Human-Robot Interaction Utilizing Asymmetric Cooperation and the Brain

by

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ABSTRACT

The interaction between humans and robots has become an important area of research as the diversity of robotic applications has grown. The cooperation of a human and robot to achieve a goal is an important area within the physical human-robot interaction (pHRI) field. The expansion of this field is toward moving robotics into applications in unstructured environments. When humans cooperate with each other, often there are leader and follower roles. These roles may change during the task. This creates a need for the robotic system to be able to exchange roles with the human during a cooperative task. The unstructured nature of the new applications in the field creates a need for robotic systems to be able to interact in six degrees of freedom (DOF). Moreover, in these unstructured environments, the robotic system will have incomplete information. This means that it will sometimes perform an incorrect action and control methods need to be able to correct for this. However, the most compelling applications for robotics are where they have capabilities that the human does not, which also creates the need for robotic systems to be able to correct human action when it detects an error. Activity in the brain precedes human action. Utilizing this activity in the brain can classify the type of interaction desired by the human. For this dissertation, the cooperation between humans and robots is improved in two main areas. First, the ability for electroencephalogram (EEG) to determine the desired cooperation role with a human is demonstrated with a correct classification rate of 65%. Second, a robotic controller is developed to allow the human and robot to cooperate in six DOF with asymmetric role exchange. This system allowed human-robot cooperation to perform a cooperative task at 100% correct rate. High, medium, and low levels of robotic automation are shown to affect performance, with the human making the greatest numbers of errors when the robotic system has a medium level of automation.

DEDICATION

To the persistent,

There is value in hard work even if it does not produce the results that were initially desired.

"An expert is a person who has made all the mistakes that can be made in a very narrow field" -Niels Bohr

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I would like to thank Dr. Panagiotis Artemiadis for the opportunity he gave me to become a member of the Human Oriented Robotics and Control (HORC) lab and for his effort in guiding my research. I want to thank the members of my committee for the time and effort they put into improving the quality of my work. The current and past members of the HORC lab have helped me a great deal in my research. I want to thank them for the numerous hours they gave of their own time to help me succeed. Most of all, I want to thank my parents. From an early age, they instilled in me a deep respect for education. Also, they have given me a great deal of encouragement during this process.

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PREFACE

The following dissertation is the culmination of my research at Arizona State University's Human Oriented Robotics and Control Laboratory. Overall, my research has produced five peer-reviewed publications. Appendix A outlines theses contributions.

The majority of the work presented in this dissertation is new and has not been previously published. Three of my previously published works contributed to this dissertation and are cited where this occurs. This occurs in two chapters of this dissertation and is noted below. Appendix B contains the permissions for using copyrighted work, and all co-authors have given me permission to include this material as noted in Appendix C.

Chapter 3 contains work that helped shape my initial motivation for this dissertation. In Mojtahedi *et al.* (2017), I was a second author of the publication. My main contribution to the work was the design, fabrication, and programming associated with manipulandum used in the experiment and the programming, control, and operation of the robotic arm used in the experiment. Whitsell and Artemiadis (2015) was an initial investigation that laid the groundwork for the future research that was conducted. This experiment was also discussed in Whitsell (2014). It is important to note that this chapter is included to give context to the rest of the dissertation. It is not considered the research contribution of this dissertation.

In Chapter 6, the research I performed on asymmetric cooperation is presented. Portions of this research were previously published (Whitsell and Artemiadis, 2017) and are cited where appropriate.

Chapter 1

INTRODUCTION

Humans have an extensive history of developing tools and machines to improve our existence. The industrial revolution saw the rise of the manufacturing industry and the use of powered machines to improve the productivity of humans. Automation was at first mechanical, as in the centrifugal governor to control the speed of engines (Maxwell, 1867). The advent of computer controlled systems created new levels of automated systems, including robotics, and the expansion of potential applications.

Some of the earliest robotic systems grew out of teleoperated devices designed to handle dangerous materials (Goertz *et al.*, 1953). Even in this early form, human interaction and force feedback were utilized. Improvement of automation capabilities leads to the creation of autonomous industrial robots, as in the Unimate industrial robot (Paul, 1981). Robotic systems became increasingly used in a fully automated setting and operating in enclosed work cells. Work cells are well-defined environments where there is little uncertainty about the location and physical properties of the objects in them. This allows robots to repeat a programmed set of previously determined motions.

New applications became possible by the investigation of controlling a robot's interaction with its environment, instead of relying solely on position control (Inoue, 1971). This opened the robotic field to utilize these systems in unstructured environments. The ability to control the interaction with the environment (such as force, impedance, and admittance) allows the robot to be controlled so that it can interact with a human.

1.1 Human-Robot Interaction

The interaction of humans and robotic systems has opened a variety of new applications. Robotic systems are being used to aid in the physical rehabilitation of humans after having a stroke (Kwakkel *et al.*, 2008). Human performance of manual labor jobs has been improved by several robotic applications (Edward *et al.*, 1996; Lee *et al.*, 2007; Schraft *et al.*, 2004, 2005). Robotic exoskeleton systems are an inherently human-robot interaction application (Kazerooni *et al.*, 2005; van der Vorm *et al.*, 2015; Walsh *et al.*, 2006). The ability for humans to regain lost capabilities has been aided by robotic systems (Brose *et al.*, 2010; Dario *et al.*, 1999; Shi, 2015). As can be seen from these examples, progress in this area of robotics is important to many areas of society.

One area of increasing research within the human-robot interaction field is human-robot cooperation (Krüger *et al.*, 2009; Mörtl *et al.*, 2012). For this dissertation, human-robot cooperation is defined as a human and robot physically interacting to achieve an overall goal. Humans will often cooperate with another human to achieve a task (Melis and Semmann, 2010; Sebanz *et al.*, 2006). Some examples are lifting and positioning large objects, carrying long objects, physical therapy, and physical training of specific motions. With an area of focus that can affect a number of areas of society, there are also a number of areas of research that contribute to the understanding of this field and the direction that it needs to progress.

1.2 Interaction and the Brain

Research into electrical signals measured from the brain and their relation to human thought has a long history (Canton, 1875; Stone and Hughes, 2013; Tudor *et al.*, 2005). The conceptual theory is that activity in the brain indicates a human's desires or intentions. This brain activity may produce measurable electrical signals through the technique of electroencephalography (EEG).

There are numerous methods that researchers have used to analyze brain signals. One method is to have the human imagine something particular or to imagine performing a basic motion. Then the system detects this and performs some action that is typically unrelated to the thought that the human was focusing on, such as in (Bell *et al.*, 2008; Galán *et al.*, 2008; Wolpaw and McFarland, 2004). Some research has been done on making the thought the human focuses on related to the action of the system, such as (King *et al.*, 2013). Another approach is trying to decode the signal received from the brain from a particular stimulus, such as (Falkenstein *et al.*, 1991; Meng *et al.*, 2015).

These concepts are potentially useful in human-robot interaction. They have the potential to aid in controlling how the robotic system interacts with the human. Additionally, analyzing what brain signals resulted from changes in how the human wants to interact with the robotic system has the potential of creating systems that can interact with the human more intuitively.

1.3 Objective

There are two main objectives of this research. The first objective of this research is to identify a method that utilizes EEG signals to determine the human's desired role (leader or follower) in human-robot cooperation. The second objective of this research is to develop a control method for human-robot interaction with specific characteristics. The first characteristic is that it is capable of six DOF human-robot cooperation. Secondly, it needs to be able to allow both the human to take over a role as leader and also the robot to be able to take over as a leader. Additionally, it must be tested in an environment where the robotic system makes mistakes. Finally, this control method needs to allow for the human to choose which DOF to be the leader of and for the robotic system to lead the other DOF in the cooperative task.

The rest of this dissertation is organized as follows. Chapter 2 examines the background literature in the various fields. Chapter 3 presents prior motivational experiments. Chapter 4 examines the use of EEG in pHRI. Chapter 5 contains the development of a pHRI test system. Asymmetric cooperation is examined in Chapter 6, and the effect of robot automation on human performance is examined in Chapter 7.

Chapter 2

BACKGROUND AND RELATED WORKS

2.1 Introduction

This dissertation brings together several different areas of research to advance the field of human-robot cooperation. To control robotic system effectively when interacting with a human, an examination of robotic control was necessary. Research into how humans control their motion as well as how they interact with other humans was also examined. A review of previous human-robot interaction research is conducted, and conclusions are drawn as to what is needed to advance the field. Human factors engineering field has prior work regarding human-machine interface that was reviewed. Finally, research into the human brain was investigated to aid in examining how it may be used to improve the interaction of the robot with the human.

2.2 Robotic Control

Some of the early forerunners to robotic systems were teleoperated devices designed to handle dangerous materials (Arzbaecher, 1960; Goertz *et al.*, 1953; Paul, 1981). In Spooner and Weaver (1956), a force reflecting teleoperated servomechanism to manipulate radioactive material was analyzed. So, from the very formation of the field, the interaction of the system with a human was of prime concern.

As computer operated control reached a level of sufficient practicality, the emphasis became robotics operating without human intervention. These robotic systems improved the efficiency of manufacturing and were adopted by numerous manufacturers (Albus, 1990; Hitz, 1987; Munson, 1978). These robotic systems, as in (Crama and Van De Klundert, 1997; Dawande *et al.*, 2005; Sethi *et al.*, 1992), operated in well-defined work cells. These work cells allowed for the position of everything in the space to be known with sufficient accuracy for the robotic system to perform its task with minimal risk of an unexpected interaction.

As robotic applications increased, a greater need arose for the ability to control the robot's interaction with the environment beyond position control. A number of researchers endeavored to find a solution to this issue (Patarinski and Botev, 1993; Siciliano and Khatib, 2008; Whitney, 1987; Zeng and Hemami, 1997). Previous strategies that used only position control would impart the maximum force the robot could generate (or perform a safety stop of the robot) if it encountered an unexpected object. This could also occur with a rigid object in only a slightly different location than expected. The robot's reaction of applying maximum input force is an attempt to drive the robot to follow the programmed position trajectory. Some robotics systems are designed to limit this, and they engage a safety stop if a high force occurs. Both of these actions have significant negatives. In the maximum force scenario, the robot and whatever it is interacting with in the environment may become damaged. In the robotic safety stop scenario, the system stops and waits for a manual restart, dramatically decreasing productivity. The ability to control the interaction with the environment can create the ability to interact with an unexpected object in a way that prevents damage and maintains productivity.

2.2.1 Interactive Robotics

Numerous methods have been created to try and address the issue of controlling the robot's interaction with the world. For this dissertation, this field will be referred to as interaction robotics. Researchers have created different methods for achieving this, such as force control, impedance/admittance control, and hybrid (force/motion) control.

Force Control

Force control is a method for controlling the robotic system's applied force to the environment that the system is interacting with, as in (Volpe and Khosla, 1992, 1993). This is distinguishable from other interactive robotics control methods because it does not consider other variables such as position or velocity.

In 1971, Inoue examined the concept of using computer controlled servomechanism to control an artificial hand (Inoue, 1971). In this investigation, the robotic hand utilized tactile sensors to control the servo mechanisms. The result was an artificial hand that could insert a pin into a block as well as performs other tasks. One significant aspect of this is the ability to control the force imparted into the environment. The control of the servomechanisms using force sensors allowed the system to align the hand properly to the object and to maintain proper contact with the object to perform the task.

The use of force control is limited. This is due to its lack of ability to utilize other potential variables. However, elements of this are combined with other variables to create additional forms of interactive robotic control. Combining force control in one or more axis with position control in the remaining axes is often referred to as hybrid control. The use of force along with motion information is combined to create impedance or admittance control.

Impedance and Admittance Control

Impedance control is at its essence the impedance of motion by an opposing force or (in the rotational case) torque. Admittance control is essentially the reverse of this. It is the admittance of motion that is created by an applied force. For impedance control, the input is motion (position, velocity, and acceleration) and the output is an applied force. For admittance control, the input is the applied force, and the output is the motion (position, velocity, and acceleration). When one system is acting in impedance control, the other interacting system is acting in admittance control. Impedance control assumes a second order system, as in Equation 2.1.

$$F_{int} = M\ddot{x} + B\dot{x} + K(x - x_{eq}) \tag{2.1}$$

In the above equation, $M\ddot{x}$ represents the inertial component. The acceleration of the end effector of the robot is $\ddot{x}$. The apparent mass is M. This is the apparent mass as the control system is applying the amount of force opposing the acceleration based on the value of M. This, as with the other components B and K, does not necessarily represent the physical properties of the system. Instead, they represent the virtual system determined by the values of the respective variables. The damping force is represented by $B\dot{x}$, with B being the damping coefficient and $\dot{x}$ being the velocity. The spring force applied is $K(x - x_{eq})$. K is the stiffness coefficient. x is the current position, and x_{eq} is the equilibrium position of the virtual spring. The F_{int} component is the interaction force applied by the robot in the opposite direction of the motion. The opposition force can be said to be impeding the motion of the end effector.

The development of impedance control began with the use of robotics systems to create a stiffness interaction where the damping and inertial components were the mechanical properties of the system.

Whitney examined using force feedback control of a robotic system to make fine adjustments of position (Whitney, 1977). In this research, he was able to control an automated system using force feedback to adjust the position of an object to aid in automated assembly. This is essentially a stiffness interaction, where the force applied to the part causes an adjustment of the position. This was done in the context of automating assembly but is useful in other interactions. Salisbury (1980) developed a dynamic stiffness controller. This was then implemented and demonstrated with a manufacturing assembly task. This utilized the dynamic stiffness to insert a part into a larger assembly. Wu and Paul (1980) developed a controller to create compliance in a robotic arm based on controlling the joint torque. This involved creating joint torque sensors and creating joint servo systems that could perform adequately. Mason examined compliance and force control of robotic manipulators (Mason, 1981). The focus of this was on the active control of the force interaction of the robotic system on its environment. Mason developed models for this strategy as well as a program interface to aid the programming of these types of systems.

Hogan examined the use of impedance control for robotics interacting with the environment (Hogan, 1985). In this influential publication, he makes a case for utilizing impedance control as a method for dealing with the complexities that are encountered when robotic systems are interacting with the environment. He examines the difference between impedance interactions and admittance interactions. The main way of characterizing this is an impedance interaction has a motion as an input, and it resists this motion with a force output. Admittance, on the other hand, has a force input and it reacts to this input with a motion output. Because the appropriate interaction varies from task to task, a robotic system should allow for the control of these impedance values. Additionally, one way to view impedance control is to view it as position control but with impedance disturbance rejection.

Hybrid (Force/Motion) Control

Hybrid control is the control of force and motion separately along different axis simultaneously, as in Raibert and Craig (1981). An example of this is interacting with a rigid surface. If the robotic system is in contact with the surface, then a force control method for the axis that is normal to the surface can be beneficial. The position of the end effector of the robot is then controlled by position control across the surface. One of the limitations to this is that it requires the correct knowledge of the environment with which the robotic system is interacting.

Summary of Interaction Robotics

The control of the interaction of the robotic system with the environment is an important area of research. Several techniques have been investigated to accommodate interaction. Impedance control allows for the robotic system to regulate the interaction with the environment without prior knowledge of the environment and is a method that will be utilized in this dissertation.

2.3 Human Subject Research

There are two main reasons to study humans in human-robot cooperation research. The first is a better understanding of the abilities, limitations, and most likely behaviors of the human in a human-robot dyad. The second is to utilize an understanding of these elements about a human to be able to create a robotic control system that acts similar or compatible with a human.

There are two main categories of studies that will be examined. The first is single subject research. This research has only one subject and helps reveal elements about human action. The second is research that has two humans interacting. This is useful to try to reveal the elements of how humans interact.

2.3.1 Single Human Research

Researchers have examined different elements of how an individual human acts and interacts with objects. This research can provide useful information as to the characteristics of a human both for duplicating this in a robotic system and anticipating the needs and actions of a human

One characteristic often found in human action is the co-contraction of opposing muscles. This co-contraction increases the stiffness of the joint associated with it. Franklin *et al.* (2003) and Burdet *et al.* (2001) found that humans increased the stiffness of their arm when interacting with unstable environments. Additionally, Osu *et al.* (2002) found that as humans learn a reaching task that the level of co-contraction of muscles in the arm and shoulder (and hence stiffness of the arm) decrease. This suggests both that stiffness to the human is a natural and expected condition that may be useful for a robotic system to emulate, and that the human may adapt their stiffness over time. This may indicate a usefulness for robotic systems to adapt to humans over time.

Human interaction by moving an object has been shown to be preplanned and that humans adapt quickly to new objects in their environment (Gordon *et al.*, 1993). This study also showed that this experience was remembered over time. Additionally, Krakauer *et al.* (1999) showed that humans build up an experiential base for interaction with objects.

Human reaction to a change in goals has been examined by a number of researchers (Desmurget and Grafton, 2000). Alteration of trajectory has been observed in less than 50ms by(Cooke and Diggles, 1984; Van Sonderen *et al.*, 1989). This suggested the use of a forward model in the human. However, using feedback to correct motion requires a longer duration of 100-700ms, (Paillard, 1996).

Flash and Hogan (1985) investigated voluntary human arm movement. This movement was found experimentally to agree with the mathematical model of jerk minimization in the Cartesian coordinate frame. This is by minimizing Equation 2.2.

$$C = \frac{1}{2}\int_0^{t_f}((\frac{d^3x}{dt^3})^2 + (\frac{d^3y}{dt^3})^2)dt \tag{2.2}$$

In this equation, C is the square of the magnitude of the jerk. x and y are the translational position values in the horizontal plane. If this minimization is performed, the result is a bell-shaped velocity profile and a trajectory determined by Equations 2.3 and 2.4.

$$x(t) = x_0 + (x_0 - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \tag{2.3}$$

$$y(t) = y_0 + (y_0 - y_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \tag{2.4}$$

In the above equations, $x(t)$ and $y(t)$ are the positions in the horizontal plane at a given time. x_0 and y_0 are the initial positions of the trajectory. x_f and y_f are the final positions of the trajectory. τ is equal to the elapsed time t divided by the total time for the trajectory completion.

However, researchers have noted that in some positions a consideration of the human arm position is needed to accurately predict the natural trajectory (Flash, 1987; Uno *et al.*, 1989). From this, the minimum jerk trajectory may be useful as a potential human-like trajectory, but it does not guarantee that the trajectory is human-like in all scenarios.

Summary of Single Human Research

From this research, we can draw a few conclusions. Humans often adapt how they interact with objects. This suggests that, in general, robotic systems need to be able to adapt as well. Humans typically interact with the environment in ways that include impedance in the interaction. Although not a perfect description, human motion often uses bell-shaped velocity profiles such as minimum jerk trajectories.

2.3.2 Human-Human Interaction

Human-Human interaction experiments are focused on the interaction of two humans. This may be from the humans interacting directly but also from humans interacting with each other using an intermediary device, such as a haptic interaction device. This research can produce insights as to the unique elements that govern human action during interaction.

Wegner and Zeaman (1956) investigated team performance of a two DOF task compared to single subject performance. They found that the best performance was from the largest teams (four humans) and the worst performing was from a single individual. They also found that the learning in one state (single or team) was transferable to the other. This study provides a possible use argument for human-robot cooperation from the standpoint of productivity. Additionally, the transferability from the learning from working with a team to a single user also creates a potential argument for using human-robot interaction to train or rehabilitate a human to be able to perform a task alone.

Basdogan *et al.* (2000) conducted a human-human interaction experiment moving a virtual bead down a curved virtual wire. The subjects interacted with a PHANTOM haptic device. They found that performance improved significantly with the inclusion of haptic feedback than with visual alone. Glynn *et al.* (2001) found that force feedback joysticks improved the performance of human-human teams cooperating to achieve a 2 DOF virtual task.

Rahman *et al.* (2001) analyzed human-human cooperation of a shared goal in one DOF of 10 subjects. They found that in some pairings both subjects applied forces that were highly correlated to the acceleration of the object. In other cases, they found that only one was highly correlative. The study examined the correlation of acceleration but did not measure acceleration directly. Instead, it measured the applied force of each subject and assumed that there were no frictional or damping forces. Very similar results were reported in Rahman *et al.* (2002b).

Madan *et al.* (2015) examined human-human cooperation using a support vector machine (SVM) analysis. In this experiment, each human subject interacted with a haptic device. From this input, a rectangle on a screen was manipulated on a plane and was limited to three DOF (two translational and one rotational). The motion of the rectangle was determined based off of a physics-based model for the object. Each subject was shown their own screen and could not see the other subject's screen. The screen displayed both the motion of the rectangle and also the course that they were to navigate through. In some of the trials, this course was only a straight path. In other trials, the course had a split in the path allowing two possible directions. Additionally, the goal location was displayed on the screen and varied from trial to trial. These goals ranged from being the same goal for both subjects, only one subject with a goal, or conflicting goals. The data from the experiment was collected and then analyzed after the experiment.

In their off-line analysis, they were able to show a correct classification of the type of interaction 86% of the time. This is an interesting result since it shows potential for using the physical interaction for leader-follower interactions. The subjects are interacting through separate haptic devices. The haptic feedback along with the visual feedback is based on a model of an object. This limits the means of interaction and manipulation to the equations in the model. The model and haptic device predetermine the types of physical interactions needed to create the motion of the object. Additionally, the motion of this research is again confined to planar motion.

Stefanov *et al.* (2009) examined human-human interaction with the concept of one human acting as the executor and the other human acting as the conductor. The executor was responsible for the execution of the task. The conductor was responsible for the decision making and control of the task. They utilized haptic force and motion data to discern the different roles of the participants. They view the roles as not exclusive, in that each participant can take either or both roles. From their data, they assign the value of executioner to the person that applies the force that is in the direction of the motion of the object. The conductor is the person that applies a force to change or initiate the motion of the object. This is a force that changes the acceleration of the object. The actual interaction tested was moving a virtual point (massless) or a virtual mass using one DOF linear haptic interface.

Groten *et al.* (2009) investigated the use of haptic feedback in human-human cooperation. In this experiment, each subject interacted with a one DOF haptic interface. The subjects jointly manipulated a virtual mass represented as a red square on the screen. They were to keep the square on a predefined path that progresses automatically on the screen. Therefore, the subjects needed to only control 1 DOF motion of the object (horizontally across the screen). At one point, they would be presented with two paths that the red square could follow. During some of the trials, they displayed different information to the subjects to induce conflict in the decision making. This was done by making different paths thicker, or easier to follow. In some experiments, the haptic device did not provide feedback to the users. The researchers found an increase in performance if there was haptic feedback to the subjects for the force interaction of the other human.

Nudehi *et al.* (2005) investigated share control for human-human-robot interaction. This experiment looks at a telesurgical system but with two humans operating. One human is there to train another human in performing the operation. Overall, they combine the interaction of the two humans and have haptic interaction between them. Then the resulting final input moves the surgical robot. They do not examine the control of the surgical robot, instead only the issue of two humans with haptic interfaces. They developed and tested two different controllers. They found differences in both of the controllers but did not declare one to be better than the other. This shows that haptic interaction can be useful for training another person.

Reed and Peshkin (2008) investigated human-human interaction. In a one DOF rotational experiment, specialization within the human dyad was found to occur. A target location was shown to each of the subjects. They could not see each other but could see the same desired rotational position. One subject would specialize in accelerating towards the target while the other human would specialize in slowing down to stop at the target. This specialization was shown to improve the overall performance.

Summary of Human-Human Research

From the above research, some important elements can be seen. Haptic feedback improves performance in human-human interaction. Human-Human cooperation can produce better results than a single human. Specialization of the roles in human-human interaction may be a natural interaction method and can improve results. There are some areas where the research has limitations. The vast majority of the research in the field is done with limited numbers of DOF. Objects in the real world have six DOF, and it is unclear if adding DOF would affect the outcome of these results. Additionally, a number of the experiments in the field utilize haptic devices over actual interaction. Haptic devices are typically designed for the human to interact using specific grips. This limits the natural interaction that can occur. These devices limit the motion of the arm in a way that often does not match with the virtual task.

2.4 Human-Robot Interaction

Human-Robot interaction research directly examines the interaction between robotics and humans. Research that is focused on the physical interaction is examined, as well as interaction through haptic devices and computer simulation.

Kucukyilmaz *et al.* (2013) examined moving a virtual ball through a virtual maze using a haptic interface and human-computer cooperation. Subjects interacted with a haptic device. If the input from the human was less than a threshold value, then the computer would take over control. The expectation was that when the subject was not inputting a force that they wanted the computer to take control and to finish guiding the ball to a precise location. Additionally, the subject is expected to be the one that provides the larger force to guide the ball initially toward the goal. The motion of the ball was determined by a physical model of the human and the computer interacting with the virtual ball through springs and dampers.

This is one of the few experiments in the field that examines a scenario where a human may want to give up control to the robotic system. However, by relying solely on a force threshold, the human must continue to apply a force to maintain control. The human cannot maintain control while allowing the ball to continue to roll in a direction. This experiment is a two DOF experiment in a plane. Users were also confused about the level of control that they had, and they had to add an additional cue so that they were aware if they or the computer were in control of the system.

A different approach that some researchers have examined for human-robot cooperation is learning by demonstration. Stefanov *et al.* (2009) looked at using learning by demonstration using both probabilistic learning and dynamical systems to train the robotic system to cooperate with a human. They are teaching the robot both force and motion constraints for the task. They analyzed the importance of these elements based on the different coordinate basis and utilize equilibrium points and virtual springs to affect the robot behavior. In a learn by demonstration strategy, each new task must be completed several times by a human for the robotic system to learn the task. This limits the application to areas where the human can perform the task and has the time and desire to train the robotic system on each task.

