Spring 2019

Effects of Control Device and Task Complexity on Performance and Task Shedding During a Robotic Arm Task

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EFFECTS OF CONTROL DEVICE AND TASK COMPLEXITY ON PERFORMANCE AND TASK SHEDDING DURING A ROBOTIC ARM TASK

by

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B.S. December 2013, Georgia Institute of Technology

A Thesis Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

PSYCHOLOGY

OLD DOMINION UNIVERSITY
May 2019

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ABSTRACT

EFFECTS OF CONTROL DEVICE AND TASK COMPLEXITY ON PERFORMANCE AND TASK SHEDDING DURING A ROBOTIC ARM TASK

Shelby K. Long
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The use of robotic arms across domains is increasing, but the relationship between control features and performance is not fully understood. The goal of this research was to investigate the difference in task performance when using two different control devices at high and low task complexities when participants can shed tasks to automation. In this experiment, 40 undergraduates (24 females) used two control devices, a Leap Motion controller and an Xbox controller, to teleoperate a robotic arm in a high or low complexity peg placement task. Simultaneously, participants were tasked with scanning images for tanks. During the experiment, participants had the option to task shed the peg task to imperfect automation. Analyses indicated a significant main effect of control device on task completion rate and time to first grasp the peg, with completion rate higher and time lower when using the Leap. However, participants made significantly more errors with the Leap Motion controller than with the Xbox controller. Participants in both conditions task shed similarly with both control devices and task shed at similar times. The 2 x 2 mixed ANOVAs somewhat supported the proposed hypotheses. The results of this study indicate that control device impacts performance on a robotic arm task. The Leap Motion controller supports increased task completion rate and quicker peg grasps in high and low task complexity when compared with the Xbox controller. This supports the extension of Control Order Theory into three-dimensional space and suggests that the Leap Motion controller can be implemented in some domains. However, the criticality and frequency of errors should be carefully considered.

This thesis is dedicated to my family and Nich, for supporting me in all ways imaginable.
I would not be here without them.

ACKNOWLEDGMENTS

I would like to acknowledge my advisor and committee chair, Dr. James Bliss, for his guidance and patience throughout this process. I would also like to thank my committee members, Dr. Yusuke Yamani and Dr. Xiaoxiao Hu for their guidance and support to make this project possible. Additionally, I'd like to thank Jordan Boyd for his assistance in coding the videos quickly and thoroughly, Alex and Will for their kind ear as I struggled with this project, and my lab mates and program mates for reading and listening to every iteration of this project.

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CHAPTER 1

INTRODUCTION

Humans use robotic arms to complete a range of tasks, from disarming improvised explosive devices (IED) to executing space station repairs (International Federation of Robotics, 2014; Yu & Zhou, 2014; Marescaux et al., 2002). Many of these tasks require precise, accurate performance. The complexity of the task varies, and operators must often complete other tasks concurrently.

Traditionally, manually operated robotic systems have relied on a master-slave paradigm. Humans use a control device, such as a joystick, to move the robotic arm to select and transport objects. Manipulation of the control device corresponds to robotic arm movement. Often, robotic arms are operated from a separate location, or teleoperated. Repetitive tasks, such as elements of automobile manufacturing, are often fully preprogrammed. Other tasks, such as IED disarmament or surgical procedures, require the adaptability and decision making of a human operator (Corliss & Johnsen, 1968; Travaglini. Sawney, Weaver, & Webster, 2016). Task responsibilities are not always dichotomously manual- or automation-controlled. Considering this, human-robot interaction becomes more complex, specifically when humans have the option to offload certain tasks to a robot for independent execution.

The purpose of the proposed study was to investigate the impact of control device on performance in tasks with high and low complexity. This research addresses the theoretical implications of control device differences, as well as the concepts of task complexity and task shedding. It also addresses current theoretical gaps and leverages experimental methodology to address them. The findings are interpreted by considering theoretical and practical implications.

Teleoperated Robotic Arms

Teleoperation has been defined as human control of remote sensors and actuators (Sheridan, 1995). Telerobotics is a specific type of remote device manipulation where a human operator, or teleoperator, controls a robot remotely. Use of teleoperated robots emerged so operators may complete manual tasks without jeopardizing safety (Sheridan, 2016). The first human-controlled robots assisted with task completion in unsafe or cramped environments. These direct-control robotic arms now also access hazardous areas, such as radioactive or underwater environments and complete tasks without risking human injury (Corliss & Johnsen, 1968; Sheridan & Verplank, 1978; Sheridan, 2016). For example, military organizations employ iRobot PackBot 510, a teleoperated robot with a mobile tracked base and a manipulator (Ebery & Stratton, 2005; Stowers, Leyva, Hancock, & Hancock, 2016; Figure 1). This robot is operated using two gamepad control devices.

Figure 1. Image of iRobot 510 PackBot used to dissemble IEDs (Army Technology, 2018).

Robotic arms have also been widely used by the National Aeronautics and Space Administration (NASA) and other space organizations to manipulate objects. For example, smaller robotic arms, such as those mounted on Robonaut2, a humanoid robot developed by NASA, are used to complete tasks in an unstructured environment, functioning autonomously at times (Figure 2; Badger, Diftler, Hart, & Joyce, 2011). These tasks vary in complexity, from simple button pressing to cleaning tasks. Previous researchers tested Robonaut2 on a task board inside of a space shuttle and on the ground (Badger et al., 2011; Diftler et al., 2014; Tzvetkova, 2014). Activities included pushing buttons, moving switches, and turning knobs (Ahlstrom et al., 2013). These efforts focused primarily on the functionality of the robot and software but did highlight the potential for switching between autonomous and manual control modes.

Figure 2. Image of Robonaut2 operating levers and switches on the International Space Station (National Aeronautics and Space Administration, 2013).

In surgery, human-operated robots are often used to complete medical procedures (Oleynikov, 2008). Currently, the most prominent medical system is the da Vinci surgical system, a robot consisting of three or four robotic arms controlled by two joystick-like control devices (Johnson, Schmidt, & Duvvuri, 2014). Researchers have begun to investigate alternative methods of control (Figure 3). Kim, Leonard, Shademan, Krieger, and Kim (2014) compared the Xbox Kinect, a motion-capture control device that translates large body movements, to two joystick-based devices. They found that operator performance with the Xbox Kinect was adequate but slower than performance with the other two devices. Kim et al. noted that the Xbox Kinect was a first-generation device and thus such devices are still promising for future use. Travaglini et al. (2016) evaluated performance in pituitary tumor resection surgery using the Leap Motion controller, a motion-capture device focused on hand movements, and a haptic joystick. This was a case study, but the operator performed similarly using both devices. The authors concluded that the Leap is a promising tool for future use, especially considering that the surgeon did not have any prior experience with the Leap Motion controller.

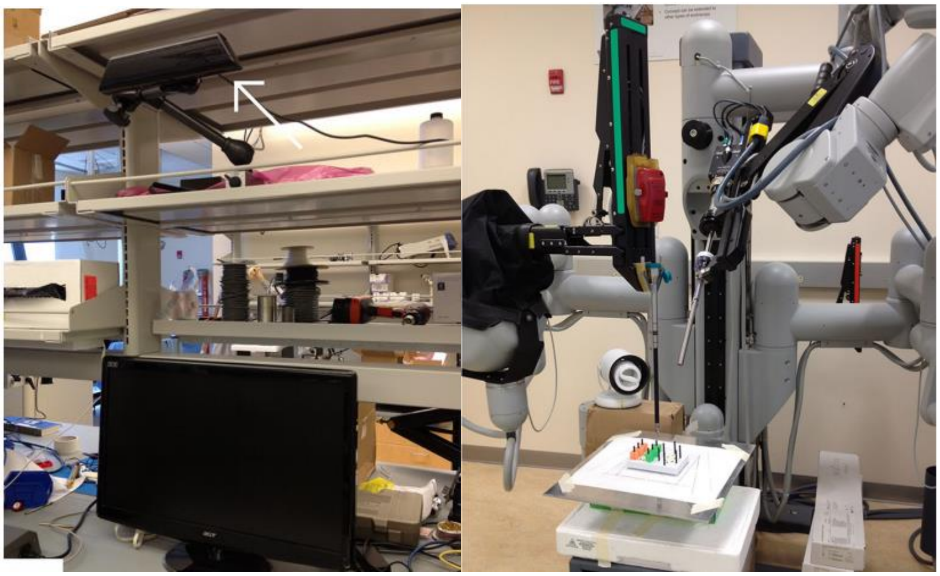

Figure 3. Picture of Xbox Kinect placement (denoted by white arrow in image on left) and the da Vinci Standard Robotic System. Adapted from Kim et al. (2014).

All of the robotic arms mentioned above have been preprogrammed to function autonomously or semi-autonomously; this is increasingly common in the field of robotics (Chen, Haas, & Barnes, 2007). In a review of medical-related robots, Beasley (2012) highlighted several current and emerging semi-autonomous robots, including TraumaPod, a semi-autonomous teleoperated surgical system. These systems necessitate that humans and automation work together to complete tasks. Thus, the relationship between the human teleoperator and automated robotic arm is relevant to consider.

Automation

Automation, defined as a machine agent used to accomplish a task that was previously accomplished by a human, is now pervasive throughout society (Parasuraman & Riley, 1997). Factors such as task complexity, trust, and risk impact automation use (Lee & See, 2004;

Parasuraman & Riley, 1997; Parasuraman, Sheridan, & Wickens, 2000). In some domains, robotic arms are preprogrammed to function independently of human interaction. In manufacturing, automated robotic arms complete repetitive tasks, usually with a human supervisor. Their use prevents human fatigue or repetitive-motion injuries, such as Carpel Tunnel Syndrome. It also helps to prevent injuries by reducing contact with harmful tools, such as welding torches.

Automated robotic arms are not without limitations. Because automated robotic arms are programmed to complete only select tasks, if any part of the predetermined process is imperfect, the system does not function correctly. For example, if an automotive part is not in the correct position, the robotic arm may stop moving until a human intervenes to correct the situation. In dire circumstances if an automated robotic arm malfunctions, it may injure or kill a human. For example, a welding factory worker entered the work envelope to adjust a part without turning the robot off. The worker was struck, electrocuted, and killed (Robotic Trends, 2015). Although there are usually safety procedures in place, such as lockout-tagout and defined work envelopes, many systems lack sensors to automatically stop if the procedures are not followed (Goetsch, 2015, p. 313).

Beyond the safety concerns, automated robotic arms are not appropriate for all tasks. For difficult tasks, complex decision making, or changing environments, human intervention or control are often necessary (Chen, Haas, & Barnes, 2007). In such situations, manual control is particularly useful. For example, manual control must be used to make novel robotic movements that can be mimicked in the future (Pardowitz, Knoop, Dillmann, & Zollner, 2007). When a robot’s sensors malfunction, humans must also intervene (Bringes, Lin, Sun, & Alqasemi, 2013). This is more common in complex and unpredictable task environments. However, performance of an automated system varies when human interaction is involved (Parasuraman, Sheridan, & Wickens, 2000). Previous research has shown that system performance cannot be predicted by automation performance alone; human performance must also be considered (Parasuraman & Riley, 1997). Performance also varies based on the extent to which system functions are automated.

Level of automation. In 1978, Sheridan and Verplank (1978; Table 1) proposed a ten-level scale to classify different levels of automation from no computer assistance (Level 1) to complete computer control (Level 10). This classification structure focuses on the automation's role in task completion. For robotic arms, automation level varies. For the purposes of this study, lower levels of automation were most relevant because the robotic arm used is controlled directly by a human with no computer aid, such as some types of laparoscopic surgery.

Table 1

Levels of Automation

LOW	
	1. The computer offers no assistance: Human must take all decisions and actions
	2. The computer offers a complete set of decision/action alternatives, or
	3. Narrows the selection down to a few, or
	4. Suggests one alternative;
	5. Executes that suggestion if the human approves, or
	6. Allows the human a restricted time to veto before automatic execution, or
	7. Executes automatically, then necessarily informs the human, and
	8. Informs the human only if asked, or
	9. Informs the human only if it, the computer decides to
	10. The computer decides everything and acts autonomously, ignoring the human
HIGH	

Note. Adapted from Sheridan, T. B. (1994). Human supervisory control. In G. Salvendy & W. Karwowski (Eds.), *Design of work and development of personnel in advanced manufacturing* (pp. 79-102). Hoboken, NJ: John Wiley and Sons, Inc.

As automation advances, human interaction with robotic arms is changing. Human operators assume different roles. Some operators have assumed more supervisory roles, such as swarm robotics control, where an operator supervises a large number of simple robots (Şahin, 2004). This option suffers from decreased operator situation awareness and poorer overall task performance (Billings & Woods, 1994; Endsley & Kaber, 1999; Parasuraman, Mouloua, & Hilburn, 1999). Others have begun collaborating with automation in different ways, such as treating the automation as a teammate instead of as a tool (Ososky et al., 2012; Phillips, Ososky, Grove, & Jentsch, 2011). This topic has become of increasing relevance as capabilities advance, allowing humans to offload tasks to robots.

Task Shedding

Task shedding is defined as a human offloading tasks to automation. Sometimes called adaptive task allocation to the machine (ATA-M; Parasuraman & Hancock, 2001), task shedding is a non-traditional alternative to static automation (Parasuraman, Mouloua, & Hilburn, 1999). In static automation, frequency of computer assistance is predetermined when designing the system. In ATA-M, aid of the operator and task allocation are dependent upon the context. Use of task shedding has been theorized to mitigate negative workload effects and improve performance beyond that of static automation (Hancock, Chignell, & Lowenthal, 1985; Parasuraman, Bahri, Deaton, Morrison, & Barnes, 1992). Additionally, task shedding has been studied to use automation capabilities to increase operator situation awareness (Byrne & Parasuraman, 1996; Bliss, Harden, & Dischinger, 2013). However, there are also drawbacks to task shedding. The decision to activate automation increases cognitive workload, but often the automation needs to be activated when the operator's workload is already high (Harris, Hancock, & Arthur, 1993). Additionally, fatigue decreases the operator's ability to activate automation in a high workload task. Harris, Hancock, Arthur, and Caird (1995) examined performance, fatigue, and workload using the multi-attribute battery task (MATB; Comstock & Arnegard, 1992) where one task was automated for some participants. The authors found that operators reported lower workload when automating the tracking task, but performance on non-automated tasks did not improve.

The issue of task shedding has become more important as more humans have begun to interact with robots that have autonomous options. To date, this has been evaluated in primarily supervisory and multi-robot scenarios. Lerman, Jones, Galstyan, and Matarić (2006) evaluated this human-robot teaming relationship in a multi-robot system. They asserted that allowing changes to robot responsibilities, such as task shedding, improves overall system performance in a fully autonomous multi-robotic system. Parasuraman, Barnes, and Cosenzo (2007) developed recommendations for supervisory control of uninhabited air and ground vehicles. They suggested that operators might be best supported by adaptive automation support systems, replacing static automation that leads to over-reliance, skill degradation, and decreased situation awareness. Kruijff-Korbayová et al. (2015) applied a user-centric approach to task shedding in robotic disaster responses, particularly search and rescue. For these rescue efforts, each robot is controlled by a first responder taking commands from a human team leader. The robots work alongside human workers in both a digital simulation (2015) and a physical search scenario (2017). In 2017, Kruijff-Korbayová et al. executed a real-life search and rescue mission to examine how human-robot teaming worked in a scenario. The use of robots was well-received, and the authors deemed such structure useful and appropriate for actual emergencies due to the similar results to a human-only scenario.

Few studies have explored human-robot task shedding in a one-on-one setting. Riley et al. (2008) examined performance and situation awareness in collaborative robot control between human teammates. In the experiment, two human operators had control of either two robots, where each human controlled their own, or three robots, where each human controlled their own and shared control of the third robot. The third robot performed an initial navigation task autonomously but then waited for the operator to indicate a new task to complete. Although the focus of the study was situation awareness and performance, the researchers found that in the shared condition, when human operators could offload tasks to the third robot, perceived workload and frustration was lower than the manual, two-robot condition (Riley et al., 2008). Importantly, the ability to task shed to a third robot improved performance on the navigation task.

Additionally, shedding tasks to robots could be beneficial over simple supervisory control. The current human-robot interaction paradigm generally involved supervisory control of a robot with human intervention as needed. Beasley (2012) cites this as a reason that medical robots, such as autonomous surgical robotic arms, are not in use or preferred by surgeons. For tasks where lower levels of automation are important due to task intricacy (e.g., IED disarmament, surgery) and automation is becoming available, task shedding behavior and the impact on performance must be considered. Additionally, other factors that may impact performance in a human-controlled robotic arm must be considered.

Control Devices

Control order. To manipulate a robot, operators use a control device. A control device is defined as a piece of equipment that converts human input to system movement. The relationship between human input and a system's actual movement is called the control order (Poulton, 1974; Sanders & McCormick, 1987). For example, a zero-order control or position control has a direct relationship between input and output. An example of zero-order control is a touchpad, where the operator's touch corresponds directly to curser movement. In contrast, the gas pedal in a car is a first-order control or rate control. The gas pedal's displacement is proportionally related with the output position of the car. The output is proportional to rate of change of the input, or the derivative. When positioning an automobile on the road, operators use a steering wheel. The steering wheel's angular position determines the x-axis position of the car. Thus, a steering wheel is second-order or acceleration control. For the operator to understand how manipulating the control device affects the final position, he or she must mentally translate using the relationship between movement and position. A visual representation of the relationships is included in Figure 4.

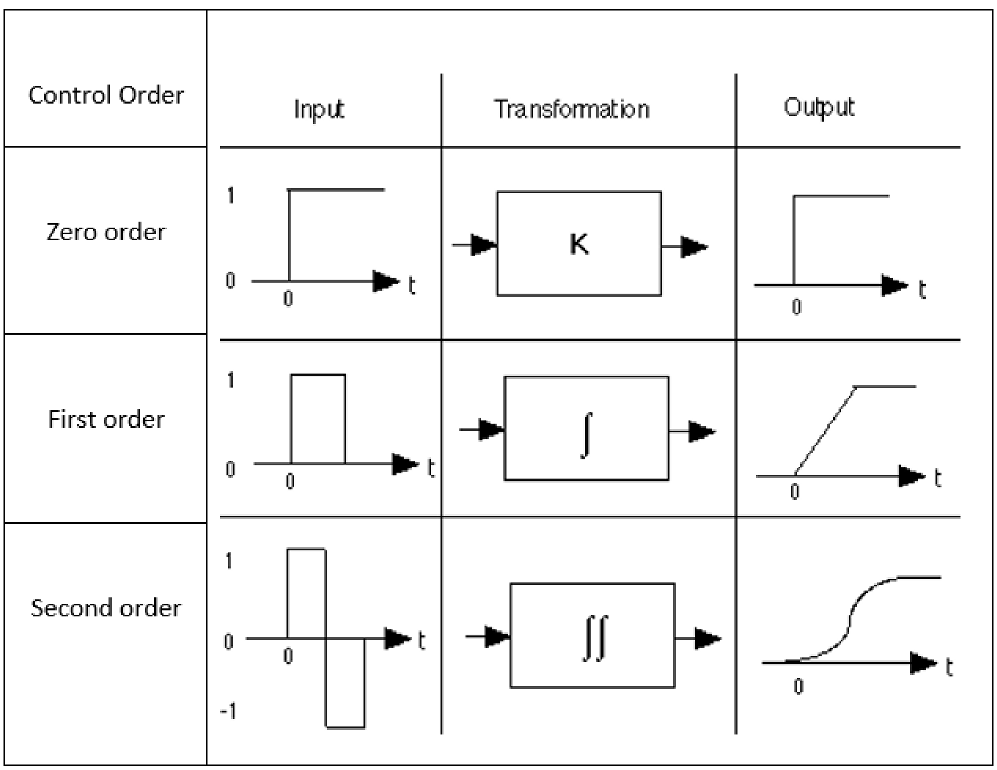

Figure 4. Relationship of control order to output movement.

Note. Adapted from Poulton, E.C. (1974). *Tracking skill and manual control*. Cambridge, MA: Academic Press.

The relationship between input and performance is difficult to control experimentally because other factors affect system control. System variables, such as lag time and equipment type, and non-system variables, such physical operator characteristics and environmental conditions, may impact performance as well (Poulton, 1974; Speight & Bickerdike, 1968). In an experimental setting, many of these variables can be controlled. Early researchers isolated the effects of independent variables on control performance by using a paper-paced contour system to compare control orders. A paper-paced contour system is a system where a paper with a continuous line moves across a frame visible by the participant (Figure 5). The participant uses a control device to align a pencil with the line and trace match the original line. These researchers found conflicting results. Some found performance with a zero-order control was superior in a tracking task (Lincoln, 1953; Regan, 1960). Others found that performance with a first-order control device was superior (Jagacinski, Hartzell, Ward, & Bishop, 1978). This disparity may be caused by a user's previous experience using joysticks.

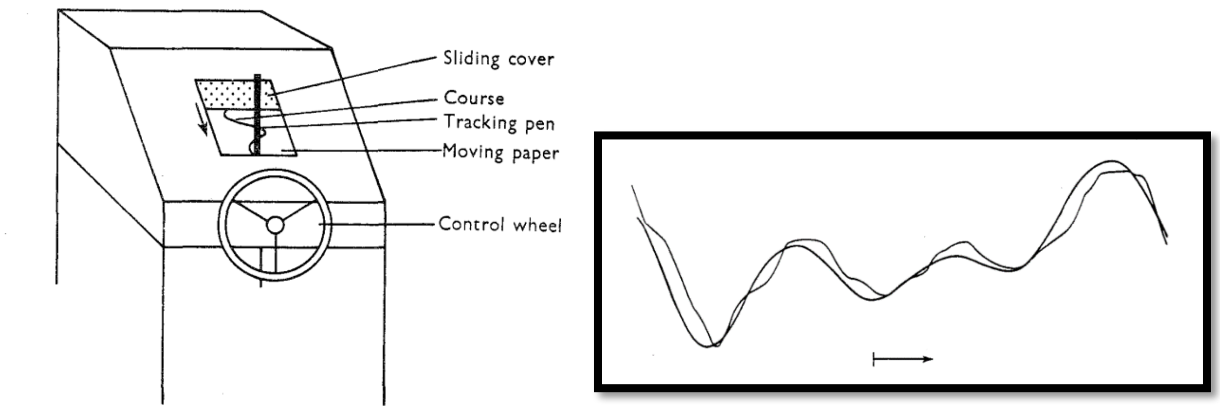

Figure 5. Layout of paper-paced contour system (left) and example of guideline and participant tracings.

Note. Adapted from Crossman, E. R. F. W. (1974). Automation and skill. In E. Edwards & F. P. Lees (Eds.), The human operator in process control (pp. 1–24). London: Taylor & Francis.

Beyond paper-paced contour systems, authors have compared performance with zero- and first-order control devices using a text selection task and a target acquisition task. Card, English, and Burr (1978) evaluated performance on a text selection task using four input devices: a mouse, a first-order joystick, step keys, and text keys. Performance using the mouse, a zero-order control device, was fastest and had fewest errors. After further testing, positioning time with the mouse was found to be almost the minimal performance time achievable, even with additional training (Card, English, & Burr, 1978). MacKenzie and Soukoreff (2003) replicated this study using updated standards for pointing devices and found similar results. Similarly, Jagacinski, Hartzell, Ward, and Bishop (1978) investigated performance on a target acquisition task using a first-order and zero-order joystick. Performance, measured in target acquisition time, was significantly better for the position, or zero-order, control than the other controller at several different levels of complexity.

Limitations of control order theory. Much of the previous control order theory research has focused on tasks with predetermined deviations, or tasks where the participants are required to adjust to the stimulus. In the paper-paced contour tasks, the participant adjusted the desired line as it moved across the page (Poulton, 1974; Speight & Bickerdike, 1968; Lincoln, 1953; Regan, 1960). In target acquisition tasks, participants manipulated the joystick to match the moving target (Jagacinski, Hartzell, Ward, & Bishop, 1978). Researchers' efforts to evaluate mouse usage exploit tasks similar to those used when testing robotic arm users (Card, English, & Burr, 1978; MacKenzie & Soukoreff, 2003). The task requires participants to identify how to complete a task and complete it to the best of their abilities using the control device. However, such tasks require movement in only two dimensions, typically on a computer screen, and neither involve robotics.

The current task diverges from past control theory research in two ways. As no previous research has evaluated control order differences within a three-dimensional space, the current task is arguably more complex. Motion-capture control devices, conceptualized as zero-order controls, lack the tactile feedback associated with moving a physical device, such as the physical feedback of a joystick on your finger. To accommodate for this, a hand overlay will be used in the experiment to give visual feedback. Additionally, a single joystick does not have the appropriate degrees of freedom to control a robotic arm, even though this is the control device traditionally used in Control Order Theory experiments. To accommodate this, two joysticks, the directional pad, and one trigger button will be used to control parts of the arm.

Joysticks. Many robotic arms used required a joystick for command input. This includes all of the paper-paced contour studies (e.g., Speight & Bickerdike, 1968) and some more recent studies with robotics (e.g. Riley et al., 2008). Joysticks can be programmed with any control order, but typically they are first-order control devices, where the input is translated proportionally to output robot motion. Joysticks are ubiquitous in video game control devices. In fact, video game control devices, such as devices for the Xbox and Playstation 3, are recommended for use in complex tasks, such as teleoperating an unmanned ground vehicle, due to performance and user preference in comparison to other joystick devices (Oppold, Rupp, Mouloua, Hancock, & Martin, 2012).

Motion-capture control devices. Researchers have investigated the use of motion capture devices, such as data gloves, cameras, or sensors, to control robots. Initially, invasive devices such as gloves or wrist bands were used to capture motion and translate to robotic motion (Fischer, van der Smagt, & Hirzinger, 1998; Sturman & Zeltzer, 1994). With the development of affordable, non-invasive, motion-capture devices, such as the Leap Motion controller and Xbox Kinect, researchers have begun to examine the possibility of using these systems to capture hand position and directly equate that to robotic movement. Harden, Bliss, and Dischinger (2013) developed a motion-capture control mechanism for a robotic arm using the Xbox Kinect. They theorized that the system would provide a zero-order, intuitive interaction for humans that would minimize training time. Moldovan and Staretu (2014) evaluated the potential for using the Xbox Kinect as a method of robotic arm control. They found that the Kinect provides sufficient information in respect to depth and position but lacks necessary specificity for human finger movements.

Weichert, Bachmann, Rudak, and Fisseler (2013) examined a preliminary version of the Leap Motion 3D controller. The Leap Motion 3D controller is a commercially available motion-capture control device (Figure 6). It recognizes hand gestures and motion using two monochromatic IR cameras and three infrared lights. Weichert et al. (2013) examined its accuracy using an industrial robot and a reference pen to mark a point. They found that task accuracy with the Microsoft Kinect to be less than the Leap Motion controller (Weichert, Bachmann, Rudak, & Fisseler, 2013). In 2016, Moldovan and Staretu evaluated the Leap Motion controller in comparison to data gloves to operate a robotic hand virtually and physically. They found the Leap Motion controller to be an appropriate, non-intrusive way to capture human hand poses when using a virtual hand and prototype RoboHand (Moldovan & Staretu, 2016; Staretu & Moldovan, 2016). Long and Bliss (2016) examined performance differences between a Leap Motion controller and a Xbox 360 controller using a Karlsson Robotics Lynxmotion ALD5D four degrees of freedom arm to complete task on a pre-made task board of linear light switches, knobs, and a dimmer. They found that participants performed comparably on light switch and dimmer tasks when using the Leap and Xbox controllers, but participants performed significantly better on the knob task when using the Xbox controller.

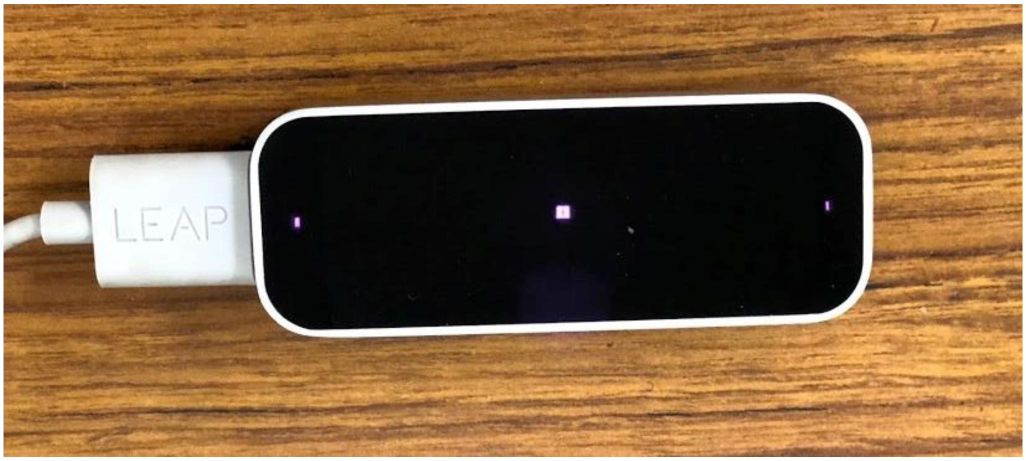

Figure 6. Leap Motion 3D controller used in the experiment.

In the human-computer interaction and computer science domains, gesture recognition devices have been categorized as natural user interfaces (NUIs). NUIs are defined as interfaces that enable users to interact with systems naturally, or the way that they interact with real-world objects (Jain, Lund, & Wixon, 2011; Steinberg, 2012). Motion-capture systems, such as the Leap Motion controller and the Xbox Kinect, are theorized to be control mechanisms similar to touch screens and mouse interactions (Wignor & Wixon, 2011). Wignor and Wixon (2011) suggested building an experience for users that feels like an extension of the body and that is easily mastered by novices. Researchers have found that NUIs facilitate increased learnability and speed (Wachs, Kölsh, Stern, & Edan, 2011). In contrast, Norman (2010) suggests that NUIs are not natural or easy to learn and recall. For example, motion-capture NUIs may not be appropriate because of the lack of tactile feedback. Unlike command line interfaces or graphical user interfaces (GUIs), NUIs lack the necessary feedback to help users troubleshoot when a mistake occurs. Because of this, errors may be more difficult to remedy. The systems require precision and are best suited for simple applications because complex system operation requires the ability to specify scope, range, temporal order, and conditional dependencies. According to Norman, operators are unable to communicate this using body gestures alone. Although earlier NUI platforms proved problematic, Wignor and Wixon (2011) assert that the success of NUIs should not be measured by these early failures because of similar early failures with GUIs, which are now widely used.

Many researchers have introduced engineering-oriented perspectives on the plausibility of motion-capture control of a robotic arm or theorized design recommendations for future devices, but few experiments yielding performance data exist (but see Long & Bliss, 2016). Additionally, none have explored the use of motion-capture controls in a complex, real-world domain to determine if motion-capture systems are best for simpler applications only. The feasibility of using motion-capture control devices at varying levels of task complexity must be explored.

Task Complexity

Although Norman (2010) theorized that motion-capture control device may be appropriate only for simple tasks, the impact of task complexity on performance when using motion-capture control devices has not been evaluated. Task complexity can be defined as the objective structure of the task (Liu & Li, 2012; Wood, 1986). Although some researchers have used the terms "task difficulty" and "task complexity" interchangeably (e.g., Rouse & Rouse, 1979), task complexity is used to define the difference in tasks based on task characteristics. Liu and Li (2012) developed a model of task complexity composed of ten dimensions: number of task components, variety of task components, ambiguity, interdependency, inaccurate or misleading information, instability of task components, novelty, incongruity of task components, physical or cognitive action complexity, and temporal demand. The experimental task proposed here focuses on manipulating physical action complexity as this task is a physical task. This is selected as it closely aligns with task complexity variance in real-world situations, such as IED disarmament.

Purpose

The purpose of the proposed research was to investigate the effect of control device type and task complexity on performance in a robotic arm task. Researchers have evaluated and demonstrated the use of a motion-capture device to control a robot arm (c.f. Harden, Bliss, & Dischinger, 2013; Staretu & Moldovan, 2016), but few have evaluated such motion control strategies experimentally. None have evaluated the impact of task complexity, a crucial factor to consider in practice as applied tasks vary in complexity. The experiment reported here evaluated the changes in task completion time, accuracy (measured in number of errors), and task shedding behavior as a function of robot control device and task complexity.

Hypotheses

H1: Participants will complete tasks more quickly using the Leap Motion controller.

H2: Participants will make fewer errors when using the Leap Motion controller.

H3: Participants will task shed less when using the Leap Motion controller.

Previous researchers have found that performance is better when using a zero-order control device over higher order devices (Card, English, & Burr, 1978; Jagacinski, Hartzell, Ward, & Bishop, 1978; Lincoln, 1953; Regan, 1960).

H4: Participants will complete tasks more quickly when in the low task complexity condition.

H5: Participants will make fewer errors when in the low task complexity condition.

H6: Participants will task shed less when in the low task complexity condition.

Task complexity has been shown to impact performance in other domains (Liu & Li, 2012; Wood, 1986). Specifically, performance suffers during more complex tasks.

H7: Participants will complete tasks more quickly using the Leap Motion controller when task complexity is low than when task complexity is high.

H8: Participants will make fewer errors using the Leap Motion controller when task complexity is low than when task complexity is high.

H9: Participants will task shed less when task complexity is low using the Leap Motion controller when task complexity is low than when task complexity is high.

Norman (2010) hypothesized that motion-capture control devices may be less suitable for complex task performance because of the inability to specify scope, range, temporal order, and conditional dependencies. Motion-capture control devices should better enable simple tasks. Thus, the high task complexity condition should impact the zero-order, motion-capture control condition more than the first-order, joystick condition, a statistically significant interaction.

CHAPTER 2

METHOD

Design

This study employed a 2 (control device: Xbox controller, Leap Motion controller, manipulated within groups) x 2 (task complexity: low, high, manipulated between groups) mixed design to test the hypotheses. In all conditions, participants were tasked with using a robotic arm to place a peg in four corners of a peg board (see Figure 7). For the high task complexity condition, the peg was placed on the outer corners of the board. For the low task complexity condition, the peg was placed in the inner corners, as described below. The task was to pick up the peg and place it in the correct peg hole. Each time the peg was placed correctly or fell, the peg was replaced to a magnet adjacent to the peg board. Participants teleoperated the robotic arm and relied on two cameras for visual task information. During the task, a cloth separated participants from the robotic arm. While completing the pegboard task, participants scanned satellite images of Baghdad, Iraq for tank targets to simulate the division of attention that often occurs on a battlefield. Before beginning the experiment, participants were told they were responsible for determining if there was a threat in the area. Mistakes could cause loss of human life. Similarly, the robotic arm task was presented to participants as equally important; participants were instructed to perform quickly and accurately. During the experiment, participants were given the option to shed the robotic arm task to automation, and they were told the automation would be reliable but imperfect. If the participant shed the task, feedback about that decision was provided in the form of a video of a successful peg transfer or an unsuccessful transfer. Three of four corners were be successful to simulate imperfect but fairly reliable automation. The video of one corner, the back right, was unsuccessful. The experimental task represented robotic arm control during which the operator would be required to manually complete a complex task while having the option to utilize automation. Such a situation could include improvised explosive device (IED) disarming.

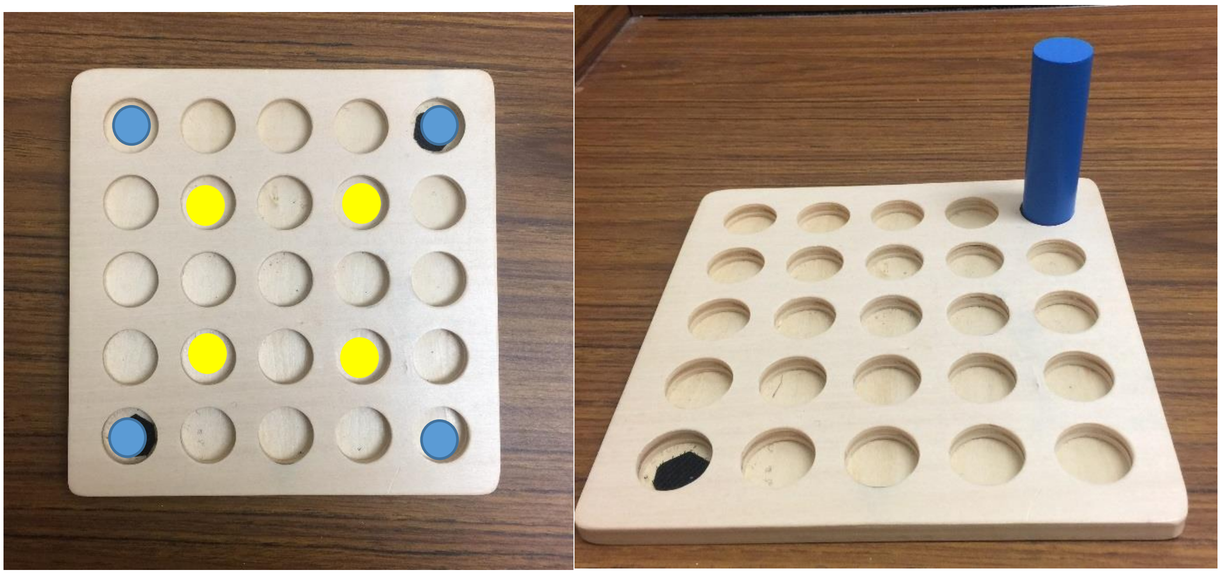

Figure 7. Peg board used in the experiment. The dimensions of the board were 19.4 cm x 19.4 cm. The high complexity task pegs (in blue) were 17.0 cm apart laterally and vertically. Low complexity task pegs (in yellow) were 10.0 cm apart laterally and vertically.

Independent variables. The first independent variable was the control device, Xbox controller or Leap Motion 3D controller, manipulated within groups. The control device used first was randomized using a random number generator for each participant to prevent carryover effects. The second independent variable was level of task complexity, manipulated between groups. Participants in the low task complexity condition completed the task with pegs closer together. The manipulation of complexity was supported by pilot testing.

Dependent variables. Dependent measures were task completion speed (in seconds), accuracy, and number of tasks (peg placements) shed to the automation. Accuracy was measured by number of errors. Task shedding was be measured by the number of tasks shed when completing the task, as well as by the amount of time in seconds the participant required to decide to task shed. Further explanation of how each variable was measured is included below.

Participants

To determine the number of participants needed, an *a priori* power analysis was conducted for a mixed experimental design using G*Power 3.1.9.2 software. The analysis indicated that 40 participants total were required to achieve a power of .80 and an effect size of $f = 0.40$ (Maxwell & Delaney, 2004). A significance threshold of $p = .05$ was established to balance and minimize the likelihood of making a Type I and Type II error.

Participants were undergraduate students from Old Dominion University, recruited using the Sona Experiment Management System. Participants received 1.5 research credits for participating in the study. The study took approximately one hour. The study was approved by Old Dominion University's Institutional Review Board, and written, informed consent was obtained from each participant prior to participation for their overall participation and for usage of photos and videos (Appendix A).

Materials

Robotic arm and software. The robotic arm used for this study was the Karlsson Robotics Lynxmotion ALD5D arm, controllable along four degrees of freedom (Figure 8). A Dell laptop with 256 GB hard drive and 16 GB RAM hosted a software program developed by Virtual Reality Rehab, LLC, specifically designed to control the robotic arm and present the user with an effective interface. The software was developed in Unity3D (Figure 9). The software provided visual feedback from two cameras, one mounted to the left of the robot and one mounted on the head. Participants were separated from the robot by a cloth partition (Figure 10) and relied upon the cameras, simulating teleoperation. For the motion-capture control device condition, the participant received visual feedback indicating hand position (Figure 11).

Figure 8. The Karlsson Robotics Lynxmotion ALD5D 4 degrees of freedom robotic arm used in the experiment.

Figure 9. Screenshot of the software used for the experiment, developed in Unity3D.

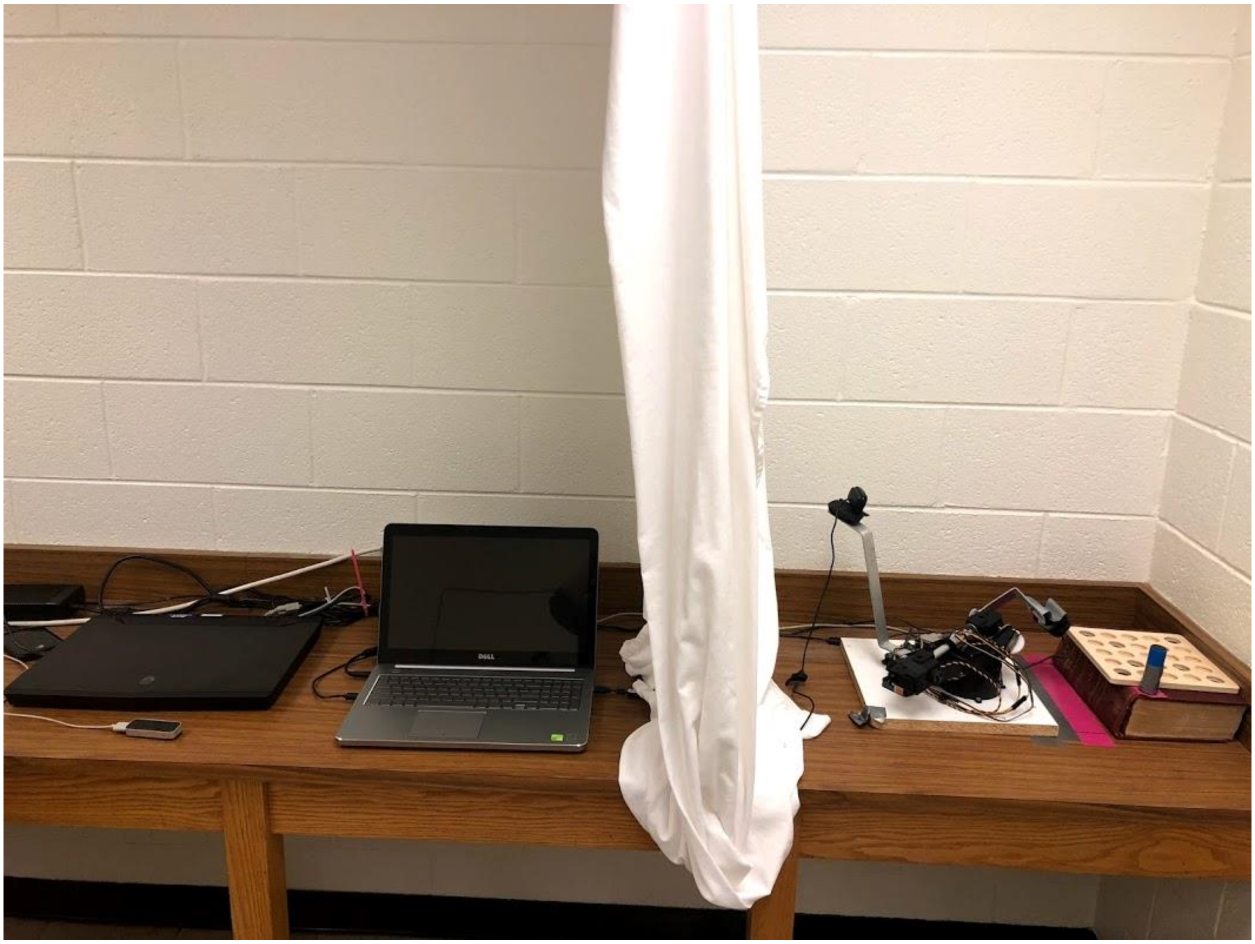

Figure 10. Experimental set up.

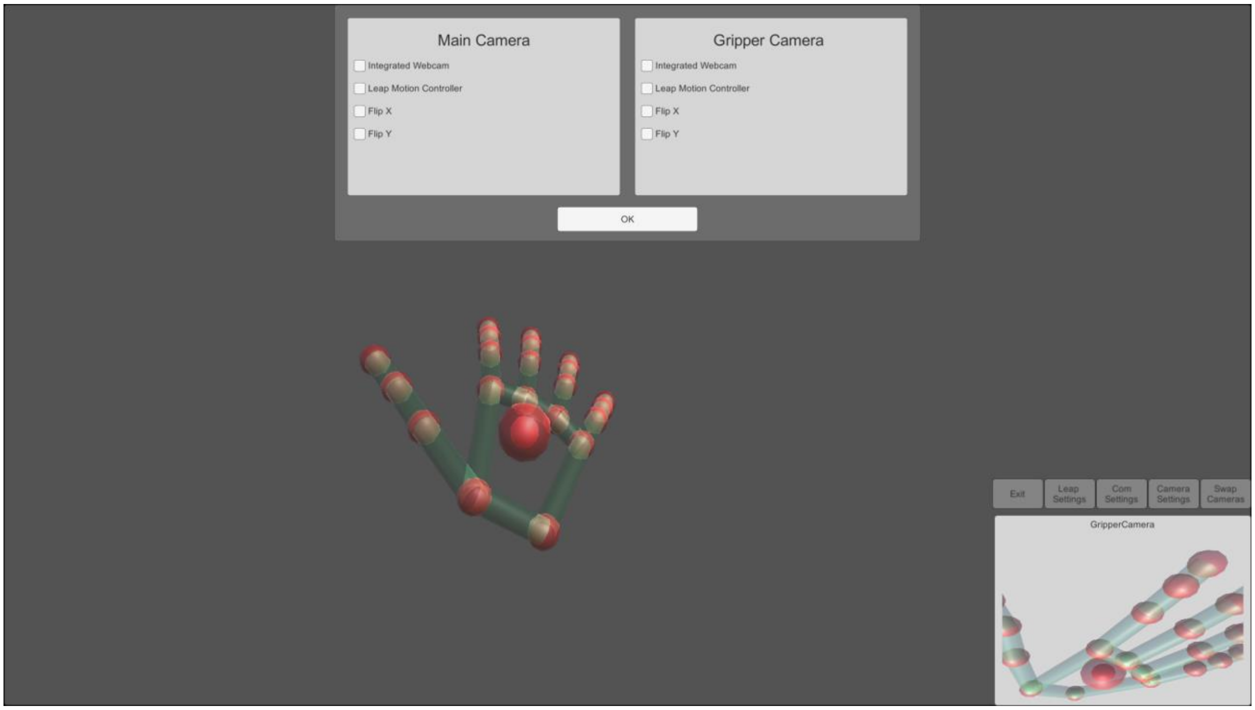

Figure 11. Example of motion-capture control feedback in the Unity3D interface.

Control device. The Xbox controller used was a controller with two analog joysticks, two analog triggers, a directional control gamepad, and nine buttons (Figure 12). For this experiment, both analog joysticks, the right analog trigger, and the directional control gamepad were used (others were disabled). The Leap Motion 3D controller is a motion-capture, gesture-driven control device (Figure 6). It recognizes hand gestures and motion using two monochromatic cameras and three infrared lights. The device is 11.25 mm x 80 mm x 30 mm (Leap Motion, 2015). According to the manufacturer, the sensor captures eight cubic feet of space, can track fingers with specificity of 0.01 mm, and can track movements at over 200 frames per second (Leap Motion, 2015; Weichert et al., 2013). Researchers have evaluated the Leap Motion controller widely, as it is used as a control device in commercial virtual reality applications (Guna, Jakus, Pogacnick, Tomazic, & Sodnick, 2014; Jakus, Guna, Tomazic, &

Sodnik, 2014; Weichert et al., 2013). Generally, these studies found that hand accuracy diminishes at distances greater than 250 mm from the device. This study did not exceed this distance. Also, individual differences in hand size, hand shape, degree of hand and finger orientation, and amount of hand occluded, affect tracking abilities (Guna, Jakus, Pogacnick, Tomazic, & Sodnick, 2014; Jakus, Guna, Tomazic, & Sodnik, 2014; Weichert et al., 2013). The Xbox and Leap each connected to a laptop using a USB cord and were compatible with the robotic arm software developed by Virtual Reality Rehab, LLC.

Figure 12. Xbox One controller used in the experiment.

Peg board. For the task, a peg board was used (Figure 7). This task was selected because of the capabilities of the robotic arm, specifically its gripper strength and reach. Additionally, it exemplified the common pick-and-place motion demonstrated by robotic arms in practice. Ultimately, this task aimed to simulate IED disarming. Although IED disarmament involves render safe procedures that are protected from civilians to prevent misuse of the information to create more dangerous IEDs, disarmament procedures include pick-and-place motion based on the components included in Figure 13 (Joint Staff, 2012). The peg board was 19.4 cm x 19.4 cm. In the high complexity task, the pegs were 17.0 cm apart. In the low complexity task, the pegs were 10.0 cm apart. Between the two tasks, there was a 65.4% reduction in area. The base of the arm was affixed 10 cm from the peg board to allow participants to reach each corner. The arm gripper's starting position was 5 cm to the right of the board.

During pilot testing, it became clear that participants struggled to place the peg into the target holes without dropping it. Therefore, a magnet was added to the bottom of the peg, as well as to eight target peg holes, to facilitate the placement task. The peg board was also elevated seven cm to ensure that participants could easily reach the corners of the board with the arm gripper.

Figure 13. Components of a typical IED. (Joint Staff, 2012)

Visual search task. Participants were shown aerial images previously used by Chancey, Bliss, Yamani, and Handley (2017) and told to search for an enemy tank. If there was no threat, the participant responded, “All clear” or “No tank.” If there was a threat, they responded, “Threat detected,” or “Tank.” This information was captured by the video camera recording. The purpose of this simultaneous task was to simulate the multi-tasking environment operators often encounter for a more accurate reflection of task shedding. Additionally, it simulated searching the environment for threats, a task that a teleoperator may complete simultaneously with controlling a robot for IED disarming (Joint Staff, 2012). Example images are included in Appendix F.

Measures

Demographics Questionnaire. Each participant completed a questionnaire indicating his or her age, sex, visual acuity, handedness, hand or arm injury, and computer confidence (APPENDIX B).

Video Game Experience Questionnaire. Participants completed a genre-specific video game experience questionnaire to assess how often they play video games per week (Orvis, Horn, & Belanich, 2008; APPENDIX C). The questionnaire included ten video game genres.

Control Device Experience Questionnaire. The video game experience questionnaire included questions about eighteen control devices (e.g., joystick, touchscreen, Xbox, Wii remote; APPENDIX D). Participants indicated how many hours per week on average they spent playing games using each control device.

Robot Experience Questionnaire. Participants rated their familiarity with thirteen types of robots e.g., manufacturing robot, research robot, robot security guard) on a five-point scale (1 = Not sure what this is; 5 = Have used or operated this robot frequently). The full questionnaire is included in**Error! Reference source not found.** (Smarr et al., 2014).

Robotic arm task performance. Proficiency of robotic arm manipulation was reflected by participants' speed and accuracy in completing the task. To measure these variables, the task was video recorded and independently evaluated by two raters.

Speed. Speed was measured by the number of seconds it required for the pick-and-place task to be completed. Completion time was measured by two raters watching the video and independently timing the task using the time stamp on the video. The coders noted time in seconds for each peg to be placed on the peg board. These values were summed for a total completion time estimate. Level of inter-rater reliability (IRR) was established using a two-way mixed intra-class correlation (Cicchetti, 1994; Hallgren, 2012). This analysis was selected because the data was coded by the same two coders for all subjects, but the coders were not randomly sampled from the population. For analyses, the time measured by each rater was averaged. A high intra-class correlation (ICC = .991) on time, a continuous variable, was achieved, indicating acceptable interrater reliability (Hallgren, 2012).

Accuracy. Task accuracy was reflected by the number of errors in the task. Errors included the number of times that the peg was not successfully grasped, was dropped, or was placed incorrectly. The number of errors were calculated for each peg and summed for a final accuracy score. If the participant dropped the peg, it was returned to its initial position by the experimenter. A high intra-class correlation (ICC = .980) on number of errors was achieved, indicating acceptable interrater reliability (Hallgren, 2012). Any discrepancies between raters concerning error interpretation were resolved by meeting and discussing until agreement was reached.

Task shedding. Task shedding was measured by the number of pegs the participant decided to shed the robotic arm control task to the automation. The participant was informed that he or she could shed as many tasks as they wished, and that the automation was reliable but imperfect. In actuality, the automation was 75% reliable. From the participant's perspective, the unsuccessful automated task was placement of the back right peg. If the participant did not task shed the back right peg, they did not see the automation fail. After shedding one or more pegs, the participant could resume the next task if time permitted, provided they did not task shed all four.

Procedure

After reading and signing the Informed Consent Form (Appendix A) stating the risks and benefits of participating in the study, as well as consenting to the recording of videos and pictures during the study, participants were randomly assigned to either a high or low task complexity condition. The participants were also randomly assigned to use one of the control devices first, either the Xbox or the Leap Motion controller.

Participants then completed the Demographics Questionnaire, Video Game Experience Questionnaire, Control Device Experience Questionnaire, and Robot Experience Questionnaire, to provide information about their experience level with games, control devices, and robots. Participants were then shown the robot arm and the camera view for teleoperation.

Next, the experimenter trained the participant to operate the first control device. The participant was given up to two minutes to operate the control device and ask questions. Participants then completed a few practice tasks demonstrating the capabilities of each degree of freedom on the robotic arm. Specifically, they used the arm to flip five switches (two vertical light switches, one dimmer, and two horizontal light switches) on a task board (Figure 13) to become more acclimated with the system. The practice session ended after five minutes or when the participant successfully completed all five switched.

After practice, the experimenter gave instructions for the experimental session. The experimental session consisted of picking up and placing a peg in four locations on a peg board. Participants in the high task complexity condition had pegs that were farther apart. This occurred simultaneously with the visual search task. While performing both tasks together, participants were told they could shed the pick-and-place task to an automated controller, but that the automation was not always successful.

Following use of the first device, the participant completed the pick-and-place task again using the second control device. As before, the experimenter trained the participant to operate the control device by having them complete the practice session described above. After the practice session, the participant completed the second experimental session. He or she then completed a Post-Experiment Opinion Questionnaire (Appendix E), was debriefed about the purpose of the experiment and dismissed.

Figure 14. Image of portion of task board used in the practice task.

CHAPTER 3

RESULTS

Data Coding and Descriptive Statistics

Following data coding, descriptive statistics were calculated and are presented in Table 2. The data were inspected to ensure there were no outliers, conditions had equal numbers, and the variables were normally distributed as determined by skewness and kurtosis values less than an absolute value of 2.0 (Maxwell & Delaney, 2004). Except for the equipment malfunctions discussed below, all scores were included because the range of performances were deemed to reflect typical extremes of human performance. Data for three participants were not included in the analyses: two due to technology malfunctions during the experiment and one due to a participant who had a physical disability affecting his arm motion. One technical malfunction was due to the battery dying before the task began, and it was replaced for future participants. The second malfunction was likely due to a stripped servo at the elbow joint. The participant with a physical disability regarding motion moved his arm with big and jerky motions. The participant did not successfully complete any of the practice tasks or the tank task, so I decided not to include those data. Two participants were missing tank-spotting data due to inability to code from the video. However, they were still included in analyses as the results of the tank-spotting task did not interfere with the hypotheses testing.

Levene's tests were used to address homogeneity of variance for the between-subjects manipulation. An alpha level of $p < .05$ was established to indicate statistical significance. Order effects were evaluated for each dependent variable. No order effect of initial control device was found for task completion time with Leap, $t(38) = 0.053$, $p = .958$, task completion time with Xbox, $t(38) = -0.500$, $p = .620$, errors with Leap, $t(38) = 1.816$, $p = .077$, errors with Xbox, $t(38)$

= 0.105, p = .917, task shedding frequency with Leap, $t(38) = 0.590$, p = .559, or task shedding frequency with Xbox, $t(38) = 0.281$, p = .780. Additionally, there was no control device by condition interaction, $F(1,36) = 0.138$, p = .712, *partial* η^2 = .004, no main effect of control device, $F(1,36) = 0.183$, p = .671, *partial* η^2 = .005, and no main effect of condition on tank correct ratio ($F(1,36) = 0.875$, p = .356, *partial* η^2 = .024). The ratio of correct responses (identifying if tank or no tank) over total number of images was 0.612 (SD = 0.155) for the Leap condition and 0.601 (SD = 0.159) for the Xbox condition.

Table 2

Descriptive Statistics

		Leap	Xbox
Task completion time (s)	Low	600.00 (0.00)	600.00 (0.00)
	High	600.00 (0.00)	600.00 (0.00)
Time to grasp first peg (s)	All	323.48 (210.98)	426.00 (221.70)
Number of errors	Low	20.50 (2.81)	8.25 (1.99)
	High	17.89 (2.65)	5.89 (1.88)
Number of tasks shed	Low	1.05 (1.36)	1.25 (1.65)
	High	1.25 (1.55)	0.90 (1.37)
Time to task shed (s)	Low	356.13 (157.58)	262.63 (144.68)
	High	291.86 (123.42)	302.00 (129.05)
Completion rate (0-1)	Low	.156 (.064)	.031 (.034)
	High	.167 (.060)	.056 (.034)

Note. Descriptive statistics for mixed ANOVA for non-task shedding participants (N = 17; 8 in low complexity, 9 in high complexity) for task completion time, errors, and completion rate. Task shedding and time to grasp first peg reflect all 40 participants. Time to task shed only includes participants who task shed in both conditions (N = 15). Standard deviations are in parentheses. Time included is speed, errors, and completion rate does not include participants who task shed. Time to grasp first peg is collapsed across task complexity because condition did not impact grasping the peg. Descriptive statistics for all participants (N = 40) are included in Appendix H.

Task Completion Time

To evaluate Hypotheses 1, 4, and 7, a 2 x 2 mixed ANOVA was conducted with Task Completion Time as the dependent variable. All non-task shedding participants used the maximum amount of time (600s), so no differences were seen between groups.

Number of Errors

To evaluate Hypotheses 2, 5, and 8, a 2 x 2 mixed ANOVA was conducted with Number of Errors as the dependent variable (see Figure 15). There was not a significant interaction of control device and task complexity, $F(1, 15) = 0.003$, $p = .958$, *partial* $\eta^2 < .001$. There was a significant effect of control device, $F(1, 15) = 27.561$, $p < .001$, *partial* $\eta^2 = .648$. Participants made more errors overall with the Leap (M = 19.12, SD = 7.82) than with the Xbox (M = 7.00, SD = 5.59). There was no significant effect of task complexity, $F(1, 15) = 1.051$, $p = .322$, *partial* $\eta^2 = .065$.

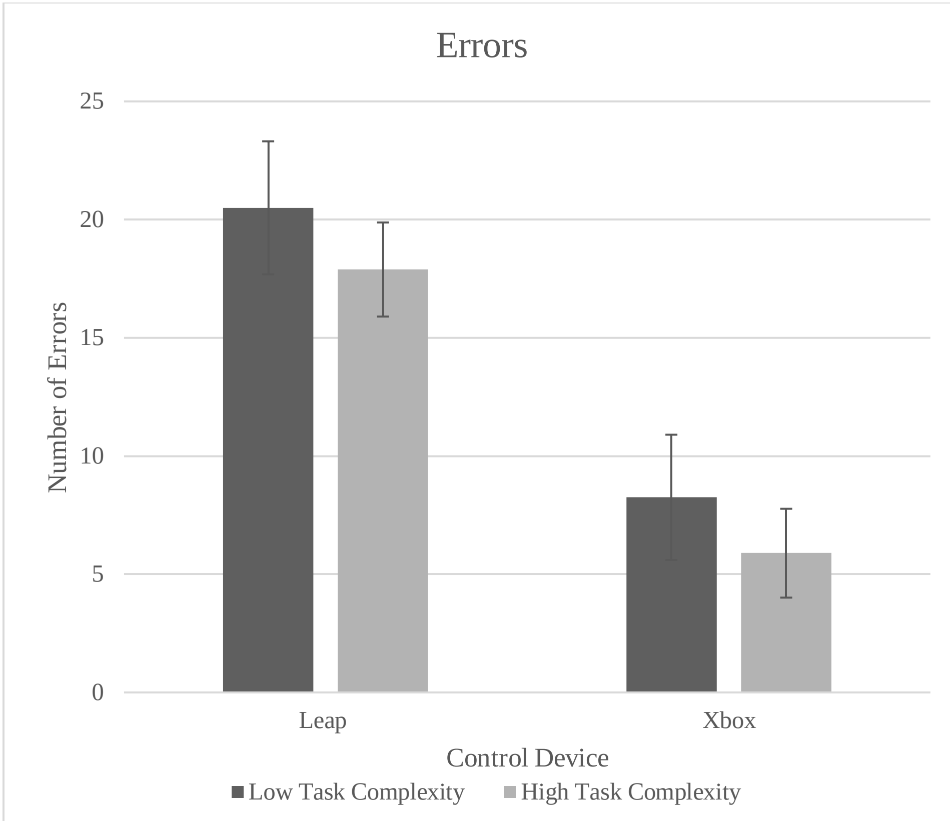

Figure 15. Errors by control device and task complexity. Error bars reflect SD.

Number of Tasks Shed

To evaluate Hypotheses 3, 6, and 9, a 2 x 2 mixed ANOVA was conducted with Number of Tasks Shed as the dependent variable. There was no significant interaction of control device and task complexity, $F(1, 38) = 1.281$, $p = .265$, *partial* $\eta^2 = .033$. There were no significant effects of control device, $F(1, 38) = 0.095$, $p = .759$, *partial* $\eta^2 = .003$, or of task complexity, $F(1, 38) = 0.350$, $p = .853$, *partial* $\eta^2 = .001$. Participants task shed similarly with the Leap (M = 2.00, SD = 1.38) and Xbox (M = 1.87, SD = 1.58). They task shed similarly in both low (M = 1.917, SD = 2.00) and high (M = 1.96, SD = 2.09) task complexities.

Post-Hoc Analyses

Correlational analyses. Pearson correlations were used to test for relationships between performance and several demographic variables, including Control Device Experience with Xbox and motion capture devices (Xbox Kinect and Leap), overall Video Game Experience, Average Computer Hours per Week, and Computer Confidence (see Appendix H). Several correlations were significant, including inverse relationships between Task Completion Time and Number of Tasks Shed. This occurred because participants who task shed spent less time on the task. Similarly, there were significant correlations between Task Completion Time and Number of Errors. This occurred because participants who spent more time on the task had more opportunity to make errors. There was also a significant correlation between Number of Tasks Shed for Leap and Xbox. This might have occurred because participants who task shed for one task shed tasks similarly with both control devices.

Task completion. To further evaluate task performance, I examined Task Completion Rate using a 2 x 2 mixed ANOVA (see Figure 16). There was not a significant interaction of control device and condition, $F(1, 15) = .016$, $p = .901$, *partial* $\eta^2 = .001$. There was a significant effect of control device, $F(1, 15) = 4.636$, $p = .048$, *partial* $\eta^2 = .236$. Participants had a higher Task Completion Rate with the Leap (M = .323, SD = .124) overall than the Xbox (M = .044, SD = .034). There was not a significant effect of task complexity, $F(1, 15) = 0.146$, $p = .708$, *partial* $\eta^2 = .010$.

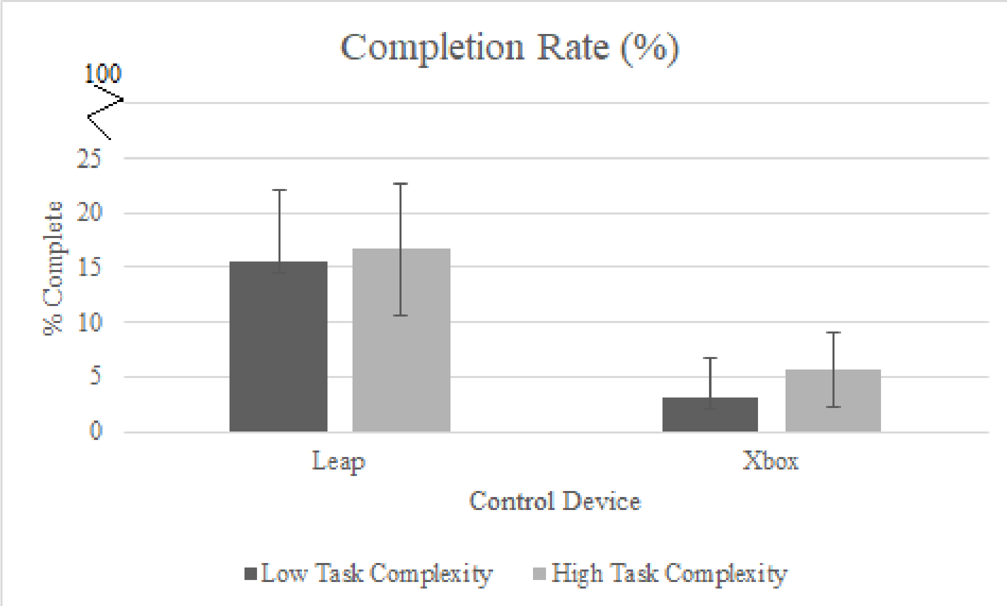

Figure 16. Completion rate by control device and task complexity. Error bars reflect SD.

Time to task shed. Additionally, I evaluated Time to Task Shed (in seconds) for the 15 participants who shed tasks (N =15; low task complexity = 8, high task complexity = 7) using a 2 x 2 mixed ANOVA. There was not a significant interaction of control device and condition, $F(1, 13) = 1.535$, $p = .237$, *partial* $\eta^2 = .106$. There was not a significant effect of control device, $F(1, 13) = 0.993$, $p = .237$, *partial* $\eta^2 = .071$. There was not a significant effect of condition, $F(1, 13) = 0.044$, $p = .837$, *partial* $\eta^2 = .003$. Participants took more time to task shed in the low task complexity Leap condition than any other condition (M = 356.13, SD = 157.58). Participants took the least amount of time in the low task complexity Xbox condition (M = 262.63, SD = 144.68). Only one participant task shed immediately in the Xbox condition; the minimum for the Leap condition was 144 s.

Time to complete first task. As all non-task shedding participants used the maximum amount of time (600 s), I decided to examine at the time to complete the first peg using a 2 x 2 mixed ANOVA with time to complete first peg as the dependent variable. From this, I found there was not a significant interaction between control device and task complexity $F(1, 15) = 0.499$, $p = .491$, *partial* $\eta^2 = .032$. There was not a significant effect of control device, $F(1, 15) = 1.177$, $p = .295$, *partial* $\eta^2 = .073$. There was not a significant effect of task complexity, $F(1, 15) = 0.081$, $p = .780$, *partial* $\eta^2 = .005$. The mean values for each condition were near the maximum time limit of 600s. Participants using the Leap completed the first peg task slightly faster on average in the low task complexity condition (M = 537.75s, SD = 101.45) than in the high task complexity condition (M = 552.67s, SD = 93.39). Participants using the Xbox completed the first peg task slightly slower in the low task complexity condition (M = 595.63s, SD = 12.37) than the high task complexity condition (M = 564.89s, SD = 104.96).

Time to grasp first peg. To help gather more information about the time differences between conditions, I coded videos for the time participants took to initially grasp the peg from the board. This eliminated the task complexity variable, but I conducted a paired samples t-test to determine if there was a difference between time to grasp the peg initially using the two control devices. I found there was a significant difference between time to initially grasp the peg, $t(39) = -2.74$, $p = .044$. Participants grasped the peg more quickly using the Leap (M = 323.48s, SD = 210.97) than the Xbox (M = 427.60s, SD = 221.70). This provides support for Hypothesis 1, that participants completed the task more quickly with the Leap.

Chi-squared of task shedding by group. To determine if there was any difference between the Number of Participants who Task Shed in each group, I conducted a chi-squared test to determine if there was a significant difference between the actual number of people who task shed in each group and half of the group (n = 10). From this, I found there was not a significant difference between the expected and actual task shedding values, X^2 (2, N = 40) = 0.600, p =

.896.

Content analysis. During the experiment, I noted comments that participants made during the experiment, as well as reasons participants mentioned for task shedding or not task shedding. After the experiment, participants gave written answers to a question about strategy (if they had any) and any final comments. I analyzed the content of these comments by frequency to help further understand performance in this experiment. A histogram of the number of participants who mentioned certain topics is included below (Figure 17).

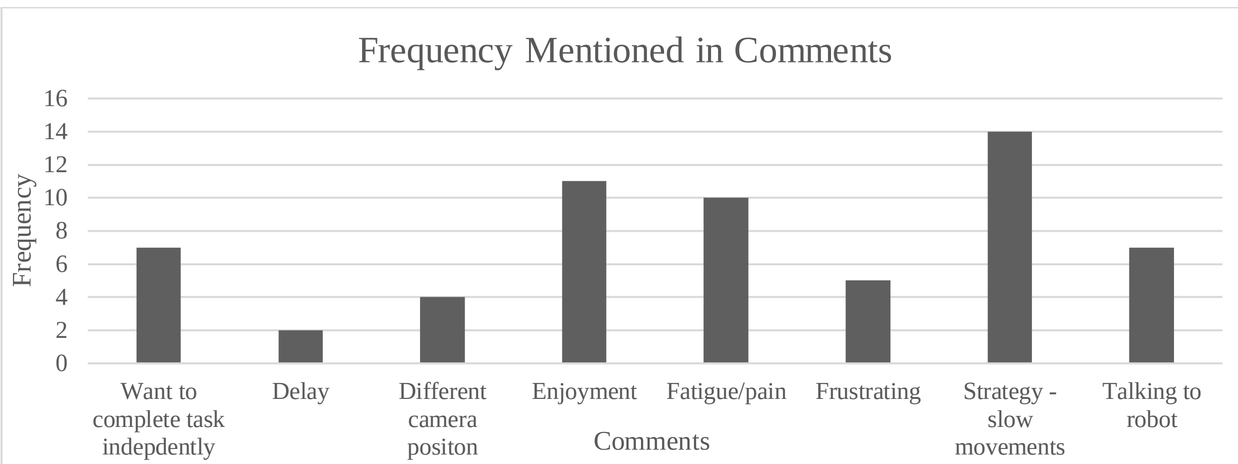

Figure 17. Histogram of the most commonly mentioned topics

CHAPTER 4

DISCUSSION

The aim of this work was to experimentally evaluate the impact of control device and task complexity on performance and task shedding behavior. From this, an experimental paradigm to observe task shedding behavior was developed. The findings of this study highlight both the potential for using motion-capture systems for robotic arm tasks as well as the shortcomings of such systems. Additionally, this experiment expanded Control Order Theory into three-dimensional spaces and provided understanding of appropriate contexts for the Leap Motion controller to be used.

Theoretical Implications

Automation and task shedding. As technology improves, Zhang et al. (2017) predicted that automation will be used widely for IED disarmament by 2030. As progress toward full autonomy occurs, humans and automation will likely share control for many years to come. However, some operators are not comfortable relying on robotic arms to complete tasks autonomously (Beasley, 2012). The results of this study support this statement. Participants were told the automation was reliable but imperfect. Overall, participants would have performed better if they had task shed to the robot (placing three of four pegs correctly, or 75%). In spite of this, nearly half of the forty participants (19 Leap, 22 Xbox) chose not to task shed, and approximately 25% (10 Leap, 5 Xbox) shed only one task.

Individuals also did not task shed to the robot in a timely manner. The earliest anyone task shed with the Leap was 144 seconds, and only one participant task shed immediately to the robot when using the Xbox. The average time to task shed for each group was higher than four minutes. There are multiple explanations for the extended time to task shed. Participants may be reluctant to rely on automation (Beasley, 2012). When participants were asked about why they chose not to task shed, seven participants explicitly mentioned wanting to complete the task independently. Slow task shed times may also reflect participants' under-reliance due to the novelty of the automation and their short exposure time with the system which left little time to calibrate. Although they were told the automation was reliable but imperfect, a chi-square revealed no significant difference from 50% task shedding in any condition.

Participants who shed tasks in one condition typically shed tasks when using both control devices, as reflected by the significant correlation between Leap tasks shed and Xbox tasks shed (r = .454, p < .01). Sixteen participants shed tasks with both Leap and Xbox, five participants shed tasks when only using the Leap, and two participants shed tasks only when using the Xbox. Overall, this correlation suggests perhaps individual differences, such as self-efficacy or technology acceptance, impacted task shedding behavior globally instead of the control device or task complexity. Researchers should continue exploring these individual differences to understand tasks shedding behavior.

Control devices. Past research investigating Control Order Theory has demonstrated that lower order control devices support better performance than higher order control devices because of decreased mental translation between input and output (Lincoln, 1953; Regan, 1960). Early studies involving paper-paced contour systems and two-dimensional screens explored this idea, but the conditions were not equivalent to executing user-generated movements of a robot in a three-dimensional world. The results of the current study partially support the extension of Control Order Theory into three-dimensional space. Completion rate with the Leap Motion controller, conceptualized as a zero-order control device, was significantly higher than with the Xbox controller, conceptualized as a first-order device. Participants were able to initially grasp the peg with the Leap Motion controller significantly faster than with the Xbox controller. However, errors were significantly higher when using the Leap than when using the Xbox. This low level of performance accuracy with the Leap does not support the theory that superior performance will occur with a lower order control device.

Based on these results, task type and consequence of error must be closely considered when deciding what type of control device is appropriate for any given task. For example, IED disarmament robots require extremely accurate and precise performance to avoid detonating a bomb. An error could be fatal, potentially injuring or killing highly trained individuals (BBC, 2010). Similarly, an error during surgery, such as grasping incorrect tissue, could irreparably injure a patient. The error number and type in this experiment would render use of the Leap Motion controller inappropriate for these applications. However, several factors must be considered before dismissing use of the Leap Motion controller for high-stakes tasks. The two control devices offer different feedback for participants. For the Xbox controller, participants receive haptic feedback when manipulating the joystick or buttons. When using the Leap Motion controller, a hand overlay was used to convey visual feedback. Participants may require additional or different feedback for more accurate performance with the Leap Motion controller.

Additionally, the Leap Motion controller is an early motion-capture control device. Improvements to both the software and hardware have been made since the beginning of this experiment, and more improvements will be made in years to come. The next generation motion-capture control devices should be evaluated independently to determine their suitability for such critical tasks, as noted by Wignor and Wixon (2011).

The results of this study refute Norman's (2010) assertion that NUIs are not natural or easy to learn. The results do support Wachs and colleagues (2011) findings that NUIs increase speed. In half of a one-hour session, participants learned to use the Leap Motion control device adequately enough to significantly outperform the Xbox control device regarding completion rate and time to first grasp the peg. Conversely, the significantly higher error rate with the Leap supports the idea that NUIs are more challenging to use due to the lack of necessary feedback to recover from errors and the need for high levels of operator precision.

Task complexity. The findings of this study offer limited insight into the impact of low and high task complexity tasks on performance and task shedding behavior. Based on pilot testing and previous studies, the task complexity manipulation and time limitations were appropriate. During pilot testing (N = 6), one participant completed all peg transfers successfully with the Leap Motion controller and one completed three of four with the Xbox controller. Participants struggled more to move the peg to the outer, high complexity corners of the peg board. There appeared to be differences between task complexity conditions, but both appeared to be manageable.

Additionally, past studies guided my decision for time limitations. Long and Bliss (2016) limited participants to ten minutes on the task board task, and participants completed slightly more than 75% of tasks on average. Participants in previous studies mentioned arm fatigue (Long and Bliss, 2016). This issue was also explicitly mentioned by ten people in the current study. These factors contributed to my decision to limit time working with the Leap Motion controller. Similarly, in Crane, Proaps, Benasutti, and Bliss (2018), participants (N = 17) used a Leap Motion controller to pick up a peg and place it in a peg hole or specific location. Sixteen participants completed the task in less than 501 seconds. One participant took 670 seconds. The means for each of the three studies were all under 300 seconds, and each subsequent trial showed improvement. From these studies and pilot testing, I expected some participants would be able to complete the task in the time limitation of 600 seconds while limiting fatigue experienced, and the task was appropriately complex. However, no significant impact of task complexity was seen for any of the dependent variables.

Upon visual inspection, there was a stronger impact of task complexity on the Leap condition than the Xbox on the number of tasks shed, time to task shed, and completion rate, mirroring the ordinal interaction predicted. The lack of effect could be due to floor and ceiling effects, as performance was generally poor. It could also be due to insufficient power to detect the interaction. Importantly, the results suggest that the task is too challenging, particularly when paired with the visual secondary task. Thus, further research with a simpler task is required to understand the impact of task complexity on control device and task shedding behavior, particularly to understand if NUI are appropriate for complex tasks.

Experimental paradigm. The tasks used in this study were designed to simulate an operator's experience when dissembling an IED while scanning the environment for threats. Based on publicly available information about IED components and the environment in which the task is completed, the experimental task appropriately approximated real-world scenarios (Joint Staff, 2012). Additionally, when pilot testing the experiment, I encountered a participant who interacted with a manually controlled robotic arm during her service in the Navy. She noted that using the Xbox controller was similar to her experience controlling the robotic arm on the ship with a joystick device. She also noted the experiment realistically portrayed her experience with robotic arms, but she mentioned it was more likely participants would shed the visual search task instead of the robot arm task based on task criticality and currently available visual-search aid technology. This participant's subject matter expertise was valuable because it further supported the use of the current paradigm and suggested the results may generalize to certain military robot arm control situations.

However, the task was not sensitive to changes in task complexity, likely due to floor and ceiling effects with performance. The task might be modified by manipulating task complexity on either a different dimension or with a simpler task. Participants were able to operate the robot, shed tasks, and monitor for tanks successfully. Changing the task to be simpler should reveal differences between groups if they exist. Adjustments to simplify the task could include the participant starting with the peg in the gripper, using a smaller or lighter peg, using a smaller board, or requiring participants to place the peg in a larger peg hole. Task complexity could also be manipulated on other dimensions instead of physical task complexity, such as temporal demand or number of task components (Liu & Li, 2012). Additionally, integrating measures that can be used when the participant has shed a task, such as eyetracking or physiological measures, might be useful to help mitigate data lost when participants shed a task and to help increase power.

Practical Applications

As noted in the Introduction, the findings of this study have far-reaching implications as manually-controlled robotic arms are widely used in a variety of domains. Although the primary application in this study was military-based, the findings can be applied to surgical and outer space domains. In the surgical domain, researchers have already begun to explore the use of the Leap Motion control device for telescopic surgery (Travalini et al., 2016). In a case study, Travalini et al (2016) found promising results for the Leap as a control device in surgery. The current study further supports that motion-capture systems could be used for surgery, but the number and type of errors should be explored before implementing widely. For use in outer space, the Leap Motion control device again could be used, particularly for operating a humanoid robot like Robonaut2 to operate switches and press buttons. However, the criticality of the task and the issue of lag time must be considered, neither of which we addressed here.

This study should also be used to inform gesture-based training. In this study, participants were trained to use the system by experimenter demonstration and hands-on experience. This method trained participants adequately enough to outperform the Xbox control device overall. Formal guidelines have not been written on how to best train users to operate a motion-capture based system. Future practitioners should consider the method used here when determining the best method of training motion-capture system users.

The current study supports the results of other similar studies. Long and Bliss (2016) similarly found that participants performed significantly better with the Leap Motion controller on most tasks over the Xbox controller. The current study also supports the findings that the Leap Motion controller is an appropriate, non-intrusive way to control a physical robotic arm (Moldovan & Staretu, 2016; Staretu & Moldovan, 2016). The current study served to fill important gaps in the literature, including experimentally comparing the Leap and Xbox control devices, demonstrating the Leap outperforms the Xbox in some regards.

Limitations and Future Research

This experiment suffers some limitations that must be noted when interpreting the results. First, the Leap Motion controller and Xbox controller, although conceptualized as zero- and first-order control devices respectively, differ from traditional zero- and first-order control devices. The Leap Motion lacks the physical feedback of a joystick programmed with zero-order control. The Xbox controller employees a directional pad and a trigger button to aid with moving each joint instead of only the two joysticks. These differences may impact their interpretation as zero- and first-order control devices. Additionally, the two control devices provided differing feedback. The Leap Motion control device provided visual feedback for participants through a hand overlay on the camera views. The Xbox controller provided haptic feedback for participants via the physical movement of joysticks and pressing buttons. These differences must be considered.

Ten participants explicitly mentioned fatigue or their arm hurting when using the Leap Motion control device. Participants did not mention this when using the Xbox controller. Although there was no evidence of it in our study due to likely floor and ceiling effects, participants may experience performance decrements due to physical workload is using the system long enough. Further research is needed to determine what typical threshold for fatigue.

The population tested was college students with little experience with teleoperation control, and it could be argued that this experiment measured performance during the early stages of learning for both control methods. Performance and task shedding behavior may have been different if the participants were experience teleoperators. Future researchers should consider using data from teleoperators or training participants further.

In the future, researchers should consider collecting qualitative data regarding the reason why participants decide to task shed or not, as well as more information on individual differences that may impact task shedding behavior. Seven of 17 non-task shedding participants explicitly commented that they did not task shed because they wanted to complete the task on their own. Measures such as self-efficacy or motivation might reveal individual differences that impact task shedding behavior, which is increasingly important to consider as humans and robots share control in the future.

Practically, new technologies are quickly outpacing the Leap Motion controller and the software used in this experiment. New control devices, such as Rigel, a mounted motion-capture system that is an improve upon the Leap Motion controller, are prognosticated to have improved tracking due to software and hardware improvements. As these products come to market, these results may not be supported in similar follow-up work. The improved fidelity of visual feedback as well as improved tracking might impact performance positively or by providing support that motion-capture system are inappropriate for complex tasks. Replication is necessary to understand if the results of this study are representative of motion-capture systems in general or of this specific system.

CHAPTER 5

CONCLUSION

This study explored the use of two control devices and task complexity on performance and task shedding behavior in a robotic arm task. This study supports the idea that participants are not comfortable shedding tasks to an autonomously performing robot, a behavior that must be further considered as technology advances and task shedding becomes more common (Beasley, 2012; Zhang et al., 2017). Additionally, this study partially supports the extension of Control Order Theory into three-dimensional, self-determined pathways, but further research with more experienced populations must be conducted to solidify this assertion. Finally, this study highlights the potential for using the Leap Motion controller on tasks traditional relegated to joystick-based control devices, such as the Xbox controller. Based on the results of this study, the application to military and other domains should be considered, but the impact of errors should be closely examined before implementation.

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APPENDIX A

INFORMED CONSENT DOCUMENT

<u>PROJECT TITLE:</u> Human Performance on a Robotic Arm Task (ARMCONTROL3)

<u>INTRODUCTION</u>
The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES.

<u>RESEARCHERS</u>
James P. Bliss, Ph.D., Old Dominion University, Psychology Department, Responsible Project Investigator
Alexandra B. Proaps, M.S., Old Dominion University, Psychology Department
Shelby K. Long, B.S., Old Dominion University, Psychology Department

<u>DESCRIPTION OF RESEARCH STUDY</u>
This experiment is interested in learning more about how to best complete a task with a robotic arm. First, you will complete a few questionnaires about demographics and video game experience. Next, you will use a control device to complete tasks using the robotic arm. After, you will complete questionnaires about your experiences during the experiment.

If you say YES, then your participation will last for approximately 60 minutes in MGB 324. Approximately 500 subjects will be participating in this research.

<u>EXCLUSIONARY CRITERIA</u>
To be eligible for this study, you must be at least 18 years of age or older.

<u>RISKS AND BENEFITS</u>
RISKS: If you decide to participate in this study, then you may face a risk of physical strain from using the Xbox controller or Leap controller, but it will be no more than from playing a video game. The researcher tried to reduce these risks by minimizing the amount of time in the study to sixty minutes. As with any research, there is some possibility that you may be subject to risks that have not yet been identified.
BENEFITS: There are no known benefits from this study.

<u>COSTS AND PAYMENTS</u>
The main payment to you for participating in this study is the extra credit or course credit points that you will earn for your class. Although researchers are unable to give you payment for participating in this study, if you decide to participate in this study, you will receive 1.5 Psychology Department research credit, which may be applied to course requirements or extra credit in your Psychology course. Equivalent credits may be obtained in other ways. You do not have to participate in this study, or any Psychology Department study, in order to obtain this credit.

<u>NEW INFORMATION</u>
If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY

The researchers will take reasonable steps to keep your private information, such as questionnaires, confidential. The researchers will store the information in a locked filing cabinet for five years, after which the data will be destroyed. The results of this study may be used in reports, presentations, and publications, but the researcher will not identify you.

WITHDRAWAL PRIVILEGE

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled. The researchers reserve the right to withdraw your participation in this study, at any time, if they observe potential problems with your continued participation.

COMPENSATION FOR ILLNESS AND INJURY:

If you agree to participate, then your consent in this document does not waive any of your legal rights. However, in the event of harm, injury, or illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr. James P. Bliss at 757-683-4051 or Dr. Tancy Vandecar-Burdin (ODU IRB Chair) at 757-683-3802.

VOLUNTARY CONSENT

By signing this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, please contact the researcher at the number above.

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. George Maihafer, the current IRB chair, at 757-683-4520, or the Old Dominion University Office of Research, at 757-683-3460.

And importantly, by signing below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Participant's Printed Name & Signature	**Date**
Investigator's Printed Name & Signature	**Date**

APPENDIX B

DEMOGRAPHICS QUESTIONNAIRE

The purpose of this questionnaire is to collect background information for participants in this experiment. This information will be used strictly for this experiment and for research purposes only. Please complete each item to the best of your ability.

1. **Age** _____

2. **Sex:** