Public Dataset Research Paper: Using Motor Imagery to Generate a BCI

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Introduction

Motor imagery is a cognitive process involving the mental simulation of movement without actual execution. This process has garnered significant interest in neuroscience and brain-computer interface (BCI) research. By decoding the neural representations of imagined movements, researchers aim to decipher the intricate relationship between mental processes and corresponding brain activity. The potential applications of this research extend beyond theoretical understanding to practical implementations aimed at enhancing the quality of life for individuals with neurological disorders or disabilities. In the study "*4-class data for BCI competition*", motor imagery data were recorded for three participants [1]. These three participants were asked to participate in motor imagery tasks involving four distinct body movements: left hand, right hand, tongue, and feet. The electroencephalography (EEG) recordings obtained from these participants were utilized for analyzing brain activity patterns associated with motor imagery. This dataset, compiled as part of the BCI Competition 2005, serves as a valuable resource for investigating the neural correlates of motor imagery and developing algorithms aimed at predicting users' intentions based on EEG signals. The dataset under investigation features EEG recordings obtained from multiple sessions, each consisting of trials where participants were instructed to imagine specific movements while EEG signals were continuously recorded. The experimenters would present an auditory signal as well as a visual symbol in the form of a cross to mark the beginning of the task, at which point the participant would begin the motor imagery task. In this paper, we present an analysis of the provided EEG dataset, focusing on extracting informative features, classifying motor imagery tasks, and evaluating classification performance. Through analyses and interpretations of the dataset, we aim to contribute to the broader understanding of motor imagery-related brain activity patterns and advance the development of EEG-based BCI systems. Our findings, despite presenting with low classification accuracy, nonetheless highlight the potential utilization of the sensorimotor cortex in motor imagery and offer insight into the potential of EEG-based BCIs in empowering individuals with severe motor disabilities to interact with their environment such as a motor imagery powered wheelchair, requiring the user only to imagine moving their muscles in order to create movement from the wheelchair itself allowing for that individual to move independently.

Methods

The dataset provided contains the EEG signals for three different subjects across 60 unique electrode channels. Despite being a 60-channel dataset, the recordings were made using a 64-channel EEG amplifier from Neuroscan [1]. The EEG electrode positioning does not follow a conventional pattern in which electrodes are ordered according to lobe (or central position) with 'z' representing the midline, odd numbers representing the left hemisphere, and even numbers representing the right hemisphere; however, C3, Cz, and C4 have been specifically labeled per the electrode map (Figure 1). The signals have been classified as test or train data, where the training data correspond to a known class label of either 1, 2, 3, or 4 (which presumably correspond to left hand, right hand, foot, or tongue motor imagery, respectively), and the test data remain unclassified as NaN. Of note, the data was prefiltered (between 1 and 50Hz using a Notchfilter).

Mu and Beta rhythms are significant components of brain activity, especially in relation to the sensorimotor cortex and thus have an essential role in signal analysis for a movement based brain-computer interface application. The mu, or sensorimotor rhythm, usually occurs in the 8-13 Hz range and is associated with the resting state of the brain. This specific range can be observed when an individual is relaxed and not engaged in a specific motor task. Through observation of changes in mu rhythm patterns, such as desynchronization during a motor imagery task, a BCI could interpret the user's intention to perform a specific movement. The beta rhythm typically occurs as a higher frequency oscillation from 13-30 Hz and is associated with functions such as active movement and motor planning. Changes in beta power are useful for motor imagery BCIs as they are particularly relevant to movement preparations and motor activation. These factors were used for our analysis of the dataset.

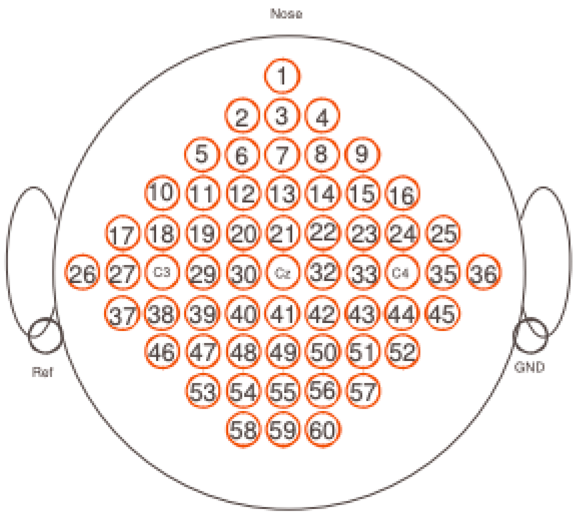

Figure 1: Position of the EEG electrodes for data collection [1].

