University of Nevada Las Vegas
Department of Electrical and Computer Engineering

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BCI Telepresence Helmet

Final Project Report

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Abstract

The BCI Telepresence Helmet is a device that will provide a user the ability to control a telepresence robot in a remote location. This project aims to fill the employment gap left behind by widespread automation by providing an interface for robotic telepresence that can be operated by many users, especially those with motor-impairment disabilities. This interface will take the form of a BCI helmet, complete with VR headset and surround-sound headphones. Brain Computer Interfaces (BCI) use technologies such as EEG to measure brain waves, classify them using machine learning techniques, and output commands to some external device. BCI systems are currently being explored in areas such as remote surgery, VR therapy, and wheelchair control. However, current BCI systems are expensive, uncomfortable, and/or have no integrated processing/classification frameworks. This project will innovate on previous designs by providing an inexpensive, all-in-one solution for BCI control, especially designed for use in robotic telepresence. The mechanical design will include a custom helmet with VR & headphones, as well as the EEG headset with adjustable size. The electrical design will involve a custom PCB that includes: 3 specialized EEG ADC modules, 32-bit microcontroller, 24 input amplifiers, and wireless communication module. Finally, the project will include designing software that handles preprocessing, feature extraction, and machine learning for the BCI control signals. The BCI Telepresence Helmet will provide a new modality for robotic telepresence and VR interactions, transforming the way that work is performed and augmenting the abilities of workers in a wide range of industries.

Introduction

More than 40 million Americans have a disability, making up over 12.7% of the United States population according to the U.S. Census Bureau [1]. Moreover, according to the Bureau of Labor Statistics only 19.1% of those suffering from disabilities were employed [2]. These staggering numbers demonstrate the large employment gap between the number of people with disabilities and those without. Recent trends indicate that the workforce is bound to change drastically with the rise in automation and artificial intelligence, ushering in a new age of the "Future of Work." Displacement of jobs due to automation will cause people with no disabilities to have an increased difficulty transitioning to future jobs; this effect will have an even larger impact on the employment of disabled persons in the global workforce. Thus, there must be novel approaches taken to increase the participation of disabled individuals in the workplace.

As part of the workplace transition, the "Future of Work" is expected to increase the use of telepresence robots in a wide variety of industries and applications. The use of telepresence robots is already increasing in industries such as medicine and education. Companies are beginning to realize what the future of work consists of, and some, such as All Nippon Airways (ANA), have taken the initiative to create the $10 million Avatar XPRIZE [3]. The competition revolves around designing an immersive avatar system that can receive inputs from humans in real-time while the robot is located anywhere in the world. In the medical industry, an example of a telepresence robot can be witnessed with the RP-VITA robot made by iRobot and InTouch Health, which provides doctors the ability to see patients virtually from anywhere in the world [4]. These examples demonstrate that the demand for telepresence robots is increasing, but current methods do not provide an efficient method for control of these robots by motor-impaired individuals.

To fill this gap, we propose the development of a new modality for robotic telepresence, combining technologies from Virtual Reality (VR), Robotics, and Neuroscience into one complete system for remote robotic telepresence control. This will involve creating a new type of helmet that combines a VR headset, surround sound headphones, and a Brain Computer Interface (BCI) into one device that can be worn with comfort by a wide variety of users. A concept design of the BCI Helmet can be seen in Figure 1.

The main idea of the project is to create a BCI helmet that can use digital signal processing (DSP) techniques, feature extraction methods, and machine learning classification methods in order to map the signals obtained from the headset to intentions from the headset user. The intents could then be mapped to a variety of outputs including remote robot control, wheelchair control, VR interactions, etc. This product can be used by a wide variety of users. An example of some applications are:

- Long-distance robotic surgery
- Enabling disabled persons through robotic telepresence or wheelchair operation

- Enhancing disabled experiences through VR
- Neuroscience research
- Remote robot control through seamless interface