Parker and Croft (2011) examined a human-robot joint carrying task. This particular carrying task was one where a long object (wooden dowel) was carried between a human at one end and a robot at the other end. The rod was moved vertically, and the motion was initiated by the robot. The human matched the motion of the robot. In some cases, the human was blindfolded, and a pivot was used to decrease haptic information. Based on the study they found that the human appears to use visual cues for low-frequency behavior and tactile cues for high-frequency response to their partner.

Passenberg *et al.* (2011) examined a human-robot assistance interaction. In this experiment, human subjects interacted with a haptic device to move a virtual block around a maze, a two DOF task. The robotic system provided assistance to help them move around the maze faster and with fewer collisions with the walls. This was largely done by creating an impedance field (or potential energy field) in the maze. In some trials, obstacles were placed in the path that the user had to negotiate around. This was done to create a conflict between the user and the previously determined optimal path. They examined if forces could be used to determine if there was a conflict and if this could be used to optimize the assistance given the user. They found that forces could be used to determine if a conflict existed between the user and the predetermined path.

Duchaine and Gosselin (2007) investigated a novel control method for human-robot cooperation. In this experiment, the robot is always assisting the human and trying to do this by estimating the human's intended motion. The motions performed in this experiment are limited to three DOF translation. The control scheme is impedance based but is based on velocity and not position. This amounts to varying the damping coefficient. When the robot perceives that the human wants to slow down, it ramps up the velocity coefficient. This shows how modifying the damping can affect the cooperation of the robotic system.

Rahman *et al.* (2000) performed an analysis of human-human interaction, single human arm impedance, and a proposed time-varying impedance controller for human-robot cooperation. The task was a one DOF task with only a common goal. The proposed time-varying impedance controller applied a higher level of impedance to the motion at the beginning of the motion. This made the motion closer to the minimum jerk trajectory when compared to a constant low impedance robot control. However, this also made the force the human had to applied greater than the constant low impedance controller. Also, the time to the target was increased, and the maximum velocity was increased.

Rahman *et al.* (2002a) attempted to characterize the impedance of a human arm while engaged in human-robot cooperation with the robotic arm leading the motion and to see if EMG values correlated to stiffness. They found that the inertial element stayed the same and that the stiffness and dampening values were highest at the start of the motion. They were unable to correlate the EMG values with stiffness.

Kosuge and Kazamura (1997) examined the performance of human-robot cooperation in a two DOF tracing task. They varied the values of the impedance control coefficients. They found that an impedance control with a low damping coefficient and appropriate inertia value performed the best. Kosuge *et al.* (1993) proposed a control method for human and multiple robots to jointly manipulate a large object with the individual robots utilizing an impedance interaction along one DOF. Kazerooni and Bobgan (1992) found that for a human-robot interface that compliance was needed in either the human arm or the robotic system for stability. This theoretical result was tested on a one DOF system. Corteville *et al.* (2007) utilized a one DOF robot to test the value of assistance from the robot in human-robot cooperation. The robot-assisted the human by utilizing a bell-shaped velocity profile. Ikeura *et al.* (1994) performed a one DOF human-human cooperation experiment. They determined that a human follower, who did not know the goal, could generally be represented by damping. They then applied this to a robot-human experiment and used subjective evaluation methods (ranking 1 to 5) for maneuverability, stability, and viscosity. They then found that their subjective evaluation matched closely with their experimental data. In a similar study, Ikeura and Inooka (1995) implemented a variable impedance controller. This was essentially a gain schedule adaptive dampening, where the damping coefficient was 15Ns/m for below 0.05m/s velocity and 8Ns/m above 15Ns/m.

Bussy *et al.* (2012) used a three DOF planar task to examined human-robot cooperation. The robot system acts only as a follower and assists the human's motion. Passenberg *et al.* (2011) used a computer simulation and a two DOF haptic device to investigate assistance provided by the robot to the human. Tsumugiwa *et al.* (2002) used a three DOF task to investigate a variable impedance controller for human-robot interaction. The variable impedance was found to improve the accurate placing of an object.

Evrard and Kheddar (2009) investigated the variation of leader/follower roles between a human and robot by creating a homotopy switching model. This model created a continuously varying level of leadership between the robot and the human. A haptic device was used to test this in a two DOF computer simulated lifting task. In a number of trials, the computer system was acting as the leader. However, the human thought they were acting as the leader.

Oguz *et al.* (2010) utilized a two DOF virtual game to examine role exchange between the human and the computer. Wojtara *et al.* (2009) made a robotic system to aid a human in placing an object on a surface. The robotic system moves to the general location, and the human makes the final placement by overcoming the stiffness of the robot. Lawitzky *et al.* (2010) examined effort distribution using a two DOF haptic device. The behaviors analyzed were the minimum effort of the robot, maximum effort by the robot, and a balance of effort between the human and robot.

Summary of Human-Robot Interaction Research

A number of researchers have investigated human-robot interaction, but there are a number of limitations to the previous research. The past research has been primarily conducted with a limited DOF of the human-robot interaction. The vast majority of the research is conducted with 3 or fewer DOF in the human-robotic interaction. This lack of DOF can raise questions as to whether the interactions would be able to be maintained in the higher complexity of six DOF human-robot interaction. Additionally, the interaction is often simulated or limited compared to the physical interaction that the task is intended to represent. This can be limiting on the methods that a human may choose to interact with the system, as well as change the physical human kinematics and dynamics involved in the interaction. Some researchers have examined conflicting goals of human and robotic systems, but this has been done with the above limitations. Overall, greater research is needed to progress robotic systems to be able to cooperate with humans in unstructured environments.

2.5 Human Machine Interface and Situation Awareness

Traditionally in human factors engineering, human-machine interfaces were measured based on workload. Workload assessments are based on the effort that it takes for a user to perform the desired task. However, as the type of interactions with machines has grown, additional ways of assessing interfaces were needed. Interactions with devices often now involve the human making decisions during the interaction. This requires that the interaction with the device provide sufficient information and understanding to make an accurate decision. The main way of assessing this type of interaction is through an assessment of the human's situation awareness. Endsley's influential paper (Endsley, 1995) indicates that there are three levels of situation awareness. Each level builds on the previous level, so if there is poor situation awareness at one level, the higher levels will also be lacking. The lowest level is perception. This is whether or not the human can perceive the basic data needed for an accurate assessment of the system. The second level is about comprehension of the current situation. The human must be able to comprehend the basic data from level one to understand what the immediate consequences are to the system. The third level of situation awareness is projection. It is the ability of the person to project the future states of the system. This enables a user to understand how to modify their actions to produce the desired results.

Calhoun *et al.* (2004) compared the use of tactile versus aural alert cues. This the examination was done within the context of unmanned ariel vehicles (UAV) control application and with a redundant visual cue. One advantage of aural and tactile cues seen by the authors is that they view the cues as omnidirectional. By this, they mean that the cue does not require the user to look at a specific area of the screen to receive the information. This is a limitation of visual only cues.

Many current UAV systems primarily utilize visual cues to alert the operator that there is some condition that needs to be resolved. The tactile alert was from a vibrational element strapped to the subject's wrist. In the experiment, two types of alert cues were used. One was label as a caution alert and the other a critical alert. The caution alert occurred 20-24 times per trial with the critical alert occurring only three times per trial. The caution alert required the user to check a value and evaluate if it was above a threshold and then hit a corresponding button based on that determination. The critical alert required the user to complete steps listed on a checklist. Additionally, during this experiment, the subjects had to perform flight navigation, enter data associated with radio calls, and to enter data based on radio queries. These tasks were performed in either a high or low auditory load environment.

For this experiment, they found no significant difference in the performance based on the cues of auditory versus tactile cues. However, the subjects noted a preference for the tactile cues in the high auditory load environment. This investigation shows that information can be communicated to the user through tactile channels as effectively (at least in this case) as aural information. This shows the usefulness of haptic information in communicating with humans.‘

Durso *et al.* (1998) examined the use of situation awareness as a predictor of performance. In this examination, the task the subjects needed to perform was air traffic control. They examined several different measurement methods for situation awareness, and this was compared with the older standard measurement of workload. The participants in the experiment were air traffic control instructors with an average of 18.8 years of experience. The comparison found that situation awareness methods performed better at predicting performance than workload measurements.

Endsley and Kiris (1995) examined the possibility of mitigating out-of-the-loop performance problems with modifying the level of automation. Out-of-the-loop performance problems can be attributed to two general areas. The first area is a loss of manual skill from the human operator. If a system is highly automated, the operator may never build up sufficient proficiency or maintain proficiency to be able to control the system adequately if manual control is required. The other area attributable to the out-of-the-loop performance problem is a decrease in situation awareness. The first area is a longer-term issue of the degradation of the capability of the user. The second area is a more immediate problem of not understand the current situation well enough to take over immediate control of the system effectively. Subjects (80 total) participated in a simulated automotive navigation task with varying levels of automation from the system they were interacting with. During the experiment, subjects were put into a situation where the automation system failed, and they had to take over full control of the system. When the level of automation was less and required the subject to participate more during normal operations, subjects were more successful at taking over control of the task and had higher levels of situation awareness. This shows the potential benefit of requiring some interaction during tasks to improve overall performance.

Rovira *et al.* (2007) examined the effects on a simulated command and control task from imperfections in automation. The experiment for this investigation involved a sensor to shooter command and control task. This task involves detecting an enemy on a computer map and then determining the correct friendly unit to shoot at the target. The subjects were given three levels (low, medium, and high) of automation for decision support. They were also tested with a completely manual system. The experiment involved varying the automation support accuracy between perfect, 80% accurate, to 60% accurate. Overall, perfect automation significantly improved the time to perform the task. When the automation accuracy was at 80%, the subjects were more likely to fail at the trial when the automation was incorrect than when the automation was correct 60% of the time. This suggests that the higher level of accuracy of the automation can induce complacency in the humans. For the 80% accuracy section, the subject's performance did not significantly vary for the level of automation (low, medium, and high). However, for the 60% accuracy section, the subject's performance decreased for the higher level of automation. This may suggest that there is a greater cost of accuracy for higher levels of automation than for manual tasks.

Rouse (1977) examined multitasking in human-computer interaction. He proposes using queuing theory for allocating the focus of the human and computer actors. This could be a valuable pursuit, but he does not account for differences in the prioritization of tasks from the computer system than from the human. Additionally, humans were not used in the experiment and instead a simulation of humans was used to interact with a computer.

Riley and Endsley (2005) examined the complexities from human collaboration with remotely piloted vehicles. In the pursuit of reducing the number of human operators needed to control multiple robotic operators, the determination of what and how to automate the robotic systems. They argue that this should be done in such a way as to maintain good situational awareness of the humans involved and that by doing so this will reduce problems when the humans need to make decisions in the processor to take over in manual control.

Haas *et al.* (2009) examined multi-modal interfaces for interaction between humans and a simulated robotic swarm. Many UAV interfaces are visual only. In this experiment, multi-modal interfaces are examined, such as visual, auditory and tactile interfaces. These were combined into four groups for evaluation: visual only; visual and auditory; visual and tactile; and visual, tactile and auditory. A virtual swarm was created, and information was passed to the subject about the swarm health, geospatial information, and swarm status information. When the subjects received a signal that corresponded to particular information about the swarm, they were to press a key to indicate the information received. Overall, the subjects were 99.9% correct in their classification of the information received. However, the trials where there was the addition of auditory, tactile, or both to the visual signal had faster response times than with visual alone. The importance of this study is that it adds to evidence that haptic information can be a useful information channel for the human.

Gold *et al.* (2013) examined the performance of drivers when asked to take over for an automated driving system. The subjects were driving a car in a high-fidelity car simulator with a highly automated driving system. While driving, an obstruction in their lane was created and the car needed to either swerve to avoid the obstruction or stop. The automated system would alert them to the need to take over either five seconds or seven seconds away from the obstruction. The drivers were successful at taking over and avoiding the obstacle. However, in the five second time trials, the subjects performed worse and made much sharper maneuvers. The seven second time trials the subjects had smoother trajectories to avoid the obstacle. One group of subjects drove without automation for a baseline. Their obstacle avoidance trajectories were the smoothest. This demonstrated the need for timely switching between roles to improve the performance of the system.

Lee and Moray (1992) examined trust and the effect that it had on automatic versus manual control of human-machine systems. The experimental scenario was to control various devices in a processing plant. These devices could be used in manual control or automatic control. The user was trying to maximize the performance of the plant while avoiding penalties for incorrect operation. Initially, the automatic systems worked correctly. In this scenario, users used a combination of automatic and manual control, but this became a static configuration that they were employing. Once there was an error in the automatic system, the users began changing these configurations to try and better control the plant. Unexpectedly, the users spent a little more time in automatic modes after the errors began occurring. The authors theorize that this may be due to lower self-confidence from some of the users that they could control it better in manual. However, they were more active during the trials with errors and changed modes (auto versus manual) more often after the errors began occurring. This could be viewed as taking a more active control mode at the high-level control while allowing the automatic mode for a component to perform the lower level control. The trust that the user had for the system decreased after the system started having errors. However, the trust level gradually rose after the user became accustomed to the error. This highlights the element of trust in using automatic control but also indicates that the human's trust of the system can be recovered after an error.

Miller (1956) examined the limitations of memory and the ability for people to make comparisons between stimulus. This paper presents a valuable and often cited element of human limitation. Humans are normally able to only remember seven items (plus or minus two) in short-term memory. However, humans can group items to extend this capability. Additionally, he presents the concept that comparisons between different items are also often limited to seven as well. One example of this comparison is for determining if a tone that is heard is one of a certain number of predefined tones. Subjects begin to confuse which tone is high when there are more than five different possible predefined tones.

These findings indicate the limitations of humans to focus and retain information about a system with which they are interacting. This suggests that one of the main ways a robotic system can aid a human is by keeping track of the additional variables needed to operate a system and to potentially control them when the human is focused on other elements of the complex task.

Madhavan *et al.* (2006) examined how trust was impacted when an automated system made an error on a task that was easier for the human compared with a task that was difficult for the human. The scenario was simply to find a correct letter on a screen with additional letters on it. The automated system would give its suggested locations. The difficulty of the task was increased with the number of non-relevant letters on the screen. When the automated system made errors only on the more difficult trials, humans trusted the system more and relied on it heavily on the easier tasks. When the system made errors only on the easy tasks and was correct on the harder tasks, the humans trusted the system less and under relied on the automation of the harder tasks. This shows that humans will judge the trustworthiness of a system based off of the successfulness of the system on tasks that the human perceives as difficult. This means that for tasks that humans are better suited for than the robotic system, errors committed by the robotic system may cause a lack of confidence in the system for tasks that the robotic system is better able to perform. This suggests that in tasks where the robotic system has greater uncertainty, it may be a better control strategy to transfer control of this task to the human.

Bartlett (1943) examined the effects of highly skilled work on fatigue. He created a system to approximate a complex machine that needed specific timing in the sequence of events to successfully interact with the system. Although not explicitly stated in the article, from the date (World War II era) and other content it appears to have been designed to mimic flying a complex manually controlled aircraft.

The main contention is that previous studies examining highly skilled behavior were not designed correctly and that the issue of timing and appropriateness of an action was not required in the previous literature. He had some very important results from this experiment. He found that as subjects progressed in the experiment their ability to properly control the machine deteriorated, but the subjects insisted that their performance was improving. This is significant when examining how systems with greater capabilities than a basic machine should interact with humans. As the human is asked to perform highly skilled work, the robotic system needs to watch for potential mistakes being performed by the human and to be able to take over control from the human when needed to prevent an error from occurring.

Mackworth (1948) examined the breakdown in visual search over time by humans. In his experiment, he examined the ability of humans to accurately detect when a clock-like mechanism moved twice the distance it normally did. These events occurred infrequently and at a random time. He found that subjects ability decreased significantly after 30 minutes of watching the device. He also had some subjects additionally listen for a phone call. While listening for the phone to ring (in addition to watching the mechanism), their performance decreased. However, after the subjects had answered the phone, there was an immediate improvement in their performance in watching of the mechanism.

These findings suggest a few important elements for human-robot interaction. The first is that a human will have difficulty maintaining vigilant observation of a robot operating a task. It may be difficult for the human operator to remain focused enough to recognize incorrect motion by the robotic system when they are only observing. The element of answering a phone call and the resulting boost of vigilance suggests that some level of additional interaction will potentially improve the subject's vigilance and ability to detect incorrect motion of the robotic system when it performs incorrectly.

Baddeley (1972) examined the effect that high danger environments had on selective attention. The author acknowledges the difficulty of studying this topic. First, one cannot ethically put people in high danger environment simply for an experiment. There are some overall statistics from the actions of people in combat situations that suggest that they behave significantly different from how they behave in training environments. Additionally, some older experiments were conducted where the subject was given a false impression of the danger that they were in and studies where people were already choosing to engage in dangerous behavior and study where additional tasks were added to this behavior. The general finding from this was that the people had a narrowing of focus in dangerous situations. This is commonly referred to as tunnel vision. This was true of most people, but it should be noted that it was not true of highly trained individuals. The higher trained individuals performed better during the dangerous situation and had a lower anxiety level that just before and after the dangerous activity. This points toward a potential benefit of a human-robot cooperative system. It is that the robotic system can maintain the same level of sensor evaluation regardless of the situation. This will allow the robot to alert the human or to deal with an issue itself when the human has a narrow focus due to impending danger.

Kaber and Endsley (1997) examined the use of intermediate levels of automation on the out-of-the-loop performance issue. The out-of-the-loop performance problem is a problem that is caused when the human involved is not sufficiently engaged in the task at hand. The experiment involved subjects engaged in a simulated process environment. The subjects had to recognize targets on a screen and select and eliminate them as they moved across the screen. Different levels of automated support were provided to the user. Overall the findings were that when the subjects had a high level of automation support, they had difficulty taking over the task manually compared to when they had a lower level automation support. This suggests that the level of automation can be adjusted in human-robot interaction to adjust the performance capabilities of the human to be able to take over a task if needed.

Summary of Human Machine Interface and Situation Awareness

Human factors engineering has important elements that need to be considered for human-robot interaction. Situation awareness of the human will impact the ability for the human to make decisions related to the task. This can be influenced by the level of automation that the system has with which the human is interacting. The human's ability to focus has limitations both on the number of simultaneous elements as well as maintaining vigilance over time. This research suggests that robotic systems may need to accommodate the human's ability to focus. Additional investigation into the effects of automation on human-robot physical interaction is needed.

2.6 Electroencephalogram(EEG)

2.6.1 Overview of EEG

To examine the function of the brain requires obtaining a signal that is related to neural processes. Three methods for creating a signal related to the neural process are functional magnetic resonance imaging (fMRI), electroencephalogram (EEG), and magnetoencephalography (MEG). Each of these methods has their strengths and their weaknesses.

Functional magnetic resonance imaging (fMRI) uses magnetic resonance imaging to determine brain activation. This is done through the use of blood oxygenation level-dependent (BOLD) fMRI measurement techniques (Ojemann *et al.*, 1997). The main benefit of this method is precise localization in the brain. The negatives of this method are cost, large equipment restricts experiment design, magnetic element requires non-magnetic test apparatus, and not usable in the field.

External electroencephalogram (EEG) uses the electrical potential (voltage) between two places on the head. This requires a conductive connection between the scalp and an external electrode. The benefit of this is excellent time resolution, the ability for real-time data, and capable of being used in applications (Handy, 2005).

Magnetoencephalography (MEG) utilizes the same concept as EEG, but instead of measuring voltage it measures the magnetic field. The benefit is that does not require a conductive connection to the scalp. The disadvantages are that it is currently more susceptible to noise and the equipment is significantly more expensive.

As explained by Luck (2014), the main signal that is measured by the EEG system is from postsynaptic pulses and not action potentials. Postsynaptic pulses are from the ions of the neurotransmitter binding to the receptors site in the brain.

One type of EEG analysis is event-related potential (ERP) technique. This technique examines the electrical potential measured following an event of interest. This focuses on measuring the magnitude of the voltage and its immediate change following an event (Luck and Kappenman, 2011). This technique has the best time resolution of other technique. This is because it does not rely on a change in frequency. When examining the data using frequency or time-frequency analysis, segments of data must be analyzed in a block of data. The smaller the block is the better the time resolution, but the worse the resolution of frequency. Conversely, the larger the segment of data is the better resolution of frequency, but the worse resolution of time. In contrast to this, ERP has both magnitude and time accuracy. The main drawback is that it does not have frequency information.

One of the issues with EEG data is artifacts in the data from outside sources. One method some researchers (Delorme *et al.*, 2011; Jung *et al.*, 2000) have used to aid in the removal of the artifacts, is to break down the EEG signal into components using independent component analysis (ICA). Additionally, using localization techniques such as dipole fitting (DIPFIT) (Delorme *et al.*, 2011) aids in the choice of which ICA components to remove from the EEG data. This source localization is used to designate all of the ICA components that are located outside of the brain and to eliminate them from the EEG data. Although, there are issues with relying too much on source localization techniques due to the assumptions inherent in these techniques. One assumption is that the sources are coming from a single source or a small number of sources. This may not be the case and if a more distributed activation occurs the localization could be significantly off. Helmholtz showed that for a non-uniform biological tissue, the voltage distribution measured from the surface could come from an infinite number of sources (Plonsey, 1963; von Helmholtz, 2004). This means additional techniques should be used for truly accurate positioning.

As can be seen from Lotte *et al.* (2007), a thorough review of classification algorithms used with EEG data, numerous different approaches have been utilized with various levels of success. The usefulness of a technique can vary significantly. When looking at combining EEG data with other features related to human-robot interaction, a generative type of classifier is desirable. Generative types of classifiers generate a probability associated with the classification and not just a binary classification. This could allow the information to be used, and weighted appropriately, with other features from physical interaction of the human with the robot.

2.6.2 Brain Computer Interface

Brain computer interface (BCI) is a system that uses the signals from the brain to control some aspect of a controlled computer system. This can be a cursor on a computer screen, swarm of robots, robotic arm, an exoskeleton, or any number of other systems. The interest in BCI systems can be seen in the popularity of general BCI software such as in Schalk *et al.* (2004).

Some researchers utilize the human's ability to imagine physical motion without actually performing the motion. This is referred to as motor imagery. Wolpaw *et al.* (1991) and then in Wolpaw and McFarland (2004) created a BCI capable of single and then two axis controls of a cursor. Pfurtscheller *et al.* (2000) utilized EEG frequency bands specific to each subject to classify the BCI interaction. Wolpaw *et al.* (2000) showed that both people with motor deficiencies and people without deficiencies could learn to modulate μ (8-12Hz) and β (13-28Hz) bands of brain waves to use a BCI. Wolpaw and McFarland (1994) showed that subjects could control a 2 DOF mouse cursor movement by utilizing 8-12Hz brain activity. Pfurtscheller and Neuper (2001) examined the use of motor imagery with right and left motor imagery classification for use with tetraplegic patient. Blankertz *et al.* (2007) were able to utilize motor imagery BCI to reduce the time needed to establish a BCI for a subject. Subjects spent 20 minutes performing calibration motor imagery and 9 out of 10 subjects were able to utilize the system. Pfurtscheller *et al.* (2006) utilized desynchronization of μ band to classify different motor imagery elements.

When a human looks at a visual cue the frequency the visual cue is displayed can evoke a change in the EEG signals. Cheng *et al.* (2002) were able to use visually evoked potentials to allow subjects to enter numbers at a rate of approximately 27 bit/min. Cheng *et al.* (2002) were able to utilize a visually evoked EEG signal to allow subjects to control the roll of a simulated aircraft.

Event-related potentials have also been investigated in BCI systems. Donchin *et al.* (2000) examined the use of the ERP component P300 in a BCI system. Hoffmann *et al.* (2008) used P300 ERP component to allow subjects to achieve a data transfer rate of 10 to 25 bits/min. Sellers and Donchin (2006) and Nijboer *et al.* (2008) showed that ALS patients were able to use a P300 ERP BCI to communicate.

McFarland *et al.* (1997) showed that common average reference and spatial filtering performed better than earlobe reference for use in a BCI. Ramoser *et al.* (2000) examined the use of spatial filtering in EEG for determining between right and left-hand motor imagery.

Kilicarslan *et al.* (2013) used a BCI to control a lower-body exoskeleton. This exoskeleton gave paraplegic subjects the ability to walk. Subjects were asked to perform several tasks. These are walk, turn, sit-down, rest, and stand-up. They were able to achieve a 97% success rate. The subjects were required not to move their upper limbs during the test.

2.6.3 Summary of EEG research

Numerous techniques have been developed to examine brain activity. Using EEG to examine brain activity has several advantages. Some of these are time resolution, the ability for real-time data, and portability of equipment. Several techniques have been developed to improve the signals processed by the EEG system such as removal of components using ICA. The event-related potential technique looks at using changes of electrical potential evoked by a stimulus and a number of components have been identified.

In the investigation of BCI, the vast majority of the research focuses on humans specifically performing mental actions to control external systems. Greater research is needed in allowing the human to think naturally and to use signals derived from this to affect the control of a system. Additionally, BCI systems often rely on the human not moving and interaction while using the system, and additional research is needed in incorporating physical interaction into BCI systems.

2.7 Discussion

Impedance control is a well-established method for controlling a robotic system to interact with the environment. This method creates a relationship between the motion of the end effector of the robot and the force applied by the robot to the end effector. Additionally, in Chapter 3 the use of stiffness as a method of communicating will be examined.