During data collection, the subjects sat relaxed, and, upon a cue, thought about performing a particular action - left hand, right hand, tongue, or foot movement - without actually performing that action. Each trial included 7 seconds of data. The first 2 seconds of the trial were quiet, essentially representing "resting" EEG data. At the 2-second mark, an auditory beep occurred, along with a visual cross upon which the participant's gaze was fixated. The next second only presented with the cross, and at the 3rd second, an arrow indicating which motor imagery task a subject would perform (up for tongue, right for right hand, left for left hand, and down for feet) appeared until the 4-second mark, at which point only the cross remained as the subject continued to think about performing the action. At the 7-second mark, the trial was over as the fixation cross disappeared.

To generate a useful BCI, the team executed several more post-processing techniques on the EEG data in an effort to successfully predict the class labels based on the training trials. Because labels were not provided for the test data, no attempted classifications were performed outside of the training data. In order to predict classes for each epoch at first we decided to examine the amplitudes around the electrodes that are most significant for motor imagery. Hence, we analyzed the amplitudes of the c3 and c4 electrodes, we took the average of all surrounding electrodes to have a more meaningful result. We also plotted the power spectrum across all epochs for each class to better identify which frequencies at the μ and β range were most impactful to predict each class individually. Once the frequencies that relate to each class of motor imagery are found we can predict each class from the epochs. Our process to find the frequencies involves manually looking at the power spectrum graphs for all epochs and individual epochs to try to find the best frequencies.

Results

Although the EEG data were observed in many states in the time domain, including as the average epoch envelope of the (bandpass filtered) data (Figure 2, Figure 3), no notable patterns were observed.

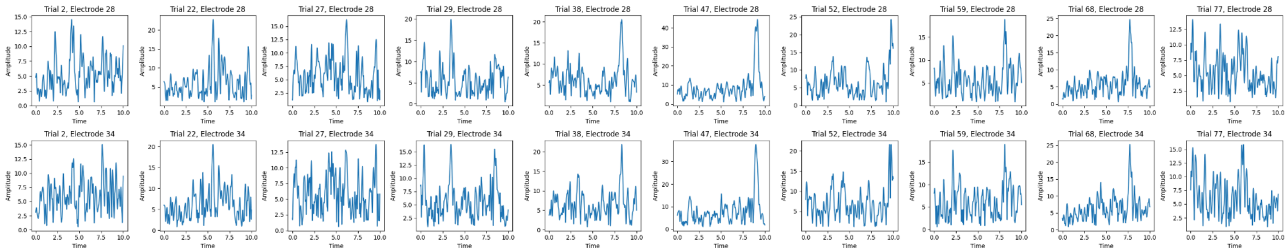

Figure 2: Average around electrodes for class 1 using enveloped epochs for subject l1b

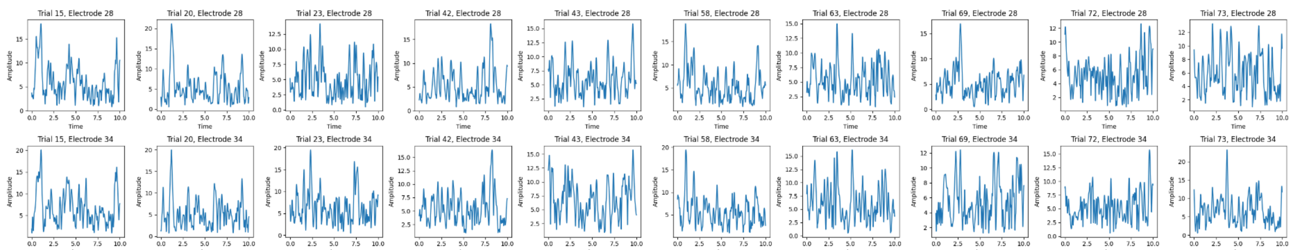

Figure 3: Average around electrodes for class 4 using enveloped epochs for subject l1b

