Optimizing Brain-Controlled Prosthetic Arm Motion

Group 8 | Project A-9
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Abstract

Current prostheses are limited in their range of use and biocompatibility. The goal of this project was to design an optimal brain-computer interface (BCI) to control a robotic prosthetic and replicate the function of a healthy human arm. The prosthetic arm was modelled in three-dimensions to conduct eight movements of the forearm, operating with the assumption that the upper arm remains still and the elbow is a hinge. This simplified model allowed the team to focus on using EEG signals to produce commands corresponding to user intention. These commands control the movement of the prosthetic using real-time linear quadratic reference tracking which actuates motor commands of the prosthetic via kinematic modelling. The proposed design solution has been conducted with all stakeholders in mind while formulating specific design criteria to adhere to. The implementation of the proposed BCI system would allow individuals with limb-loss or paralysis to control robotic protheses with their thoughts and intentions. This ground breaking technology will continue to revolutionize the medical industry as this project aims to be an initial step in significantly improving the quality of life of prosthetic users.

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1 Background

1.1 Introduction

An estimated 0.5% of people are living with an amputated limb due to injury or disease [3]. Limb loss of the leg, arm, or hand drastically changes the daily activities and way of life of an individual. Artificial limbs have advanced over many years from being made of wood and leather to using light weight carbon fiber materials. Recently, there has been an increase in the use of robotic technology as a method for controlling prosthetics to restore biologically accurate motion [4]. In fact, assistive robots are becoming common in the medical field for use in wheelchairs, surgical tools, rehabilitation devices, and many other mechanisms. However, many of these applications do not encompass the goal of acting as a biological extension to a human body. This shortcoming leads to the involvement of a manual operation tool such as a joystick or a keyboard [5].

Prosthetic design is an imperative medical application of assistive robots, however, the use of manual commands would be unrealistic in everyday life as it contradicts the way a healthy human limb operates. Specifically, the objective of prosthetic design is to replicate the function of the missing limb. A brain-computer interface (BCI) that transmits neural signals to a computer has the potential to allow a person to control a robotic limb with their thoughts and intentions. With the development of an effective BCI system, artificial limbs can act as an extension to the human body and remove the need for external input devices.

Current BCI systems for prostheses have a range of limitations including the variability, complexity, and accuracy of tasks that can be executed. Therefore, BCIs cannot yet optimally operate prosthetic limbs. In this project, the team has explored BCI development to provide amputees with a system of limb control that is receptive to a greater variety of their needs, in comparison to existing prostheses. The team focused on optimizing the transmission of neural signals to the decoder, accurately interpreting these signals, and actuating the neural intentions to perform physical tasks on a prosthetic limb.

1.2 Current Prostheses and Their Limitations

The limitations regarding current prostheses give researchers the motivation to further develop BCI robotic limbs. One type of prosthetic arm is a body-powered system in which a three-harness cable allows the user to operate the limb [6]. This would be done using other parts of the body. No external energy is required and the devices are low weight and easy to use. A costly compromise for this model is the sacrifice of movement precision. [6].

Myoelectric prosthetic arms are becoming increasingly popular. When the brain sends a signal to a body part to complete a task, the nerve activity is sent to the residual limb.

This is then interpreted and the intent is estimated, for the robotic limb to carry out the task [7]. Myoelectric prostheses read the electromyographic (EMG) signal at the limb ending; not directly from the brain. Many amputees do not have the required use of nerves or muscles in the residual limb due to various health conditions. Therefore, myoelectric systems must vary per patient, depending on the amount of limb loss and the condition of residual nerve endings. Although these devices have increased functionality compared to previous prosthetic models, the team has elected to further analyze BCI systems due to the limited potential of current myoelectric prosthetics.

1.3 Brain Computer Interfaces

A Brain Computer Interface (BCI) is a system that provides a communication channel between a human and some external hardware [8]. A BCI system includes a number of elements: a sensor that records the user's brain signals, an algorithm that interprets this neural activity as a control mechanism for the external hardware, and a means of sending feedback to the user about the result [9]. When used to control prosthetic arm movement, a BCI system provides a real-time, interactive, and non-muscular output and ultimately becomes an integrated extension of the user. The varying types of BCI applications and signal acquisition methods will be further discussed in this report.

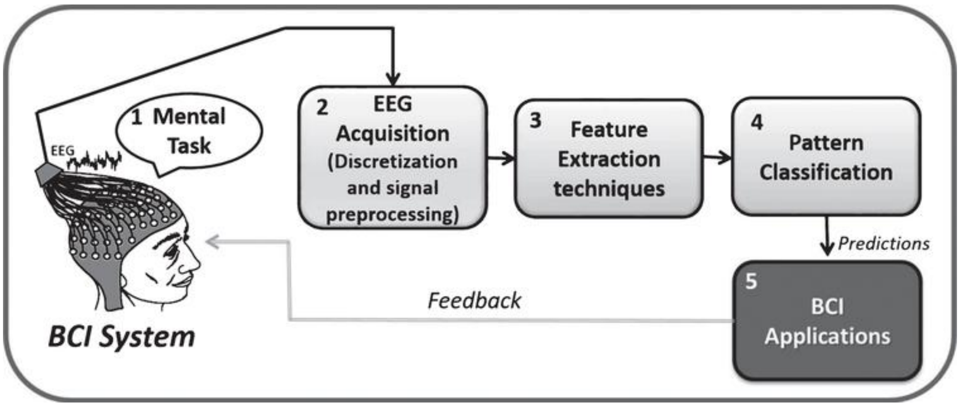

Figure 1: General block diagram of an electroencephalogram (EEG) based BCI system. [1]

1.4 Data Acquisition Methods

The first step in the BCI system is to record neural activity. This task has been accomplished by an array of methods considered in previous studies and it can be done both invasively and non-invasively. Invasive data acquisition methods use sensors such as an electrocorticography (ECoG) or intracortical electrodes [10]; these are placed in the primary motor cortex of the brain [11]. Alternatively, non-invasive methods exist such as an electroencephalograph (EEG) [12]. This entails a measurement of the waveforms representing cortical electrical activity and signals are acquired by electrodes placed on the scalp [13].

The non-invasive method was chosen for this project because it is more cost-effective and no surgery is required, which reduces the risk for the patient [14]. However, when contrasted to invasive methods, there are drawbacks to recording the electrical activity at a further distance rather than at the source. For example, the electrical signal is distorted, has a weaker amplitude, and is noisy [15]. Noise is any part of the recorded signal that is not directly from the brain and therefore makes the data more difficult to analyze. Noise may be due to movement, intrinsic noise from signal amplification, or ambient noise [16].

After the EEG data has been recorded, it must be interpreted to act as an input to the BCI system. Different ways of analyzing EEG signals have been studied and will be discussed in the following section.

1.5 Classification of Signals

In order to interpret EEG signals, they may be compared to EMG signals, which are measured using electrodes that detect electrical activity in the muscles at the surface of the skin, most often near the residual limb in question [17]. In this process, EEG and EMG data are simultaneously collected [18]. Classification of the EMG signals corresponding to muscular movement is done by an experimentally-determined variance threshold [19]. This allows characteristics in EEG signals to be associated with the user intent.

However, due to the high signal to noise ratio inherent in biological signals, it is not currently feasible to directly interpret precise muscular activation [17]. Within the scope of this project, it is assumed that correct classification of EEG signals to movement types is possible. This includes the flexion of a particular muscle group. The muscle activation then occurs by translating the brain's intentions to cause calculated rotation to specific joints of the prosthetic. The pattern of combinations of joint flexion would lead the prosthetic accomplishing a specific task.

2 Design Process

2.1 Problem Description

Current non-BCI robotic prostheses have many limitations that restrict their extent of use and lead to their lack of bio-compatibility. Additionally, BCI systems are not compatible with the level of operation an artificial limb must have to resemble similar functionality to that of a human body part. BCI technology must be further developed to allow accurate and reliable prosthesis operation. Advancements must be made to address the following limitations associated with current BCI systems: accuracy of execution, number of possible actions, reliability, and time to execute. Furthermore, multiple requirements exist such as: extensive user training, user feedback, use of counter-intuitive commands, and potentially invasive signal acquisition. Taking into consideration the needs of the performance of the interface as well as the needs of all stakeholders involves, the goal was to design a BCI system that addresses these concerns and presents the possibility of intent-controlled prosthetic limbs.

2.2 Problem Scope

The scope of the project will be restricted to using a BCI system to control a prosthetic limb, as this choice will target amputees. The chosen BCI system interprets EEG signals directly from the user's brain which services a larger scope of patients and applications. Other models such as myoelectric prostheses are limited to patients with particular amounts of limb damage. This is because there is a minimum number of nerve endings required on the residual limb to properly interpret EMG signals. The BCI signal the team intends to model will use signals interpreted directly from the brain allowing use for all amputee patients regardless of neuromuscular damage in residual limbs.

There are many limitations and assumptions that must be made to design a suitable BCI system, largely due to the lack of knowledge on the communication channel from the brain to human limbs. This barrier leads us to solving the information theoretic problem where the team will focus on the transmission of the neural signals to the decoder and the accurate interpretation of these signals as physical tasks. The group will need to solve a series of optimization problems while the artificial limb is executing a task. This will involve constantly updating the path according to visual and tactic feedback. The feedback will be need occur over a finite time horizon. The system, though primitive, models 8 movements of the forearm- operating with the assumption that the upper arm remains still and elbow is a hinge. The inputs to the system are modelled as force and torque values, which would move the forearm in a specific task. The brain signal sensors, the BCI, and the prosthetic arm, will be modelled in three-dimensions and results will be assessed against various design criteria.

During the design process, the needs of all stakeholders will be taken into account yet the BCI users will still be the highest priority. Thus far, the team has decided to focus on modelling a BCI system for a prosthetic arm, however the conclusions will have applications to all artificial limbs. Assumptions have been made that the users' neurons properly release signals according to their task intent. These signals must be received by sensors that do not greatly affect the lifestyle of the user, therefore further research will be done to determine limitations in this area. As well, it is assumed that the channel will be noisy and the computer interface must filter this noise in order to read and interpret the signals. After additional research, further simplifications may be made to idealize the problem.

2.3 Stakeholders

Potential stakeholders for the project include patients, prosthetic arm manufacturers, hospitals, and the government. The motive that is driving this project is improving the functionality of a prosthetic arm. The current control design available for patients has been characterized as not user-friendly, expensive and very distant from the mechanics of the natural function of an arm. Therefore, providing a non-invasive solution that closely mimics the operation of the neural control of a human arm would greatly benefit patients and would easily distinguish itself from industry competitors.

Any form of prosthetic or medically assisted device is constructed to help improve the quality of life for its user. The patients within the scope of this project are those suffering with Amyotrophic Lateral Sclerosis (ALS, Lou Gehrig's disease), locked-in syndrome, amputees, and other inhibiting diseases disallowing them to use their physical bodies to perform simple tasks that a healthy-bodied person would be able to. The realism of the prosthetic and the amount of integration between their brain's intentions and the arm's actions directly impacts their quality of life. The more sophistication and life-like movements the model has, the more it allows the patients to behave as if they were a healthy-bodied human. However, the safety and well-being of the user must also be taken into consideration. The team has already elected to use non-invasive methods for the reading of brain signals due to the health risks they invasive methods possess. Moreover, the final design must be as cost-effective as possible while still maintaining optimal performance. By making an affordable product, it becomes more accessible for the customers and hospitals to use.

As mentioned above, prosthetic arm technology still requires considerable development until the product can perfectly mimic regular human arm. A design that approaches this goal becomes a larger consequence to manufacturers. Using materials which are both cost effective as well as promote high performance will be difficult for manufactures to find. To balance these two factors, the design must have efficient integration between brain signals and prosthetic movements. This will allow for greater longevity for the device allowing the manufacturers to be more flexible on the material they choose for production. Furthermore, the ease of implementation on a physical prosthetic and user-ability is of high importance and must be considering in the manufacturing process.

Hospitals are charged with the task of installing prostheses on patients. The link between the BCI and its user is forged through intensive training and becoming comfortable with the device. If the design of our project can mitigate the required training time for adequate integration, there will be less dependence by the patients on medical staff. Therefore, a design which is non-invasive and has minimal training time greatly benefits the hospital financially and temporally.

The government allocates funding for those who require prostheses. Therefore, an affordable design means the government could save money or provide coverage for more patients in need of a prosthetic limb. The government will also need to implement new legislation regarding BCI technology. It is unprecedented to have a device with this transparent of access to a user's thoughts and intentions. Therefore, there will need to be government intervention to ensure the safety of all users.

2.4 Triple Bottom Line Analysis

2.4.1 Economic Considerations

Providing a cost-effective solution to the problem at hand will have a significant economic effect and benefit all stakeholders. Currently, the Canadian government provides 75% to 100% coverage of prosthesis for a patient, [20]. Hence, a lower cost benefits the actual patient and allows the government to either provide more people with coverage or increase their percentage of coverage.

An easier implementation process however, will reduce the necessary surgeries and may consequently lose hospitals money. As surgeries are a large contributor to a hospital's revenue, they will not be needed if the design is non-invasive [20]. Although, if the patient's operation of the technology is intuitive for them, they will avoid spending money on paying staff to teach and train them [20]. Therefore, maintenance will become the job of specialist engineers, with the upkeep of the software of the BCI.

