Rochester Institute of Technology

Thesis Proposal

Data Representation for Motor Imagery Classification

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Abstract

While much progress has been made to the advancement of brain-controlled interfaces (BCI), there remains an information gap between the various domains involved in progressing this area of research. Thus, this thesis seeks to address this gap through creation of a method of representing brainwave signals in a manner that is intuitive and easy to interpret for both neuroscientists and computer scientists. This method of data representation will then be evaluated against current state-of-the-art model for the task of motor imagery classification by offering a control system which allows a user to control a video game character through thought alone.

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1 Introduction

Recent advances in the hardware required for small-scale and non-intrusive methods of measuring brain activity offer an unprecedented level of potential for the development of brain-controlled interfaces (BCI). Where this type of technology used to be accessible only to the professional medical community [2, 25], hobbyists are now able to approach this domain as a viable method of control. NeuroSky and Emotiv both provide cost-effective boards for recording electroencephalograms (EEG) for developers to use for experiments along with a thriving community for novices and experts alike. OpenBCI takes this a step further by open-sourcing both the software and the hardware for their boards, the Ganglion and the Cyton.

Despite the explosive growth of the field since the 90's, drawing meaning from the understanding of the brain remains a difficult challenge. The open-source community tends to focus on interpreting the signals in an effort to create control systems requiring thought alone. This is an attempt to solve the inverse problem in EEG, where we try to infer the inputs given a set of outputs, leaving open the forward problem, where we attempt to discern what types of outputs we can expect to see given a set of inputs. The forward problem is left to large research labs with extensive resources, but to create a truly effective BCI, both the forward and inverse problems in EEG must be addressed in tandem to ensure that the system operates based on theoretical truth of the functionality of the brain.

1.1 Thesis Statement

The work for this thesis will attempt to address the issue of bringing together solutions for the forward and inverse problems in EEG. By offering a novel method of representing the multivariate electrical signals captured by EEG systems, developers and researchers outside of large, heavily funded medical institutions will be able to better advance their models due to a better understanding of the theoretical operation of the brain. The proposed method of presenting this data is similar to the form taken by spectrograms and will leverage the current understanding of the mind by building upon a common method of representing EEG signals: EEG montages. To this end, neuroscientists, computer scientists, and hobbyists will all be able to more readily interpret the complex EEG signals, facilitating the advancement of research both towards understanding the function of the brain as well as how to use that understanding to develop better and more robust brain-controlled interfaces.

1.2 Objectives

My primary focus in conducting this research work is to present a novel method for representation of EEG data that is understandable for subject matter experts in separate domains. To this end, I will provide a library which allows for data to be quickly and easily imported for analysis and to efficiently generate the spectrograms for deeper analysis or classification.

BCI systems are intended to offer a method of communication and control to an outside environment [5]. Any method of data representation of EEG should be able to be used towards this task. This desired characteristic will be tested by using the spectrograms of the EEG signals to train a classifier that is able to distinguish between two motor imagery event-related potentials: moving left and moving right. This will allow a user to control a character through a maze on a computer using only their mind as the control input.

All of this work will be captured in a detailed report capturing the theoretical neuroscience of the system, the reasoning for the proposed, novel method of data representation, how it leverages state-of-the-art techniques in the separate fields, and an evaluation of the effectiveness of the representation when used in a real-world environment. Explicitly put, this thesis will deliver the following items:

1. Python library to read in EEG data, provide analysis functionality, and generate spectrograms for analysis and classification
2. Proof-of-concept of using the proposed method of data representation to allow a user to use their mind to navigate through a maze
3. Technical report on the research conducted and the results obtained

1.3 Evaluation

The work for this thesis can be seen as taking on two forms: the method of data representation and the proof-of-concept application that allows a user to play a game using their mind. The first part of the thesis will be evaluated on the basis of intuition and ability to infer information useful for solving the forward and inverse problems of EEG. This will require that distinct brain signals produce noticeable distinct spectrograms. The analysis should be able to not only detect that there is a difference, but also actually highlight the part of the spectrogram that is responsible for the distinction. As for the proof-of-concept game, the evaluation will be based on a comparison against current, state-of-the-art techniques for classification of binary event-related potentials. As it is a game, there should be as little lag as possible between input and character movement. Thus, the evaluation will include a timing analysis of the classification ability along with the amount of time it takes for the system to detect that an input was provided by the user.

