Successfully Controlled BCI Through Minimal Dry Electrodes

By

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ABSTRACT:

There are approximately 185,000 amputations a year in the United States according to the Amputee Coalition with the number of amputations going up. While it is common for someone with a lower limb amputation to use a prosthetic, approximately 84%, it is not as common for people with upper limb amputations, approximately 56% (Raichle et al., 2008). The time it takes an amputee to get a prosthetic affects the likelihood of use, in addition to functionality (Miller et al., 2020). The purpose of this project is to show proof of concept of an EEG-controlled prosthetic, using only 2 dry-electrodes, through the use of BCI2000 using imagined movements. Eight (N-8) participants were recruited to complete a pre-training mu task, a 1D cursor training task, a 2D cursor training task, and the main 2D cursor task.

After a frequency was established for each participant, they completed 200 trials of the 1D cursor task for three different conditions (left, right, and both hand(s)) or reached a success rate of 80% for 4 trials in a row with random targets. The participants then completed the 2D cursor task with random targets until a success rate of 70% for 4 trials in a row was achieved, followed by a 2D cursor task where the targets were pre-determined. A chi-squared test determined the goodness of fit for the success rate was significant ($p < 0.001$) for all participants completing the 1D cursor

task. The combined success rate for the participants during task 1 for their right hand was 30.16%, 47.11% for their left hand, and 61.47% for both hands. The combined success rate for task 2 was 69.40% and 79.59% for the main task.

Overall, this study successfully showed that 2 dry electrodes can be used to detect imagined movements through BCI. While the accuracy can still be improved, by enhancing the equipment and developing the training protocol, both participants that completed the main task were able to surpass the expected overall accuracy and surpass 4 out of the 6 individual accuracies. Whether it is to control a mechanical arm, leg, or other body part, the framework of this study grants development opportunities for BCI from a few dry electrodes.

Successfully Controlled BCI Through Minimal Dry Electrodes

A Thesis

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In Partial Fulfillment of the Requirements for the Degree

Master of Science in Kinesiology

By

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List of Symbols or Abbreviations

US – United States

TMR – Targeted Muscle Reinnervation

EMG – Electromyography

EEG – Electroencephalogram

BCI – Brain Computer Interface

6 DoF – 6-degree-of-freedom

ICA – Independent Component Analysis

ASR – Artifact Subspace Reconstruction

IC – Individual Component

FFT – Fast Fourier Transform

PSD – Power Spectral Density

PSE – Power Spectral Entropy

ERS – Event-Related Synchronization

ERD – Event-Related Desynchronization

ERSP – Event-Related Spectral Perturbation

IM – Imagined Movement

TCREs – tri-polar concentric ring electrodes

FMA – Fugl-Meyer Assessment

UDP – User Datagram Protocol

Chapter 1: Introduction

There are approximately 185,000 amputations a year in the United States according to the Amputee Coalition with the number of amputations going up (Ziegler-Graham et al., 2008). Based on estimates from 2008 from Ziegler-Graham et al., there were currently 2.1 million Americans living with limb loss, it is projected that there will be 3.6 million Americans suffering with limb loss in 2050. The main cause of upper limb amputations is trauma (80%) followed by cancer/tumors (Maduri & Akhondi, 2019), compared to lower limb amputations which are most commonly due to diabetes (Godlwana et al., 2008). While it is common for someone with a lower limb amputation to use a prosthetic, approximately 84%, it is not as common for people with upper limb amputations, approximately 56% (Raichle et al., 2008).

While there are multiple types of prosthetics, passive prosthetics are the most common. These prosthetics are also called cosmetic prosthetics as their main function is to appear natural, however, these prosthetics are limited to only pushing, pulling, or stabilizing a held object (Ovadia & Askari, 2015). There is a difference in lower- vs upper-limb passive prosthetics as the upper-limb passive prosthetics are nowhere close to replicating functionality, as the technology needs to increase to provide as much functionality as the lower-limb passive prosthetics (Smail et al., 2021). Another type of prosthetic, myoelectric prosthetics, are commonly used with targeted muscle reinnervation (TMR), which reinnervates the nerves of the limb with the prosthetic, giving the individual control of the prosthetic, however, this is an invasive, expensive, and time-consuming method. Extensive physical and occupational therapy is needed to regain control of the prosthetic, with it taking 5 months to see low levels of muscle activation through electromyography (EMG) in the prosthetic limb (Schweisfurth et al., 2017). While gaining control of the prosthetic is ideal, TMR is both monetarily and timely expensive. The ability to control your prosthetic without invasive surgery or extensive therapy appointments would be optimal for amputees. Myoelectric prosthetics, including ones combined with TMR, use EMGs to evaluate muscle activity. Body-powered prosthetics are another type of prosthetic currently offered to those in need. These prosthetics offer more functionality than a passive prosthetic, as there is typically a gripper associated with upper body models, and are cheaper than mechanical devices, however, they do not offer as much functionality as an electric prosthetic. In addition, mechanical prosthetics have more control, look better, are accepted more for light-intensity work, and may help limit phantom pain (Carey et al., 2015). Electroencephalogram (EEG) controlled prosthetics offer the ability of prosthetic functionality with minimal training and no surgery.

EEGs measure the electrical activity in the brain. Studies have shown similar EEG signals in executed and imagined movements (Sleight et al., 2009; Yuan et al., 2010; Ofner, et al., 2017). Different waves are heightened during different levels of alertness, with lower frequencies associated with sleep, and higher frequencies with heightened anxiety. The findings of similar EEG signals suggest an ability to have continuous complex control of a prosthetic through a non-invasive brain-computer interface (BCI) (Yuan et al., 2010). Real-time EEG analysis through BCI aims to receive as little information as possible while maintaining maximal accuracy and optimizing efficiency. Past studies have eliminated electrodes that do not affect accuracy using 16 (Pressaco et al., 2011), or as few as 12 (Presacco et al., 2012) electrodes. Success with identifying movements has been found using low-frequency bands (delta waves) in both lower (Presacco et al., 2012; Presacco et al., 2011) and upper (Bradberry et al., 2009; Paek et al., 2013) extremities. To help limit the data to increase efficiency, the only data to make it through the initial filters are the delta frequency (0.1 – 3.5 Hz) of the specific electrodes used.

The initial data collected in past studies include samples of EEG data when a subject is simultaneously performing a movement (Paek et al., 2013) and imagining a movement (Ofner et al., 2017). Another frequency commonly used in BCI studies is mu frequency which is typically 8-12 Hz and recorded over the sensorimotor cortex that desynchronizes with movement and motor imagery (McFarland et al., 2000). This study will have the participants imagine movements, then the data will be run through a Wiener filter where a range of signals is calculated for each movement.

Purpose

The purpose of this project is to show proof of concept of an EEG-controlled prosthetic, using only 2 dry-electrodes, through the use of BCI2000.

Hypothesis

It is expected that the participants will have an average success rate above 75% for each target hit, and overall success rate.

Delimitations

1.) Control subjects will be males or females 18 years or older.

Limitations

1.) The inability to use a real prosthetic.

2.) Not testing the effectiveness with an upper extremity amputee.

Chapter 2: Review of the Literature

In order to gain a better understanding of the current thesis project, and present the information to the reader, a literature review was performed. This literature review will examine previous research conducted in the following fields of interest: 1) the prevalence, incidence, and mental toll of limb loss and prosthetics 2) EEG, and 3) BCI.

Limb Loss & Prosthetics

Prevalence and Incidence

Approximately 185,000 amputations occur yearly in the United States, with an expectation that the number of amputations will steadily increase, according to the Amputee Coalition. In a study conducted in 2008, it was found that 1.6 million Americans were living with the loss of a limb in 2005 (1 in 190 Americans). The study predicts that the number of American Amputees will increase to 3.6 million by the year 2050 (Ziegler-Gram et al., 2008). The Hanger Clinic reports that currently there are 2 million Americans living with some type of limb loss and another 28 million Americans at risk of losing a limb through surgery.