2.4.2 Environmental Considerations

There will be no physical prototype or material manufacturing of our design. Moreover, the environmental considerations will be made under the assumption the interface and prosthesis will eventually be manufactured. Environmentally conscious production decisions will need to be made by those delegated to building the physical design. This entails deciding the quantity and type of materials to be used. The components in the design must also be sourced and produced in an ethical and sustainable way to reduce the product's ecological footprint. Our team would make recommendations to the manufacturer ensuring the materials used are recyclable and create minimal plastic waste during the assembling process. Reducing the amount of waste once the user is finished using the BCI will be the most crucial environmental impact of the design. Since BCI's are specialized to the user, it will be difficult to reuse the machinery. The interface has been rigorously trained to synchronize with its former user and their neurological intentions. The BCI's compatibility will not come organically with a new user and measures must be taken to avoid our design from being a one-time use product. The design must therefore have the capability to be re-calibrated to a blank slate. If this can be accomplished, it can allow the BCI to fully integrate with the new patient's neural activities. If the machinery become unusable, the design will aim to be fully recyclable and suffice the electronic recycling standard established by Electronic Product Stewardship Canada (EPSC) [21].

2.4.3 Social Considerations

As BCI technology stems from therapeutic purposes, it is essential our design improves the user's quality of life without hindering any aspects of the user's current lifestyle. The overarching goal for the BCI system is to limit the impacts of the user's disability on their everyday life in both a physical and social sense. To accomplish this, social considerations are mandatory. The design must not deter the user's ability to perform essential daily functions such as eating, exercise, breathing, hearing, and vision. This is enforced under the Quality Systems ISO 13485 legislation by the government of Canada as it requires all medical device manufacturers to have a quality system certificate as evidence of compliance to the appropriate quality system requirement [22]. The social aspects of the user's lifestyle must also be maintained. Their ability to practice their religion, wear specific cultural garments, communicate, and their ability to travel must not be inhibited. This enforces a non-invasive design which can also be transported with ease with straight-forward calibration for the user. Since each user will have varying needs for the design (locked in syndrome, amputee, ALS, etc.), the design should also be constructed to cater each individual case.

The acquisition of neural information will be done in a non-invasive manner which induces considerably less medical risk than invasive methods. The proposed non-invasive system still raises questions regarding the correlation between BCI usage and brain plasticity. Accounted for in the design specifications, naturally there will be high repetition of specific pathways utilized to perform tasks. This leads to the possibility of negative effects on brain structure and functioning via long-term stereotyped use of specific brain signals [23]. This possibility has been linked to impacting the user's mobility and creativity when needing to solve a new task in a different way causing 'rearrangement' problems. These arise when the BCI does not function as expected and the user is unable to adapt. This can lead to negative feelings and low self-esteem, which increases the risk of adverse psychological effects. In current and future trials, it is important to monitor and analyze possible rearrangement effects that may result from BCI usage.

2.5 Design Considerations

2.5.1 Contributions to Prosthetics

Improving BCI-controlled prostheses by rigorously developing the mathematics for the subject, has the potential to radically change the prosthetic industry and positively affect all stakeholders. The contributions this will make to the field of prosthetic design are: creating movement that more closely resembles a human arm, provide methods of communication and interaction to those with neuro-muscular degenerative diseases such as ALS, multiple sclerosis (MS), and locked-in syndrome. Table 1 lists the complications caused by various neuro-muscular diseases and their affect on the functionality of BCI-control. In the case of neuro-muscular disease, the BCI would be implemented with an exoskeleton rather than a prosthesis.

Table 1: Effects of Neuro-Muscular diseases and their implications on BCI

Disease	Effects	Implications
Amyotrophic Lateral Sclerosis (ALS) [24]	Motor neuron death causing an interruption to the transmission of motor signals. Rates of progression vary which can lead to lock in syndrome and often respiratory failure.	Given only motor neurons are affected, an EEG would still be able to gather relevant signals from the brain as motor neurons simply receive then transmit signals for the brain.
Locked In Syndrome [25]	Damage to the pons, a region of the brainstem containing important neural pathways between the cerebrum, spinal cord and cerebellum. This prevents all voluntary muscle movement except for limited eye movement.	If damage is localized to the pons, then an EEG is still able to collect relevant signals from the brain as the pons acts mostly as a communication site.
Multiple Sclerosis (MS) [26]	MS is characterized by deterioration and scarring of the myelin and nerve fibers in the brain, spinal cord and optic nerves. Myelin facilitates electrical transmission across the nerve fibers.	Given that MS causes deterioration of signals in the brain a BCI may not be able to effectively communicate with all pathways. This will vary with patients as the deterioration is unpredictable and poorly understood. It may be possible to overcome this issue using different calibration for patients with altered brain pathways.

BCI-controlled prostheses also have the potential to drastically reduce the amount of rehabilitation an individual requires in order to effectively operate their prosthesis. This is achieved by emulating the operation of a natural limb. A limitation to this rapid rehabilitation is the variance between individual brains. The weighting of this issue dramatically increases when considering children as their brains are in a development phase. This produces more unknowns and will require a method to calibrate the prosthesis at an individual level [27]. This technology also has applications in virtual training/rehabilitation and in the commercial video game market if the technology becomes sufficiently advanced [28]. This will be further discussed as a social impact of BCI technology.

2.5.2 Complying with Regulations

To make BCI-controlled prostheses viable, they must also be a competitive option. This means a comparable price point, while balancing functionality and comfort, and ensuring relevant regulations and standards are met to ensure safety of the user and surroundings. The issue of adaptability to all users is also a component of optimal functionality of the device. Operationally the BCI will be required to issue actionable commands in real time. This will impose a feedback and data transfer limitation to the system which stresses the need for optimal interpretation of brain signals.

The use of integrated sensors requiring surgical implantation will not be recommended in this project. The is mainly attributed to user safety and the fact rigorous standards have yet to be adopted to govern such implants. Regulatory bodies such as the FDA have published recommended guidelines, however, more research and analysis of the risks involved are required before recommending such sensors for implementation. The advantages of such sensors are note worthy as they can provide superior data [29].

While the scope of this project will focus on the feasibility of implementing BCI-controlled prostheses and applying the mathematics to optimize the system, there is still concern regarding the implementation process. The applicable regulations and standards governing a medical prosthesis, electrical components, and the physiological closed loop control system must be considered.Table 2 lists major standards and regulations that will need to be followed while implementing BCI-controlled prostheses. The largest concerns being the encoding of the personal data for privacy and security, and ensuring the BCI is safe for long term operation. For example, the longevity of the device so that it will not cause damage to the wearer in any way.

Presently, the Canadian Government is implementing an Action plan to revise the regulations for medical devices. Any changes pertaining to the implementation of a BCI-controlled prosthesis will be considered moving forward [30].

Table 2: Regulations and Standards Applicable to BCI-controlled prostheses

Organization	**Code**	**Application to BCI**
International Organization for Standardization (ISO)	ISO 22077-1:2015	Encoding medical reading data for privacy and security of personal information [31]
International Electrotechnical Commission (IEC)	IEC 60601-1-10	Standard Governing physiological closed loop controllers. [32]
ISO/IEC	23005-3:2019	Sensory information for feedback to user [33]
Standards Council of Canada (SCC)	Z323.3.1-1982 (R2008)	Standard for electrical aids for physically disabled persons [34]
Government of Canada (SOR)	SOR/98-282	Canadian regulations for medical devices [35]

2.5.3 Design Criteria

A solution to implementing BCI-control into the prosthetic industry will evaluate the feasibility of the system. The problem at hand has been identified, it now becomes imperative see how well the design will solve this problem. Explicit design metrics must be made to ensure the design's optimality can be gauged. Each criterion must adhere to both stakeholder needs as well as take into consideration the limitation of the design project. To achieve peak effectiveness, the BCI system should also mimic human motions as closely as possible and still be reasonably intuitive to use. This entails analyzing the system's accuracy, rate of operation, number of possible arm actions, adaptability, usability, and other design metrics. Furthermore, various methods of data acquisition from the brain and prostheses will be explored for implementation in the model. Further brainstorming and explanations of design criteria can be seen below.

Table 3: Table of specific design criteria and their corresponding metric for evaluation.

Criteria	**Metric for Evaluation**
Accuracy of command implementation	An acceptable minimum amount of distortion between the executed trajectory (user action) and the desired trajectory (user intention) of the limb is accomplished.
Mimicry of human motion	The prosthetic takes the most direct and smooth path as possible. Uses multiple pivot points and takes into consideration the biomechanics of a healthy arm leading to life-like motion.
User training requirements	An able minded individual is able to intuitively learn to use the device with minimal difficulty and time.
User safety	Non-invasive methods are used and the user/caregiver is comfortable with using/administrating the device.
Cost of product	Should manufacture under $ 10,000 CAD and retail under $ 100,000 CAD making it competitive in the brain-controlled prosthetics market (See Economic Considerations & Impact).
Environmental sustainability	Design is made with sustainable products and has a lifetime longer than a single use (see Environmental Considerations & Impact).

3 Solution Design

3.1 System Model

The prosthetic arm is modelled as a rod of uniform density (representing the forearm) with one end fixed in place (representing the elbow). This rod will then be constrained to rotate in the plane ignoring the effects of gravity. The model also has the ability to rotate in order to capture pronation of the forearm. This simplified model is being used as the project will focus on how to use EEG or EMG signals to produce commands corresponding to the movement of the modeled arm to enable prosthetic arm control in real time.

3.1.1 State Space Representation of the Model

The initial state space representation of the model was as follows

$$\begin{bmatrix} \dot{\theta} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -\xi \end{bmatrix} \begin{bmatrix} \theta \\ \omega \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{4}{mr^2} \end{bmatrix} \tau \tag{1}$$

Here, θ and ω are the angle of the rod in the plane and the angular velocity in the plane respectively, ξ represents the damping coefficient (modelled with $\xi = 1$), and τ is the torque applied about the pined axis of rotation (i.e. the elbow).

The simulation for the model was then extended to reach a steady state location, this represents the ability to pose and execute a sequential gesture such as a grasp.

3.1.2 Dynamic Modelling

The dynamic model alluded to above, tackles the challenge of taking these intentions and actuating them into motion commands. These commands must direct a prosthetic limb to accomplish a certain task; similar to a brain launching muscle activation. The biomechanical research for this project led to two proposed modelling schemes: dynamic and kinematic modelling.

The dynamic modelling involves interpreting EEG signals as torques of varying magnitudes. For practicality, our system model would be a rod of uniform density (representing the forearm) with one end fixed in place (representing the elbow). This rod would be free to rotate in a circular and two dimensional plane. To approach an intended trajectory on this plane, the EEG signals would relay torque magnitudes to the limb over a specific time horizon. After each horizon the torque outputs would update until the limb reaches the intended destination.

This modelling made use of the preliminary research conducted, however, kinematic modelling was ultimately the scheme used for this project. This is because dynamic modelling failed multiple design criteria, especially the mimicry of human motion. The human arm has several joints and axes of rotation to effectuate wrist and finger motions to move freely in 3-D space. Modelling the system as a uniform rod only able to rotate in 2-D is too primitive of a model to effectively mimic a human arm. Additionally, with dynamic modelling the torque commands were consistently larger than required causing the prosthetic to overshoot its target. This seldom, if ever, occurs with an able bodied human being. For example, a person with a healthy arm does not reach to pick up an object and continuously reaches too far causing them to miss the object. Furthermore, there is still extensive research required to indicate what type of data EEG signals send for muscle activation. Taking EEG data as strictly torques for the dynamic model is too large of an assumption given the amount of knowledge currently known about EEG signals.

3.1.3 Kinematic Modelling

The dynamic model above was exchanged for its kinematic counter part below due to the dynamic model's tendency to overshoot the desired location in the design simulation.

$$\begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix} \tag{2}$$

The new kinematic model incorporates a second axis of rotation, this model no longer suffers from the issue of overshoot and allows for the analysis of simultaneous movement of different joints. This is highly relevant given that the goal is to design a prosthetic with life-like characteristics. Having the ability to simultaneously perform elbow extension and supination is essential for a natural outward reach. In the kinematic model describe by Equation 2 θ_1 is the angle of elbow flexion, π radians at full extension with positive rotation in Extension, while θ_2 represents the angle of pronation, zero radians in full supination with positive rotation in pronation. Figure 2 illustrates the types of motion captured by the model.

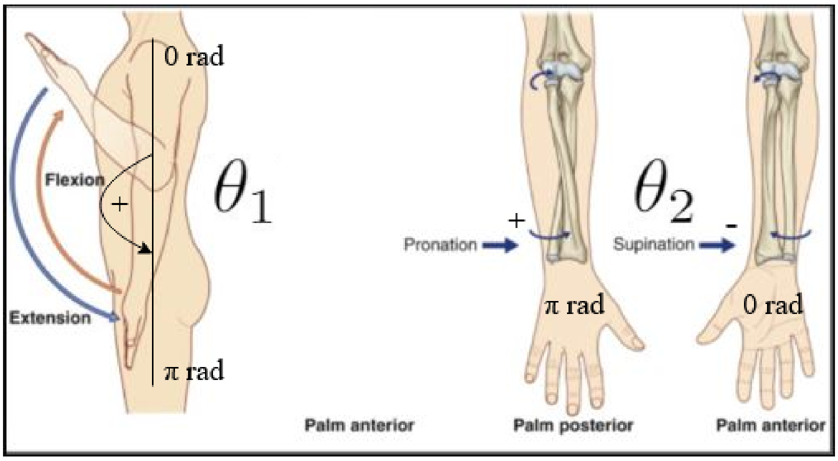

Figure 2: Simulated elbow movement [2]

In both cases the model is discretized with respect to the appropriate time step. This is done before simulation as the control application is digital. The control model used to simulate human control of an arm will be of the form seen below in Equation 3. When using the kinematic model, the system is simplified as there is no drift term (F = 0). In using such a model we are making the assumption that Linear Quadratic Regulator (LQR) control is a sufficient proxy to the human control system to make useful conclusions. This is not strictly true as there are more sophisticated methods of modelling biological systems. For the case of elbow flexion and pronation, however, LQR methods approximate the motion made by a human arm to a sufficient degree. We will also be abstracting the control signals as reference trajectories. In other words, a vector of desired model states.