2 Problem Statement

The potential for BCI is often characterized by its potential to offer a unique means of control and communication in that it requires no muscle movement by a user [25]. Development of such a system inherently requires an understanding of theoretical neuroscience as well as classification and data analysis techniques [4]. This requires teams to be proficient in numerous knowledge domains running the gamut from neuroscience to computer science to information theory, leading to a necessity for communication between these various domains. Communication between different numerous individuals with differing areas of expertise inevitably leads to a breakdown in the ability to convey information across domain boundaries.

One solution teams will often take to avoid the issue of the breakdown of communication is to limit the areas of expertise required to solve a problem. That is, teams of neuroscience will progress the capabilities of BCI systems by advancing the theoretical neuroscience, while teams of data scientists will attempt to improve classification and recognition of the event using data analysis techniques

[27]. This means that the domains remain disparate and sharing information is wrought with the potential for misunderstanding due to differing experiences and language use.

An arguably more robust solution is to form a team with a diverse skill-set. Unfortunately, a team can only grow so large before becoming unmanageable, and there will still inevitably exist a gaps in expertise areas due to the complex nature of such a system.

2.1 Motivation

Based on the aforementioned concern, it would prove fruitful to provide both researchers and hobbyists a common means of understanding between the distinct theoretical aspects involved in advancing the capabilities of BCI systems [1]. That is, provide a method for the subject matter experts, in this case, the neuroscientists, to communicate and provide the information and data to the computer scientists in such a manner that it is able to leverage the current state-of-the-art methods for data analysis and classification.

Neural networks are often cited as being black boxes in the sense that it is difficult to reason as to the how or why certain predictions are made, though progress is being made to this end, particularly with regards to the domain of image classification. If the knowledge representation were able to be more closely aligned to the progress currently being made by the field of computer vision, it would offer the ability for the domain of neuroscience to leverage the research currently being undertaken by this field of computer science [24]. In this way, the inner-workings of the brain can be more directly explored and may offer insights with regards to the forward and inverse problems of EEG.

2.2 Prior Work

Much of the prior work in this field has been a two pronged approach: neuroscientists working to extract meaningful features from the generated signals and computer scientists working to use those features to perform data analysis and classification. The features often rely on common digital processing techniques which are applied to different montages, or methods of representing the signals. For the work done by data scientists, the signals are often viewed as multivariate time series. Common classification techniques involve models well-situated to dealing with this type of data, such as recurrent neural networks [16, 28] or logistic regression models [20]. The EEG signal can be seen as holding information in a spatio-temporal form, and neuroscientists are able to perform feature extraction based on this insight. These features are non-linear in nature and can be effectively fed to either a typical convolutional neural network [23], recurrent neural network [10], or a recurrent convolutional neural network [35] for classification.

When approaching the problem of classification of motor imagery events, subject matter experts often perform manual feature extraction [30, 32] based on the theoretical underpinnings of the neuroscience involved. These features often take the form of Hjorth Parameters [34], Fourier or Laplacian transforms, or wavelet transforms, which are then fed into machine learning classifiers (SVMs, logistic regresseion models, artificial neural networks [31]). Evaluation of these models commonly reports on the accuracy of the models, despite the fact that the datasets are skewed with regards to normal brainwaves versus the signals indicative of an event of interest. Another method of evaluation is a transient analysis of the system with regards to the timing involved in recognizing and classifying an event [14]. In this method of evaluating the performance of classifying event related potentials, a plot shows the start of an event as boundary marks. The plot additionally shows where the system made predictions about the onset and end of an event. This then allows the researchers to visually inspect the ability of the model to accurately identify oddball events as well as how long it took for a particular event to be recognized, assuming that the event was successfully recognized by the classifier.

Another common approach for solving this task is to employ reinforcement learning algorithms [8]. These have been shown to be able to not only solve event-related potentials, but also the problem of error-related potentials, in which the system attempts to detect when a user thinks they have made a mistake [21]. Not only has this approach been implemented in augmented reality simulations [11], but also in the physical realm by training robots [17] to recognize and respond to EEG signals.

3 Approach

This effort will require both a hardware and software component. The hardware component will be the Ganglion board, developed by OpenBCI. This board is among the cheaper options of consumer-level EEG systems while still providing access to the raw data read by the electrodes. The software component will be primarily Python based, allowing for leveraging the community-developed machine learning and AI libraries, such as Keras and Scikit-learn. These tools will be used in the development of a method of representing the signals generated by the Ganglion.

