IMPLIMENTATION AND EVALUATION OF A BRAIN COMPUTER INTERFACE USING A CONSUMER GRADE EEG HEADSET

SUMMER RESEARCH REPORT

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SUMMARY

Tim Maloney, a Concordia University Co-op student in electrical engineering, was awarded an NSERC Undergraduate Research Grant for the summer of 2017. He was invited to do research in the Intelligent Signal & Information Processing lab under the supervision of Dr. Arash Mohammadi on the subject of implementing brain-computer interfaces (BCIs) to control a robot. This report details some of his findings over the course of the work term, including a summary of his literature review on BCIs, the technical details of the implementation of a BCI for the I-SIP lab, and the results of the implemented BCI. The outcomes of the summer research project were mixed since the objectives of implementing a BCI were met and research was done beyond the original scope, however, limitations in the quality of the hardware left the final implemented BCI wanting. Performance of the final BCI suffered because brain activity was measured using a consumer grade electroencephalogram. Nonetheless, the work was fruitful for the I-SIP lab, since there is now a complete BCI system in place with which they can gather new data or experiment with new algorithms. At the time of writing the report, the internship was not over yet, and new possibilities were being explored to gain access to better hardware.

INTRODUCTION

For the summer of 2017 I was invited to do research on the implementation of a brain-computer interface to control a robot. The research was to be done under the supervision of Dr. Arash Mohammadi at Concordia's Intelligent Signal and Information Processing Laboratory, and funded by NSERC through a USRA research grant. Ph.D. student Soroosh Shahtalebi and Master's student Golnar Kalantar of the I-SIP Lab were also available to aid in my work, since both had done research in the field of brain-computer interface.

A brain-computer interface(BCI) is a communication system that measures and interprets brain activity into some sort of output. [1] In its simplest form, BCI's are used to roughly measure emotional state, however, more advanced BCI's can be used for example to interpret the thoughts of a paralyzed individual thinking about specific motor movements, granting them a way to control a motorized wheelchair. There are many different implementations of BCI systems, but for many reasons electroencephalography(EEG) is the preferred method of measuring brain activity for BCIs. [1] Firing neurons in the brain create electric potentials which can be measured with sensors. One major benefit of EEG is that it can take measurements of brain activity using electrodes on the scalp, without the need of large equipment like FMRI's or invasive methods like surgery. However, there are many challenges in interpreting the EEG signal since the measurements are being done from across the skull. Both Soroosh's and Golnar's work in BCI have been in the development of machine learning algorithms to improve the interpretation of brain signals in BCI systems. To date, their work has been done on EEG data from external sources. As such, they have been working with what we call offline BCI, since the signal processing is not done on live data.

One exciting aspect of my summer's work was that I would be implementing an entire BCI system in the I-SIP Lab, including the EEG headset, recording software, BCI algorithms and the robot which would serve as the output device. My work over the summer would let future researchers in the I-SIP lab collect their own EEG data and allow them to design their own research that is not constrained to externally sourced data. Furthermore, my work would open new research possibilities in online BCI. Algorithms could now be implemented and tested using live data from the EEG headset and give real time feedback as, for example, the movement of a robot.

Key aspects of my summer's work in implementing an online BCI are documented in this report. First, the finding of my literature review give some important background information on BCIs. This is followed by a description of the complete implementation of the BCI system. Finally, I discuss the functioning of the implemented BCI, and touch on some of the research that was done using it.

Outline of Project

(Minimum 1000 characters; maximum 1800 characters or 18 lines whichever comes first)

Brain-computer interface (BCI) is a communication system aiming to provide a non-muscular channel for the brain to control external devices using electrical activities of the brain. BCI systems have several practical applications of engineering importance including controlling a wheelchair or neuro-prosthesis for disabled individuals; navigation in virtual environment; Emotion recognition, and; Rehabilitation. Electroencephalography (EEG) is the most commonly used measurement modality for monitoring brain activity due to its non-invasive nature, unsurpassed temporal resolution, being wearable, and being more affordable than other neuroimaging techniques. Despite recent development of EEG-based BCI systems, however, performance of such artificial interfaces still requires significant improvements for real-time applications. In this project and motivated by the urgent need of paralyzed patients for advanced controlling assisted-devices that support their mobility, EEG-based signal processing solutions will be investigated/implemented for online control of a robotic device. This project aims to achieve the following key objectives: (i) Characterize evoked responses obtained from EEG to use them as control signals to operate a robotic device; (ii) Test innovative online learning algorithms to classify signals from a headset into corresponding activity commands; (iii) Generate high-level commands for controlling a robotic manipulator in three dimensions, and; (iv) Implement developed techniques in an online BCI. A prototype system will be designed based on EMOTIV EPOC+ neuroheadset, and Lego Mindstorms NXT robot and tested for performance evaluation with healthy subjects performing two different types of foot movements associated with different levels of force and speed.

Student's Role

(Minimum 300 characters; maximum 500 characters or 5 lines whichever comes first)

Student will install/setup the EMOTIV EPOC+ headset and the LEGO robot, prepare the configurations of the experiments, collect data from the neuroheadset, integrate the neuroheadset and robot into the BCI system via developing required MATLAB functions, implement the provided online learning algorithms to classify the signals from the headset into corresponding action commands, and transmit activity commands to the robot to enable the BCI system to control the robot effectively and accurately.

LITERATURE REVIEW

To begin working with brain-computer interfaces (BCIs) requires an understanding of several fields of study. As such, my summer research began with a rather interdisciplinary literature review. The extensive body of psychological research gave background in understanding thought processes and experimental design. An understanding of anatomy and physiology proved important for understanding how we might measure physiological processes that are somehow indicators of thought. Then there is the field of signal processing, which is the main topic of research in the I-SIP lab. Machine learning is an important subsection of signal processing which is needed for interpreting the complex signals from an EEG. Finally, implementing the BCI and robot required reviewing and learning new programming skills. Some key technical concepts are summarized in this section to give the required background for the later sections of the report.

BCI AND EEG BACKGROUND KNOWLEDGE

The very definition of a brain-computer interface (BCI) has been topic of debate over the years, however, generally it can be defined as a communication system that bypasses the normal brain output pathways. [1] BCIs rely on sensors to measure brain activity and create an input signal. Methods of measuring brain activity include electroencephalography (EEG), magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), electrocorticography(ECoG), and intracortical electrode recordings. [1] EEG is most commonly used for BCIs due benefits such as high temporal resolution, low cost and ease of use. Furthermore, the field of BCIs with EEGs benefits from having an extensive body of literature on the subject. [1]

ANATOMY AND PHYSIOLOGY OF THE CENTRAL NERVOUS SYSTEM

Since a BCI measures brain activity, it is important to understand some of the physiological processes involved. Neuronal activity in the brain produces dendritic currents. [2] Currently, it is impossible to measure the effect of each neuron from outside of the skull, however, when many neurons in a close area act together, they create a local field potential that is measurable from an EEG. [2] With this limitation we can only hope to measure large scale effects in the brain. There are conventions for the placement of EEG electrodes on the scalp, such as the international 10/20 system which uses 21 electrodes, and other variations for more or fewer electrodes[3, p. 20]. Knowing where the electrodes are positioned can be helpful in developing BCIs since different regions of the brain are associated with different functions.

STANDARD INTERNATIONAL MAPPING SYSTEMS OF EEG ELECTRODES

There are conventions for the placement of EEG electrodes on the scalp, such as the international 10/20 system which uses 21 electrodes, and other variations for more or fewer electrodes[3, p.

20]. Knowing where the electrodes are positioned can be helpful in developing BCIs since different regions of the brain are associated with different functions.

FUNCTIONAL MAPPING

Different areas of the brain specialize in different functions. Although the exact layout of the brain varies for each individual, there are general regions in the brain dedicated to specific functions. For example, motor movement and motor imagery are associated with the frontal and parietal cortices. [1] Often the entire body's motor control is mapped according to the classic motor homunculus. [4] The occipital cortex is often synonymous with visual cortex, showing how closely linked the area is linked to functions of sight. [5] Still other regions are often strongly associated with functions such as language or various emotions. [6], [7] A knowledge of the functional mapping of the brain can inform strategies on how to interpret EEG signals, or how to design experiments. Motor imagery experiments using left and right movements, for example, might expect to see corresponding right and left hemisphere responses.

An additional complication to functional mapping is the phenomenon of paradoxical lateralization. Neural activity below an EEG electrode may not actually be registered by that electrode depending on the direction of the polarity of the induced potential. If for example the activity occurs in a sulcus of the brain, the polarity of the potential arises perpendicular to the closes electrode. As a result, a signal is only registered by electrodes farther away making it difficult to locate the origin of activity from the EEG signal.[4]

NOISE AND ARTEFACTS

The electric potentials created by brain activity are very small, and the electrodes of an EEG must be able to detect the electric potential at the scalp at a micro volt scale. EEG signals are therefore prone to degradation from noise and artefacts. Noise is induced from sources such as electricity (60hz), cellular signals, Bluetooth, Wi-Fi, electronics, movement etc. [8] Artefacts in a signal are produced from muscle movements, especially from the jaw, brow and eyes [9], [10] . These unwanted portions of the signal can usually be removed using filters. Often times in research, artifacts are excluded through visual inspection, however, this technique is obviously quite involved and limited to offline applications. Signals are also improved by proper EEG setup with well placed reference electrodes and good conductivity to the scalp using gels or saline solutions. Hair is often an obstacle to getting good contact with the scalp and makes EEG setup much more time consuming.

TYPES OF EEG SIGNALS

It is also important to understand some of the patterns that we can see in brain activity. There are several types, but my work focused on event-related potentials (ERP) and sensorimotor activity

[1]. ERPs are visible as some kind of signal spike in response to certain stimuli [10]. Sensorimotor activity on the other hand is seen in changes in different spectrums of the signals, also known as μ and β rhythms [1].

In the case of EEG BCIs, the most commonly used neural response patterns are event-related potentials (ERP), steady-state evoked potentials (SSEP), sensorimotor activity, and slow cortical potentials (SCP) **[1]**.