3.1.4 Optimal Control: Iterative Linear Quadratic

The controller being used to model human control of an arm is an optimal reference tracking controller over a finite time horizon, T, using a quadratic cost function. The desired objective of optimal reference tracking in the context of this project is to tune the weighting matrices Q and R to appropriate sizes (necessarily positive definite in continuous case, R can be relaxed to semi-positive definite for discrete methods). This is done to simulate the control imposed by the brain. These matrices should be designed to reflect the performance metrics and the constraints of a human arm. This will be a reflection of design factors such as maximum torque, range of motion and possibly other parameters. It is probable that an iterative LQR controller is more representative of biological control and would be the next progression of the current model.

Suppose the plant is given by Equation 3. When this is the case, the performance index is given by Equation 4 and the optimal control is given by Equation 5.

$$x(t+1) = F(t)x(t) + G(t)u(t) \tag{3}$$

The performance index/cost function is given by Equation 4. To be minimized, this function needs to achieve optimal control.

$$V(x(t_0), u(.), t_0) = \sum_{t=t_0+1}^{T} \{[x(t) - \tilde{x}(t)]'Q(t)[x(t) - \tilde{x}(t)] + u'(t-1)R(t)u(t-1)\} \tag{4}$$

where $\tilde{x}(.)$ is the reference trajectory. The optimal control is then given by:

$$u^*(t) = -[G'(t)s(t+1)G(t) + R(t+1)]^{-1}G'(t)[s(t+1)F(t)x(t) + b(t+1)] \tag{5}$$

$$b(t) = -[F'(t) + K(t)G'(t)] * b(t+1) - Q(t)\tilde{x}(t) \tag{6}$$

In order maintain optimization with disturbances present, the control must be recomputed at each time step. In the case of this project, this is caused by quantizing the control signal. This is done to ensure that the model accounts for how a person would react differently to a prosthetic that may not move to the same location as intended. This emulates a more adaptive simulation.

3.2 Classification and Quantization of control inputs

The difficulty of using biological signals as control inputs is that there is a fixed channel capacity and the channels have a high signal to noise ratio. Thus, it arises the need to reduce the dimensionality of the set of input vectors. In the case of prostheses controlled by myoelectric signals, often one can only execute one type of motion at a time. This simplifies the problem from a design standpoint, however, it leads to unnatural movements. For the this project, where EEG signals are used, signal classification has been deemed outside of the scope. Despite this, analysis will continue for how best to produce control inputs given a classification of a control signal from the body.

Given the model described in Section 3.1, it is assumed that classification of EEG signals from the brain to corresponding muscle activation is possible. With the particular model being used, elbow flexion, extension, pronation, and supination will be modelled, as well as any other appropriate combinations listed in column three of Table 4 . In order to classify these signals, in the simulated human control, numerical simulated control will be used and classification will be done based on the inputs ω_1 and ω_2 as follows.

Table 4: Classification of control inputs based on modelled control system

Sign of ω_1	**Sign of ω_2**	**Muscle Activation**	**Code**
+	0	Extension	1
+	+	Extension & Pronation	2
+	-	Extension & Supination	3
-	0	Flexion	4
-	+	Flexion & Pronation	5
-	-	Flexion & Supination	6
0	+	Pronation	7
0	-	Supination	8

The proposed method to obtain optimal control inputs involves collecting sample data from healthy individuals. Data acquisition would involve placing sensors on test individuals that are capable of measuring the angle of pronation and flexion of the elbow. In addition, these sensors will measure the angular rate of both motions in accordance with our model. The data would then be used to produce the probability mass function in Equation 7.

$$p(\theta_1, \theta_2, \omega_1, \omega_2, c) = P(\Theta_1 = \theta_1, \Theta_2 = \theta_2, W_1 = \omega_1, W_2 = \omega_2, C = c) \tag{7}$$

where random variables are defined as follows:

- $\Theta_1 \in n\frac{\pi}{N}, n \in 0, 1, \ldots, N-1, N$ which represents the value of θ_1
- $\Theta_2 \in n\frac{\pi}{N}, n \in 0, 1, \ldots, N-1, N$ which represents the value of θ_2
- $W_1 \in nv, n \in \mathbb{N}_{\geq 0}$ which represents the value of ω_1
- $W_2 \in nv, n \in \mathbb{N}_{\geq 0}$ which represents the value of ω_2
- $C \in 1, \ldots, 8$ represents the control classification as per Table 4.

where v is the resolution of the tachometer in use and $\frac{\pi}{N}$ is the resolution of the encoder in use.

From here, we define our optimum control policy as follows:

$$u(\theta_1, \theta_2, c) = (E[W_1 \mid \Theta_1 = \theta_1, \Theta_2 = \theta_2, C = c], E[W_2 \mid \Theta_1 = \theta_1, \Theta_2 = \theta_2, C = c]) \quad (8)$$

This method assumes that only the current state of the prosthetic (θ_1, θ_2) and the control classification for the pending input is known. In this case we choose the expected value of the control input which will minimizes the velocity error at every time step. One way to improve this control would be to consider previous states of the prosthetic. This may involve the possibility of incorporating additional sensors to estimate states. For example, sensors information relative to the shoulder in order to predict the type of motion which is being executed. In this case one could update the probability of inputs to reflect the most likely trajectories in order to improve the control. It is also important to note that this method requires a large collection of sample data in order to ensure the sample is representative of the actual control inputs.

3.2.1 Quantizing inputs over a finite time horizon

The following derivation was done prior to changing the model and approach of the project. Nonetheless, it still remains useful. One of the issues of the updated control scheme is that it is not robust in the face of actions of the same classification which pass through the same state. This leads to the system being unable to differentiate between different trajectories. Given another source of data, it would be possible to distinguish between different trajectories. An example would be the orientation of the shoulder, which could be estimated using embedded sensors. With this information, one could derive a similar metric for the new model to use with a modified kmeans algorithm. This would identify the closest classification resulting in the optimal output.

Derivation of quadratic distortion metric

Equation 9 describes the position at time t_0, where $\mathbf{Q}$ is a function to the quantized space.

$$x_0 = \mathbf{Q}(x_0) \quad (9)$$

Equation 10 and 11 describe the position and quantized position, respectively. This occurs at time t_1, where F and G are matrices describing the state-space system.

$$x_1 = Fx_0 + Gu_0 \tag{10}$$

$$\mathbf{Q}(x_1) = Fx_0 + G\mathbf{Q}(u)_0 \tag{11}$$

The distortion at time t_1 is then given by Equation 12. This can also be stated as the difference between the quantized position and the actual position.

$$V = x_1 - \mathbf{Q}(x_1) = [Gu_0 - G\mathbf{Q}(u)_0] \tag{12}$$

Similarly, the position, quantized position, and distortion at time t_2 are given below.

$$x_2 = Fx_1 + Gu_1 = F^2x_0 + FG(u_0) + G(u_1) \tag{13}$$

$$\mathbf{Q}(x_2) = F(\mathbf{Q}(x_1)) + G\mathbf{Q}(u)_1 = F^2x_0 + FG\mathbf{Q}(u)_0 + G\mathbf{Q}(u)_1 \tag{14}$$

$$V = x_2 - \mathbf{Q}(x_2) = FG(u_0 - \mathbf{Q}(u)_0) + G(u_1 - \mathbf{Q}(u)_1) \tag{15}$$

The position, quantized position, and distortion can be similarly defined for the following time steps.

The generalized equation for distortion at any time, t_i can be seen in Equation 16.

$$V = \sum_{k=0}^{i-1} F^{(i-1-k)} G\delta u_k \tag{16}$$

In the above equation, $\delta u_k = u_k - \mathbf{Q}(u)_k$.

Weighting the distortion in terms of the model (quadratic cost), the weighting matrix, $Q \in \mathbb{R}^{n\times n}$, will now be used. This is positive definite from the system model to assign a cost to the distortion. It so happens that this cost can be represented in terms of δu_i^2 and $\delta u_i \delta u_j$ (squares and cross-products).

The quadratic cost function of the distortion at a time t_i is given in Equation 17, where D can be referred to in Equation 18.

$$C = V^TQV \tag{17}$$

$$V = \sum_{k=0}^{i-1} F^{(i-1-k)} G\delta u_k = \begin{bmatrix} a_0\delta u_0 + ... + a_{i-1}\delta u_{i-1} \\ b_0\delta u_0 + ... + b_{i-1}\delta u_{i-1} \end{bmatrix} \in \mathbb{R}^2 \tag{18}$$

The top and bottom rows of the matrix in Equation 18 can be represented by a_k and b_k, respectively.

$$a_k = [F^{(i-1-k)}]_{1,\cdot}G \tag{19}$$

$$b_k = [F^{(i-1-k)}]_{2,\cdot}G \tag{20}$$

By expanding the quadratic cost function with two row entries, Equation 21 is achieved. Where V_1^2, V_2^2, and V_1V_2 are displayed explicitly in Equation 22 to Equation 24.

$$V^TQV = V_1^2Q_{11} + V_2^2Q_{22} + 2V_1V_2Q_{12} \tag{21}$$

On the right hand side of the following three equations, the expressions are separated into quadratic products and cross products.

$$V_1^2 = \sum_{j=0}^{i-1}\sum_{k=0}^{i-1} a_ja_k\delta u_j\delta u_k = \sum_{k=0}^{i-1} a_k^2\delta u_k + \sum_{j=0}^{i-1}\sum_{k=0(j\neq k)}^{i-1} a_ja_k\delta u_j\delta u_k \tag{22}$$

$$V_2^2 = \sum_{j=0}^{i-1}\sum_{k=0}^{i-1} b_jb_k\delta u_j\delta u_k = \sum_{k=0}^{i-1} b_k^2\delta u_k + \sum_{j=0}^{i-1}\sum_{k=0(j\neq k)}^{i-1} b_jb_k\delta u_j\delta u_k \tag{23}$$

$$V_1V_2 = \sum_{j=0}^{i-1}\sum_{k=0}^{i-1} a_jb_k\delta u_j\delta u_k = \sum_{k=0}^{i-1} a_kb_k\delta u_k^2 + \sum_{j=0}^{i-1}\sum_{k=0(j\neq k)}^{i-1} a_jb_k\delta u_j\delta u_k \tag{24}$$

The quadratic cost function can then be expanded into the expression in Equation 25.

$$V^TQV = \sum_{k=0}^{i-1}([a_k^2Q_{11}+b_k^2Q_{22}+2a_kb_kQ_{12}]\delta u_k^2)+\sum_{j=0}^{i-1}\sum_{k=0}^{i-1}([a_ja_kQ_{11}+b_jb_kQ_{22}+2a_jb_kQ_{12}]\delta u_j\delta u_k) \tag{25}$$

$$D(u_0,u_1,u_2) = \begin{bmatrix}\delta u_0 & \delta u_1 & \delta u_2\end{bmatrix}\begin{bmatrix}w_{00} & w_{01} & w_{02}\\ w_{10} & w_{11} & w_{12}\\ w_{20} & w_{21} & w_{22}\end{bmatrix}\begin{bmatrix}\delta u_0\\ \delta u_1\\ \delta u_2\end{bmatrix} = \sum_{k=0}^{2}[w_{kk}\delta u_k^2]+\sum_{j=0(j<k)}^{2}\sum_{k=0}^{2}2w_{jk}\delta u_ju_k \tag{26}$$

$$q_{jk} = a_ja_kQ_{11} + b_jb_kQ_{22} + 2a_jb_kQ_{12} \tag{27}$$

3.2.2 KMeans implementation for dynamic model

Before implementing the kmeans algorithm in MATLAB code, research was done to determine the ideal method to do so. It was found that the main weakness of the kmeans algorithm is the initialization of clusters. Normally, these points are chosen arbitrarily and this method is often referred to as naive kmeans. The performance of numerous existing alternatives have been compared and quantified, such as is Celebi et. al. 2012. Based on this study, the refinement method to initialize clusters was chosen. This method is described in detail in Bradley and Fayyad, 1998 [36] [37].

For the purposes of this project, a modified version of the kmeans code was needed that used a weighting matrix instead of a distance metric. This weighted kmeans algorithm was implemented in MATLAB with the 'W' matrix generated in the earlier code as the weighting matrix. The previously described initialization method was also implemented in MATLAB and used in the weighted kmeans algorithm.

4 Implementation and Results

The control solution was implemented using Matlab in several stages. The model as seen in Equation 2 was coded in Matlab and a control function was coded to implement the linear quadratic reference tracking control. The model was discretized using a time step of 0.125 seconds. This is the minimum time required to classify an EMG signal [38]. This is also half the average human reaction to visual stimulus. The weighting matrices for the LQR control were then tuned to achieve realistic settling times. This model was now the proxy for a real human arm.

4.1 Simulating Sample Data

In order to simulate sample data, 9 distinct reference trajectories were designed to simulate tasks, a list of which can be found in Table 5. After examining the model's behaviour, it seemed most representative to provide the model with a reference trajectory that was the terminal state for the action. By doing do the reference trajectories provide the behaviour of approaching the desired state more rapidly the further one is from the state. This create closer mimicry of healthy human arm behaviour. The simplified model does not capture more complex human behaviour which makes it sub-optimal for simulating data. The lack of capturing of complex behaviour is remedied by the fact the simulated control's intent is identical in both the human arm and prosthetic arm cases.