The data representation of a single sample will take the form of an image, where each image generated correlates to a series of time samples of the data channels collected by the Ganglion board. Typically, these signals would be fed directly into a machine learning algorithm, such as a recurrent neural network. This method of preparing the data will be compared against other state-of-the-art techniques for performing motor imagery classification.

3.1 Intuition

Teams composed of different areas of expertise will inevitably face an issue of terminology. One domain will use terms and phrases which are either not common-place, or may even be contradictory, to similar terms used by the other domain. Using common phraseology can go a long way in establishing an effective method of communication between the various domain experts. Some teams attempt to solve this problem by having an ever-growing compendium of common terms. Not only can this quickly become unmanageable, but it still offers the potential for confusion if there happens to be any missing terms. On the other hand, images and graphics tend to be more universally interpreted. The human mind perceives images in a fairly ubiquitous manner in that the mind tends to search for particular features in an image: corners, edges, and color splotches. Leveraging this characteristic of how humans perceive visual information would allow the different experts to point more directly to certain properties or artifacts present in the image. It is this same insight which allows convolutional neural networks to perform well on the task of image recognition.

Intellect is often seen as an ability to recognize patterns and is the basis for intelligence quotient (IQ) quizzes. Performing such a task, however, is not strictly dependent on ones ability to recognize a pattern, but also on how an individual views the information in their mind. Some individuals view mathematical concepts as shapes which fit together in various ways; viewing numbers in this way can prove beneficial in performing mental arithmetic operations or to extend complex mathematical concepts to new domains. It is based on this insight that representing information in a graphical manner will prove advantageous for machine learning models to learn to classify complex event-related potentials. Rather than relying on expert and human oversight in order to guide the learning capabilities of a model, the model would be able to learn shapes and forms inherent in the data in order to derive insights about how to distinguish between the different classes.

3.2 Data Acquisition

The data used to build out and validate the proposed system and method of data representation will be pulled from existing datasets as well as manually generated through use of an EEG headset. The use of existing datasets allows for a direct comparison against prior research [30] as well as facilitates development of the system due to the fact that many of these datasets have been pre-cleaned or offer a baseline method for cleaning. If there is a statistically significant disparity between the performance of the system on the pre-existing datasets in comparison to the manually collected data, this could signify that the data collected from the EEG headset may have been improperly collected or cleaned.

The manually collected data is a required asset due to the necessity of having a method to collect, in real-time, the signals from a user's brain. In order to create the actual system which allows a user to control the character in a game, the method of data acquisition is already a requirement which can be further leveraged in order to better create and validate not only the models, but also the methods employed for data acquisition and cleaning.

3.3 Data Representation

The meat of the proposed approach comes in the form of creation of the method of representing the data. From a high-level, the data representation has the following requirements.

1. Holds true to the theoretical principles of the underlying data
2. Easily interpreted by both subject matter experts and artificial intelligence engineers
3. Offers classification performance comparable to current state-of-the-art models

The first point essentially captures the idea that the data must not be represented in a form that leverages some undesired characteristic that may happen to be present in the dataset. For instance, when a user blinks their eye, a noticeable artifact is produced. However, this artifact is not actually indicative of the desired event. The data representation must not attempt to use such a feature when attempting to classify between right and left movement.

The second point is the requirement which captures the essence of representing data in this manner. It is meant to bridge the gap between the areas of expertise offered by the neuroscientist domain experts and the skill-set of an artificial intelligence engineer. By requiring that the data be understandable to both sets of research experts, it should allow for a more direct line of communication about how and why the model may be performing as it is. Development of accurate and robust models is simplified and ensures the team is able to communicate more effectively.

The third point ensures that the machine learning model is actually able to use the data in this form in order to accurately classify between the desired types of events. If this were not the case, the proposed method of data representation would serve little purpose beyond being another method for representing the information such as is done by current EEG montages. Furthermore, it stipulates that not only does it perform adequately, but it must be able to keep pace with current, top models. It is likely that certain parameters will have to be identified which offer tuning of certain parameters used to create the spectrogram [29]such as the number of past, discrete data points in a single image. For instance, the effect of a stimulus is not expected to be present for longer than five seconds. There would be little to no reason to include such a long range of time in identifying a particular event. It is likely that the period of interest is much shorter than half a second. However, the actual length of time is unknown and is an area which must be explored in order to determine the optimal length of time for motor imagery event detection.