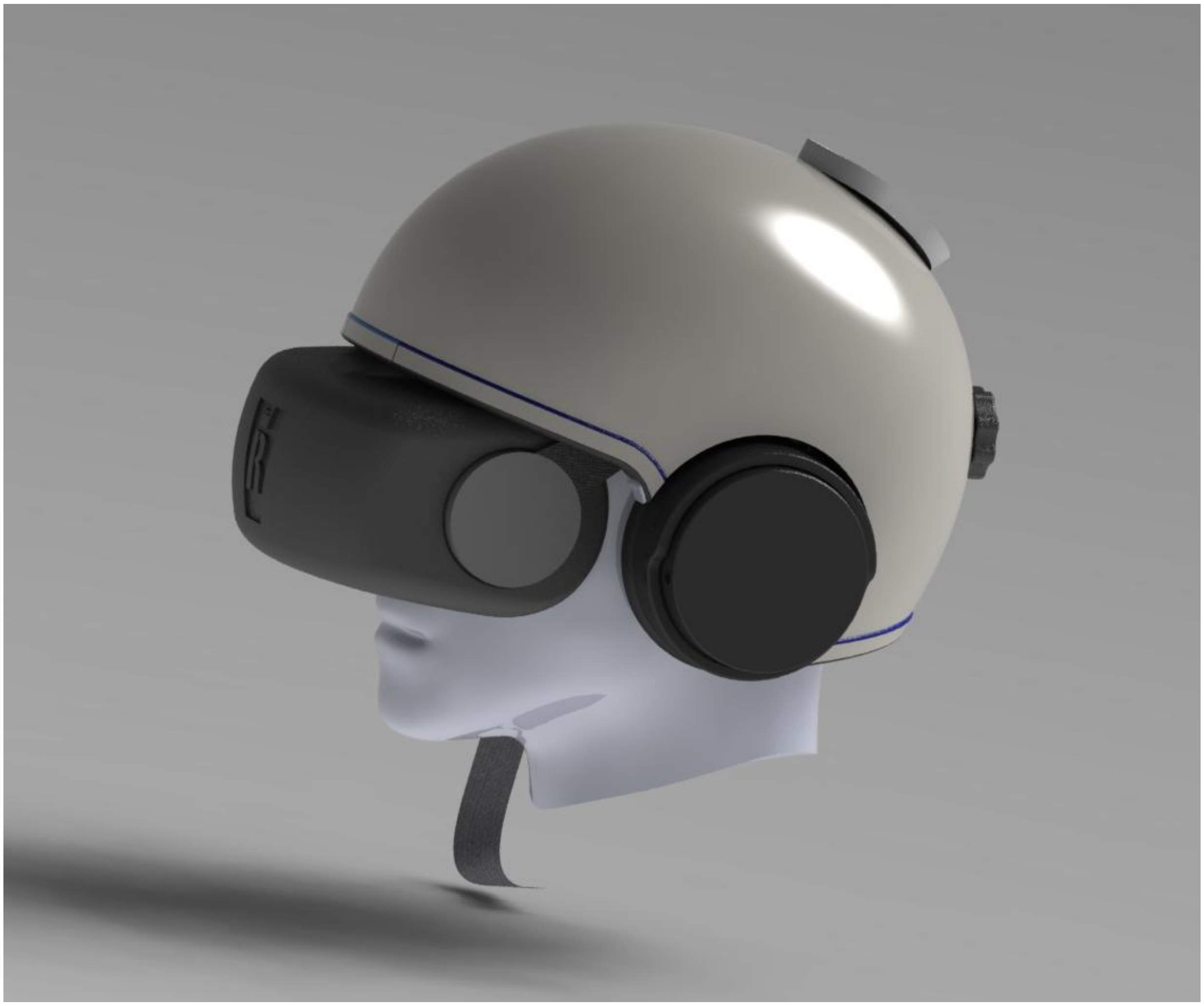

Fig. 1 Concept Design of the BCI Helmet

The primary devices used for this project are the EEG headset and the telepresence robot. The EEG headset will maintain the fidelity of current SoTA headsets, allowing 22 + 2 channel EEG measurement with minimum resolution of 26 bits (1 µV). The EEG headset will improve on current designs by implementing the following on 1 board (no add-on board required) at a reasonable price point for researchers, while adding the ability to sense EMG signals with special sensors placed in the headset frame. The new headset will also improve on current designs by implementing dynamic biasing and by implementing DSP on-chip instead of through software on a separate computer. The BCI Helmet will be used to control an existing service robot/telepresence robot. This is just an example application of the EEG headset, but it will show the full range of capabilities using the headset. The robot being used for this control will be the FURO service robot, made by Future Robot (already have in our lab). The robot will be controlled by the headset by associating the classified output with wheel velocities on the robot through ROS. This will give the user full control over the movement of the robot.

Background

Previous patent designs have attempted to manufacture a similar product to the one proposed, but a helmet with a VR headset, surround sound, EEG, and fNIRS has not been demonstrated before. One search found an inflatable EEG helmet that could be used on a variety of head sizes by using an inflatable headset, which would bring the electrodes closer to the scalp and provide better support [5]. Another search found an EEG cap, which helps maintain pressure on the scalp by using a headband [5]. It could be uncomfortable to wear, and there would be no other method of attaching other sensors to it. The only patent found that was somewhat close to the team's project is the EEG Headset with VR [6]. It uses a VR headset attached to straps that provide excellent support on the head. Motion cameras track the position of the helmet. While this product does provide EEG and a VR headset, it fails to include audio as well as other sensors. There could potentially be a patent for the helmet that the team is designing.

The basic control of mobile robots using BCI headsets for people with motor disabilities has been demonstrated in previous publications. *Leeb et. al.* have worked on creating shared control for a BCI telepresence robot [7]. They demonstrated that shared control, in which a BCI is used for high level control, and navigation algorithms are used for low-level control (i.e. obstacle avoidance), was successful in allowing people with motor disabilities to control the robot. The obstacle avoidance algorithm, part of the low-level control, prevented the robot from getting damaged, and also relieved some pressure on the operator to perform safely the whole time while using the BCI headset. All the users, healthy and people with motor disabilities, were able to have the robot complete the tasks given. The idea of this research was to use robotic telepresence to connect friends and families, and does not explore the use of these robots in any sort of workplace scenario. Furthermore, the authors do not include start or stopping functions that would be beneficial in the control of a mobile robot.

The idea of BCI controlled robots extends beyond the use of ground robots. *Nourmohammadi et. al.* present the idea of BCI to control an unmanned aerial vehicle (UAV) [8]. Although this research presents the strategies that will be needed to to effectively fly a UAV using a BCI headset, there is no mention of the actual data being processed. The paper does not actually demonstrate the data acquired or even the prediction results of the classifier. The work also covers the deficiencies presented in other papers, but does not present how the authors overcome these issues.

BCI headsets have even been used in applications not related to robotic control, such as virtual reality (VR) applications. *Martisius et. al.* present results using BCI for a VR shooting game [9]. This research explains the classification processes and overall methodology toward using BCI in virtual reality, and the challenges involved in this domain. Using SSVEP as the stimulus method, the authors were able to get real-time accuracy of 80.5% while using SVM classification. This work also demonstrated that high accuracy can be gained from consumer BCI headsets. Nonetheless, accuracy of ERD/ERP BCI signals was not demonstrated in this work.

Gargava et. al. demonstrate the control of an Arduino robot using BCI [10]. The authors claim to have 100% accuracy using SVM based on eye blinking and eye movements, but they did not claim to use any other types of BCI signals such as ERD/ERS or SSVEP. The authors chose not to use ERD/ERS since the data has to be taken for each operator. Moreover, the authors use only 22 trials for their classification, which could result in overfitting for their training data.

Research has been conducted in using BCI headsets for controlling only the speed of the robot. *Katona et. al.* demonstrated the use of the Neurosky EEG headset to control the speed of Robotino, a mobile robot [11]. The authors claim that operators had a difficult time stopping the robot, since it relied on reaching a calm state. This was countered by having them practice extensively beforehand. Moreover, no results were presented for the classification.