After analyzing the time domain data associated with the motor imagery epochs, the frequency domain was considered. Specifically, the frequency data while the subject was at rest (the first 2 seconds of the epoch) and actively performing motor imagery (the final 4 seconds of the epoch) were observed to investigate potential changes in the power spectra. For several subjects, there appears to be a power increase around the mu rhythm frequencies at slightly higher frequencies than while at rest (Figure 4, Figure 5, Figure 6). Additionally, greater variability between classes is clearly apparent during active motor imagery than at rest (Figure 4, Figure 5).

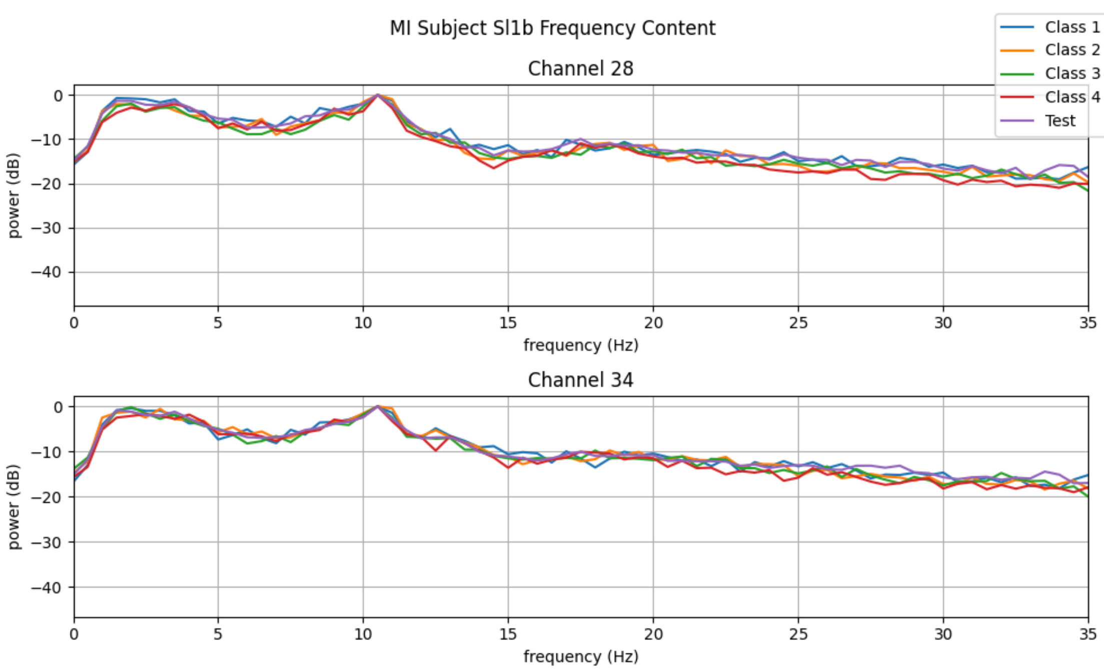

Figure 4: Power spectrum for subject l1b of at rest epochs for all classes on select channels.