3.4 Classifier Models

Since the mid-80s, several different techniques have been applied in order to distinguish between different events as well as different mental states [33]. Despite this variability in the specifics, due to the nature of the problem itself, the classifiers are typically derived from a set of parent classification techniques. These classification techniques employed are often representative of the background of the team of the researchers involved. For instance, many neuroscience focused teams employ techniques which allow them to leverage their theoretical understanding of the mind. This requires significant effort in performing feature extraction and is better situated to being fed to models such as logistic regression techniques or support vector machines. Computer science minded teams tend towards classifiers following an artificial neural network architecture due to the ability of these models to perform automatic feature extraction to an extent, requiring less of a deep-dive into the theoretical underpinnings of the neuroscience involved in forming the decision boundaries.

3.4.1 Logistic Regression

Logistic regression relies primarily on a statistical analysis of the classes involved in a logistic model. It observes the samples, or data points, and attempts to build a function which mathematically represents the samples. In the case of EEG analysis of motor imagery events, each sample is a single, oddball event [31]. Each event is then described by various features, such as entropy or spatial-temporal spectral energy. In this way, each sample can be considered as a set of parameters, and the regression model fits the best hyper-plane to describe those parameters.

This model offers particular benefit to subject matter experts due to the ease of interpretation. As it is based in statistics, a wide number of fields are able to readily understand the method by which this model is able to perform classification, which is a large benefit over certain forms of neural networks which may require more expertise to interpret. Additionally, this type of model explicitly operates on extracted features, allowing those same experts to understand the actual information the model is using to perform its predictions.

3.4.2 Support Vector Machine

Just as with logistic regression, support vector machines operate on a discrete set of features. However, this does not mean that each feature must be discrete; it means that the information presented to the model can be used to form a hyper-plane which differentiates between the various classes present in the dataset. It offers a similar benefit to subject matter experts in that they are easily understood with respect to how and why they are making their predictions. Furthermore, they offer a benefit over neural networks in that they typically require less information in order to perform adequately for a large number of tasks. This is particularly useful in the task of motor imagery classification as it can cost a significant amount of resources to preform a single EEG recording session.

3.4.3 Convolutional Neural Network

Convolutional neural networks have been shown to perform extremely well for the tasks of computer vision and pattern recognition. Primarily, this is due to the fact that images and patterns can often be interpreted as a discrete or continuous signal. Convolution is able to match particular signal forms as well as recognize arbitrarily complex forms in signals. Furthermore, they offer the benefit of operating directly on images rather than requiring manual feature extraction. In addition to training being more automated than models such as logistic regression and support vector machines, these models have the benefit that they are able to recognize latent variables which may be hidden or unknown to human researchers. Unfortunately, this can also obscure reasoning behind why a model makes a particular prediction.

3.4.4 Recurrent Neural Network

Recurrent neural networks are typically an intuitive choice when dealing with time-related information, such as the stock market or information flows. This is largely due to the fact that they are specifically designed to retain past information for a length of time. For example, in a long short-term memory (LSTM) architecture, a typical cell is comprised of an input gate, an output gate, and a forget gate. These three gates work in conjunction to retain information for an arbitrary length of time based on activation states of the cell. LSTMs specifically were designed to deal with the issue of vanishing and exploding gradients. Other RNNs have been specially crafted in order to perform better in a particular domain [13].

RNNs have the unfortunate characteristic that they are considered difficult to train in the sense that it can take a lot of information in order to properly learn the time-dependent functions which form the decision boundaries of the classifier. To this end, they can be considered more sensitive to spurious or uncleaned data which is often characteristic of EEG signals. It is expected that this classifier model would preform worse when attempting to apply transfer learning; the trained model will likely not be as successful at generalizing to new users even if it is able to generalize to different tasks for a particular user.

3.5 Experiment Setup

This thesis is expected to require three different forms of experiments. The first will be an initial data collection stage where the ~~victims~~ volunteers will have their brainwaves monitored and recorded while performing a simple motor imagery task. The second phase of the experiment will be the attempts to represent the data in a meaningful manner and to train the classifiers on the user-generated data. The final phase of the experiment will occur at a separate time and will require the user to attempt to use the system to control an on-screen character using only their mind.

3.5.1 Phase One

For the data acquisition phase of the experiment, the brainwaves of at least two users will be recorded while performing a motor imagery task. This task will take on the form of attempting to follow the directions presented to them. The information recorded for this will be comprised of the following:

1. The start of an event
2. The end of the event
3. The electrical potentials from each EEG channel during the entire session

In this way, the markers for each trial can be placed in order to determine a set of time-related potentials which should be associated with a particular event. For instance, it is expected that a typical stimulus in the oddball paradigm will take between $150ms$ and $300ms$ to be present on an EEG recording. This many samples following the event will demarcate the start and end of the event boundaries, allowing for creation of a labeled dataset which can be fed to the classifiers for training.

3.5.2 Phase Two

The second phase of the experiment will consist of training the classifiers on the generated data. This will require various, high-level steps. The first will be to split the dataset in order to build a training set and a validation set. The second will be an attempt to replicate existing work in order to build a baseline classifier for comparison. For this, echo state network will be built, as it has been shown to achieve state-of-the-art performance on event-related potential classification. Furthermore, there exists Python bindings to a C++ library which should facilitate the building of a baseline model.

Following implementation of the baseline model, the data will be represented using the aforementioned transformation in order to generate a spectral image correlating time versus frequency and time versus channel. The actual samples will contain the same numerical information as the previously used samples, and a single image will be produced for each data sample. This will allow for direct transformation of the dataset from a Pandas dataframe into a set of labeled images. These images will be fed into a CNN architecture for the task of classifying the samples. Due to the skew in the class sparsity, accuracy will likely not be an adequate metric of performance. Instead, the model will be evaluated on the basis of timing, precision, and recall.

3.5.3 Phase Three

The final phase of the experiment will be where the system is tested in a real-world environment; the same users previously used to collect the training data will attempt to use the built system to control a character on a screen. In order to reduce complexity and ensure that the testing captures the ability of the user to use the system rather than effectively play the game, the game will be a simple 2D maze game with no time dependence on moving the character. In other words, they will not have to carefully control the timing of when the character moves left or right. Rather, it will be a continuous movement back-and-forth. The alternative would be a game such as Snake, where the player must make a specific movement at a specific time in order to collect the rewards for growing the snake.

By structuring the evaluation phase of the experiment in this way, it allows for the system's performance to be measured both in terms of precision and recall, as well as by a timing analysis. The first is done by simply comparing the expected result versus the result of the classification based on the user's input. The timing analysis will be done by marking the start of when a user should start to move a certain direction. The salient feature here would then be the amount of time it takes for the system to detect an attempt to move the character in that direction. An important consideration here occurs in the case where the system misclassifies the motor imagery event, eg, interpreting a left movement as a right movement. In this case, no further timing analysis should occur, as it is likely the case that a user will react and be better able to move a character in a particular direction. For instance, moving left and right is closely tied to moving the left or right hand respectively. It is expected that the system will be able to perform faster when the user attempts to move in the direction associated with their dominant hand. As such, there will be a difference in the timings for each direction that will likely be of interest for further analysis and should thus be distinguished between when performing the timing analysis.

3.6 Expected Challenges

Many projects and work tends to focus on approaches which focus on gathering signals from specific areas of the brain. Namely, these signals have been used to measure levels of attention and relaxation. Both NeuroSky and Emotiv have proprietary algorithms for transforming signals measured from the prefrontal locations of the international 10-20 system into values which represent how focused or relaxed a user is at a given point in time.

3.6.1 Theoretical

There are several issues with this approach. Arguably the largest is that it focuses work on only a single type of signal. From a theoretical perspective, the region of the brain that is most active when a user is performing some action is dependent on the actual action or activity. For example, the occipital cortex is responsible for processing visual information, while the temporal cortex is active in matters related to speech and natural language [12]. While researchers and developers have been attempting to solve problems such as correlating signals to language, approaches have often fallen back on clever manipulations of measurements taken from the prefrontal cortex rather than measuring and analyzing signals from the portions of the brain that are primarily responsible for these actions. While certain levels of success can be attained in this manner [15], it limits the possibilities by which humans may be able to interact with computer systems through thought alone.

A further issue is with regards to a user's ability to manipulate these various states of mind. Various studies have shown that not everyone is equally capable of manipulating their brain patterns in such a way as to be able to effectively use a BCI system [26, 19]. As such, researchers often simply disregard those trials, which tends to be a fairly manual task involving a high level of expert insight and training. This is costly both with regards to time as well as personnel, as this expert must dedicate their knowledge towards cleaning the dataset. Unfortunately, this task cannot be crowd-sourced in the same manner as many other data preparation tasks can be, eg. sorting and labeling images of animals, due to the high level of expertise required in understanding the various ways in which EEG signals can be represented. It is required that experts interpret these montages in order to distinguish between relevant event-related potentials and undesired noise and artifacts.