Human subject and human-robot research have significant findings. Humans tend to pre-plan motion based on previous experience but quickly adapt to situations that do not match with expectations. Humans typically move objects in a bell-shaped velocity profile such as a minimum jerk trajectory, but this can vary depending on the location of the motion relative to the human. Additionally, humans increase the impedance of their arms are to stabilize and interaction. This also occurs if the motion is new. However, they may decrease this impedance as they become more accustom to the motion. In human-human interaction, humans may specialize when completing a joint task. In human-robot cooperative research, some areas need greater research. Overall, there is a lack of research in interaction with six DOF tasks and tasks where there are contradictory goals. Additionally, a large portion of the research has limited physical interaction with a robotic system where the task is simulated, and a haptic device is used. This constrains the human to only interact in with the physical system in limited ways and limits the kinematic and dynamic elements needed to be performed by the human.

In human factors engineering, the importance of situation awareness and limitations of human focus are shown to be important. Situation awareness allows the human to perform better at decision-making when interacting with a system. High levels of automation can degrade situation awareness and performance. Humans ability to focus on large numbers of elements as well as maintaining vigilance over time is limited.

In EEG research, there are a number of important elements. First, there are numerous potential noise issues that may arise, and there have been some techniques developed to reduce this issue, but it cannot eliminate it. In BCI research, the focus is on conscious thought used to control a system. This often utilizes motor imagery or relies on the human not moving their arms.

Chapter 3

PRELIMINARY MOTIVATIONS

Two experiments that were motivational for the research in this dissertation are examined. Detailed information about my contribution to these experiments can be found in the preface. In the first experiment, stiffness as a means of communicating a preferred direction is examined. In the second experiment, human-robot role exchange is examined.

3.1 Human-Human Impedance Cooperation

As discussed in Chapter 2, increasing stiffness is a natural reaction to a human interacting with an unstable environment. Additionally, humans have higher levels of stiffness for motions when they are new to them. From the previous work, it had not been determined if humans can use stiffness as a method of communication with another human.

In Mojtahedi *et al.* (2017), 20 subjects (10 dyads) were tested to explore if human dyads can use stiffness as a means of communicating a preferred direction of motion. The physical setup of the experiment can be seen in 3.1A. A flat-screen is horizontally located above the participants' hands. This obscures the participants from seeing the position of their hand or the other participant's hand. The subjects grasp a manipulandum, as seen in the 3.1B. This measures the force applied by the subjects in the horizontal plane. The flat screen displays 12 lines to the dyad with a 30° separation between the lines. In the visual information experiments, the subjects also see a dot on the screen that represents the position of the manipulandum. In the no visual information experiments, this is not displayed.

For this experiment, the Kuka LBR 4+ is utilized to limit the motion to the horizontal plane. It also prevents rotation, thus limiting the interaction to two DOF.

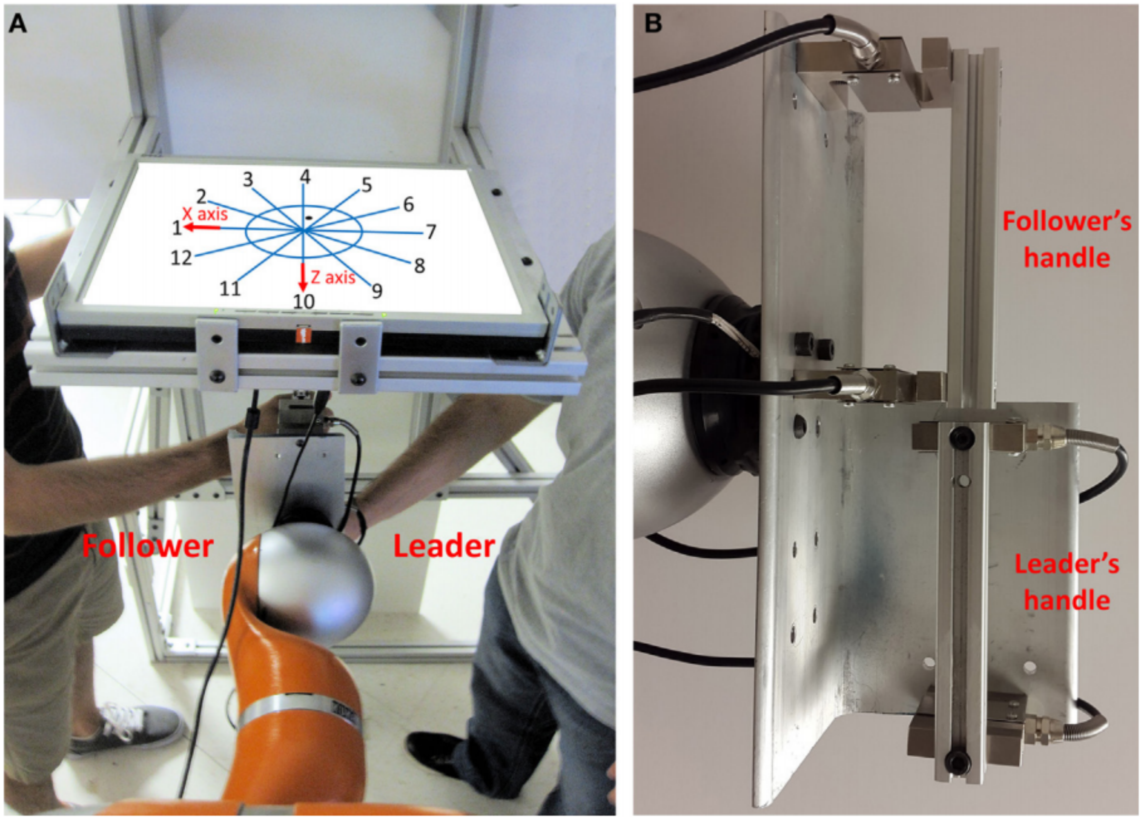

Figure 3.1: Experimental Setup: A) Computer screen displays directions to subjects. The subjects grasp the handles of the manipulandum. The robot are limits the motion to translation in the horizontal plane. B) Manipulandum measures applied force of the leader and follower. (From Mojtahedi *et al.* (2017))

The robotic system utilized the KRC robotic controller and an additional computer running the control system program. This additional computer records the position data from the robotic system and the load cells in the manipulandum to measure the forces applied by the subjects.

One subject of the dyad is designated as the leader during the experiment. The leader role does not change during the experiment. The other subject is designated as the follower in the experiment. The leader is shown a number indicating which is the preferred direction of the 12 labeled lines on the display. A start signal is played, and the follower is to determine the desired direction of the leader. The subjects are informed not to allow the manipulandum to move outside of the 5cm diameter circle

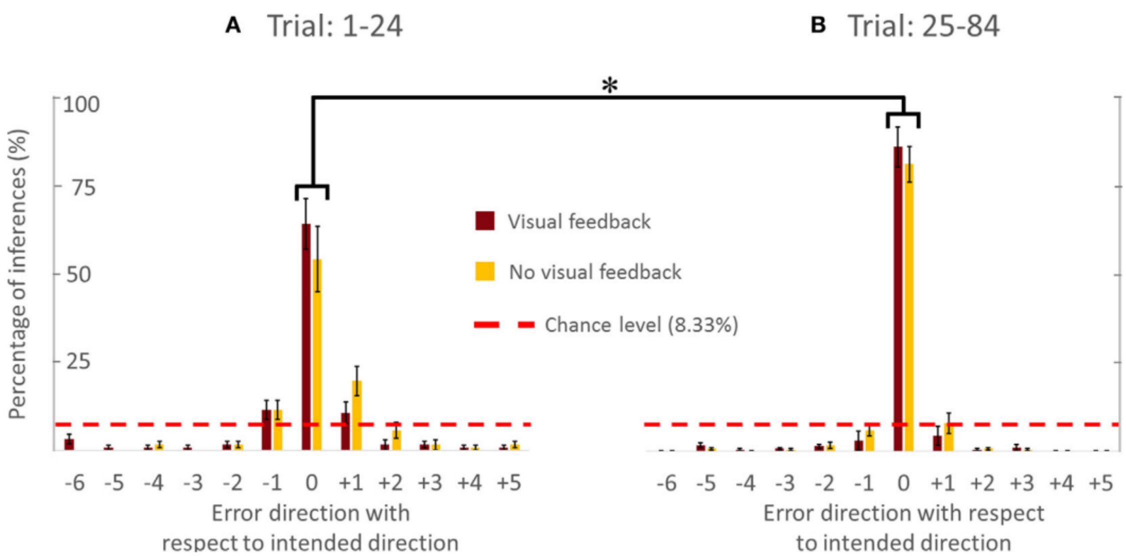

Figure 3.2: Human-Human Results - Accuracy of inferences of preferred direction of the follower. Percentage of accurate inferences of follower (all subjects). (A) Training Set. (B) Test Set. Data are means averaged across all subjects. Standard Error of the mean is indicated by vertical bars . Statistical significant difference ($p < 0.001$) are indicated by an asterisk. (From Mojtahedi *et al.* (2017))

on the display. The leader uses the stiffness of their arm to communicate the desired direction.

Dyads performed an initial 24 trial set to allow for learning of the task. They then performed an additional 60 trials. The accuracy of the results can be seen in Figure 3.2.

3.1.1 Results Human-Human experiment

Humans were able to correctly identify the preferred direction 87% when the human had visual feedback and 83% of the time when they did not have visual feedback. This is significantly above the chance level of 8.33%. Additionally, even during the initial training period humans were able to correctly identify the preferred direction significantly above the level of chance

These results show that humans can utilize an interaction that is predominantly a stiffness interaction to communicate the desired direction to another human. This extends stiffness and impedance to be potentially useful, not only for control and stabilization but also as a potential means of communication.

3.2 Human-Robot Cooperation

In Whitsell and Artemiadis (2015), a controller was developed and tested for human-robot cooperation. In this experiment, the task is a four DOF task of transporting a ball along the horizontal plane while preventing the ball from rolling off of the fixture. Two DOF are from the translation in the horizontal plane. The other two DOF are from maintaining the rotation of the device holding the ball.

3.2.1 Experimental Setup

Figure 3.3 shows the physical setup for the experiment. The Kuka LBR 4+ robotic arm was used for the experiment. Additionally, the Kuka robotic controller (KRC) was used to provide lower-level control and power to the robotic arm. The KRC interfaced with a control computer running Kuka's fast research interface (FRI). The FRI allowed the control computer to provide the higher level control commands to the KRC and to receive data from the robotic arm.

Attached to the end of the robotic arm is a ball transport manipulandum (BTM). The BTM allows the human to grasp one side while the other side of it was bolted to the end of the robot. In the middle of the BTM is a small square ridge created from layers of paper being taped down. This creates a small target area where the ball can rest.

The task of the experiment is to transport the ball on the BTM to one of the two bins. The trajectory for this transportation follows within a 'T' shaped path. The

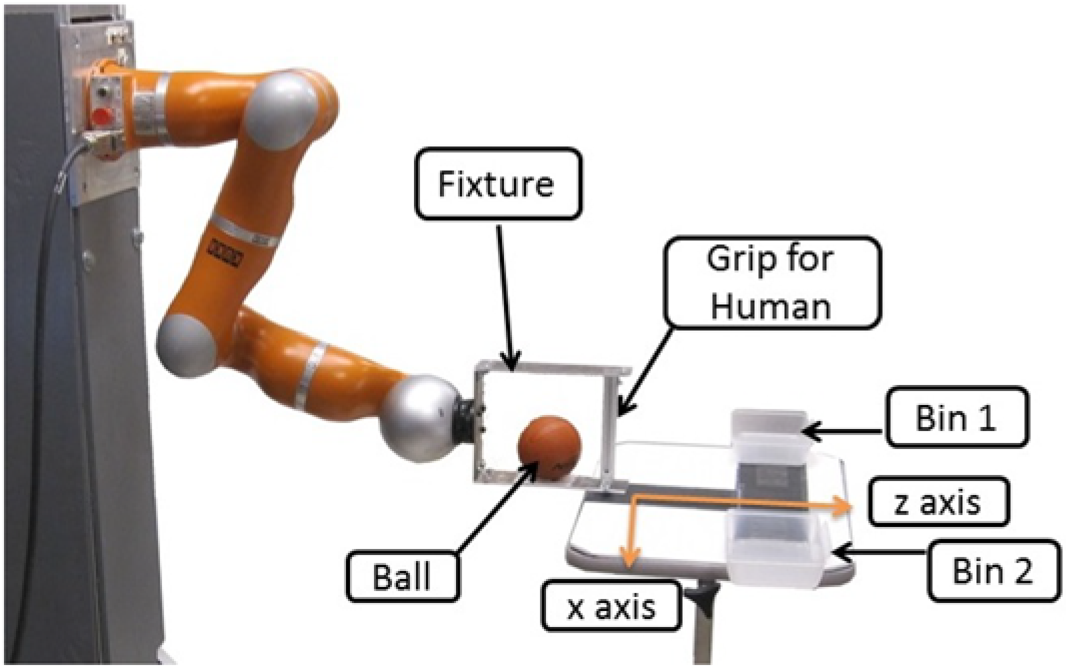

Figure 3.3: Physical Setup for Human-Robot Experiment Whitsell and Artemiadis (2015) ©2015 IEEE

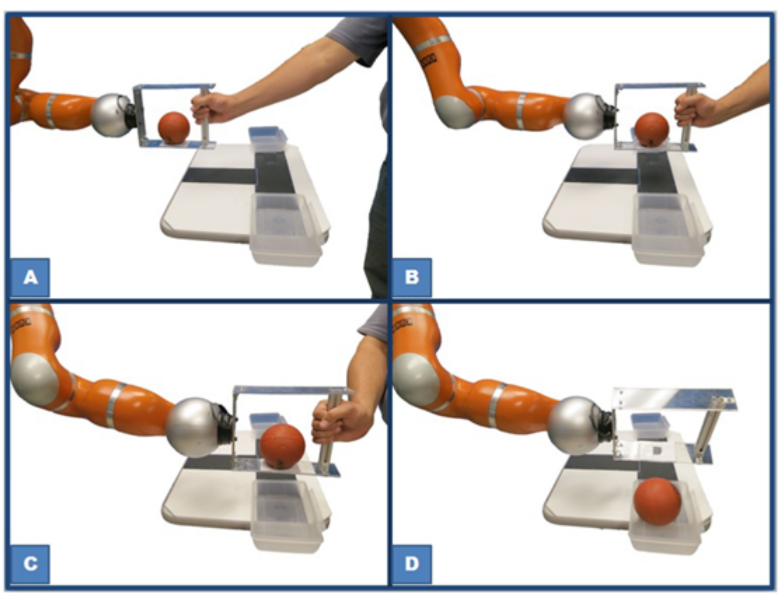

Figure 3.4: Motion of Trial From: Whitsell and Artemiadis (2015) ©2015 IEEE

human is informed at the beginning of each trial which bin is the correct bin for the trial. At the start of the experiment, the human is the leader of two rotational DOF. These rotational DOF correspond to keeping the BTM level, and this prevents the ball from rolling off. The robot begins the experiment as leader of 2 translational DOF. These DOF correspond to translation in the horizontal plane. At the end of the transport task, the robotic system takes over control and performs a rotation of the BTM designed to roll the ball into the bin. The ball rolls into the bin, and this is designed as a way of scoring the successfulness of the trial.

For this experiment, the robot was controlled in Cartesian impedance mode. Utilizing this control mode allowed the higher level controller to specify the equilibrium position and orientation and the stiffness and damping ratio to be applied in the Cartesian coordinates of the task space. This robotic control is governed by the Equations 3.1 - 3.4. In order to minimize the motion in the two DOF not used in this experiment, high stiffness values were used for them. For the vertical axis (y) a stiffness of 5000N/m for k_{ty} was used. For the rotational DOF about the y-axis, a stiffness of 300 Nm/rad for k_{ry} was used. These values constrained the experiment to the horizon $x - z$ plane and rotation about the x and z axes.

$$\begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix} = \overline{\mathbf{M}}\ddot{x} - \overline{\mathbf{B_t}}\dot{x} - \overline{\mathbf{K_t}}x \tag{3.1}$$

$$\begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} = \overline{\mathbf{J}}\ddot{\theta} - \overline{\mathbf{B_r}}\dot{\theta} - \overline{\mathbf{K_r}}\theta \tag{3.2}$$

$$\overline{\mathbf{K_t}} = \begin{bmatrix} k_{tx} & 0 & 0 \\ 0 & k_{ty} & 0 \\ 0 & 0 & k_{tz} \end{bmatrix} \quad \text{and} \quad \overline{\mathbf{K_r}} = \begin{bmatrix} k_{rx} & 0 & 0 \\ 0 & k_{ry} & 0 \\ 0 & 0 & k_{rz} \end{bmatrix} \tag{3.3}$$

$$\mathbf{x} = \begin{bmatrix} x_p - x_e \\ y_p - y_e \\ z_p - z_e \end{bmatrix} \quad \text{and} \quad \theta = \begin{bmatrix} \alpha_p - \alpha_e \\ \beta_p - \beta_e \\ \gamma_p - \gamma_e \end{bmatrix} \tag{3.4}$$

The force the robotic arm applies along x, y, and z axes are F_x, F_y, and F_z respectively. T_x, T_y, and T_z are the torques that were generated around the x, y, and z axes respectively. The mass matrix $\overline{\mathbf{M}}$ and rotational inertia matrix $\overline{\mathbf{J}}$ is determined by the robotic control system. The damping coefficient $\overline{\mathbf{B_t}}$ and $\overline{\mathbf{B_r}}$ are determined by the damping ratio, which was set at 0.7 for the experiment. The stiffness that the system has is determined by the $\overline{\mathbf{K_t}}$ and $\overline{\mathbf{K_r}}$ matrices. This is multiplied by the difference of the current position (x_p, y_p, z_p, α_p, β_p, γ_p) and the equilibrium position (x_e, y_e, z_e, α_e, β_e, γ_e) set by the higher level controller to generate a spring force exerted by the robotic system. The high-level controller then creates a force (or torque in the rotational case) to move the robotic system along a trajectory by changing the equilibrium point to be sequential points along a trajectory.

3.2.2 Experiment Process and Control

The robot starts as the leader of translation and the follower of rotation at the beginning of each trial. The human starts as the leader of rotation and as the follower of translation. If the robotic system detects that the human wants to exchange roles, then a simultaneous role exchange is initiated. When this occurs, the human then becomes the leader of translation, and the robot becomes the leader of rotation.

Figure 3.4, shows the motion of a single trial. The robotic system moves toward the human along the black path in Figure 3.4. It then moves either to the right or the left toward one of the bins. If the robot performs correctly, the human should remain the leader of rotation and allow the robot to continue as the leader of translation. However, if the robot makes a mistake than the human should correct the robotic motion and this will trigger a role exchange where the human becomes the leader of translation, and the robot leads rotation.

The trial ends once the BTM has been moved sufficiently far along the y-axis that it would line up with a bin. Then the robot takes over all DOF and performs a rotational motion to drop the ball into the bin. A trial is scored as successful if the ball falls into the bin.

In this experiment, the robotic system needs two methods for determining the next impedance control command. One command was for the case where the robotic system is leading translation and following rotation. The other is the opposite case of this. For the case where it is leading in translation, the robot utilizes the preprogrammed trajectory for the equilibrium points along the 'T' shaped path. For the robotic system to follow the rotational DOF, it sets a low stiffness value for the two rotational DOF. The rotational DOF are in the local end effector frame, and the human will be working to ensure it remains level, so there will be only small amounts of rotation. When the robot is following in translational DOF, then a low stiffness value is set, and the equilibrium point is set as the last measure position for the respective DOF, as in $x_e = x_p$ and $z_e = z_p$.

The transition from one set of roles to another is another issue that needs to be addressed. The robotic system needs to gradually transition from one type of leader/follower roles to another. To do this, the system generates both equilibrium points that it would command for the next point. It then gradually transitions between these points. To perform a smooth transition, a fifth order spline is used in the familiar minimum jerk formulation from (Flash and Hogan, 1985). This is represented by equations 3.5 and 3.6.

$$x_{tr} = x_{e(k)} + (x_p - x_{e(k)})(10(c/n)^3 - 15(c/n)^4 + 6(c/n)^5) \tag{3.5}$$

$$z_{tr} = z_{e(k)} + (z_p - z_{e(k)})(10(c/n)^3 - 15(c/n)^4 + 6(c/n)^5) \tag{3.6}$$

$$k_m = 300(c/n)N\frac{m}{rad} \tag{3.7}$$

In these equations, c is the current number of cycles that have been performed in the transition. n is the total number of cycles that are performed to complete the transition. x_{tr} and z_{tr} are the next equilibrium point to be commanded by the system. Additionally, the rotational stiffness is transitioned to high stiffness according to Equation 3.7.

The determination of when the robotic system is to exchange roles with the human is of interest in this experiment. Two methods are evaluated. The first is a threshold method where the roles are exchanged if the forces applied exceed the threshold. The second is an adaptive version, where the threshold is adapted to the individual subject.

$$\phi_e = ArcTan2(z_{e(k)} - z_{e(k-1)}, x_{e(k)} - x_{e(k-1)}) \tag{3.8}$$

$$\phi_f = ArcTan2(F_{int(z)}, F_{int(x)}) \tag{3.9}$$

$$\|F_{int}\| = \sqrt{F^2_{int(x)} + F^2_{int(z)}} \tag{3.10}$$

$$\phi_d = |\phi_e - \phi_f| \tag{3.11}$$

$$s = \begin{cases} 1, & \text{if } \phi_d \leq 90 \text{ and } \|F_{int}\| \geq F_{th} \\ 0, & \text{otherwise} \end{cases} \tag{3.12}$$

The method used to determine if to switch roles is described in equations 3.8-3.12. $x_{e(k)}$ and $z_{e(k)}$ are the current equilibrium points . $x_{e(k-1)}$ and $z_{e(k-1)}$ are the previous equilibrium points. The concept behind these equations is to determine if the interaction force is acting in an opposing direction from the equilibrium trajectory of the robotic system. If it is and if the magnitude is greater that the threshold value, then the system initiates a role exchange.

For the initial case, where the robot begins as the leader of translation and follower in rotation, equations 3.13 and 3.14 apply.

$$\begin{bmatrix} x_{e(k+1)} \\ z_{e(k+1)} \end{bmatrix} = \begin{bmatrix} x_j \\ z_j \end{bmatrix} \tag{3.13}$$

$$\begin{bmatrix} k_{tx} \\ k_{ty} \\ k_{tz} \end{bmatrix} = \begin{bmatrix} 500N/m \\ 500N/m \\ 500N/m \end{bmatrix} \text{ and } \begin{bmatrix} k_{rx} \\ k_{ry} \\ k_{rz} \end{bmatrix} = \begin{bmatrix} 1Nm/rad \\ 300Nm/rad \\ 1Nm/rad \end{bmatrix} \tag{3.14}$$

During the transition of roles, equations 3.15and 3.16 apply.

$$\begin{bmatrix} x_{e(k+1)} \\ z_{e(k+1)} \end{bmatrix} = \begin{bmatrix} x_{tr} \\ z_{tr} \end{bmatrix} \tag{3.15}$$

$$\begin{bmatrix} k_{rx} \\ k_{ry} \\ k_{rz} \end{bmatrix} = \begin{bmatrix} k_m \\ 300Nm/rad \\ k_m \end{bmatrix} \tag{3.16}$$

After role exchange has occurred, equations 3.17 and 3.18 apply.

$$\begin{bmatrix} x_{e(k+1)} \\ z_{e(k+1)} \end{bmatrix} = \begin{bmatrix} x_p \\ z_p \end{bmatrix} \tag{3.17}$$

$$\begin{bmatrix} k_{tx} \\ k_{ty} \\ k_{tz} \end{bmatrix} = \begin{bmatrix} 1N/m \\ 5000N/m \\ 1N/m \end{bmatrix} \text{ and } \begin{bmatrix} k_{rx} \\ k_{ry} \\ k_{rz} \end{bmatrix} = \begin{bmatrix} 300Nm/rad \\ 300Nm/rad \\ 300Nm/rad \end{bmatrix} \tag{3.18}$$

The initial version of the experiment is a simple threshold experiment. The second experiment is an adaptive version of this experiment. This adaptation only changes the threshold value used to test if the human desires a role exchange.

The initial value for the threshold for the adaptive version is 15N. If the robot remained the leader during the experiment, the system checks to determine if the threshold should be decreased. If the maximum interaction force plus a buffer value, $Bf = 3N$, was below the threshold value then the threshold was decreased by the decrement value, d. Initially, $d = 1$. However, if a false switch was detected, then $d = 0.5$. A false switch was determined when the robot switched roles, and the human continued the translation toward the bin that the robot was translating towards prior to the switch If this occurred, 2N was added to the threshold and d is set to 0.5.

3.2.3 Experimental Protocol

Four different subjects were used in each experiment. Each subject performed 42 trials. In half of the trials, the robot was programmed to move to the incorrect bin. In the first experiment, three different thresholds were used (5, 15, and 25N). In the adaptive experiment, the initial threshold was set at 15N and allowed to adapt during the remaining trials.

3.2.4 Results

Results For the initial experiment, 15N threshold performed the best and had the lowest number of false positives and negatives. The overall results for each subject can be seen in Table 3.1. Due to the performance of the 15N threshold, it was chosen for the threshold for the start of the adaptive version. The results of this can be seen in Table 3.2.

Table 3.1: Leader/Follower Results (adapted from Whitsell and Artemiadis (2015), ©2015 IEEE).

	False +	False -	Dropped Balls	Successful
Subject 1	3	1	5	36
Subject 2	5	1	8	33
Subject 3	3	1	3	38
Subject 4	4	0	7	35
Mean	3.75	0.75	5.75	35.5
Std. Dev.	0.96	0.50	2.22	2.08

Overall, the adaptive version performed better than the non-adaptive version in false positive, false negative, and dropped balls. Additionally, the adaptive version allowed the threshold to adapt to different values for subjects as can be seen in Figure 3.5.

In this experiment, a simultaneous role exchange controller was developed and tested. From this, the adaptive version performed better than the non-adaptive version. Additionally, the threshold was adapted to the individual subject. This shows the value of allowing the system to adapt to the human.