Khorshidtalab and Salami compare the different methods for signal classification from EEG data [12]. The most common platform for classification is Linear Discriminant Analysis (LDA) since computational effort is low. Another method presented in the paper is Support Vector Machines (SVM), which results in lower error than other methods. Furthermore, SVM allow for both linear and nonlinear classification. The authors also state that SVM are preferable due to their small errors.

Bi, Fan, and Liu discuss the methods required before classification [13]. The work presented by the authors is a review of BCI robot control based on previous work and their own results. Above all, the research performed by the authors show the process required for transforming EEG data into robot movement, including preprocessing, feature extraction, and classification methods used. This work is a great review of the current methods used for BCI robot control, and presentsthebenefitsandshortcomingstodifferentprocessing and classification methods that have been used in previous work.

Current Market Solutions

The current market for EEG devices is mostly located within the realm of medical research. Research applications range from using the headset to monitor patients with emotional, intellectual, or social disabilities or to giving physically disabled patients the ability to control new prosthetics. However, with the advances in EEG technology recently, EEG headsets will have broader implications outside of research. These include giving disabled patients further control over their lives and expanding their mobility and experiences through telepresence robotics and VR. Furthermore, EEG headsets have broad applications in robot control, as they can offer a new input modality that can make use of new methods of control not previously used in robotics.

Some current EEG headsets exist on the market. One popular choice for researchers is the Emotiv Epoch EEG headset, which supports 14 EEG channels for a price point of $799 [14]. While this headset has had success as a research platform in the past, its weaknesses lie in the variability of electrode placement and the interference of EMG signals with EEG signals, causing erroneous or non-complete readings. Another headset on the market is the OpenBCI

Ultracortex Mark IV, which supports 8 or 16 channels for a price point of $900-1400 (8 or 16 channels) [15]. This headset has more rigid electrode placement allowing for more consistent readings but provides no ability for EMG measurements.

A table comparing available device specifications and price with our proposed device can be seen in Table 1. A table comparing the strengths and weaknesses of the available devices and our proposed device can be seen in Table 2.

	Vendor	**Input Channels**	**Resolution**	**Wireless**	**On-board DSP**	**Price**	**Comment**
Ultracortex	OpenBCI	8 or 16	16 bits	Y	N	$1,600	Open source
Epoch	Emotiv	14	12 bits	Y	N	$800	Meant for medical research
Our dev.	You	22 + 2	24 bits	Y	Y	$1,200	Targets both medical and engineering research

Table 1. Comparison of available devices

	Resolution	**Battery life**	**Price**	**Strengths**	**Weaknesses**
Ultracortex	Medium	Long	High	▪ Good resolution ▪ Long battery life	▪ High price ▪ Requires knowledge of DSP and ML to use
Epoch	Low	Medium	Low	▪ Long battery life ▪ Affordable price	▪ Low resolution ▪ Medium battery life ▪ Not designed for motor imagery
Your dev.	High	Longest	Affordable	▪ High resolution ▪ Low price ▪ Will cost less than current BCI solutions ▪ Will work on robotic platforms & for EEG, EMG, ECG research	▪ May cost more than some current market solutions

Table 2. Strengths and weaknesses of available devices

Research and Testing Results

After obtaining the OpenBCI hardware we immediately conducted tests to measure overall robustness, accuracy and efficiency with respect to acquiring brain wave data. Repeated use of the helmet showed poorly made electrodes mounted on the helmet that were inefficient at consistently obtaining data from the user. Constant fidgeting, adjusting and repositioning of the helmet to fit the nodes onto the scalp and acquire consistent data is an issue with the current design and must be improved upon. In order to increase data acquisition from the helmet, improved electrodes need to be used. One route is to look for available products on the market and implement them into our helmet design. "Wet" electrodes are an alternative that can provide more consistent data acquisition and also increase comfort and robustness. A second option would be to create our own custom electrodes. If cheap and reliable market options are not possible then custom electrodes would be an alternative and can be tailored specifically to our device.

Further research has been conducted on the classification system created to process the data obtained from the helmet. Support Vector Machines (SVM) are the classification method being used in the design as of now. However, this classification system has its shortcomings and does not create an accurate enough classification for the purposes of this system. In order to improve the classification to meet required standards two solutions must be implemented. First, a more effective preprocessing system that can filter out unwanted data obtained from the helmet. Eye movements, facial expressions, and voltage biases can skew data and need to be filtered out so that processing with machine learning can yield better classification. Second, a different type of learning must be used in place of SVM. Artificial Neural Network implementation to replace the current SVM system would increase classification accuracy as ANN is a more robust form of machine learning. Simultaneous implementation of the aforementioned solutions will increase classification accuracy and yield better output data for the remote robot to process.

Specifications

Functionality & conceptual design:

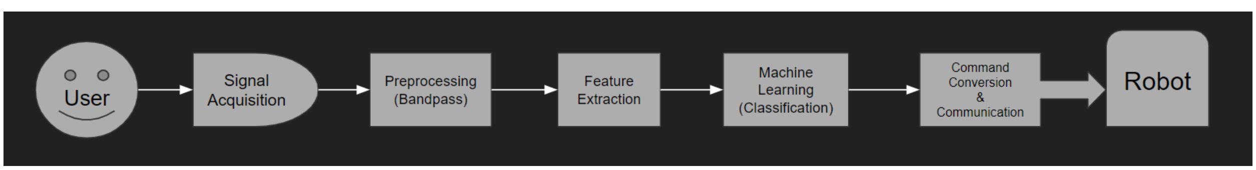

Fig. 2 BCI System Diagram

The high-level system diagram for the BCI Helmet can be seen in Figure 2. The system starts with acquiring EEG data from electrodes placed on the user's scalp. Data is then passed from the EEG data board through the wireless communication channel to the processing computer. The data is then processed into bins with sliding windows that represent segmented EEG data for each electrode channel. These data bins are then individually preprocessed, which involves bandpass filtering each channel's data bins into 5 main frequency bands that represent major distinctions in thought patterns within EEG signals. The EEG data is then passed through a feature extraction process, which involves taking the Fast Fourier Transform, and then obtaining the Power Spectral Density from this FFT representation. The Power Spectral Density for each channel-band combo will be the main feature that is passed into the machine learning classifier. This classifier could be a complicated structure such as an Artificial Neural Network, or a simpler model such as a Support Vector Machine. Either way, the machine learning classifier will need to be trained on previously obtained EEG data. The classifier will output a discrete number that represents a control command for the telepresence robot, which could vary depending on the robot control scheme and application. The robot will then process the discrete control command into a control output such as navigational movement, high-level commands, or emergency-stop procedures.