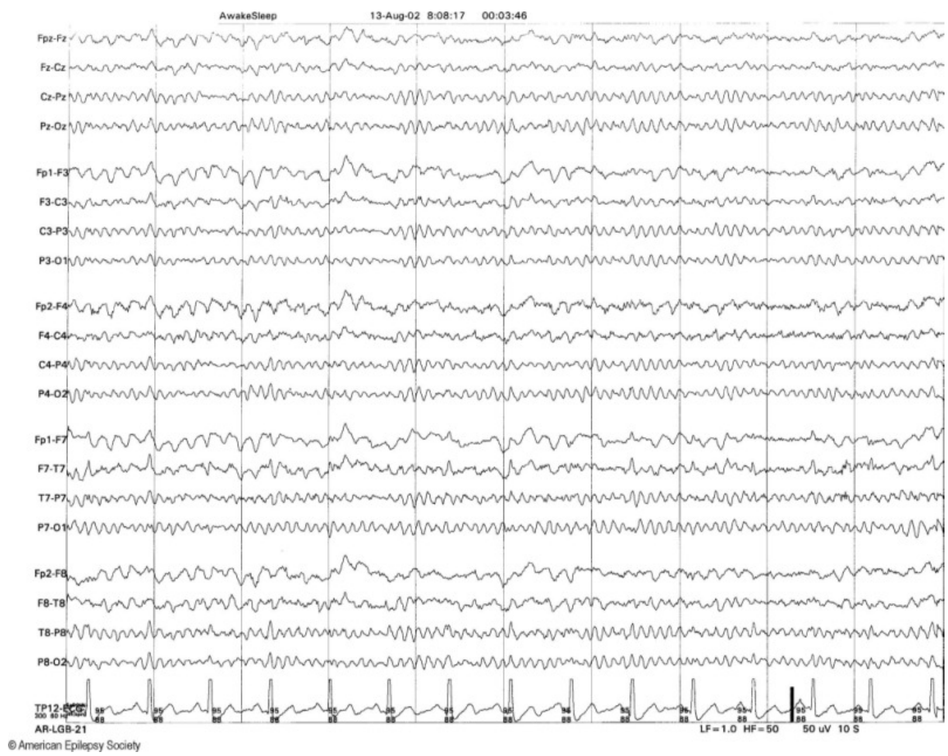


Figure 1: Eye Flutter Artifact [7]

For example, consider the the transverse bipolar montage depicted in figure 1, which depicts eye flutter by a user. This artifact occurs when the user moves their eyes, inducing a changing potential in the frontopolar leads. It would not be reasonable to expect this to be common knowledge which could be easily identified by a non-expert, though it has been found that similar types of tasks can be gamified with rather decent results, as was done by MIT in identifying protein folding structures. However, this still requires validation by a subject matter expert in order to verify that the data has been properly cleaned and prepared.