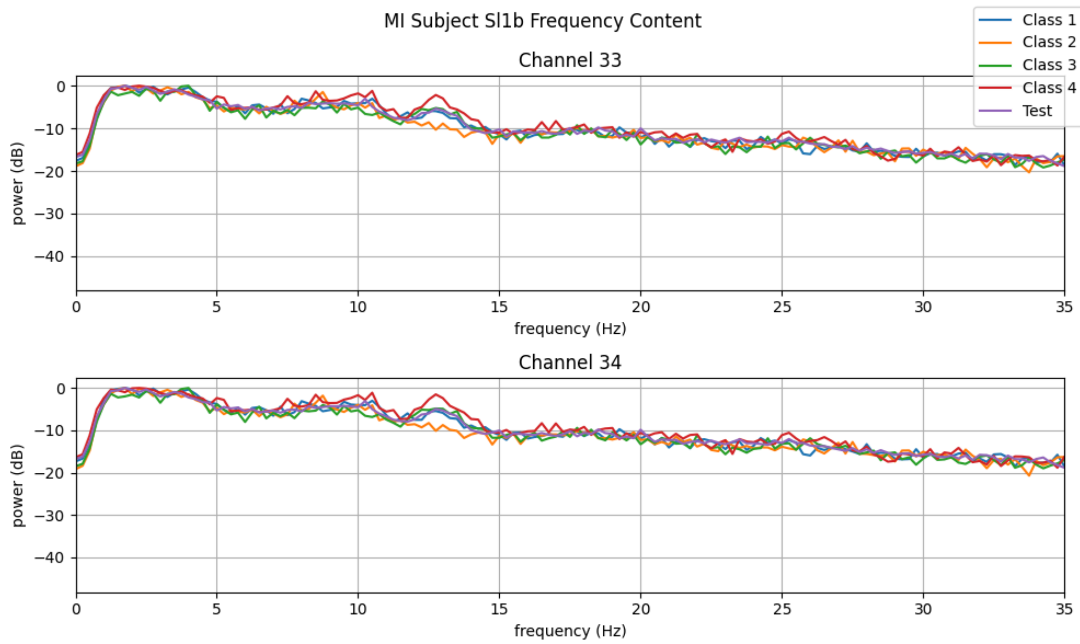

Figure 5: Power spectrum for subject l1b of active epochs for all classes on select channels.

Some of the subjects' frequency spectra more clearly depict the power of the Test data in contrast to the training data; it can be observed that the Test data appears roughly as an average of each of the individual classes (Figure 6).

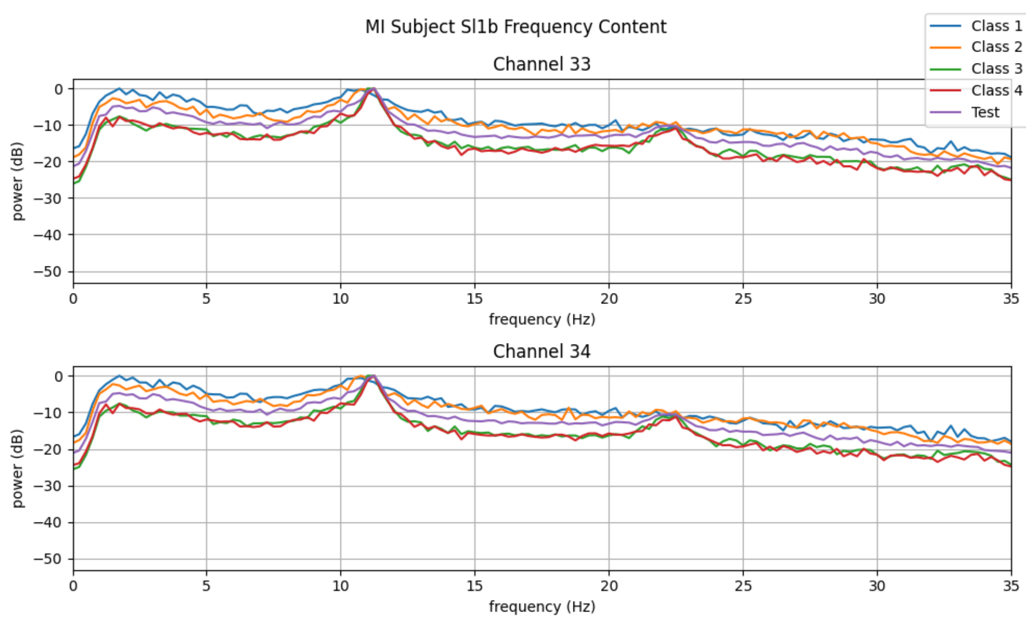

Figure 6: Power spectrum for subject k3b of active epochs for all classes on select channels.

All accuracies were obtained after analyzing the figures above and looking at epochs individually to find the best frequencies for the thresholds to make predictions for subject l1b, expecting potential extension of that power threshold to other subjects (Table 1). Additionally, no discernible pattern was observed in the confusion matrices for any subject (Figure 7 and 8).