With the increase in amputees, prosthetics need to be improved. Previous research has found that approximately 84% of lower-limb amputees use a prosthetic, while only approximately 56% of upper-limb amputees use prosthetics (Raichle et al., 2008). The time it takes an amputee to get a prosthetic affects the likelihood of use, in addition to functionality (Miller et al., 2020). Lower limb amputees with greater phantom pain intensity reported that prosthesis use worsened their phantom limb pain. In addition, lower limb amputees that wore their prosthesis significantly more than other participants reported that prosthesis use contributes to residual leg pain.

Phantom limb pain is the perception or sensation experienced by an amputee in a limb that is no longer there, whereas residual limb pain is a type of pain felt in the extremity (stump) that is left after an amputation (Valerio et al., 2019). Upper limb prosthetics have been continuously abandoned, however, all the reasons behind abandonment are not well known, as more research needs to be done. The two main factors that were found to cause abandonment are comfort and function; with weight, temperature, and perspiration as the main complaints for comfort, and a lack of control and sensory feedback being the main causes of abandonment due to function, as it leads to the amputees feeling more functional without a prosthetic (Smail et al., 2020).

Mental Toll

A 2015 study linked amputations with a greater risk of depression, anxiety, and postinjury suicide. However, the same study concluded that the mental health status of amputees is indicative of their functionality in society, thus emphasizing the need for functional prosthetics (Ladlow et al., 2015). Retaining function post-amputation has been found to be especially important for upper limb amputees' mental health/life satisfaction (Østlie et al., 2010; Resnik et al., 2019; Resnik et al., 2020). Resnik et al., (2020) found that their amputated participants who did not use a prosthesis or used just a cosmetic prosthesis had more problems with their activities of daily living when compared to body-powered and myoelectric prosthetics. While Resnik et al., (2019) found that among the amputees tested, there was substantial interest in prosthetics with better movement control.

EEG

Electroencephalography (EEG) is one of the strongest approaches to linking cognition and disease to the electrophysiological dynamics of the brain (Cohen, 2017). The electrical potentials emitted from the brain are recorded by either dry or sponge electrodes placed in specific areas of the head, typically ranging from 32-128 electrodes with multiple references. There are five different frequencies: Delta (0.1-4 Hz), Theta (4-8 Hz), Alpha (8-13), Beta (13-

30), and Gamma (30+). Delta activity is typically highest when in deep sleep, Theta activity spikes with drowsiness and sleep, Alpha waves are present during relaxing times, Beta waves are seen in a person who is alert or anxious, and little is known about Gamma waves (Subha et al., 2010). Beta waves have a strong increase in power following movement (Parkes et al., 2005), making it a commonly used frequency when doing EEG movement analysis (Packheiser et al., 2020; Mohseni et al., 2020; Kirkland & Holton, 2019; Du et al., 2023), with some of these studies take it a step further using beta waves for imagined (Korik et al., 2018) and mirrored (McAuliffe et al., 2019) movement. Korik et al. (2018) determined the best way to ability to classify movements by testing the most commonly used frequency in imagined movement research, delta waves (~1 Hz), mu (8-12 Hz), beta (12-28 Hz), and low gamma (28-40 Hz). Using power spectral density to decode the movements, the researchers found the highest accuracy occurred in both the mu and beta bands (Korik et al., 2018). For the current thesis study, the software used will determine the best frequency, however, it is expected to be in the 8-28 Hz range.

EEG Signal Filtering

Artifact is very common with EEG data, typically coming from the subjects' movements or undesired noise (Jiang et al., 2019). Removing artifacts from EEG signals in real-time is essential for reducing errors and decreasing processing time, however, this is a delicate process as valuable information can be damaged. The most common artifacts are muscle artifacts, electro-oculographic artifacts, and 50 Hz (60 Hz in the U.S.) background noise (Val-Calvo, et al., 2019). Some other specific common artifacts include fluorescent light noise, eye movement/blinks, cardiac noise, and facial/tongue movements (Britton et al., 2016). To ensure that the data received from an EEG is usable for data analysis, the signals are filtered specifically for each study, removing as much artifact as possible without removing useful signals. Typically, only the signals from the electrodes desired are filtered to receive data, then the signal is put through a high-pass filter, where signals lower than a specific frequency are removed, and a low-pass filter, where signals above a desired frequency are removed. This helps consolidate the data to only the signals that are within the desired range, requiring less artifact removal and computer power. While there are infinite different types of filtering, Independent Component Analysis (ICA) is a commonly used technique, introduced in 1996, as it allows one to isolate and subtract the individual sources of artifacts (Chaumon et al., 2015; Makeig et al., 1996), and can deal with all kinds of artifacts occurring in EEG recordings (Jiang et al., 2019). There are multiple methodologies for using ICA with real-time data, Val-Calvo et al. (2019) compared two of the most common types, EAWICA (Mammone & Morabito, 2014) and ICA-W (Mahajan & Morshed, 2014), with the EAWICA method performing better with the real-time data. EEGLAB, a software package for MATLAB, has helped popularize ICA filtering by using ICA, time-frequency analysis, and multi-trial visualization (Delorme & Makeig, 2004). The technique of combining these three variables was validated in past studies by Delorme & Makeig, the creators of EEGLAB, as well as others (Delorme & Makeig, 2003; Delorme et al., 2002; Makeig et al., 2002; Makeig et al., 1999). The graphical interface helps simplify the process as well as having useful filters built-in, for example, Artifact Subspace Reconstruction (ASR) which is used to reduce the effects of eye movement artifacts on IC (Individual Component) EEG signals (*MathWorks, Natick, MA, USA*). ASR estimates that a large amount of variance is associated with non-brain signals in EEG data, online or offline, which can be detected using statistical properties in the principal component analysis (Blum et al., 2019). Blum et al. (2019) acknowledge the usefulness of ASR and further developed it to include Riemannian geometry, creating rASR, which performed better on sensitivity, specificity, and efficiency compared to ASR.

EEG Cap Positioning

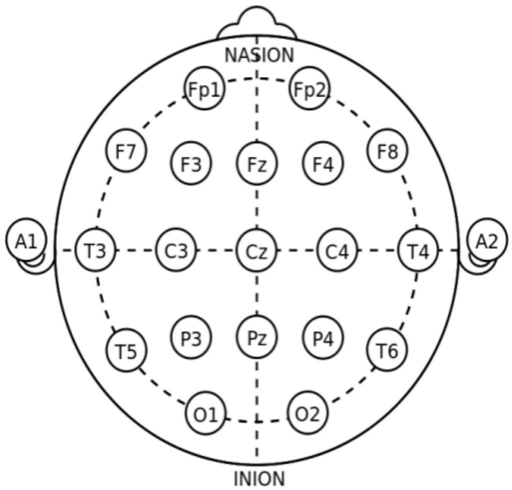

Figure 1. The image above shows the arrangement of electrodes for the 10-20 system (Khazi et al., 2012)

The positioning of the EEG cap is internationally standardized, for example, the 10-5, the 10-10, and the 10-20 systems (Jurcak et al., 2007). The 10-20 system has remained the most used for over 50 years as it is the standard for 1-81 electrodes, while the 10-10 system is used for up to 256 electrodes, and the 10-5 system is used for 300+ electrodes. The 10-20 system, as seen in Figure 1, uses the relative distance of anatomical landmarks (nasion and inion), with the purpose of creating a reproducible method for using lower amounts of electrodes over different studies, without the need for precise placement of electrodes or high spatial resolution (Jasper, 1958). The EEG cap used in this study is a 32-electrode cap, so the 10-20 system will be used. A measurement will be taken from the nasion to the inion in centimeters, 1/10 of the distance is found, and a mark is placed on the subject's forehead. The cap is positioned so that the front is aligned with the forehead dot, ensuring the correct and reproducible locations of the electrodes.