The following use cases are proposed for the project:

- The operator puts on the BCI Helmet along with VR attachment in order to be transported to the remote environment of the robot. The operator provides input in the form of hand interactions (if motor-enabled), EEG brain signals (classified to control outputs), and any high-level control frameworks available in the virtual environment (e.g. HUD controls, voice commands, gaze direction). The operator is provided output in the form of 3D visual feedback in the VR environment (provided by robot's visual sensors), surround-sound through the headphones (provided by robot's microphone array), and any possible haptic feedback, if used (provided by force sensors on robot's hands). The robot receives high-level commands from the BCI classification in order to control things such as navigational direction, state (e.g. walking, sitting, standing), and emergency procedures (i.e. fall recovery).
- The operator puts on the BCI Helmet along with VR attachment in order to be transported to a purely virtual environment. The operator provides input in the form of hand interactions (if motor-enabled), EEG brain signals (classified to control outputs), and any high-level control frameworks available in the virtual environment (e.g. HUD controls, voice commands, gaze direction). The operator is provided output in the form of 3D visual feedback in the VR environment (provided by simulation), surround-sound

through the headphones (provided by simulation), and any possible haptic feedback, if used (provided by force simulation).

Architecture:

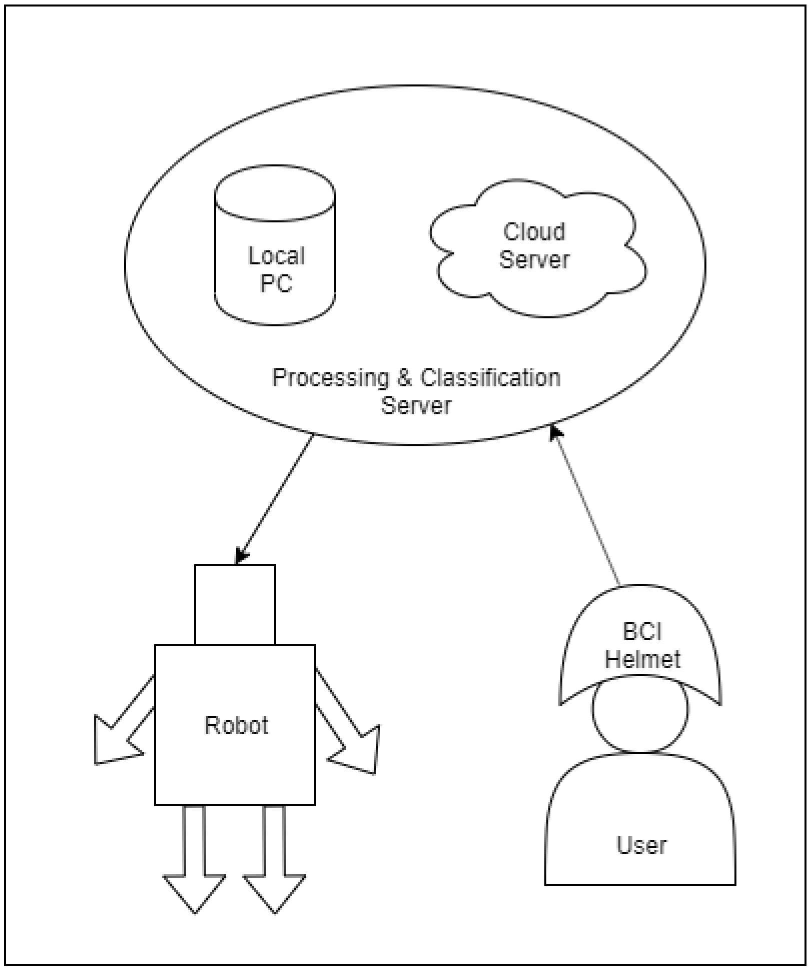

Fig. 3 High-level Diagram of BCI Helmet System

The high-level diagram of the BCI Helmet system can be seen in Figure 3. As seen, the three major components are the BCI Helmet, a processing & classification server, and a robot for control. The user will provide EEG brain signals as input to the BCI Helmet, which will digitally acquire and process these signals, sending the signals to the processing server through wireless communication. The processing server will perform necessary feature extraction and machine learning, as well as performing any online training of machine learning classifiers for the system. The processing server will then output discrete control commands to the robot. The robot will take these commands as input and operate on them according to the platform and the control scheme. The main design component for the project will focus on the BCI Helmet.