Table 5: Simulated Tasks

Tasks	**Initial State**	**Terminal State**
Rotating wrist to write	$\left[\frac{\pi}{2}, \pi\right]$	$\left[\frac{\pi}{2}, \frac{\pi}{2}\right]$
Rotating wrist to rest	$\left[\frac{\pi}{2}, \frac{\pi}{2}\right]$	$\left[\frac{\pi}{2}, \pi\right]$
Scratching head	$\left[\pi, \frac{3\pi}{4}\right]$	$\left[\frac{\pi}{6}, \frac{3\pi}{4}\right]$
Relax arm after scratching head	$\left[\frac{\pi}{6}, \frac{3\pi}{4}\right]$	$\left[\pi, \frac{3\pi}{4}\right]$
Outward reach	$\left[\frac{\pi}{2}, \frac{3\pi}{4}\right]$	$[\pi, 0]$
Relax arm after outward reach	$[\pi, 0]$	$\left[\frac{\pi}{2}, \frac{3\pi}{4}\right]$
Support head with hand	$\left[\frac{\pi}{2}, \frac{3\pi}{4}\right]$	$\left[\frac{\pi}{6}, 0\right]$
Unsupport head	$\left[\frac{\pi}{6}, 0\right]$	$\left[\frac{\pi}{2}, \frac{3\pi}{4}\right]$
Throwing	$[\pi, 0]$	$\left[\frac{5\pi}{6}, \pi\right]$

The code seen in Appendix A.1 was used to simulate the above actions and implement the methods seen in Section 3.2. This was done to generate a data array that operates as the function for the optimal control policy. The sample data, real time state, and classification as given in Equation 8. This array is then safe to be used in order to simulate the prosthetic control and compare it to the modeled control of a human arm.

The simulation was then ran for the 9 actions listed in Table 5 using the code from Appendix A.2. The performance plots from this simulation are seen in Figures 3-11. As a prelude to the evaluation, one should note that the simulated data was not adequate to provide representative data. This could be rectified in further simulations, however, given the constraints of the project this was not feasible for this deliverable. In order to compensate for the lack of sufficient sample data, sub-optimal methods were used to complete the simulation. In these cases the control input for states and control classification that did not have any data were computed by averaging over all the states in the given configuration classification. This is reflected in the constant angular velocity for much of the simulations.

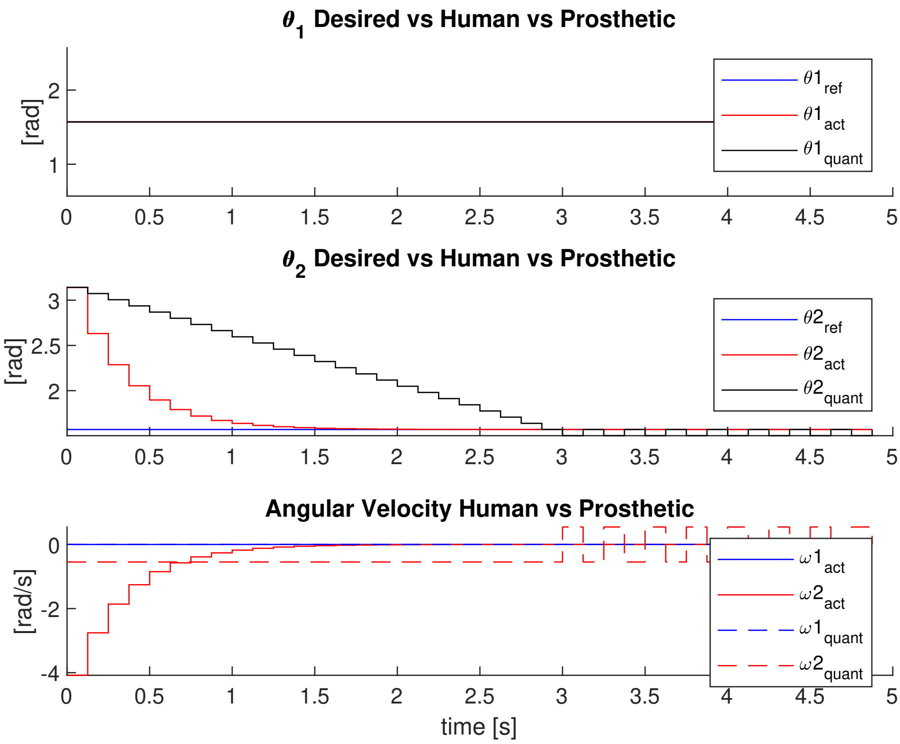

Figure 3: Performance for Action 1

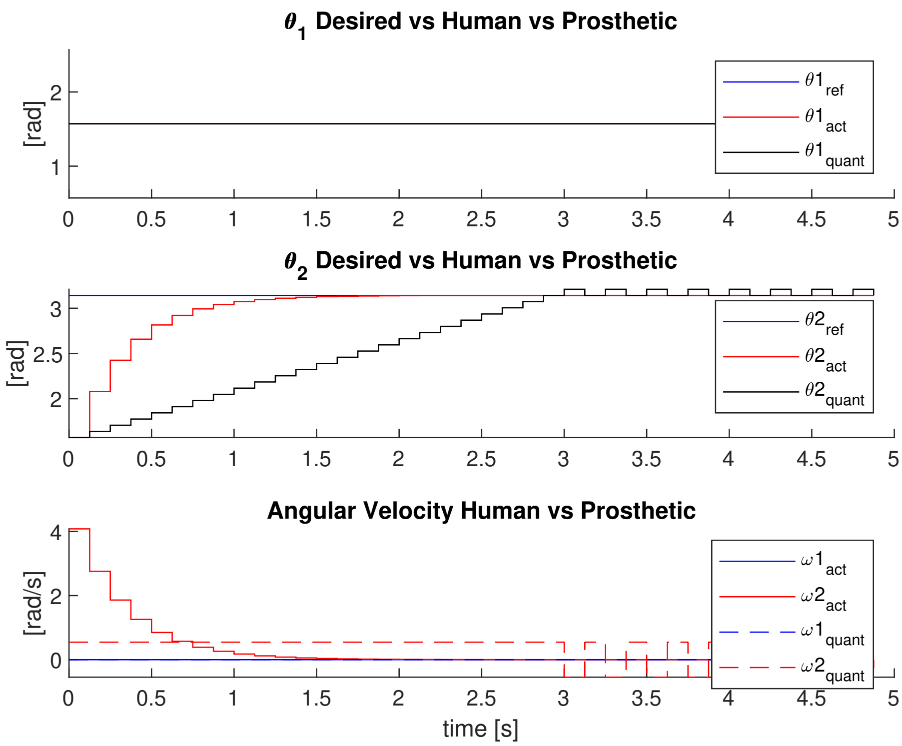

Figure 4: Performance for Action 2

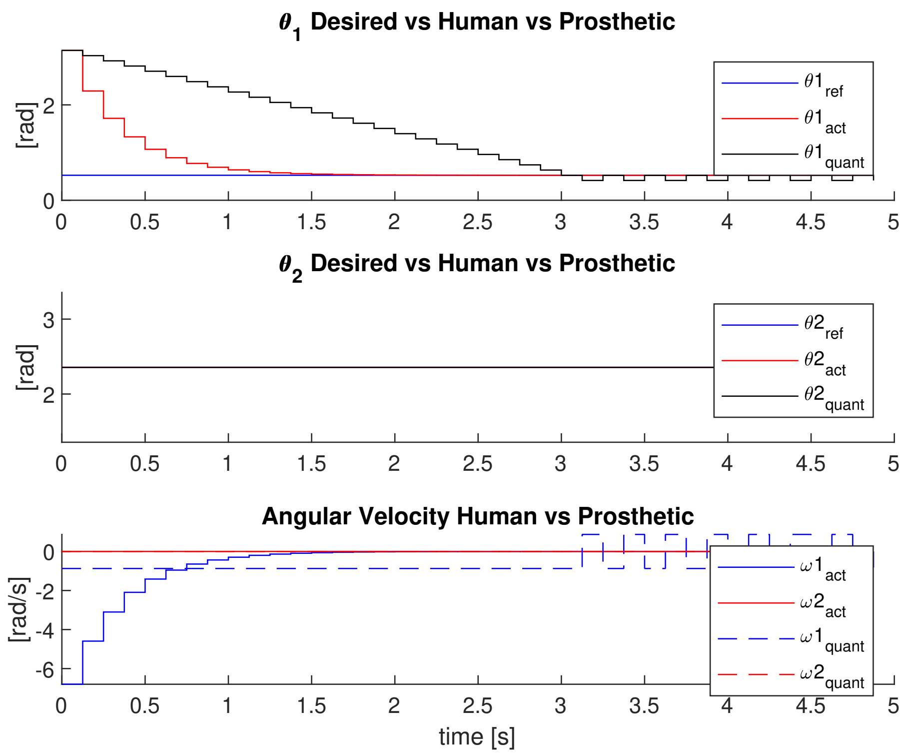

Figure 5: Performance for Action 3

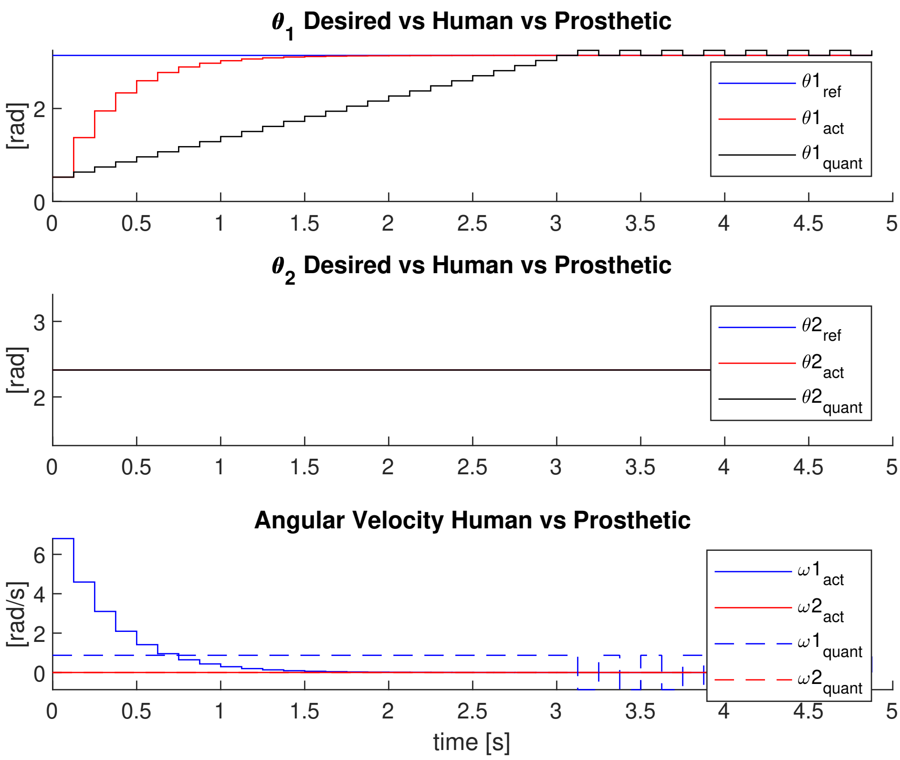

Figure 6: Performance for Action 4

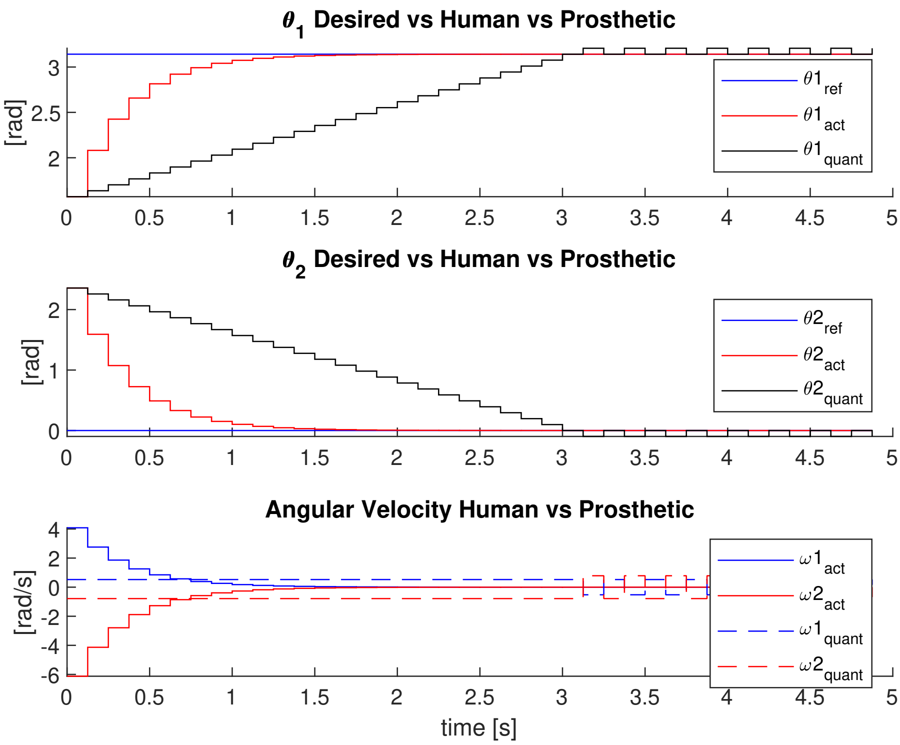

Figure 7: Performance for Action 5

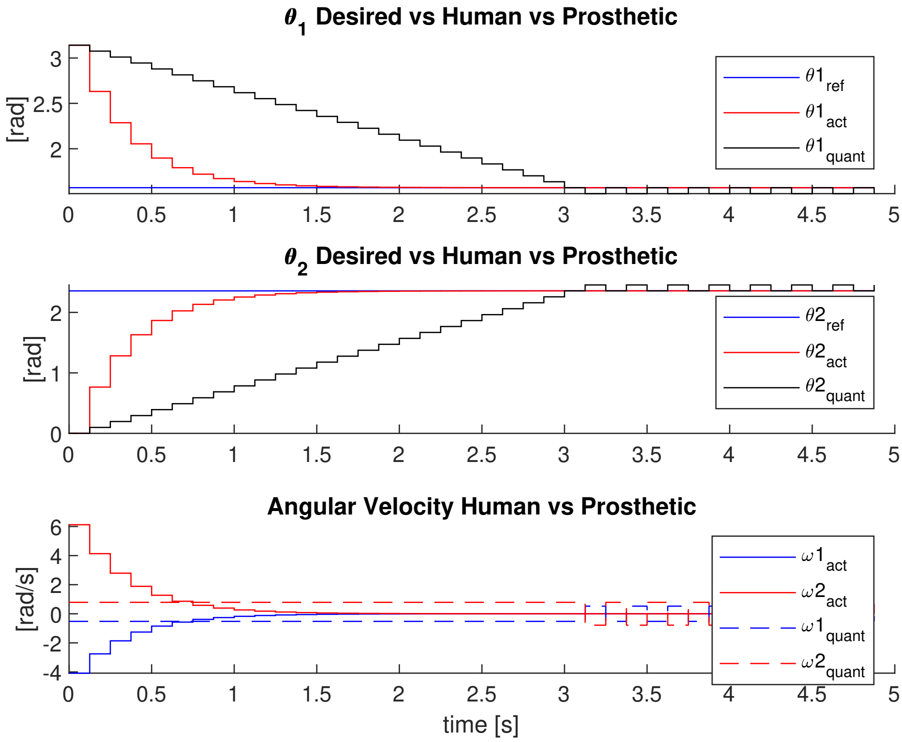

Figure 8: Performance for Action 6

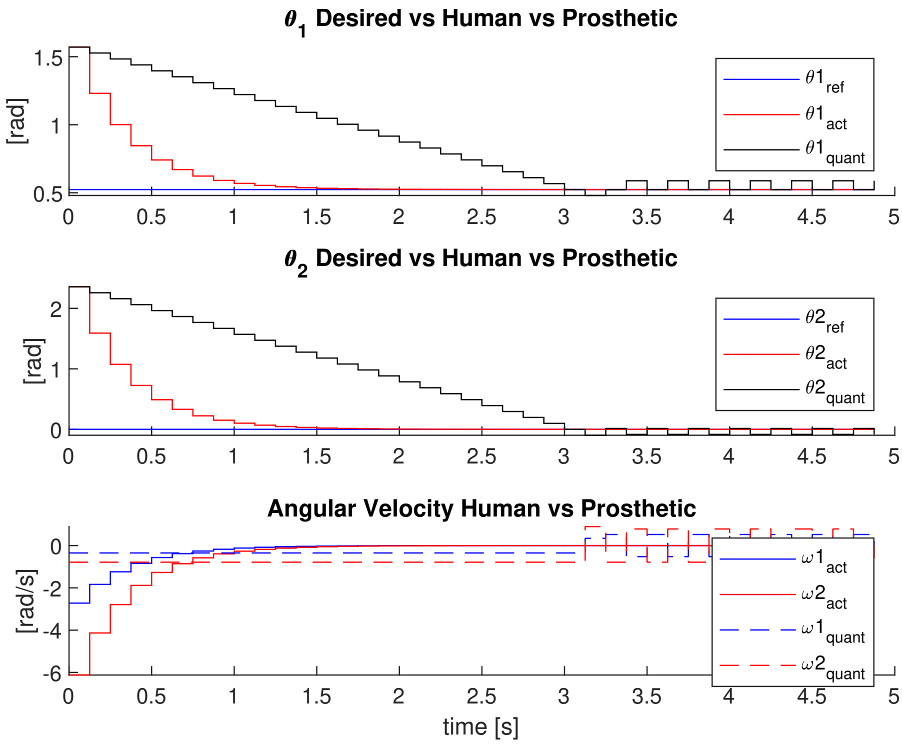

Figure 9: Performance for Action 7

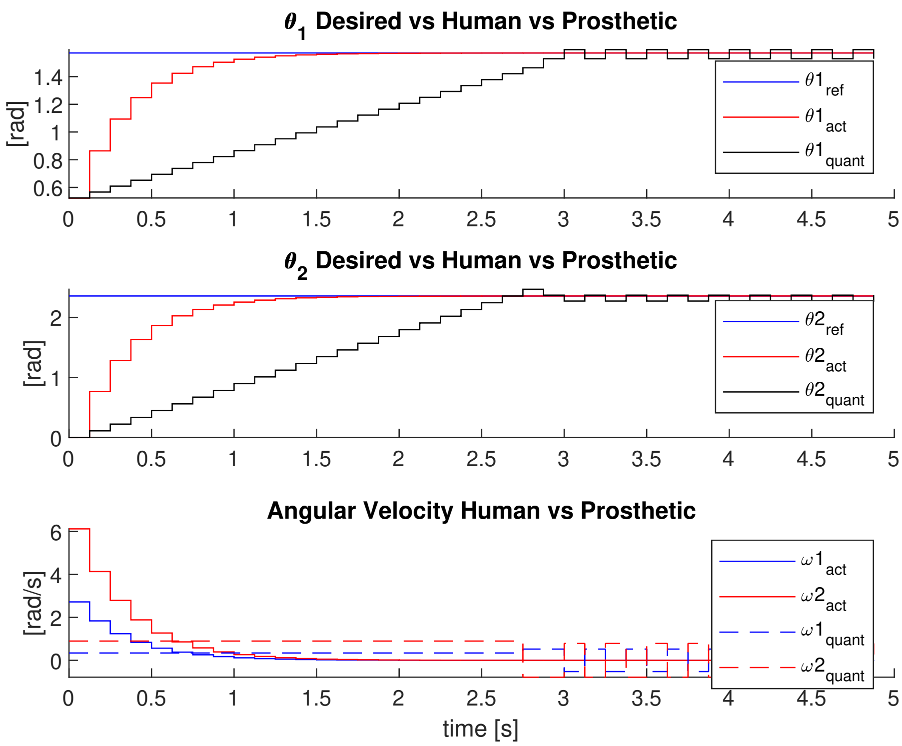

Figure 10: Performance for Action 8

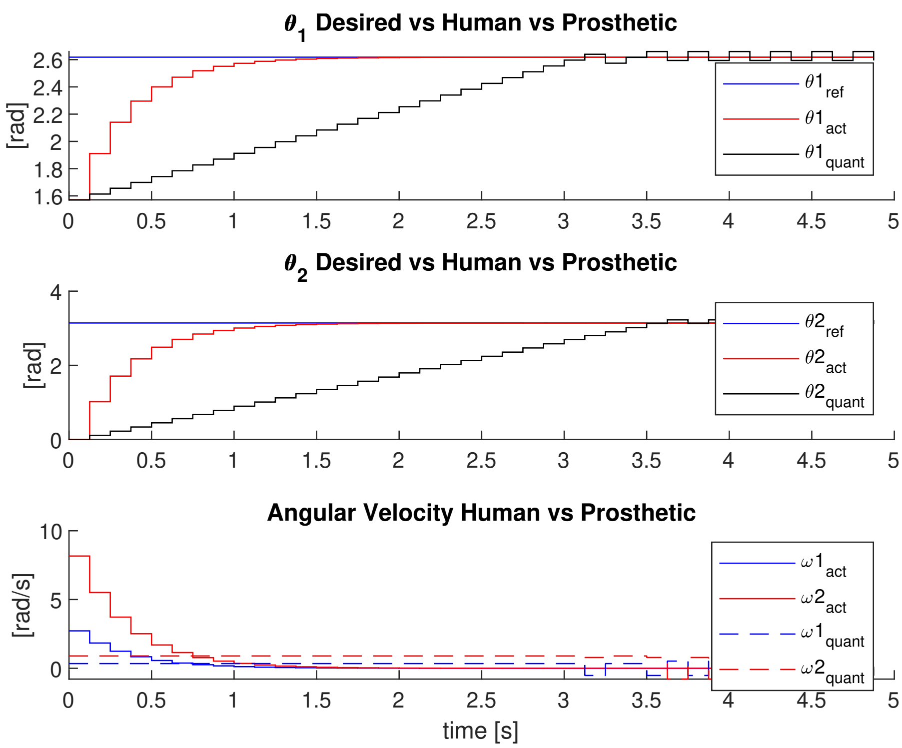

Figure 11: Performance for Action 9

5 Design Evaluation

The current design does not meet the expectations for a successful control system. While in all test scenarios the prosthetic control does reach an equilibrium around the desired terminal state, it takes approximately twice as long as the model for human control. It also tends to oscillate about the trajectory. While it is likely that the user would compensate to avoid these oscillations, this fact represents the incompleteness of the model. In practice a human cannot identify the state of the arm to the level of precision assumed by this model and therefore would be unlikely to experience the oscillations around the terminal state. This leads to the belief the user would rather have a constant steady state error.

The most notable flaw in the simulation is that it failed to capture the behaviour of the 9 simulated actions as intended. This could be for one of two reasons. It is possible that the simulation has an indexing bug which categorizes the state angles incorrectly. The other possibility being there is not enough sample data to produce an accurate representation. The later creates a more prominent altercation. Any state and classification combination (θ_1, θ_2, c) that was not reached during the simulation is simply assigned the input of the average input over all states for the given classification. This makes the possibility of an indexing bug very difficult to identify whether or not it is at fault.

5.1 Performance Against Design Criteria

Under the current model, the classification of user intent is accurate and the users intention is carried out. Albeit in a limited capacity. Given the limited sample data, it is evident that the simulated control model has not captured the modeled human control aspects. The simulated control model simply demonstrates categorically robotic movement and often maintaining the same angular rate for extended periods of time. The habitual oscillation around the trajectory will also make it more difficult for users to train with the model. For fully effective use of the device they will need to become in-tune with these oscillations. This fails to meet the design criteria for user training because even an able minded user will find this task incredibly difficult.

This being said, the control policy would allow for an individual to control the prosthetic to a reasonable degree. This control would be done with significantly slower and less precise than a human arm. In regard to the lowered precision, it still offers a reasonable range of utility. In addition, the control did not exhibit any extreme behaviour under the simulation that may harm the user or cause the user distress.

Other design criteria is subject to manufacturing process and releasing the product to market. As addressed by the economic analysis, in the near future the product has little chance of becoming cost effective within a manufacture price of $ 10,000 CAD and a retail price under $ 100,000 CAD. This would make our design model less competitive in the brain-controlled prosthetics market. Additionally, the design can be restarted and implemented for new patients. This negates the BCI as a one-time use device. The ability to reuse the device and manufacture ethically will meet the requirements of environmental sustainability.

6 Impact of Engineering

6.1 Environmental Impact

One of the largest stakeholders for this design are patients suffering from locked in syndrome, MS, amputes, ALS, and the medical industry as a whole. The main service of our BCI design will be to accommodate these people by replacing or reducing the need for current methods of treatment. The medical industry heavily relies on plastics as up to 85% of hospital garbage is nonhazardous solid waste. Major contributors are plastic packaging (many surgical products are double-wrapped) and blue sterile wrap used to cover surgical instruments [39]. A common treatment for ALS patients is the use of Edaravone (Radicava) which contributes to the plastic waste hospitals experience. Used to reduce the decline of daily functioning, the drug is given by intravenous infusion which uses a variety of plastic products [40]. The BCI design's impact could reduce the use of this treatment and therefore limit the amount of plastic waste produced while tending to patients.

The BCI technology to control robotic arms using EEG rhythms can also be applied to a variety of industries by increasing the accuracy of HCI systems. This would result in BCI contributions in various fields such as industry, educational, advertising, entertainment, and smart transportation. As BCI technology progresses, able bodied people will also be able to apply the interface to perform tasks. These tasks have the potential to be carried out with enhanced precision and safety compared to if they were done physically. A direct environmental impact is the use of BCI in the manufacturing industry. By directly training machinery or an able-bodied person using a BCI, increased efficiency within production sites may occur which consequently will reduce waste. As our design will not be manufactured, the environmental impact of this project is limited. It is the concept of the design in the grand scope of BCI progression which has the capabilities to have substantial environmental impact in the future.

6.2 Social Impact

Since BCI's are currently used only in research contexts, it is critical to gauge the social impacts of this technological before it becomes widespread amongst patients. As social media dominates an increasing amount of our lives, it is feasible to expect patients will someday be able to interact socially with healthy subjects on a BCI-controlled web browser interface. The interpretation of brain signals into physical motions, as seen in this project, would allow a BCI user to virtually participate in the online community. This would enable users to not only browse web pages, but access web-based services and applications in general [41]. This gives a user the ability for social interactions, exploration, self-expression, and consumption. BCI's would allow user inhibited by the aforementioned diseases to stay actively involved online and create their own social media presence. This can considerably increase independence and self-esteem, as it creates a way for users to participate as an equal in family and social life. Additionally, gaming controlled by BCI will play a pivotal role in the lives of BCI users. The BCI is a sophisticated and demanding technical system which is tailored to accommodate each user based on their neurological intentions. A natural synchronization between brain and interface can only be accomplished through extensive training. This requires users to invest considerable time and effort learning to navigate the system. Gaming can be excellent motivation for spending time and immersing oneself with the technology to achieve better control. Self-immersion for this virtual escape will increase independence for users who otherwise are dependent on continuous assisted care. Future BCI-controlled gaming applications will also aid social integration, as a paralyzed player can team up or compete against other, possibly healthy gamers. A slow strategic game such as chess will place a healthy player and a patient on common ground while they express and compare their cognitive abilities. Through emphasis on a mental level, the degree of virtual disability is reduced [42]. By continuing to enhance BCI neural processing, the gap between BCI users and healthy gamers will shrink.