Fast Fourier Transform/Power Spectral Density

One way of analyzing post-processed (filtered) EEG data is to use Fast Fourier Transform (FFT), a method using mathematical tools on the signals to output power spectral density (PSD) (Al-Fahoum & Al-Fraihat, 2014). PSD is the measure of the spectral power per unit of frequency, showing which frequency variations are strong or weak (Murugappan et al., 2014; Unde & Shriram, 2014). There are different methods of finding PSD such as the Welch method and the Periodogram method, with both methods finding accurate values (Unde & Shriram, 2014). An increase in PSD in a specific wave is indicative of how a person is feeling. A past study used Welch's method to find PSD and conclude that alpha and theta band powers increase significantly when a driver moves from an alert to a drowsy state (Awais et al., 2014). The level of power can also be used as a comparison, as it was used to compare the PSD reached by healthy subjects to insomnia patients taking a specific medication (Ma et al., 2014). Visual attention is a specific example of what can be determined from PSD data and can be used to determine an action or predicted action, which is useful for BCI (KumarAhirwal & Iondhe, 2012). From PSD, power spectral entropy (PSE) can be determined. PSE only needs a small amount of data and works well with imaginary movements due to the good metrical effect for the change of nonlinear dynamic states (Zhang et al., 2008). Zhang et al. (2008) used PSE to differentiate different imagined hand movements, with 90% accuracy, claiming the method was quick and simple to use with real-time EEG data and BCI.

PSD is used to determine Event-Related Synchronization (ERS) and Event-Related Desynchronization. When analyzing data for ERS/ERD the time component of the power is crucial, so Event-Related Spectral Perturbation (ERSP) is used, as it is a time-frequency analysis method that averages the sliding latency window across trials (Yeom & Sim, 2008). The time component is crucial for ERS/ERD as ERSP can be used to determine the length and time point of when ERS or ERD occurs during imagined movement.

ERS/ERD

When you imagine a movement, ERS and ERD occur at different times, or an increase and decrease in sensorimotor rhythms, respectively (Arpaia et al., 2022; Durka et al., 2001). ERD occurs during the process of imagining the movement, while ERS occurs after the movement is complete (Pfurtscheller, 1992). This research is validated in a study that looked at ERD during imagined movements with each hand, finding a well-characterized response ipsilateral to the imagined hand (LaFleur et al., 2013). Due to the well-characterized response, knowing which electrode to analyze for ERD/ERS is clear, as seen in Figure 2.

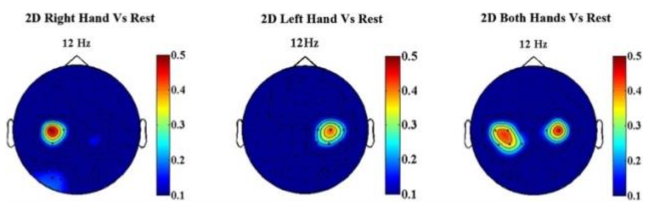

Figure 2. The image above shows the difference in spectral activity of the brain, at 12 Hz, across three different states of imagined movements compared to rest. This illustrates the vast difference in localized areas due to ERS/ERD and can be used to determine which electrodes will be useful (LaFluer et al., 2013).

BCI

Brain-computer interface (BCI) is commonly done through EEG signals, using classification algorithms to differentiate distinct brain functions. This is typically done with real-time EEG signals being processed, as quickly as possible, and the signal relaying back to the external device. BCI started being used for populations with disabilities, including making communicative devices for patients with Amyotrophic Lateral Sclerosis disease (Allison et al., 2013). More recently, BCI has continued to develop into new avenues for healthy individuals for example, the video game industry (Ahn et al., 2014), extended (i.e., virtual, augmented, and mixed) reality (Kohli et al., 2022), and controlling robotics (Kim et al., 2021; LaFluer et al., 2013; Paek et al., 2013). Combining BCI with extended reality has been shown to be useful in hands-free interactions and hopes to continue to develop with implantable sensors (Kohli et al., 2022). The control of robotics is vast, with past studies controlling drones (Kim et al., 2021; LaFluer et al., 2013), cursors (LaFluer et al., 2013), and robotic arms (Paek et al., 2013). PSD is commonly used to determine ERS/ERD to help distinguish between the different movements/directions (Kim et al., 2021; LaFluer et al., 2013; Paek et al., 2013). As more interest is drawn, and more studies are published regarding BCI, the technology will continue to rapidly develop, with possibilities of altering brain signals via neurofeedback and more to come (Värbu et al., 2022).

Imagined Movement

A recent systematic review created a representative example of a synchronous imagined movement (IM) experiment with BCI, which usually took place over several sessions and days. The four steps are (1) starting with a relaxed phase signaled by an acoustic trigger, with the user's eyes fixated, limiting eye movement; (2) cue phase, the user is signaled to perform the IM; (3) time when user is performing the IM (usually 3-5 second movement); (4) ending with a relaxed phase, for a random duration to prevent any timing of the steps (Arpaia et al., 2022). With the motor strip being mapped out precisely, electrode locations can be used with PSD to determine which body part the imagined movement is in. In this study, participants will complete trials of imagining a movement, and trials of rest, which will be averaged together to determine which electrodes should be used to determine the movement. As described previously, ERS/ERD will be used to determine the power differences between the active/relaxed states. Past studies have successfully determined and differentiated different imagined movements through real-time

EEG (Sleight et al., 2009; Szczuko et al., 2018), including different finger movements from one hand (Alzahrani & Anderson, 2021). Sleight et al. (2009) used ICA for artifact removal and were successful in differentiating between hands with accuracies in the mid-60s, however, they stated that their findings were individualized and had to be uniquely developed for each participant (Sleight et al., 2009). Other studies have found similar results of needing to individualize the classification to the subject, however, the accuracy has continued to improve with time with accuracy reported above 80% (Szczuko et al., 2018). To differentiate between fingers on the same hand, power spectral changes were not accurate enough (34.03 ± 5.03%) so the investigators used tri-polar concentric ring electrodes (TCREs) to increase the spatial resolution, resulting in increased accuracy (63.3 ± 5.8%) (Alzahrani & Anderson, 2021). For the current thesis study, power spectral changes will be sufficient as the different imagined movements are using different limbs, not the same hand. While the participants will imagine movements with different hands, both the participant and the software need to be trained to control/observe the imagined movements.

Training

To help improve the accuracy of BCI with IM, the participants are encouraged to train. Training with BCI has shown significant improvements in upper extremity motor function recovery following a stroke across multiple studies compared to conventional therapy (Kruse et al., 2020). The effectiveness of BCI training on stroke patients was determined across 10 studies using the Fugl-Meyer Assessment (FMA), with an increased score of 5.4-8.1 being statistically significant, although 3 of the studies used a modified version (Kruse et al., 2020). FMA is a way of scoring a patient's motor status following a stroke (See et al., 2013). The score is determined based on their range of motion and limb symmetry and has been shown to be reliable and valid with a critical review (Gladstone et al., 2002). Given the success of training on upper extremity motor function recovery, studies incorporate training to help identify and recruit which subjects will perform the BCI tasks most accurately.

LaFluer et al. (2013) used four different levels of training to fly a BCI-controlled drone. The subjects started with a 1D cursor task that involved moving a cursor in the left or right directions by thinking about their left or right hand respectively, only progressing to the next training task when a score of 80% accuracy was achieved either in 4 consecutive 3-minute trials or as an average across 10 or more trials. The second task was another 1D cursor task where they moved a cursor up or down by thinking of clenching their fists or volitional rest, respectively. Once the same 80% was achieved, the subjects performed a 2D cursor task, where they had to move the cursor to one of the four targets from the previous two training tasks. For the 2D task, an accuracy of 70% was required to proceed to the final training task, which was controlling a virtual helicopter in a 3D simulation, with the 4 degrees of freedom (DoF) they performed in their past trainings (LaFleur et al., 2013).

Other recent studies had their participants perform imagined and real movements during training to increase accuracy for the imagined movement (Sleight et al., 2009; Szczuko et al., 2018; Alzahrani & Anderson, 2021). Specifically, Alzahrani & Anderson (2021) recorded the individual accuracies of real and imagined movements of their participants, finding that the real movements were more accurate, as expected (70.0 ± 7.7% vs 63.3 ± 5.8% using TCREs, and 46.13 ± 6.77% vs 34.03 ± 5.03% using PSD). For the current thesis study only imagined movements were used, however, if accuracy problems persist, the inclusion of real movements was re-evaluated. The goal is to only use imagined movements because the technology is being developed to eventually be used by an amputee.

