

ABSTRACT

Title of Thesis: CONTROLLING A NON-INVASIVE UPPER-LIMB PROSTHETIC DEVICE VIA A MACHINE-LEARNING ASSISTED BRAIN-COMPUTER INTERFACE

Team BCIPRO, 2023

Thesis Directed By: Dr. Anil Deane
Institute for Physical Science and Technology

The goal of our research was to improve the accessibility of current upper-limb prostheses. We aimed to maintain non-invasive aspects of an Electroencephalography (EEG), use affordable material and resources, and match the accuracy and control of conventional prostheses alongside improved training methods. Our process began with us designing a method of data collection that uses a 3D-printed headset with dry electrodes to record brain signal data through EEG software. We then analyzed the signals, applied preprocessing to reduce noise, and used machine learning (ML) models to classify EEG signals with respect to specific actions such as the opening and closing of a hand. Finally, we constructed a 3D-printed hand that is actuated by servos with Arduino to demonstrate the physical actions interpreted through analysis, and we leveraged novel techniques to build a virtual reality (VR) environment to serve as a tool for prosthetic rehabilitation. We successfully met the goals set for data collection and prosthetic arm actuation. Additionally, we have created a functional algorithm for action prediction but were not able to

achieve the desired accuracy. Overall, we achieved our primary goal of collecting brain signal data, analyzing that data through an algorithm, and actuating a prosthetic arm with actions interpreted from the brain signals all in real-time. Moving forward, there is room to increase accessibility and quality of prostheses through further development of non-invasive brain-computer interface (BCI) based technology for 3D-printed prostheses and VR environment prosthetic models.

CONTROLLING A NON-INVASIVE UPPER-LIMB PROSTHETIC DEVICE VIA A
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by

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Introduction

There are an estimated 2.2 million individuals living with limb loss in the United States (Ziegler-Graham et al., 2008). Individuals living with limb loss or **congenital** differences can experience difficulties in life. In addition to limb loss present at birth, limb loss can be brought about through a broad range of circumstances. One such circumstance is through **amputation** as a treatment for various conditions including blood vessel disease, diabetes, or blood clots; injuries from accidents or trauma; and surgery, such as the removal of tumors from bones and muscle (Stanford Healthcare, n.d.).

While it is not impossible to adapt and manage daily tasks without additional support, the inability to perform certain activities without support can negatively impact the individual's health. There are both mobility issues as well as psychological effects that can present as feelings of inadequacy due to loss of independence in such individuals' daily lives, which can be seen from the fact that 94% of people with incapacitating hand injuries suffer from mental health effects such as depression, anxiety, and stress disorders (*Mental Health and Partial Hand Amputation*, 2019). Particular concerns also stem from the history of **ableism** entrenched within society. Ableism is a powerful driver for exclusion which, in turn, can harm self-esteem and lead to anxiety and depression.

A way to support and provide a sense of normalcy for individuals living with limb loss is through **prosthetic** devices or **protheses**. Having artificial limbs allows individuals to regain a sense of independence despite the visual and physical differences. However, some prosthetic devices only serve an aesthetic function and most lack precise control of motor functions. Modern prosthetic models come with increased functionality but are still limited by their accuracy and precision, and do not typically perform at the same level of ease, precision, and

comfort as biological limbs (Bright et al., 2016).

There have been significant prosthetic-based technological advancements in the medical community over recent years. A new approach to advancing prosthetic devices is with **brain-computer interfaces (BCI)**, also known as **brain-machine interfaces (BMI)**, which have been successfully used to allow individuals to control prosthetic devices with their thoughts. A BCI involves the fusion of biology and technology into a communication and control system. This system enables users to send neural signals as commands to a computer or external device, without the need for muscle control (Jeunet et al., 2016). Generally, specific patterns of the user's brain activity that indicate different commands are detected, processed, and then decoded by signal processing tools to identify the message or command before being delivered to the output device (Guger & Allison, 2014). As a closed-loop system, BCIs provide real-time information which reflect the intended messages or commands. That is, BCI controlled prosthetic devices permit higher quality of life for **amputees** due to greater autonomy and control over movements. However, most BCI technologies being studied are invasive, meaning they require surgical attachment. Our project aims to research the effectiveness of non-invasive BCI prostheses.

Additional research into the application of BCIs range from medicine to business to gaming. Clinically, BCI technology utilizing **electroencephalograph (EEG)** extracted signal features has been used to translate device commands that control assistive technologies for communication (e.g. spelling), movement control (e.g. a neuroprosthesis), locomotion (e.g. driving an electric wheelchair), and rehabilitation (e.g. therapy for impaired brain areas and connections after a stroke) (Mak & Wolpaw, 2009). Businesses, alternatively, are interested in environmental control in regards to hardware interfaces for phones, temperature, TVs, light, and

other smart devices. In entertainment, BCIs are being used in video games to control avatars, actions, and objects (Abdulkader et al., 2015).

By building upon existing research, we demonstrated that it is possible to generate an end-to-end system using commercially available components to mock up a non-invasive prosthetic device. By combining the use of EEG technology, open-source databases, open-source **machine learning (ML)** models, and 3D-printing, our approach offers a cost-efficient, non-invasive method that would not only be effective at interpreting brain waves to generate prosthetic movement, but also be made available to those who need it.

Literature Review

Acquisition

Our baseline collection method is an EEG, which measures electrical activity in the brain as brain wave patterns using electrodes, which are small metal disks. The electrical activity measured are the electrical signals, or nerve impulses, between cells called neurons in the brain. Movements of the body, such as lifting an arm, are caused by specific patterns of nerve impulses sent from the brain. An EEG allows for these brain waves to be read so that they can be analyzed.

Each electrode records a sampling-rate-dependent constant stream of data similar to sound or frequency data. EEG data is often analyzed via a spectrogram, which is a time dependent graph that plots relative power for each electrode. These bandwidths are divided into **Delta, Theta, Alpha, Beta, and Gamma** which are associated with the numeric frequency bandwidths of 0-4 Hz, 4-7 Hz, 8-15 Hz, 16-31 Hz, and 32-60 Hz respectively. Alpha band power, particularly at the 10 Hz frequency, is significantly involved in sensory inhibition, attention modulation, and working memory whereas the Beta band is most commonly studied in relation to sensorimotor behavior. It is known that beta band power decreases during the preparation and execution of voluntary movements and bursts after the termination of the act (Jeunet et al., 2016). Beta bands have also been identified as markers for sensorimotor signals. When voluntary movements are planned and performed, the power on the beta bands decreases. This trend is still observed when the movement is thought about but not followed by any physical action. Gamma bands have been identified as markers for sensorimotor stimuli (Suurmets, 2018).

Action signals are identified by an increase in power in one or more of the frequency bandwidths. After an amputation, observed frequency bandwidths may change, as well as general brain signals in certain regions of the brain (Lyu et al., 2016). An EEG records measurements using an active electrode-reference electrode pair—by measuring the potential difference between the electrodes over time (X. Li et al., 2017). The brain signals for motor and limb function are common in specific parts of the brain, for example, within the parietal lobe. However, as a general rule, an increase in the number of electrodes leads to measuring more data points, which can potentially lead to more accuracy at the expense of increased cost.

There are several types of electrodes that can be used with an EEG. The main categories are dry electrodes, wet electrodes, and semi-dry electrodes. Wet and semi-dry electrode EEG systems use a solution to maintain brain signals by providing an ionic conducting path. This allows for minimal degradation of the brain signals before they can be recorded by the EEG. Some of the solutions used with EEGs include gel, saline, and semi-dry (water or humidity). Dry electrode EEG systems are easier to use, require less time to set up, and are more convenient; however, they are less accurate than wet and semi-dry electrodes. We used dry because of their accessibility, cost-effectiveness, and convenience.

We considered NeuroSky's MindWave Mobile 2: Brainwave Starter Kit, NextMind's Dev Kit hardware, and OpenBCI's Ultracortex Mark IV as potential EEG sources ranging from \$110 to \$1300. The NeuroSky MindWave headset is an inexpensive, lightweight, portable device with wireless communication. NextMind's Dev Kit is a wearable EEG system that translates signals into commands that can control a digital interface, and is primarily used in video game applications. The development kit was unfortunately not yet available for purchase when we needed to construct the headset to begin data acquisition. Due to OpenBCI's availability,

affordability, and versatility, the Ultracortex Mark IV and 8-channel Cyton Biosensing board were used in our study. OpenBCI provided 3D-printable files for the structure of the headset as well as electrical materials, such as electrodes and wires. Furthermore, OpenBCI provided a user interface to allow for ease of data collection and live streaming of data in Python.

Implementation

Our implementation method is a physical **prosthesis** that is able to demonstrate simple actions such as opening and closing a hand, as well as moving individual fingers. There are many ready-to-buy prosthetic arm devices which exist on the market at a variety of prices. There are also other prosthetic options that can be explored via 3D-printing.

Current State of BCI-Prosthetics

Past research on BCI technology in the application of prosthetics has explored advanced methods for deciphering data from EEGs, developed sophisticated algorithms to analyze data, and researched into how effective prosthetic limbs can be built. Some general categories of prostheses organized by price are as follows:

1. High-end (\$7,800-\$50,000): TrueLimb, Grippy, HeroArm, KalArm, Manifesto Hand, OHand 2-Channel, BrainCo, Ability Hand, BrainRobotics Hand, MeHandB, Nexus Hand, OHand 8-Channel, Zeus Hand, Adam's Hand, Bebionic Hand, MeHandA, Vincent Evolution, i-Limb Access, Atom Touch, i-Limb Ultra & Quantum, LUKE Arm, Michelangelo Hand, TASKA Hand
2. Mid-level (\$100-\$500): LewanSoul, Tinkersphere, Hiwonder uHandPi
3. Low-level (3D-Printed options available online): NIH 3D Print Exchange



Figure 1. *Hero Arm Demonstration.* The Hero Arm is holding a Rubik's Cube while the user's biological hand is positioned close by (Williams, 2021).



Figure 2. *Zeus Hand Demonstration.* The hand is shown squeezing a ball (Williams, 2020).



Figure 3. *LewanSoul Hand.* The hand is shown positioned upright, curling the thumb and pointer finger while the other fingers are positioned open (*Robot Hand Five Fingers Solely Movement Bionic Robot Mechanical Arm DIY (Right Hand)*, n.d.).



Figure 4. *Tinkersphere Hand.* The hand is shown positioned upright and open (*Robotic Hand Kit - Servos Included*, n.d.).

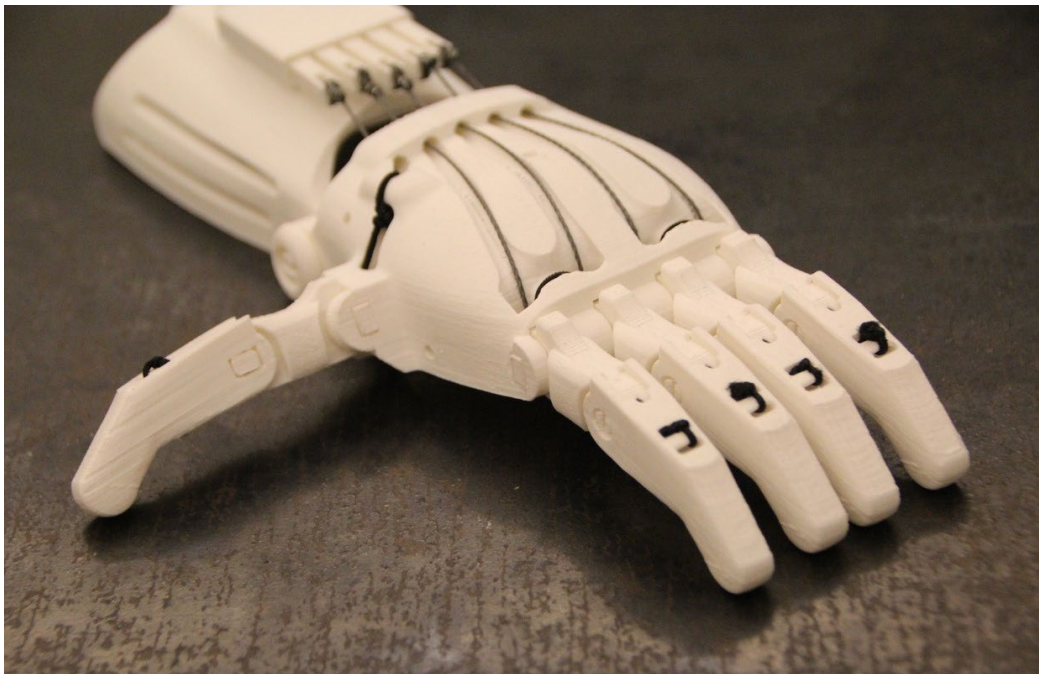


Figure 5. *Raptor Reloaded.* The hand is shown palm down on a surface. Raptor Reloaded is a 3D-printable prosthetic arm with a print file available for download from the NIH 3D Print Exchange website (*NIH 3D - Raptor Reloaded*, n.d.).

There is a wide variety of commercial prosthetic devices available, with more expensive prostheses often having **myoelectric** based control, which refers to control from input of electrical signals generated by muscles in the **residual limb**. To accomplish such control, invasive surgery is needed to get to those residual limb muscles to link with wiring. Our approach is constrained by the fact that we are seeking a non-invasive approach, so we eliminated high-end prosthetic devices from our research.

The mid-level commercial prosthetic devices available have wiring that is able to interface with Arduino or other microcontrollers, allowing for more non-invasive control for individuals. However, since we have collected non-invasive EEG data, this limits the accuracy with which we are able to classify the observed brain activity. As a result, we expected to only be able to identify more broad categories of movement, such as opening or closing a hand or a finger, and not the specifics to exactly how much a finger or hand should move. Mid-level prosthetic devices have fingers with multiple degrees of rotation, but as our EEG data is not accurate enough to take advantage of that freedom, we eliminated them as a choice for our research.

These design eliminations left us with 3D-based prosthetic devices, which fit the more basic physical control requirements we are seeking. 3D-printed prosthetic devices typically function mechanically—where the hand is attached to an individual's wrist and/or residual limb—and have mechanical wires that open and close fingers in tandem with the opening and closing of the wrist joint. Another benefit of 3D-printing prosthetic devices is affordability compared to commercial options due to the costs of materials and labor to print. However, 3D printers can be thousands of dollars for individuals without access to public 3D printers, so accessibility is a concern here. Although the cost of owning a 3D printer limits accessibility, it is

possible to order 3D-printed pieces online relatively inexpensively, so the expense issues could be counteracted. Also, it should be noted that in terms of FDA (U.S. Food and Drug Administration) approval, 3D-printed prosthetics would need approval if they were to become common commercially for users. The FDA does approve 3D-printed medical devices, so in theory 3D-printed prosthetics should be feasible for approval (Health, 2022). Therefore, when doing 3D-printed prosthetic research it is important to consider future FDA approvals, especially if participants are involved in the research.

When researching prosthetic models available to print from online, we explored a website called The NIH 3D Print Exchange. There, we saw various prosthetic designs to choose from, and chose to print the popular ‘Raptor Reloaded’ hand (*NIH 3D - Raptor Reloaded*, n.d.).

An important part of designing a prosthesis is the control system. Wired connections are commonly used, but wireless connections are available as well. One device we explored was a Bluetooth transmitter which would work in conjunction with an Arduino in order to transmit commands from our lab computer to the Arduino in order to control the prosthetic arm. Ultimately, we went with wiring the Arduino directly to a desktop computer, but since the OpenBCI headset used Bluetooth, we were able to have participants sit some distance away from the computer.