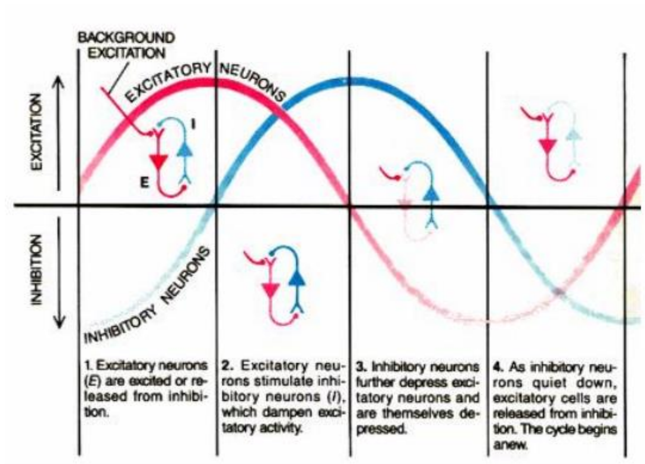
EEG-BCIs usually rely on one of six main groups of neural response patterns: sensorimotor activity, event-related potentials, steady-state evoked potentials, response to mental tasks, slow cortical potentials, and other power changes.

FREQUENCY RANGES

Typical EEG Component Bands

- Delta (1 – 4 Hz)
- Theta (4 – 7 Hz)
- Alpha (8 – 12 Hz)
- Low Beta (12 – 15 Hz)
- Beta (15 – 20 Hz)
- High Beta (20 – 30 Hz)
- Gamma (40 Hz and above)
- Ranges are typical, not definitive

Thalamo-Cortical Cycles



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MM, MI, SENSORIMOTOR ACTIVITY

neural response patterns that arise with motor execution (ME) or imagery (MI). Specifically, frontal and parietal cortices exhibit rhythmic activity in the 8–12 Hz and 13–30 Hz ranges, respectively called μ and β rhythms, when no sensorimotor activity is ongoing. Whenever a voluntary movement is triggered or imagined, however, these rhythms fade out, a phenomenon termed event-related desynchronization (ERD). Similarly, once the movement is over, these rhythms emerge again and produce an event-related synchronization (ERS). Another type of sensorimotor neural response pattern is a low-frequency, bilateral potential called movement-related potential (MRP) that arises around 1–1.5 s before a movement occurs.[1]

ERP, VISUAL, AUDITORY, P300,

Positive or negative deflections in the EEG signal caused by specific stimuli. The most preponderant ERP in the BCI literature is the P300, a positive deflection in the electrical activity of the parietal cortex occurring around 300 ms after the presentation of a rare stimulus, such as a visual, auditory or tactile cue. The error potential (ErrP) is another type of ERP that is measured when an individual recognizes an error that was made.[1]

The exogenous (or sensory) ERPs are elicited within the first 100 milliseconds from the stimulus and its characteristics are largely depend on the physical properties of the external stimulus.

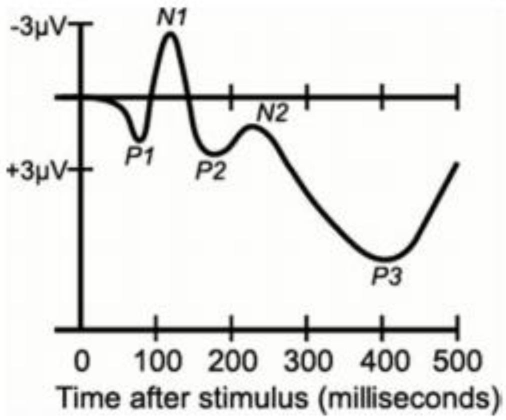

Figure 1. Components of a typical ERP waveform (adapted from wikipedia)

[10]

Deriving P300 using the oddball paradigm According to literature (Fabiani et al., 2007; Makeig, Debener, Onton, & Delorme, 2004; Sur & Sinha, 2009), P300 occurs as a positive deflection in the voltage (2-5µV) with a latency range of 250-400 milliseconds from the stimulus onset and it is typically measured by placing electrodes covering the regions of Fz, Cz, and Pz in the standard 10-20 system (Tatum, Husain, Benbadis, & Kaplan, 2008; Teplan, 2002) as represented in Figure 2. Since, the strength of an ERP is very low compared to EEG (which is about 50 µV), ERPs are usually hidden within noise and not visible in a typical EEG waveform. Therefore, to obtain a visible ERP, several segments of EEG signals (containing single-trial ERPs called epochs) have to be averaged by repeating the same experimental stimuli for several times. However, before averaging, it is necessary to filter the EEG signals using a bandpass filter having a pass band range of about 1-20 Hz and to remove artifacts resulting from sources such as eye movements. Fortunately, there are computational tools, such as the EEGLAB toolbox (Delorme & Makeig, 2004), to analyze EEG data by obtaining ERPs[10]

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SSEP

Steady-state evoked potentials (SSEP) are elicited by oscillatory stimuli with a constant-frequency component. In response to this rhythmic stimulation, the sensory cortex exhibits phase-locked spectral activity with the same frequency as the stimulus. For BCI applications, they are often produced with visual stimuli and recorded over the visual cortex, and therefore called steady-state visually evoked potentials (SSVEP). However, somatosensory and auditory stimuli are also capable of eliciting this kind of neural response pattern (SSSEP and SSAEP, respectively).[1]

MENTAL TASKS

Mental tasks are also known to elicit particular brain activity patterns. For example, mental calculation, mental rotation, covert spatial attention, and selective sensation all produce different activation patterns that recruit different brain regions and follow different time courses. Motor imagery, although described more precisely with neural response patterns such as ERD/ERS, is another example of a well-studied mental task. When volitionally evoked, reaching certain mental states such as a concentrated or relaxed state can also be considered as mental tasks.[1]

SLOW CORTICAL POTENTIALS (SCP)

Slow cortical potentials (SCPs), in turn, are slow oscillations in the EEG arising from cortical polarization. One can consciously control them through adequate training[1]

POWER CHANGES

power changes in other frequency bands or brain regions can be used to infer a user's affective states. As seen in Section 1.2, this is important for passive BCIs. [1]

INTERPRETING EEG

Interpreting the signal using machine learning usually occurs in two steps: feature extraction and classification [1]. Feature extraction is the process of reducing the size of the data down to much fewer "features" which are less computationally demanding to deal with. These features are then used to classify a given signal into one category or another. There are many variants on how this is accomplished,

After recording signals: Second, processing of the recorded signal(s) is done following three general steps: artifact processing, feature generation, and feature translation [1]. Feature generation, in turn, aims at extracting relevant features from the raw signals and can be divided into three subcomponents: preprocessing, feature extraction, and feature selection. [1]

active, reactive and passive (operation mode, similar to exogenous and endogenous);

synchronous and asynchronous;

discrete and continuous.

A BCI is synchronous if its inputs are analyzed during predefined periods of time, initiated by the interface. An asynchronous BCI, on the other hand, continuously analyzes its inputs and can thus respond to commands at any given time. [1]

a discrete BCI has few outputs that typically arise from a classification stage implying a choice between a few different possibilities, whereas a continuous BCI has outputs that can take any value in a specific range and is thus more suited to tasks such as cursor control.[1]

MACHINE LEARNING & ALGORITHMS

PREPROCESSING

#bandbpass

FEATURE EXTRACTION

TRAINING

CLASSIFICATION

#supervised/unsupervised

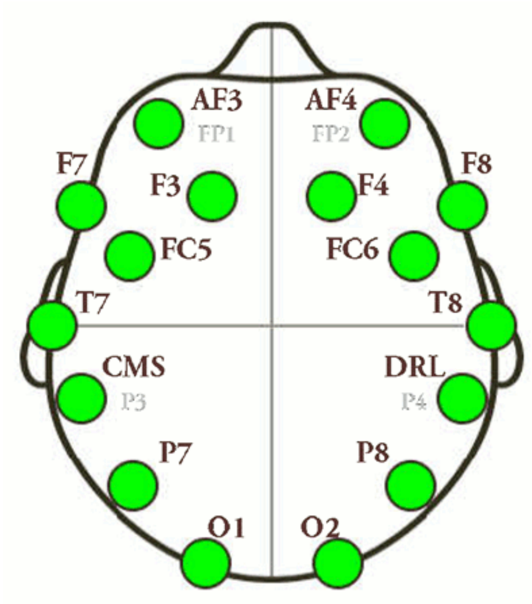
DIMENSION REDUCTION

ONLINE/OFFLINE

EMOTIV EPOC+ HEADSET LITERATURE REVIEW

EMOTIV EPOC+ HEADSET SPECIFICATIONS

"The EMOTIV EPOC+ is a high resolution, multi-channel, portable system which has been designed for practical research applications"[11]. 14 channels (plus CMS/DRL references, P3/P4 locations) Channel names (International 10-20 locations) AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 Sampling method Sequential sampling. Single ADC Sampling rate 128 SPS (2048 Hz internal) Resolution 14 bits 1 LSB = 0.51μV, Bandwidth 0.2 - 45Hz, digital notch flters at 50Hz and 60Hz Filtering Built in digital 5th order Sinc flter Dynamic range (input referred) 8400μV (pp) Coupling mode AC coupled Connectivity Proprietary wireless, 2.4GHz band Power LiPoly Battery life (typical) 12 hours Impedance Measurement Real-time contact quality using patented system



SCIENTIFIC RESEARCH ON THE EMOTIV HEADSET

I did more literature review on experiments done with the EMOTIV headset [9], [10], [12]–[16] . I found that most of the work with the EMOTIV headset have been looking at ERPs with varying success, and only a few have explored motor imagery with limited success.

Hiran Ekanayake 2010, and updated 2015: experimented with the EMOTIV to measure P3 ERP signals using P300- speller based on the oddball paradigm[10]. They confirmed that the headset can pick up 'true' or 'real' EEG, but found differences between headsets. They also used the Openvibe software which I believe I can reproduce.

Hidenori Boutani and Mieko Ohsuga 20013: did similar studies with P3 ERP and oddball session with 200 stimuli composed of either backward "C"s (target) or normal "C"s (non-target) in a ratio of 2:8, presented at a 1000 ms stimulus interval [9]. The participants were required to count target stimuli.They describe methods for removing artifacts and show that the P3 components obtained by the headset and by commercial plate electrodes and a multipurpose bioelectric amplifier during an oddball task were comparable.

Nicholas A. Badcock et al 2013: also look at the EMOTIV EPOC+ with auditory ERPs, and show that the auditory ERP was measurable[12]. The experiment compared two EEG devices having subjects listen to tones and count "deviant" tones. It concludes that the EMOTIV was comparable to commercial EEGs for ERPs such as the P1, N1, P2, N2, and P3 measured at the frontal sites

Cornelia Kranczioch et al 2013: describe a modified eeg setup based on the EMOTIV headset where the electrodes are re-positioned to optimize P300 recordings[13]. Using what sounds like the same EEG setup, Catharina Zich et all 2014 use online algorithms with MI and show MI learning effects with daily practice[14].

Hadeel Al-Negheimish et al 2013: compares P300 and MI methods on the EMOTIV to determine the best approach for BCI typing [15]. Both methods performed similarly with selection accuracy of 50% mean, but P300 was much faster. Unfortunately, for MI, they simply used the EMOTIV software, so it tells us nothing about the algorithm.

Francesco Carrino et al 2012: actually use the EMOTIV headset with MI to control a wheelchair[16]. They also use the openvibe software. Their experiment only controlled the wheelchair with left and right. Interestingly, they ran into problems with electrode placement, and ended up using the headset tilted to get more sensors over the motor cortex. Also, in the end they opted for actual motor movement instead of motor imagery.

EMOTIV EPOC+ HEADSET

To implement the BCI I was supplied with a consumer grade EEG headset called the EMOTIV EPOC+. The headset is not of professional grade like those typically used in medical labs, but part of my objective was to see if we can make a functioning BCI with it. While the quality of the signal from the EMOTIV headset was yet unknown, it did have some advantages over professional EEGs, such as price, portability, ease of setup and use, and wireless interfacing with the computer. One disadvantage is that it had fewer electrodes than the standard 10/20 system, with 14 rather than 21, which obviously gives a lower resolution map of brain activity.

EMOTIV CONTROL PANEL

The EMOTIVe control panel is a proprietary software that can be downloaded from the EMOTIVe website [17]. It gives information on the status of the connection with the headset as well as the quality of the signal from each electrode. This software was used before every experiment to make sure that the quality of the signal was good. Electrodes that do not read a good signal can be adjusted to make better contact to the scalp by either moving it, parting the hair, or adding more saline solution.

EMOKIT

The headset connected to the computer with the supplied wireless receiver and software. However, the software included does not supply raw EEG signals, and only provides outputs which are already processed by proprietary algorithms. Software development kits (SDKs) exist for the headset which allow access to the raw EEG signals, however they require a subscription, the cost of which was prohibitive to the lab. Furthermore, the SDK imposed a limit on the number and duration of EEG recordings which would be infeasible for a research setting. As a workaround, I used an open source decryption software called Emokit, which could read the raw sensor data from the headset. Emokit was implemented in both Python [18] and C[19]. Since the Python branch of emokit was the most maintained, and other software I would be using were also implemented in Python, I decided to use the Python version of Emokit. I wrote a small program to extract the sensor data from the EMOTIV headset and stream it into Lab Streaming Layer (LSL).

LAB STREAMING LAYER

Lab Streaming Layer (LSL) is a program that manages multiple data streams and lets you import them into other programs such as MATLAB, or simply record the data to a file. [20] LSL was an important component of the BCI implementation since it let me input parallel streams from other sources which acted as markers for later analysis. LSL was developed by the Swartz Center for Computational Neuroscience for the original purpose of being used with BCIs. As such, it also came with multiple applications that were either immediately useful, or may be useful for future work.

LAB RECORDER

A simple LSL app that can record multiple streams into a single file for later analysis. This was used to record the data from all offline experiments.

MATLAB LSL LIBRARY

A MATLAB LSL library which lets MATLAB import live streams from LSL, or import recordings from Lab Recorder.

MATLAB VISUALIZATION

A LSL app for use with MATLAB. MATLAB Visualization can be run in the MATLAB scripting environment to produce a live graph of the incoming EEG data. It was helpful for setting up the hardware and software components to be able to see whether an actual EEG signal was coming in.

KEYBOARD AND MOUSE RECORDER

Another LSL app for creating LSL data streams for keyboard keys, mouse position and clicks. This was never used in any experiments over the summer, however, it has potential for generating many different markers in future experiments.

OPENVIBE

Website [21]

PSYCHOPY

PsychoPy is a Python based psychology research presentation software. [22] PsychoPy was used in the design of experiments where certain stimuli were presented on screen while someone was wearing the EEG headset. PsychoPy was chosen because it is highly customizable and lets us input snippets of code to create a new LSL stream. Markers from the software were sent into LSL where all the data was labeled with common time stamps. The PsychoPy presentation gave visual cues to the subject to perform certain tasks like imagining lifting a left or right hand. Simple pictures such as left or right hands were used as visual cues for each class, while a unique marker for each class was passed to LSL at the beginning of each new image.

MATLAB

Quite a lot of setup was required to get the EEG data and markers working properly, however, the actual signal processing started once this data was imported into MATLAB. The data was brought into MATLAB either as a pre-recorded file, or as a live stream of data. As a pre-recorded file, we could test offline algorithms. These have the advantage of being able to re-run experiments with the same data and compare between different BCI implementations. Processing live data is done with online algorithms, which require faster code that can keep up with the incoming data, and give instant feedback in response to a person's brain activity.

There were several MATLAB plugins that were used over the course of the project, which are described below.

EEG LAB

EEG lab is another program developed by the Swartz Center for Computational Neuroscience [23]. It was designed to facilitate research in BCI using MATLAB. It has many built in features for handling EEG and marker data, such as filters and machine learning algorithms. However, EEG lab is limited to working with offline data. EEG lab was used to filter some of the data while I was having difficulty with my own filters in MATLAB. It was helpful to see the expected filtered signal from a widely used implementation to compare with my own implimentations.

BCI LAB

BCI lab was also made by the Swartz Center for Computational Neuroscience and was built on top of EEG lab to expand into research on online BCI [24]. BCI lab allows for training different BCI paradigms and then can apply the model to live data. An additional feature of BCI lab is that it can generate filter maps showing the spatial filters resulting from the feature extraction model. BCI lab was very difficult to get working since it is not compatible with newer versions of MATLAB. I finally got it to work by using it with MATLAB 2012b. Furthermore, BCI lab would only work within the paradigm of having a training set supplied from offline data, and producing a model for online analysis. This was not compatible with most of my experiments where training sets would be adaptive.

ARDUINO HARDWARE SUPPORT PACKAGE FOR MATLAB

The Arduino Hardware support package was used in MATLAB to let MATLAB scripts interact with an Arduino microcontroller.[25] The support package allows both reading and writing to and from the microcontroller. As such, the microcontroller could be used for both marker inputs using push buttons, and for classification outputs using LEDs.

MATLAB SUPPORT PACKAGE FOR LEGO MINDSTORMS EV3 HARDWARE

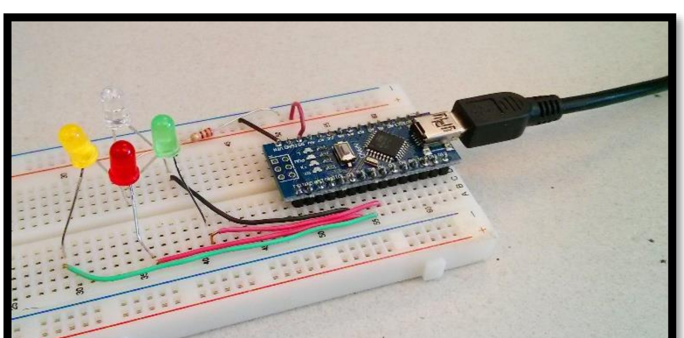
The MATLAB Support Package for LEGO MINDSTORMS EV3 Hardware was used to express BCI classification outputs as specific movements in a LEGO robot.[26] The support package allows both reading from sensors and controlling motors, lights and sounds.

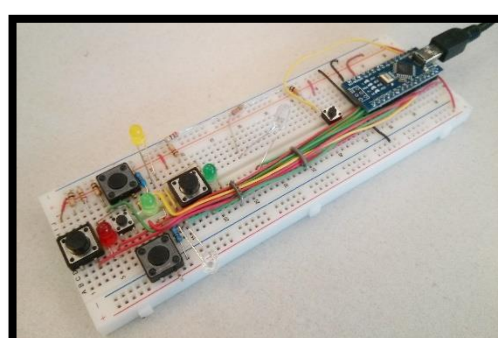
BCI OUTPUTS

We used three different outputs for the BCI. The simplest output was just showing the classification results output from MATLAB in the console. This was later used to produce more interesting outputs such as controlling lights through an Arduino microcontroller, or controlling the movement of a robot.

ARDUINO MICROCONTROLLER

Before we had a robot in the lab, the Arduino microcontroller was used as a visual output for online BCI algorithms. LEDs were used to distinguish between classes. In some experiments the output was a flash after an epoch was evaluated. In other cases, we had a continuous evaluation over a sliding window. In these cases, PWM was used to intuitively show probability for each class with the intensity of the light.





Later, buttons were also implemented to allow Matlab scripts to record true labels for training purposes.

LEGO MINDSTORMS EV3 ROBOT

We used a LEGO MINDSTORMS EV3 robot as another output for online algorithms. Implementing the robot was easy with MATLAB since there was a MATLAB toolbox already made for the job. The motors were used to implement a left and right track to allow the control of movement forwards, backwards and rotation in either direction. Five possible classes, forward, backwards, rotate left, rotate right, and rest, were experimented with in different combinations.

EXPERIMENTS

With all the hardware and software components in place as described above, the BCI was essentially functional. However getting it to work well was going to be the most complicated part of the project. I spent most of my time designing experiments, recording data, and coding and testing machine learning algorithms to try to find an implementation of the BCI that worked well. My original objective was to implement learning algorithms that were provided, but not necessarily to develop the algorithms. For the algorithms, I had the help of my colleagues Golnar and Soroosh. Although both have experience with BCI's, implementing and testing the algorithms for use with the Emotiv headset proved to be challenging, and lead me into much experimentation with machine learning algorithms.

Much of my work involved motor imagery (MI), and to keep things simple, most of my work was done with only two "classes". For example, in an experiment a subject might imagine moving either their left or right hand.