Table 3.2: Adaptive Leader/Follower Results (adapted from Whitsell and Artemiadis (2015), ©2015 IEEE).

	False +	False -	Dropped Balls	Successful
Subject 1	1	0	3	39
Subject 2	1	0	3	39
Subject 3	0	0	1	41
Subject 4	1	0	2	40
Mean	0.75	0	2.25	39.75
Std. Dev.	0.50	0	0.96	0.96

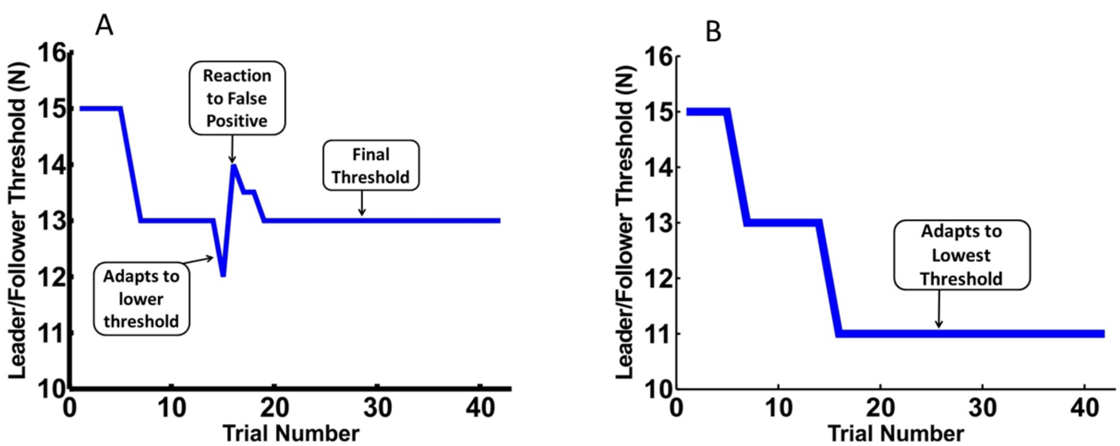

Figure 3.5: Adaptation of Threshold (From: Whitsell and Artemiadis (2015), ©2015 IEEE)

3.3 Discussion

Two previous motivational experiments that influenced this dissertation were discussed. The first experiment was between two humans. This experiment showed that stiffness could be used as a method of communication between two humans. This means that impedance control, which has a stiffness component, may be useful to convey the desired direction, in addition to, being used as a method of robotic control. In the second experiment, a human-robot controller was tested. This experiment was in four DOF, but there was only one DOF that was in conflict during this experiment. The adaptive version performed better than the non-adaptive. This shows the value of allowing the robotic system to adapt to the human.

Chapter 4

EEG AND HUMAN-ROBOT INTERACTION

4.1 Introduction

Human-Robot interaction in an unstructured environment poses several challenges. One of primary concern is that the situation and environment the interaction is being conducted in may change at any time. This could be manifested by a change of goals by the human as an example. The robotic system needs to be able to determine the appropriate way to interact with the human. Utilizing the human's brain activity could be a beneficial way to help determine the type of interaction that the robot should have with the human. Typically brain activity precedes action by the human. This means that brain activity could be used potentially to improve interaction with the robotics system

As discussed previously, there are a number of methods to measure potential brain activity. Of those methods, EEG was chosen as the method to be used. This was due to the potential portability of the system for future applications. The temporal resolution of EEG is superior to fMRI methods. It is also a method that is beginning to find its way into consumer products such as the Emotiv Epoc (Emotiv, 2017). This demonstrates the ability of this method to be cost effective enough to be potentially used in applications.

4.2 Overview of Experiments

An experiment was conducted to examine the usefulness of EEG to detect the type of interaction the robot should have with a human. The human-robot interaction was similar to Whitsell and Artemiadis (2015). However, there were a number of modifications. The subject was to determine if the robot moved in the correct or incorrect direction. The subject then entered a key on the keyboard with their left hand indicating if the robot was performing correctly or incorrectly. This was done to limit the EEG from potentially picking up the motion planning and effort applied by the human to overcome the robotic system. The human did have their right hand on the test fixture. This provided the human with not only visual but also proprioceptive and sensory feedback.

4.3 Physical Setup of Experiments

For this experiment, the human subjects were sitting in a chair. This was done to minimize their motion or shifting of position with regard to the EEG system. However, portable EEG systems can be used in applications. To accommodate the human's position the robot's motion was limited. The fixture would move 10cm towards the subject and then move to the left or the right of a distance of 10cm. The ball that was used in the previous experiment was eliminated. This was done to facilitate the human only examining where the robot had moved in the correct or incorrect direction.

4.4 EEG Setup

The EEG system utilized has several components. It is a BrainVision EEG system, and it utilizes the actiChamp amplifier. This system has 128 electrodes plus a ground electrode. It uses a cap with a 10/20 electrode distribution. The system relies on a high viscosity conductive gel to make an electrical connection between the electrodes and the subject's scalp. The robotic system and the EEG system recorded information

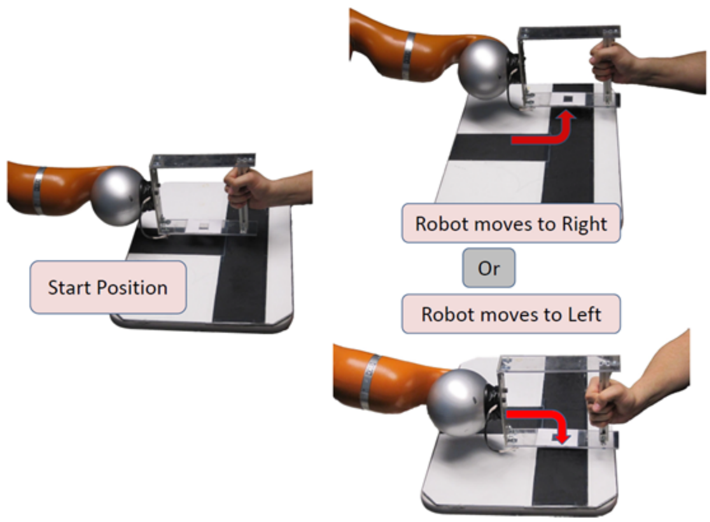

Figure 4.1: Motion of Human-Robot EEG Experiment

separately during this experiment. Whenever data is recorded in multiple locations during an experiment, the issue of synchronicity has to be resolved. The EEG data were recorded continuously during the experiment. This created one long file that would later be broken down to individual trials to match up with the robotic data which was recorded only during the individual trials. This was done so that filters could be applied to the EEG data with minimum concern about inducing filter related artifacts at the beginning and end of the data, as this portion was not used for analysis. To coordinate between the two systems, an additional optical sensor was utilized on an auxiliary channel on the EEG system to record signals to match the data from the two systems.

The optical sensor was used in this experiment to detect changes on a computer monitor. The data from this sensor was recorded simultaneously with the other data from the EEG system. A computer program was written to display a white circle when the robot started a trial and all black when the robot was completed with a trial and returning to the start position. This sensor was temporarily attached to the monitor with an adhesive sticker. This auxiliary channel was processed separately in the data processing phase and was utilized to break up the EEG data into trial segments. To detect the start of a trial a threshold value was used for the photosensor data. The data point before the sensor data crossing this threshold was then selected as the start of the trial. The refresh rate of the monitor does have a delay. This, however, was deemed insignificant for this type of experiment but in an experiment where the precise timing is needed a separate clock signal simultaneously sent to both systems should be used.

The end of the trial was determined by the number of cycles recorded for that trial in the robotic system, and then an additional buffer of ten cycles was added. This ensured all of the trial data was captured.

When the EEG data was broken up into individual trials, this information was checked to ensure that it matched with the robotic trial data. EEGLab was used to process the data (Delorme *et al.*, 2011). The trials were marked with the human's indication that the robot had performed correctly or incorrectly. Additionally, the place in the EEG data where the robot turned either to the right or the left was marked. This represents the beginning of when the human could tell if the robot was making the correct move or the incorrect move.

EEG data from a single subject is known to change over time (Bauer *et al.*, 1989; Hennighausen *et al.*, 1993; Nitschke *et al.*, 1998). This occurs both in the magnitude and frequency domains. To deal with the magnitude drift or DC offset, a baseline was taken before the robot turning left or right for each trial. This baseline is the mean value for each channel for 200ms before the robot turns. This is then subtracted from the data after the turn for each trial and each channel, as in Equation 4.1.

$$S_{\beta(k)} = \frac{S_{\alpha(k)}}{\sum_{n=-1}^{-200} \frac{S_{\alpha(n)}}{200}} \tag{4.1}$$

where $S_{\alpha(k)}$ is the measured value. $S_{\beta(k)}$ is the value after the baseline correction. $S_{\alpha(n)}$ is the value measured at sample n. n represents the sample number prior to the robotic turn. As an example, $n = -1$ is the sample one cycle prior to the robotic system turning.

4.5 EEG Processing

EEG is at its core a measurement of the voltage or the electrical potential difference between two points. This is typically conducted between each of the 128 electrodes and the ground electrode. The voltages are typically very small. This makes the electrical measurements susceptible to noise. Some of the sources of electrical noise are from the EEG amplifiers, the robot, additional electrical equipment and electrical wiring nearby. The fast Fourier transform (FFT) of the raw EEG signal can be seen in Figure 4.2. This is the measured voltage difference between the 'CZ' electrode, located at the center top of the head, and the ground electrode located center of the forehead. One method for reducing noise is to use a reference signal that is subtracted from the EEG signal. A number of different reference channels have been used (Dien, 1998; Junghöfer *et al.*, 1999). Different potential reference channels are examined for use. They are an average reference, both mastoids, single mastoid, and earlobe.

An average reference is a reference signal that averages the current signal of all of the electrodes and then subtracts this average from each channel. The concept behind this is that signals that are picked up across all electrodes are from outside

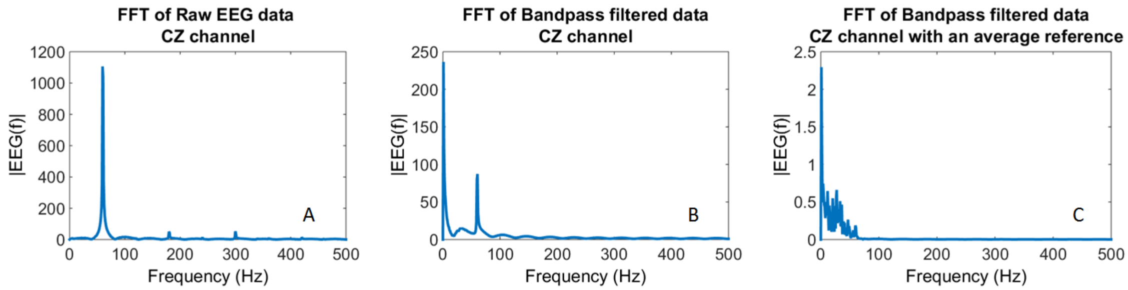

Figure 4.2: Comparison of FFT of EEG data

sources and not a source inside the brain. This is one of the most commonly used references

Mastoid references utilize one or both of the electrodes near the mastoid process. This is located near the base of the skull at the rear of the head. The concept behind this as a reference is that this area does not have significant brain activity near it, so most of the signal recorded should be noise and not brain activity.

Earlobe reference, as the name implies, is a reference from the signal from an electrode placed on the earlobe. This should not record any brain activity since it is not near the brain.

Overall, the average reference contained the least amount of noise. Due to this, the average reference was chosen as the reference signal. There are numerous other possible references, and this may be an area of further development.

To further decrease the effect of noise on the EEG system, a bandpass filter is used. For this a 6^{th} order Butterworth bandpass filter was used with 0.1Hz and 40Hz cutoff frequencies. In Figure 4.2, the difference in the frequency domain can be seen.

Additional noise may remain in the EEG data. One method that can be beneficial is to utilize blind source separation. Blind source separation, as discussed in Chapter 2, is a method of decomposing a signal into its potential sources. Independent component analysis (ICA) is a blind source separation method. It is an iterative process where the algorithm tries to minimize entropy (Stone, 2004). This minimization helps to break the signal into components that are the most independent from each other.

The specific ICA algorithm used is based on the Infomax algorithm (Makeig *et al.*, 1997). This transforms the 128 EEG channels into 128 components. This is then examined to determine which components are probably from noise and not mental activity. To do this, the location of the independent components is determined using source localization methods.

Source localization can be used as a way to eliminate noise by detecting which of the ICA components originate from a source that is located outside of the head of the human. To do this, a model of the head is needed. For applications where precise localization is being attempted a precise model of the human subject's head is needed as well as the precise location of the sensors on the head. However, for only determining the location of the source as to whether it is inside or outside of the brain volume, a general model of the human head can be used. For our purposes, a head model from EEGLAB was used. The location of the sensors was then warped to the head. This can be a useful method, but it should be noted that for source localization in the brain the best method is considered to be fMRI utilizing BOLD method. However, for reasons previously discussed, EEG has been chosen as the method for obtaining brain signals for this research.

For this experiment, the source localization algorithm DIPFIT was used (Ossa *et al.*, 2015). This utilized the ICA components determined in EEGLAB and used the standard head model provided. An example of the location of a dipole outside of the head volume can be seen in Figure 4.3. This source is clearly outside the brain volume and can be eliminated from further consideration and removed from the EEG data.

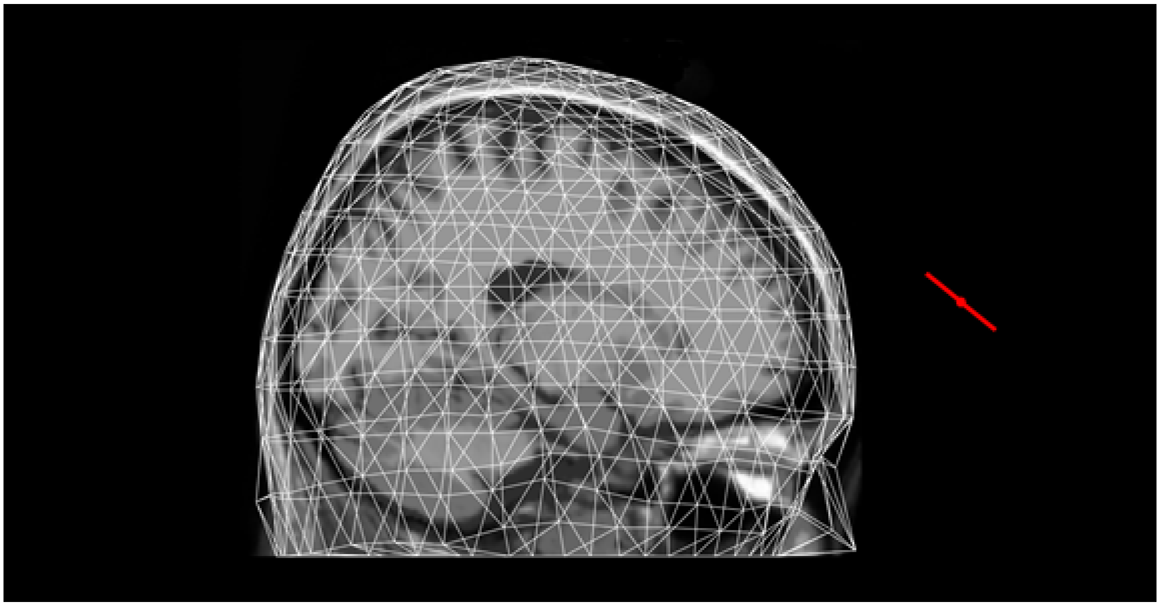

Figure 4.3: ICA dipole located outside of head (created ussing EEGLAB and DIP-FIT)

4.6 EEG Machine Learning

The goal of utilizing EEG in human-robot interaction is to use activity in the human brain to influence how the robotic system interacts with the human. There is a need to classify the way the human wants to interact with the robot based on their brain signals. To investigate this, a machine learning approach was taken. There are a number of potential machine learning algorithms and techniques. For this experiment, Bayes' theorem (or Bayes' rule) was used. Bayes' theorem gives a potential advantage over some of the other algorithms. This method provides a probability that the system is one type of case or the other. This potentially allows the system to influence the robotic system's actions in cases where it is more certain of the human's desire.

The determination of features to be used from the data is a critical element of any machine learning process. Features are essentially the input into the machine learning algorithm and represent the information that is believed to be important

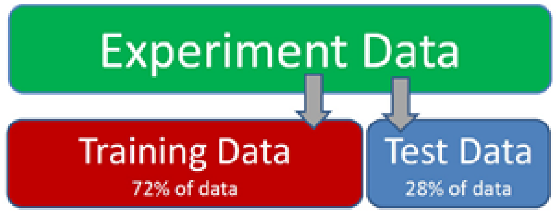

Figure 4.4: Separation of EEG Data

for the system to classify the system. The location that the robot turns is known in this experiment. This would also be a piece of information that would also be known in an application. This is the point where the human would be determining if the robot performed a correct action or not. The 200ms before the turn was average as a baseline and subtracted from the data. This removes the baseline drift from the EEG system and could also be done in a real application.

For this experiment, the machine learning process is performed offline. This could be performed online after the initial training of the system. The system used a portion of the data as training data and a portion of the data as test data to determine the strength of the classification. A number of researchers when performing this type of training and testing combination will randomly select training and test data. However, this may provide better results than should be expected in an application. By randomly selecting the data for training the trials used to come from throughout the experimental timeline. This will help average out any effects of the signals changing over time. In an application, the training will necessarily proceed testing and as such the training data selected should be sequential data that proceeds testing data to maintain the realism of the experiment.

For this experiment, the features needed to be defined. The data was separated into trials where the robot performed correctly and incorrectly. The average value from the 200ms before the turn was subtracted from the data to reset the baseline, and the 600ms of data after the robot began turning was analyzed. To find useful areas to examine an unpaired t-test was applied to each data point comparing the different groups in the trials (robot moves correctly versus incorrectly), as in Equation 4.2 from MathWorks (2017). These results were averaged over 10 point block. This resulted in 7680 potential features. The feature with the lowest average t-test value (10 points) was selected as the first feature.

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n} + \frac{s_y^2}{m}}} \tag{4.2}$$

where t is the probability of the null hypothesis (or that they are from the same population). n and m are the number of data points in each sample of x and y respectively. $\bar{x}$ and $\bar{y}$ are the mean of x and y samples. Additionally, s_x and s_y are the standard deviations of these samples.

Utilizing the first feature, the training data was used in a leave six out cross validation method and paired with each potential additional feature. This was performed using all of the remaining features. The best performing pair of features was selected. This was then repeated, and the top 50 features were selected.

It should be noted that only the first feature was selected by using the t-test. The rest of the features were selected by the best performing combination of the selected features. To put it another way, the feature that added to the previously selected group that best improves the classification is selected and added to the group. This process is continued until there are 50 features.

After the features were selected, the system needed to be trained for classification. The mean and standard deviation were calculated for each condition. The assumption was made that the distributions were Gaussian and a probability density function (PDF) was generated as in Equation 4.3.

$$y = PDF(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-1(x-\mu)^2}{2\sigma^2}} \tag{4.3}$$

where σ is the standard deviation and μ is the mean of the data.

The PDF creates the ability to calculate the probability of something occurring. To do this, a bounded integral calculates the probability of a value occurring within a specific range, as in Equation 4.4. A range of values is needed because the probability that a single exact value would occur approaches zero. Due to this, a range is needed. This small additional value is added and subtracted from the measured value to determine the probability that it would occur for a particular case.

$$P(a \pm b|C_1) = \int_{a-b}^{a+b} PDF_{c1}(x)dx \tag{4.4}$$

where $P(a \pm b|C_1)$ is the probability of a value occurring within category 1, $c1$, in the range of $a \pm b$. PDF_{c1} is the probability density function for category 1.

$$P(a \pm b) = \int_{a-b}^{a+b} PDF_{full}(x)dx \tag{4.5}$$

where $P(a \pm b)$ is the probability of a value occurring under any category in the range of $a \pm b$. PDF_{full} is the probability density function for the full experiment and include both categories.

$$P(C_1) = 0.5 \tag{4.6}$$

where $P(C_1)$ is the probability of condition 1 occurring. Here it is 50% due to the design of the experiment.

$$P(C_1|a \pm b) = \frac{P(a \pm b|C_1)P(C_1)}{P(a \pm b)} \tag{4.7}$$

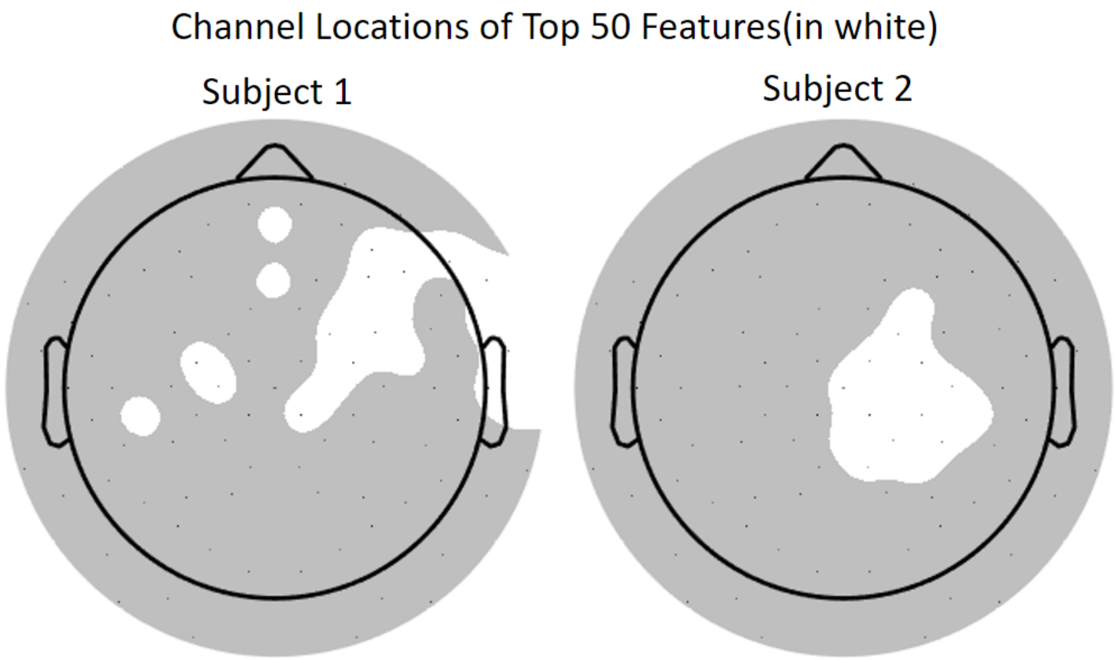

Figure 4.5: Channel Locations of Top 50 Features

where $P(C_1|a \pm b)$ is the probability that given a value in the range of $a \pm b$ that the category is category 1. Because there are only two possible categories, $P(C_2|a \pm b) = 1 - P(C_1|a \pm b)$. In these experiments, category 1 is the case where the human thinks that the robot has performed correctly and category 2 is the opposite of this.

4.7 Results and Conclusions

In Figure 4.5, the locations of the top 50 features are plotted for each subject on a representation of a human head. There are significant differences between subjects. This shows the need for the system to learn each individual subject.

To classify a trial as either a case where the robot performed correctly or incorrectly, the average probability is taken across the 50 features. One of the values of using Bayes' theorem is that a threshold can be created for when to classify a trial. This means that if the average is, for example, 50.1%, then it may be beneficial not

Table 4.1: EEG Classification Performance

$P_{th} =$	0.50	0.52	0.54	0.56
% Correct	65	63	72	75
% Classified	100	78	63	55

to classify the trial from EEG data and to rely on other data. It is important to note that this average value is the average probability based off of the training data. This is then applied to the test data. The drawback of using a threshold is fewer trials are classified. In Table 4.1, the effect of increasing the threshold can be seen. P_{th} is the minimum average probability that is needed in order to classify a trial. This generally, although not always, increases the correct classification as the threshold is increased. However, fewer trials meet this criterion and would not be classified by the system. For trials that were not classified, the system would need to rely on non-EEG data.

Chapter 5

HUMAN-ROBOT INTERACTION SYSTEM

As discussed earlier, there are several elements that are lacking in the current state of human-robot cooperation field. The majority of research is done in limited degrees of freedom. The interactions are often simulated on a computer or are significantly modified from the real-world interactions of the task being studied. There is limited research done where the human and robotic system have conflicting goals.

One of the main elements in advancing human-robot interaction is the testing of this interaction in a full six DOF environment. This required the creation of a system that would allow this type of interaction in a safe environment. Additionally, to test if a human and robot can successfully cooperate in six DOF, a way of indicating to the human the need to cooperate in six DOF is also necessary. Initially, I examined using physical restrictions and requirements of a motion to convey the need for six DOF cooperation to the human. This, however, would create a few problems.

The first problem is safety. Human behavior is never guaranteed. Anytime a human is a part of the overall control loop, the stability of the system cannot be guaranteed. There are greater risks to the human test subject if additional fixtures are added to the work environment of the test.

The second problem is the potential for destruction of equipment. If the robotic arm comes into contact with the fixtures in an unforeseen way, damage may occur to the test set up. This could result in damage to the robot itself but also damage to the fixtures. Either occurrence would potentially result in an end to the testing process.

The final problem is a lack of adaptability. By creating physical restrictions, the test becomes very limited, and the mechanics of changing out test fixtures can dramatically increase the length of time to conduct an experiment. This can result in a more limited approach being adopted where the same choice is repeatedly offered to the subject out of efficiency of testing and not out of focus on producing the best experiment.