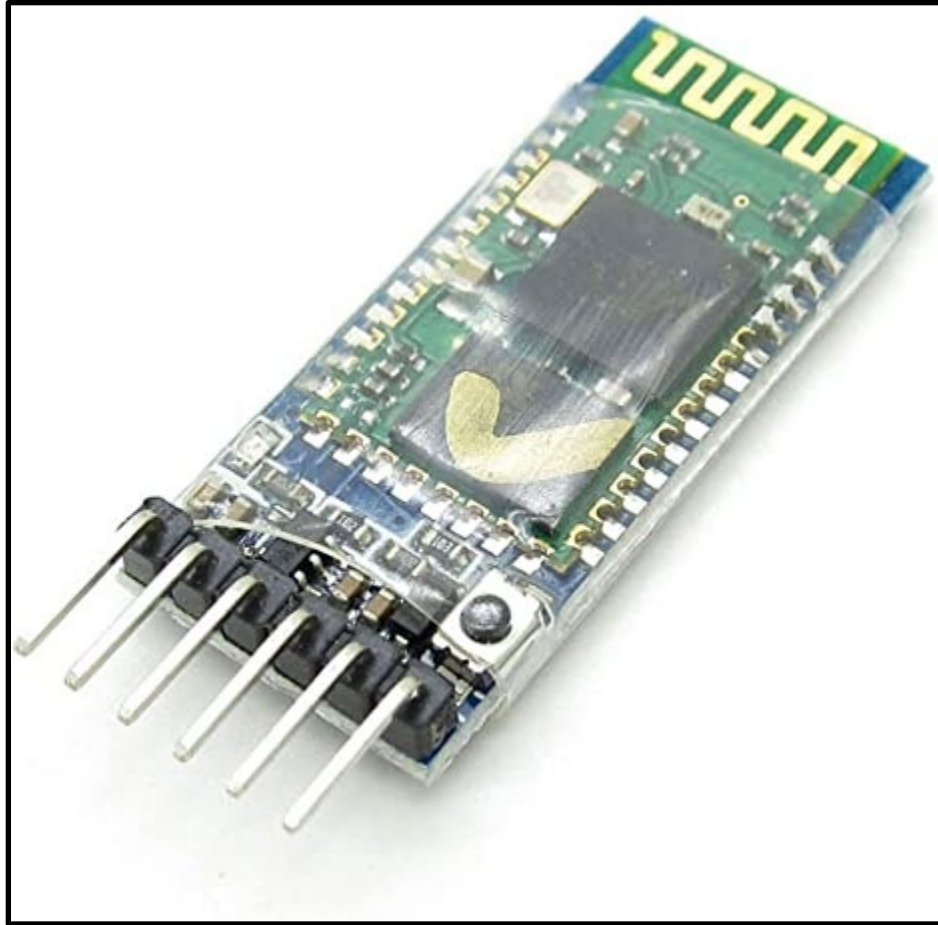


Figure 6. *Bluetooth Module for Arduino.* The module would allow for Bluetooth communication with an Arduino (HC-05 Wireless Bluetooth Receiver RF Transceiver Module Serial Port Transmitter Module: Electronics, n.d.).

Typically, an upper-limb amputee would use a prosthetic arm such as the ‘Raptor Reloaded’ while it is attached to their wrist area, and wrist bending would allow for opening and closing of the prosthetic arm (Dally et al., 2015). Variations of prosthetic usage exist which involve using attached servo motors to allow software controlled physical action (Donaldson, n.d.).

We decided to connect the prosthetic arm using servo motors and Arduino to allow for computer-based control, which allows for precision in movement. This was different from utilizing the prosthesis for its standard mechanical-based control. In comparison, mechanical control uses wrist bending to open and close the hand, and is more practical for user’s than

prostheses involving servo motors. We used standard connections to connect five different servo motors to the Arduino board. The Arduino software our project uses is based on existing servo control commands, but it utilizes serial output communication to receive command code from our data analysis and implement the code as movement.

Virtual Reality Environment for Prosthetic Rehabilitation

The goal behind a virtual simulation is to make our novel prosthetic interface more accessible and improve the experience of prosthetic rehabilitation. While we initially sought to explore a 3D simulation of our prosthetic for the purposes of demonstration, by recognizing the unique capabilities of VR as an assistive technology, we decided to build a proof-of-concept environment that aims to aid clinicians and patients in pain management, prosthetic orientation, and prosthetic training. By immersing the user in an environment capable of simulating real-life prosthetic interactions and exercises, along with the portable convenience of minimal setup and a fully customizable user experience, VR is a powerful technology that has the potential to improve the rehabilitation process.

With current VR-assisted prosthetic rehabilitation efforts, adoption of these novel techniques in clinical practice has been minimal due to many factors. These include barriers based on unfamiliarity from patients and clinicians to the technology, the upfront cost from medical institutions in acquiring VR hardware and training clinicians outweighing perceived value, and the technological limitations of VR to fully represent the complexities of rapidly advancing prosthetic technologies (Gaballa et al., 2022). Despite these issues, several case studies have been conducted showcasing the positives of integrating Extended Reality technologies, which consist of VR, Augmented Reality (AR), and Mixed Reality (MR), within Upper-Arm Amputee training, though the majority of the control strategies that have been tested

are of myoelectric signals, and EEG control has only been briefly explored as a possible input modalities (Hauschild et al., 2007). Due to ongoing BCI research, there are multiple research-grade EEG systems that have full VR integration including the DSI-VR300 offered by NeuroSpec and the Galea from OpenBCI (*DSI-VR300*, n.d.; *Galea*, n.d.). However, both options are expensive (around \$25,000) and difficult to obtain, and so far there has not been any significant research using these **Head-Mounted Displays (HMD)** within the field of prosthetic rehabilitation. Our solution would be to provide an affordable pathway for VR to improve our novel, affordable EEG interface, especially by focusing on portability, ease-of-use, and customization within the rehabilitation process.

It is clear where our VR environment could be integrated throughout the lengthy postoperative and prosthetic training program for a recent amputee. Soon after their operation, the patient will be especially dependent on their healthcare team which would consist of physicians, nurses, and occupational and physical therapists. In the early stages, the goals of this program would be to maximize the patient's independence and increase muscle strength and range of motion which is especially crucial for the placement and function of a prosthetic device (Atkins, 2002). The patient will likely experience phantom limb pain, which is a feeling of persistent pain in an amputated limb and has been recorded to affect approximately 70% of amputees. VR environments have shown promising results in serving as a tool to deliver effective, low-cost, self-administered treatment for this kind of pain, which can serve as precedent for the use of technology within rehabilitation (Ambron et al., 2018). Throughout this process, the healthcare team would be exploring the patient's goals and orienting the patient with prosthetic options and training. One use case for our VR environment would be as an interactive demonstration of our brain-computer interface, promoting the cost benefits of our prosthetic.

As the patient transitions into the training phase of their rehabilitation, their relationship with their occupational therapist becomes even more crucial, as it will be the responsibility of the therapist to manage and monitor the amputee's acclimation to the prosthetic. It must be said that when we propose a VR component to rehabilitation therapy, this is not meant to be a replacement to the traditional therapeutic methods which rely on the input of a clinician. Since a major component of the therapy requires the haptic feedback and physical presence of the therapist, a fully-virtual simulation environment that could be used as a form of immersive 'distance-learning' would not be feasible given current technology. However, recent studies have introduced a force feedback from a physical robotic arm in order to add realistic weight to the control of a prosthetic limb in a VR environment (Chappell et al., 2022).

The VR environment would be best utilized for the exercises that comprise prosthetic controls training. Initially, prosthetic training would consist of prehension control practice including reaching, grasping, moving, positioning, and releasing; those being the motion elements that are primarily used in hand manipulation (Atkins, 2002). Once the individual has reached a satisfactory level of practice, they would typically attempt other commonly used indicators of upper-limb mobility and function including the Box and Block test, the Nine Hole Peg Test, and the Target Achievement Control (Gaballa et al., 2022). Finally, the user would have the opportunity to engage in functional use training, which would be completing ordinary everyday tasks by using their prosthetic. This is likely the most difficult and prolonged stage of the training process, and the stage which VR can most effectively accelerate. In order to more effectively monitor and alter the situation, a VR environment would allow the occupational therapist to quickly make adjustments to the patient's virtual environment. Since the scene is a controlled environment, the therapist could easily adjust the position or dimensions of the

prosthetic, quickly alter the scene and objects within them, and accurately conduct an analysis on the user's performance. The therapist also has the capability of providing simulated demonstrations to the patient to help them better follow along with the exercise. It is important that the options for customization are plentiful and made accessible to the clinician, and it would be best that the final design for a fully customizable environment be vetted by several distinguished healthcare professionals. While we do want to specify that most of the actual training would be supervised by the occupational therapist, the portability of the VR environment could allow the patient to take part in self-administered at-home practice that is assigned by the therapist.

Despite the virtual environment's ability to simulate the majority of exercises within prosthetic rehabilitation, it will not replace the training of the actual prosthetic. To maximize the feeling of independence of the user, a proposed rehabilitation process would look to wane off the reliance of the VR environment for training. We still hope that the environment would improve the comfort of the user in the early stages, especially in establishing a feeling of ownership and control over their prosthetic.





Figure 7. *VR HMD and Peripherals.* (Top Left) Meta Quest 2 HMD. (Top Right) Left Controller. (Bottom Left) HTC Vive Tracker 3.0. (Bottom Middle) Skywin VR Tracker Strap. (Bottom Right) HTC Vive Base Station (*Base Station | VIVE United States, n.d.; Oculus Quest 2 Transparent PNG - StickPNG, n.d.; Skywin VR Tracker Strap for HTC VIVE System Tracker Puck, n.d.; VIVE Tracker | VIVE Business United States, n.d.*).

When analyzing the HMDs that are available on the market in order to set up our environment, our main concern was to use a headset that was widely available and cost-effective, as accessibility is one of our priorities. Most of our initial development was accomplished using the HTC Vive Pro 2 Full Kit, an expensive HMD valued at \$1,399 which also requires the device to be wired to a computer that runs our software. In order to track the movement of the HMD, trackers, and controllers, it is also required to set up multiple base stations in the corners of the user's physical space that rapidly emit sync pulses and laser lines to calculate the position of the VR devices (known as outside-in tracking). Due to the high cost and difficult setup of the HTC Vive HMD, we opted to use the much more consumer-friendly Meta (formerly Oculus) Quest 2. As opposed to using base stations, the Quest 2 tracks its HMD and controller position through inside-out tracking, calculating position in 3D space through cameras on the HMD that employ a computer vision model that looks for reference points in the physical environment to deduce the user's position in the virtual space. As the HMD contains an internal CPU and GPU, the device is able to run a standalone Android-based operating system, which allows the user to remain untethered to an external computer. Both due to its affordability (\$399) and being wireless, we preferred to use the Quest 2 as the HMD of choice.

To allow for body tracking, specifically to track the position of the user's elbow, we chose the HTC Vive Tracker 3.0, valued at \$130. Unfortunately, the Tracker requires the usage of physical base stations, which would need to be mounted and secured high in the walls of the play area in order to track position. In the near future, we would hope to convert to using inside-out trackers through the recently announced HTC Vive Self-Tracking Trackers, which wouldn't require the installation of base stations.



Figure 8. *HTC VIVE Self-Tracking Tracker.* An inside-out tracking peripheral that will be released later in 2023. Does not require the use of Base Stations (*VIVE Self-Tracking Tracker*, n.d.).

Methods

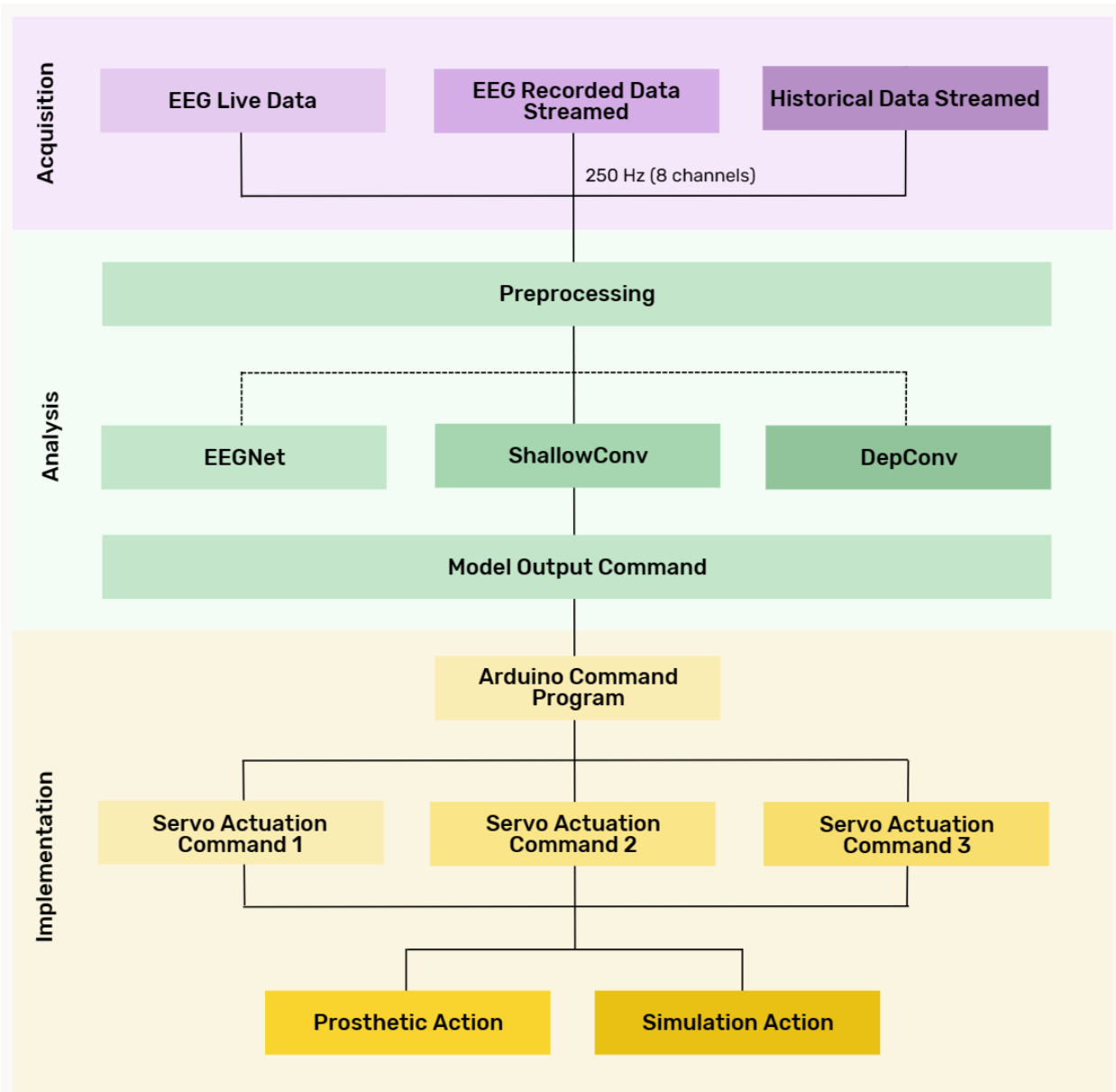


Figure 9. *Overview of Methodology.* Where the data flows from Acquisition to Analysis to Implementation.

A detailed participant testing protocol can be reviewed in Appendix B. An overview of our methodology is shown in Figure 9 above. Methodology is split into three phases: Data Acquisition, Data Analysis, and Data Implementation.

To summarize the process, we first connected the EEG headset to a computer to detect and record brain waves. Second, recorded brain waves were used as data for the purpose of analysis and classification. We analyzed the data to investigate what motor function the recorded brain wave is trying to control. We then sent classified actions as outputs to use for implementation in the simulation or prosthetic device. Along the way, we worked to tweak the accuracy of our process by testing various machine learning models and applying hyperparameter tuning on them. Setting up this end-to-end workflow helped to provide a baseline for how our process works.

Data Acquisition

70 EEG signal data sets were collected from six healthy individuals affiliated with the University of Maryland with no history of seizures who were 18 years of age or older. The following criteria were required to be eligible to participate:

- Have no injury nor condition that limits hand exercises required by our procedure
- Have not consumed recreational drugs or alcohol within 24 hours of testing
- Right hand dominant
- No braids or other protective styles during testing

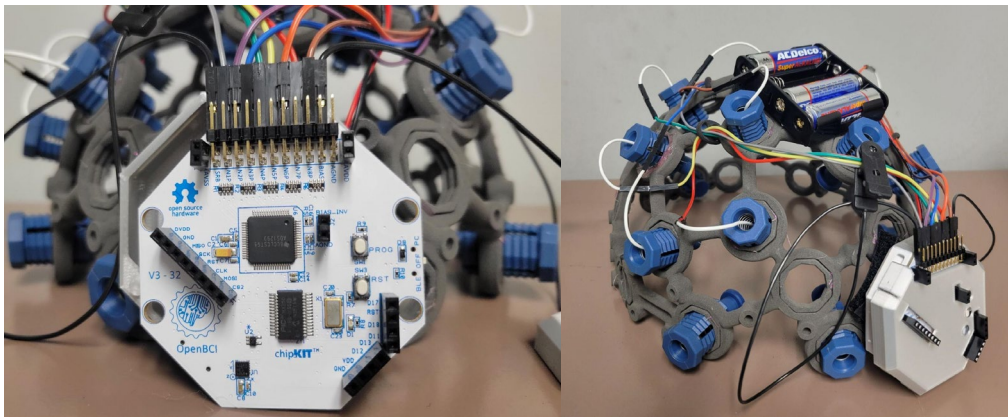
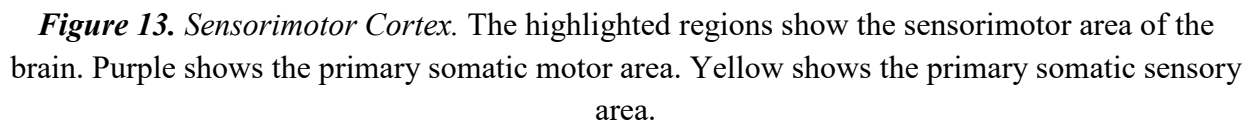
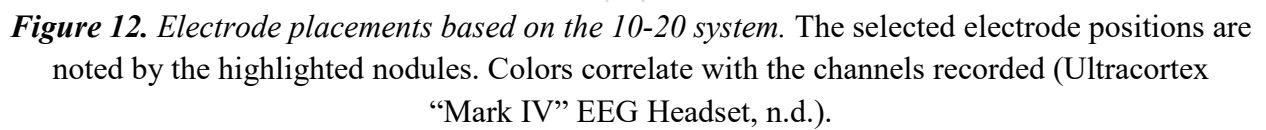


Figure 10. The Cyton Biosensing board (left) and the Ultracortex Mark IV (right) from OpenBCI. The Cyton Biosensing board is attached to the 3D-printed Ultracortex Mark IV.



