 7488, pp. 406–409, Feb. 2005.

[3] https://www.nscisc.uab.edu/Public/Facts%20and%20Figures%202019%20-%20Final.pdf

[4] “Five innovative assistive devices for people living with quadriplegia,” *NS Medical Devices*, Dec. 16, 2019. https://www.nsmedicaldevices.com/analysis/assistive-devices-quadriplegia/ (accessed Dec. 15, 2021).

[5] “Commanding a robotic wheelchair with a high-frequency steady-state visual evoked potential based brain–computer interface - ScienceDirect.” https://www.sciencedirect.com/science/article/abs/pii/S1350453312003335 (accessed Dec. 16, 2021).