Number of Electrodes

One of the goals of BCI is to limit the amount of data received to help with computing time. Using fewer electrodes to get similar accuracy with the data is being continuously tested. In Presacco et al., 2011, 16 electrodes were used to accurately detect when subjects imagined themselves walking, although they claimed only 14 electrodes were needed. Following this, Presacco et al., (2012) improved their decoding to achieve high accuracy with both intra- and inter-limb kinematics for walking with only 12 electrodes. This was further improved by LaFleur et al., (2013) in which participants accurately controlled a drone using only the C3 and C4 electrodes for each participant, however, they were limited to 4 DoF (up, down, left, right).

BCI2000

BCI2000 is commonly used in BCI studies due to its user-friendly graphical interphase. The software offers a variety of cursor trainings, both 1D and 2D, to help train the participants' brains to imagine the movements in an effective way. There are two protocols that are commonly used for signal analysis in BCI2000, using ERS/ERD offline and using P300. BCI2000 offers an Offline Analysis toolbox to help the statistical optimization during training (Schalk et al., 2004). A visual representation of the offline analysis run with the EEG data collected during training (See Figure 2). The offline analysis helps the researchers determine the specific electrodes and frequency presented the most ERS/ERD activations during the imagined movements (LaFleur et al., 2013). It is common to use a combination of the cursor tasks with the offline analysis toolbox, as it was used in another study to control a 6 DoF mechanical arm (Kilmarx et al., 2018). The study had the participants train with all three of the cursor tasks and used the cursor task layout to move the arm. Kilmarx et al. (2018) also used a UDP to communicate between BCI2000 and a microcontroller (Raspberry Pi). Another benefit of using BCI2000 is performing P300 experiments, which are widely used for BCI systems. P300 refers to 300 ms after an event-related potential, which is generally active during the process of decision-making (Jeon & Shin 2015). P300 experiments are typically used in BCI2000 to help a patient communicate by allowing them to type words through BCI (Jeon & Shin 2015; Kalika et al., 2017). Kalika et al. (2017) combined eye-tracking and P300 to develop a hybrid BCI, surpassing the effectiveness and accuracy of P300 by itself. While P300 has been successful in past studies, it is typically used in word development (Jeon & Shin 2015; Kalika et al., 2017), so analyzing ERS/ERD offline was used in the current thesis project as past studies support this protocol with controlling mechanical objects (Kilmarx et al., 2018, LaFleur et al., 2013).

Chapter 3: Methods

Participants

Eight participants were recruited to participate in this study, with three of the participants dropping out. The inclusion criteria for the participants is that they are over the age of 18. The exclusion criteria for participants are if they are under 18 or unable to complete the training tasks.

Preparation

Before arriving at the study, the participants were sent an informed consent. Upon arrival, the study was explained to the participant, who then signed the informed consent. Once the informed consent was signed, the participants were fitted into a 32-dry channel g.Nautilus EEG using the 10-20 system. This required a measurement to be taken in cm from the nasion to the inion, then divided by 10, and a mark is made at the values distance in cm from the nasion. This mark indicated where the front of the EEG cap sat to ensure reliable and repeatable data collection. The ground and reference wires for the EEG were attached at the mastoid behind each of the participants' ears. Before the ground and reference electrodes were placed, an abrasive gel was used followed by a paper towel to eliminate skin artifacts, then the electrodes were placed. Once the EEG was placed on the participant's head, the signal was tested for accuracy with blinks and teeth clenches. When the EEG signal was acceptable, tubular netting was placed over the cap to keep the electrodes pressed firmly against the skull. The EEG signal was checked again to ensure accuracy, then the pre-training task was started.

Pre-Training- Mu Task

The first task the participants completed was finding their specific mu rhythm when performing/imagining a movement. The participants completed this task by looking at a computer screen that said, ‘Left Hand’, ‘Right Hand’, or ‘Both Hands’ in random order while squeezing a tennis ball with the hand(s) that were shown. The participants were instructed to relax in between being shown which hand(s) were to be active. They were shown each word for 3s followed by a 3s break, with 25 stimuli, totaling 5 minutes. Once the task was completed, the data were analyzed, and if the data was satisfactory, they moved on to task 1. The data were deemed satisfactory if clear activation was found in the electrode expected (C3, C4, or both) at and/or close to a mu frequency (8-12Hz).

Training Protocol-Task 1

To start, the participants completed trials of the 1D cursor task, moving the cursor either to a target at the top or bottom by relaxing or imagining movements with their specific hand(s) respectively. They were allowed to choose any imagined movement they would like, however, they were told of the importance of only using the hand(s) being tested. The participants were also allowed to do a trial while squeezing the tennis ball to help them refresh their imagining of the movement. The software signaled which target the cursor should move to and recorded whether the participants were successful or not. The participants started the training tasks, progressing to the next hand when a score of 80% accuracy is achieved either in 4 consecutive 2-minute trials or an average of 80% across 10 or more trials. Participants also progressed to the next trial when they reached 200 targets if accuracy was not reached. Throughout the training trials, the software received the participant's brain waves, creating a personalized range of signals for each direction, while the participants developed an increased ability to control their thoughts while imagining movements. Once the participants completed their left, right, and both hands they progressed to the next task.

Training Protocol-Task 2

This task was a 2D cursor task where the participants moved the cursor to one of the four previous targets from the past tasks. To finish this task and the training, 70% accuracy was required either in 4 consecutive 3-minute trials or as an average across the past 10 or more trials.

Main Task

After completing the training protocol, the participants continued to use the 2D cursor task as they were then tested on how accurate they were at hitting targets in a chosen order. The desired cursor task outcomes were left, down, up, right, down, then up, making each decision within 15 seconds. For the current study, 2 electrodes were used to differentiate between imagined movements, determined by locating the signals in the brain using PSD with ERS/ERD at C3 and C4 (Kilmarx et al., 2018). This was performed 20 times with the success rate of each direction of the cursor being recorded. An overview of the training can be seen in Figure 3.

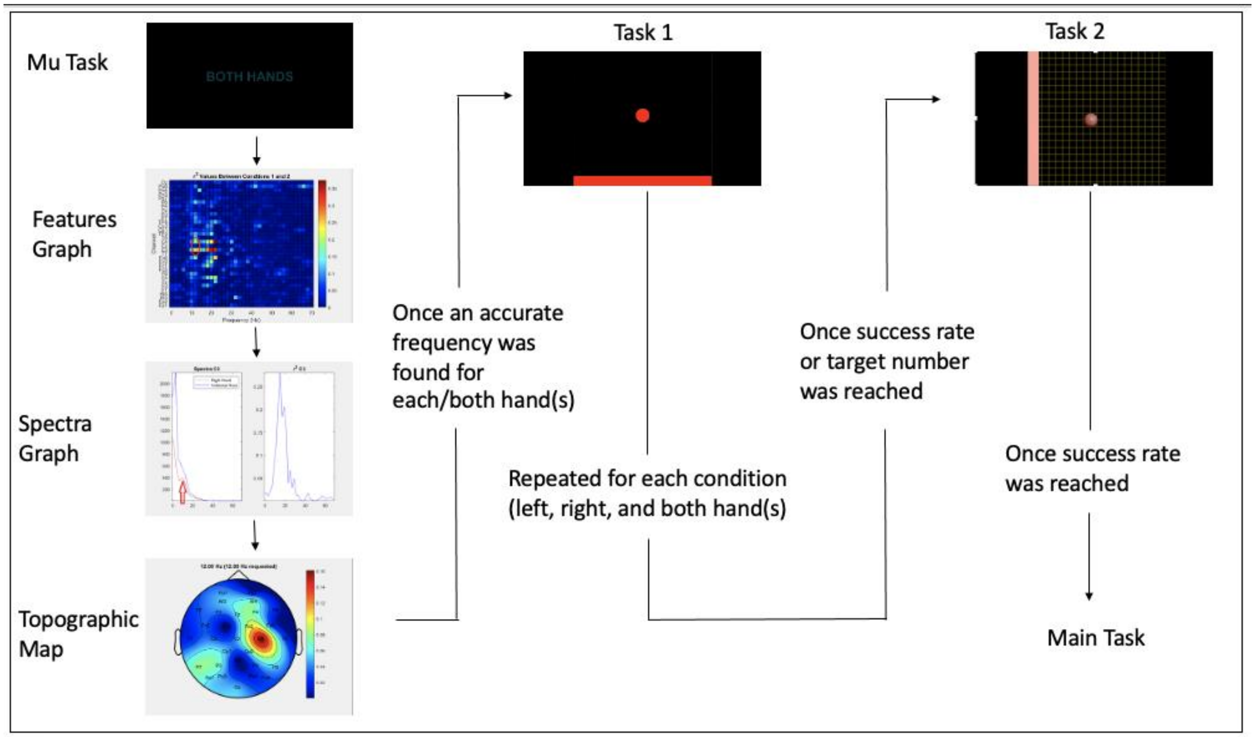

Figure 3. Training Task Overview. This is a representation of the progression through training tasks.