Figure 11. OpenBCI Graphical User Interface. Example of collecting raw data using the OpenBCI Graphic User Interface.

An 8-channel Cyton Biosensing board was used with the Ultracortex Mark IV – an open-source, 3D-printable headset – from OpenBCI to acquire the EEG signals via the OpenBCI Graphical User Interface (GUI) shown in Figure 11 above. The electrode positions are FC1, FC2, C3, C4, Cz, CP5, CP1, and P3 based on the 10-20 system for electrode placement as shown in Figure 12 below. Two ear clip electrodes are used in addition to the eight active electrodes. The left ear clip electrode is the reference while the right ear clip electrode is the ground with common-mode noise rejection, also known as the bias (*Ultracortex Mark IV | OpenBCI Documentation*, n.d.).



We measured signals that arise in the sensorimotor area of the brain as highlighted in Figure 13 above. The sensorimotor area consists of the premotor cortex, primary motor cortex, supplementary motor area, primary somatosensory cortex, and posterior parietal cortex. The

premotor cortex deals with signals that coordinate movement in extrapersonal space. In contrast, the primary motor cortex encodes for voluntary movement within personal space, such as arm's reach. The supplementary motor area is involved with initiation of movement while the primary somatosensory cortex processes sensory information from all areas of the body. The posterior parietal cortex is specifically involved in sensorimotor integration and sends signals to the primary and supplementary motor cortices (Purves et al., 2018).

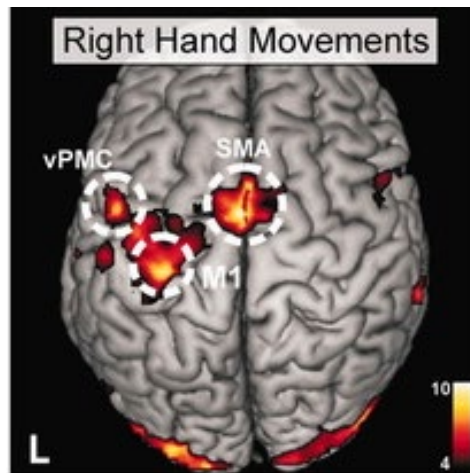


Figure 14. *Sensorimotor regions activated by right hand movements. Functional Magnetic Resonance Imaging (fMRI) showing activation of the left-lateralized sensorimotor region, particularly in M1, SMA and vPMC, due to right hand movements (Sarfeld et al., 2012).*

In order to measure the desired signals through the headset, participants were asked to perform one of two actions: opening and closing one's right hand around a stress ball or opening and closing each digit separately. Participants were informed that the execution of each action would be mediated by a countdown timer and that multiple repetitions of an action would take place during each measurement. Before recording, each action was demonstrated to the participants and they were able to request a redemonstration if needed before each data collection step. Each full hand measurement was taken via Google Timer and began with a 10/5/5 sequence –10 seconds at rest, 5 seconds open hand, and 5 seconds closed hand– followed by a 5/5 sequence of opened and closed hands until the end of that portion of data collection.

Measurements for each finger and thumb were taken at 1-second increments throughout data collection.

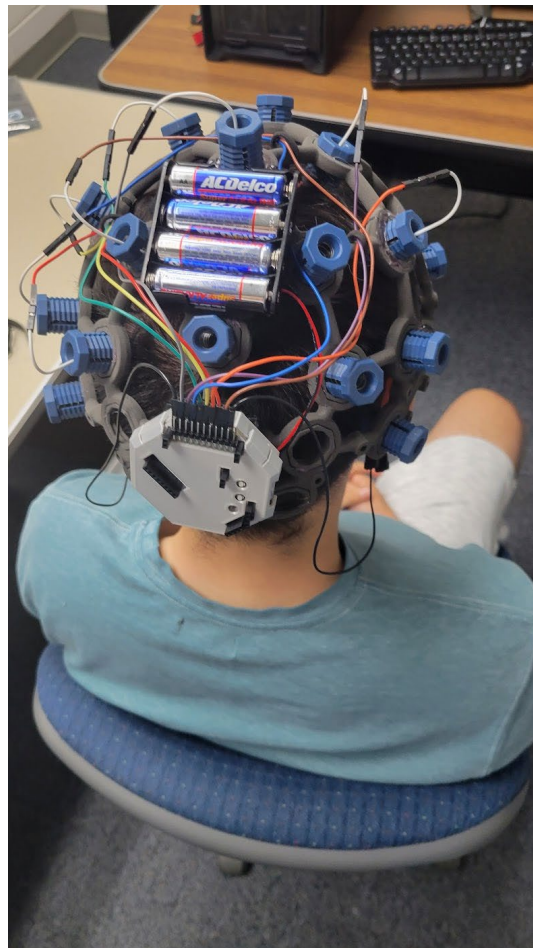


Figure 15. *Participant Set-up.* Example of a participant in the lab fully set-up in the EEG and ready to collect data using the OpenBCI Graphic User Interface.

The data collected from the participants focused on the 4-13 Hz frequency band, which was chosen based on analysis done by Leocani et al. and Manganotti et al.. Leocani's study focused on analyzing right-handed index finger movement within the 10 Hz and 20 Hz frequency bands, while Manganotti studied right-handed finger movements focused on the 8-20 Hz frequency band (Leocani et al., 1997; Manganotti et al., 1998). The ranges in both studies correspond with the values noted from our aforementioned literature review, which relate alpha and beta band values (8-20 Hz) with affecting motor movement. It should be noted that the 8-12

Hz frequency band also corresponds heavily with visual signals (such as blinking) which may confound data. Our data collection procedure, as noted, does not place any forehead electrodes, and we believe that there will be minimal visual interference in our data.

Data Analysis

We then extracted useful information from the raw EEG data that was acquired via data acquisition. Using initial experimentation with historical EEG data, data preprocessing, and data analysis through neural networks, we generated results in a sequence of numerical predictions that were then translated into machine readable actions.

Initial Experimentation

As our first step, we explored which libraries and models would be useful for our purposes. We found a Python library named **MNE** which provided us with a swath of preprocessing, processing, and visualization tools for EEG data (Gramfort et al., 2013). We also learned about the Python library **scikit-learn** which came with various ML models we could test on (Pedregosa et al., n.d.). We chose the models we would utilize by testing them on sample EEG data provided by MNE. This was done to make sure the results of the models were reproducible and to ensure we were implementing them properly.

Data Preprocessing

Data preprocessing was a multistep process that transformed the raw EEG data into something that could be processed by our ML models. First, the program reads the raw output files from the OpenBCI GUI with MNE. We then applied a **bandpass filter** from four to thirteen hertz using infinite impulse response (IIR) filters. Next, we dropped channels with no recordings in them, cropped the data to remove the **buffer**, and added annotations (Open or Closed) as shown in Figure 16 below. After these steps, we concatenated each file into a single dataset. We

then converted all of the data into three second windowed **epochs** and normalized it. Finally, we randomized the data and split it into three sets: 50% for training, 25% for validation, and 25% for testing.

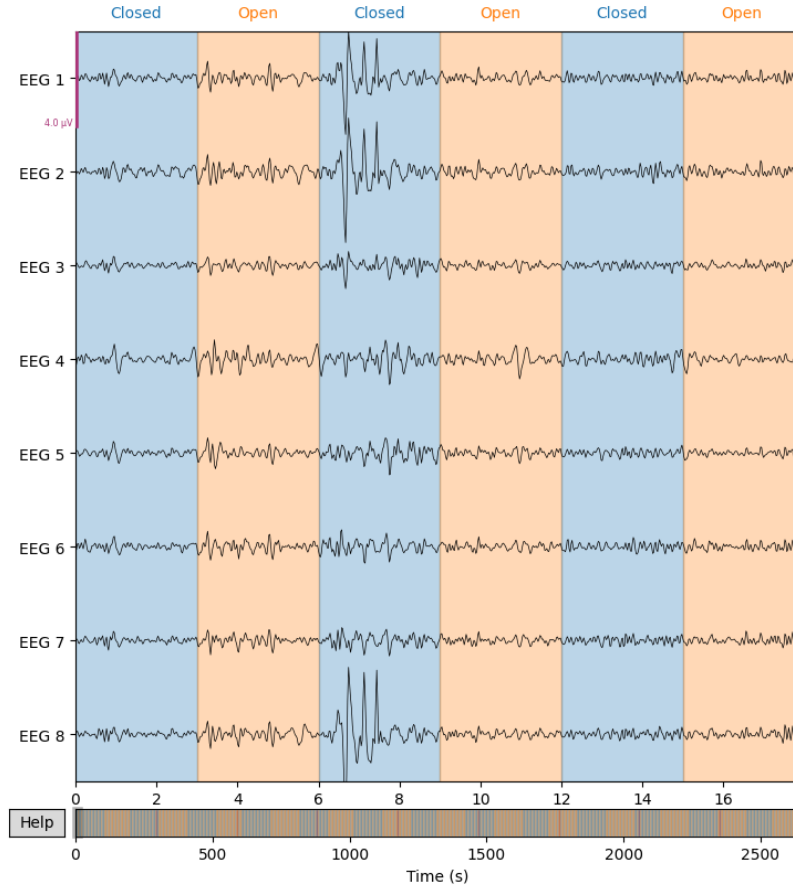


Figure 16. *Annotated Spectrogram.* Plot of a sample from our dataset that has been preprocessed and annotated through MNE.

Models

The first model we tested was not a deep learning model, but rather was a combination of a spatial filtering model called **xDawn** + **Riemannian Geometry Classifier (xDawn + RG)**. To introduce this model, we first discuss the xDawn component. This model estimates spatial filters which aim to enhance the EEG signal associated with the target action through a series of matrix decompositions. These spatial filters allow dimension reduction of the streamed EEG data and allow the target response signals to be enhanced, allowing for easier classification of our target

EEG responses (Rivet et al., 2009). The Riemannian Geometry Classifier works by mapping the EEG data onto a Riemannian manifold and then using a clustering algorithm to classify the data. This Riemannian manifold is a non-Euclidean space where the neighborhood of each point in the manifold is homeomorphic to a Euclidean space. Upon mapping the data to this Riemannian manifold, the Riemannian distance (the distance between points on the Riemannian manifold) is used to compute clusters of data in the Riemannian manifold so that a classification can be determined. The combined xDawn + RG method works by initially computing the spatial filter using xDawn, then taking the resulting filter and using the filtered input data to train the Riemannian Geometry Classifier. To implement this model, we utilized the PyRiemann library to define a model combining xDawn and Riemannian Geometry and decoded the data with a logistic regression (F. Li et al., 2020). The code for the model was retrieved from the PyRiemann ERP sample script example. In order to get the model to work with our data, we had to adjust various parameters including the number of components, the data shapes, and the output shape.

EEGNet was a **Convolutional Neural Network (CNN)** model we tested. This model specifically utilizes temporal convolutions and depthwise separable convolutions. Temporal convolutions adapt regular CNNs so that they can be used for sequential data which EEG signals are. Depthwise separable convolutions were used to reduce the size of the model as well as helped extract spatial filtering features. The original study tested the model on a variety of paradigms including datasets involving motor imagery and movement in which EEGNet had high performance compared to several other algorithms (Lawhern et al., 2018). We trained and tested our dataset with the same model implemented in **Keras** with some minor additions. At every epoch, we chose the best model based on the lowest validation loss. Additionally, various hyperparameters such as dropout rate, batch size, epoch size, and kernel length were optimized

to find values that best fit our dataset. One notable change from the original study was that their dataset contained 64 channels while ours only contained 8 channels.

ShallowConv is another convolutional CNN we tested with our data. This model consists of two layers. The first layer is a convolutional layer with convolutions on the temporal axis as well as a spatial filter along the electrodes designed for EEG data. The second layer is a dense **softmax** classification layer.

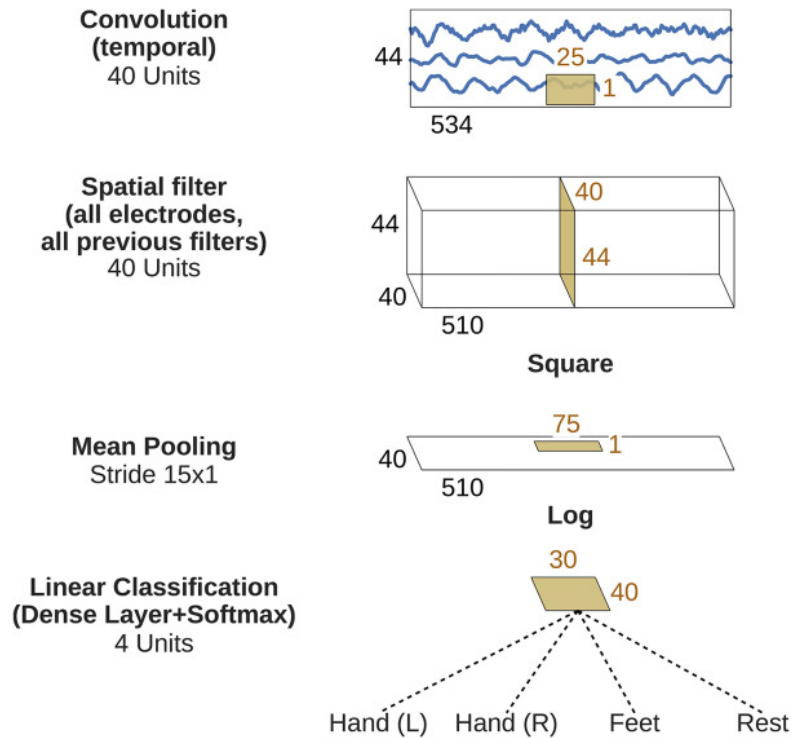


Figure 17. *ShallowConv*. The architecture of the ShallowConv model showing its convolutional and dense layer (Schirrmeister et al., 2017).

DeepConv is a larger version of the ShallowConv CNN described in the same paper. The DeepConv network consists of 5 layers as opposed to ShallowConv's 2 layers. The DeepConv model's first layer is a convolutional layer in the temporal dimension with spacial filters. This layer is specially designed to handle EEG input. The next 3 layers are standard convolution max-pooling layers that lead into a final dense softmax classification layer.