One potential benefit of the physical restrictions is the realism. By using actual fixtures, the subject and robot can interact with them in a realistic environment.

A solution to these issues is to create a virtual human-robot interaction system. The system would need to maintain actual physical interaction of the human and the robot but present virtual requirement to the human.

The realism of the human-robot interaction is preserved by having actual, and not simulated, physical interaction with the human and robot. The kinematics, dynamics, and control of the human are the same, or very similar, in the experiment as it would be in an application. The only difference is that the potentially hazardous objects are removed from the workspace. Additionally, this allows the environment of the experiment to be dictated by the design of the experiment and not the physical location of the robot.

5.1 Development of Human-Robot Interaction Test System

To meet the desired capabilities of the human-robot interaction test system, a combination of several components were created. The overview of the system can be seen in Figure 5.1.

The Kuka LBR iiwa robot is powered and controlled by the control cabinet (KRC). The KRC sends the lower level control signals to the robot arm and runs Java based programs onboard the cabinet. The cabinet is connected to the cooperative control computer using an Ethernet connection. The cabinet sends position, force and torque data to the control computer. The cooperative control computer sends back to the

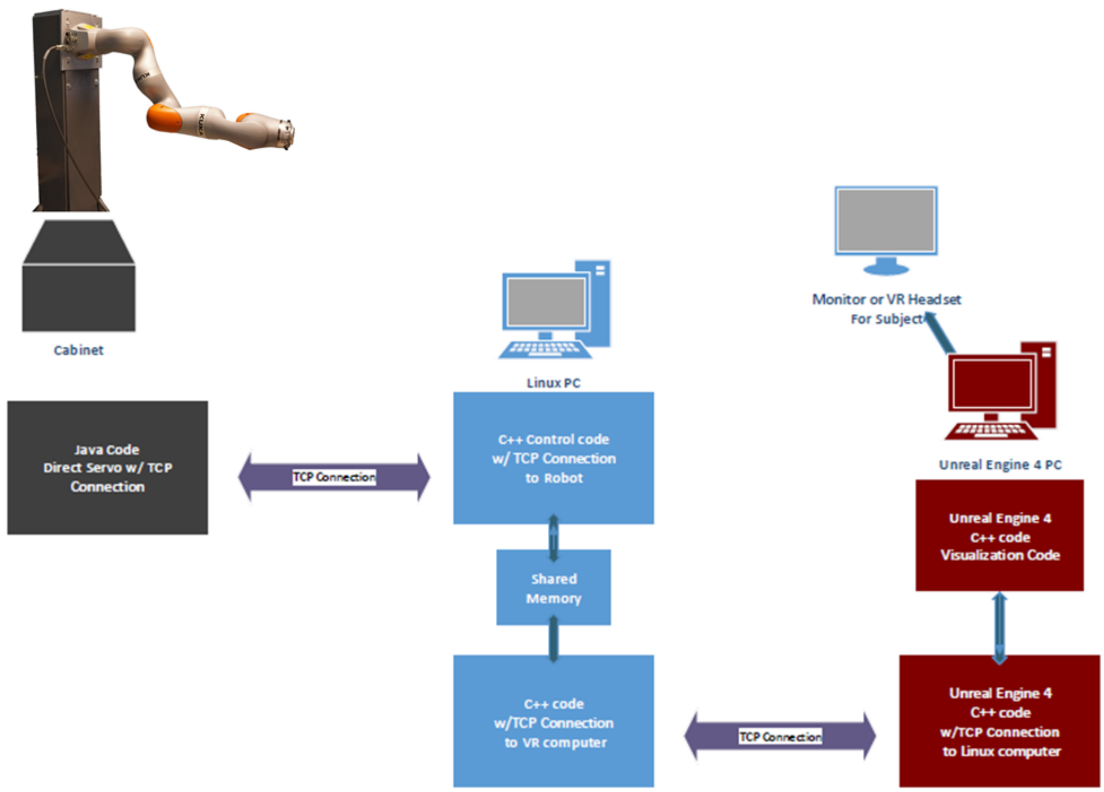

Figure 5.1: Overall Combined System

cabinet the next Cartesian impedance control command. The cooperative control computer has a separate connection to the visualization computer, and it sends data as to the position of the end effector to the visualization computer.

To allow for cooperation between a human and robot in six DOF, a robotic system that allows for motion in six DOF must be used. To fulfill this requirement the Kuka LBR iiwa robot was used for this test system. This robotic arm has seven DOF. This extra degree of freedom means that the robotic arm is kinematically redundant. There are six DOF required to specify the location and orientation of an object. When a robotic system is kinematically redundant, it allows the configuration of the arm to be in different positions but the end position in the same location. In linear algebra terms, the extra DOF in the robot arm creates a null space where there is theoretically an infinite number of possible solutions.

The robot does not have a force sensor at the end of the robotic arm. The robotic system estimates the force and torque that is applied to the end effector by measuring the torque at the joints and taking into account the dynamics of the arm and the object connected to the end effector. The accuracy of this measurement varies in the workspace. As the robot arm configuration approaches a singularity, the accuracy of this measurement decreases.

The robotic system control cabinet controls the robotic arm. It is connected to the robot arm by one cable that provides both the power that controls for the seven joints but also receives data (joint position, torque values, etc.) from the arm. The control cabinet then utilizes the data to control the power sent to the joints based on the control scheme being employed on the control cabinet.

The robotic control cabinet utilizes KUKA SunriseOS software (version 1.7). This software allows for a few different control modules to be used to control the robotic arm. It utilizes proprietary software libraries written for use in a Java programming environment. In developing a control method for the human-robot interaction system, the different control modules available needed to be evaluated. These control modules are SmartServo, DirectServo, and Fast Robot Interface (FRI).

To examine which control module would be the best for the human-robot interaction system, a determination of the specific type of control method to be used needed to be made. From the previous experiments in Chapter 3 and the review of the literature in Chapter 2, interacting with the human using impedance control has been shown to produce useful results. The task space for the human-robot interaction system can be readily described using the Cartesian coordinate system. This would allow the initial experiment and future experiments to utilize Cartesian coordinates of the task space in the higher-level control algorithm. From this, the choice was made to use Cartesian impedance control as the control method for the system.

The SmartServo control module is designed for applications performing visual servoing or similar applications (Kuka Roboter GmbH, 2015b, 11). This module has the slowest of the response times to a step input. It is designed for applications where the desired position is going to change slower than the other modes. For these reasons, this mode was not selected.

The Fast Robot Interface (FRI) has the fastest command cycle time (1ms) of any of the modules (Kuka Roboter GmbH, 2015a, 23). This module also offers what it describes as a Cartesian impedance control method. However, it requires that the equilibrium be specified in joint angles instead of in Cartesian space. This can be problematic since the robotic system is kinematically redundant. Additionally, it does not allow stiffness to be modified over the FRI connection.

The DirectServo module is designed for use in haptic applications (Kuka Roboter GmbH, 2015b, 11). This module was chosen for its ability to perform Cartesian impedance control where the equilibrium point can be commanded in Cartesian space as well as modifying the stiffness value during the experiment. To facilitate this, a transmission control protocol (TCP) Ethernet connection was created between the KRC and the cooperative control computer. Over this link, the control cabinet sends to the cooperative control computer the measured position of the end effector and the estimate of the applied forces and torques to the end effector of the robot. Additionally, a time stamp from the robot controller is sent with this data. The cooperative control computer sends back to the KRC the command for the next cycle. This command consists of the equilibrium position (x, y, z, roll, pitch, yaw) and the stiffness along each of the axis. The variation of the timing in the DirectServo method had to be evaluated to determine if it is acceptable. A histogram of the timing variation

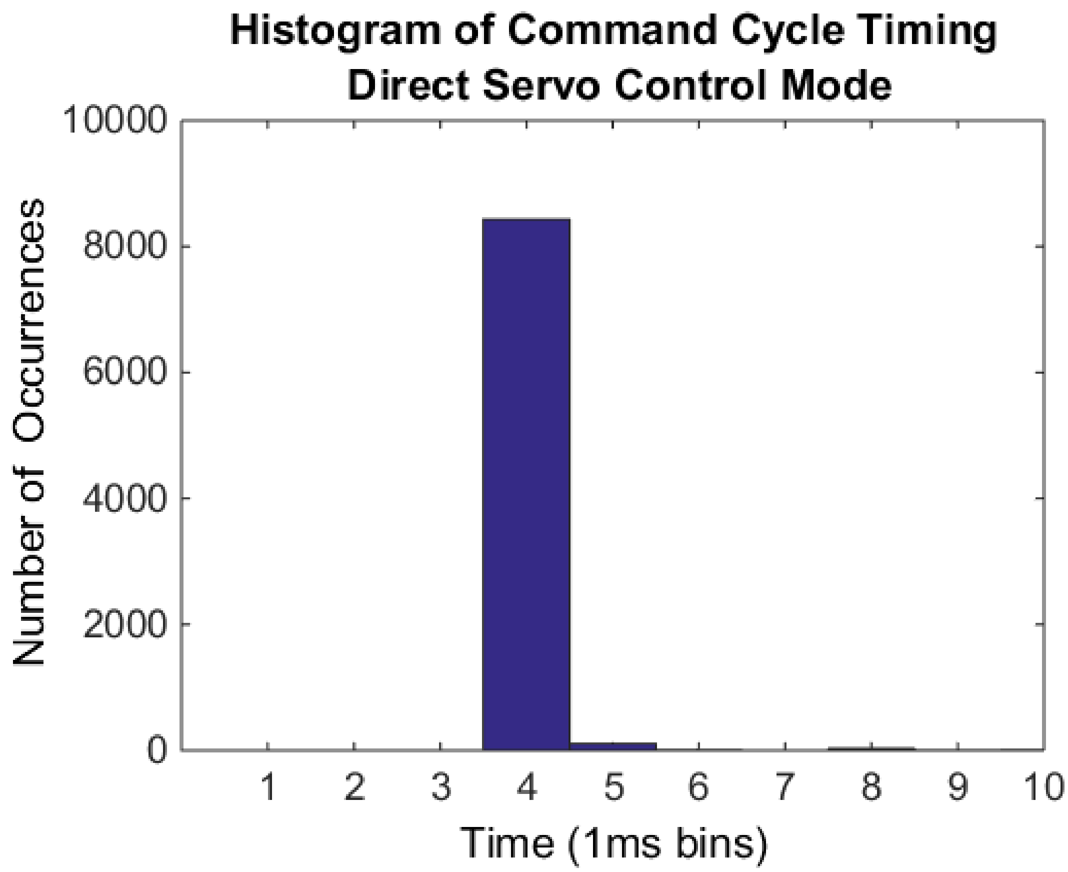

Figure 5.2: Histogram of DirectServo Command Cycle

can be seen in Figure 5.2. The majority of the command cycles are at 4ms for this experiment. For our purposes, the robot does not need to be able to duplicate a precisely timed trajectory. Because of this, the consistency of the timing is sufficient for this type of dynamic interaction. This is the control module that is used to control the robotic system for the rest of this dissertation.

5.1.1 Visual System

To create virtual restrictions displayed to the user, a visual display system is needed. There are several potential systems or methods that can be used such as OpenGL, Unity engine, Unreal Engine, or similar. For this system, Unreal Engine 4

(UE4) was chosen. It provides several positive attributes. It allows the use of either monitors or virtual reality systems (Use of virtual reality will be discussed in Chapter 6). It has a visual scripting language and allows for C++ coding. Additionally, there is a significant amount of online documentation, tutorials, and videos (Epic Games, 2017).

The visual system has three main components. First is the communication code for communicating with the cooperative control computer. The second is a virtual world to display to the user. The third is a virtual representation of the joint object.

Communication between the visual system and the cooperative control computer is essential. For this system, we decided to utilize a stand-alone computer to operate the visual system. This was to prevent the possibility that the visual system might cause any adverse effects on the performance of the cooperative control computer. By running it on a separate computer, we avoid any possible negative effects of a delay in the visual system, or that the increased computational load of the visual system might cause a slowdown of the execution of the control code on the cooperative control computer. This choice created the need for an Ethernet connection with the visual system from the cooperative control computer. (This is in addition to the connection between the cooperative control computer and the robot control cabinet.) For this connection, a TCP connection was chosen over a user datagram protocol (UDP) connection. This was because we wanted to guarantee the timing and order of the messages exchanged. In our implementation, we only utilize the information sent from the cooperative control computer to the visual system, but we wanted to leave open for future development the utilization of communication going from the visual system to the cooperative control cabinet. This would possibly be utilized in the future to use the physics engine and collision detection in UE4 to affect the real-world control of the object.

To create the communication on the visual system side, a C++ class was created that established the TCP connection and handled the receiving and sending of messages. A separate C++ computer program was created on the cooperative control computer system. This program created a connection with the visual system and sent and received messages to the visual system. The program utilized the data from the control program that was stored in shared memory and sent the information to the visual system. The information sent was the position and orientation of the joint object and which hole to display in the visual system.

A virtual world was needed to display to the subject during the experiment. For this initial experiment, a single level was used for the experiment. This meant that different elements needed to be changed in real time during the trial. We needed a virtual representation of the joint object and restrictions that required six DOF cooperation needed to be displayed. To achieve this, a block that was not symmetrical was created as the joint object. A computer model of the joint object was imported into UE4 to ensure the accuracy of the dimensions of the virtual object with the real-world object. A virtual wall was created with holes in the wall in different positions were created. The holes in the wall allow the object to fit through the wall in different orientations. For this experiment, we are examining the interaction of the robotic system and the human before the final insertion of the block into the hole. For this reason, we did not include any physical feedback of hitting the wall (Physical feedback was added to the system in Chapter 7). Additionally, a sparse virtual world was created where the only visual elements were the wall, joint object, and the floor. This was done to limit the subjects focus on the elements of the experiment. (A more complex environment was used in Chapter 7).

An object was created for this experiment, as in Figure 5.3. This object is referred to as a joint object for two reasons. First, the physical object is jointly manipulated

Figure 5.3: Joint Object

by both the human and the robotic system. Secondly, this object is jointly represented in the real world by the physical object and as a virtual representation in the visual system. The object was designed not to be symmetric. This is so that there would be only one orientation of the object that would correspond to a hole in the wall. Additionally, this object was designed without any obvious handles or places specifically designed for the human to grip. This allows the subject to change grips to whatever they feel is natural to them during the experiment and to allow for both manual and bimanual manipulation by the human. The virtual representation of this object was created in the virtual world as discussed previously.

5.1.2 Control Computer

The cooperative control computer has a separate TCP connection to the robotic control cabinet and the visual computer. This computer runs the control code that generates the higher level Cartesian impedance command. It does this based on the control algorithm based off of the data that it receives from the robotic control cabinet. This system also communicates with the visual system and sends it the information regarding the position and orientation of the joint object as well as which hole to display to the user. Additionally, this computer handles recording the data from the experiment as well as all needed experimenter user input during the experiment.

5.2 Physical Human-Robot Cooperation Experiment

5.2.1 Overview

This experiment has several elements. First, this experiment will evaluate the human-robot test system and three different control methods. It utilizes actual, and not simulated, interactions that are realistic to a number of potential human-robot applications. This will be conducted in an environment where both the human and the robotic system will make mistakes and need to be corrected by the other agent.

The experiment will evaluate the use three different algorithms to determine if the robot should swap lead roles with the human in translation and rotation. All of these algorithms are using a straightforward threshold method. In this method, a threshold value is initially determined from pilot experiments, and if the variable under consideration exceeds this value, then the robotic system switches leader roles with the human. The three variables are a force (and torque in rotation DOF), estimated applied work, and difference in position equilibrium. Each of these was evaluated in separate sessions.

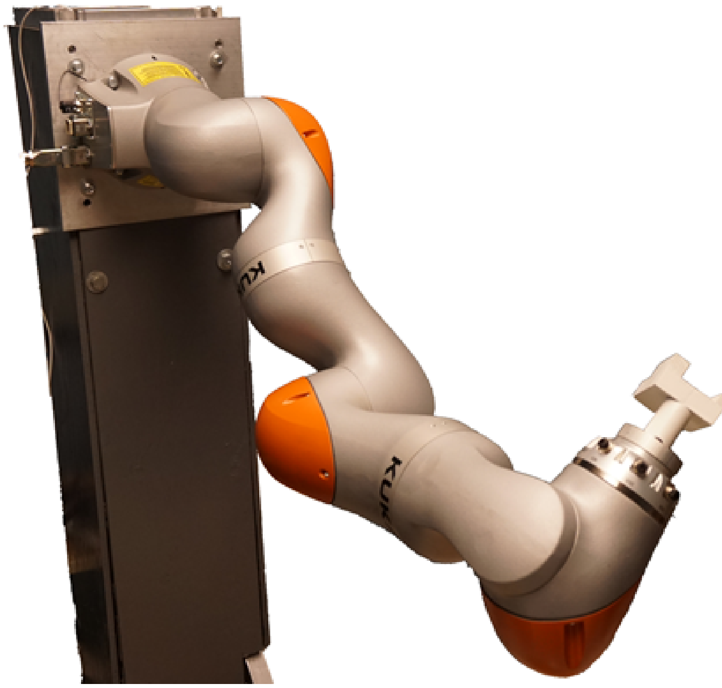

Figure 5.4: Initiail Position of the Kuka LBR iiwa robotic arm. End effector attached to the robot is the joint object.

5.2.2 Visual Elements

To display six DOF restrictions to the user a virtual wall was created. This wall has a hole in the wall that requires six DOF motion from the initial position. Three different positions and orientations of the hole were used.

The visual information displayed to the user can be seen in Figure 5.5. It was displayed on a flat screen monitor to the subjects left. The display is shown to the user in a split screen mode. The bottom of the screen is showing the rear view of the virtual world. The line of view is perpendicular to the wall. This view helps the user determine x and y alignment as well as orientation alignment. The top view on the split screen is the top down view in the virtual world. This view helps the user determine the distance from the wall, z, as well as orientation alignment.

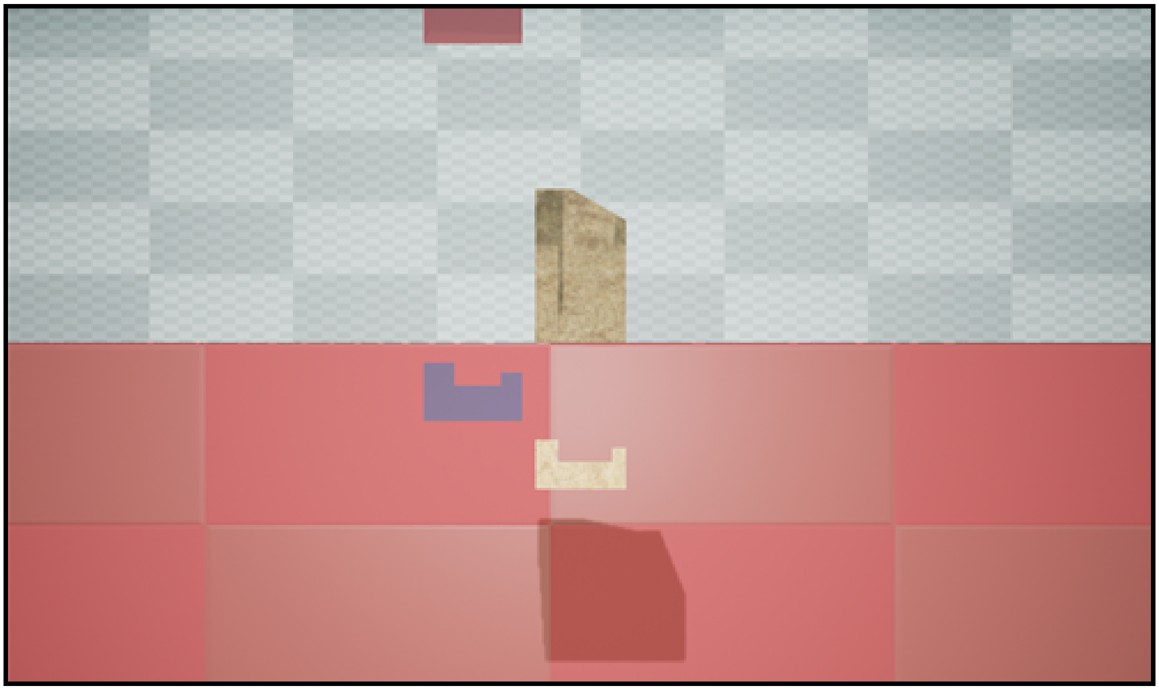

Figure 5.5: Visual Information Displayed to the Subject: Top half is a top down view. The bottom half is a view from the behind the joint object looking towards the wall.

In this experiment, the robotic system will sometimes perform incorrectly. The robot acts incorrectly by moving to an incorrect location or orientation of the hole that shows the human. If the robot is leading translational DOF, it acts incorrectly by leading the translation to an incorrect location. These incorrect locations are limited to the three possible locations for holes in the wall. If the robot is leading rotational DOF, it acts incorrectly by rotating the joint object to an incorrect orientation. Similarly, to the translational case, the incorrect orientations are limited to one of the three orientations used in the holes in the wall.

The human will also perform incorrectly during the experiment. This is done by showing two possible goal states for the DOF they are leading. Before the start of the experiment, it is explained to the subject that if there are two possible choices, they are to choose one. If they choose the wrong one, the robot will correct them. To guarantee the same number of trials of incorrect choices by humans across trials,

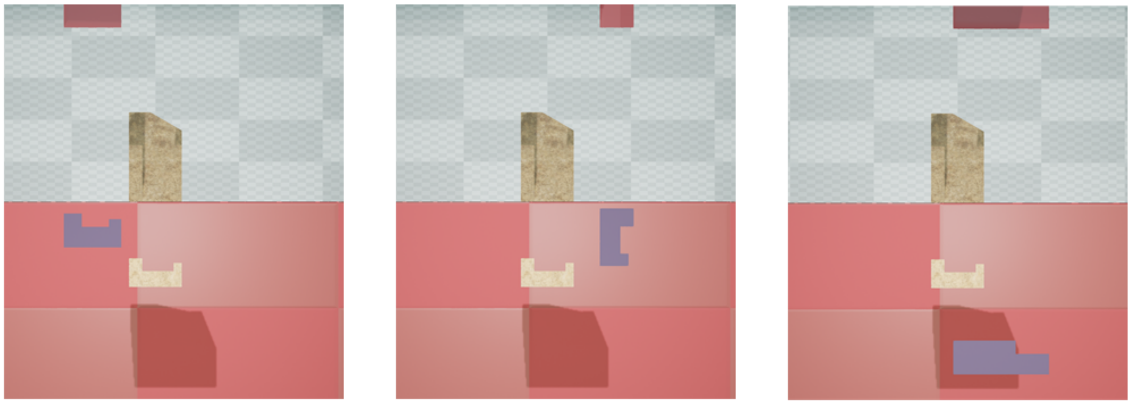

Figure 5.6: Three Position Walls: Three different hole locations and hole orientations are show. The orientation of the hole is not specific to a location and any of the orientations can occur at any of the locations (9 possible combinations).

half of the time they are shown a choice whichever one they choose will be wrong. This is done by waiting for the human to start moving towards one of the choices and then the robot system takes over leader for the DOF the human is controlling and sets the other choice as the goal. For the case where the human starts as a leader of the translational DOFs and is offered a choice of locations, an example of the wall can be seen in Figure 5.7A. In this case, the same orientation for the hole is used so that the only difference in choice is along translational DOF. An example of a wall with a rotational DOF choice can be seen in Figure 5.7B. Similar to the translational choice, the rotational choice only offers differences in the rotation, and the translation is essentially the same. (Slight differences of translation can occur depending on the exact point on the joint object the rotation occurs about.)

For this experiment, there are 72 trials per session. There are nine combinations of position and rotation. There are 18 trials where there are dual translational positions shown to the subject. There are also 18 trials where dual rotational orientations are shown to the subject. This can be seen in Figures 5.7A and 5.7B respectively.

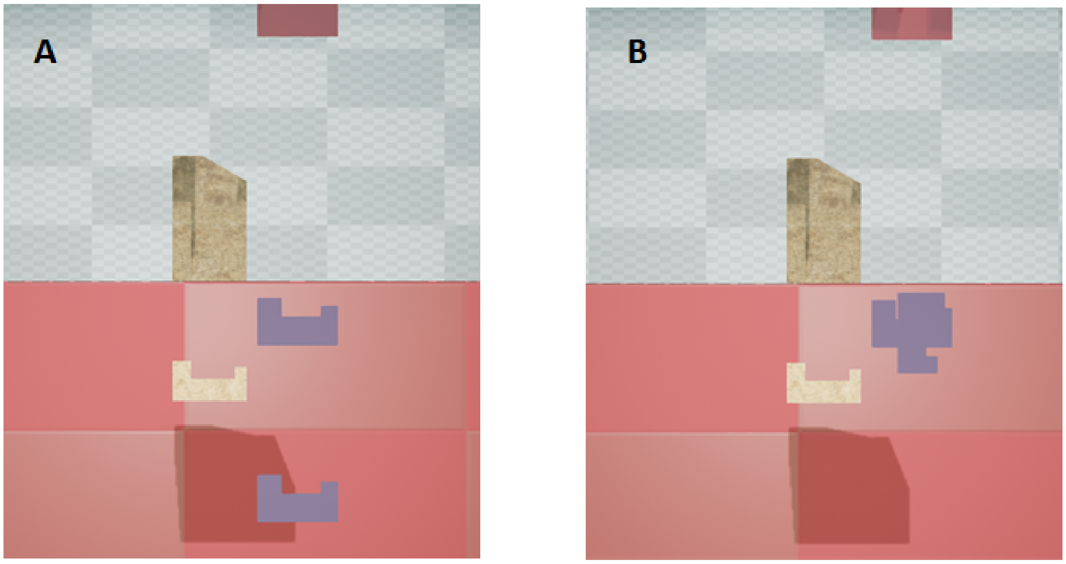

Figure 5.7: Walls with Choice: These are presented to the subject to force them to make a mistake that the robot will correct. A) This is an example of a choice of location but the orientation of the hole is the same. B) this is a choice of orientation with the same location.