Data Processing

Before data collection started, g.Recorder was opened and the settings for g.Nautilus were changed to have an input range of (+/-)562.5 mV, standard for dry electrode collection (Petersamer, 2017) compared to (+/-)187.5 mV which is the default input range, standard for wet channel electrodes (Llorella et al., 2021). All the EEG data were processed through BCI2000. After the data were received it passed through a filter with a frequency band of 0.5 Hz to 30 Hz, a notch filter of 58-62 Hz was also applied, eliminating noise while leaving the optimal Hz for BCI. The first processing applied to the EEG data occurred after completing the mu task. A features graph, spectra graph, and a topographic map were shown for the electrodes and frequencies identified. The optimal Hz was determined through BCI2000 based on the training data of each subject, the frequency where the r^2 value was high indicating a difference in brain function during movement/imagined movement and rest, as shown in the features graph (LaFleur et al., 2013). Two more graphs were shown with the spectra graph showing spectral power change over all frequencies at a given electrode. The topographic maps showed where the largest change in spectral power occurred during the stimulus compared to rest over all electrodes at a given frequency. For task 1, a specific electrode(s) was selected to receive data, C3 for right-handed imagined movements, C4 for left-handed imagined movements, and both C3 and C4 for both-handed imagined movements. After the filters were applied to the signal, a multiple regression algorithm was applied to determine the projected output velocities at time (t) in the vertical and horizontal directions. The data were then analyzed using the offline analysis linear regression model, applied to each subject using leave-one-trial-out cross-validation from all the trials in each direction, with the extracted sets of linear regression coefficients averaged together and reported (Kilmarx et al., 2018).

Data Analysis

For analyzing errors, the percent hit rate was recorded for each participant individually for every task after mu. The subject's percentages were also separated after every ten 2-minute trials for task 1, and the change in success rate was recorded. For the main task, the percent hit rate for each direction was also determined, although the overall success rate of the main task was determined by the completion of moving the cursor left, down, up, right, down, then up without fail.

Once all the participants had completed their tasks, a chi-squares test was run on each participant for each task, including three tests for each hand(s) on task 1, to compare the observed results with the expected values. This helped determine the differences in the observed and expected values are due to a goodness of fit between the variables or due to chance. The expected values used are equal to the criteria needed to progress to the next for tasks 1 and 2, 80% and 70% respectively, while the hypothesized success rate, 75%, was used for the main task.

Chapter 4: Results

After completing the mu task, frequencies were found for individual and both hand(s), with the results shown in Table 1. The frequencies were determined by the largest change in spectral power during movements using a features graph (Figure 4), a spectra graph (Figure 5), and a topographic map (Figure 6). The features graph and topographic map use a heat map, with warmer colors indicating the amount an area is influenced by the participant's task, or the r^2 value.

Participant	Right Hand (Hz)	Left Hand (Hz)	Both Hands (Hz)
P01	14	10	12
P02	12	12	10
P03	10	10	12
P04	10	8	N/A
P05	8	10	N/A

Table 1. The results shown are the strongest frequencies for each movement determined after mu task.

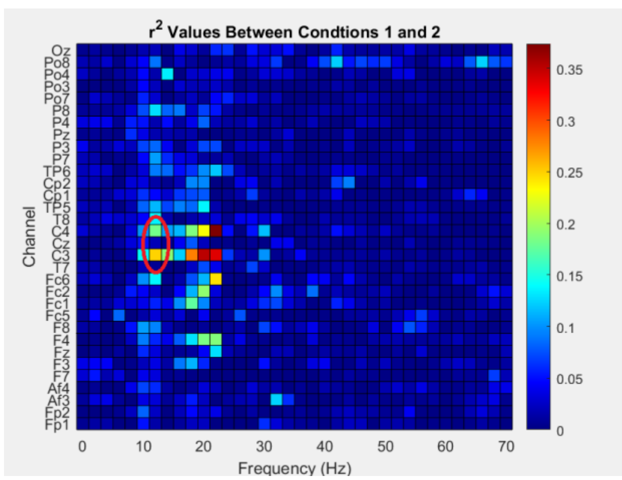

Figure 4. Features graph. This is an example of features graph for both-handed movements during the mu task. The first dual sign of activation at C3 & C4 occurs at 12 Hz, indicated by the red oval.

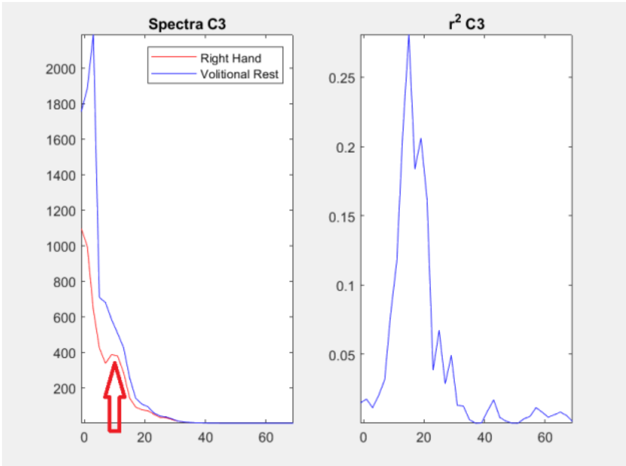

Figure 5. Spectra graph. Exemplary spectra graph for his right-handed movements during the mu task. The first clear sign of activation at C3 occurs at 14 Hz, indicated by the red arrow.

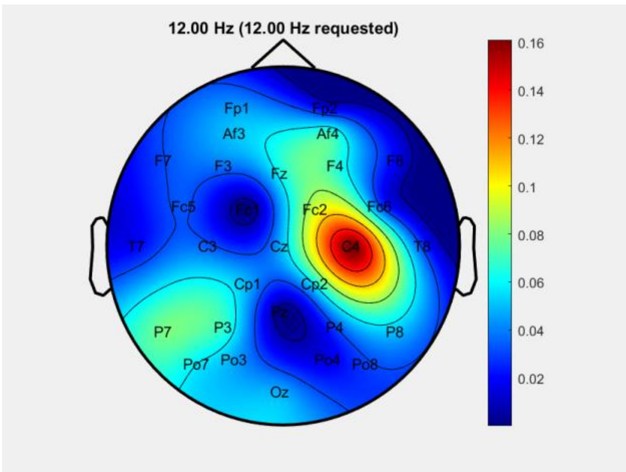

Figure 6. Topographic map. Exemplary topographic map for his left-handed movements during the mu task. The clearest sign of activation at C4 occurs at 12 Hz.

The number of hits, total targets, and success rate were determined for task 1, as shown for the participant's right hands in Table 2, left hands in Table 3, and both hands in Table 4. The change in percentages after each 10 trials is reported in Table 5. P02 had the largest jump from one set of 10 to the next set of 10 during his both-hands testing (disregarding P01's left-hand percentage jump from only one trial). The only participant to achieve 80% or higher on 4 consecutive trials was P04 with her left hand, who finished with the highest percentage of any participant during the three task 1 conditions at 64.8%.