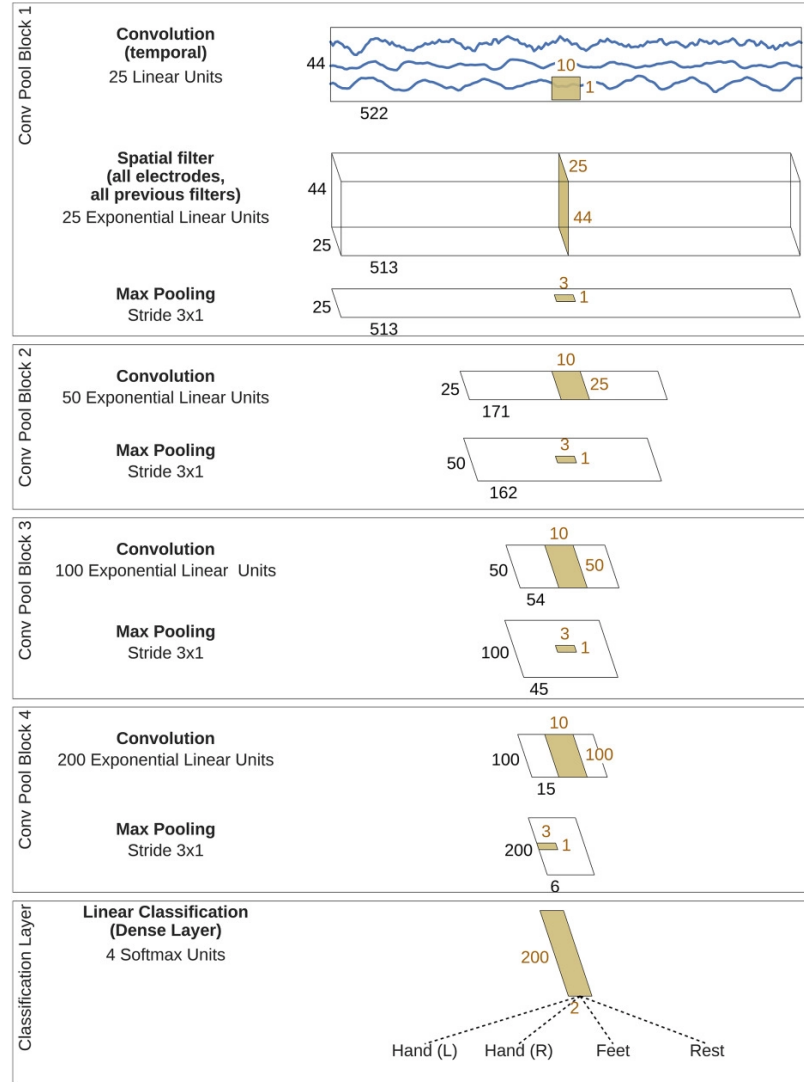


Figure 18. *DeepConv.* The architecture of the DeepConv model showing the four convolutional layers and final dense classification layer (Schirrmeister et al., 2017).

Both DeepConv and ShallowConv were tested against multiple datasets that included both motor-imagery and non-motor-imagery data including hand movement, foot movement, and word generation. Both the DeepConv and ShallowConv models performed well compared to the widely used filter bank common spatial patterns (FBCSP) algorithm which was used as a baseline in the study (Schirrmeister et al., 2017). We tested our dataset against both ShallowConv and DeepConv implemented in Keras and trained the models in a similar way to

how the EEGNet model was trained. At each epoch we calculated validation loss and saved the model weights of the model that had the lowest validation loss.

Translation

The purpose of the translation step was to convert the predicted outcomes from classification into a structure that the implementation can read and apply to actuate the prosthesis. First EEG data was streamed live with the **BrainFlow** Python library. However, before classifying this data, the window of streamed data required additional preprocessing compared to that described in the preprocessing section in order to transform it into data accepted by the model. The raw data had to be converted from V to μV and turned into an MNE RawArray. After an initial buffer period of three seconds, our ShallowConv model made a classification every second predicting if the hand was grasping or not. The classification was then converted into a '11111' for grasping or '00000' for open which was then sent to the Arduino via the Python library **Pyserial** using a serial USB connection.

Data Implementation

Implementation of the analysis into a prosthesis involved sending the analyzed non-invasive EEG-based data into a BCI prosthetic arm system to help users with reduced or no residual limb functionality. The aim of implementation was to find a prosthetic device that is affordable, accessible, efficient, precise, and intuitive. An existing prosthetic arm model known as 'Raptor Reloaded' was found online on the NIH 3D Print Exchange website, and was printed at the Makerspace in the University of Maryland STEM Library using 3D printers which are available free to students. For this project, we utilized the prosthesis in a unique way that involved connecting it to servo motors, rather than using the hand mechanically with no motor connection.

Actuation of the Prosthesis

The individual prosthetic arm parts were printed with **polylactic acid (PLA)** building material using a Prusa I3 Mk3s printer, and then assembled by connecting the parts with printed pins and caps to secure the connections in place. Various assembly instruction manuals can be found online for the ‘Raptor Reloaded’ design, but we used one written by Andreas Bastian, an engineer with an interest in 3D-printing technologies (andreasbastian, n.d.). Bastian had posted an instructional manual on the Instructables website, a site for instructional how-to guides for a variety of projects that includes technology and science (*Yours for the Making*, n.d.). After the hand was assembled, we glued the hand to a surface with the palm facing upwards so that the hand would stay in place when the fingers moved. Flexor cords were used to attach the fingertips to five different servo motors. We designed a tray with designated slots to keep the servo motors in place, and then glued the tray to the same surface as the hand. The wrist piece was 180 degrees about the attached hand piece, before the wrist piece was also attached to the same surface. It should be noted that this layout is different from how this design is commonly assembled. Then, connected the servo motors to an Arduino Uno which was plugged into the lab computer.

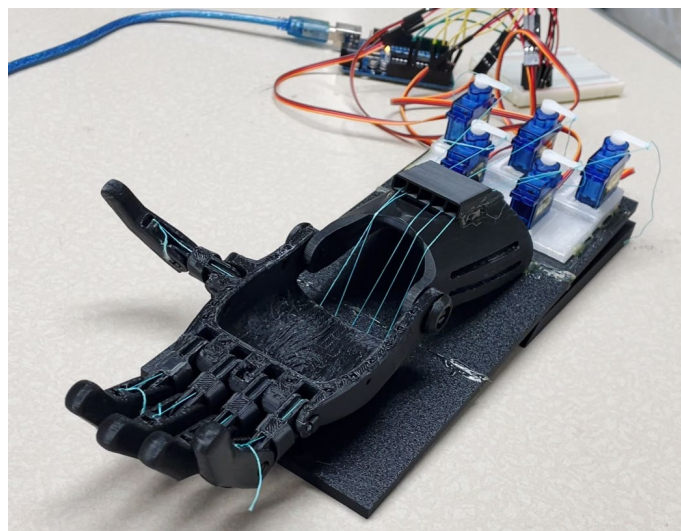


Figure 19. *BCIPRO 3D-Printed Prosthesis.* Our 3D-printed prosthetic arm with flexor wire and servo motor attachments. Hand is in a closed position.

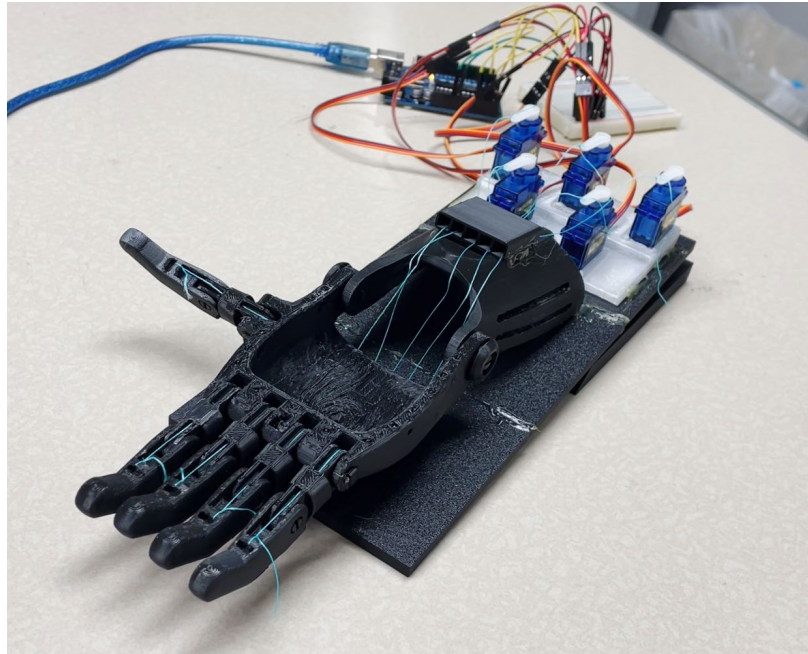


Figure 20. *BCIPRO 3D-Printed Prosthesis.* Our 3D-printed prosthetic arm with flexor wire and servo motor attachments. Hand is in an open position.

We programmed software that takes in a five-bit serial input from data analysis and interprets the input signals as commands to open and close specific fingers. The Python program used for data analysis uses a Pyserial program that sends the commands from the Python to the Arduino software. The open position results in a completely extended digit and the closed position results in a somewhat closed digit. The closing action is currently for demonstrative purposes only, and is not intended to function as a forceful grasp. The closed position pulls the cords to lift the fingers up via tension, while the open position releases the tension and allows gravity to bring the fingers down so the hand is open. Each of the five input bits control the actions of a specific digit, with '1' indicating flexed closed and '0' indicating open. For example, '11111' is fully closed and '00000' is fully open. The software checks the input every second and updates the servo positions immediately, as well as outputting the serial input

to the serial motor. Commands are received about every second, so the software updates every second accordingly.

```
void loop() {
  if (Serial.available() > 1) {
    if (Serial.available() != 0) {
      long n1 = Serial.parseInt();
      for (int i = 4; i >= 0; i--) {
        int orientation = n1%10;
        n1 = n1/10;
        ss[i].write(90*orientation);
        String s = String(i+1);
      }
    }
  }
}
```

Figure 21. *Arduino Code.* Section of the Arduino code we used to control the prosthesis.

Virtual Reality Environment

In providing an accessible alternative to normal prosthetic rehabilitation, we investigated VR as a low-cost, convenient, and personalized tool for our users. Upon engaging with our environment, our users would be able to control a virtual version of the Raptor Reloaded prosthetic arm within a 3D environment that consists of common household objects to interact with. The final version of our design would seek to integrate the Ultracortex Mark IV headset and HMD, opening and closing the specific fingers of the prosthesis within the simulation environment based on the output of our machine learning model. The idea would be as follows.

1. The user displays intention for a device to move (in the case of an able-bodied individual, they would physically also execute the actions).
2. The signals are collected and processed through the data analysis algorithm, translating them into machine commands
3. These machine commands are then processed in one of two ways

- a. The machine commands are processed to move a prosthetic device
- b. The machine commands are processed to interact with the HMD

The goal of this integration is to allow us to utilize the headset-to-implementation system during all steps of the rehabilitation process, allowing those that interact with the system to gain experience with the system before having a full prosthetic device.

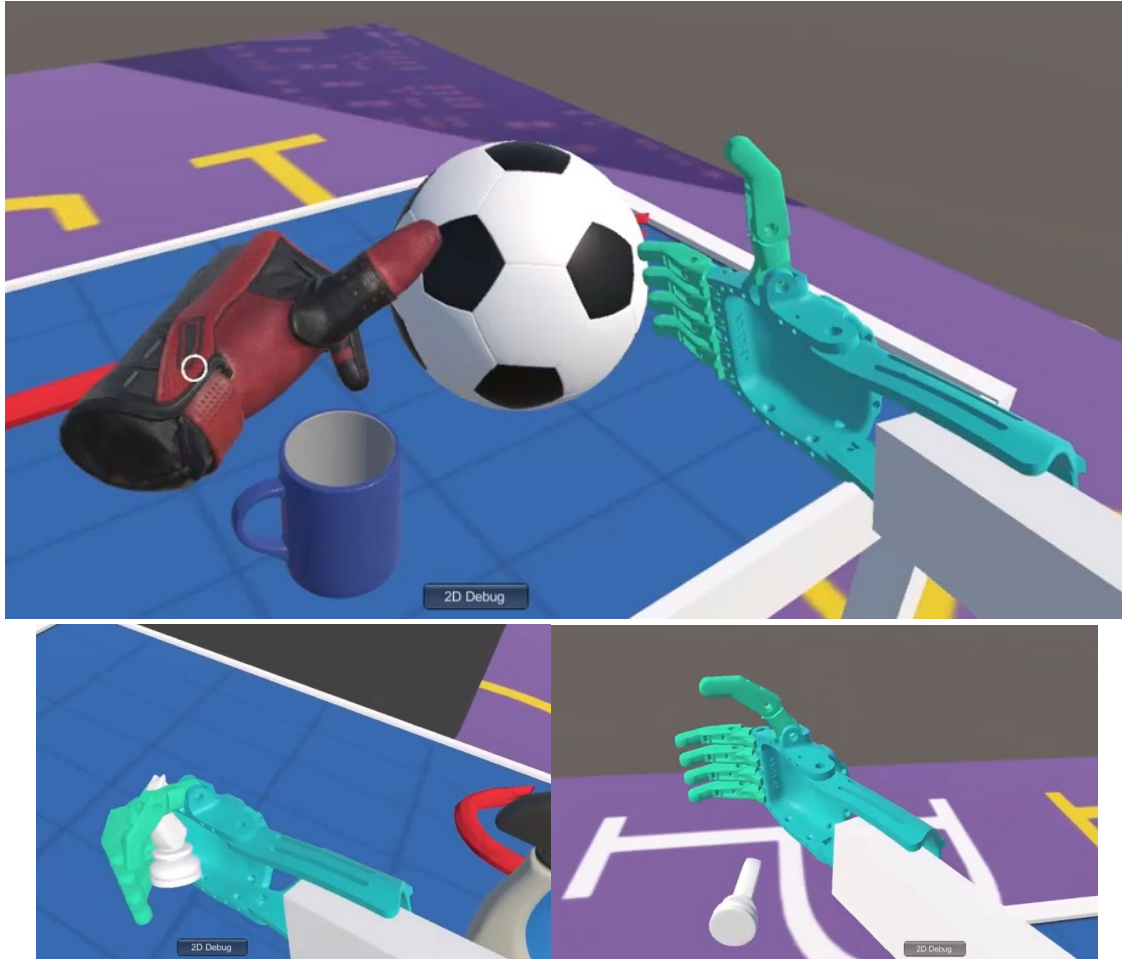


Figure 22. *VR Interaction.* (Top) Left Controller represented by a red-gloved hand while HTC Tracker represented by prosthetic hand with a simple arm representation of customizable length. (Bottom Left) User picking up white chess piece by closing the prosthetic hand. (Right) User drops white chess piece by opening the prosthetic hand.

Our prosthetic simulation was built in Unity, a popular game engine used for 3D and VR development. The pieces for the prosthetic hand used for 3D-printing were imported and assembled. We actuated our prosthetic by writing a C# script to rotate each of the prosthetic

digits around their pivots to either an “open” or “closed” state. Finally, we added interactivity between our virtual prosthesis and its environment by adding custom colliders to the fingertips of the model, allowing the user to reach, grasp, move, position, and release gameObjects within a 3D space.

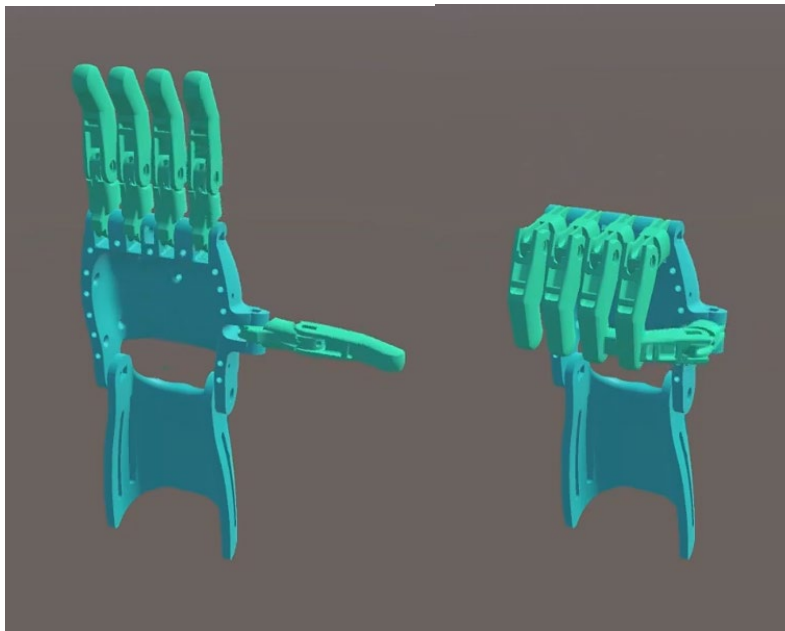


Figure 23. *Prosthetic Closed-Open States in Unity.* Assembled prosthetic hand shown in closed (Left) and open (Right) states within Unity. Digits can be controlled independently or together.

Within our VR Environment, the participant would be placed in front of a table, on top of which there are several everyday objects of various shapes and sizes. These include a doll, chess piece, spray bottle, ball, crowbar, and mug. These objects will behave according to Unity’s built-in 3D physics engine, allowing the participant to interact with them. For demonstration purposes, the grasping of objects has been simulated, making it easier for the user to pick up objects. A simple user interface is present that marks the items that have been picked up as well as the current offset representing the missing arm length of the prosthetic.