5.2.3 Robotic Control

The robotic system is being controlled using Cartesian impedance control. As discussed earlier, impedance interaction can be described by Equations 5.1-5.3.

$$\begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix} = \overline{\mathbf{M}}\ddot{\mathbf{x}} - \overline{\mathbf{B_t}}\dot{\mathbf{x}} - \overline{\mathbf{K_t}}\mathbf{x} \qquad \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} = \overline{\mathbf{J}}\ddot{\theta} - \overline{\mathbf{B_t}}\dot{\theta} - \overline{\mathbf{K_t}}\theta \tag{5.1}$$

$$\overline{\mathbf{K_t}} = \begin{bmatrix} k_{tx} & 0 & 0 \\ 0 & k_{ty} & 0 \\ 0 & 0 & k_{tz} \end{bmatrix} \text{ and } \overline{\mathbf{K_r}} = \begin{bmatrix} k_{rx} & 0 & 0 \\ 0 & k_{ry} & 0 \\ 0 & 0 & k_{rz} \end{bmatrix} \tag{5.2}$$

$$\mathbf{x} = \begin{bmatrix} x_p - x_e \\ y_p - y_e \\ z_p - z_e \end{bmatrix} \quad \text{and} \quad \theta = \begin{bmatrix} \alpha_p - \alpha_e \\ \beta_p - \beta_e \\ \gamma_p - \gamma_e \end{bmatrix} \tag{5.3}$$

For this experiment, when the robotic system is acting as the leader of translation DOF and the follower of rotational DOF, $k_{tx} = k_{tx} = k_{tx} = 600N/m$ and $k_{rx} = k_{rx} = k_{rx} = 0.01Nm/rad$. When the robotic system is acting as the leader of rotational DOF and the follower of translational DOF, $k_{tx} = k_{tx} = k_{tx} = 3N/m$ and $k_{rx} = k_{rx} = k_{rx} = 20Nm/rad$.

5.2.4 Role Determination

There are two role determination elements that are evaluated simultaneously. They are to determine if the human wants to take the lead of the robot's current DOF and should the robot take control of the human's current DOF. Evaluating if the human wants to take the lead of the robot's DOF is based on one of the three variables mentioned earlier (force, estimated work, and equilibrium distance) depending on the experimental session.

In one of the three sessions, applied force (or torque in the rotational case) is used as the variable to evaluate if the human wants to take the lead of the robot's DOF. The concept behind this is that when the human recognizes that the robot is performing something incorrectly, they will apply force (or torque) to correct the incorrect action by the robot. This is represented in Equations 5.4 and 5.5. One of the drawbacks of this approach is that the force and torque values are estimates of the force and torque applied to the end effector, $\mathbf{F_{int}}$ and $\mathbf{T_{int}}$ respectively. These are estimates based on the measured torque values at the joints of the robot. These estimated values vary based on the accuracy of the joint torque measurements, the accuracy of the robot's dynamic model, and are sensitive to the position of the robotic system. If S_t or S_r are equal to one, then it indicates that an exchange of roles is needed.

$$S_t = \begin{cases} 1, & \text{if } |\mathbf{F_{int}}| > 12N \\ 0, & \text{otherwise} \end{cases} \tag{5.4}$$

$$S_r = \begin{cases} 1, & \text{if } |\mathbf{T_{int}}| > 2Nm/rad \\ 0, & \text{otherwise} \end{cases} \tag{5.5}$$

The estimated applied work is another variable that is used in one of the three sessions to determine if the human desired to take the lead of the robot's DOF. Work is defined as a force applied over a distance as in Equations 5.6. This was calculated every command cycle based on the change in position of the end effector and the estimated applied force. A 10 sample moving average was used to smooth out noisy values. This can be seen in Equations 5.6-5.9. The concept of using work is that when the human realizes the robot is moving in the wrong direction that the human would apply force but that the force applied would be to change the position of the robot. This creates work (force applied over a distance). There are also problems associated with using work. First, it relies on the estimated applied force value and as such is subject to its inaccuracies as discussed above. Additionally, the measurements are taken at discrete moments. The distance traveled between two points is assumed to be a straight line and the force applied is assumed to be constant over this distance change.

$$\begin{bmatrix} W_{tx} \\ W_{ty} \\ W_{tz} \end{bmatrix} = \begin{bmatrix} |F_x \ \Delta x| \\ |F_y \ \Delta y| \\ |F_z \ \Delta z| \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} W_{rx} \\ W_{ry} \\ W_{rz} \end{bmatrix} = \begin{bmatrix} |T_x \ \Delta\alpha| \\ |T_y \ \Delta\beta| \\ |T_z \ \Delta\gamma| \end{bmatrix} \tag{5.6}$$

$$W_{sma} = \sum_{i=0}^{9} \frac{W_{k-i}}{10} \tag{5.7}$$

$$S_t = \begin{cases} 1, & \text{if translational } W_{sma} > 0.5Nmm \\ 0, & \text{otherwise} \end{cases} \tag{5.8}$$

$$S_r = \begin{cases} 1, & \text{if rotational } W_{sma} > 0.0006Nm/rad \\ 0, & \text{otherwise} \end{cases} \tag{5.9}$$

The third variable used in one of the sessions is the difference between the current position and the impedance equilibrium position. Since the robotic system is being controlled using Cartesian impedance control, this difference is related to force or torque applied to the system. One advantage of using this is that it eliminates the need for using the estimated force values. This potentially reduces the noisiness of this value. This, however, is a damped system with mass. This means that the force will precede the difference in measured values. Additionally, this type of measurement could be used on lower cost robotic systems that do not have torque sensors at the joints. This variable is represented by Equations 5.10-5.13.

$$D = |\mathbf{x_{eq}} - \mathbf{x_p}| \tag{5.10}$$

$$A = |\alpha_{eq} - \alpha_p| + |\beta_{eq} - \beta_p| + |\gamma_{eq} - \gamma_p| \tag{5.11}$$

$$S_t = \begin{cases} 1, & \text{if } D > 20mm \\ 0, & \text{otherwise} \end{cases} \tag{5.12}$$

$$S_r = \begin{cases} 1, & \text{if } A > 0.15rad \\ 0, & \text{otherwise} \end{cases} \tag{5.13}$$

where $\mathbf{x_{eq}}$ is the vector representing the current translational equilibrium point and $\mathbf{x_p}$ is a vector representing the current translational position. α_{eq} ,β_{eq} ,γ_{eq} are the roll, pith, and yaw of the equilibrium position for rotation. α_p, β_p, and γ_p are the roll pith and yaw of the measure rotational position.

For this experiment, the determination if the human is going the wrong direction needed to be made. The robotic system creates a trajectory to the goal location or orientation. The difference between this trajectory and the current position and orientation are calculated. At the beginning of a trial, this value may be larger than when the block nears the hole in the wall. Due to this a buffer value was established. This buffer decreases as the block approaches the wall. If the difference calculated is greater than the buffer then the robot switches to take over as leader of this type of DOF. This can be seen in Equations5.14 and 5.15.

$$Bf_t = 25mm + 20mm\left(1 - \left|\frac{\mathbf{x_p} - \mathbf{x_{in}}}{\mathbf{x_f} - \mathbf{x_{in}}}\right|\right) \tag{5.14}$$

$$Bf_r = \frac{\pi}{60} + \pi\left(1 - \left|\frac{\alpha_\mathbf{p} - \alpha_\mathbf{in}}{\alpha_\mathbf{f} - \alpha_\mathbf{in}}\right| + \left|\frac{\beta_\mathbf{p} - \beta_\mathbf{in}}{\beta_\mathbf{f} - \beta_\mathbf{in}}\right| + \left|\frac{\gamma_\mathbf{p} - \gamma_\mathbf{in}}{\gamma_\mathbf{f} - \gamma_\mathbf{in}}\right|\right) \tag{5.15}$$

where $\mathbf{x_{in}}$ and $\mathbf{x_f}$ are the translational position vectors for the initial position and final position of the trajectory. $\alpha_\mathbf{in}$, $\beta_\mathbf{in}$, and $\gamma_\mathbf{in}$ are the roll, pith, and yaw of the initial position. $\alpha_\mathbf{f}$, $\beta_\mathbf{f}$, $\gamma_\mathbf{f}$ are the roll, pitch, and yaw of the final position in the trajectory.

For both leading the motion along DOFs and for checking if the human is going the wrong direction, trajectories needed to be generated. To do this, fifth order splines were used that minimize jerk, as in Flash and Hogan (1985) and in Equations 5.16 and 5.17. For this experiment, translation was based on time, and the rotation trajectories were based on the distance from the wall.

$$\mathbf{x_{tr}} = \mathbf{x_{in}} + (\mathbf{x_f} - \mathbf{x_{in}})(10\tau_1^3 - 15\tau_1^4 + 6\tau_1^5)) \tag{5.16}$$

$$\phi_{\mathbf{tr}} = \phi_{\mathbf{in}} + (\phi_{\mathbf{f}} - \phi_{\mathbf{in}})(10\tau_1^3 - 15\tau_1^4 + 6\tau_1^5)) \tag{5.17}$$

where $\mathbf{x_{tr}}$ is the new translational equilibrium point for the trajectory. $\phi_{\mathbf{tr}}$ is the vector of roll, pitch, and yaw for the new equilibrium point for the trajectory. τ_1 is the current elapsed time divided by 6 seconds.

A method of exchanging roles between leader and follower was needed for the robotics system. In human-robot cooperation, the human is interacting with the robot physically. Due to this the changing of roles by the robotic system needs to be performed in a way so that the human understands that a change in roles is occurring. For this experiment, the role exchange occurred over 250 command cycles. This is approximately 1 second. To transition between the two states, the equilibrium point and stiffness are determined for both the leader state and the follower state for the DOF. Then a virtual trajectory is created between these two equilibriums. This can be seen in Equation 3.5. This gradually shifts the current command from one type of role to the other.

5.2.5 Trial Procedure

The procedure for each trial was the same. The hole for that trial was displayed. The subject was told if they were starting as the leader of either the translation DOF or the rotational ones. An audible tone was played at the start. When the block reached the end position as judged by the experimenter from the representation on the virtual display or the subject quit trying to achieve the end goal, the experimenter ended the trial. No tone was played or other indication given for the exchange of roles. The subject had to detect this from the change in the action of the robotics system. Additionally, no information was given to the subject as to why the robot switched. The human had to infer the reason.

5.2.6 Results

In this experiment, three different methods are used for the robot to evaluate if the human wants to become the leader of either translational of rotational DOF. These methods are examined based on false positive role exchanges and false negative role exchanges.

A false positive role exchange is if the robot exchanged roles with the human when it was unnecessary. The percentage of trials where the robot was performing correctly can be seen in Figure 5.8. Overall, the work method was more inefficient in that it switches roles unnecessarily at a higher rate than other methods. This suggests that the threshold value set for this method may have been too low. This could also be remedied by allowing the value to adapt to the subject.

A false negative role exchange is where the robot did not exchange roles with the human when the human desired. These values are low, but they do constitute a failure of cooperation and are more problematic than inefficient false positives.

The robotic system in this experiment would take as leader of translational or rotational DOF if the human made an incorrect choice. This occurred in trials where two possible locations or two possible orientations were shown to the subject. During this experiment, this type of role exchange was 100% successful, and the correct location or orientation was achieved by the robotic system taking the lead.

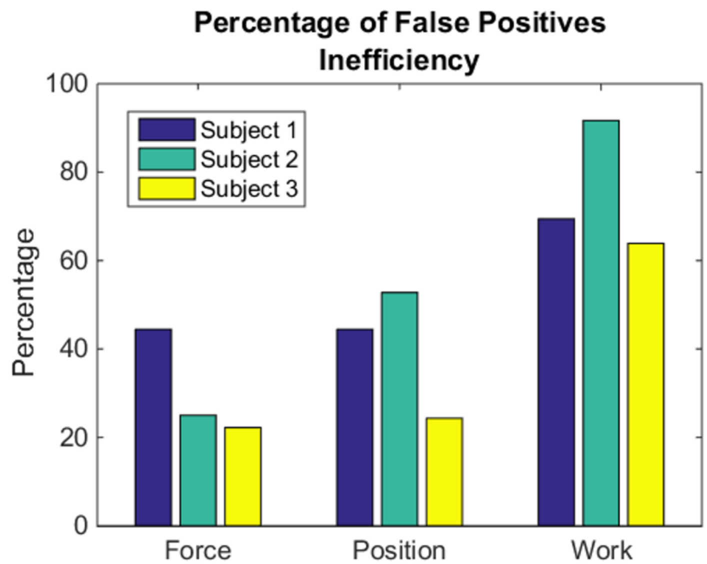

Figure 5.8: False Positive Percentage: This represents inefficiency in the interaction. Higher values for Work method may suggest that the threshold values are too low.

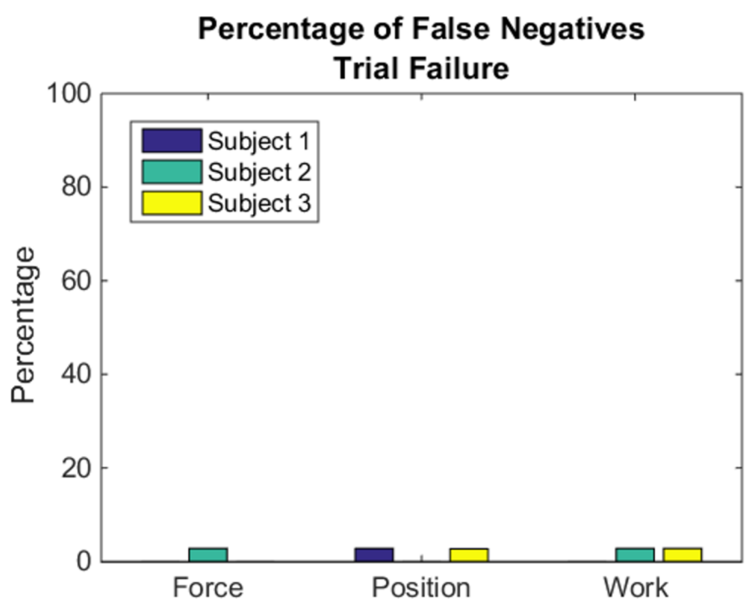

Figure 5.9: False Negative Percentage: This represents a failure of cooperation. The human wanted to be the leader but the robot failed to switch and the human stoped attempting to become leader.

5.3 Discussion

Several important elements were gained from this experiment. A human-robot interaction system was developed and tested. This system uses virtual obstacles and goals to convey to the subject the need for six DOF cooperation but without the safety issues of physical restrictions. A six DOF human-robot controller was created and tested. This controller performed role exchanges by swapping leader-follower roles for either translational or rotational DOF. This means that the human was always leading three DOF and the robot was always was leading three DOF. An improvement to this will be addressed in the next chapter, and this will allow asymmetry in the number of leader/follower roles. Humans-Robot cooperation was also successful where the robot took over as leader of the task from the human due to an error by the human. Finally, three methods for determining when the human desires to lead different DOF were tested. Overall, they were successful with only a few failures (false negatives). The inefficiency (false positives) could potentially improve by allowing adaptability of the system to the subject.

Chapter 6

ASYMMETRIC HUMAN-ROBOT COOPERATION

Humans are highly adaptable. To effectively interact with humans, robotic systems should also be adaptable. Additionally, humans perform a wide array of tasks. Many of these have different geometric constraints, and it is useful if a robotic control method allows for the possibility of different interaction along a different axis. To meet these challenges, the asymmetric cooperation control was developed.

Asymmetric cooperation, for this dissertation, is cooperation between a human and robot. However, it allows for an asymmetric distribution of roles. The human could be the leader of only one DOF, all six DOF, or anything in between. The robot in these cases would be the follower in all DOF the human was leading and the leader in all DOF the human was not leading. This allows the human to focus and lead DOF that the human determines are important for him/her to lead and to allow the robot to lead axis that the human does not feel that she/he need to lead. To enact and test this control concept, the previously developed human-robot interaction test system will be used. However, there will be some changes that are noted below.

There are several objectives of this experiment. First is to implement and test asymmetric cooperation control method. This is tested in a six DOF human-robot cooperation environment and maintains realistic physical human-robot interaction. This will be tested in an environment where the robot makes mistakes and where the robot can take over as leader of a DOF. The effect of using a machine learning algorithm to determine when to exchange roles in a DOF is evaluated. Additionally, the human-robot interaction test system is improved to utilize a virtual reality display.

6.1 Overview

For this experiment, the overall task will be to cooperate with the robot to insert the joint object into a virtual hole in a wall. This portion of the experiment is similar to the experiment in Chapter 5. The joint object, the virtual world, and the size and locations of the holes are all the same. The difference with regard to task is that the there will not be walls shown to the subject where there are two holes. In the previous experiment, this was tested, but in this experiment, it was eliminated to aid in shortening the experiment length.

At the beginning of the experiment, the robot is the leader of either three translational or rotational DOF. The human is the leader of the other three DOF. This is also the same as the prior experiment. However, after the start of the experiment, there is a significant difference between the previous experiment. This difference is that the human and robot can exchange roles asymmetrically. Previously, the human and robot would exchange all six roles simultaneously when a role change was detected. If the human was the leader of rotational DOF and a role exchange was initiated in the previous experiment, the human would become the leader of the three translational DOF and the follower of the three rotational DOF. In this experiment, this is not the case. If the human is the leader of rotational DOF and the human desires to take over as the leader of the x-axis, then only the x-axis is affected. Additionally, the robot can take over as leader of a DOF. For this experiment, this is only done if the motion and force (torque in rotational case) are below a threshold. Then the robot will take over that axis and maintain it in its current position using increased impedance.

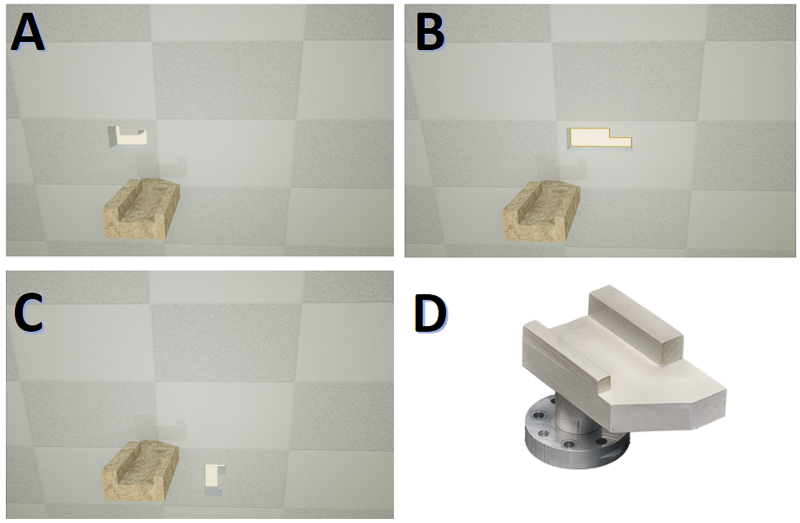

Figure 6.1: Virtual Wall and Joint Object: A, B, and C are three virtual holes in different locations and different orientations. D is the real-world object that is virtually displayed in A, B, and C. (from Whitsell and Artemiadis (2017), ©2017 IEEE

In this experiment, the robot will make an error in the DOF that it is leading at the start of the experiment. This occurs randomly 50% of the time.

6.2 Visual System

To create a task that necessitates human-robot cooperation in six DOF, a visualization system was developed. This system builds on the previously developed system in Chapter 5. A physical object that has both a real-world presence and is also displayed in the virtual world was utilized, as in Chapter 5. Additionally, a virtual wall was created with three different locations of holes was created. Each of the locations had three possible holes. Each one represented the hole that the joint object would make in the wall in three orthogonal orientations. The dimensions of the hole were enlarged by 1cm on all sides. Unreal Engine 4 was used to create the visualization of the virtual world, as in Chapter 5. This can be seen in Figure 6.1.

For this experiment, only one hole was displayed at a time. This correct hole to display was sent over a TCP connection to the visualization computer along with the position and orientation of the joint object on the end effector. For this experiment, physical feedback with the wall was determined not to be necessary because the interaction of interest between human and robot occurs before the wall. (However, physical interaction is necessary for the experiment in Chapter 7.)

A virtual reality system was needed to display the visual world to the subject. The Oculus Rift commercial version 1 (CV1) was used for this purpose. This version of the Oculus Rift has a separate position sensor. This position sensor detects motions of the headset with an absolute reference frame related to the physical position of the sensor. This is accomplished by tracking infrared light emitting diodes embedded in the headset (IFIXIT, 2017).The benefit of this is that it takes into account the rotation and translation of the headset. However, the reference frame concerning the real-world room changes if the sensor is moved or rotated.

6.2.1 Visual System Calibration

For this experiment, the human will be interacting with a physical object and will be viewing a virtual representation of the object. It is important that the virtual representation aligns with the actual object. The position sensor could be located in a physical position to align the virtual to the real world. However, this causes some issues. First, the location of the sensor may not be in a good location to see the headset for the task. Second, if the sensor is disturbed, it will misalign the virtual and real worlds. Due to these issues, a calibration method needed to be developed to align the virtual and real worlds.

A calibration procedure was created to align the virtual and real worlds. The CV1 has an internal menu that can allow the position of the headset to be reset. This means that the location of the headset when it is reset becomes the new reference frame from the CV1. In the UE4 program for this experiment, the initial reference frame for the headset is determined by the initial position of a camera in the virtual world. Given this, to align the virtual and real world, the headset needs to be in a known position in the real world and the virtual world when it is rest. The robot during the initial setup of each session was put in a commanded joint position of $(-90°, 45°, 0°, 45°, 0°, -90°, 0°)$. This position was commanded in joint position control to be as accurate as possible. A fixture was created to hold the CV1 in a particular position and with a bolt pattern to bolt onto the end of the robot arm. This means that the position of the headset was known in the real world when the robot was in this configuration and the headset was in the alignment fixture, as in Figure 6.2. Then the camera in the virtual world was moved to the appropriate position to align with the physical location of the headset. This allowed the CV1 to be reset and to align the real world with the virtual world. It is difficult to measure any misalignment between the two worlds precisely, but it always appeared to be less than 5mm off in any direction. Additionally, four out of the six subjects experimenting made spontaneous positive comments on the accuracy of the virtual world concerning matching the real-world location of the joint object. None of the subjects made negative comments about this accuracy.

6.3 Robotic System and Control

In this experiment, the human and robot will be interacting in six DOF. This requires that the robotic system used has at least six DOF. For this experiment, the Kuka LBR iiwa was used as used previously in an experiment in Chapter 5.

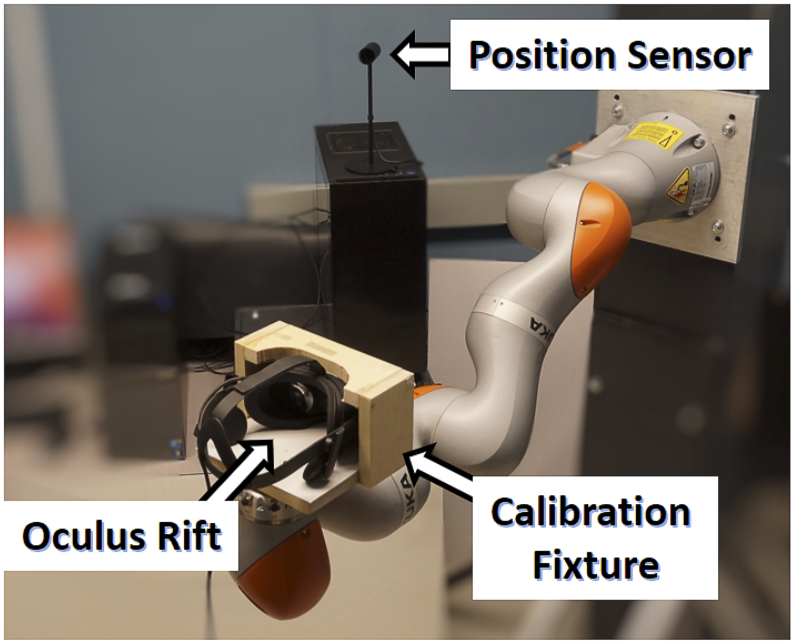

Figure 6.2: VR calibration (from Whitsell and Artemiadis (2017), ©2017 IEEE

For this experiment, the damping ratio was set at 1 for the entire experiment. For the case where the robot was acting as the leader the of a DOF, the stiffness value for translational DOF (k_{tx}, k_{ty}, and k_{tz}) was set at 600N/m. In the rotational DOF, the stiffness value (k_{rx}, k_{ry}, and k_{rz}) was set at 15Nm/rad.

When the robot was acting as the follower in a translational DOF, the stiffness value for that DOF (k_{tx}, k_{ty}, and k_{tz}) was set at 300N/m. In the rotational case, this remained at 15Nm/rad. As discussed in Chapter 5, by having stiffness during the follow role additional damping is added to the system.

For this experiment, Kuka's DirectServo control mode was used as described in Chapter 5. For this experiment, the overall average of the command cycle time was 5ms. The robotic system has three different trajectory generation modes. They are the robot leading in a DOF, following, or transitioning between the two. The difference in this experiment from previous is that these modes are independent for each DOF. This is what allows asymmetric cooperation to be performed.