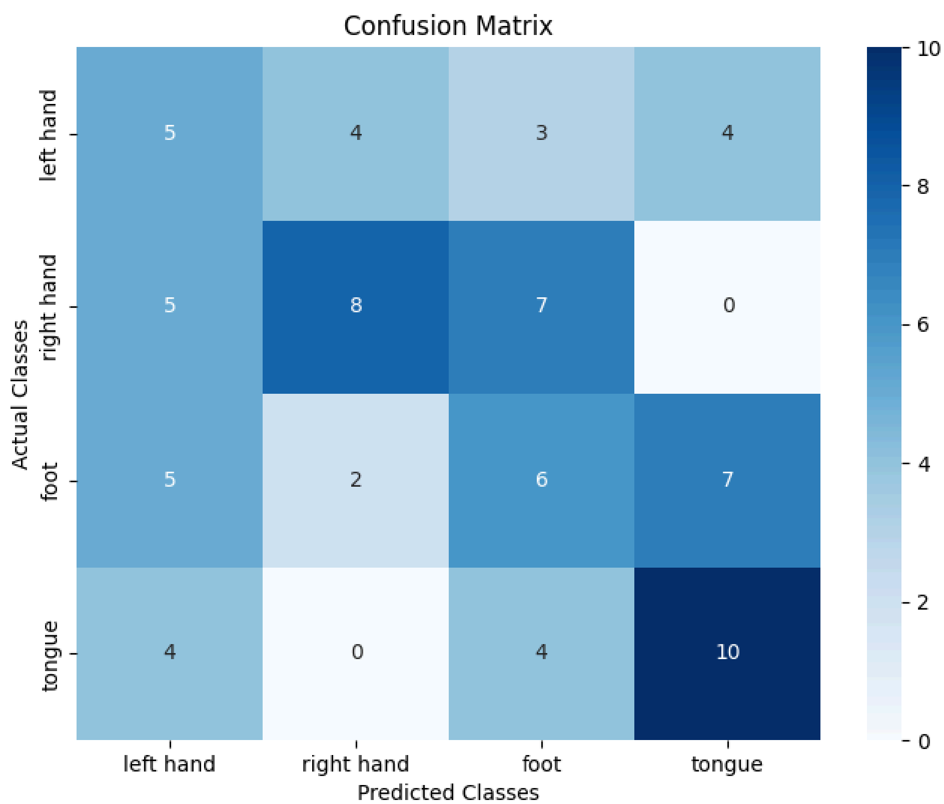

Figure 7: Confusion matrix for subject l1b of predicting each class using the selected frequencies