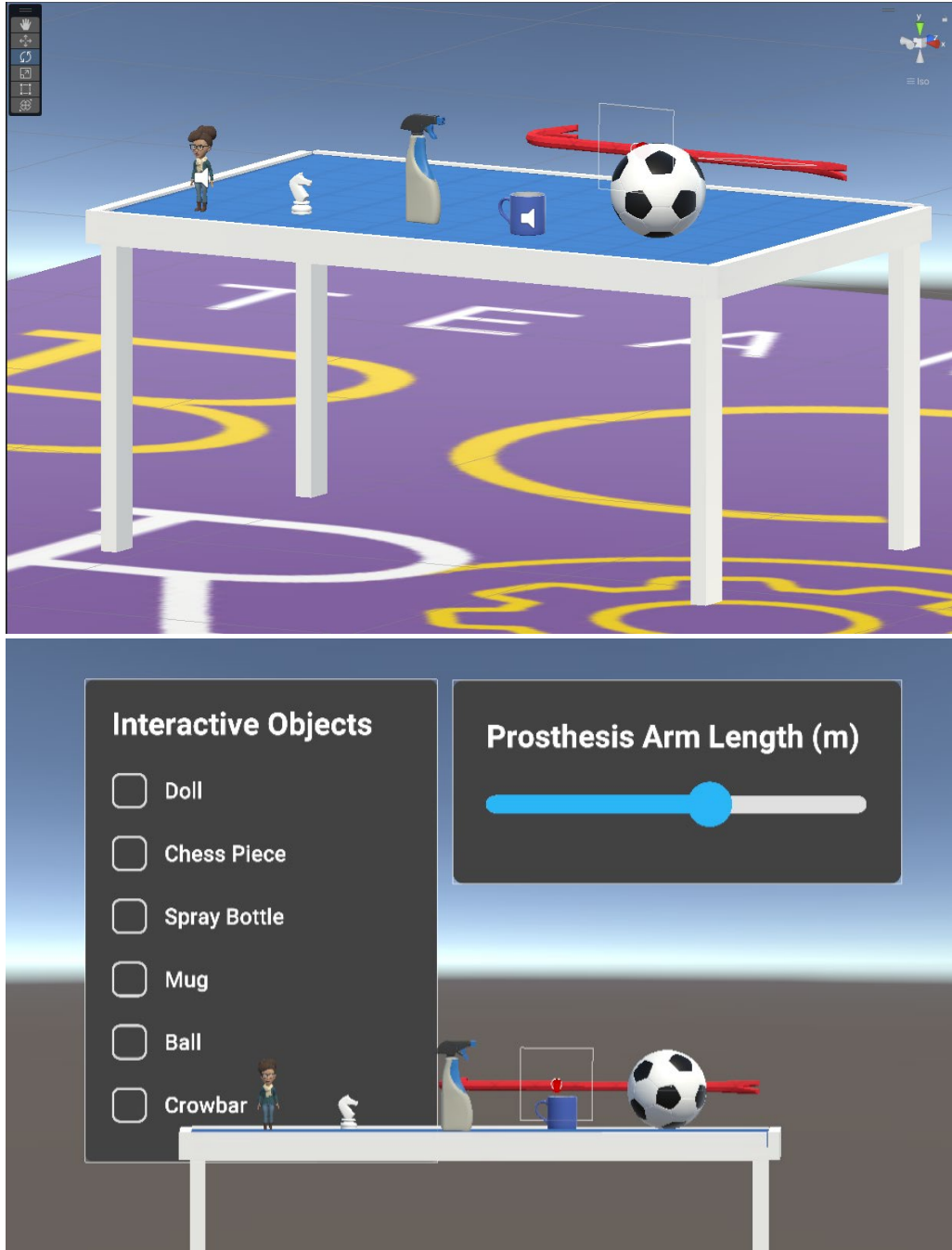


Figure 24. *3D Environment in Unity.* (Top) Isometric view of Interactable gameObjects in Unity scene. (Bottom) Front view of gameObjects in front of basic UI elements.

In order to implement our VR hardware with our Unity build, we used a variety of free software, plugins, and packages. We used SteamVR, which utilizes the OpenXR standard, to connect our HMD, controllers, base stations, and trackers. We used Unity's XR Interaction Toolkit package to bring input from our devices into Unity, and it allowed us to use free assets

and scripts to implement locomotion within our scene. In order to integrate the Quest 2 HMD and HTC Vive Tracker's different tracking systems, we had to calibrate the devices by using the OpenVR Space Calibrator, an open-source plug-in to SteamVR that integrates both the inside-out and outside-in tracking systems.



Figure 25. *Physical VR Set-Up.* (Right) Vive Tracker strapped below the user's elbow. (Middle) User wearing Quest 2 HMD and handling Left Controller. (Right) Location of Vive Base Station relative to the user, indicated by red circle.

Figure 24 suggests the desired physical setup for a participant to engage with our virtual environment. It is necessary that the user has ample space to move around in, so we recommend that a play area is cleared of any obstacles and the user standing or sitting in the center. For tracking of the HTC Vive tracker, the corresponding HTC Vive Base Stations must be mounted to a high up point next to the play area, prior to beginning the virtual session. The user can then attach the HTC Vive Tracker to below the elbow of the desired limb to train, tightening the velcro strap to fix it in place. In their opposite hand, they will hold the corresponding Oculus Quest 2 Controller. Finally, the user can place the Oculus Quest 2 HMD over their eyes, tightening the HMD strap to stay firmly in place during the session. During the development stage of our environment, we would be seated next to the computer running our program with a

wired connection to our HMD as shown in Figure 26. The final program would be built and run on the standalone HMD, but a wired connection could allow for graphical or performance improvements based on the power of the connected computer.

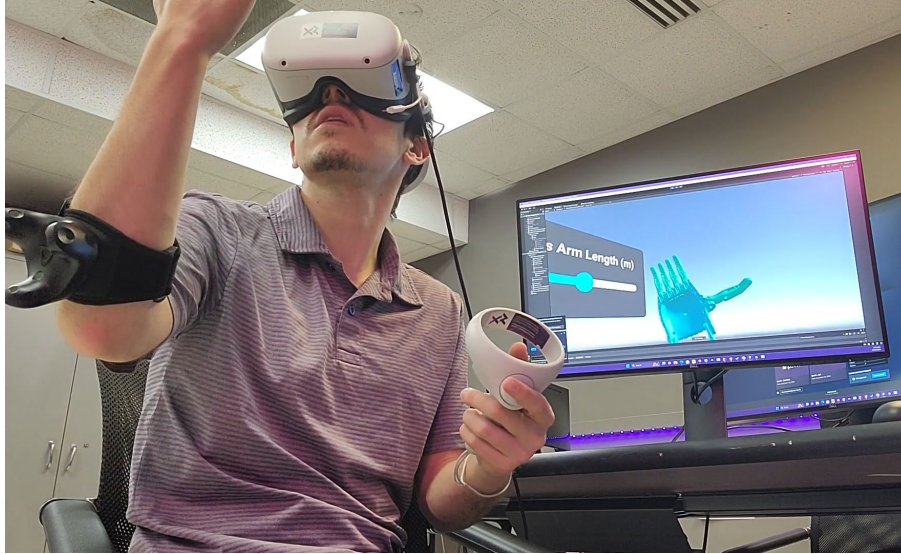


Figure 26. *VR Demonstration.* Simultaneous view of VR scene and seated user.

Despite demonstrating a working proof-of-concept for a virtual scene that would be used by our brain-computer interface, we were unable to complete the full end-to-end system that includes the EEG headset, machine learning model, and VR environment. By making alterations to the Ultracortex Mark IV model, we would attach the EEG headset to the Oculus HMD so that the user could wear both simultaneously and our VR environment could take input from the processed EEG output.

Results

Data Collection and Modeling

We generated a data collection system using a commercially available EEG. The 8-channel Cyton Biosensing board was used with the Ultracortex Mark IV – an open-source, 3D-

printable headset – from OpenBCI to acquire the EEG signals via the OpenBCI Graphical User Interface. EEG data was collected while the right hand was opening and closing. Sections of the data were classified as open or closed corresponding to the time of the action. The algorithm was trained by this data to be able to predict whether brain signal data represents the open or closed action. Using this method, we were able to generate a model that can read EEG data and output the estimated movement.

Both the EEGNet and xDawn + RG model were first tested on a sample dataset from MNE in order to ensure the results found in the original paper for the models were reproducible. The dataset contained four classes which were left ear auditory simulation, right ear auditory simulation, left visual field, and right visual field. The xDawn + RG model had an average accuracy of 68.06% on the dataset while the EEGNet model had an average accuracy of 93.06%. Figure 27 found below shows a confusion matrix for the two models showing that the xDawn + RG model was unable to classify auditory stimuli as well as the visual stimuli while EEGNet did very well on the left visual field and the right ear.

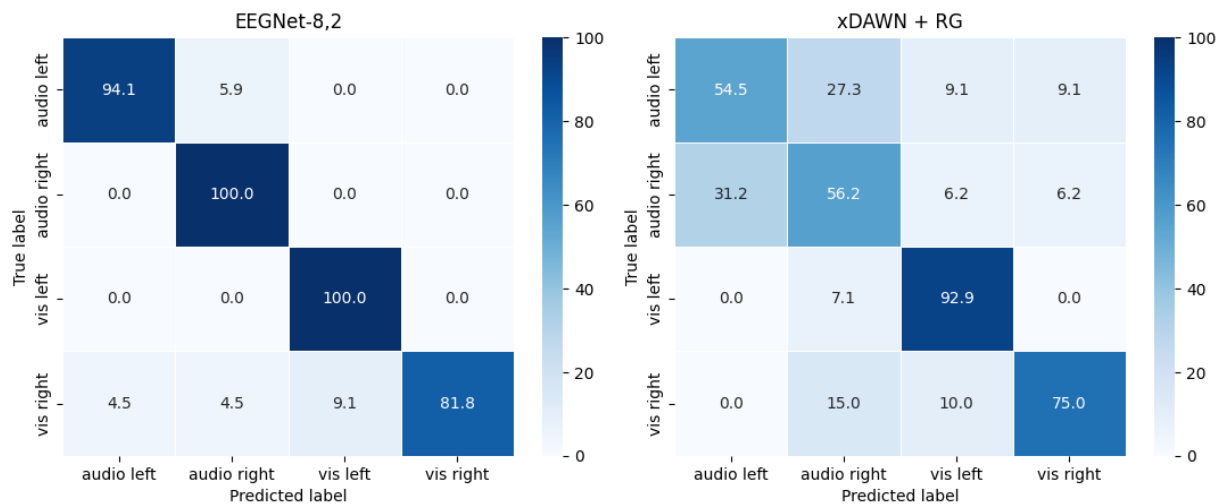


Figure 27. Confusion Matrices. (Left) A confusion matrix of the sample MNE dataset being classified with xDawn + RG. (Right) A confusion matrix of the sample MNE dataset being classified with EEGNet.

The four models, xDawn + RG, EEGNet, ShallowConv, and DeepConv were used to train and test our preprocessed data. We found that ShallowConv did the best with an accuracy of 58.7% followed by EEGNet (55.4%), then DeepConv and xDawn + RG which both had an accuracy of 54.6%. While ShallowConv did the best, it is clear from the confusion matrix found in Figure 28 that it had a bias for the hand opening.

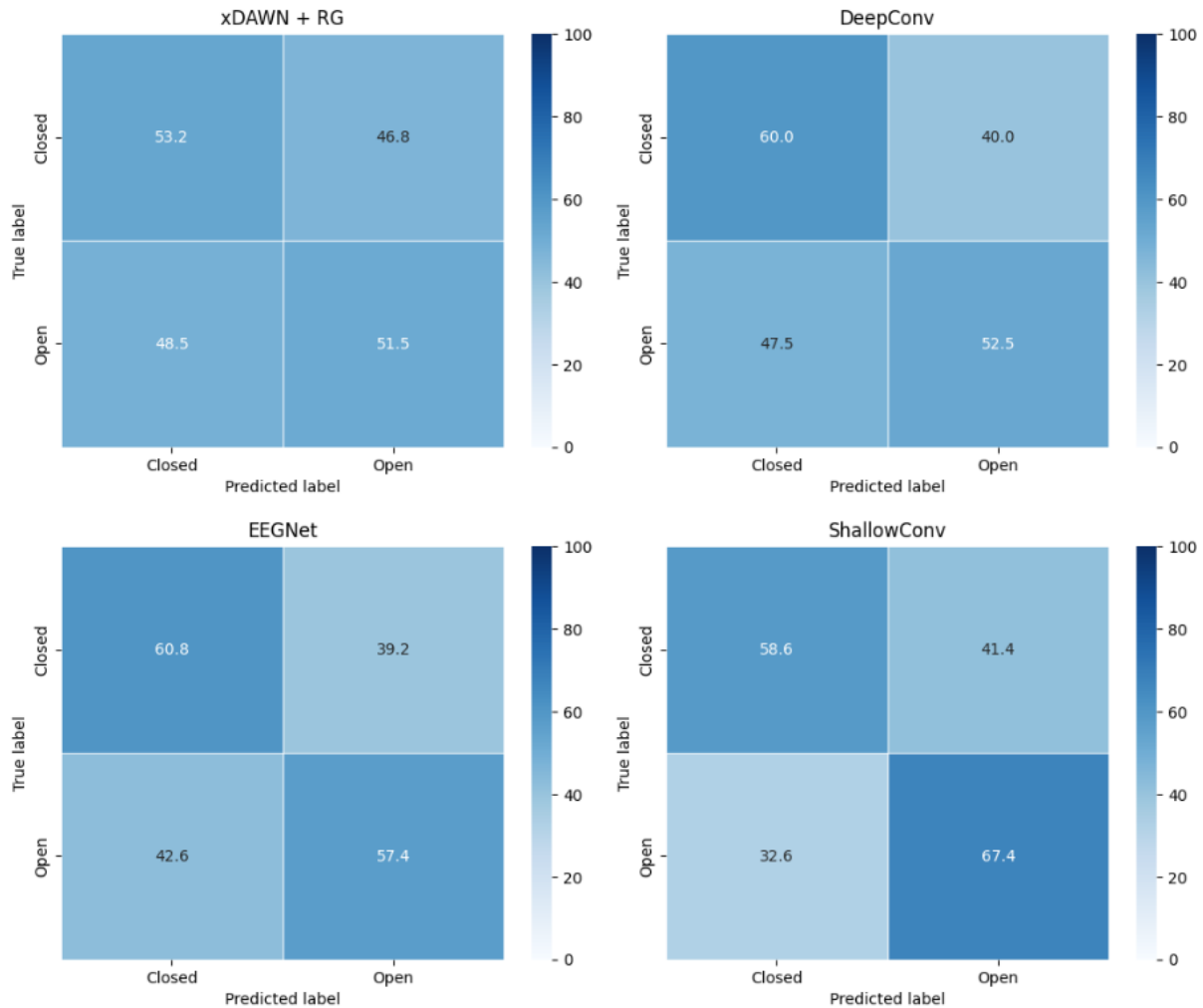


Figure 28. Confusion Matrices. (Top Left) A confusion matrix of our dataset being classified with xDawn + RG. (Top Right) A confusion matrix of our dataset being classified with DeepConv. (Bottom Left) A confusion matrix of our dataset being classified with EEGNet. (Bottom Right) A confusion matrix of our dataset being classified with ShallowConv.

Real-time Deployment of Prosthetic Device

We developed a real-time deployment system in two ways. The first is a simulation which uses the **Computer-Aided Design (CAD)** files of the prosthetic arm, and the second is the physical 3D-printed prosthesis actuated by servos through Arduino. EEG data is recorded from the OpenBCI GUI and then translated by the algorithm, via Python, which then predicts an action based on the collected brain signals. Using Pyserial, a Python-to-Arduino software converter, we transferred instructional movement data in real-time from the prediction to the 3D-printed prosthesis in the form of binary code.

Discussion

We included several steps in our participant testing procedure to ensure accurate acquisition of data. We checked that the electrodes had sufficient contact with the scalp by making sure none of the electrode signals were **railed**, or appeared as a flat line. Additionally, we performed impedance testing on each electrode to check the quality of the data being collected. We understand that using an OpenBCI EEG headset comes at a cost of lower spatial resolution, and with low quality data, there is more potential for error. However, the primary accuracy of our predictions was determined by our choice of algorithm. Many different algorithms were tested with varying accuracies (e.g. xDawn + RG, EEGNet, ShallowConv, and DeepConv). Although we were not able to obtain as high a level of accuracy as we desired, our algorithm functions well by allowing for data to flow from data acquisition to prosthetic implementation in real-time. As such, the prosthetic arm is able to receive signal commands from our algorithm which enables the prosthetic arm to be actuated by brain signals in real-time. Additionally, the benefits of a non-invasive EEG system allow for easy user usage, which makes up for reductions in prediction accuracy.

Future Research and Development

In summary, our project succeeded in establishing an end-to-end workflow starting from EEG recorded participant data and ending in action implementation in a physical prosthesis. However, there is still room for improvement, especially in terms of data detection accuracy. As our project has developed, we have considered several potential focuses that other additional research could explore in the future.