ONLINE EXPERIMENT 1: REPLICATION OF WORK BY YANTAO LI ET AL

PURPOSE

Write the first MATLAB script to process EEG data into a classified output

EXPERIMENTAL DESIGN

My research was kicked off by the encouraging results of Yantao Li et al, and their online experiments with the EMOTIV headset[27]. This was the logical place to begin experimenting by simply replicating their methods and results. With the implemented hardware and software, all that was needed was to implement their described algorithm which was based on k-means clustering and PCA. In the described experiment, a LEGO MINDSTORMS robot was used as an output. Since we did not have the robot at the time, I used the MATLAB console and LEDs on the microcontroller as outputs.

RESULTS AND DISCUSSION

Initially I had trouble with replicating work due to many questions and unknowns regarding the experimental setup. At the time, I knew very little about machine learning algorithms and assumed I was lacking the knowledge to implement the algorithm described. However, as I researched more in the topic I began to doubt the paper's results more and more. It had many issues with the paper such as their extremely small sample sizes, lack of signal pre-processing, undescribed stimuli, etc. Even whether the algorithms they described as online were actually online seemed very ambiguous. There was too much missing information to implement the algorithm without making many assumptions about, for example how to pre-process the data, how to initialize the centroids and how to even classify the final output. My doubts were corroborated through discussion with Golnar and Soroosh, who both found the choice and implementation of algorithms unconventional and unclear.

I did my best to implement the algorithm in MATLAB despite the many doubts. I used myself as a test subject. The results were unsurprisingly erratic and unusable. The LEDs would flicker uncontrollably between each other. Trying different kinds of stimuli such as motor imagery, motor movement and different mental states did not seem to make the output any less random. No formal data collection was performed since the algorithm was clearly unusable as it was.

Following this experiment, I realized that I would need to try to replicate results from more widely used implementations of BCIs. I did more literature review on experiments done with the EMOTIV headset [9], [10], [12]–[16] . I found that most of the work with the EMOTIV headset have been looking at ERPs with varying success, and only a few have explored motor imagery with limited success. Another conclusion was that I should try to implement offline algorithms first since they are easier to test and compare results with.

OFFLINE EXPERIMENT 1:TILTED FOR MOTOR IMAGERY

PURPOSE

Gather 2-class motor imagery data using the EMOTIV EPOC+ headset for analysis with offline algorithms, and to compare results with the same algorithms used on data from BCI Competition III - IVa.

EXPERIMENTAL DESIGN

Stimulus: Motor Imagery
3-5 seconds/stimulus trial
100 trials for training
100 trials for testing

1-3 second break between trials
2 classes:

Forward arrow - > Right hand
Imagine lifting your own right hand continuously for 3 seconds. Imagine both the sight and proprioception of lifting your hand.

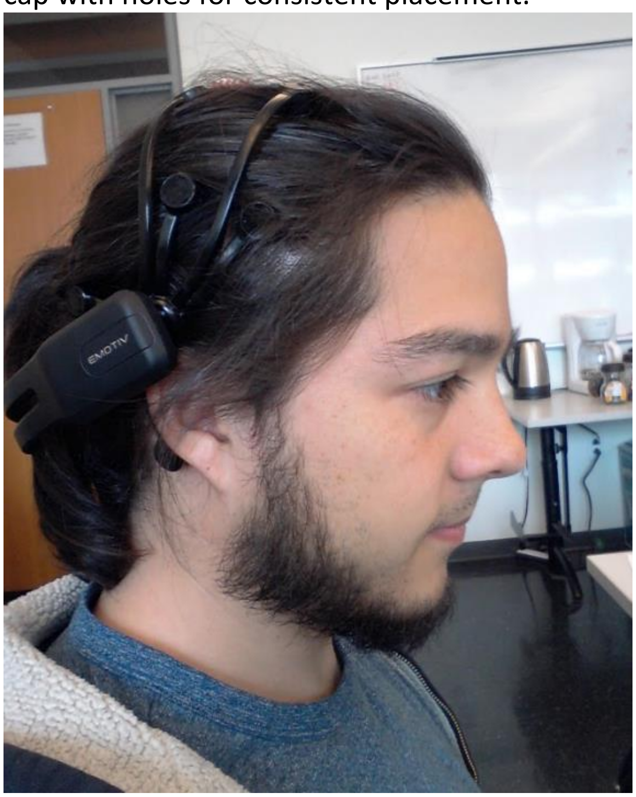
Backward arrow - > Right foot
Imagine lifting your own right foot continuously for 3 seconds. Imagine both the sight and proprioception of lifting your foot.

Test subjects
Number of subjects: 1
Info to gather:

- Information and consent form
- Age, Gender
- 200 trials

Venue: EV 8 lab

Headset placement:
Tilted back to cover C3 and C4 motor cortex areas. Exact placement to be determined by a rubber cap with holes for consistent placement.



Data acquisition
Laptop: with Bluetooth dongle connected to headset, and display for stimulus presentation.

Software: python, emokit(to extract raw data), PsychoPy2 (for stimulus presentation and data markers), LSL(Lab streaming layer to save data streams to file)

Data processing
Using Golnar's offline algorithms

RESULTS AND DISCUSSION

Filter problems

Feature extraction

OFFLINE EXPERIMENT 2: MOTOR IMAGERY WITH MORE SUBJECTS

PURPOSE

Similar to Offline experiment 1, to gather 2-class motor imagery data using the EMOTIV EPOC+ headset for analysis with offline algorithms, and to compare results with the same algorithms used on data from BCI Competition III - IVa. This time with other participants, and with ¼ as many trials. Same two classes except this time repeated twice to compare motor imagery with motor movement. Also, headset is not tilted back this time.

EXPERIMENTAL DESIGN

Stimulus: Motor Imagery
5 seconds/stimulus trial
100 trials for training
100 trials for testing
1.5 second break between trials
2 classes:

> **Forward arrow - > Right hand**
> Imagine lifting your own right hand continuously for 3 seconds. Imagine both the sight and proprioception of lifting your hand.
> **Backward arrow - > Right foot**
> Imagine lifting your own right foot continuously for 3 seconds. Imagine both the sight and proprioception of lifting your foot.

Test subjects
Number of subjects: 4?
Info to gather:

- Information and consent form
- Age, Gender
- 2 X 50 trials
- Post-experiment questions

Venue: EV 2.260

Headset placement:
Worn normally, no exact measurement performed to verify electrode placement.

Data acquisition
Laptop: with Bluetooth dongle connected to headset, and display for stimulus presentation. Software: python, emokit(to extract raw data), PsychoPy2 (for stimulus presentation and data markers), LSL(Lab streaming layer to save data streams to file)

Data processing
Using Golnar's offline algorithms ….Using k-means clustering

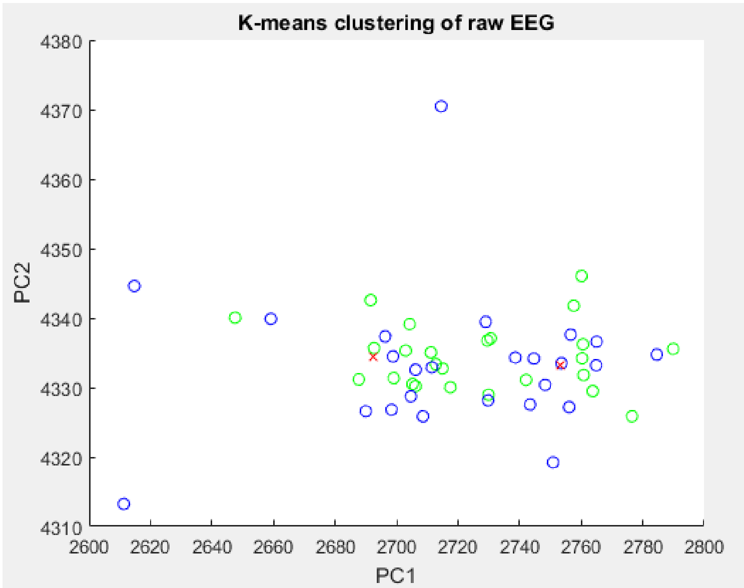
RESULTS AND DISCUSSION

Data collected was processed using different methods for comparison

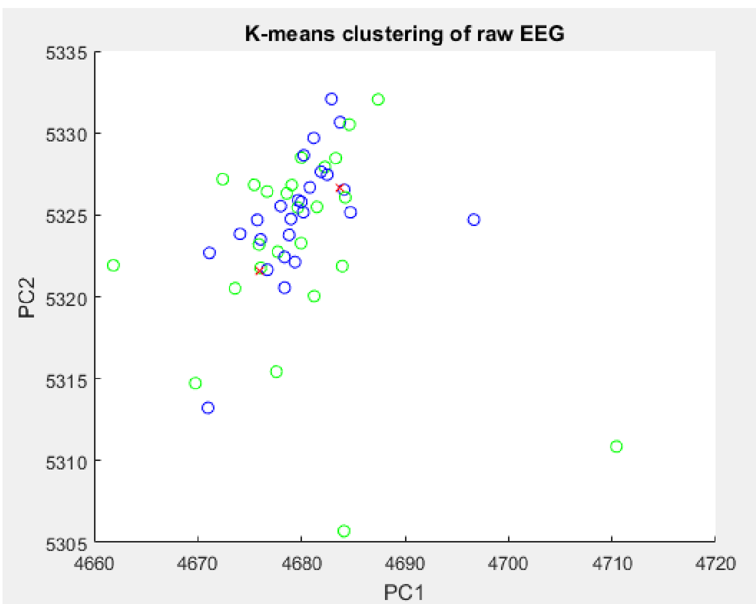
k-means clustering

raw EEG data from 2 class experiment with motor movement and motor imagery (AA_MM.xdf, AA_MI.xdf).

The raw data was unprocessed other than being split into epochs. The epochs were then averaged over the duration of the epoch to a single 14 dimension vector per trial. The set of trials were then run through k-means clustering to produce two 14d centroids. The entire set, and the centroids were reduced to two dimensions using PCA for visualization. As can be seen in the graph, the two classes are in different colors, and do not have any visible correlation with the clusters. Centroids are marked by x's.