Participant	Hits	Targets	Success Rate (%)
**P01	100	227	44.05
*P02	92	298	30.87
P03	132	407	32.43
P04	78	296	26.35
P05	73	427	17.10

*Table 2. The results shown are for right-handed movements during task 1. * Indicates prior practice before protocol change. ** Indicates participant started task 1 with their left hand.*

Participant	Hits	Targets	Success Rate (%)
* **P01	86	209	41.45
P02	94	201	46.77
P03	114	250	45.60
P04	144	222	64.86
P05	83	225	36.89

*Table 3. The results shown are for left-handed movements during task 1. * Indicates prior practice before protocol change ** Indicates participant started task 1 with their left hand.*

Participant	Hits	Targets	Success Rate (%)
P01	143	223	64.13
P02	119	200	59.50
P03	124	204	60.78

Table 4. The results shown are for both-handed movements during task 1.

Participant (Handedness)	First 10 to Second 10 (Percentage Change)	Second 10 to Third 10 (Percentage Change)	Third 10 to Fourth 10 (Percentage Change)
**P01 (R)	-21.05	+6.34	N/A
*P02 (R)	-4.92	+14.29	N/A
P03 (R)	+6.00	+17.29	+5.15
P04 (R)	+4.36	+2.90	N/A
P05 (R)	+9.46	-1.39	-6.70
* **P01 (L)	+30.54	+38.02***	N/A
P02 (L)	-5.44	N/A	N/A
P03 (L)	+15.06	+0.75	N/A
P04 (L)	+25.15	N/A	N/A
P05 (L)	+10.27	-5.54	N/A
P01 (B)	+16.77	N/A	N/A
P02 (B)	+31.56	N/A	N/A
P03 (B)	-7.84	N/A	N/A

*Table 5. The results shown are the changes in percentage after 10 trials. * Indicates prior practice before protocol change. ** Indicates participant started task 1 with their left hand. *** Indicates only 1 trial was used for the second set of 10 trials.*

After task 1 was completed, three of the participants moved on to task 2. Table 6 shows the hits, targets, and success rates for the participants for the 4 targets available during task 2, with 15 seconds allowed for each target hit. All three participants hit 70% or above on 4 consecutive trials, allowing them to progress to the main task, with P01 and P03 achieving the feat in 5 trials, while it took P02 6 trials.

Participant	Hits	Targets	Success Rate (%)
P01	33	48	68.75
P02	50	72	69.44
P03	35	50	70.00

Table 6. The results shown are for task 2. There are a low number of targets due to the success of the participants.

Following the completion of task 2, two participants moved on to the main task. There was a total of 20 targets for each movement for the main task, with 15 seconds allowed for each target hit. The number of hits, overall success rate, and number of perfect trials are provided in Table 7. A perfect trial was achieved when the participant was able to hit all 6 targets during one trial without fail.

Participant	Left Hits	Down 1 Hits	Up 1 Hits	Right Hits	Down 2 Hits	Up 2 Hits	Overall Success Rate (%)	Perfect Trials
P01	14	15	20	11	16	20	80.00	4
P02	12	14	19	16	17	17	79.17	5

Table 7. The results shown are for the main task. All targets were 20 for this task.

After the participants finished all their tasks, a chi-squares test was run using the observed and expected data, as seen in Table 8. All participants had significant chi-square tests for task 1, indicating that the proportions did differ by success rate. All five chi-square tests performed on task 2 and the main task did not have significance, as there is a high probability the values have no difference.

Participant	Right Hand	Left Hand	Both Hands	Task 2	Main Task
P01	X^2 (1, N = 227) = 183.33, p < .001*	X^2 (1, N = 209) = 197.17, p < .001*	X^2 (1, N = 223) = 35.12, p < .001*	X^2 (1, N = 48) = 1.00, p = .317	X^2 (1, N = 120) = 1.60, p = .206
P02	X^2 (1, N = 298) = 449.52, p < .001*	X^2 (1, N = 201) = 138.75, p < .001*	X^2 (1, N = 200) = 52.53, p < .001*	X^2 (1, N = 72) = 0.01, p = .918	X^2 (1, N = 120) = 1.11, p = .292
P03	X^2 (1, N = 407) = 575.57, p < .001*	X^2 (1, N = 250) = 184.90, p < .001*	X^2 (1, N = 204) = 47.08, p < .001*	X^2 (1, N = 50) = 0.00, p = 1.00	N/A
P04	X^2 (1, N = 296) = 532.46, p < .001*	X^2 (1, N = 22) = 31.78, p < .001*	N/A	N/A	N/A
P05	X^2 (1, N = 427) = 1056.00, p < .001*	X^2 (1, N = 225) = 261.36, p < .001*	N/A	N/A	N/A

*Table 8. The results shown are for a chi-square test based on expected values. (.8 for individual/both hand(s), .7 for 4 targets, and .75 for main task). * Indicates significance*

Chapter 5: Discussion

Both participants that completed the main task successfully achieved above 75% for their overall accuracy, and both were above 75% for 4 of the individual movements. This followed all 3 participants that were able to complete task 2, achieving >70% on four consecutive trials in 5 attempts for P01 and P03 and 6 attempts for P02. While for task 1, only P04 was able to achieve >80% accuracy and for only one movement, with every other participant progressing to task 2 by achieving 200+ targets for each and both hand(s).

During the main task, P01 was able to achieve a slightly higher percentage at 80% compared to P02's 79.19%, however, P02 completed 5 perfect runs, compared to P01's 4. The two imagined movements that P01 performed under 75% were his left- (70%) and right-handed (55%) movements. P01 was also able to achieve a 100% success rate for both of the volitional rest targets, which was the only target that was the same for every task, besides mu. P02's two imagined movements that had lower than a 75% success rate was their left-handed movements (60%) and their first both-handed movement (70%). The increase in accuracy throughout the progression of the tasks can easily be observed in Table 8 with the chi-square test values, as all three tests for task 1 were significant for all participants, while no significance was found for task 2 and the main task for the participants.

Once testing had started it was clear that there were needed adjustments to the protocol of this study. Originally, the participants were only given 4 seconds to hit each target for task 1. After P01 and P02 were unsuccessful in hitting a single target, the participants were given 10 seconds to hit each target for task 1, which is why P01 and P02 had prior imagined movement practice.

For the majority of participants, the initial criteria was not achieved for moving from one hand to another in task 1, however, they were able to achieve the needed success rate to move on from task 2 to the main task. Due to the participant's inability to reach the criteria in task 1, a protocol change occurred, as the criteria to move on to the next hand(s) changed from only success rate to either trial number (>200 targets) or success rate. One explanation for the lack of success can be associated with the lack of variability during practice. A previous study that tested 3 different experiments found that practice variability strengthened motor learning when compared to blocked and constant practice (Chua et al., 2019). In addition, a review of 10 studies found that cognitive engagement was greater with randomized (variable) practice compared to constant/blocked training (Lage et al., 2015). Specifically, Lage et al. found that during the acquisition phase of random practice as opposed to blocked practice, there is greater activation of neural structures involved in skill planning and execution. Further, Wulf et al., (2014) found that providing a choice for the participant, even if it is insignificant, increased their willingness to perform the task. This could have been incorporated into the current study by allowing the participants to choose which hand(s) they would have liked to train for the day during task 1. Allowing the participants to choose would increase the variability for the training and increase willingness, so external factors don’t play as much of a part. For task 2, no protocol changes were required as all participants were able to achieve the success rate needed to move on to the main task, within 6 trials. The success on task 2 for all participants was indicative that learning occurred during task 1, even with the success rate being lower than expected. The dramatic increase in success was appreciated by the participants, who stated at first it felt more like work, however, when they were hitting the targets consistently, it felt more like a game. This change of state may have had a positive impact on the success rate of the participants for the main task as the two participants claimed they felt less stress as they were recently successful, while higher levels of stress were shown to have a negative impact on success rate, discussed later.