Future research may focus on modifying an existing commercial prosthetic arm, as those are generally preprogrammed to be controlled easily; or modifying our own existing prosthetic arm to add innovative features such as additional **degrees of freedom**. Another step could be to design and 3D-print a new prosthesis. If applicable to specific prosthesis features, calculations such as stress on the material or dynamic calculations of how many angles a joint is able to rotate, etc., will need to be done to determine the constraints for that feature before selecting materials. The features could then be implemented into the prosthetic arm and tested.

For our VR environment, our initial goal was to complete a proof-of-concept scene that could be used for the purposes of prosthetic rehabilitation. The next step would be to speak with healthcare industry professionals, especially occupational therapists who have dealt with upper-arm prosthetic training and discuss their desires for customization options for a VR environment. Conducting this survey would allow us to understand more current day rehabilitation methods in order to improve our design. We felt that certain elements such as haptic feedback were lacking, which would have improved the immersion of the user within the virtual scene. Overall, we want to have the user feel connected to their virtual prosthetic, which we could accomplish by including an accurate anthropometric virtual avatar body to improve the viewer's self-body perception. Our environment could then make use of the 'Self-Avatar Follower Effect' to better

guide the user's motor functions through their virtual avatar to result in more effective prosthetic training (Gonzalez-Franco et al., 2020). Lastly, we would like to complete case studies and collect surveys in order to gauge a participant's feeling of immersion within our scene and to test their ability to complete common training exercises.

Another focus could be improving aesthetics or functionality to make a prosthetic arm look and feel more realistic, which could help a user be more comfortable with the device. This could emerge in ways such as designing finger tips that activate a touch screen, especially in our society which is heavily influenced by touch screen technology. Adding a sensory-synthetic skin—a thin film that can be placed on a surface to recognize pain due to heat, cold, and pressure—would give users a more realistic prosthesis experience. Another feature could be changing material selections and using polymers. Experimenting with this could positively change the strength and weight of a prosthesis. Energy efficiency through battery selection, power usage, and energy recycling is also important to consider. Whether wireless or not, a prosthesis with low power costs is ideal. This may be implemented by having the prosthesis be chargeable via a wall socket or powered by smaller, affordable batteries, such as a set of four AAA batteries.

For noninvasive technologies specifically, there are two emerging methods of how the technology could function: direct kinetic control, and reverse kinetic control (McFarland & Wolpaw, 2008). **Direct kinetic control** is controlled specifically by the user, and therefore could be more effective for unique physical actions such as picking up objects with variable sizes. Direct control is considered to be an **active control**, meaning that a specific action is thought of by the user, and the BCI is able to communicate to the prosthetic to perform that exact action. **Reverse kinetic control** involves automatic pre-programmed actions, which could be more

effective for common physical actions, like gripping a standard-sized pencil. Reverse control is considered to be a **passive control**, meaning that a general idea or concept is thought of, not necessarily a specific action. For example, a user's brain could be classified as being in an overloaded or underloaded state, and this information could be used to have an algorithm adapt so that a user is better calibrated with and in control of their prosthetic (for example, a more or less engaging system of controlling a prosthetic could be activated). In the example of a preprogrammed action to pick up a pencil, the user of course won't think of the exact actions to grip a pencil; a more general mental state could be detected and subsequently implemented with actions. Passive control has other possibilities as well, such as identifying general mental states that can help distinguish between different users when it comes to using prosthetics, along with having the algorithm of the BCI become better calibrated with an individual user.

Future developments in this technology will likely involve prosthetic limbs which have more degrees of freedom. Also, developments into reverse kinetic control seem promising. Such developments could mean a user having less exact control, but they would be able to choose a preprogrammed action to perform, for example, gripping an object with specified dimensions. Reverse kinetic control actions would be chosen by the user, but the BCI would automatically perform those actions according to a predetermined program. As time goes on, this function could develop to perform gradually more complicated tasks that may not be possible with direct kinetic control.

The OpenBCI EEG headset used in this study came with pre-defined reference and ground electrode placements on the ear lobes. It is important to note that the placement of these grounds can affect the clarity of the signals we sought to measure. Ideally, the reference placement should produce as close to zero or constant potential, however no point on the body

has been identified that fulfills this condition. Even if this requirement is fulfilled, placement of the electrode would depend on the desired signal (Yao et al., 2019). Future studies could focus on testing and identifying the optimal placement for these reference and ground electrodes.

While this study mainly focused on CNNs as its primary source for classification models, other deep learning techniques remain unexplored. One such example is **transformers** which have been revolutionary in various fields like natural language processing and computer vision (Devlin et al., 2018). One advantage a transformer model could have over CNNs is that transformers are able to track both local and global sequential context, while CNNs only look at chunks of local context with no regard for order.

Our participant testing experience evolved as we did our testing throughout the project. When testing with participants, we had them look at a stopwatch on a screen and told them to perform actions every five seconds, and started EEG recording in sync with the stopwatch. We assumed that the participant actions should sync up well with the EEG recording, and that the actions accurately aligned with every five-second interval for the hand and every one-second interval for the fingers that we specified. However, there is human error possible due to participants not properly performing actions in synchronization with the stopwatch, and due to our team not properly syncing EEG recorded data with the stopwatch and the participant actions.

A way to help mitigate recording delays and also errors syncing up with time intervals would be to manually record the start of physical actions. One possible way would be to record an additional electrode physically separate from the participant, which we could touch whenever we observe the participant performing a specific action. This additional electrode could mark when in time participant actions are performed more accurately and could improve the accuracy

of the data. Although we did not implement this, we believe it would be a method for more accurate timing associations with EEG signals in future research.

Another direction we could have explored for participant testing is having solid color screens come up for the participants that simply show the current action word, either ‘open’ or ‘close’. This is simpler than our protocol of having a participant actively thinking about the stopwatch and when they need to perform actions. This could have a possible effect on data and it is an idea to be explored at a later time.

Our participant testing involved a specific demographic: able-bodied individuals. We took EEG data from multiple participants, though all of them were able-bodied. Individuals with an amputation exist with a wide range of amputations at varying locations on limbs. Testing individuals with a variety of amputation locations would help account for different complexities of prostheses needed. Amputees can also have a variety of affected signal pathways in the brain and/or nerves, which means they would likely need to be trained on a different training model as EEG signals would be noticeably different. Studies have observed that specific differences in alpha and beta bands between able-bodied people and amputees, suggesting that changes in the sensorimotor area of the brain occur after limb loss is sustained (Lyu et al., 2016).

Animal studies provide further evidence for cerebral rewiring after amputation. One study reported that in adult owl monkeys who had a finger removed, the brain region associated with the amputated finger had been completely taken over by areas that were associated with the remaining fingers within three months (Merzenich et al., 1984). Though we acknowledge that because of these discrepancies our device may not be suitable for those with limb loss at this time, our hope is that our model for able-bodied individuals can be applied to an amputee dataset and still maintain efficiency. Machine learning is a fundamental aspect of our project, which

allows us to accommodate differences in somatosensory organization. Furthermore, it is important to mention that neuroplasticity, or changes in brain connectivity, is a continuous process in our brain that happens in all people regardless of age or ability. Our existing dataset and reliance on machine learning provides a robust foundation upon which to build a functional device for EEG signal acquisition and prosthesis for those who are differently abled.

Collecting data from participants with limb loss and adjusting our model accordingly would be a logical next step for future research. The testing could be similar to the testing we already did. In future testing, participants would think about gripping a stress ball (instead of physically gripping a stress ball) with their missing limb rather than actually doing so. Or, if needed, they could think about moving a different existing limb to grip a stress ball. These thoughts would be used to control the prosthetic arm gripping. Feedback could be implemented in the form of a prosthesis that detects that a ball is being compressed when squeezing it, and in response notifies the participant via physical feedback (touching the participant, audio, or visual feedback, etc.).

We made assumptions during our research to help clarify things. For example, when measuring the EEG signal as the user moved their hand or squeezed a ball, we assumed that action to be initiated by a specific singular signal. In reality, there are two signals involved in hand motion: sensory feedback and motor commands. A ‘sensorimotor’ signal involves both of these aspects, and factoring this knowledge into account and separating the two could have future prospects for improving data analysis accuracy. Another assumption we made was that EEG signals correspond directly to an action. The reality is that the brain is complex, and EEG signals tend to drift and represent other thoughts, which complicates interpreting the signals. Future research could look into targeted instance tests that try to isolate a singular action, so that

a corresponding EEG signal can be more confidently associated with that action. Research exists regarding targeted individual validation, so this can feasibly be further explored (Sperrin et al., 2022). Another assumption was that we could use the same trained model across multiple participants. Every participant is different, so future research could involve specific training model data for individuals, which could potentially yield higher prediction accuracy.

Equity Impact Report

A fundamental challenge that our team faced was balancing the scientific and social impact our device would have. That is, our team needed to create an original solution for individuals living with limb loss without alienating the most in-need populations. In order to do this, we incorporated knowledge and application of diversity, equity, and inclusion, within each step of the research process. Our literature review provided a foundation of knowledge that has informed our decisions across all aspects of the project, from the materials used to the cost-benefit analysis. Throughout our literature review, we uncovered a web of disparities that exist surrounding accessibility to prosthetic devices that can be best explained by examining the intersection between race, socioeconomic status, and healthcare as a whole.

Causes of Inequities and Adverse Impacts

Central to understanding the diversity of our target population was not only recognizing the main causes of limb loss, but also the identities that those affected by limb loss may have and how those identities might exacerbate living with limb loss. For instance, we discovered that 54% of limb loss in the United States is due to vascular disease (“Limb Loss Statistics,” 2015). Delving further into the demographics of vascular disease revealed that a disproportionate amount of marginalized racial groups are at greater risk for developing and sustaining adverse effects of vascular disease, such as amputation. These discoveries were substantiated by other

statistical evidence offered by Ohio State University, which reported that African Americans are four times more likely to need a prosthetic device due to limb loss (*The Ohio State University*, n.d.). This is due to a multitude of factors, such as lower socio-economic status on average and lower likelihood of possessing insurance to assist in the cost of either a cosmetic or functional prosthesis.

The median income for Hispanic individuals is around \$20,000 less than White individuals, and the median income for African Americans is around \$30,000 less than White individuals (Wilson, 2020). Moreover, African Americans are half as likely to have health insurance, such as Medicare or Medicaid, and Hispanic individuals are one third as likely to have health insurance as White Americans (Sohn, 2017). Understanding the socio-economic realities of individuals who are in need of prosthetic devices provides insight into why there are issues in acquiring them. Not only do cosmetic upper-limb prostheses cost upwards of \$3,000, but functional or **myoelectric prostheses** are much more expensive, with the cheapest available devices starting at around \$30,000 (Vandersea, n.d.). Moreover, myoelectric devices are often invasive, which then pose increased health risks and longer recovery periods, further driving up expenses. Those who are struggling financially, uninsured, or both, may not realistically be able to afford a prosthetic device. Considering the prices of prosthetic devices on the market, and the median income and insurance rates for the groups that need them the most, we can see that there is a great need for a new iteration of a prosthetic device that increases financial accessibility.

We also recognize that design flaws in the EEG device itself may also reflect systemic racism (Choy et al., 2022). EEGs rely on the ability of the electrodes to reach the scalp of the individual in order to properly read signals, though this process can be interrupted and become

less reliable with someone who has curly or coily hair. In addition to financial concerns, it is also important that the device addresses inequities that may arise due to its structure.

Recommendation

In our approach to lowering the price of prosthetic devices, we considered three main sources of cost: reading and translating brain signals, the actual mechanical prosthesis, and reducing rehabilitation expenses. Our main focus was addressing the first source. One of the ways in which our team was able to do this was to rely on 3D-printing for our headset. Through 3D-printing, the headset is accessible both in terms of cost and location, and is even customizable to account for changes in age and differences in **curl patterns**, as the user can adjust for size and electrode type that best accommodate their hair (Krueger et al., 2022).

3D printers can be found at almost any major institution, and as the technology becomes increasingly advanced, the cost to print and the time needed to print will decrease. Currently, printing the headset at our institution costs between \$10-\$30. Electrodes from either Amazon or websites such as OpenBCI range from \$30-\$50. Finally, the boards needed for the acquisition of EEG data are available through OpenBCI, though simpler circuit boards are compatible with the device, and prices range from \$50-\$800. In total, the cost for reading and translating brain signals with our device becomes \$90 and the low end to \$880 at the high end. This can be compared to the \$30,000 invasive devices that are commercially available.

Utilizing 3D-printing for the headset and using easily attainable materials for our device allows users to enjoy a non-invasive, inexpensive way to transform brain signals into digital signals, which effectively minimizes the cost of our prosthesis. In terms of the actual mechanical prosthetic device, recent changes in FDA policies have approved methods to print a prosthetic device. 3D printed devices are regulated in the same way that medical devices are. Although

biocompatible materials can be 3D printed, we want to emphasize that the majority of the cost lies within the functionality and not mechanical ability.

With the prescription of a prosthetic, a necessary component of prosthetic acceptance and function is the long process of prosthetic rehabilitation. The user will likely need years of costly therapy sessions, which is definitely a barrier to choosing prosthetics as an option. While our VR environment is still in the early stages, we remarked how this technology can accelerate prosthetic training, resulting in less costs for the user. Our setup was also extremely affordable, using consumer products such as the Oculus Quest 2 HMD and the HTC Vive Tracker, which is a total value of \$530. With VR HMDs and peripherals becoming more widely available, these technologies definitely have the potential to significantly reduce the overall cost to the patient.

In essence, decreasing the cost to replicate human motion increases accessibility and restores quality of life to marginalized populations. By being cognizant of disparities throughout the entirety of our project, we have not only discovered new approaches to non-invasive BCIs, but also succeeded in uplifting disenfranchised communities that would most benefit from our work. Our project is not just about prosthetics research; rather, it is about integrating innovative features in devices that solve systematic disparities and spark a greater conversation about medical ethics and healthcare inequity.

Bibliography

- Abdulkader, S., Atia, A., & Mostafa, M.-S. (2015). Brain computer interfacing: Applications and challenges. *Egyptian Informatics Journal*, 16(2), 213–230.
<https://doi.org/10.1016/j.eij.2015.06.002>
- Ambros, E., Miller, A., Kuchenbecker, K. J., Buxbaum, L. J., & Coslett, H. B. (2018). Immersive Low-Cost Virtual Reality Treatment for Phantom Limb Pain: Evidence from Two Cases. *Frontiers in Neurology*, 9.
<https://www.frontiersin.org/articles/10.3389/fneur.2018.00067>
- andreasbastian. (n.d.). *Assembly of E-NABLE's Raptor Reloaded Hand*. Instructables.
Retrieved April 23, 2023, from <https://www.instructables.com/Assembly-of-e-NABLEs-Raptor-Reloaded-Hand/>
- Atkins, D. (2002). Adult Upper Limb Prosthetic Training. In *Adult Upper Limb Prosthetic Training* (2nd ed.). Mosby Year Book. <https://www.oandplibrary.org/alp/chap11-01.asp>
- BCIPRO · GitHub. (n.d.). Retrieved April 27, 2023, from <https://github.com/BCIPRO>
- Bright, D., Nair, A., Salvekar, D., & Bhisikar, S. (2016). EEG-based brain controlled prosthetic arm. *2016 Conference on Advances in Signal Processing (CASP)*, 479–483.
<https://doi.org/10.1109/CASP.2016.7746219>
- Chappell, D., Son, H. W., Clark, A. B., Yang, Z., Bello, F., Kormushev, P., & Rojas, N. (2022). Virtual Reality Pre-Prosthetic Hand Training With Physics Simulation and Robotic Force Interaction. *IEEE Robotics and Automation Letters*, 7(2), 4550–4557.
<https://doi.org/10.1109/LRA.2022.3151569>
- Choy, T., Baker, E., & Stavropoulos, K. (2022). Systemic Racism in EEG Research: Considerations and Potential Solutions. *Affective Science*, 3(1), 14–20.

<https://doi.org/10.1007/s42761-021-00050-0>

Dally, C., Johnson, D., Canon, M., Ritter, S., & Mehta, K. (2015). Characteristics of a 3D-printed prosthetic hand for use in developing countries. *2015 IEEE Global Humanitarian Technology Conference (GHTC)*, 66–70.

<https://doi.org/10.1109/GHTC.2015.7343956>

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018, October 11). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. ArXiv.Org.

<https://arxiv.org/abs/1810.04805v2>

Donaldson, W. (n.d.). *Robotic Arm 3D Printed (DIY Initial Prosthetic Prototype)*.