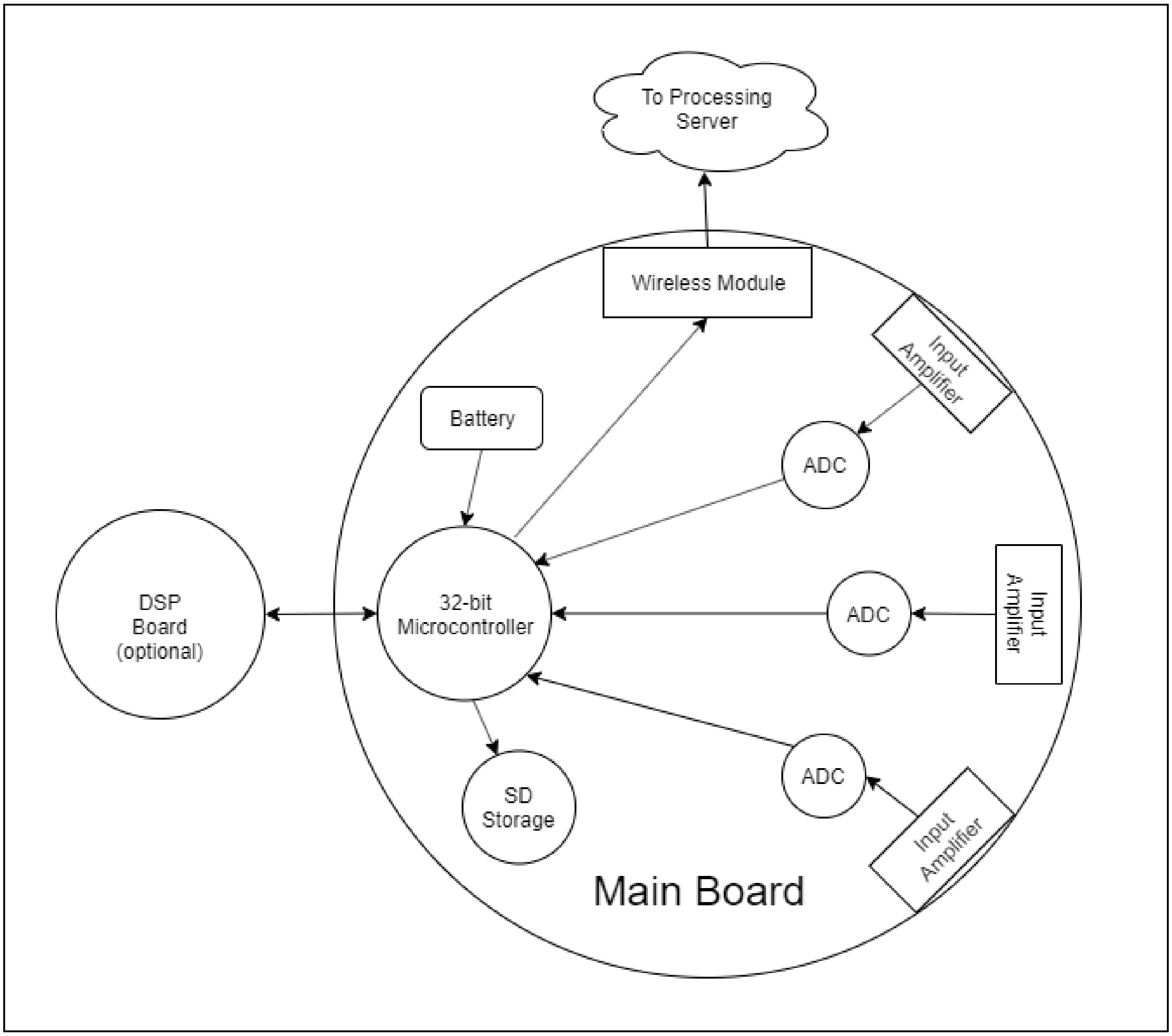

Fig. 4 BCI Helmet PCB Module Diagram

The module diagram for the BCI Helmet PCB can be seen in Figure 4. The main electrical design component for the BCI helmet will be to create a custom PCB for digital EEG data acquisition. This PCB must support the specialized EEG Analog-to-Digital Converters, input amplifiers, 32-bit microcontroller for digital processing, RF and/or wifi communication chip, and SD card storage. Unlike previous EEG headsets, our helmet will integrate 24 channels onto one board by daisy-chaining the ADC modules using the SPI communication interface and multiplexed inputs to the microcontroller. Additionally, the Microcontroller will have the option to interface with the DSP board, which can provide on-board preprocessing and feature extraction of BCI signals, streamlining the integration of the BCI Helmet into any robot control scheme.