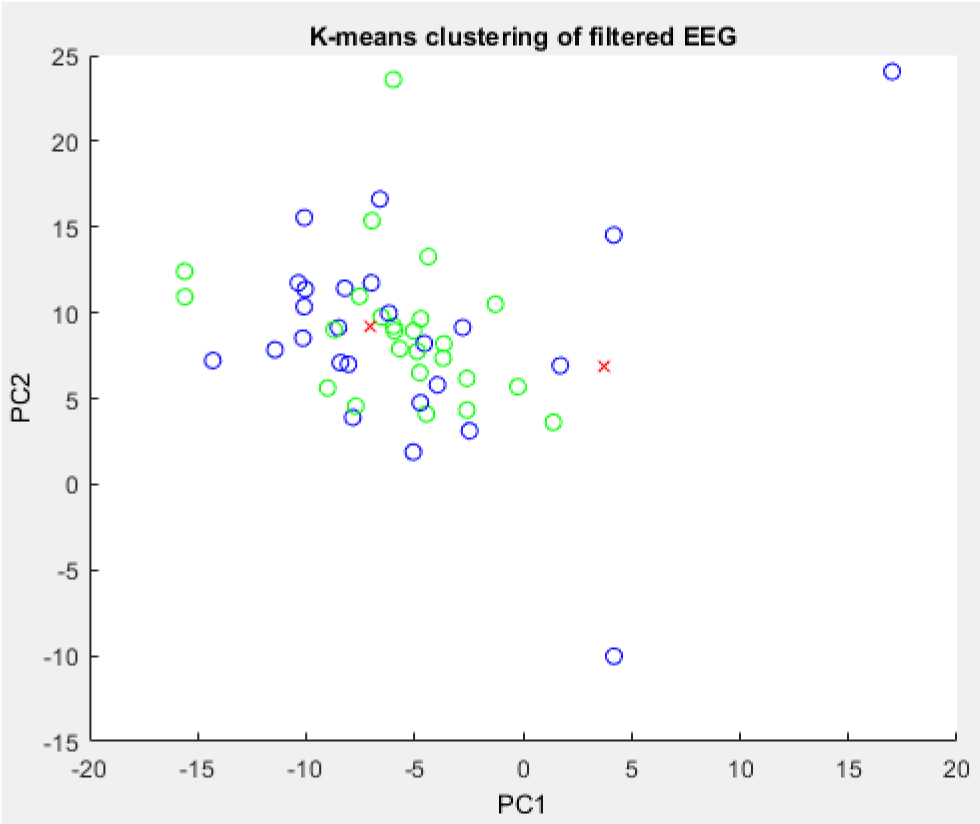


Motor movement

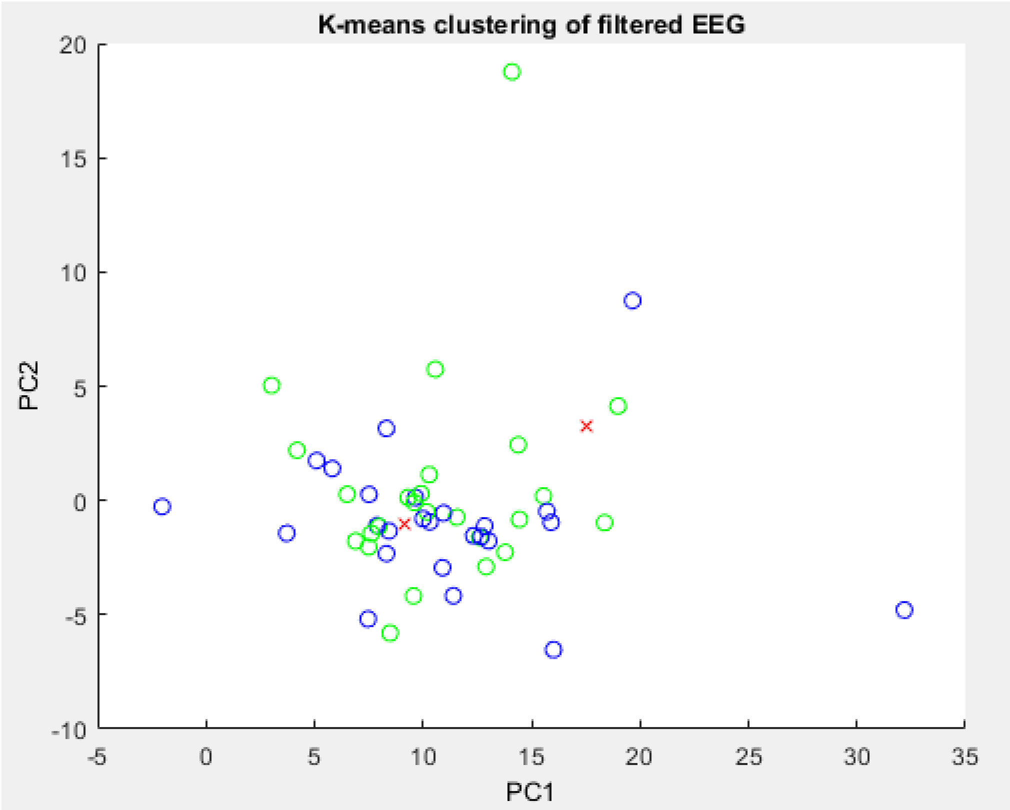


Motor imagery

Running the same experiment without dc values (highpass above 0.1 hz) data is shown below.

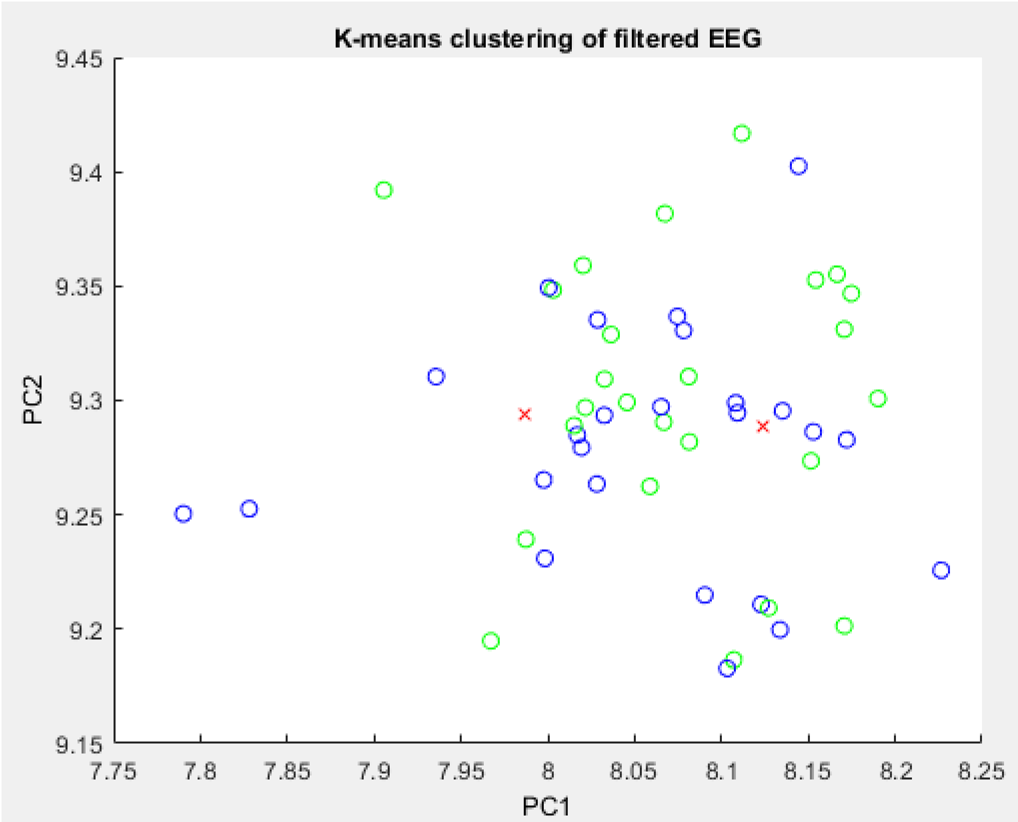


Motor movement

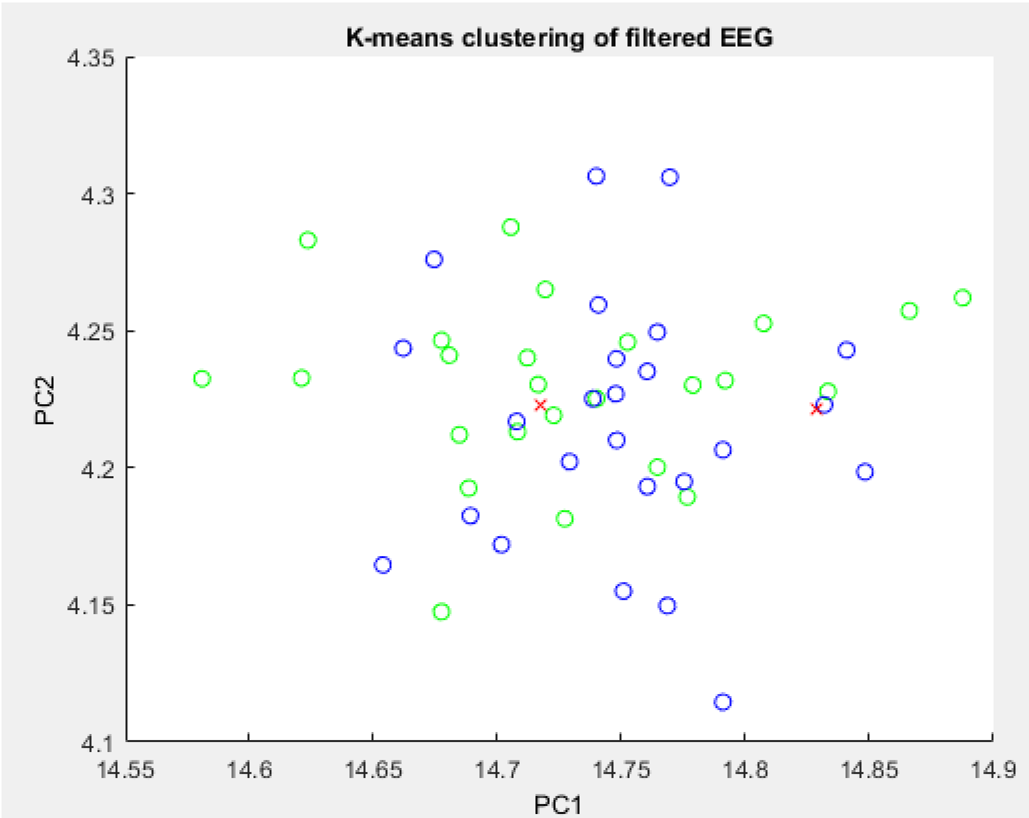


Motor imagery

Running the same experiment with filtered (bandpass 7-30 hz for motor cortex) data is shown below.