The accuracy levels achieved in less than a month of testing with BCI are very promising for prosthetics, as again, it took over 5 months for any muscle activation to be seen after an invasive TMI procedure with the goal of returning functionality (Schweisfurth et al., 2017). The high levels of success on the main task show the ability of BCI to increase functionality, which will hopefully lead to an increase in use in the estimated 44% of upper-limb amputees that do not use prosthetics (Raichle et al., 2008). Increasing the functionality will hopefully lead to healthier mental states for the amputees, as function has been directly linked to an amputees' mental health/life satisfaction (Østlie et al., 2010; Resnik et al., 2019; Resnik et al., 2020). In addition, the use of only 2 dry electrodes to differentiate between movements shows the improvements made in the last 10+ years as only using 16 (Pressaco et al., 2011) and 12 electrodes (Pressaco et al., 2012) was seen as a success in past studies. Only using 2 electrodes increases the functionality of BCI as a full cap is not needed to ensure movement detection.

EEG/BCI

Following protocol modifications, high-quality EEG data were consistently achieved. Blink and teeth-clenching signal testing helped to ensure reliable data were collected (Lawhern et al., 2012; Alhakeem, Ali & Abd-Alhameed, 2020; Jiang et al., 2023). The mu task was repeated until clear activation was found on the relevant electrode(s) and there was an absence of activation elsewhere. When performing the offline analysis of the mu tasks to determine which frequencies provided the strongest data, common average reference was the EEG spatial filtering method used, as it has been shown to test superiorly to four types of bipolar manners and small- and medium-Laplacian filters and tested similarly to a large-Laplacian filter (Tsuchimoto et al., 2021). After applying the common average reference, the features graph was produced to identify the initial activation, followed by the spectra graph to see the individual electrode, and finally, the topographic map to visualize the activation across the entire head to ensure no activation was seen in areas of the brain not tested. BCI2000 recommended finding the first strong activation, starting at 8 Hz (mu is 8-12 Hz), which is why 12 Hz was used in Figure 4 (P03 both hands) as opposed to 24 Hz which had slightly stronger activation, and 14 Hz was used in Figure 5 (P01 right hand) despite it being slightly out of mu range, helping avoid misconfiguration due to noise.

A factor that may influence any BCI is that headaches may impact the accuracy of the test and the BCI may be influenced by the person's state. There was a clear difference when a participant had a headache or high levels of stress versus not, as they were unable to hit the volitional rest target and had more success hitting the imagined movement targets with a headache. For one participant in particular, their results looked exactly like they usually did when someone had a headache and testing was stopped, although they claimed that they felt fine. The next two mornings, however, they were unable to participate due to a migraine.

Individual Participants

Throughout the training protocol, notes were taken from each of the participants on how they were approaching each task. These notes were shared with each participant, to help them continue to develop a strategy that works best for them. It is important to note that P01 and P02 had extra training with Training Protocol- Task 1 before the cursor was set to move for 10 seconds. Previously, the time for the cursor to hit the target was set to 4 seconds and both participants were unable to hit the targets, however, they were gaining experience.

After the initial mu task was completed for P01, they had good activation of C4 at 10Hz during left-handed movement. This meant they were able to start Training Protocol- Task 1. For this task, P01 found that looking at their hand on the table was essential for imagining movement. This is supported by past literature that claimed visual feedback is relied on the most for arm position estimates for vector planning (Sober & Sabes, 2003). The movement they were imagining was squeezing some fruit ‘with the juices going all over their hand’. P01 also stated it was important to see the tennis ball, which was immediately tested and supported as they missed a higher percentage when the tennis ball was behind the screen for the two trials tested. To hit the volitional rest target, P01 first decided to sing a song from Frozen in his head, with mixed results. Once he heard from other participants that relaxing and even closing their eyes helped them hit the top target, P01 adopted this, stopped singing in their head, and became much more successful at hitting the top target. The evolution of P01's success is easily seen in the data as their success rate jumped 30.54% from their first 10 trials to their second 10 trials with their left hand. P01's strategy continued to develop as they progressed through the training with their right- and both-hand(s). They stated that they originally started with imagined squeezing, which then turned into visualizing a movement with squeezing if the target was not hit initially. P01 continued to imagine squeezing fruit as one of his visual tasks, however, they stated they also thought about gripping and swinging a golf club, a sport they play roughly once a month. During the initial testing for their right hand, it was found that 14 Hz was the ideal frequency, slightly higher than mu signals but usable. They got off to a strong start with their right hand, hitting 54.72% of targets during his first ten trials, although they dropped 21.05% in accuracy during their second ten trials. P01 finished with 44.05% accuracy with his right hand on 227 targets. When P01 performed both-handed imagined movements, 12 Hz showed the strongest activation in both C3 and C4. This was their most accurate testing so far, starting with 56.30% accuracy during the first ten, and jumping to 65.09% total accuracy after 212 targets. P01 was able to progress past task 2 in only 5 trials as they hit above 70% for four trials in a row, finishing with a 68.75% success rate on the task. While completing task 2, P01 stated that they had more success when looking at the ball as opposed to his hands, something he carried on doing during the main task. For the main task, P01 was able to perform all 6 required movements successfully 4 times, while achieving an 80% overall success rate. They were impressively perfect on both of their volitional rest targets throughout all trials during the main task.

P02 showed the expected activation of C3 at 12Hz and C4 at 10Hz during right- and left-handed movements respectively, progressing to the first task. During Task 1 P02 started off strong then regressed during his second set of 10 trials with his right hand. P02 saw success early as they found that closing their eyes helped them relax and hit the volitional rest target. However, they stated they had a headache and struggled to hit the volitional rest target more than the imagined movement target during the second set of 10 trials, as they dropped 4.92% in accuracy. This helped develop the testing protocol to avoid testing participants on days when they have a headache as it was harder to reach the relaxed state. When P02 returned feeling better, he found he was more successful when keeping his eyes open while looking to the right of the screen for both targets, increasing his accuracy by 14.29% from the second ten to the third set of ten trials, finishing with 30.87% accuracy with their right hand with 298 targets. They stated that they imagined feeling the signal coming from their brain to their hand, and they just imagined flexing their hand. They alternated between having their hand on the table and not, and having the tennis ball in sight and not, with the results not varying noticeably. With the initial testing for P02's left hand showing clean activation of C4 at 10 Hz, they started testing and achieved 49.12% accuracy during the first 10 trials, although dropping to 46.77% accuracy overall when all 201 trials were completed. This participant was consistently hitting the movement targets but struggled to hit the volitional rest target, reporting slight headaches and high levels of stress. P02 completed the initial mu test again, finding that 10 Hz was the desired frequency when they used both hands. This participant was the only one of the three to test below 50% during his first ten trials of both hands vs rest, however, that was followed by the largest jump, 31.56%, of any participant for either/both hand(s), finishing with a 59.5% success rate. For task 2, P02 had a 69.44% success rate during the 6 attempts it took to hit at least 70% four times in a row, allowing them to move on to the main task. The participant stated that they continued their strategy of looking away from the screen/hands for all targets. After completing 20 trials of the main task, P02 finished with a 79.19% overall success rate, while performing 5 perfect trials.

P03 showed activation at C3 and C4 at 10 Hz during the initial mu task for her right and left hand respectively. P03 went on to show consistent improvement with their success rate jumping 6.00%, 17.29%, and 5.15% from first to second, second to third, and third to the fourth set of 10 trials with their right hand, respectively. This participant stayed true to their method throughout the trials. Their method involved thinking of their neurons signaling down to their hand for different movements, not as focused on performing a specific movement itself. They always kept their hand on the table and looked at it when imagining movements, while closing their eyes helped them relax to hit the top target. With their left hand, they finished with a success rate of 45.60% after starting at 36.36% for the first 10 trials. An interesting note is that during one of the days of testing, this participant was unable to hit the top targets and they were asked to finish testing early. When asked if they had a headache, they stated that they didn’t, however, they were unable to test for the next two days due to a migraine. After performing the initial testing again, it was found that activation of C3 and C4 occurred at 12 Hz when performing movements with both hands. When performing the both-handed task, they proclaimed that looking at only one of their hands was not as successful as looking in the middle and seeing both during imagined movements. This was P03's most successful task, finishing with a 60.78% success rate on 204 targets. P03 had the highest success rate with task 2 of all participants, finishing at 70%. It took P03 only five attempts to hit 70% or above on all of the targets four times in a row, allowing them to complete the task. They repeatably stated that they looked in between both of their hands, able to see both, as when they only looked at one hand, they were often unsuccessful. Unfortunately, due to a lack of availability, task 2 was the final task P03 completed.