For any cutting-edge technology with tremendous potential, legislation will need to be placed to prevent the violation of societal rights and freedoms. In order to function, BCIs must monitor neural activity and by doing so collect intrinsic and private information relating to their users. If BCI's become compatible with online interfaces, then this computer-based communication could be monitored by a third party including caregivers, researchers, and web developers. In Section 8 of the Canadian Chart of Rights and Freedoms it states "everyone has the right to be secure against unreasonable search" [43]. This vague diction indicates that the privacy of one's thoughts is not explicitly covered and would need to be amended to aid the privacy of BCI users. Theoretically, the technology aims to reach the capability to identify contents of thoughts of monitored people which would seriously threaten the freedom of thought. This ability to "search" into a person's mind would need significant legislation to be made to combat those attempting to overstep the uses of this technology. As BCI technology becomes a ubiquitous treatment, the scope of its impact will also grow. Each patient's intrinsic information will be exposed making them susceptible to be taken advantage of by those reading their data. Regulations paralleling information privacy laws and data protection laws will need to be considered to safeguard the user's well-being.

6.3 Economic Analysis

Unfortunately for those who are in need of prostheses, the cost of a prosthetic is quite high. Even higher prices are used for those that are controlled. In today's market, a non-functional prosthetic arm is valued just under $ 7,000 CAD [44]. To purchase a more life-like model which is functional (without a hand) is valued over $ 14,000 CAD [44]. The Ontario government lists all vendors of myoelectric prosthetic arms present within the province. Under investigation, the possible myoelectric arms from these vendors were found to cost anywhere from $ 28,000 to $ 141,000 [44].

Through its Assistive Device Program (ADP), the Ontario government promises to cover at least 75% of the prosthetic cost, with a maximum coverage of 100% for those who are enrolled in specific programs. These programs include Ontario Works, Ontario Disability Support Program, and Assistance for Children with Severe Disabilities [20]. Comparatively to all of Canada, Ontario is the leader in prosthetic subsidies.

Advancement in the field of prostheses requires high-intensive research by specialist engineers and scientists. Meaning that, albeit the material cost can be minimized and optimized to be cost effective, the price of upgrading current models becomes increasingly expensive. This problem is compounded by the fact that there exists a very small market size which has negligible growth. Consequently, the vendors of the models cannot lower the prices of the devices significantly. This is important when considering the possibility of a commercial BCI controlled prosthesis's entrance into the market.

Currently, there exists no commercial BCI controlled prostheses available for consumers. This can be attributed to the sophistication of the long-term support for the amputee, and the involved nature of this support - especially, when maintaining the BCI [45]. Without an increase in the amount of consumers, an investment by a company for further BCI development is risky. The financial uncertainty is why there exist no purchasable BCI prostheses today.

Under the constraints the design model was not manufactured or put to market, an estimated financial analysis can be constructed. A non-invasive, robust, and EEG capturing head cap costs approximately $5,000. This includes manufacturing and accompanying software. The team's prosthetic will cost an additional $7,000. To proceed with building the product, manufacturing and licensing is estimated to be supplementary $ 2,000 [44]. This brings the total to $ 14,000 CAD.

Unfortunately, the Ontario ADP program supplies a maximum subsidy worth $ 10,000 for an individual prosthetic model. This is done whether the $ 10,000 is 75% of the cost or not [20]. For this report's design, an Ontarian would have to pay $ 4,000 in residual cost after government subsidy. This is quite expensive as it is almost half the amount of the model's total cost, however, it is cheaper than the most inexpensive myoelectric model.

7 Ethics and Equity

The current state of BCI technology creates limited ethical dilemmas as the product is largely in a development and research phase. Our design project is a preliminary example of the potential of BCI technology aligned with human prosthesis. As more patients begin to incorporate BCI's to aid their daily lives, the technology will mature and concerns of ethics will proportionally grow. Our design solution is a non-invasive BCI design which disregards any ethical concern for devices being implanted under the skull or skin. A predictive concern which does entail non-invasive BCI's will be the device's impact on brain plasticity. A concern is whether or not the brain's plasticity in still-developing children or even adults could bring unknown negative side-effects from BCI use. There is frequent questioning whether or not the user's brain would return to normal once a dependence on a BCI system is established. This could even have the potential to precipitate a change in character, that the patient would no longer act like themselves [46]. Full dependence on any device is a general cause for concern. As users become more reliant on the device, partial device failures or errors become more significant. One example would be a locked in syndrome patient needing to pick up an arbitrary object. A slight malfunction would cause the object to fall or be unable to be picked up. Greater trauma occurs for the heavily dependent patient controlling a wheelchair with a BCI. If the BCI malfunctions while the user is crossing the street, the result could be deadly. The users must be all-knowing of the risks of scientific uncertainty before consenting to trust BCI's for medical assistance.

Once perceived as science fiction, a serious question is the predicament of a BCI's impact on the user's body schema and ultimately if the user becomes a type of "cyborg". A cyborg, being an individual whose physical abilities are extended by mechanical elements. For our design project, the line between machine and man is quite clear. It is in future derivatives of this device this may not be the case. On a philosophical level, this question regards a BCI's effect on humanity and equity. One school of thought relates BCIs to artificial hips or other medical interventions to the human body. The procedure of adding machinery to the human body is therefore not unique to BCI's. In contrast, many believe BCI's have the potential to impact our humanity. The concept of being more robotic and consequently making one "less human" would then apply for the dependence of a user on an automated arm. This unprecedented connection between brain and machine which is inherent to BCI may also cause users to not be entirely comfortable with the device.

There still pertains the possibility that BCI's surpass the effectiveness of a natural human body. This would create an inequity between those with and without the assistive device. Before this becomes a societal issue, the device should be limited to those with the greatest need for the device to increase their quality of life. These would be clients with diseases such as ALS and locked-in syndrome. The goal of our design project is to grant equity to patients with these inhibiting diseases so they can perform the same tasks of healthy human.

8 Lifelong Learning

Numerous research methods were implemented in order to properly inform this report. An early obstacle for our team was procuring information to use in the report with significant academic backing. There was constant condensation and revision of journal articles describing technological hardware and rigorous mathematical theory. Within the first weeks of working together, sources from a variety of educational institution and research facilities were used to give a preliminary knowledge on various fields pertaining to BCI's. As research continued, each team member specialized in gaining information for a specific facet of the design. In this report each source was specifically chosen to enforce the credibility of our proposed design. It is vital to any engineering project that one should examine an idea's validity based on past research. For design inspiration, current products utilizing similar control systems were analyzed. For example, in-depth research was conducted on the use of myoelectric systems, reading of EEG signals versus EMG signals, and experiments regarding the biomechanics of a healthy human arm.

Contrasting with current models is most evident within the background section of this report. Here, there is thorough elaboration on BCI's and their accompanying choice of data acquisition method. Various sources were required in order to arrive at the decision for which technological elements were implemented. All sources were meticulously tested under the CRAAP test. It was a team decision to mandate this test to be performed before any source was cited. This test allows a reader to ascertain the quality of a source. The acronym "CRAAP" indicates different metrics a source must pertain to in order to be considered viable. The source must be current (C), relevant (R), hold authority (A), be accurate (A), and serve a purpose (P) for our report. This test was crucial to produce a report built on the information from trusted academic institutions. The test proved extremely effective as all sources were procured to have authority, currency, and objectivity. For example, the oldest source used for this report which is still relatively recent. Even though this source still holds true in current scientific discussions, it is a chronological outlier. The vast majority of our sources are between the years 2015-2019. Using the CRAAP test gave team members the ability to skillfully determine which sources are credible thus effectuating quality information to be used in this report.

A substantial portion of our information on mathematical concepts came from courses taught at Queen's University. This institution is a leader in the field of mathematics, especially with the incorporation of mathematics into engineering principles. Information from MTHE 332 was imperative in providing compulsory knowledge for control theory. MTHE 474 established a valuable foundation for understanding the information theoretic approach to the design problem. MTHE 472 lectures notes were also used to aid the quantization and stochastic control portions of design process. Finally, to inform the structure and proper ordering of this report the rubric provided and previous reports were religiously referenced.

9 Next Steps

Taking into consideration a twenty-four-week timeline and an undergraduate level of knowledge in the field, the scope of this project is limited. Upon gathering insight on BCI's, several recommendations have been made for the continuation of this project as well as the future development of BCI technology.

9.1 Continuing the Project

The ultimate goal for this design and those constructing BCI's in the field is to create a prosthetic as functionally realistic as possible. The design model uses 8 movements of the forearm - operating with the assumption that the upper arm remains still and the elbow is a hinge. The inputs to the system are modelled as force and torque values, which would move the forearm to complete a specific task. The brain signal sensors, the BCI, and the prosthetic arm, will be modelled in three-dimensions. The continuation of this project would entail extending our model by adding pivot points representing individual fingers. Upon solving for the reference trajectory, this model would approach the destination with an ability to perform desirable hand and finger motions. These advancements would significantly improve the ability to mimic the performance of a healthy human arm.

The system model moves ignoring the effects of gravity. Additional research into the biomechanics of a healthy human arm and their application to prosthetics is essential moving forward. With further understanding, gravity will be able to be incorporated as a restricting force to enhance the realism of our prosthetic arm.

The intricacies of the human sensory system are also absent from this model. One can approximate the eyes as position sensors with gaussian noise and internal feedback as accelerometers. To enhance this, gyroscopes with sensor noise and tactile feedback as environment recognition can be used but are both absent in modern prosthetics.

9.2 Future of the Industry

Two major challenges for the future of BCI research will be gaining information on the meaning of signals measured and data acquisition. Modelling the brain as a communication channel is relatively cutting-edge research in the field. This has lead plenty of researchers to make mathematical simplifications when expressing their perception of the brain. A joint effort from the engineering and scientific communities will be needed to grasp a further understanding of the brain and apply it to BCI prototypes. Currently, the conception of the brain holds properties of being non-linear, time-varying, with feedback and memory. However, this is often not considered in order to gain traction on the problem. As well, the exact parameters, functions, mechanisms, and motor imagery processes are currently unknown [47]. The actual coding scheme that the brain uses to encode information is still highly debated. It is therefore essential to improve our understanding of the adaptive nature of the brain. With years of research, BCI application will become more effective once clearer characterization of the brain, EEG signals, and their relationship to muscle movements are discovered.

Data acquisition is a currently a troublesome challenge due to a poor ability to extract the relevant information from monitored brain activity. Current activities to monitor the brain at different levels involves substantial noise amongst the signal channels. Developing EEG sensory and transmission equipment with further noise-reduction capabilities than current models is critical. Moreover, the activity changes continuously. This is either due to technical problems such as unstable recordings or due to the inherent adaptive nature of the brain itself, which modifies its activity to the subject's experience [48]. Hardware augmentation will yield increased processing power which will allow the BCI to adapt to these continuously changing activities. As well, advanced hardware will be able to encode larger amounts of EEG data and still have reasonable precision for the prosthetic arm. Motivated by the inspiring potential BCI's have, with a collective research effort, a future where BCI's can help those in need is imminent.

As stated in the Economic Analysis, due to the finite number of consumers, companies are less inclined to make investment into the innovation in the area of BCI protetheses. A way of combatting this, is for the government to incentivize this field of study. This would subsequently result in a larger dedication to advancements in this field. Moreover, a greater commitment to the innovation of BCI's will uncover its utility in various other applications: such as manufacturing, education or video games.

References

[1] N. Hussein, "Hands-free drawing using electroencephalogram (eeg) systems and eye tracking," *Electrical Electronics (EE) Engineering Programme*, 2014. [Online]. Available: http://utpedia.utp.edu.my/14829/1/final20report_dhiya_14434.pdf

[2] Quizlet, *Elbow Joint Movement*. Quizlet, 2020. [Online]. Available: https://o.quizlet.com/uP581WK2uXQceYRMBWIiGA.png

[3] D. P. Murphy, O. Bai, A. S. Gorgey, J. Fox, W. T. Lovegreen, B. W. Burkhardt, R. Atri, J. S. Marquez, Q. Li, and D.-Y. Fei, "Electroencephalogram-Based Brain–Computer Interface and Lower-Limb Prosthesis Control: A Case Study," *Frontiers in Neurology*, vol. 8, Dec. 2017. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5736540/

[4] "Timeline: Prosthetic Limbs Through the Years," Mar. 2015. [Online]. Available: https://share.upmc.com/2015/03/timeline-prosthetic-limbs-years/

[5] L. Bi, F. xin'an, and Y. Liu, "EEG-Based Brain-Controlled Mobile Robots: A Survey," *Human-Machine Systems, IEEE Transactions on*, vol. 43, pp. 161–176, Mar. 2013.