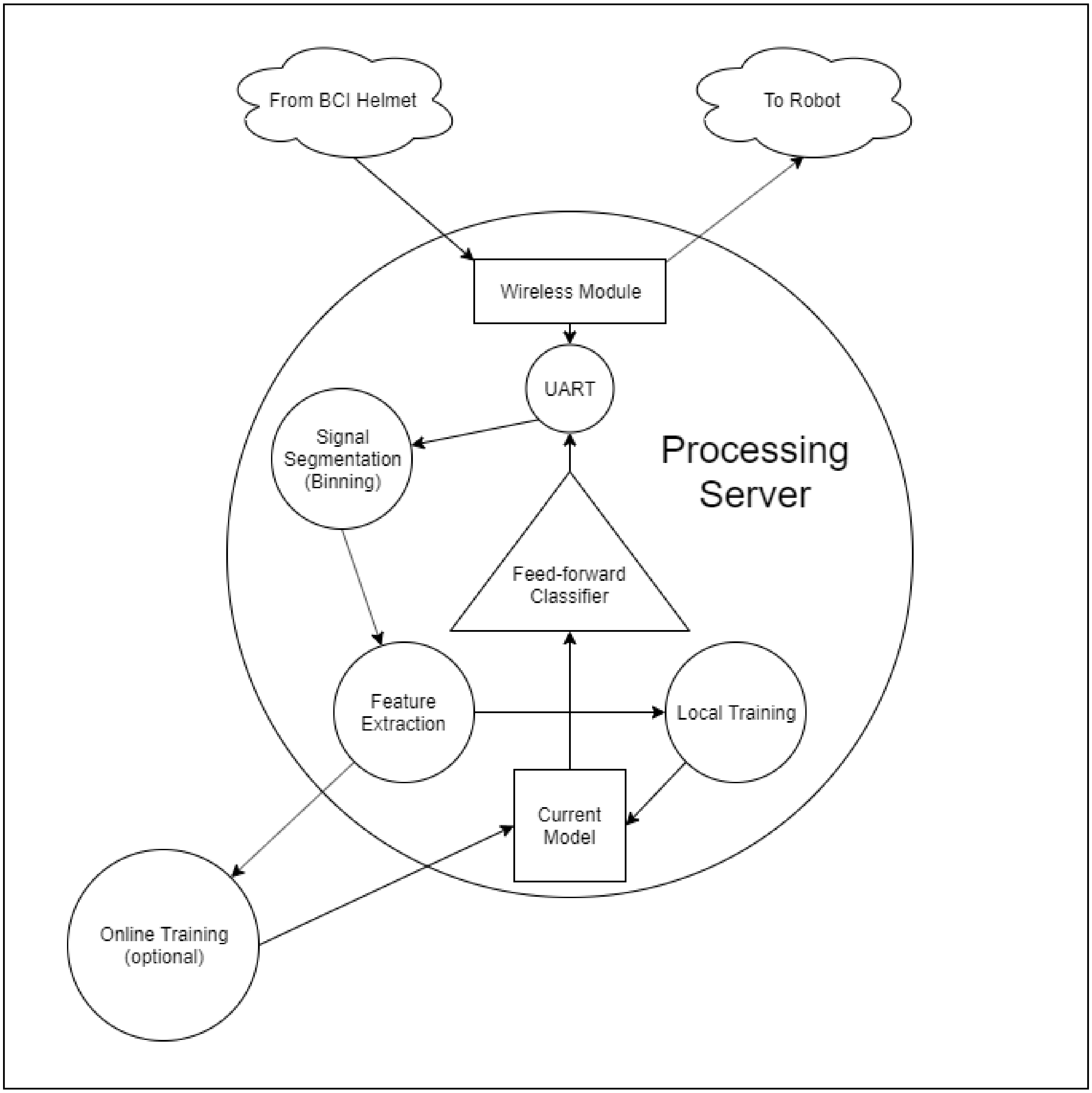

Fig. 5 Processing Computer Module Diagram

The module diagram for the processing server can be seen in Figure 5. Data is passed from the EEG data board through the wireless communication channel to the processing server.

The data is then processed into bins with sliding windows that represent segmented EEG data for each electrode channel. These data bins are then individually preprocessed, which involves bandpass filtering each channel's data bins into 5 main frequency bands that represent major distinctions in thought patterns within EEG signals. The EEG data is then passed through a feature extraction process, which involves taking the Fast Fourier Transform, and then obtaining the Power Spectral Density from this FFT representation. The Power Spectral Density for each channel-band combo will be the main feature that is passed into the machine learning classifier. The classifier can be a range of potential architectures, such as Artificial Neural Network (ANN) or Support Vector Machines (SVM). The classifier can either be trained online (i.e. cloud processing), or locally on the processing server. The classifier will output a discrete number that represents a control command for the telepresence robot, which could vary depending on the robot control scheme and application. The robot will then process the discrete control command into a control output such as navigational movement, high-level commands, or emergency-stop procedures.

Design:

The final design of the helmet will consist of a VR headset, 3D surround sound headphones, EEG, and fNIRS, as seen in Figure 1. Also, the headset will have a knob at the back, which will adjust the force of the headband underneath to allow the helmet to fit any size head. The rectangular-shaped capsule at the top of the head will consist of the WIFI module that communicates with the computer, as well as the PCB and battery for the helmet. The inside of the helmet will be lined with metal to block any unnecessary frequency waves and help cancel noise in the system. In addition, the headphones will be attached to the helmet on the outside, which gives them the freedom to swivel outwards when removing the headset, and then inwards, applying little pressure on the head.

The interior of the helmet will consist of the headband, which holds the electrodes, knob, and VR headset. The knob at the back will be used to bring together two pieces of plastic, thus reducing the circumference of the headset. Varying the circumference allows for different head sizes to fit inside the headset. The VR headset will be attached to a plastic part on the side, which will act as a support but also helps keep the headset fit on the operator. The final design is shown in Figure 6. The headband, shown as light gray, will be made of an elastic material that adjusts to the operator's head.The purchased helmet will fit a head circumference between 60.5-62.5cm to allow for the headset to fit inside. The surface minimum surface area of the electrodes will be 30 mm^2.