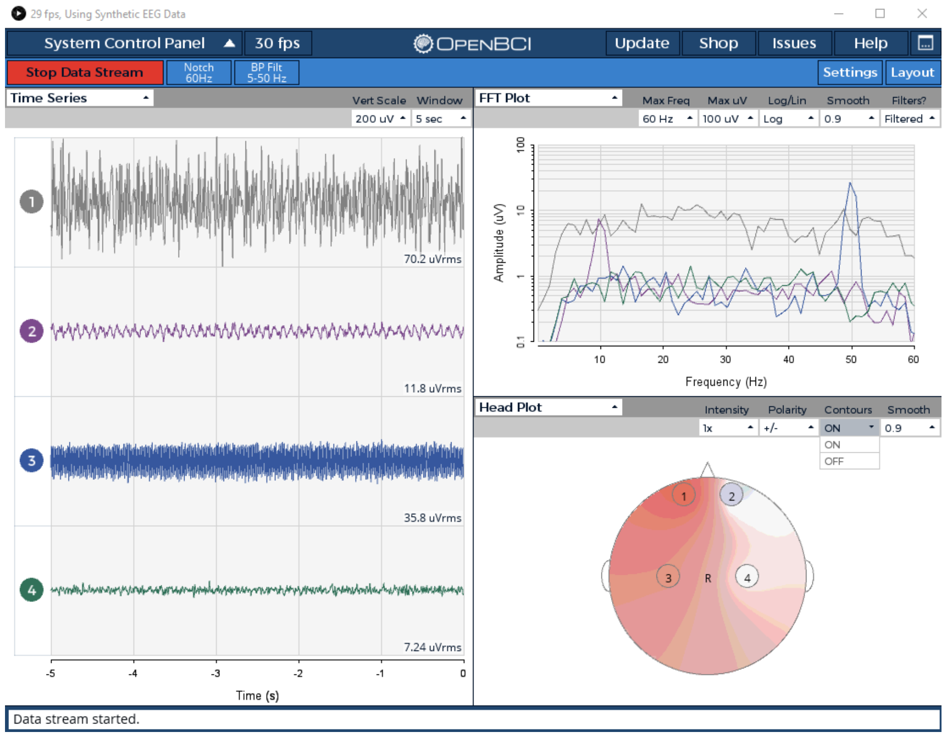


Figure 2: OpenBCI Gui

3.6.2 Technical

As this thesis intends to provide a proof-of-concept of the feasibility of a certain method of classification, it is necessary to develop a system which is capable of recording the EEG signals directly from a user. The Ganglion board was selected for this purpose. However, this board presents several challenges when using the released GUI tool meant to collect and display the readings from the channels on the board. For instance, consider figure 2. The tool is configured to display the values streamed from the board along with the Fourier transforms, as provided by the tool itself. This information is not directly accessible except for visual analysis and to get it into a form usable for use outside of the OpenBCI environment, the data must be exported in some way or otherwise made accessible as a data stream. This presents a challenge in the fact that the developed library is not particularly stable or robust with regards to its ability to provide access to the raw data collected by the board. Furthermore, its ability to interface with a Windows environment is a known limitation due to the underlying Bluetooth library. On the other hand, certain other libraries, such as CUDA, can be more easily configured on Windows; Selecting one platform for development requires sacrificing usability of one library for usability of another.

A common trope in machine learning is that there is no substitute for clean data. This holds particularly true for EEG tasks due to the low signal-to-noise ratio (SNR) inherent in the data itself, regardless of the method used for collecting the data. The data be obfuscated by experimental setup, such as electronics in the test environment or use of dry versus wet electrodes. This can be further confounded upon due to variances in the test subject themselves. EEG data is meant to capture the electrical potentials which occur when a user performs some action which requires use of the brain and is inherently dependent on the actual mental state of the user, including hunger, fatigue, and general contentment. Altering any of these states has the potential to be reflected in the EEG recordings when performing the same task. One solution to this issue is to continuously build out a larger and larger dataset which represents the user in various states of mind. This quickly becomes intractable due to the exponential growth of adding a single feature to the set of monitored states; Adding a single feature to monitor (hunger, sleep level, happiness, stress, etc) increases the number of potential mental states by a factor proportional to the number of discrete states of the new feature.

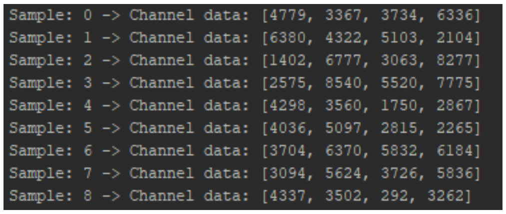
4 Current Status

The majority of the work to date, beyond initial research and theory development, has been focused on addressing the issue of gathering clean data in a manner which is usable for the purposes of the experiment. For the purposes of gathering clean data, this has taken on two forms: locating clean datasets and building a system for manual data acquisition. As EEG signal analysis and classification is not a new problem, there are numerous datasets in the public domain, released both as part of a competition or by researchers hoping to spur the progress of the field. These include several versions of a dataset used at Neural Information Processing Systems (NIPS) in the early to mid 2000's [6] as well as from various Kaggle competitions, such as the Grasp-and-Lift competition [9, 22]. Specifically for the task of motor-imagery classification, a large-scale dataset was released by a team of researchers in an attempt to address the lack of a standard dataset that can be used for the purposes of developing and evaluating approaches to solve the problem of motor-imagery classification [18]. Finally, Mohit Agarwal hosts a list of public EEG datasets [3] on GitHub.