Motor movement



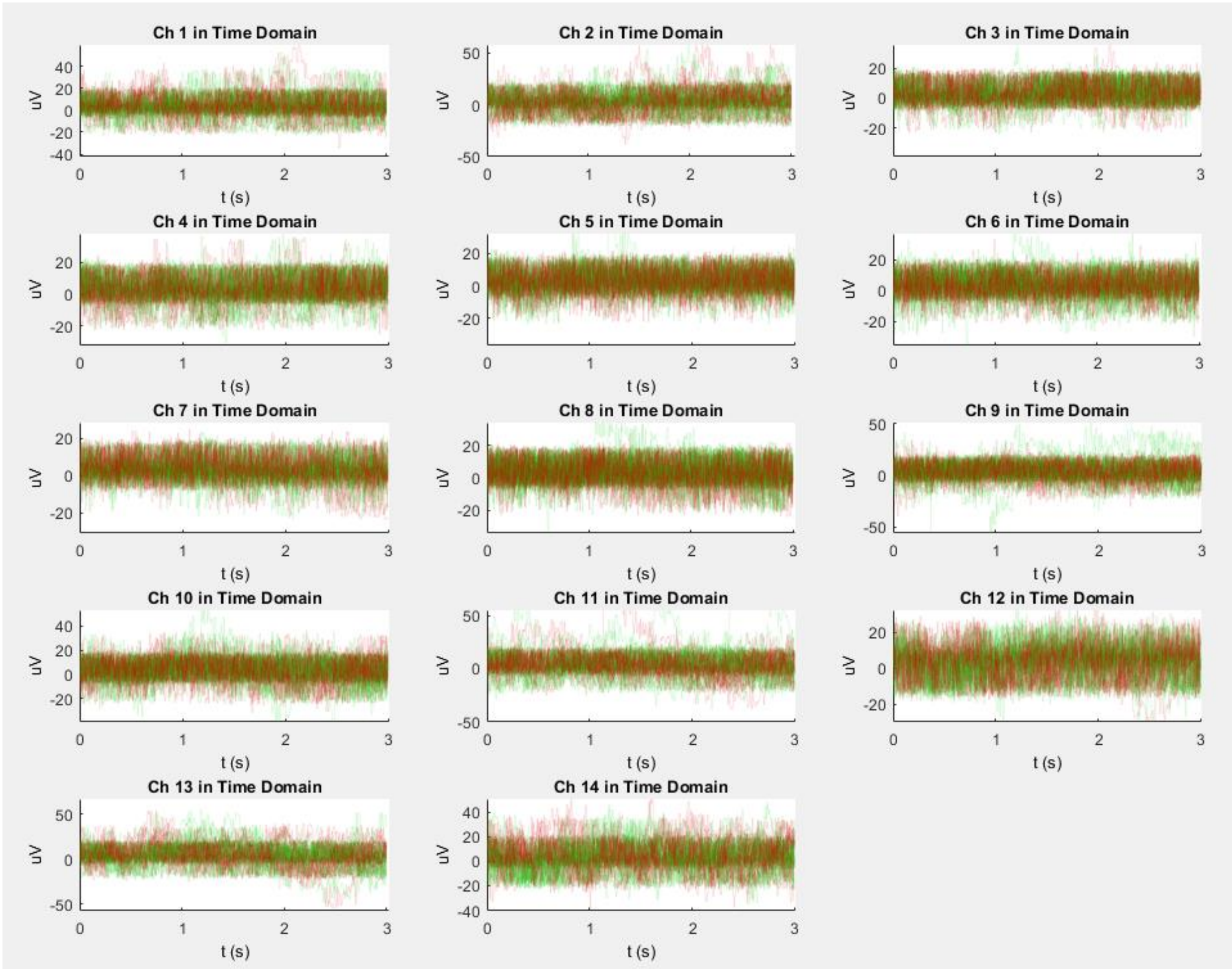
Motor imagery

Visual inspection of temporal or spectral patterns in epochs

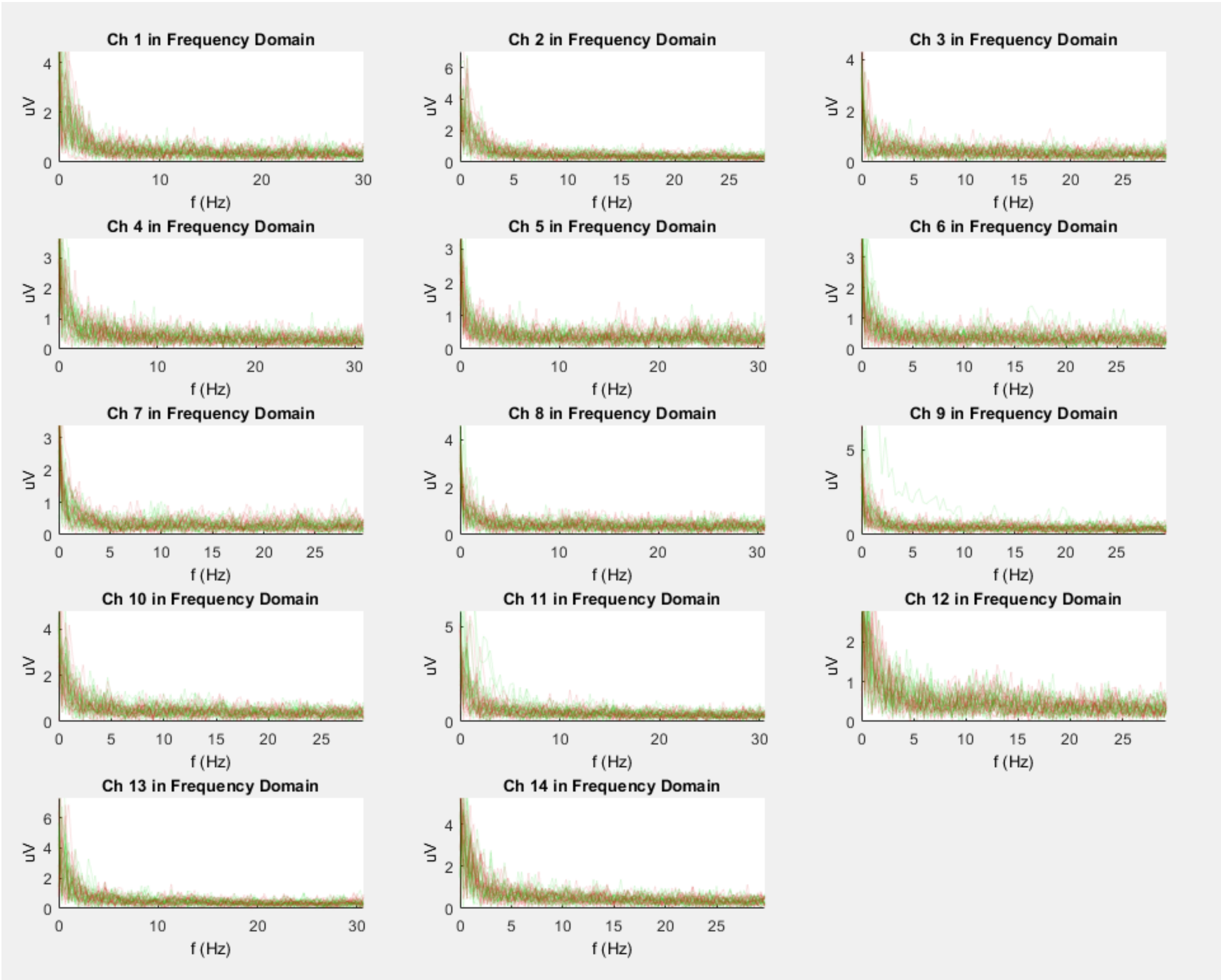
One method used in BCI is windowed means, where features are extracted from the average value over time windows in specific segments of an epoch. To see whether this may be a valid method for the gathered data, the filtered data for all trials were plotted together and inspected visually. The same approach was done to the frequency spectrum as well.

AA_MI.xdf

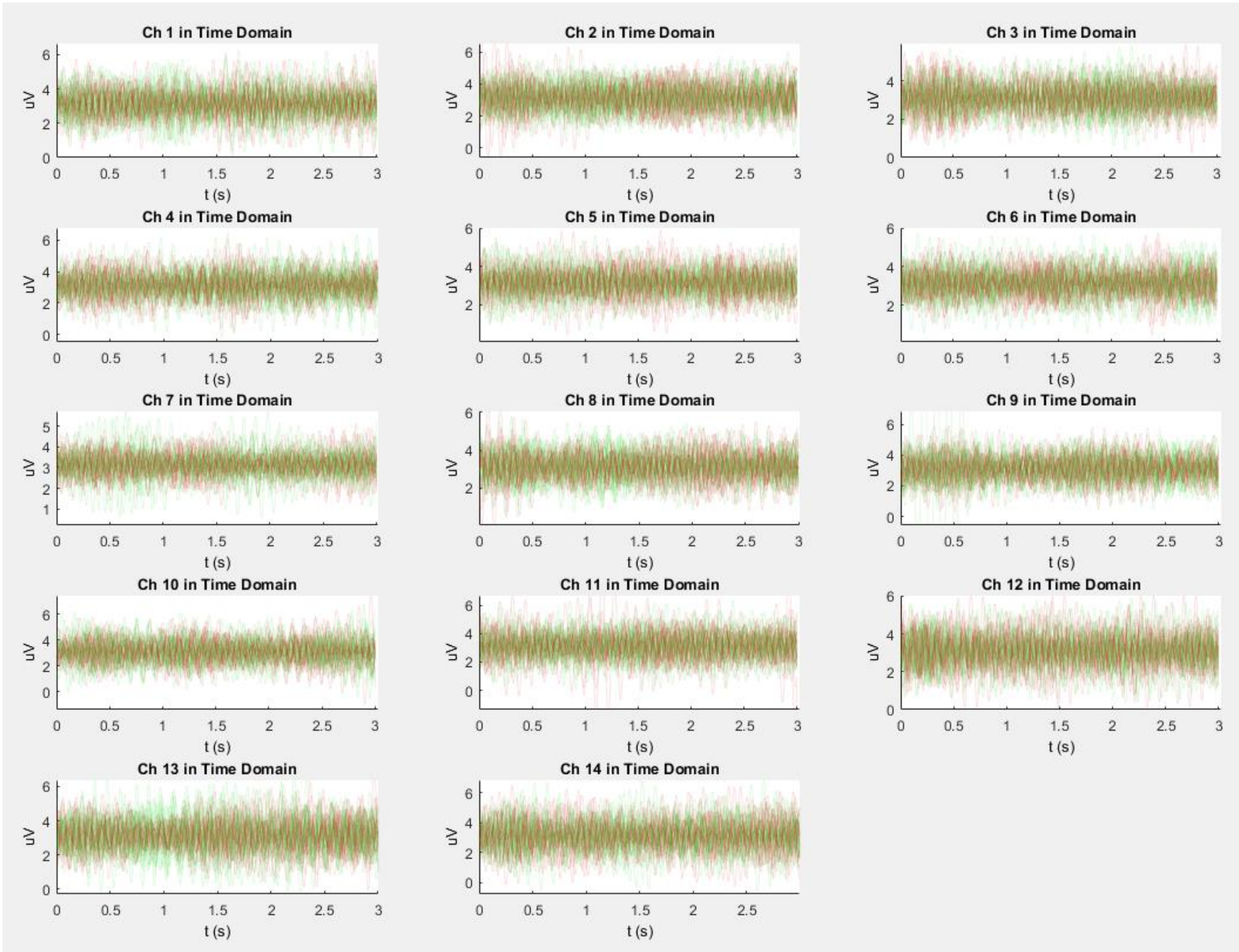
DC removed:



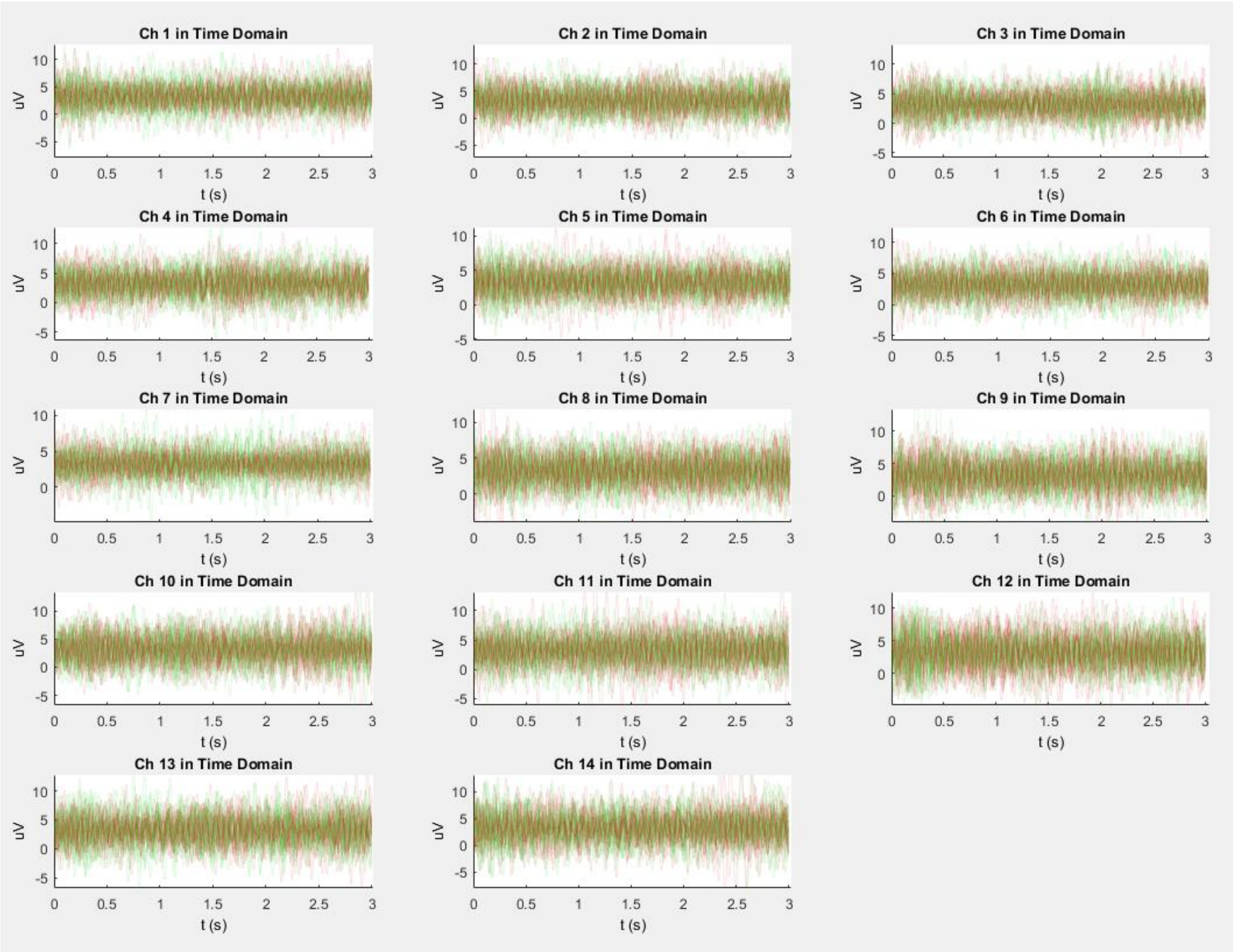
Ch 1 in Time Domain
Ch 2 in Time Domain
Ch 3 in Time Domain
Ch 4 in Time Domain
Ch 5 in Time Domain
Ch 6 in Time Domain
Ch 7 in Time Domain
Ch 8 in Time Domain
Ch 9 in Time Domain
Ch 10 in Time Domain
Ch 11 in Time Domain
Ch 12 in Time Domain
Ch 13 in Time Domain
Ch 14 in Time Domain
uV
t (s)



Bandpass 8-9 hz



Bandpass 8-12 Hz



Results seem mostly random, making it hard to notice useful features. There may be something to investigate in the 8-9 hz window.

QUESTIONS TO PARTICIPANTS

ONLINE EXPERIMENT 2: SYNCHRONOUS CSP

Online BCI with synchronous epoch timing. LEDs on the Arduino would turn on for 3 seconds either indicating left or right. The LED indicating that it is recording the EEG signal also illuminates. During this 3 second epoch, the subject performs the corresponding MI. Following the epoch, the recording is added to a training set. Once a preset number of training epochs are accumulated, a model is generated using CSP and LDA or QDA. Each new epoch thereafter is followed by an LED flash indicating the classification output and the newly recorded epoch is added to the training set and the model is re-evaluated.

At times subjects felt like the algorithm was working, but after a training set reached a certain size, the results seemed to get worse.

There was what seemed like too long a delay between thinking of the class, and getting feedback. In reality, this was only a second's delay or less, but it would be better to get feedback during a thought.

Quantitative results were never above 60% accurate once the number of epochs was in the 30's. No formal experiments were conducted with this setup since preliminary results were not promising. It seemed like a sliding window may be a better online implementation since it can give a subject closer to instant feedback.

OFFLINE EXPERIMENT 3: THREE PART EXPERIMENT

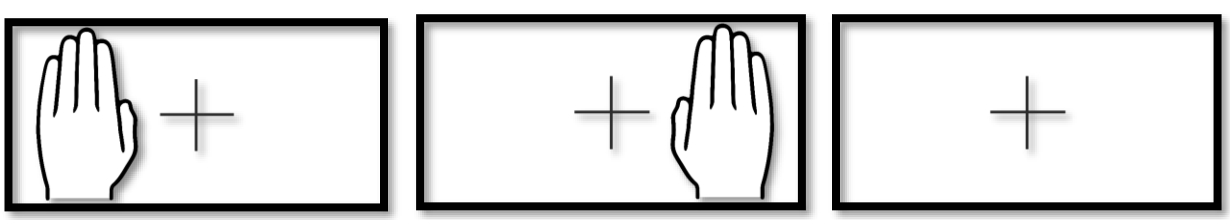
PURPOSE

Similar to Offline experiment 1 and 2, to gather 2-class motor imagery data using the EMOTIV EPOC+ headset for analysis with offline algorithms, and to compare results with the same algorithms used on data from BCI Competition III - IVa. This time we decided to do three different experiments to compare between two different sets of 2 classes, and to compare between externally prompted MI and subject prompted MI.

EXPERIMENTAL DESIGN

LEFT/RIGHT EXPERIMENT

This is a 2 class MI experiment where the subject imagines lifting a left or right hand. The subject is instructed to lift the appropriate hand when cued by left or right hand images presented randomly on screen by PsychoPy. Each image lasts for a 3.5 second duration and is followed by a 2 second pause between trials. In total, there are 3 sets of 26 trials.



PUSH/PULL EXPERIMENT

This experiment is a duplicate of the previous with the only difference being the classes and the images used to prompt them. In this case the two classes are MI for the action of pushing or pulling an object. As stimuli, images of two hands palms forward (for push) and two hands pulling a rope (for pull) were used.

SUBJECT PROMPTED MI EXPERIMENT

In this experiment we selected one of the above two class sets depending on which one each subject performed better with based on CSP and LDA analysis. The same experimental format was repeated except this time there was no presentation software used. Instead, the subject was asked to press one of two buttons on the Arduino microcontroller corresponding to one of the two classes. Upon pressing the button, a recording light would illuminate, prompting the subject to start thinking about the MI. The duration of the epoch was the same as for the above experiments, but the duration of the pauses was up to the subject to decide based on when they pressed the button.

OTHER DETAILS

Subjects: AA, AM, DD, SD, GK, TM

Venue: EV 2.260

Hardware: EMOTIV EPOC+ with Bluetooth dongle, laptop and Arduino microcontroller with LEDs and buttons.

Headset placement: Worn normally, no exact measurement performed to verify electrode placement.