[6] hortonsopnew, "Electric vs. Body-Powered Prosthetic Arms," Apr. 2017. [Online]. Available: https://www.hortonsoandp.com/electric-vs-body-powered-prosthetic-arms/

[7] "Myoelectric prosthetics 101 | Ottobock US." [Online]. Available: https://www.ottobockus.com/prosthetics/info-for-new-amputees/prosthetics-101/myoelectric-prosthetics-101/

[8] "The Science of Neural Interface Systems | Annual Review of Neuroscience." [Online]. Available: https://www.annualreviews.org/doi/abs/10.1146/annurev.neuro.051508.135241

[9] C. Omar, A. Akce, M. Johnson, T. Bretl, R. Ma, E. Maclin, M. McCormick, and T. P. Coleman, "A Feedback Information-Theoretic Approach to the Design of Brain–Computer Interfaces," *International Journal of Human–Computer Interaction*, vol. 27, no. 1, pp. 5–23, Dec. 2010, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10447318.2011.535749. [Online]. Available: https://doi.org/10.1080/10447318.2011.535749

[10] E. Leuthardt, K. Miller, G. Schalk, R. Rao, and J. Ojemann, "Electrocorticography-based brain computer Interface-the seattle experience," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, pp. 194–198, Jun. 2006, conference Name: IEEE Transactions on Neural Systems and Rehabilitation Engineering.

[11] C. Kemere, K. Shenoy, and T. Meng, "Model-based neural decoding of reaching movements: a maximum likelihood approach," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 925–932, Jun. 2004, conference Name: IEEE Transactions on Biomedical Engineering.

[12] G. Fabiani, D. McFarland, J. Wolpaw, and G. Pfurtscheller, "Conversion of EEG activity into cursor movement by a brain-computer interface (BCI)," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 12, no. 3, pp. 331–338, Sep. 2004, conference Name: IEEE Transactions on Neural Systems and Rehabilitation Engineering.

[13] "EEG." [Online]. Available: https://www.medicine.mcgill.ca/physio/vlab/biomed_signals/eeg_n.htm

[14] A. GuruvaReddy and S. Narava, "Artifact Removal from EEG Signals," *International Journal of Computer Applications*, vol. 77, no. 13, pp. 17–19, Sep. 2013.

[15] M. Sazgar and M. G. Young, "EEG Artifacts," in *Absolute Epilepsy and EEG Rotation Review: Essentials for Trainees*, M. Sazgar and M. G. Young, Eds. Cham: Springer International Publishing, 2019, pp. 149–162. [Online]. Available: https://doi.org/10.1007/978-3-030-03511-2_8

[16] "The nature of the unavoidable EEG artefacts (and how to deal with them)," Dec. 2014, library Catalog: www.neuroelectrics.com Section: Uncategorized. [Online]. Available: https://www.neuroelectrics.com/blog/2014/12/18/the-nature-of-the-unavoidable-eeg-artefacts-and-how-to-deal-with-them/

[17] G. Lange, C. Y. Low, K. Johar, F. A. Hanapiah, and F. Kamaruzaman, "Classification of Electroencephalogram Data from Hand Grasp and Release Movements for BCI Controlled Prosthesis," *Procedia Technology*, vol. 26, pp. 374–381, 2016. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2212017316303954

[18] "(1) Intelligent Robotic Wheelchair with EMG-, Gesture-, and Voice-based Interfaces | Request PDF," library Catalog: www.researchgate.net. [Online]. Available: https://www.researchgate.net/publication/4046077_Intelligent_Robotic_Wheelchair_with_EMG-_Gesture-_and_Voice-based_Interfaces

[19] A. Ferreira, R. L. Silva, W. C. Celeste, T. F. B. Filho, and M. S. Filho, "Human–machine interface based on muscular and brain signals applied to a robotic wheelchair," *Journal of Physics: Conference Series*, vol. 90, p. 012094, Nov. 2007. [Online]. Available: http://stacks.iop.org/1742-6596/90/i=1/a=012094?key=crossref.6ee0f2eddc3901982189055badee983b

[20] "Prosthetic arms and limbs," Mar 2018. [Online]. Available: https://www.ontario.ca/page/breast-prostheses-and-artificial-limbs

[21] M. VanderPol, “Overview of e-waste management in canada,” Hanoi, Vietnam, p. 7, Jul 2014. [Online]. Available: https://www.epa.gov/sites/production/files/2014-08/documents/canada_country_presentation.pdf

[22] H. Canada, “Government of canada,” Feb 2019. [Online]. Available: https://www.canada.ca/en/health-canada/services/drugs-health-products/medical-devices/quality-systems-13485.html

[23] E. Hildt, “Brain-computer interaction and medical access to the brain: Individual, social and ethical implications,” *Studies in Ethics, Law, and Technology*, vol. 4, pp. 1–20, 2010. [Online]. Available: https://heinonline.org/HOL/Page?collection=journals&handle=hein.journals/selt4&id=294&men_tab=srchresults#

[24] NORD, “Amyotrophic lateral sclerosis,” 2004. [Online]. Available: https://rarediseases.org/rare-diseases/amyotrophic-lateral-sclerosis/

[25] ——, “Locked in syndrome,” 2018. [Online]. Available: https://rarediseases.org/rare-diseases/locked-in-syndrome/

[26] ——, “Multiple sclerosis,” 2017. [Online]. Available: https://rarediseases.org/rare-diseases/multiple-sclerosis/

[27] T. T. Brown, “Individual differences in human brain development,” *WIREs Cognitive Science*, vol. 8, no. 1389, p. 1–8, Dec 2016. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/wcs.1389

[28] A. Vourvopoulos, O. M. Pardo, S. Lefebvre, M. Neureither, D. Saldana, E. Jahng, and S.-L. Liew, “Effects of a brain-computer interface with virtual reality (vr) neurofeedback: A pilot study in chronic stroke patients,” *Frontiers in Human Neuroscience*, vol. 13, 2019.

[29] K. Bowsher, E. F. Civillico, J. Coburn, J. Collinger, J. L. Contreras-Vidal, T. Denison, J. Donoghue, J. French, N. Getzoff, L. R. Hochberg, and et al., “Brain–computer interface devices for patients with paralysis and amputation: a meeting report,” *Journal of Neural Engineering*, vol. 13, no. 2, p. 023001, 2016. [Online]. Available: https://iopscience.iop.org/article/10.1088/1741-2560/13/2/023001/pdf

[30] “Government of canada,” Mar 2019. [Online]. Available: https://www.canada.ca/en/health-canada/services/drugs-health-products/medical-devices.html

[31] ISO, “Health informatics, medical waveform format, part 1: Encoding rules,” 2015. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso:22077:-1:ed-1:v1:en

[32] P. Selvey, “Iec 60601-1-10 scope (physiological closed loop controllers),” Jan 2017. [Online]. Available: https://www.medteq.net/article/iec-60601-1-10-scope-physiological-closed-loop-controllers

[33] ISO/IEC, "Information technology, media context and control, part 3: Sensory information," 2019. [Online]. Available: https://www.iso.org/obp/ui/#iso:std:iso-iec:23005:-3:ed-4:v1:en

[34] SCC, "Z323.3.1-1982 (r2008)," 2009. [Online]. Available: https://www.scc.ca/en/standardsdb/standards/2743

[35] L. S. Branch, "Consolidated federal laws of canada, medical devices regulations," Sep 2019. [Online]. Available: https://laws-lois.justice.gc.ca/eng/regulations/sor-98-282/page-1.html

[36] M. E. Celebi, H. A. Kingravi, and P. A. Vela, "A comparative study of efficient initialization methods for the k-means clustering algorithm," *CoRR*, vol. abs/1209.1960, 2012. [Online]. Available: http://arxiv.org/abs/1209.1960

[37] P. S. Bradley and U. M. Fayyad, "Refining initial points for k-means clustering," 1998.

[38] M. Hakonen, H. Piitulainen, and A. Visala, "Current state of digital signal processing in myoelectric interfaces and related applications," *Biomedical Signal Processing and Control*, vol. 18, p. 334–359, 2015.

[39] S. Kirkey, "Syringes, iv tubing, saline bags, packaging: Canada's hospitals couldn't function without single-use plastics," Jun 2019. [Online]. Available: https://nationalpost.com/news/canada/single-use-plastics

[40] "Amyotrophic lateral sclerosis (als)," Aug 2019. [Online]. Available: https://www.mayoclinic.org/diseases-conditions/amyotrophic-lateral-sclerosis/diagnosis-treatment/drc-20354027

[41] N. B. Birbaumer, "Nessi: An EEG-Controlled Web Browser for Severely Paralyzed Patients," vol. 2007, p. 5, 2007.

[42] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. Ramsey, I. Sturm, G. Curio, and K. Mueller, "The Berlin Brain–Computer Interface: Non-Medical Uses of BCI Technology," *Frontiers in Neuroscience*, vol. 4, p. 198, 2010. [Online]. Available: https://www.frontiersin.org/article/10.3389/fnins.2010.00198

[43] Charterpedia and D. of Justice, "Section 8 – search and seizure," Jun 2019. [Online]. Available: https://www.justice.gc.ca/eng/csj-sjc/rfc-dlc/ccrf-ccdl/check/art8.html

[44] "How much does a prosthetic arm cost? - costhelper.com." [Online]. Available: https://health.costhelper.com/prosthetic-arms.html

[45] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interfaces in medicine," Mar 2012. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3497935/

[46] S. Burwell, M. Sample, and E. Racine, "Ethical aspects of brain computer interfaces: a scoping review," *BMC Medical Ethics*, vol. 4, 2017. [Online]. Available: https://bmcmedethics.biomedcentral.com/articles/10.1186/s12910-017-0220-y#citeas

[47] S. Yuksel, B. Bonham-Carter, M. Landon-Brac i, and N. Rottman, "Brain-computer interface design for prosthetic arm control," p. 8, Apr. 2019.

[48] E. Vaadia and N. Birbaumer, "Grand challenges of brain computer interfaces in the years to come," Sep 2009. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2751651/

A Appendix - MATLAB Code

A.1 Data Simulation

Listing 1: "Simulate Data: Code Body"

```
%% Clear workspace
clc; clear all; close all;

%% Define time variables initialize reference trajectory
% inputs
d = 8; %number of states in reference trajectory
dt = 0.125; %% Time step
T = dt*d; %% Time Horizon
r = d+1; %number of states in reference trajectory
sim = 40; % number of time steps in simulation
t = 0:dt:(sim-1)*dt; %% time index vector
conv = 0.005; % radius of convergence
%% Define system model for planar rotating link

[F,G,Q_0,R] = ModelKIN(dt);
[n,m] = size(G);

%% Define reference trajectory
List = refGen(d);
SampleData = double.empty(5,0);

for Lval = 1:9

t = 0:dt:(sim-1)*dt; %% time index vector
[xref1,x0] = Reference_TrajectoryKIN(List(:,:,Lval),d,sim);
xref = xref1;
%% LQR Trajectory optimization
xact = zeros(n,sim);
xact(:,1) = x0;
uact = zeros(m,sim);
endt = sim;

for i = 1:sim-1
[xact(:,i+1),uact(:,i)] = LQRKINIter(r,sim,t,F,G,Q_0,R,xref,xact(:,i));

norm(uact(:,i));
if norm(uact(:,i)) <= 1e-3;
    endt = i;
```

```
    break
end

xref(:,1) = xact(:,i+1);
    for k = 2:r-i
    xref(:,k) = xref(:,k+1);
    end
end

error = xref - xact;
T_conv = [0,0];
for i = r+1:sim
   if abs(error(1,i)) <= conv
       T_conv = [t(i),i];

       if T_conv(1) > 0
           break
       end
   end
end

xact = xact(:,1:endt);
uact = uact(:,1:endt);
xref1 = xref1(:,1:endt);
t = t(1:endt);

u_ts = timeseries(uact,t,'Name','u');
x_ts = timeseries(xact,t,'Name','x');

%% Data
c = zeros(1,endt);
for i = 1:endt
    c(i) = Classifier(uact(:,i));
end

SampleData = [SampleData,[xact;uact;c]];
end
%%
tic = 16;
C = 8;
U = SortData(SampleData,tic,C);
```

A.1.1 Functions

Listing 2: "Generate List of reference trajectories"

```
function [List] = refGen(d)

    List = zeros(2,d+1,9);

    refs = [pi/2, pi/2, pi/6, pi, pi, pi/2, pi/6, pi/2,(5/6)*pi;
            pi/2, pi, (3/4)*pi, (3/4)*pi, 0, (3/4)*pi, 0, (3/4)*pi, pi];

    inipos = [pi/2, pi/2, pi, pi/6, pi/2, pi, pi/2, pi/6, pi/2;
              pi, pi/2, (3/4)*pi, (3/4)*pi, (3/4)*pi, 0,(3/4)*pi, 0, 0];

    for i = 1:9
        List(1,1:d,i) = ones(1,d)*refs(1,i);
        List(1,9,i) = inipos(1,i);
        List(2,1:d,i) = ones(1,d)*refs(2,i);
        List(2,9,i) = inipos(2,i);
    end

end
```

Listing 3: "Classify output"

```
function [c] = Classifier(u)

    if u(1) > 1e-4
       if abs(u(2)) <= 1e-4
           c = 1;
       elseif u(2) > 0
           c = 2;
       else
           c = 3;
       end
    elseif u(1) < -1e-4
       if abs(u(2)) <= 1e-4
           c = 4;
       elseif u(2) > 0
           c = 5;
       else
           c = 6;
       end
    else
        if u(2) > 1e-4
```

```
            c = 7;
        elseif u(2) < -1e-4
            c = 8;
        else
            c = 9;
        end
    end

end
```