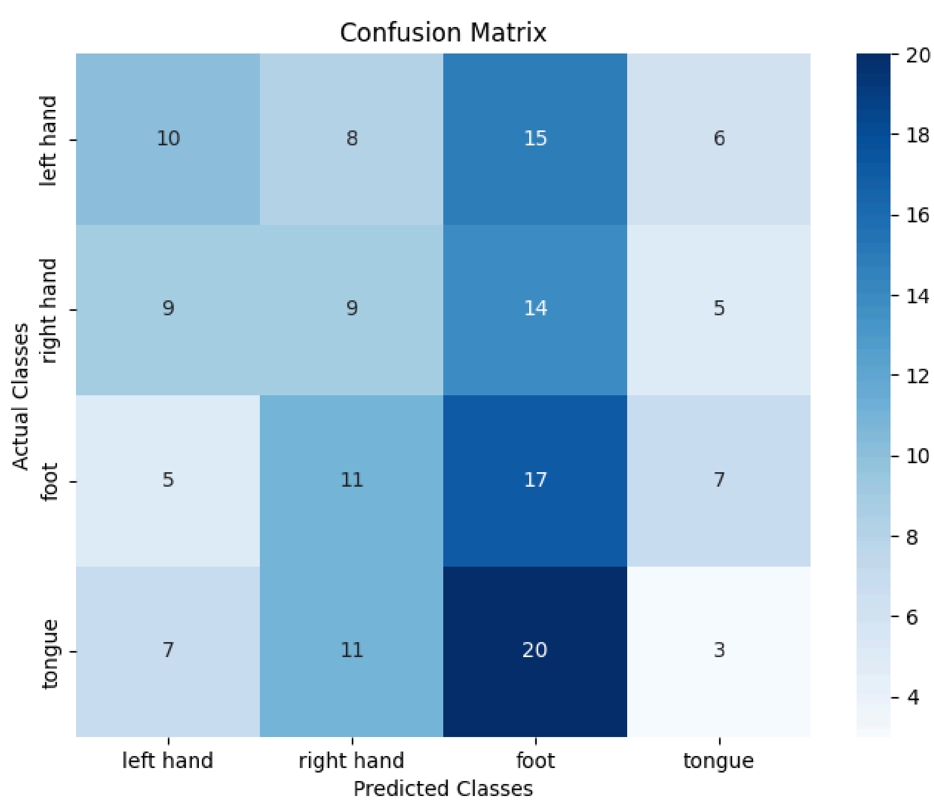

Figure 8: Confusion matrix for subject k3b of predicting each class using the selected frequencies

Table 1: Class prediction accuracies.

Subject	Class 1 (Left)	Class 2 (Right)	Class 3 (Foot)	Class 4 (Tongue)
l1b	31.25%	40%	30%	55.56%
k6b	31.82%	19.05%	33.33%	0%
k3b	25.64%	24.32%	42.50%	7.32%

Discussion

Because the EEG data did not produce any notable patterns in the time domain, the team switched to an analysis in the frequency domain. The power spectra demonstrated very small changes in the mu rhythm region, as is typical with motor imagery data. However, the changes did not appear, at least following the processing techniques, readily apparent to serve as a sound measure of classification, especially not across 4 unique classes. Consequently, minor patterns were observed among the active motor imagery power spectrum, and those patterns were used to generate the predictions. As seen in Table 1, these predictions were not highly accurate, and the best classifications were based on subject l1b, suggesting the quantitative thresholds selected were not applicable to all individuals. Nonetheless, Figure 6 clearly distinguishes the power for each class, suggesting that mu rhythm attenuation or amplification is a consequence of motor imagery. Finally, as the test data (an amalgamation of each class without identification of a specific class) appeared to be roughly an average or median of the distinguished class data (Figure 6), the data show promise that the particular motor imagery performed may have greater differences than the accuracies produced would imply.

It is expected that the user of this BCI would be quadriplegic, and, without the BCI, would be completely dependent upon another individual for movement. Quadriplegia is a condition in which an individual has lost motor function of the four limbs as a consequence of a condition or injury relating to the nervous system (brain, spinal cord, or peripheral nervous system) [2]. Individuals with locked-in syndrome are also potential candidates for the BCI, as locked-in syndrome is a special case of quadriplegia in which an individual exhibits additional paralysis and retains only consciousness and possibly limited eye movements [2]. Since a BCI involving motor imagery naturally translates to movement, it is possible that a well-designed BCI could restore independent movement to these individuals with minimal training or instruction.

An example of the protocol used for this BCI could exhibit similarities to the way in which the data were collected; however, a user would want to use the BCI on demand rather than being told what direction they will go, so inevitably some changes to the training would be implemented. Unlike during data collection, there would not be an acoustic stimulus to indicate the beginning of the trial for the user, as the user now dictates when they would like to perform a movement of the device (and therefore when they exercise motor imagery). Conversely, it is likely that a fixation target will be integrated into the device in some capacity (as a screen or a component of the mobility device), and the user will be instructed to look at this target. In this capacity, it is reasonable to consider that the user would need towards the location of intended movement, making a “heads up” mirror a potential location for this fixation target, allowing the user to see forward and backward despite potentially having limited head or neck mobility while ideally reducing potential EEG noise from additional visual stimuli. The user would then have the process of motor imagery explained, where it is described how thinking about moving the right hand would move the device to the right, thinking about moving the left hand would move the device to the left, thinking about moving the feet would move the device strictly forward, and thinking about moving the tongue would move the device backward. It is worth noting that the user would need to think about the movements for several seconds before any action is executed.