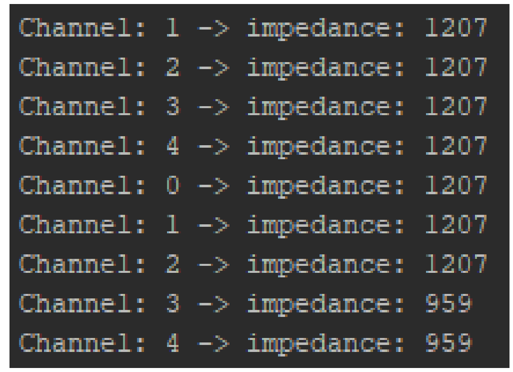
Current work has also involved addressing the difficulties in working with the Ganglion board. The decided upon approach for accessing the data stream was to bypass the GUI tool altogether and communicate directly with the hub the board uses to communicate to the GUI. While this requires additional effort due to requiring that the data acquisition application conforms to the specifications required by the communication hub, this method provides the benefit of a more direct line of communication with the board. Figure 3a shows several data samples received from the Ganglion board that are ready for further processing.

Communicating with the board in this way facilitates the ability to do impedance checking. This offers the ability to check the quality of the signal. However, low impedance values do not necessarily guarantee a high signal-to-noise ratio; it means that the majority of the received signal is from the head of the user rather than from the board. Several example samples are shown in figure 3b.

The current code is currently hosted on GitHub. Along with the code, this repository contains a list of papers, links, dissertations, and other theses which may prove beneficial in execution of this thesis. The progress of this thesis will be tracked on my personal website, www.andrewtfesta.com and will additionally contains links to the most current version of the report and any other relevant documents.



(a) Data Samples



(b) Impedance Samples

Figure 3: Recorded Samples from the Ganglion Board

5 Next Steps

Due to the nature of the work involved in testing the hypothesis and building the anticipated deliverables, the majority of the time is expected to be dedicated to the tasks of data acquisition and analysis. From a high-level perspective, the work for this thesis can be roughly broken down into various tasks, as outlined in table 1.

Phase	**Anticipated Length**	**Technical Goals**
Logistics and Preparation	2 weeks	Setup a foundation to work from Work to limit future challenges Layout tasks for rest of the thesis work
Data Acquisition	2 weeks	Locate external datasets for testing Collect raw data from users
Data Cleaning and Analysis	4 weeks	Prepare dataset for analysis Remove anomaly samples Format dataset for classifier use
Model Building	3 weeks	Build out testing architectures Test various classifier models
Evaluate Results	2 weeks	Visualize results of models Identify strengths of various models Identify weaknesses of various models
Finalize Report	2 weeks	Edit and revise thesis report Prepare for thesis defense

Table 1: Thesis Phases

This is a cursory overview of the general steps involved in performing the research tasks described hereto. Table 2 outlines the expected work on a week-by-week basis starting from the start of the Fall 2019 semester to the targeted defense date of December 16th, 2019.

Start Date	End Date	Task(s)
Aug 26	Sept 2	Acquire required signature for approval Layout semester plan with reader and chair Set up website for status reporting
Sept 2	Sept 9	Ensure thesis is properly approved and enrolled Finish PyGame implementation to aid in data acquisition Gather at least 2 ~~victims~~ volunteers for recording brain activity
Sept 9	Sept 16	Record 30 minutes of brain activity for each volunteer Break data into expected format for ease of manipulation Gather feedback to improve further recording sessions
Sept 16	Sept 23	Record 30 minutes of brain activity from each volunteer See Elton John in concert in Vancouver Organize the inevitable chaos that has arisen
Sept 23	Sept 30	Record 30 minutes of brain activity from each volunteer Break recordings into time-boxed samples Remove samples with noticeable eye and head movement artifacts Build user profile for baseline brain activity
Sept 30	Oct 7	Perform signal de-noising based on average signal per user Build dataset based on de-noised signals Perform inter- and intra-rater comparisons between samples
Oct 7	Oct 14	Identify outlier and anomalous data points Build signal maps to feed to classifiers
Oct 14	Oct 21	Outline structure of classifier based on signal shapes Implement waveform transforms for comparison classifiers
Oct 21	Oct 21	Implement convolutional neural network architecture Build logistic regressor and SVM models
Oct 28	Nov 4	Train CNN, SVM, and logistic regression models
Nov 4	Nov 11	Perform simple fine-tuning of models Implement ability to feed predictions into PyGame controls
Nov 11	Nov 18	Perform timing analysis to determine control delay Gather AUC metrics of model performance
Nov 18	Nov 25	Determine meaningful representations of evaluation Generate graphics to include in report
Nov 25	Dec 2	Thesis report editing Thesis defense practice
Dec 2	Dec 9	Thesis report editing Thesis defense practice
Dec 9	Dec 16	Thesis Defense

Table 2: Estimated Time Table

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