Software: python, emokit, PsychoPy2, LSL, Matlab

RESULTS AND DISCUSSION

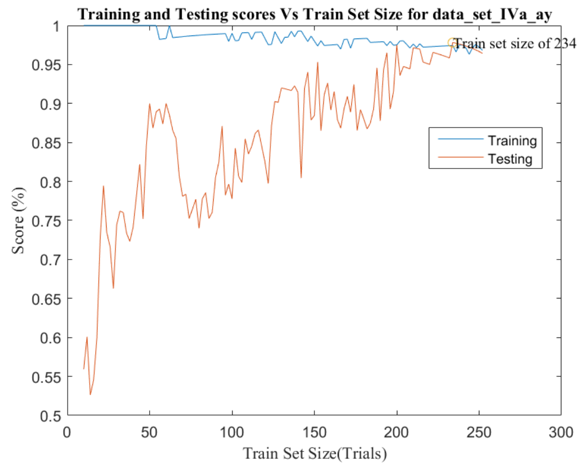
EPOCH LENGTH ANALYSIS

The markers in the data sets mark the onset of an image. However, we expect there is a delay between when the image is presented and when the subject starts to think about the desired action, and produces the corresponding features. To test this, CSP and LDA models were evaluated for each data set for a range of delays. Larger delays also meant that the epoch lengths were shorter. The best performing delays varied drastically from person to person, and even at times between the three experiments for the same person. For the data from the BCI competition, all the delays performed best at one second or less. For the data taken with the EMOTIV headset, the delay ranged from 0.2 seconds all the way to 3 seconds in one case. A 3 second delay left an epoch of only 0.5 seconds.

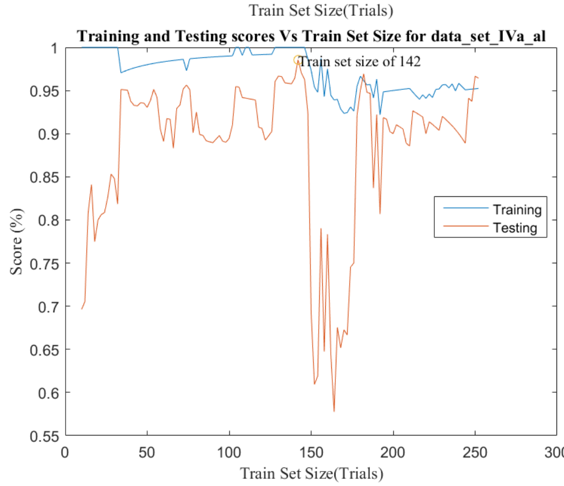
TRAINING SET SIZE ANALYSIS

The next analysis was looking at the effects of the training set size on the performance of the model. A model was generated for each data set over a range of training set sizes. The remainder of the data was used for testing. When plotted in this way, we saw that the best performing data collected from the EMOTIV headset was 85.7% accurate with a training set size of 50 out of the total 78 epochs. Several others made it into the 70's while many others were in the 60's and below. There was no consistent pattern to show definitive diminishing returns on the training set size. I suspect that the sample size needs to be larger to see any kind of pattern emerge. Furthermore, there was no set of classes that seemed to do better for everyone. Some subjects were better at left and right hand MI, while others were better at push pull MI. The better performing of the two classes was used for the third experiment with the push buttons.

The data from the BCI competition was better for exploring the effects of training set size since the number of epochs recorded are much larger. Subjects aw and ay both show an ever increasing performance trend with training set size.

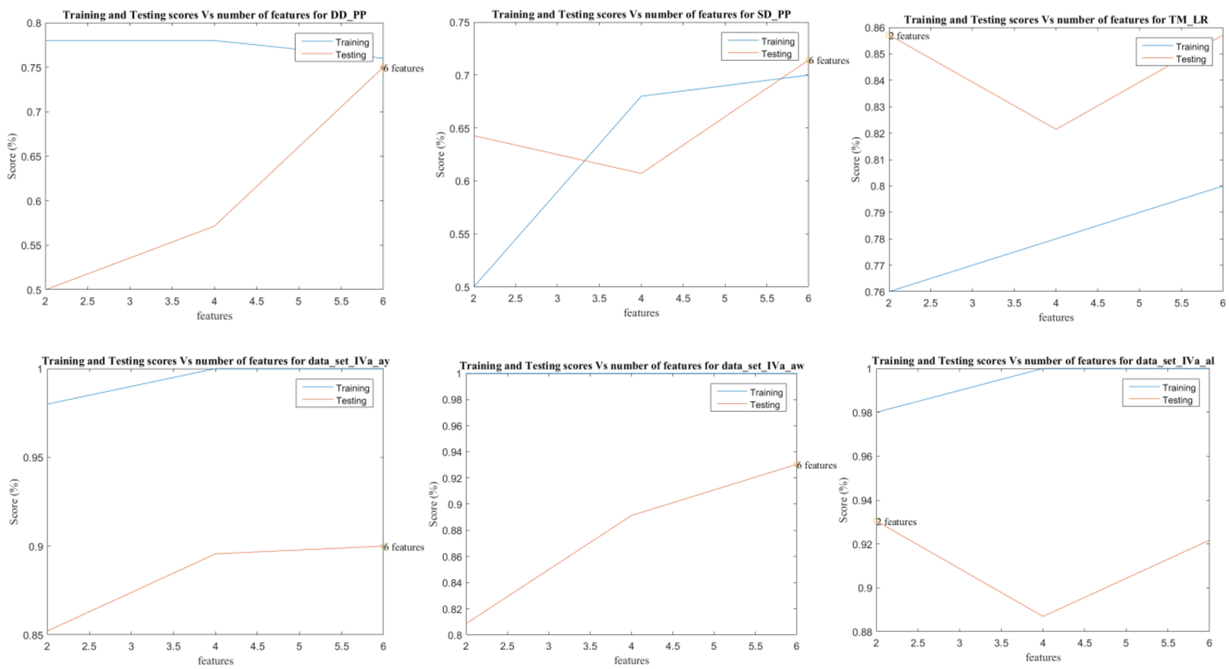


Subject aa on the other hand shows clear deminishing performance after the training set reaches a particular size. The remaining two subjects show neither of the two trends very clearly.



FEATURE ANALYSIS

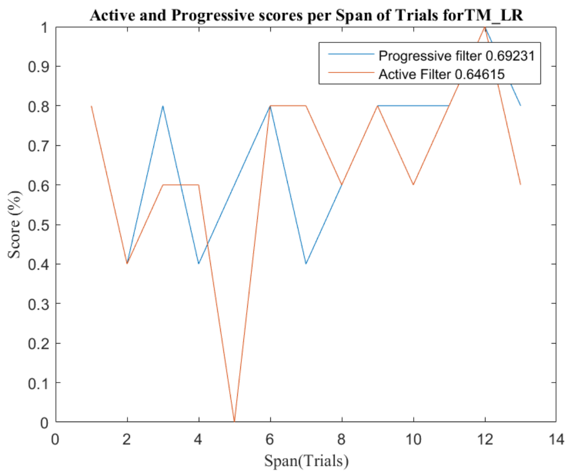
Next, we compared the performance of models on each data set with varying number of features extracted from CSP. The analysis looked compared the performance of 2, 4 or 6 features. There was again quite a bit of variation in results, even among data sets from the same individual. Overall, 6 features perform best, and although there are cases where fewer features performs better the benefit is not very large.

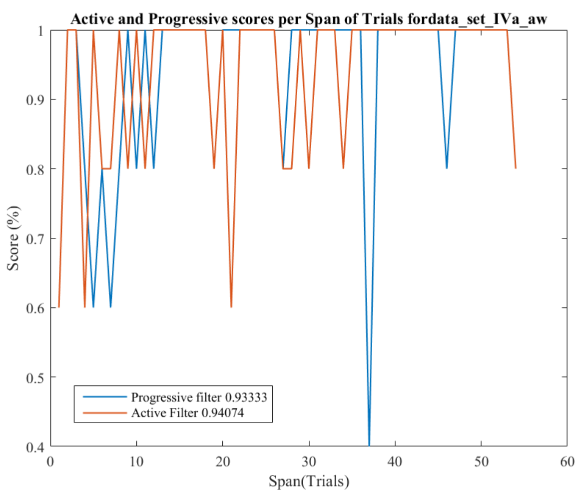


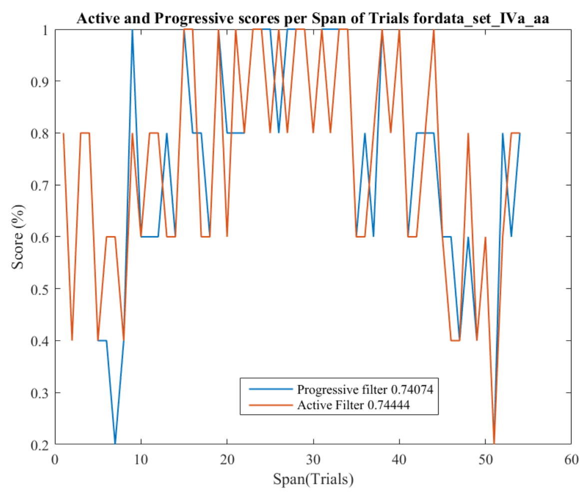
MULTI-RATE ANALYSIS

A multi-rate analysis was designed with two simultaneous algorithms called the active and progressive filters. The active filter was based on a CSP and LDA model which produced a classification every epoch. The progressive filter, was used to re-evaluate the CSP and LDA model every 5 epochs. Every 5 epochs, the performance of the currently used model in the active filter is compared to the performance of the updated model from the progressive filter, and the better of the two is kept.

The multi-rate analysis was performed on all three sets of experimental data for all 6 subjects, and also on the data from all 5 subjects from the BCI competition 3 IVa. [28] The resulting overall performance for all the data recorded with the EMOTIV headset was in the 50’s or lower with the exception of GK_LR and TM_LR. The performance of subjects from the BCI competition were much better, although the sample size was also much larger.







ONLINE EXPERIMENT 3: SLIDING WINDOW CSP

CONCLUSION

Implementing the hardware and software for the BCI had its challenges, but the majority of the summer's research was spent on experimenting with algorithms. Many experiments were performed, and many test results returned negative with very little ability to properly discern between the two classes. The experiments tried different stimuli, different classes, different setups, different data sources and different machine learning algorithms such as k-means, windowed means, common spatial patterns (CSP), etc. Each new experiment improved on the previous, eliminating variables and trying to explain why the BCI performance was lacking. CSP seemed to perform the best, however it only worked for some test subjects. While the implemented algorithms didn't work consistently with the emotive headset, some worked quite well with data from BCI competitions recorded with professional grade EEGs. This lead me to suspect that the limitations in my BCI are due to the quality of the EMOTIV headset. At the time of writing this report, I am still researching this topic, and we just got permission to use a professional grade EEG from another lab. Further research may allow me to confirm this suspicion.

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