For the BCI to perform as intended, EEG data would be converted to the frequency spectra immediately, and because the data are interpreted in epochs, the data would also need to be stored in a type of moving average. In other words, several seconds' worth (4 seconds, for example, like the duration of the motor imagery task) of data would be stored, and the moving average of the frequency spectrum for each electrode would be calculated in real time. To this spectrum, the threshold values that dictate the classifications for the task would be compared; upon classification, the BCI task would be executed. Classification to the most accurate extent would also require real-time handling of artifacts, as artifacts can greatly change the accuracy of the classification. Consequently, the BCI must recognize artifacts, which could include (but are certainly not limited to) the powerline artifact (50Hz or 60Hz frequencies depending on region [3]) or blinks (which manifest as dramatic increases in voltage, especially around frontal electrodes). A Notchfilter has been applied to BCI Competition Dataset IIIa [1]; however, the BCI must integrate such a filter, as well as potentially a common spatial patterns (CSP) filter to perform to its greatest capacity [4]. These tasks could be performed by a mobility device: As a four-class dataset, each class may represent a different type of movement. Alluding to the training required to use the BCI, the user would perform motor imagery of the feet, and the device would move forward, whereas motor imagery of the tongue would cause the device to move backward; similarly, motor imagery of either hand would move the device in either direction.

The classification accuracy results across different subjects (l1b, k6b, and k3b) and classes (left hand, right hand, foot, and tongue) show varying levels of accuracy. For example, subject l1b achieved relatively higher accuracies for classes such as right hand (40%) and tongue (55.56%), while subject k3b exhibited higher accuracy for class 3 (foot) at 42.50%. However, all failed to achieve high accuracy across all classes, with some classes yielding particularly low accuracy rates, such as class 4 (tongue) for subject k3b, which was only 7.32%. These results highlight the challenges faced in accurately decoding motor imagery tasks based on EEG signals alone. This may show that a personalized approach to this kind of BCI development is necessary. Overall, while the achieved accuracies may not meet the desired levels for practical BCI applications they do help rule out certain techniques and give us insight into the use case for a dataset such as this.

Conclusions & Challenges

Based on the performance of the BCI, producing a mobility device that uses motor imagery to provide a user with independent movement will be challenging from a technical perspective. The more accurate the classifier, the better the BCI performs; thus, because the accuracy was low, the user of the device could not be confident that the device would work as expected. As such, the product would not be unsuccessful on the market due to its unpredictability. Moreover, it would be unethical to provide a device with low accuracy due to the risks involved with unintended movement posed towards both the user or other individuals. Additionally, privacy is always a concern, especially considering the device does require the (at least temporary) storage of data over time. Of the most concern is that patients with spinal cord injuries, including those who are quadriplegic, exhibit greater difficulty in performing motor imagery tasks [5], potentially being more inaccessible, even if usable, to the target population. However, one potential benefit of the proposed BCI is its use of select channels in the region of the sensorimotor cortex: Although the accuracies achieved through this process were notably low, only electrodes near the supplementary motor area (region of the superior frontal gyrus involved in planning complex actions [6]) and the primary motor cortex (region of the precentral gyrus responsible for voluntary movement [7]) were considered [8], suggesting fewer electrodes need be placed and reducing the data collected, invasiveness, and inconvenience of the BCI while achieving predictions that are an improvement to strictly guessing. Despite the results achieved using the aforementioned data processing techniques, other algorithms and data wrangling processes, including the use of CSP filters, have demonstrated greater than 99% accuracy with classifying this dataset [4], suggesting multi-class motor imagery data could produce a viable BCI with the intended purpose as described.

Contributions

Because the team's initial approach of evaluating motor imagery as an event-related potential was inaccurate due to EEG signals exhibiting changes in the mu and beta rhythms [Yu et al.], the actual contributions varied drastically from the expected contributions. Every team member contributed to the main test script and project write up while also individually creating modules and functions to carry out the various tasks needed for our analysis. There were also several functions created by every team member that did not end up being used for the project as we explored multiple options for analysis and single processing. The authors of each script can be seen in the file headers for each module script.

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