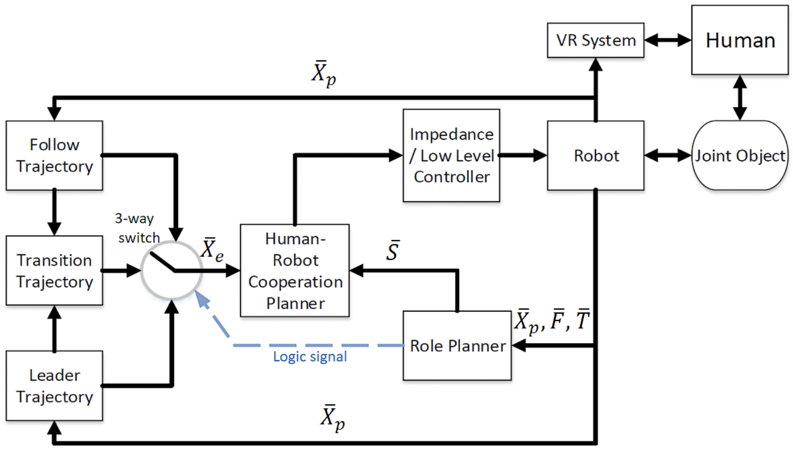

Figure 6.3: Asymmetric Control Diagram (from Whitsell and Artemiadis (2017), ©2017 IEEE

Figure 6.3 shows the control diagram for this experiment. In this control diagram, the human and robot are interacting with the joint object that is attached to the end effector of the robot. The VR System is displaying the virtual image of the joint object and the wall with the goal location hole to the human.

From the robotic system, the motion of the end effector, the estimated interaction force, and interaction torque is sent to the Role Planner. The role planner individually assesses the role of each DOF separately. If the role planner determines a change of roles is needed for a DOF, then it sends the information to the Human-Robot Cooperation Planner. In this planner, the progress of any transition of leader roles is determined. If a transition is in progress, it will continue until it is completed. Additionally, this planner combines the commands for each of the separate DOF and creates an impedance control command to send to the robot control systems impedance/low-level controller. This is done through the DirectServo link. This produces the action that results in the robotic system's action and interaction with the human.

To generate the leader trajectory, the next position in the pre-programmed trajectory is used. The stiffness value used for translational DOF is 600N/m and for rotational DOF is 15Nm/rad. The combination of the stiffness and the moving of the equilibrium position along a trajectory path creates a force (or torque in rotational case) to move the end effector toward the desired equilibrium point.

To generate the follow trajectory, the current measured position is used as the new equilibrium position. This creates a robotic system that is passively following the human leader along a DOF for this experiment. However, this approach is not limited to passive follow method, and this could be modified for an active following control method. The stiffness used in the rotational DOF was maintained at 15Nm/rad. For the translational DOF, the stiffness was set to 300N/m. By having stiffness at these levels, it has the effect of adding damping on the system.

The transition trajectory creates a smooth transition from one trajectory to the other. This is done by utilizing the equations and method discussed in Chapter 5. The transition was conducted over 125 command cycles of the robot. This is approximately 0.6 seconds. This was done to allow the human time to understand and begin to react to the change in leader roles.

Determination of the leader/follower role for the robotic system is an important element in this experiment. Two different methods will be evaluated in this experiment. The first is using a simple force (torque in rotational DOF) threshold value to determine if the human wants to become the leader of a DOF. The second method is to utilize a reinforced learning algorithm to determine if the human wants to become the leader of a DOF. These methods were used in different sessions so that any learning or adaptation the human was doing was in response to a single type of algorithm.

The threshold method for determining if the human wants to lead a DOF is a similar method used before in Chapter 5. The main difference is that this is now separated into individual DOF. The absolute value of the force being applied along a translational DOF (torque for the rotational DOF case) is tested to see if it exceeds a threshold value. If it does, then it the robot gives up being the leader along this DOF to the human. This is done using the switching process described earlier. The threshold values were chosen base on input from previous studies. For each translational DOF, the threshold is 12N. It is 2Nm for each of the rotational cases. This is described in Equations 6.1-6.6.

$$\overline{\mathbf{S}} = \begin{bmatrix} S_x \; S_y \; S_z \; S_\alpha \; S_\beta \; S_\gamma \end{bmatrix} \tag{6.1}$$

$$\overline{\mathbf{R}} = \begin{bmatrix} R_x \; R_y \; R_z \; R_\alpha \; R_\beta \; R_\gamma \end{bmatrix} \tag{6.2}$$

$$R_c = \begin{cases} 1, & \text{robot leads DOF} \\ 0, & \text{otherwise} \end{cases} \tag{6.3}$$

$$S_a = \begin{cases} 1, & \text{if } F_a > C_1 \text{ and } R_a = 1 \\ 0, & \text{otherwise} \end{cases} \tag{6.4}$$

$$S_b = \begin{cases} 1, & \text{if } T_b > C_2 \text{ and } R_b = 1 \\ 0, & \text{otherwise} \end{cases} \tag{6.5}$$

$$a \in \{x, y, z\} \quad b \in \{\alpha, \beta, \gamma\} \;\; c \in \{x, y, z, \alpha, \beta, \gamma\} \tag{6.6}$$

For the sake of clarity and compactness, if a variable has a subscript of a, then it applies to all translational variables. If a variable has a subscript of b, then it applies to all rotational DOF. If it has a subscript of c, then it applies to all DOF. $C_1 =$

12N and $C_2 = 2$Nm for this experiment. If $S_c = 1$ then a switch along that DOF is initiated. If $R_c = 1$ then the robot is the leader of this DOF.

6.3.1 Machine Learning

The other method used to determine if the human wants to become the leader of a DOF is a reinforcement learning algorithm. Reinforcement learning algorithms are a type of unsupervised learning (in-depth information about this can be found in Sutton and Barto (1998)).

In supervised learning algorithms, the data that is given to the algorithm is designated as to which type of data it is. For this experiment, this would be giving the algorithm data to learn from that was specified as data that was from when the human wanted to be a leader and when the human did not want to be the leader. This can be a useful method in many machine learning applications, but it would create additional problems in this type of application. To perform this type of learning, a supervisor is needed. In practice, this typically requires additional human interaction to designate the data as one type or the other. In a research setting, this is easy since the type of data is known based on the experimental setup. However, in the application, this is not known and is determined by the real-time environment and differences between users. As previously stated the purpose of this research is focused on advancing the field closer toward application. For this reason, the choice was made to utilize a learning algorithm that would be more compatible with the future real-world application of the system. This is the reason that an unsupervised learning algorithm, such as a reinforcement learning algorithm, was chosen.

In reinforcement learning the system makes choices based on the expected rewards it will receive for that choice. There are different ways for a system to determine what the expected rewards are for a choice. Two main ways are to use a predetermined model or to use the past experience that the system has to predict the future rewards.

Using a model to determine the value of the future rewards that the system would get by making a choice is one way of determining the future rewards. When this is implemented, it creates a system that is very similar to an optimal control system. The choice can then be optimized for the maximum rewards. However, there are assumptions made with this approach. The first is that an adequate model can be predetermined. This is difficult for this application due to the general complexity of human interaction as well as the variation between humans. Another assumption of this approach is that the system does not change over time. However, humans are known to adapt and change their interaction with systems over time. For these reasons, a predetermined model was not selected as a method to use for the reinforcement algorithm.

The method used for this experiment was to predict the value of future rewards based off of the experience of the system. This means that as the system operates, it keeps track of the decisions that were made and then stores the value of the rewards that were achieved. This requires the system to score the performance after a period of time. In the experimental setup, this will be done after each trial. In an application, this can be done after a period of time or after the system reaches an end goal point or waypoint in a trajectory. There is an additional difficulty with this approach. It causes some initial inefficiency in operating when it first starts, and it does not yet have any data as to how to decide on the correct choice.

One of the fundamental elements of any reinforcement learning program is the algorithm that determines what is rewarded or penalized. For this experiment, there were two main objectives. The first was to reduce the difficulty for the human to take over as leader of a DOF. The second balances the first, and it is to prevent the system from giving the leader to the human when the human did not intend to take control.

This balancing effect can be easily seen by examining each of these elements without the other. If the system only wanted to minimize the effort that the human needed to apply to become the leader, the way to guarantee maximum rewards would be to require zero effort. This would mean that the system would always give the leader role to the human along all axes. The other objective of preventing giving the human the leader when they did not desire it would have the opposite effect if executed by itself. The way to ensure that the system gets the maximum reward for not switching when the human did not desire it is to never give the human the lead. When these two elements are combined, they balance each other out. Their implementation determines the exact way that they balance out.

First, we will examine the implementation of the minimization of the effort that the human applies to become the leader. An initial element of this is to determine the method to determine effort. For this experiment, an estimate of the applied mechanical power by the human to the end effector of the robot was used. This estimate is based on the applied work as discussed in Chapter 5 but examines it as a time rate of work. As mentioned previously, the use of the estimated force has its difficulties and limitations but is useful in that it does not require the use of additional sensors.

The estimated applied power of the human interacting with the system is used as a negative reward. The greater the amount of power the human applies the greater the penalty or negative reward for the system. The input of this system is the currently applied force. This is then used to predict the future power that will be applied to the system. This is done for each DOF independently. This allows the system to learn different values for one axis of motion than for another axis of motion. This creates the potential for additional adaptability of the system.

To calculate the power input, the estimated applied force and the distance traveled are used. This is calculated as the average power applied over time as in Equation 6.7-6.9.

$$W_a = \int |F_a| \, da \qquad\qquad W_b = \int |T_b| \, db \tag{6.7}$$

$$P = \frac{dW}{dt} \tag{6.8}$$

$$P_c = \frac{\sum_{n=i}^{i+g} W_{c(n)}}{t_{(i+g)} - t_{(i)}} \tag{6.9}$$

where P_c is the average power of a DOF beginning at sample i and ending at sample $i + g$. $g = 199$ if no switch along that DOF occurs during within this set of 200 samples. If there is a switch, g is the number of samples between the current sample and the sample before a switch.

In addition to reducing the power applied to the system, the system needs to minimize unnecessary switching. If the robot switched when the human did not intend to take over as leader of an axis, this creates a system that can perform inefficiently and require the human to lead DOF that the human does not desire to lead. To minimize this, a penalty was created. A switch of leadership is assumed incorrectly if at the end of the switch transition there is a low velocity along that DOF. This is expressed in Equations 6.10 and 6.11.

$$Q_a = \begin{cases} 1, & \mid q_{(j+h)} - q_{(j+h-1)} \mid < C_3 \\ 0, & \text{otherwise} \end{cases} \tag{6.10}$$

$$Q_b = \begin{cases} 1, & \mid u_{(j+h)} - u_{(j+h-1)} \mid < C_4 \\ 0, & \text{otherwise} \end{cases} \tag{6.11}$$

where Q is the penalty for the individual DOF. $C_3 = 1.0mm$ and $C_4 = 0.2mrad$. The translational position is q and u is the rotational position. j is the index at the beginning of the role exchange. $h = 126$.

$$V_t = -P_c \tag{6.12}$$

$$V_w = -P_c - Q_c \tag{6.13}$$

where the value of the rewards for staying is V_t and V_w for switching.

The reinforcement algorithm learns the expected future rewards based on the systems current state and choice of action. For this algorithm, the current state is the applied force along a DOF, and the choice of action is to switch leadership to the human or to remain the leader. The force input was discretized into bins to facilitate taking an average across similarly applied forces. This was done to aid in averaging out potentially noisy values. This can be seen in Equations 6.14 and 6.15.

$$N_b\left(T_b\right) = \begin{cases} 1, & \mid T_b \mid < \ C_4 \\ \lfloor (\mid T_b \mid - C_4) \times 4 \rfloor, & \text{otherwise} \\ 10, & \mid T_b \mid \geq C_5 \end{cases} \tag{6.14}$$

$$N_a(F_a) = \begin{cases} 1, & \text{if } |F_a| < C_6 \\ \lfloor \ |F_a| \ \rfloor - C_6, & \text{otherwise} \\ 10, & \text{if } |F_a| \geq C_7 \end{cases} \tag{6.15}$$

where $\lfloor x \rfloor = max\{n \,\epsilon\, \mathbb{Z} | n \leq x\}$. The bin number for the applied force or torque is N_c. $C_4 = 1.0Nm$, $C_5 = 3.0Nm$, $C_6 = 7.0N$, and $C_7 = 15.0N$ These values were chosen based on prior studies and pilot testing.

$$A1_c(N_c) = \frac{\sum_{n=1}^{l_1} V_{t(n)}}{l_1} \tag{6.16}$$

$$A2_c(N_c) = \frac{\sum_{n=1}^{l_2} V_{w(n)}}{l_2} \tag{6.17}$$

where for each DOF $A1_c$ is the average of the rewards for staying and $A2_c$ is the average of the rewards for switching.

One element of reinforcement algorithms is that they need to explore different values in addition to utilizing (exploiting) the information it has already learned. This allows the system to seek out other potential solutions and to adapt to a changing environment. However, in a robotic system that is interacting with a human, the exploration of different ways to interact needs to be done with some caution. To do this, a random number is generated with an even distribution for value from 0 to 1. As in Equations 6.18-6.20, this random number alters the bin being compared in the decision of whether to switch or not. This allows the system to explore one bin up or down from its current value either way. This is done in all six DOF simultaneously.

$$r_n \sim U([0\ 1]) \tag{6.18}$$

$$E = \begin{cases} -1, & r_n < 0.25 \\ 0, & 0.25 \leq r_n \leq 0.75 \\ 1, & r_n > 0.75 \end{cases} \tag{6.19}$$

$$A2_c\left(N_c + E\right) > A1_c\left(N_c\right) \wedge R_c = 1 \rightarrow S_c = 1 \tag{6.20}$$

where r_n is a random number from a uniform distribution between 0 and 1. The exploration value is E.

For this experiment, the reinforcement learning algorithm began without any information from previous sessions. This is to represent the desire for learning algorithms in applications to be able to be used from the beginning. The difficulty is that the system needs some values to utilize at the beginning of the session. The initial values for the system are propagated, as in Equations 6.21 and 6.22, to initially work as a threshold system at $N_c = 5$.

$$N_c \leq 4 \rightarrow \left(A1_c\left(N_c\right) = 0 \wedge A2_c\left(N_c\right) = -1\right) \tag{6.21}$$

$$N_c > 4 \rightarrow \left(A1_c\left(N_c\right) = -1 \wedge A2_c\left(N_c\right) = 0\right) \tag{6.22}$$

An additional ability of the system proposed is for the robotic system to take back over as the lead of a DOF. This allows for bi-directional role exchange. This allows the human to focus on a lower number of DOF when the robotic system takes over as leader of DOF that are not currently being used. The concept behind this type of role exchange is if the human is not moving or applying force along an axis over time that the robot would take over leadership of this DOF. For this experiment, when the robot takes the leader from the human it sets the new goal as the current location. This means that the robot stabilizes and maintains the current position instead of the human needing to maintain the position. This lack of motion or force is detected based on a 200 sample moving average, as in Equations 6.23-6.27.

$$h_a = \frac{1}{C_8} \sum_{n=i-C_8}^{i} F_{a(n)} \tag{6.23}$$

$$h_b = \frac{1}{C_8} \sum_{n=i-C_8}^{i} T_{b(n)} \tag{6.24}$$

$$j_c = \frac{1}{C_8} \sum_{n=i-C_8}^{i} w_{c(n)} - w_{c(n-1)} \tag{6.25}$$

$$\mid h_a \mid > C_9 \wedge \mid j_c \mid > C_{10} \wedge R_a = 0 \rightarrow S_a = 1 \tag{6.26}$$

$$\mid h_b \mid > C_{11} \wedge \mid j_c \mid > C_{12} \wedge R_b = 0 \rightarrow \ S_b = 1 \tag{6.27}$$

where $c_8 = 200cycles$, $C_9 = 0.3N$, $C_{10} = 1.0mm/cycle$, $C_{11} = 3.0N/mm$, $C_{12} = 0.02mrad/sec$. h_a is the moving average of the applied force (h_b for torque). j_c is the moving average of position.

The initial pose of the robotic arm can be seen in Figure 6.4. This position is set as (0mm, 0mm , 0mm, 35°, -30°, 35°). The final positions are (165mm, 75mm, 50mm, 0°, 0°, 0°), (165mm, -75mm, 50mm, 0°, 0°, 90°), and (165mm, -75mm, -110mm, 90°, 0°, 0°). These final positions can be seen in Figure 6.4. The arm pose for the final position can vary due to the kinematic redundancy of a 7 DOF robotic arm.

For this experiment, there were six human subjects. Each subject performed five sessions. Each of the sessions was performed on a different day. The first session was conducted for training the subjects. The subjects were not told that this was for training purposes ahead of time. The method used for determining if the robot should give leadership to the human during the training session was the threshold method.

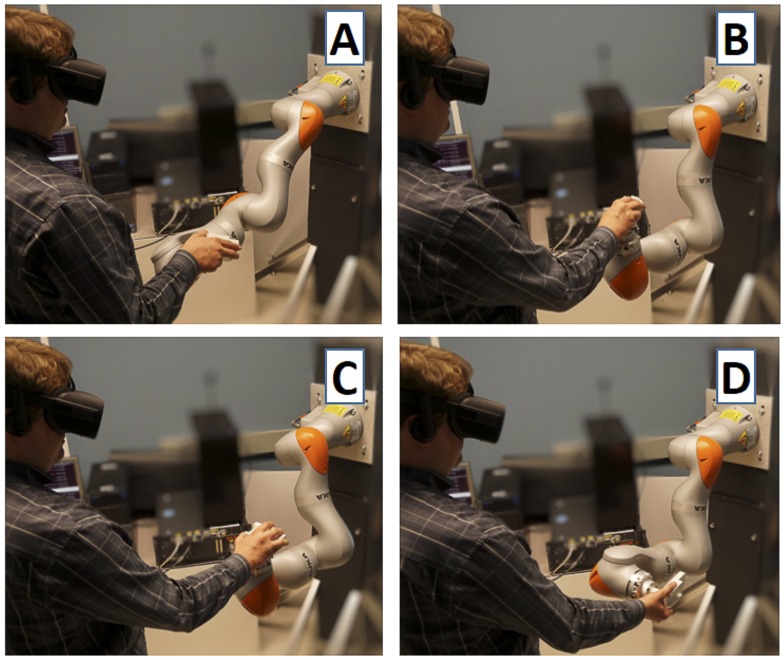

Figure 6.4: Experimental Setup (from Whitsell and Artemiadis (2017), ©2017 IEEE)

6.4 Experimental Methods

Of the four non-training sessions, there were two that utilized the threshold method, and two the utilized the machine learning method. Half of the subjects started with machine learning session, and the other half started with the threshold method after the training session. The subsequent sessions for a subject alternated between machine learning and threshold. The subjects were not told what type of algorithm was being used or what the pattern was to the types of algorithm.

Within each session, there were 60 trials. Each of the three different hole locations was used for 20 trials. In half of the trials (30), the robot made a mistake and operated correctly in the other half. The mistakes that the robot would make were to go to one of the hole locations or orientations that were not the one that was currently shown but was one of the three holes. Half of the trials the human started leading the 3

DOF for translation and the robot leading 3 DOF for rotation. In the other half, the roles were reversed at the start.

Overall, each subject performed 240 trials excluding the training session. For all six subjects, this equates to 1440 trials. The subjects were told to cooperate with the robot to move the object to the correct position and orientation. Each hole in the wall was 5mm larger around each edge. The human and robot would cooperate to obtain the final position and orientation. When they reached this position or stopped trying to reach this position, the experimenter would indicate an end to the trial.

At the beginning of the trial, the subject leads three DOF, and the robot leads the other three. The subject is told which three they are leading at the start. They are also instructed that they can exchange roles with the robot and that the robot will sometimes perform an incorrect action and they will need to correct that action. They are also informed that the robot may take back the lead of a DOF if it thinks that the human is not using it. The ability for them to change grip and to use either manual or bimanual manipulation is explained to them. Finally, the subjects are encouraged to interact naturally with the robot. These experiments were conducted in accordance with ASU IRB# STUDY00004933.

6.5 Results

The cooperation between the human and the robotic system overall was successful. The human-robot cooperation was able to correctly position the joint object in position and in rotation 100% of the time. In previous experiments, this was not always the case. In the past subjects would occasionally give up and assume that there was an error in the robotic system when they felt that the robotic system was

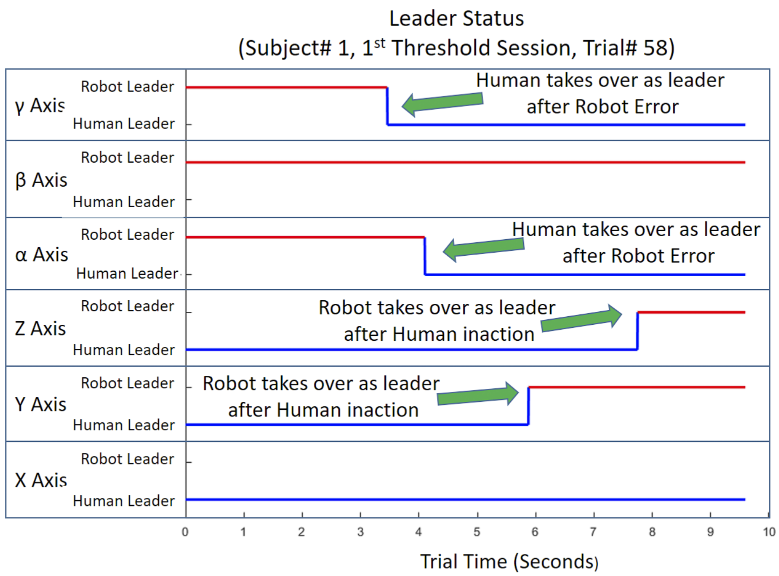

Figure 6.5: Change In Leader/Follower Roles (from Whitsell and Artemiadis (2017), ©2017 IEEE)

not responsive to them. This did not occur in this experiment.

Table 6.1: Role Exchanges Asymmetric Cooperation(adapted from Whitsell and Artemiadis (2017), ©2017 IEEE).

Role Exchanges per Trial	0	1	2	3	4	> 4
Total	113	363	379	307	157	121
Percentage of Trials	7.8	25.2	26.3	21.3	10.9	8.4

As can be seen in Table 6.1, the human and robotic system were frequently able to exchange roles. This shows that the system was effective at allowing the human and robot to exchange roles in a six DOF human robot cooperation task.

The asymmetric cooperation element allowed for a customized solution of the human-robot cooperation. An example of this can be seen in Figure 6.5. Here, subject 1 interacts with the robotic system. The figure shows which agent is the current leader. In rotation DOF, the human took over as the leader in response to the robotic system making an error and rotating toward the incorrect orientation. As the trial progresses, the robot takes over as leader of two translational DOF and allows the human to focus on fewer DOF.

The robotic system would take back the lead of a DOF if the human was not moving or applying a significant force along a DOF. Over all subjects, sessions (excluding training), and all trials the robot took over as leader 1702 times. After the robot took back the lead of the DOF, the human only took back the lead role for the DOF 76 times. This means that 95.6% of the time the robot was able to take over control of the DOF and perform sufficiently well that the human did not need to retake the leadership role.

Asymmetric cooperation also allowed subjects to behave in a way different than expected. The way that the controls elements and trajectory generation were designed in this experiment made the motion along x, towards the wall, control the pace of the other DOF along their trajectories. By taking over the lead in the x DOF, the human can control the pace of the individual trial and, in aggregate, the pace of the overall experiment. Some subjects used this to complete the experiment faster than anticipated. This can be seen in Figure 6.6.

In Figure 6.6, subject four took over as leader of the x DOF 100% of the time and was the fastest in completing the overall experiment. In 55% of the trials, subject 4 took over leadership of only the x DOF. Additionally, subject four took over leadership of x and one other DOF in 36.7 % of the trials. This means that in 91.7 % of the trials the robot remained the leader of at least one DOF in translation. This means the subject was able to allow the robotic system to maintain leadership of this DOF and alleviated the need for the human to lead that DOF.

In Figure 6.6, subject one is the slowest subject to complete the experiment. In the experiment, the robot is moving in the wrong direction 50% of the trials. Subject

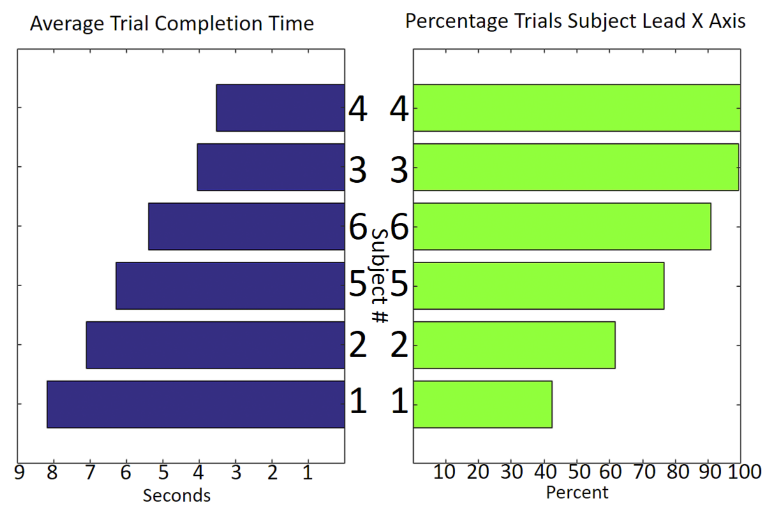

Figure 6.6: Completion Time and Leader of x Whitsell and Artemiadis (2017), ©2017 IEEE

one was able to correct the incorrect motion of y and z DOF while sometimes still allowing the robot to remain the leader of the x DOF. This demonstrates that if the human subject wanted to proceed at the pace that the robot was dictating by leading the x-axis, this was also accommodated by asymmetric cooperation.

6.5.1 Machine Learning

The machine learning algorithm in this experiment adapts when the robot gives human the lead in a DOF. The current state that is evaluated is the force or torque that the human is estimated to have applied to the end effector. This algorithm uses reinforcement learning to gain the most rewards, or in this case, the least penalties or negative rewards. There are two penalties in this experiment. The first is the estimated power applied by the human. This penalty is to reduce the effort that the human needs to apply to the system. The second penalty is assessed if the velocity of the end effector is low after the DOF has been switched. The concept behind this is that if the human wanted to lead that DOF, then there would be some movement after the human took over as leader. This is to reduce the unnecessary and undesired switch of leader to the human. Each of the DOF was analyzed separately. This allows for a customization along a DOF to potentially account for differences in task environments. The results of this can be seen in Table 6.2

Table 6.2: Average power used to exchange roles for ML trials(as a % of the subjects average for threshold trials). (adapted from Whitsell and Artemiadis (2017), ©2017 IEEE).

Subject Number	1	2	3	4	5	6
Translational DOF %	37	82.5	83.3	70.4	74.9	64.1
Rotational DOF %	103.5	97.5	43.2	89.5	85.7	105.4
All DOF %	70.3	90	63.3	80.5	80.3	84.7

The force and torque values were discretized into bins and the value of the rewards that they earned we average for that bin. To compare the results of this with the threshold method, the concept of effective threshold was used. The effective threshold is the point that the system would choose to switch if the input was a force or torque that was rising from an initial value of zero. The effective bin at the end of the machine learning sessions was calculated. This was compared with the other machine learning session that the human performed and the differences in the bin numbers were created. This was compared across all DOF and all subjects (36 comparisons). This can be seen in Figure 6.7. Overall there is a high level of agreement between the machine learning sessions for each subject with 52% within one bin. However, there may also be a day to day variations from the human as well as adaptation over time.

The learning the algorithm performs can be seen in the change of the effective threshold over time. An example of this can be seen in Figure 6.8. The effective threshold adapts to a lower value. However, it adapts too low and causes a false

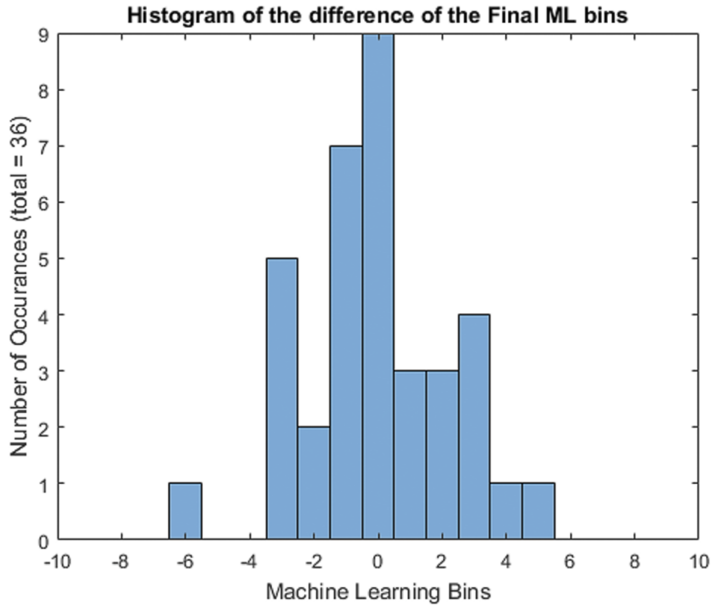

Figure 6.7: Comparison of Machine Learning from different sessions (from Whitsell and Artemiadis (2017), ©2017 IEEE)

trigger penalty and adapts to a higher value and then settles at this value. This shows how the machine learning system allows for the adaptation of the system to an individual subject.

6.6 Conclusions

This experiment showed the effectiveness of six DOF human-robot interaction with asymmetric cooperation. Overall, the subjects and robotic system were able to cooperate to achieve the desired outcome in 100% of the trials. The asymmetric cooperation allowed for the human to choose which DOF to lead and which DOF to allow the robotic system to lead. Additionally, the human-robot interaction test system was further developed with a virtual reality display system and a calibration method for aligning virtual and real-world objects.

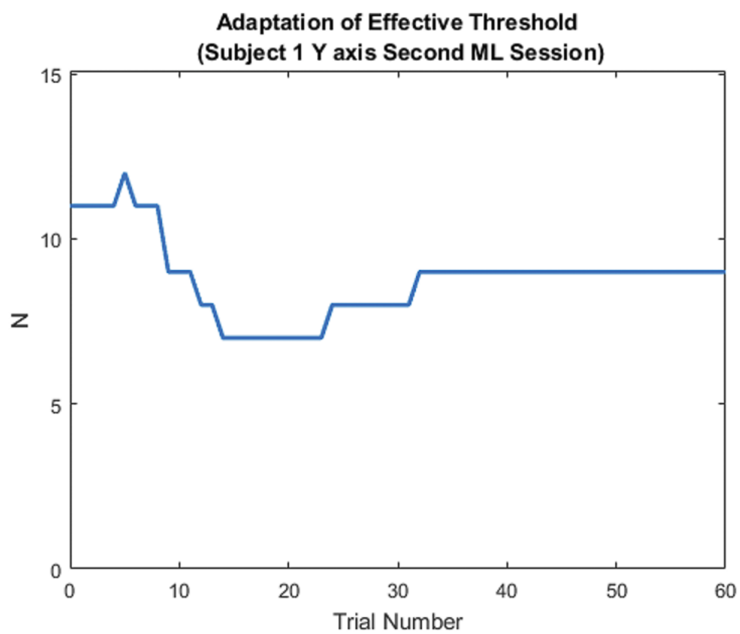

Figure 6.8: Adaptation of Effective Threshold (from Whitsell and Artemiadis (2017), ©2017 IEEE)

Chapter 7

LEVELS OF AUTOMATION AND HUMAN ERROR

Kaber and Endsley (1997) showed that levels of automation of a system that a human interacts which can affect the human's ability to take over when the automation fails. This is of particular interest for human-robot applications. The higher the level of automation of the system the greater difficulty the human has in taking control when the automation fails. However, the research in this field primarily focuses on simulated tasks with higher level reasoning or on the interaction of highly complex systems such as flying a large aircraft. There is a lack of research in this field in applications performing a more direct motion oriented task, like a repetitive assembly line task. Additionally, Reed (2012) found the benefit of specialization in a simple human-human task. This suggests that in a simple human-robot application where the human is specializing in correcting a translational error by the robot may benefit from greater automation by allowing the human to focus on this specialization.

From the previous research, it is unclear if a robotic system that is more automated would increase the performance of a human interacting with the robot occasionally to prevent robotic error. Due to this, the hypothesis for this experiment is that the level of automation of the robotic system in performing a simple task does not affect the performance of a human whose main role is to prevent the robot from making a rare (2.5%) error.

7.1 Experiment scenario

To test this hypothesis, an industrial human-robot task was created. The task is to perform a repetitive action on an assembly line. In this task, the robot will perform correctly 97.5% of the time. This high level of consistency may affect the ability of the human to maintain vigilance in ensuring proper performance of the robot. To vary the levels of automation that the robot performs during the task, three different levels of control by the robot are used. The task was limited to 3 DOF translation. As can be seen in Figure 7.2, the y-axis is the axis that moves down the part. The z-axis determines height. The x-axis is the axis where the robot will potentially make a mistake.

In the level with the highest level of automation, the robot will control all three translational axes (x, y, and z). The human's task will be to follow the motion of the robot and only to intervene if the robot makes an error.

The middle level of automation is where the robot controls the x and z-axes and the human controls the y-axis. The motion of the robot in the x and z-axis will be a function of the position of the end effector along the y-axis. This means that the human will be controlling the pace of the trial.

The lowest level of automation is where the robot only controls the x-axis. The human is controlling the motion down the part as well as the height off of the part. Additionally, the motion along the x-axis is a function of the motion along the y-axis. This experiment will utilize the human-robot interactive test system to present the requirements to the human as discussed in Chapter 6. A virtual industrial environment was created to give the subjects the proper context for the experiment, as in Figure 7.1.

A virtual part was created. This part has three buttons on it. Button 1, as seen in Figure 7.4, will always be green. The green color signifies that it is a button that needs to be touched by the tip of the end effector. The beginning of the trial the end effector moves from the start position and touches button 1. Then the end effector moves over the yellow center block and touches either button 2a or 2b. With regards to button 2a and 2b, the button that is green is the button that the robot is to touch. Button 2a and 2b swap red and green colors randomly during the experiment. The

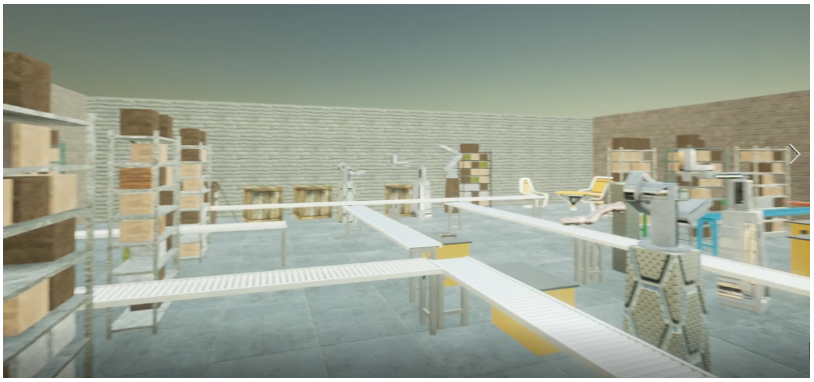

Figure 7.1: Industrial Virtual Environment

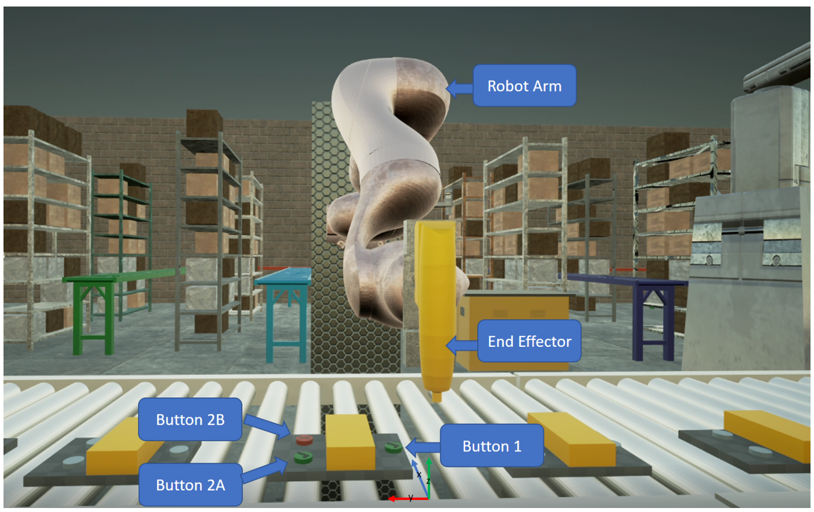

Figure 7.2: Virtual Task Setup

motion of a trial can be seen in Figure 7.3. In summation, the end effector moves from the start and touches button 1. It then moves to either button 2a or 2b avoiding the yellow block in the middle. If the button it goes to is green, then it is performing correctly. If it goes to the red button, then the robot is performing incorrectly.

7.2 Experiment Setup

To display the virtual world to the subject, the VR system used in the asymmetric cooperation experiment was used. Additionally, the calibration method previously described was used to ensure the real-world objects match with the virtual world location.

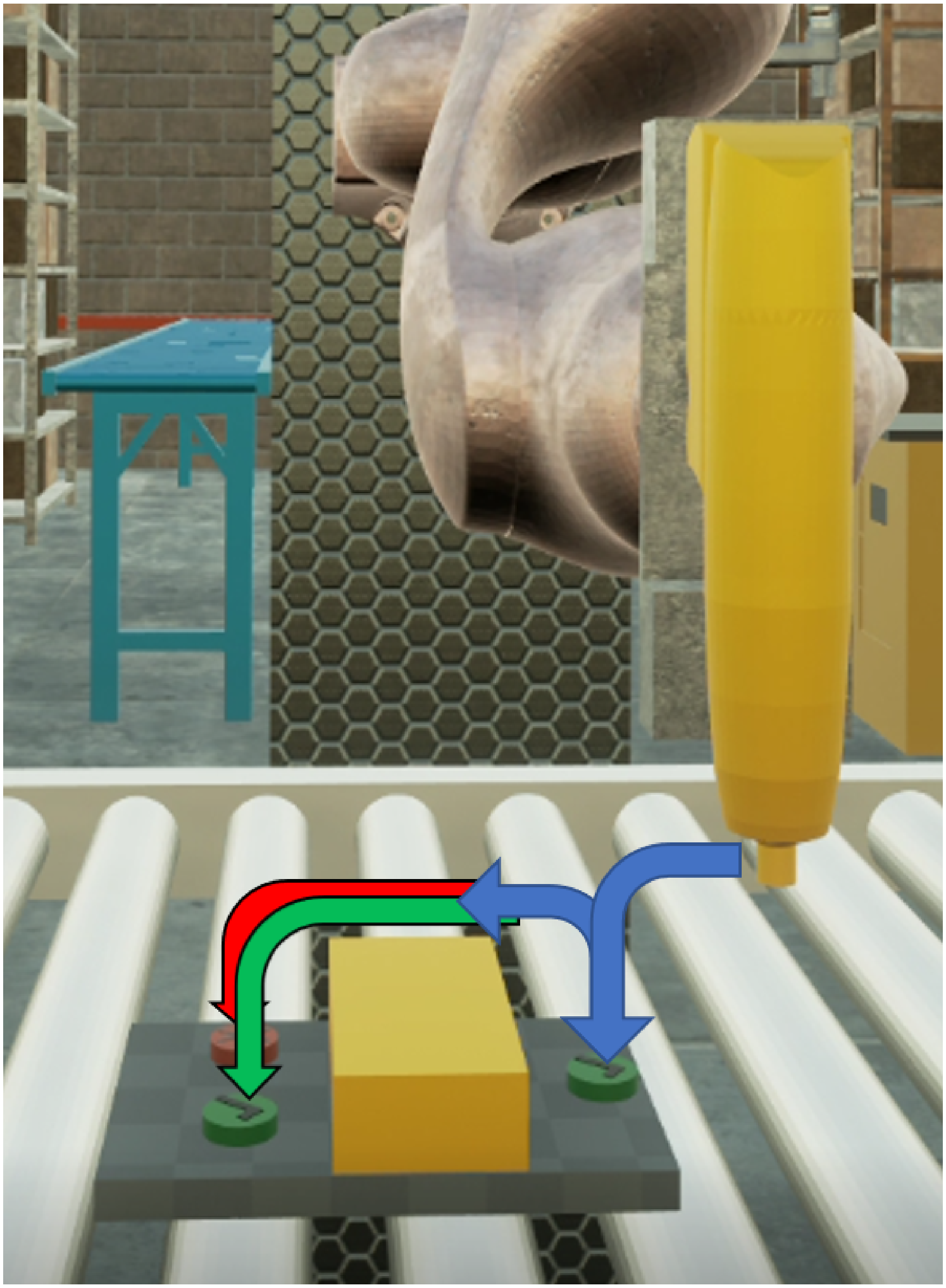

Figure 7.3: Single Trial Path: All trials beginning with the motion in blue. Then the trajectory deviates either to the correct button (green) or the incorrect button(red).

In this experiment, the robot arm is visible in the virtual reality display. This is achieved by inserting a model of the robot into the virtual world and updating the position of the arm based on the joint angles of the robot obtained from the robot controller.

For this experiment, the Kuka LBR iiwa was used, and an industrial-like tool was attached as the end effector, as in Figure 7.4. The robot was controlled similarly to the asymmetric cooperation experiment with a few exceptions. The task is limited to translation. If the human exerts a force greater than 12N along the x-axis, the robot switches to follow on all translational axis.

For this experiment, the simulation of physical interaction with the virtual world is desired since the task involves touching buttons as well as avoiding the yellow block in the center of the part. To achieve this the location of the virtual objects were programmed into the robot control code. If the tip of the end effector contacted a surface of a virtual object, the stiffness along that axis was increased to 1000N/m, and the equilibrium point was not allowed to be inside of a virtual object. This produced an interaction similar to contact with a stiff object. Additionally, when any of the buttons was touched, a click sound was played as an additional cue to the subject that contact was made with a button.

7.3 Protocol

Six subjects participated in this experiment. Three sessions were performed by each subject. Each of the sessions corresponded to a different level of robotic automation. The order of these sessions was varied, so all six permutations of the order of the three sessions were performed. This was to eliminate the possibility that the order of the sessions affected the performance.

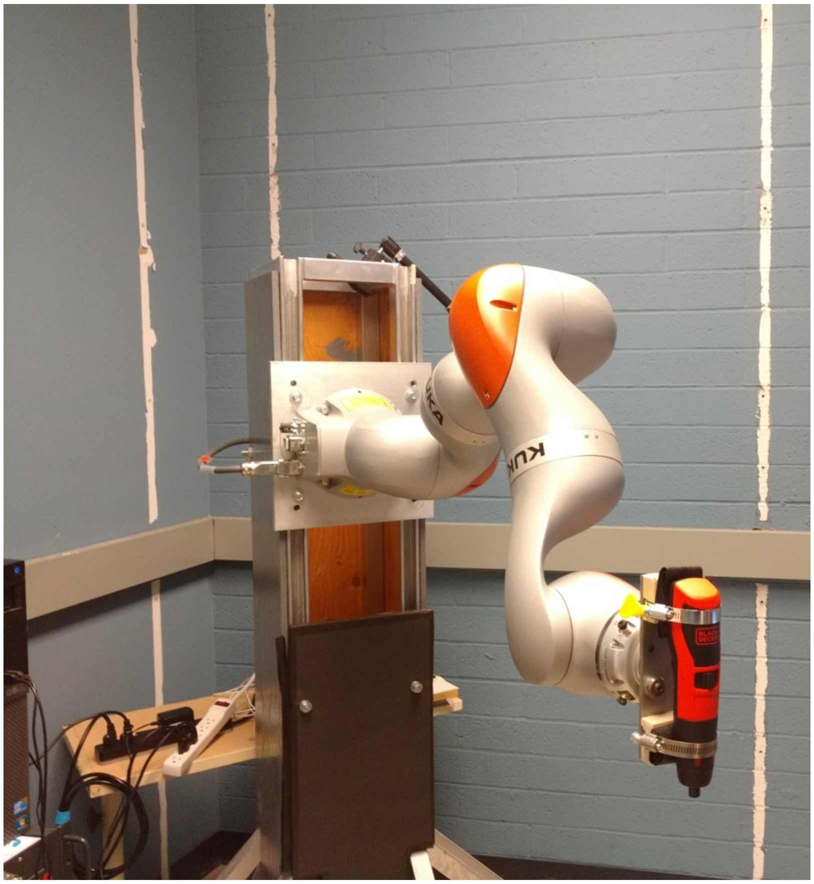

Figure 7.4: Physical Robot Setup

In each session, 200 trials were conducted. The session ran continuously to simulate a factory environment. This meant that each session took approximately 20 minutes to complete. The robot performed the wrong action 2.5% of the time. This means that there were five trials per session where the robot would make an error that the human needed to correct.

7.4 Results

The results, as seen in Table 7.1, are clear that the sessions where the robot lead the x and z-axis performed the worst. All human errors occurred during this session. This is the level of middle automation. This disproves the hypothesis and establishes that the human is affected by the level of robotic automation. The better

Table 7.1: Percentage of Human Failure to Stop Robot Error

Subject Number	1	2	3	4	5	6	All
Robot Leads XYZ	0	0	0	0	0	0	0
Robot Leads XZ	0	0	20	20	80	20	23.3
Robot Leads X	0	0	0	0	0	0	0

performance of both the higher and lower automation suggest that there may be two effects. The higher level of automation may be performing better due to the concept of specialization discussed earlier. This may allow the human to react faster by allowing them only to focus on stopping incorrect motion. The performance of the lower level of automation may be due to the human being more engaged as suggested by out of the loop syndrome research. Additional experiments are needed to confirm this.

Chapter 8

CONCLUSIONS

This research focused on two main objectives. The identification of a method to determine the human's desired role (leader or follower) using EEG signals was the first objective. The advancement of the field of human-robot cooperation by the development of a control method with certain characteristics was the second objective of this dissertation. The determination of the characteristics needed to advance the field was based on the previous research in the field and a focus on moving towards application in the field.

A method for using EEG to help determine if the human wants to interact with the robot as a leader or a follower was developed. This system still maintained physical interaction between the human and robotic system. The greatest potential area of improvement would be an increase in the accuracy of the system. The prior literature and the results of the research in this dissertation suggest that the lower level of accuracy may be caused due to the additional signals in the brain from the physical interaction. Future research may be able to identify these signals, and this would allow them to be removed from the system.

The prior research in the field of pHRI had a number of areas for potential improvement. The majority of research in the field focused on research with limited numbers of degrees of freedom of the human-robot interaction. An unrestrained object in the real world has six degrees of freedom. This means that six variables are needed to describe its position or its motion along these different degrees of freedom. In order to move the field forward toward real-world application, a control method that used six degrees of freedom was developed.

The most compelling applications of human-robot interaction are where the human and robot both have the ability to contribute to the interaction. To facilitate this, the characteristic of allowing either the robot or the human to be the leader of an aspect of the interaction was incorporated into the controller. Some prior research in the field has examined the potential of leader/follower role exchange between a human and robot. However, this prior research typically examined exchanging the roles across all elements of interaction. This does not allow for the human to adapt to different tasks and situations. A control method, asymmetric cooperation, was developed that allowed the human and robot to exchange roles along individual degrees of freedom. This allows for the human to adapt the level of leadership based on the dynamic environment

Additionally, the above combined elements were tested in an environment that stressed realism toward application. This realism can be seen in two main elements. The first is that there is actual physical interaction between the human and robot. This interaction is often simulated or significantly limited in most of the prior research. The second element is that the interaction between the human and the robotic system is tested in an environment where the robotic system makes mistakes. In a real-world environment, the robotic system will have limited information and due to this will make mistakes. Control systems for human-robot interaction need to be tested in this type of environment to ensure that they are capable of operating safely and effectively in this type of environment.

There are a number of ways that the field can be further advanced toward application. In this research, a number of quantities were chosen based off of previous experiments and pilot studies. This was useful in allowing the control methods to be developed and tested in a reasonable amount of time. However, a universal approach would be to allow for these values to be adjusted through an adaptive or machine learning element. Caution should be used with this approach, however. When multiple adapting systems interact, there is a tendency for seeking behavior. Additionally, each element needs to remain stable while it and the other elements change over time. This is not a trivial task.

In this research, six DOF cooperation was performed. These degrees of freedom were aligned with the robotic system. A potentially useful advancement would be to allow these DOF to be aligned with the current task being performed. This could allow a machine vision (or similar) system to determine the best axis alignment to give the human the most relevant choices of which DOF to lead or to follow.

Finally, this research focused on DOF that represent position or orientation. An additional advancement would be to examine DOF that go beyond this limitation. There are a number of potential examples of this such as to grasp/release an object; to start, operate, or stop an independent piece of equipment; or to perform a series of preprogrammed actions.

Human-Robot interaction is a field that can have a positive effect on several areas of society. Further research in the field can potentially improve the way humans work, the ability to overcome injury or illness, the restoration of function to the permanently disabled, and the ability to perform actions beyond normal human capabilities. Research in the field needs to focus on moving these areas toward application to realize the potential of this field.

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APPENDIX A

LIST OF PUBLICATIONS

Durring my time in the Human Oreinted Robotics Lab, I have been an author on 5 peer reviewed publications listed below. Portions of the first three of these publications have been used in the dissertation and are cited within the text. The remaining two were from collaborations that were beyond the scope of this dissertation.

1. Bryan Whitsell and Panagiotis Artemiadis, On the role duality and switching in human-robot cooperation: An adaptive approach, in Robotics and Automation (ICRA), 2015 IEEE International Conference on, pp. 37703775 (IEEE, 2015).

2. Bryan Whitsell and Panagiotis Artemiadis, Physical Human-Robot Interaction (pHRI) in 6 DOF with Asymmetric Cooperation, IEEE Access (2017).

3. Keivan Mojtahedi, Bryan Whitsell, Panagiotis Artemiadis and Marco Santello, Communication and Inference of Intended Movement Direction during Human-Human Physical Interaction, Frontiers in Neurorobotics 11 (2017).

4. Mark Ison, Ivan Vujaklija, Bryan Whitsell, Dario Farina and Panagiotis Artemiadis, Simultaneous myoelectric control of a robot arm using muscle synergy-inspired inputs from highdensity electrode grids, in Robotics and Automation (ICRA), 2015 IEEE International Conference on, pp. 64696474 (IEEE, 2015).

5. Mark Ison, Ivan Vujaklija, Bryan Whitsell, Dario Farina and Panagiotis Artemiadis, High-density electromyography and motor skill learning for robust long-term control of a 7-dof robot arm, IEEE Transactions on Neural Systems and Rehabilitation Engineering 24,4, 424433 (2016).

APPENDIX B

COPYRIGHTED MATERIAL

APPENDIX C

CO-AUTHOR PERMISSION

All co-authors have given permission for inclusion of material from published co-authored papers in this dissertation.

APPENDIX D

HUMAN SUBJECT TESTING

All subjects participating the various studies in this dissertation gave informed consent prior to participating in the study. All experiments were conducted in agrrement with the approved Insitution Review Board (IRB) procedure ASU IRB # STUDY00002544 and STUDY00004933.