When P04 completed the initial mu task, they showed activation on C3 at 10Hz during right-handed movements. They started out looking away from the screen for both targets with her hands in their lap, then decided to switch early on to closing their eyes for the top target and looking at her hand on the table for the bottom target. Interestingly, P04 also noticed that they were able to consistently hit the top target by smiling, or even thinking of smiling, something that only worked for them. This participant described their imagined movement as opening a can or a jar with only the hand(s) being tested however, they claimed they switched it up sometimes if they were unsuccessful for multiple targets in a row. P04 showed slow but steady progress as their success rate climbed 4.36% from the first 10 trials to the second, and 2.90% from the second 10 to the third. After finding that 8 Hz is ideal for their left hand, they began testing and started off very strong with 52.63% accuracy. This then jumped to 64.86% accuracy overall, the highest of anyone's task 1, after they performed significantly better during their second set of 10 trials. They ended with hitting over 80% on 4 consecutive trials 86.67%, 94.11%, 95.23%, and

100%, the only participant to achieve this feat during task 1. They claimed they did not change their strategy much but focused on the emotions smiling brought when hitting the volitional rest target. Unfortunately, due to a lack of availability, testing their left hand was the final task P04 completed.

Every participant performed better when imagining movements compared to when they squeezed the tennis ball, however, P05 was the only participant to still prefer to use the tennis ball when testing despite having worse results. After completing the mu task and showing activation at C3 at 8Hz and C4 at 10Hz, P05 started his first task with his right hand (C3). They consistently refreshed their imagined movements by choosing to do trials with the tennis ball. When they were imagining movements, the movement they imagine was still squeezing a tennis ball, with their hand out of sight below the table. This participant stuck with their ways after an early 9.46% jump from the first to the second set of 10 trials and continued to stick with their ways while falling 1.39% and 6.7% from the second to third and third to fourth set of ten trials respectively, finishing with a success rate of 17.1% the lowest of anyone's initial hand. While their success rate more than doubled for their second hand at 36.89% on 225 targets, this was still the lowest success rate of anyone’s second hand. Unfortunately, due to a lack of availability, testing their left hand was the final task P05 completed.

Three of the participants, P06, P07, and P08, were unable to achieve proper activation during the initial mu task. One commonality between these 3 participants is that they had the smallest heads when measuring their nasion to their inion. With only having one cap size that can be stretched, it was determined that the cap was not tight enough to provide useful data as some electrodes were not in contact with the skin, even with the tubular netting overtop the electrodes. Due to no activation being seen in either C3 or C4, these participants were informed that they would not advance to the next testing stage.

A commonality among all the participants is that they were enjoying the training/testing more when they started to become more successful. They talked about it more like a game than training/testing, seemingly having a better attitude, which may have increased the accuracy further. While the task 1 training clearly lead to improved accuracy during task 2 and the main test, gamifying the initial training more may have increased morale, leading to improved initial accuracy.

Limitations

The main limitation of this study was time/availability. Each trial for the mu task took 5 minutes, task 1 took a minimum of 2 minutes per trial, while every trial for task 2 took a minimum of 3 minutes. This added up as the participants did up to 45 trials for each movement for task 1. The time also does not include set-up, which took a while on occasion to see good EEG data, and the resting in between each trial. For the participants that did not complete the final testing, it is estimated that they were tested for around 25-30 hours. For those who did complete all the testing, it is estimated that they were tested for around 35-40 hours.

There was also a limit as to how many trials a participant could perform at a time, as the longer the participant wore the cap the more uncomfortable it became, leading to headaches, which would stop data collection for the day. Once the tubular netting was introduced, the headaches came sooner as the cap was being squeezed on the participant's heads, resulting in even fewer trials per session. Another limitation is the lack of recorded caffeine usage by the participants.

The last limitation was the equipment itself. While it is known that there is a much higher skin-electrode impedance for dry-electrode EEGs compared to gel, a past study was able to achieve similar accuracies between gel- and dry-electrodes using the same g.tec EEG with a g.USBamp (Guger, Krausz & Edlinger, 2011). Guger et al. claimed that since dry electrodes pick up more artifacts and are more sensitive to movement, they integrated the g.USBamp into each electrode itself with a 24 Bit analog-to-digital converter, resulting in similar accuracies to gel electrodes. Unfortunately, the current study did not have access to a g.USBamp, relying on the amplifier embedded in the cap, which has the potential to decrease the quality of the signals. Another limitation with the equipment was that the cap being used did not fit everyone's head perfectly, and no other sizes were available, as individuals with larger heads would stretch out the cap, making it harder to collect individuals with smaller heads. Due to this, tubular netting was placed over the EEG for every participant. Unfortunately, even with this addition, three of the participants' heads were too small for accurate data collection with the given cap.

Future Studies

BCI is a growing space that needs more research done, as the benefits can be significant, including having complete control of a prosthetic. For future studies, more research should be done with dry electrodes without an amplifier, to help reduce the equipment needed and increase functionality. I would also recommend variable training, switching between which hand(s) are being tested throughout task 1, instead of finishing one and moving on to the next. Lastly, I would recommend adding a mechanical prosthetic to control as this may affect an individual's ability to imagine movement, for better or worse.

Conclusion

Overall, this study successfully showed that 2 dry electrodes can be used to detect imagined movements through BCI. With only using 2 electrodes, it is easy to improve cosmoses, implementing the electrodes into a bandana/hair band. While the accuracy can still be improved, by enhancing the equipment and developing the training protocol, both participants that completed the main task were able to surpass the expected overall accuracy and surpass 4 out of the 6 individual accuracies. Whether it is to control a mechanical arm, leg, or other body part, the framework of this study grants development opportunities for BCI from a few dry electrodes.

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Appendix:IRB Approval Memo

EAST CAROLINA UNIVERSITY
University & Medical Center Institutional Review Board
4N-64 Βροδψ ΜεδιχαλΣχιενχεσΒυιλδινγ•ΜαιλΣτοπ 682
600 Μοψε Βουλεϖαρδ •Γρεενϖιλλε, NX 27834
Οφφιχε **252-744-2914** •Φαξ **252-744-2284** •
rede.ecu.edu/umcirb/

Notification of Amendment Approval

From:	Biomedical IRB
To:	Joshua Lawton
CC:	Nicholas Murray
Date:	6/9/2023
Re:	Ame1_UMCIRB 23-000824 UMCIRB 23-000824 EEG Controlled Mechanical Arm

Your Amendment has been reviewed and approved using expedited review on 6/8/2023. It was the determination of the UMCIRB Chairperson (or designee) that this revision does not impact the overall risk/benefit ratio of the study and is appropriate for the population and procedures proposed.

Please note that any further changes to this approved research may not be initiated without UMCIRB review except when necessary to eliminate an apparent immediate hazard to the participant. All unanticipated problems involving risks to participants and others must be promptly reported to the UMCIRB. The investigator must submit a Final Report application to the UMCIRB prior to the Expected End Date provided in the IRB application. If the study is not completed by this date, an Amendment will need to be submitted to extend the Expected End Date. The investigator must adhere to all reporting requirements for this study.

Approved consent documents with the IRB approval date stamped on the document should be used to consent participants (consent documents with the IRB approval date stamp are found under the Documents tab in the study workspace).

The approval includes the following items:

Document	Description
Extending the study end date to 5/15/2024.	

For research studies where a waiver or alteration of HIPAA Authorization has been approved, the IRB states that each of the waiver criteria in 45 CFR 164.512(i)(1)(i)(A) and (2)(i) through (v) have been met. Additionally, the elements of PHI to be collected as described in items 1 and 2 of the Application for Waiver of Authorization have been determined to be the minimal necessary for the specified research.

The Chairperson (or designee) does not have a potential for conflict of interest on this study.