Listing 4: "Create Array to call the averaged inputs"

```
function [Ufunction] = SortData(SampleData,tic,C)

    cs = cell(C+1,2);
    L = length(SampleData);
    %%
    for i = 1:C+1
        cs{i,1} = zeros(1,L);
        cs{i,2} = 1;
    end
    %%
    for i = 1:L
            cs{SampleData(5,i),1}(cs{SampleData(5,i),2}) = i;
            cs{SampleData(5,i),2} = cs{SampleData(5,i),2}+1;
    end

    for i = 1:C+1
        cs{i,1} = cs{i,1}(:,1:(cs{i,2}-1));
    end

    Cdata = cell(C,2);

    for i = 1:C
        Cdata{i,1} = SampleData(:,cs{i,1});
    end
    %%
    for i = 1:C
        Cdata{i,2} = 0*Cdata{i,1}(1:2,:);
        for j = 1:length(Cdata{i,1}(1,:))
          Cdata{i,2}(1,j) = min(max(1,floor(Cdata{i,1}(1,j)*(tic/pi))+1),
              tic);
          Cdata{i,2}(2,j) = min(max(1,floor(Cdata{i,1}(2,j)*(tic/pi))+1),
              tic);
```

```
        end
    end
    %%
    Ufunction = cell(C,2);
    Uavg = cell(2,1);
            Uavg{1}=zeros(2,C);
            Uavg{2}=zeros(1,C);
    for i = 1:C
        Ufunction{i,1}=cell(tic,tic);
        Ufunction{i,2}=zeros(tic,tic);
        for h = 1:tic
            for k = 1:tic
                Ufunction{i,1}{h,k} = zeros(2,1);
            end
        end
    end
    %%
    for i = 1:C
        for j = 1:length(Cdata{i,2}(1,:))
            Ufunction{i,1}{Cdata{i,2}(1,j),Cdata{i,2}(2,j)} = ((Ufunction{i,2}(Cdata{i,2}(1,j),Cdata{i,2}(2,j))*Ufunction{i,1}{Cdata{i,2}(1,j),Cdata{i,2}(2,j)}+Cdata{i,1}(3:4,j))/(Ufunction{i,2}(Cdata{i,2}(1,j),Cdata{i,2}(2,j))+1));
            Uavg{1}(:,i) = Uavg{1}(:,i) + Cdata{i,1}(3:4,j);
            Ufunction{i,2}(Cdata{i,2}(1,j),Cdata{i,2}(2,j)) = Ufunction{i,2}(Cdata{i,2}(1,j),Cdata{i,2}(2,j))+1 ;
            Uavg{2}(i) = Uavg{2}(i)+1;
        end
    end

    for i = 1:C
        if Uavg{2}(i) == 0
          Uavg{1}(:,i) = 0 ;
        else
          Uavg{1}(:,i) = Uavg{1}(:,i)/Uavg{2}(i);
        end
    end

    for i = 1:C
        for j = 1:tic
            for k = 1:tic
                if Ufunction{i,2}(j,k) == 0
            Ufunction{i,1}{j,k} = Uavg{1}(:,i);
                end
```

```
            end
        end
    end

    Ufunction = Ufunction(:,1);

end
```

A.2 Evaluate Performance of Controller

Listing 5: "Evaluate Performance of Controller"

```
%% Clear workspace
clc; clear all; close all;

load('C:\Users\Eric Lefaive\Directory\School\Core Program\4th year\MTHE 493 Prothetic\3.Matlab\Extended time\Kinematic\LQR_Functions\List.mat')
load('C:\Users\Eric Lefaive\Directory\School\Core Program\4th year\MTHE 493 Prothetic\3.Matlab\Extended time\Kinematic\LQR_Functions\U.mat')
%% Define time variables initialize reference trajectory
% inputs
tic = 8;
d = 8; %number of states in reference trajectory
dt = 0.125; %% Time step
T = dt*d; %% Time Horizon
r = d+1; %number of states in reference trajectory
sim = 40; % number of time steps in simulation
t = 0:dt:(sim-1)*dt; %% time index vector
conv = 0.005; % radius of convergence

x0 = [0;pi/2]; %% initial state vector = [position; velocity]
%% Define system model for planar rotating link

[F,G,Q_0,R] = ModelKIN(dt);
[n,m] = size(G);

%% Define reference trajectory
[xref1,x0] = Reference_TrajectoryKIN(List(:,:,1),d,sim);
x0 = x0;
xref = zeros(n,sim,2);
xref(:,:,1) = xref1;
xref(:,:,2) = xref1;

%% LQR Trajectory optimization
xact = zeros(n,sim,2);
xact(:,1,1) = x0;
xact(:,1,2) = x0;
uact = zeros(m,sim,2);
endt = sim;

for i = 1:sim-1
```

```
    [xact(:,i+1,1),uact(:,i,1)] = LQRKINIter(r,sim,t,F,G,Q_0,R,xref
        (:,:,1),xact(:,i,1));
    [xact(:,i+1,2),uact(:,i,2)] = LQRKINIterQuan(r,sim,t,F,G,Q_0,R,xref
        (:,:,2),xact(:,i,2),U,tic);

    for vers = 1:2
        xref(:,1,vers) = xact(:,i+1,vers);
        for k = 2:r-i
            xref(:,k,vers) = xref(:,k+1,vers);
        end
    end
end

T_conv = [0,0];

u_ts = timeseries(uact(:,:,1),t,'Name','u');
x_ts = timeseries(xact(:,:,1),t,'Name','x');

Qu_ts = timeseries(uact(:,:,2),t,'Name','u');
Qx_ts = timeseries(xact(:,:,2),t,'Name','x');

%% Plot Figures For Standard LQR
Plot_Quant_LQRKIN(xref1,xact(:,:,1),uact(:,:,1),xact(:,:,2),uact(:,:,2),t
    )
%Plot_LQRKIN(xref1,xact(:,:,1),uact(:,:,1),u_ts,t,T_conv)
%Plot_LQRKIN(xref1,xact(:,:,2),uact(:,:,2),u_ts,t,T_conv)
```

A.2.1 Functions

Listing 6: "Simulate human Control"

```
function [x_t,u] = LQRKINIter(r,sim,t,F,G,Q_0,R,xref,x0)

    %% LQR Trajectory optimization
    [n,m] = size(G);

    P = cell(sim, 1) ; %initialize variables for P(t)
    S = cell(sim, 1) ; %initialize variables for S(t)
    Q = cell(sim, 1) ; %initialize variables for Q(t)
    K = cell(sim, 1) ; %initialize variables for K(t) [a factor in
        computing b(t)]
    b = cell(sim, 1) ; %initialize variables for b(t) [a factor in
        computing u(t)]
```

```matlab
c = cell(sim, 1) ; %initialize variables for c(t) [a factor in computing V(x(t),t) performance index]

% set values for final time
P{sim} = zeros(size(Q_0)) ; %Set P(T) = 0
Q{sim} = Q_0 ;              % Define Q(T) (currently Q is a constant matrix)
S{sim} = Q{sim} ;           % Define S(T) = Q(T)
K{sim} = zeros(1,2) ; % Define K(T) = 0 [not used in computations]
b{sim} = -Q_0*xref(:,sim) ; % Set b(T) = -Q(T)*xref(T)
c{sim} = xref(:,sim)'*Q_0*xref(:,sim) ; % Set b(T) = -Q(T)*xref(T)

% the below loop is the 'backwards-solving' of the algorithm
for k = 1 : sim-1
    % Define F,G,R if time varying
    %{
    F{n-k} =
    G{n-k} =
    R{n-k} =
    %}

    Q{sim-k} = Q_0; % Define Q(t)

    S_1 = S{sim-k+1}; % Define S(t+1)

    S{sim-k} = F'*(S_1 - S_1*G*inv(G'*S_1*G + R)*G'*S_1)*F + Q{sim-k}; %Compute S(t)

    P{sim-k} = F'*(S_1 - S_1*G*inv(G'*S_1*G + R)*G'*S_1)*F ; % Compute P(t)

    K{sim-k} = (-inv(G'*S_1*G + R)*G'*S_1*F)'; %Compute K(t)

    b{sim-k} = (F' + K{sim-k}*G')*b{sim+1-k} - Q{sim-k}*xref(:,sim-k); % Compute b(t)
end

% below is forwards solving using matrices computed above
x_t = x0; % Define x variable

% Compute optimal control for next time step
u = -inv(G'*S{2}*G + R)*G'*(S{2}*F*x_t + b{2} );
x_t = F*x_t + G*u;

```

```
    end
```

Listing 7: "Simulate prosthetic Control"

```
function [x_t,u] = LQRKINIterQuan(r,sim,t,F,G,Q_0,R,xref,x0,U,tic)

    %% LQR Trajectory optimization
    [n,m] = size(G);

    P = cell(sim, 1) ; %initialize variables for P(t)
    S = cell(sim, 1) ; %initialize variables for S(t)
    Q = cell(sim, 1) ; %initialize variables for Q(t)
    K = cell(sim, 1) ; %initialize variables for K(t) [a factor in computing b(t)]
    b = cell(sim, 1) ; %initialize variables for b(t) [a factor in computing u(t)]

    % set values for final time
    P{sim} = zeros(size(Q_0)) ; %Set P(T) = 0
    Q{sim} = Q_0 ;               % Define Q(T) (currently Q is a constant matrix)
    S{sim} = Q{sim} ;           % Define S(T) = Q(T)
    K{sim} = zeros(1,2) ; % Define K(T) = 0 [not used in computations]
    b{sim} = -Q_0*xref(:,sim) ; % Set b(T) = -Q(T)*xref(T)

    % the below loop is the 'backwards-solving' of the algorithm
    for k = 1 : sim-1
        % Define F,G,R if time varying
        %{
        F{n-k} =
        G{n-k} =
        R{n-k} =
        %}

        Q{sim-k} = Q_0; % Define Q(t)

        S_1 = S{sim-k+1}; % Define S(t+1)

        S{sim-k} = F'*(S_1 - S_1*G*inv(G'*S_1*G + R)*G'*S_1)*F + Q{sim-k}; %Compute S(t)

        P{sim-k} = F'*(S_1 - S_1*G*inv(G'*S_1*G + R)*G'*S_1)*F ; % Compute P(t)

```

```
        K{sim-k} = (-inv(G'*S_1*G + R)*G'*S_1*F)'; %Compute K(t)

        b{sim-k} = (F' + K{sim-k}*G')*b{sim+1-k} - Q{sim-k}*xref(:,sim-k); % Compute b(t)
    end

    % below is forwards solving using matrices computed above
    x_t = x0; % Define x variable

    % Compute optimal control for next time step
    u = -inv(G'*S{2}*G + R)*G'*(S{2}*F*x_t + b{2} );
    c = Classifier(u);
    u = U{c}{min(max(1,floor(x_t(1)*(tic/pi))+1),tic),min(max(1,floor(x_t(2)*(tic/pi))+1),tic)};
    x_t = F*x_t + G*u;

    end
```

Listing 8: "Define Model Parameters and Discritize"

```
function [F,G,Q_0,R] = ModelKIN(dt)
    %% Define weighting Matrices

    % Currently defined two Q matrices for convenience and trouble shooting
    % Q weights deviation from reference trajectory
    Q_0 = 10*[10,0;
              0,10];
    % R weights control input
    R = 10*[1,0;
         0,1];
    %% Define StateSpace Equations

    % Drift characteristics
    A = [0, 0;
         0, 0];

    % Input Characteristics
    B = [1,0;
         0,1];

    % Output from system
    C = [1,0;
         0,1];
```

```

    D = zeros(size(C,1),size(B,2));
    % ----------------------------------------------------------------------------

    % Define continuous system
    sys = ss(A,B,C,D);
    POLE = pole(sys);
    % confirming ctrb/obsv properties of system
    rank(ctrb(sys));
    rank(obsv(sys));

    %% Discretize system

    sys_dis = c2d(sys, dt);

    % System information
    POLEV = pole(sys_dis);
    rank(ctrb(sys_dis));

    % Rename matrices to match notation from textbook
    F = sys_dis.A;
    G = sys_dis.B;

end
```

Listing 9: "Generate Extended Reference Trajectory"

```
function [xref,x0] = Reference_TrajectoryKIN(List1,d,sim)

    xref = List1(:,1:d); % initialize reference trajectory to zeros
    x0 = List1(:,d+1);

    for i = d+1:sim
        xref(1,i)=xref(1,d); % converge to last desired position
        xref(2,i)=xref(2,d); % at zero velocity
    end

end
```

Listing 10: "Plot Results"

```
function [] = Plot_Quant_LQRKIN(xref,xact,uact,xquant,uquant,t)

    % Angle plot for elbow flexion
```

```
    figure()
    subplot(3,1,1)
    hold on
    stairs(t,xref(1,:),'b');
    stairs(t,xact(1,:),'r');
    stairs(t,xquant(1,:),'k');
    legend('\theta1_{ref}','\theta1_{act}','\theta1_{quant}')
    title("\theta_1 Desired vs Human vs Prosthetic")
    ylabel('[rad]')
    hold off

    % Angle plot for elbow pronation
    subplot(3,1,2)
    hold on
    stairs(t,xref(2,:),'b');
    stairs(t,xact(2,:),'r');
    stairs(t,xquant(2,:),'k');
    legend('\theta2_{ref}','\theta2_{act}','\theta2_{quant}')
    title("\theta_2 Desired vs Human vs Prosthetic")
    ylabel('[rad]')
    hold off

    % Angular velocity plot
    subplot(3,1,3)
    hold on
    stairs(t,uact(1,:),'b');
    stairs(t,uact(2,:),'r');
    stairs(t,uquant(1,:),'-- b');
    stairs(t,uquant(2,:),'-- r');
    legend('\omega1_{act}','\omega2_{act}','\omega1_{quant}','\omega2_{quant}')
    title("Angular Velocity Human vs Prosthetic")
    xlabel('time [s]')
    ylabel('[rad/s]')
    hold off

end
```