Instructables. Retrieved April 23, 2023, from <https://www.instructables.com/Robotic-Arm-3D-Printed-DIY-Initial-Prosthetic-Prot/>

DSI-VR300. (n.d.). NEUROSPEC AG Research Neurosciences. Retrieved April 30, 2023, from <https://www.neurospec.com/Products/Details/1077/dsi-vr300>

Farrens, J., Simmons, A., Luck, S., & Kappenman, E. (2019). *Electroencephalogram (EEG) Recording Protocol for Cognitive and Affective Human Neuroscience Research*.

<https://doi.org/10.21203/rs.2.18328/v1>

Gaballa, A., Cavalcante, R. S., Lamounier, E., Soares, A., & Cabibihan, J.-J. (2022).

Extended Reality “X-Reality” for Prosthesis Training of Upper-Limb Amputees: A Review on Current and Future Clinical Potential. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 30, 1652–1663.

<https://doi.org/10.1109/TNSRE.2022.3179327>

Galea. (n.d.). Retrieved April 30, 2023, from <https://galea.co>

Gonzalez-Franco, M., Cohn, B., Ofek, E., Burin, D., & Maselli, A. (2020). The Self-Avatar

- Follower Effect in Virtual Reality. *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 18–25. <https://doi.org/10.1109/VR46266.2020.00019>
- Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7. <https://www.frontiersin.org/articles/10.3389/fnins.2013.00267>
- Guger, C., & Allison, B. Z. (2014). Recent Advances in Brain-Computer Interface Research—The BCI Award 2013. In C. Guger, T. Vaughan, & B. Allison (Eds.), *Brain-Computer Interface Research: A State-of-the-Art Summary 3* (pp. 1–6). Springer International Publishing. https://doi.org/10.1007/978-3-319-09979-8_1
- Hauschild, M., Davoodi, R., & Loeb, G. E. (2007). A Virtual Reality Environment for Designing and Fitting Neural Prosthetic Limbs. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 15(1), 9–15. <https://doi.org/10.1109/TNSRE.2007.891369>
- HC-05 Wireless Bluetooth Receiver RF Transceiver Module Serial Port Transmitter Module: Electronics. (n.d.). Retrieved April 12, 2023, from <https://www.amazon.com/Wireless-Bluetooth-Receiver-Transceiver-Transmitter/dp/B01MQKX7VP>
- Health, C. for D. and R. (2022, February 17). *3D Printing of Medical Devices*. FDA; FDA. <https://www.fda.gov/medical-devices/products-and-medical-procedures/3d-printing-medical-devices>
- Jeunet, C., N’Kaoua, B., & Lotte, F. (2016). Chapter 1 - Advances in user-training for mental-imagery-based BCI control: Psychological and cognitive factors and their neural

- correlates. In D. Coyle (Ed.), *Progress in Brain Research* (Vol. 228, pp. 3–35). Elsevier. <https://doi.org/10.1016/bs.pbr.2016.04.002>
- Krueger, L., Aguh, C., Peterson, E., Thomas, J., James, J., Lo Sicco, K., & Shapiro, J. (2022). Curl pattern classification: A potential tool for communication and risk stratification. *International Journal of Women's Dermatology*, 8(2), e015. <https://doi.org/10.1097/JW9.0000000000000015>
- Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of Neural Engineering*, 15(5), 056013. <https://doi.org/10.1088/1741-2552/aace8c>
- Leocani, L., Toro, C., Manganotti, P., Zhuang, P., & Hallett, M. (1997). Event-related coherence and event-related desynchronization/synchronization in the 10 Hz and 20 Hz EEG during self-paced movements. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, 104(3), 199–206. [https://doi.org/10.1016/S0168-5597\(96\)96051-7](https://doi.org/10.1016/S0168-5597(96)96051-7)
- Li, F., Xia, Y., Wang, F., Zhang, D., Li, X., & He, F. (2020). Transfer Learning Algorithm of P300-EEG Signal Based on XDAWN Spatial Filter and Riemannian Geometry Classifier. *Applied Sciences*, 10(5). <https://doi.org/10.3390/app10051804>
- Li, X., Samuel, O. W., Zhang, X., Wang, H., Fang, P., & Li, G. (2017). A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. *Journal of NeuroEngineering and Rehabilitation*, 14. <https://doi.org/10.1186/s12984-016-0212-z>
- Lyu, Y., Guo, X., Wang, Z., & Tong, S. (2016). Resting-state EEG network change in alpha

- and beta bands after upper limb amputation. *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 49–52.
<https://doi.org/10.1109/EMBC.2016.7590637>
- Mak, J. N., & Wolpaw, J. R. (2009). Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects. *IEEE Reviews in Biomedical Engineering*, 2, 187–199. <https://doi.org/10.1109/RBME.2009.2035356>
- Manganotti, P., Gerloff, C., Toro, C., Katsuta, H., Sadato, N., Zhuang, P., Leocani, L., & Hallett, M. (1998). Task-related coherence and task-related spectral power changes during sequential finger movements. *Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control*, 109(1), 50–62.
[https://doi.org/10.1016/S0924-980X\(97\)00074-X](https://doi.org/10.1016/S0924-980X(97)00074-X)
- Mental Health and Partial Hand Amputation: It's More Important Than You Think*. (2019, July 9). Naked Prosthetics. <https://www.npdevices.com/mental-health-and-partial-hand-amputation-its-more-important-than-you-think/>
- Merzenich, M. M., Nelson, R. J., Stryker, M. P., Cynader, M. S., Schoppmann, A., & Zook, J. M. (1984). Somatosensory cortical map changes following digit amputation in adult monkeys. *Journal of Comparative Neurology*, 224(4), 591–605.
<https://doi.org/10.1002/cne.902240408>
- NIH 3D - Raptor Reloaded*. (n.d.). Retrieved April 12, 2023, from
<https://3d.nih.gov/entries/3dpx-000997>
- Oculus Quest 2 transparent PNG - StickPNG*. (n.d.). Retrieved April 12, 2023, from
<https://www.stickpng.com/img/electronics/vr-headsets/oculus-quest-2>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel,

- M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., & Cournapeau, D. (n.d.). Scikit-learn: Machine Learning in Python. *MACHINE LEARNING IN PYTHON*.
- Purves, D., Augustine, G. J., Fitzpatrick, D., Hall, W. C., LaMantia, A.-S., Mooney, R. D., Platt, M. L., & White, L. E. (Eds.). (2018). *Neuroscience* (6th ed.).
- Rivet, B., Souloumiac, A., Attina, V., & Gibert, G. (2009). xDAWN Algorithm to Enhance Evoked Potentials: Application to Brain–Computer Interface. *IEEE Transactions on Biomedical Engineering*, 56(8), 2035–2043.
<https://doi.org/10.1109/TBME.2009.2012869>
- Robot Hand Five Fingers Solely Movement Bionic Robot Mechanical Arm DIY (Right Hand)*. (n.d.). Retrieved April 12, 2023, from https://www.amazon.com/Fingers-Movement-Bionic-Mechanical-DIY%EF%BC%88Right/dp/B081RR4224/ref=asc_df_B081RR4224/?tag=&linkCode=df0&hvadid=416747928437&hvpos=&hvnetw=g&hvrnd=6785185035868997874&hvpon=&hvptwo=&hvqmt=&hvdev=c&hvdvcmdl=&hvlocint=&hvlocphy=9060031&hvtargid=pla-880687155736&ref=&adgrpid=93457065349&th=1
- Robotic Hand Kit—Servos Included*. (n.d.). Tinkersphere. Retrieved April 12, 2023, from <http://tinkersphere.com/raspberry-pi-compatible-components/2322-robotic-hand-kit-servos-included.html>
- Sarfeld, A.-S., Diekhoff, S., Wang, L. E., Liuzzi, G., Uludağ, K., Eickhoff, S. B., Fink, G. R., & Grefkes, C. (2012). Convergence of human brain mapping tools: Neuronavigated TMS Parameters and fMRI activity in the hand motor area. *Human Brain Mapping*, 33(5), 1107–1123. <https://doi.org/10.1002/hbm.21272>

- Schirrmaster, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggersperger, K., Tangemann, M., Hutter, F., Burgard, W., & Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. *Human Brain Mapping*, 38(11), 5391–5420. <https://doi.org/10.1002/hbm.23730>
- Sohn, H. (2017). Racial and Ethnic Disparities in Health Insurance Coverage: Dynamics of Gaining and Losing Coverage over the Life-Course. *Population Research and Policy Review*, 36(2), 181–201. <https://doi.org/10.1007/s11113-016-9416-y>
- Sperrin, M., Riley, R. D., Collins, G. S., & Martin, G. P. (2022). Targeted validation: Validating clinical prediction models in their intended population and setting. *Diagnostic and Prognostic Research*, 6, 24. <https://doi.org/10.1186/s41512-022-00136-8>
- Stanford Healthcare. (n.d.). *Amputation Causes*. Retrieved October 3, 2020, from <https://stanfordhealthcare.org/medical-conditions/bones-joints-and-muscles/amputation/causes.html>
- Suurmets, S. (2018, February 20). *Neural Oscillations—Interpreting EEG Frequency Bands*. Imotions. <https://imotions.com/blog/neural-oscillations/>
- The Ohio State University. (n.d.). *Limb Loss Stats*. Retrieved March 27, 2023, from <https://u.osu.edu/fitness4all/loss-limb-stats/>
- Ultracortex Mark IV | OpenBCI Documentation*. (n.d.). Retrieved October 30, 2021, from <https://openbci.github.io/AddOns/Headwear/MarkIV/>
- Ultracortex “Mark IV” EEG Headset*. (n.d.). OpenBCI Online Store. Retrieved March 13, 2023, from <https://shop.openbci.com/products/ultracortex-mark-iv>
- Vandersea, J. (n.d.). *The Complete Guide To Arm & Hand Amputations and Prosthetics*.

- Medical Center Orthodontics & Prosthetics (MCOP)*. Retrieved February 25, 2021, from <https://mcopro.com/blog/resources/arm-hand-prosthetics/>
- VIVE Self-Tracking Tracker*. (n.d.). Retrieved April 27, 2023, from <https://developer.vive.com/resources/tracker/>
- What Is Ableism?* (n.d.). Retrieved October 3, 2020, from <http://www.stopableism.org/p/what-is-ableism.html>
- Williams, W. (2020, December 7). Zeus Hand From Aether Biomedical. *Bionics For Everyone*. <https://bionicsforeveryone.com/zeus-hand-from-aether-biomedical/>
- Williams, W. (2021, February 10). Open Bionics Hero Arm. *Bionics For Everyone*. <https://bionicsforeveryone.com/open-bionics-hero-arm/>
- Wilson, V. (2020, September 16). *Racial disparities in income and poverty remain largely unchanged amid strong income growth in 2019*. Economic Policy Institute. <https://www.epi.org/blog/racial-disparities-in-income-and-poverty-remain-largely-unchanged-amid-strong-income-growth-in-2019/>
- Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: An overview and application in radiology. *Insights into Imaging*, 9(4), 611–629. <https://doi.org/10.1007/s13244-018-0639-9>
- Yao, D., Qin, Y., Hu, S., Dong, L., Bringas Vega, M. L., & Valdés Sosa, P. A. (2019). Which Reference Should We Use for EEG and ERP practice? *Brain Topography*, 32(4), 530–549. <https://doi.org/10.1007/s10548-019-00707-x>
- Yours for the making*. (n.d.). Instructables. Retrieved April 23, 2023, from <https://www.instructables.com/>
- Ziegler-Graham, K., MacKenzie, E. J., Ephraim, P. L., Travison, T. G., & Brookmeyer, R.

(2008). Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050.

Archives of Physical Medicine and Rehabilitation, 89(3), 422–429.

<https://doi.org/10.1016/j.apmr.2007.11.005>

Appendices

Appendix A - Glossary

1. Ableism: “The practices and dominant attitudes in society that devalue and limit the potential of persons with disabilities” according to the Stop Ableism Organization (*What Is Ableism?*, n.d.).
2. Active control: A way of controlling actions where a specific action is thought of by a user, and where this thought is the action directly implemented by the prosthetic.
3. Alpha: EEG bandwidth ranging from 7-12 Hz. Associated with task performance and inversely related to increased activation of the prefrontal cortex, which has largely been implicated in motivation and emotion pathways.
4. Amputation: The surgical removal of all or part of a limb.
5. Amputee: An individual with a limb that has been surgically removed, or an amputation.
6. Bandpass filter: A filter that passes frequencies within a certain range and rejects frequencies outside of that range.
7. Beta: EEG bandwidth ranging from 16-31 Hz, which indicates planning and execution of voluntary movement.
8. Brain-Computer Interface (BCI) or Brain-Machine Interface (BMI): A communication and control system that enables users to send commands to a computer or external device with brain signals alone without the need for muscle control (Jeunet et al., 2016).
9. BrainFlow: A Python library that streams, parses, and processes EEG and other signals.
10. Buffer: A process by which newly-acquired data is held in memory until there is a given amount of data stored, is potentially changed or processed, and then is all used at once. The process is then repeated for future data.

11. Computer-Aided Design (CAD): The use of computers in the creation and editing of a design, typically in regards to designing 3D-printing files.
12. Congenital: Present from birth.
13. Convolutional Neural Network (CNN): A convolutional neural network is composed of multiple building blocks, such as convolution layers, pooling layers, and fully connected layers, and is designed to automatically and adaptively learn spatial hierarchies of features through a backpropagation algorithm (Yamashita et al., 2018).
14. Curl patterns: Hair texture is typically divided into four categories: straight, wavy, curly, and coily. The latter three can be further divided into subcategories. Curl patterns play a large role in how one styles their hair and the hair products they are able to use.
15. DeepConv: A deep learning model that classifies EEG signals.
16. Degrees of Freedom: The independent axes of motion a mechanical object can move along.
17. Delta: EEG bandwidth less than 4 Hz. Implicated in dopamine reward systems, hunger, thirst, and sleep rhythms.
18. Direct Kinetic Control: A type of prosthetic control where the user directly controls motor function.
19. Electroencephalogram (EEG): A neuromonitoring method used to evaluate the electrical activity in the brain. Brain cells communicate with each other through electrical impulses. An EEG can be used to help detect potential problems associated with this activity. An EEG tracks and records brain wave patterns.
20. EEGNet: A deep learning model that can be trained to classify EEG data.
21. Epoch: A single pass of all data points in the training set.
22. Functional Magnetic Resonance Imaging (fMRI): A method of measuring blood flow

changes in the brain associated with different mental activities using magnetic fields (Guger & Allison, 2014).

23. Gamma- EEG bandwidth ranging from 32-60 Hz, which indicates sensorimotor integration
24. -gram, -graph, and -graphy: (1) A -gram is the record or the results of the recording, (2) a -graph is the instrument used for recording, and (3) a -graphy is the process of recording.
25. Head-Mounted Display: Devices that are mounted to the operator's head consisting of displays that are in front of each eye. Virtual Reality headsets are an example of these.
26. Keras: A Python library that allows users to train and test deep learning models.
27. Machine Learning (ML): A computer algorithm that utilizes training data to learn to automatically accomplish a task.
28. MNE: A Python library for processing and visualizing neurophysiological data.
29. Myoelectric: Pertaining to the electrical impulses, known electromyography (EMG) signals, generated by muscles.
30. Myoelectric Prosthesis: A type of prosthesis that is controlled by EMG signals that are naturally produced by muscles.
31. Passive control: A way of having a more general brain state measured from the user (such as overstimulation or understimulation), and using the information about the classified brain state as a way to adapt or tweak the process of control (for example making the control program more or less stimulating).
32. Polylactic acid (PLA): a polyester that is commonly used in 3D-printing.
33. Prosthesis: An artificial limb.
34. Prosthetic: Relating to an artificial limb; The branch of medicine regarding the production and use of artificial limbs.

35. Pyserial: A Python library that allows Python to read from serial ports.
36. Railed: When data remains at zero. For our research, this is when an electrode is not measuring any brain signal potentials while the headset is running. This typically occurs when the electrode is not in contact with the scalp.
37. Residual Limb: Remaining part of a body that has been amputated.
38. Reverse Kinetic Control: A type of prosthetic control which involves automatic pre-programmed actions, where the user chooses an automated action to perform.
39. Scikit-learn: An open-source python library that comes with various machine learning tools.
40. ShallowConv: A deep learning model that classifies EEG signals.
41. Softmax: A function that converts a vector of N real numbers into a probability distribution of N possible outcomes. Often used as an activation function in machine learning contexts.
42. Theta: EEG bandwidth ranging from 4-7 Hz. Implicated in memory and emotional regulation.
43. Transformer Model: A machine learning model that is able to learn context by tracking relationships in sequential data.
44. Virtual Reality (VR): A simulated experience created with computer technology and can be experienced through various devices, allowing users to interact with and immerse themselves in a virtual environment.
45. xDawn + Riemannian Geometry Classifier (xDawn + RG): A machine learning classification model.