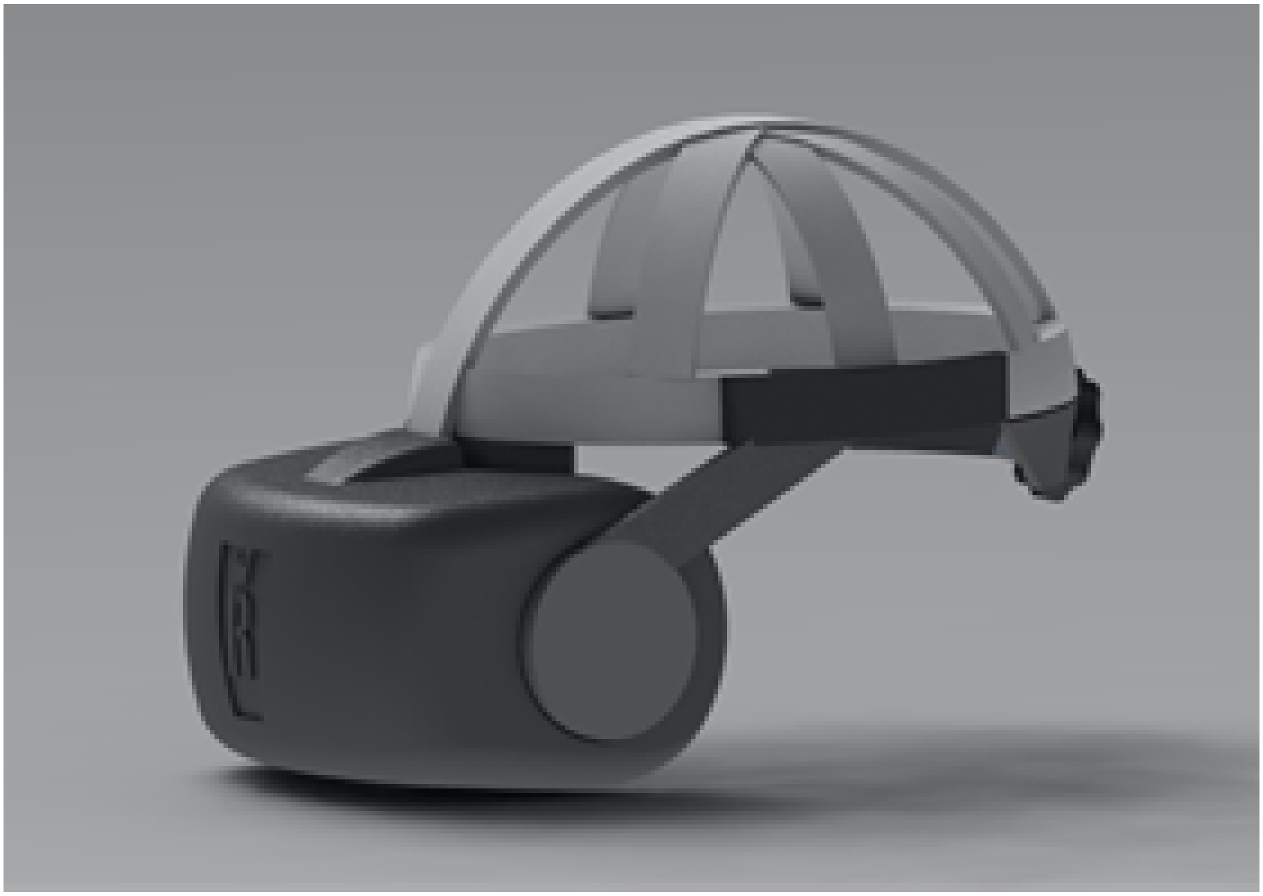

Fig. 6 Internal EEG Headset Concept Design

The components needed for creating a live point of view and a 3D environment are provided for the lab. These consist of a VR headset for the operator and a LIDAR camera system for creating a live point of view and for creating the 3D environment. The team working on this will perform high-level software integration and networking. First, the LIDAR camera system on top of the Hubo will be used to reconstruct a 3D model of the robot's surroundings. The two webcams on the side, the wide-lense fisheye camera in the middle, and the LIDAR scanner should be able to provide enough data to perform computer vision. There are open-source SLAM and 3D mapping algorithm that the team can explore to create a 3D mesh model of the environment. The data will need to be streamed back to the computer with a VR headset attached. The team member has developed a Unity application for VR with a 3D model of Hubo. The VR user can observe the action of Hubo in real-time. The increased awareness of the surrounding environment combined with feedback from haptic glove can dramatically improve the performance of the teleoperation of the robot.

Simulation:

To test the ability of the BCI Helmet for robot control, initial simulations were performed using the OpenBCI Headset with custom data obtained from our training process. To do this, a Python program was made on Google Collaboratory to take advantage of cloud processing for machine learning. The results were evaluated using the SVM classifier, and they came out to be very good, as shown in Table 3. However, the alpha band resulted in a 100% prediction accuracy. These are more likely due to blinking and less to the actual brain activity. Blinking is a natural process that occurs and can be treated as an external source of error. While the ideas do show that the results are viable, it also warrants future work to achieve a perfect prediction when using real-time control.

Freq. Band	Direction	Classification Accuracy (%)
Delta	Forward	95.6
	Left	95.3
	Right	95.0
	Backward	94.7
	Stop	95.6
Theta	Forward	97.5
	Left	97.5
	Right	97.8
	Backward	97.5
	Stop	98.1
Alpha	Forward	100
	Left	100
	Right	100
	Backward	100
	Stop	100
Beta	Forward	99.1
	Left	99.4
	Right	99.7
	Backward	98.8
	Stop	99.4
Gamma	Forward	98.2
	Left	98.8
	Right	98.2
	Backward	97.6
	Stop	98.5

Table 3: Simulation Classifier Results

Testing

To test the capabilities of the software and ensure the success of the project, the team has created testing procedures. These are in the form of checkpoints, and the team must answer "yes" to all of them before being able to consider this project a success. If the team manages to complete all procedures before the due date, then experimentation with other classifiers and more challenging tasks can be achieved. Table 4 includes the checkpoints for the classifier and using that to drive Hubo around while in wheel mode.

#	Check Points	Yes	No
01	Does the code run without any errors?		
02	Is the classification accuracy above 80%?		
03	Does the code publish velocity commands to ROS Topic?		
04	Is the ML training time under 10 hours?		
05	Is the operator able to control the velocity of the smaller service robot, Furo?		
06	Is the real-time accuracy rate above 80%?		
07	Can Hubo be driven around in wheel mode?		
08	Are there safety measures (limits) put in place to prevent damaging Hubo?		
09	Is the real-time accuracy rate above 80%?		

Table 4: Software Testing Procedures

The hardware checkpoints presented in Table 4 deal with the helmet design, including the devices attached to it. The BCI helmet will be built at the same time as the code is being developed. The first goal will be to purchase a helmet, make all the necessary cuts for the knob, transmitter, and headphones. The headphones will then be attached to the helmet. After that, the headset that fits inside the helmet will be designed. The headset, with the knob, and electronics will be mounted inside the helmet. The helmet must meet all testing standards.

#	Check Points	Yes	No
01	Does the helmet include the VR headset, headphones, fNIRS sensors, and EEG?		
02	Can the helmet fit the desired range of head sizes (80^{th} percentile of normal distribution)?		
03	Is the helmet considered comfortable by most users?		
04	Are all the electrodes making contact with the scalp?		
05	Is the operator able to have a 2D and 3D view of the robot and its environment using the VR headset?		
06	Is the system without lag?		
07	Can the operator hear sounds from the robot's environment?		
08	Can the operator easily remove the headset?		
09	Can the headset be worn for a long duration of time?		