Appendix B - Participant Testing Protocol

Protocol Developed From Electroencephalogram (EEG) Recording Protocol for Cognitive and Affective Human Neuroscience Research (Farrens et al., 2020).

Note: We will remain compliant with IRB recommendations and requirements regarding COVID-19 restrictions.

Prior to Arrival

1. Present the participant with a link to the attached interest survey through their emails to determine if they meet the requirements to participate in the study.
See attached “Eligibility Survey” document for more information.
2. If the participant meets the requirements, ask the participant to schedule a testing time using the following template.

Draft email:

Subject:

Schedule A Time For Participation In On-Campus Research Participation; Help Advance Research In Brain-Computer Interface Prosthetics

Description:

Hello,

Our team is ready for you to schedule a time to come in for research in this study. Please reply to this email with upcoming (within two weeks) dates and times in which you would be able to come in for a session. As a reminder, a session can take up to an hour so please make sure to account for this.

Team BCIPRO

Contact info.bcipro@gmail.com for questions.

Contact Person: Team BCIPRO

Contact Email: info.bcipro@gmail.com

Website URL: <https://bcipro.github.io/>

3. Send a reminder to the participant via email 1-2 business days before the study. Include the time, date, and location of the testing session, as well as information about the general testing

procedure (e.g., what to expect, how long it will take, why certain data is needed such as demographics, etc.). Include a list of reminders, such as: “Participants need to be completely awake during the experiment, so please have sufficient sleep before arriving. Arrive with clean, dry hair, and remove all ponytails, braids, wigs, extensions, hair clips, hats, etc., prior to arrival.”

- a. If a participant arrives wearing inappropriate clothing, provide a disposable gown for the participant to wear over their clothing to avoid damage.
- b. Draft Email

Subject:

REMINDER: Upcoming Appointment for Participation In On-Campus Research Participation; Help Advance Research In Brain-Computer Interface Prosthetics

Description:

Hello,

We would like to remind you that you have an upcoming appointment on <date and time of appointment>. As another reminder, a session can take up to an hour so please make sure to account for this.

We will see you soon and we are looking forward to your participation!

Team BCIPRO

Contact info.bcipro@gmail.com for questions.

Contact Person: Team BCIPRO

Contact Email: info.bcipro@gmail.com

Website URL: <https://bcipro.github.io/>

4. Lay out as much of the equipment prior to the participant’s arrival as you can. This includes the gloves, tape measure, and alcohol wipes
 - a. Test equipment for functionality before participants are brought to the lab.
 - b. Disinfect all equipment with isopropyl alcohol before its first use, and disinfect all equipment with isopropyl alcohol after each individual use.

Arrival

1. Participants will be directed to go to room 4364 of the Atlantic Building at the University of Maryland.
2. After arrival, provide participants with the QR code, link, or electronic device to use to fill out the consent form and/or demographics survey.
3. Ask participants to read through the consent form and to affirm or deny their consent.

Electrode Application

1. Obtain consent according to the procedure approved by the Institutional Review Board.
2. Seat the participant in a comfortable low-backed chair in the prep area.
3. Have the participant comb their hair using a provided plastic comb, instructing them to concentrate on their scalp. The purpose is to loosen up some of the dead skin on the scalp, which will help reduce electrode impedances. Use a plastic comb instead of a hair brush; hair brushes soak up an excessive amount of disinfectant and are much harder to clean in between participants.
 - a. If the participant arrives with wet hair or is sweaty, have them dry their hair with a hair dryer before beginning.
 - b. If your participant arrives with a ponytail, braid, wig, barrettes, hair clips, or extensions of any kind, have the participant remove them before continuing.
4. Put on a pair of gloves.
5. Measure the circumference of the participant's head (in cm) using a soft tape measure, using the nasion and inion to define the measurement axis.
6. Use an alcohol wipe to clean skin areas along the hairline and behind the participant's ears.

Data Collection

1. Take the participant into the testing room, leaving their backpack, purse, cellphone, etc. outside the testing room. The testing room will consist of 3 height-adjustable tables (one for demonstration, one for the participant, and one for the monitor and computer), 3 chairs (one for demonstration, one for the participant, and one for the researcher), 2 monitors (one for

data collection and one to display the data being collected to the participant), a computer (to collect data), an EEG headset (to collect data), and alcohol wipes (to clean and sanitize).

2. Have the participant sit in the following manner:
 - a. Have the participant sit with their feet flat on the floor and their bottom all the way to the back of the chair.
 - b. Adjust the chair height so the participant is sitting with their knees bent at a comfortable angle ($\sim 90^\circ$), and then adjust the height of the monitor on the height-adjustable table so that the center of the screen is level with their eye gaze.
3. Place the EEG cap (with up to 16 electrodes) on the participant's head. Use the soft measuring tape to make sure the cap is centered. The Cz (vertex) electrode holder should be exactly half way between the nasion and inion and exactly halfway between the left and right preauricular points. To readjust the cap, use both hands to slide/push the cap into place; avoid grabbing individual electrode holders and tugging or pulling the cap into place. Once the cap is centered front to back, visually ensure the cap is centered side to side. Re-adjust as necessary.
 - a. If the headset needs to be changed for a smaller/larger size, disconnect the Cyton board from the previous headset and move it into the board holder on the appropriately sized headset. Reattach the wires, following the instructions at <https://docs.openbci.com/AddOns/Headwear/MarkIV/>
4. Adjust the non-electrode feet (by screwing them into or out of their holders) until the cap fits snugly on the head of the participant. The participant should attest that the cap is not applying an uncomfortable amount of pressure.
5. Adjust each scalp electrode (by screwing them into or out of their holders) until the participant attests to feeling the electrode on their scalp.
6. Adjust each forehead electrode (by screwing them into or out of their holders) until the participant attests to feeling the electrode on their forehead.
7. Attach the two black ear clips to each ear. These are used for grounding and biasing.
 - a. For help with steps 4-7, please reference the OpenBCI documentation found at <https://docs.openbci.com/AddOns/Headwear/MarkIV/>
8. Plug the battery into the amplifier.
9. Open the OpenBCI GUI on the data acquisition PC.

10. Plug in the Cyton USB dongle into a USB port on the data acquisition PC
11. Turn on the Cyton Biosensing Board by setting the switch to PC mode
12. Connect to the Cyton board using the following procedure
 - a. In the data source panel, select LIVE (from Cyton)
 - b. Under the “Pick Transfer Protocol” popup, select Serial (from Dongle)
 - c. Under the CHANNEL COUNT header, select either 8 or 16 channels (corresponding to the number of electrodes in the cap)
 - d. Under the SERIAL CONNECT header, select AUTO-CONNECT
 - e. Click the START SESSION button
13. Make the testing room monitor a clone of the data acquisition monitor using the HDMI cable.
14. Show the participant their EEG signals on the monitor. Describe common movement artifacts, how to prevent them, and why they matter. This helps the participant understand why they are being asked to minimize certain behaviors and allows you to ensure that all artifacts are easily identified with the placement of the electrodes.
 - a. Eyeblinks: Ask participants to look at the center of the recording screen and to blink 4-5 times in rapid succession. This shows them what their blinks look like and why you may need them to minimize how often they blink during the trials. Check to make sure the blinks are appearing in the proper channels; there should be little to no blink activity detected in the HEOG (Horizontal Electrooculogram) channels. If you see large blink activity in either HEOG channel, you will need to remove the electrode and place it more evenly in line with the participant’s canthus, and make sure the polarity of the VEOG (Vertical Electrooculogram) Lower electrode is negative and that the signal is the expected size. If you see large blink activity It is possible that an electrode was placed in the wrong location (for example HEOG Left in VEOG Lower’s place).
 - b. Eye Movements: Ask the participant to look at the center of the recording screen and to look back and forth between the left and right edges of the monitor a few times while leaving their head stationary. This should produce large, rectangular deflections in the HEOG Left and HEOG Right channels (with opposite-polarity deflections for the Left and Right channels). If this is not the case, re-adjust the electrode(s) as necessary and check to confirm they are placed correctly to the left and right sides of the eyes.
 - c. Concentration Face: Ask the participant to clench their teeth and furrow their brow. This demonstrates the most common artifacts caused by a participant’s “concentration face.”

Remind the participant that it is important to keep their face, jaw, and neck as relaxed as possible throughout the experiment to help minimize this muscle noise.

- d. Chewing: Ask the participant to pretend to chew gum. This demonstrates why it is important for them to completely finish eating their snack(s) before beginning the next block of the task. It is also a good opportunity to make sure your participant is not chewing gum before beginning.
 - e. Alpha waves: For most participants, asking them to close their eyes while relaxed should produce visible bursts of alpha waves. This is a brainwave that is undesirable in this experiment and will illustrate the need to stay awake during the experiment.
15. Check the temperature of the room and the lighting level. Adjust as necessary for the comfort and the participant.
16. When ready to begin the experiment, pull up the timer that the participant will be following on the participant's screen.
17. Explain the tasks to the participant. The task is for participants to watch a timer that will coordinate their actions.
- a. Participants will be told an action to execute by investigators. They will be told that the execution of an action will be mediated by a countdown timer, where blocks of time on the timer correspond with a movement (ex. The first 10 seconds are at rest, the following 5 seconds correspond with keeping the right hand open, the next following 5 seconds correspond with closing the right hand around a stress ball, the next 5 seconds correspond with opening the right hand again, etc.). These actions will be expected to be repeated multiple times during the duration of data collection. The actions will be
 - i. Opening and closing the hand (gripping a foam stress ball when the hand is closed)
 - ii. Opening and closing each finger individually
18. Demonstrate the tasks to the participant, following the **Action Demonstration Protocols**
- a. Inform participants that they may request a redemonstration of the action before each data collection step.
19. Reiterate any special EEG artifact instructions like maintaining fixation or reducing the rate of blinking until a certain time. Assure the participant that there are many breaks throughout the experiment and they are free to move around as much as they need to during those

portions of the experiment. However, before beginning the task again, they must return to a still and relaxed position.

20. To begin recording the EEG, hit the 'Start Recording' button. Start your recording approximately 10 seconds before the task begins and end the recording approximately 10 seconds after the task ends. This minimizes edge artifacts when filtering the EEG data offline.
21. Monitor the EEG data closely at all times. Do not read books or journal articles, do homework, look at websites, read email, send texts, etc. In most cases, the experimenter should not have their cell phone nearby, which reduces the temptation to engage in distracting activities.
 - a. Check behavioral performance continually to ensure that the participant understands the instructions, is complying, and is not becoming drowsy or unmotivated (e.g., is keeping their eyes open and fixated on the screen, etc.).
 - b. If you see evidence of a problem with the recording (e.g., excessive noise, excessive artifacts, etc.), fix the issue as soon as possible. Depending on the task and the type of problem, this can be accomplished at the next break, or it may be beneficial to pause the task to address the issue before continuing.
 - c. If the participant exhibits artifacts that are particularly problematic for the experiment being run (e.g., eye movements, blinks that frequently occur during the presentation of a visual stimulus, etc.), gently remind the participant to avoid that artifact.
 - d. If a participant is unable to perform the task with an appropriate level of accuracy or without excessive artifacts, terminate the session early and document the issue(s).
 - e. Regularly check the participant to make sure that the participant is behaving appropriately (e.g., feet still flat on the floor, remaining still, maintaining fixation, etc.).
 - f. If the participant is becoming drowsy (as evidenced by poor task performance, excessive alpha waves, or visibly nodding off), turn the lights to full brightness and allow the participant to stand and stretch their legs at the next break to help alleviate drowsiness.
22. Inform participants that their first action will be opening and closing their right hand, gripping on a stress ball when they close their hands, at 5 second intervals for up to 300 seconds, which corresponds with up to 30 actions. Inform participants that this action will be

repeated for up to 2 rounds, and that they will be given up to a 5-minute break between each round. Ask participants if they require or would like a redemonstration of the action.

23. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
24. Give participants up to a 5-minute break. Participants may stretch and move around while seated during this time.
25. Repeat data collection of opening and closing the right hand (steps 21-22) up to 2 times.
26. Inform participants that their next action will be opening and closing their right thumb at 1 second intervals for up to 40 seconds. Ask participants if they require or would like a redemonstration of the action.
27. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
28. Give participants up to a 1-minute break. Participants may stretch and move around during this time.
29. Inform participants that their next action will be opening and closing their right pointer finger at 1 second intervals for up to 40 seconds. Ask participants if they require or would like a redemonstration of the action.
30. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
31. Give participants up to a 1-minute break. Participants may stretch and move around during this time.
32. Inform participants that their next action will be opening and closing their right middle finger at 1 second intervals for up to 40 seconds. Ask participants if they require or would like a redemonstration of the action.

33. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
34. Give participants up to a 1-minute break. Participants may stretch and move around during this time.
35. Inform participants that their next action will be opening and closing their right ring finger at 1 second intervals for up to 40 seconds. Ask participants if they require or would like a redemonstration of the action.
36. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second) countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
37. Give participants up to a 1-minute break. Participants may stretch and move around during this time.
38. Inform participants that their next action will be opening and closing their right pinkie finger at 1 second intervals for up to 40 seconds. Ask participants if they require or would like a redemonstration of the action.
39. Have the participant start with their palm open. Start the EEG recording and wait at least ten seconds then start the google timer after a verbal three-second countdown. Stop the EEG recording at least 10 seconds after the timer reaches 0.
40. Give participants a up to 1-minute break. Participants may stretch and move around during this time.
41. Repeat steps 24-38 up to one more time.
42. Provide an alcohol swab to the participant for them to wipe their forehead.

Clean Up.

1. Gently slide the cap backwards off the participant's head. Set everything aside.
2. Allow the participant to comb their hair if they wish. Do not make them wait while you clean everything up. Explain to the participant that they will be compensated with \$10 through their Terrapin Express account for completing testing. Notify them that there will be a raffle

where three randomly chosen participants will each win \$50 which will be awarded through Terrapin Express and be notified by email if they win once the data collection phase of research is completed. Allow participants to scan a QR code, enter a link, or use an electronic device to fill out a form that will collect name and UID which are needed for compensation as well as whether the participant wants to be entered in the raffle. Afterwards, inform them that the experiment is over and indicate to them that they may leave.

3. Once the participant has left the lab, unplug each electrode from the cap by gently sliding the electrode up and out of its holder with your thumb and forefinger.
4. Disinfect the electrodes, cap, and comb by wiping them with isopropyl alcohol wipes. Rinse thoroughly with water to remove all of the isopropyl alcohol when done.
5. Disinfect the prep station by wiping it with isopropyl alcohol. Rinse thoroughly with water when done and let dry.
6. Leave the cap out on the table or use a small fan to dry. Do not dry with the hair dryer.
7. Disinfect the comb used at the beginning of the experiment by wiping it with isopropyl alcohol. Rinse with water when done. Comb will be disinfected as well before first use.
8. Clean up the prep station and wipe down the testing area with isopropyl alcohol. The prep station will be disinfected as well before first use.

Post Testing

1. Each participant who completes the session in full will be compensated with \$10 through Terrapin Express, and there will be an optional raffle to award \$50 to each of three participants through Terrapin Express. Requests for compensation can be posted up to twice per month.
2. Send a follow up email thanking the participant for participating in the study.

Draft email

Subject:

REMINDER: Thank You! For On-Campus Research Participation; Help Advance Research In Brain-Computer Interface Prosthetics

Description:

Hello,

We wanted to say thank you for your participation in our research study! Your contribution plays a part in understanding how to analyze measured EEG brain waves to identify physical actions. This contribution will be used to develop algorithms to develop the analysis of EEG waves, which will help develop technology for prosthetic users. Thank you again for making a difference and helping a good cause!

Team BCIPRO

Contact info.bcipro@gmail.com for questions.

Contact Person: Team BCIPRO

Contact Email: info.bcipro@gmail.com

Website URL: <https://bcipro.github.io/>

3. Send an email announcing the winners of the raffle.

Draft email

Subject:

Raffle Winners For On-Campus Research Participation; Help Advance Research In Brain-Computer Interface Prosthetics

Description:

Hello,

We again wanted to say thank you for your participation in our research study! Also, you are one of the raffle winners! \$50 will be deposited into your Terrapin Express account. Congratulations and thanks again for participating in the study!

Team BCIPRO

Contact info.bcipro@gmail.com for questions.

Contact Person: Team BCIPRO

Contact Email: info.bcipro@gmail.com

Website URL: <https://bcipro.github.io/>

4. Data collected in this study will be analyzed to determine which brain signal patterns correlate to the specific movements of opening the hand, closing the hand, opening each finger individually, and closing each finger individually.
5. Raffle will be at completion of data collection. Requests for compensation of participants will be made up to twice per month as participants complete data collection.