Table 5: Hardware Testing Procedures

Roles & skills in the project

	Required skills
Role 1 - Alex Cater	Microcontroller & DSP programming
Role 2 - Leonardo Georgescu	EEG, EMG, EOG, & ECG Sensing
Role 3 - Dylan Wallace	Machine learning and neural networks
Role 4 - Yu Hang He	High-level software integration and networking
Microcontroller programmer	▪ Knowledge of ATMEGA168 microcontroller ▪ C++ programming ▪ AVR Studio experience ▪ DSP and analog design experience
EEG, ECG, EMG	▪ Knowledge of strain gauges, body sensors, and EEG sensors ▪ Knowledge of basics signal processing methods and mechanical strain equations
CAD designer	▪ Nonplanar & form-fitting design experience ▪ Experience with different fabrication methods (e.g. CNC, 3D Printing, Resin casting, etc.)
Software integrator	▪ Knowledge of computer networks and cloud computing ▪ Knowledge of serial communications

Table 4. Roles & skills

Parts list

Part type	Vendor	Model	Parameters	Link
Microcontroller	Microchip	**PIC32MX 250F128B**	1 ns time 32-bit 2 UART	https://www.microchip.com/wwwproducts/en/PIC32MX250F128B
EEG ADC	Texas Instruments	ADS1299	8-channel 24-bit	http://www.ti.com/product/ADS1299
WiFi Module	SparkFun	ESP8266	Integrated TCP/IP	https://www.sparkfun.com/products/13678
Custom PCB				
EEG Electrodes	OpenBCI	N/A	Gold-plated 10 mm dia.	https://shop.openbci.com/collections/frontpage/products/openbci-gold-cup-electrodes?variant=9056028163
EEG Cap	OpenBCI	N/A	Form-fitting	https://shop.openbci.com/collections/frontpage/products/openbci-eeg-electrocap
RasPi Compute Module	Raspberry Pi Foundation	CM3+	Cortex-A53 64-bit 1 GB RAM	https://www.raspberrypi.org/products/compute-module-3-plus/?variant=compute-module-3plus-32gb
Analog input protector	Texas Instruments	TPD4E1B06	4-channel EDS	http://www.ti.com/product/TPD4E1B06
Accelerometer	ST	LIS3DH	3-axis MEMS I2C/SPI	https://www.st.com/en/mems-and-sensors/lis3dh.html

Table 5. Parts List

Current form of project

Currently our project is able to collect data from the OpenBCI headset, classify the input, and then communicate the data to a remote robot, to move based on the data received. The robot being used currently is the Furo service robot, although future robots for control could include the DRC-Hubo humanoid robot or Spot Mini quadruped robot from Boston Dynamics. Furo can move forward, rotate left, and rotate right based on the output from the classification system using input from the OpenBCI headset. Our next steps to fully complete the project require us to effectively filter out unwanted data, create a stronger classification system, develop a more comfortable and user friendly helmet that includes headphones and visual display, as well as develop our own PCB hardware to connect our headset to. Additionally, we will focus on creating a better training process for obtaining EEG data for robot control, as well as implementing certain robot control methods such as obstacle avoidance that can mitigate BCI control error.

Since this project is also part of the Avatar XPrize Competition, a qualifying submission report was submitted in November. The team created an outline and has been populated with important information to qualify for the XPrize competition. Feedback and status from the competition is currently pending. Lastly, the team has written a research paper for the Computing and Communications Workshop and Conference (CCWC) on the BCI research performed. This paper summarized the efforts to train SVM to control the FURO service robot, and discussed our findings in pursuing this research topic. The paper was recently accepted and will be presented in January of 2020 at the conference.

Project timeline

Week	Actions planned
Week 1 (Jan 20-27th)	• Strengthen classification system by using artificial neural networks in place of SVM. • Strengthen filter to effectively remove unwanted data that may skew results • Submit first PCB Design for production
Week 2 (Jan 28-Feb 4th)	• Begin inclusion of sound and visual systems on the helmet • Aid ME partners with helmet design that increases comfort and obtains better brain wave data
Week 3 (Feb 5-12th)	• Work on robot control methods such as obstacle avoidance that can mitigate BCI control error on Furo robot • Continue efforts on classification and filter system • Test first PCB design
Week 4 (Feb 13-20th)	• Continue design of PCB • Continue helmet design (including updated electrodes) • Send any possible PCB revisions
Week 5 (Feb 21-28th)	• Help integrate initial helmet design into one component • Begin attachment of PCB to helmet
Week 6 (Feb 29-March 6th)	• Ensure integrated PCB on helmet works as expected • Continue helmet design and touch ups • Begin implementation with DRC-Hubo
Week 7 (March 7- 14th)	• Complete classification system using ANN • Complete preprocessing filter to remove unwanted data • Begin use of finished helmet and processing on DRC-Hubo and Furo Robot
Week 8 (March 15-22nd)	• Continue DRC-Hubo implementation with helmet • Create simple tasks for DRC-Hubo such as moving arm, closing/opening fists, move in wheel mode, etc
Week 9 (March 23-30th)	• Continue expanding on DRC-Hubo movements to possibly include more complex movements
Week 10 (April 1-8th)	• Begin final paper and presentation • Implement any touch ups needed on overall project
Week 11 (April 9-16th)	• Continue paper and presentation • Continue research with DRC-Hubo and Furo Robot

Week 12 (April 10-17th)	● Have a completed and working system ● Run testbench and verify robustness ● Continue on paper and presentation to include all data and research captured
Week 13 (April 18-25th)	● Have a completed paper and presentation

Table 5. Timeline

Problems to solve

- **Preprocessing** - data obtained from the helmet must go through preprocessing to remove any unwanted data that may skew results. Currently, the preprocessing system does not filter all unwanted data, such as eye and facial movements.

- **Classification** - After preprocessing the data must be processed through machine learning to give a classification. Currently, the use of SVM does not yield accurate enough results. Moving to a more effective machine learning system such as artificial neural networks would yield more accurate classification.

- **Helmet Electrodes** - The current electrodes provided by the OpenBCI helmet are not robust enough for long term use. They are poorly made and do not consistently obtain accurate data from the user's scalp. A custom or market solution needs to be used.

- **Helmet Comfort** - The current helmet is uncomfortable.

Final remarks

In summary, our project is aimed at creating an EEG helmet that uses DSP techniques, feature extraction, and machine learning classification methods to map signals created by the users brain to a variety of outputs for robotic telepresence. These outputs include, but are not limited to: remote robot control, wheelchair control, VR interactions, and surgical devices. Our project is aimed to aid in a variety of applications and fields of study such as neuroscience, remote surgery operations, VR therapy, military defense, and disability research. However, the greatest application will be to open up the “Future of Work” to a new population of workers that are eager to enter the workforce.

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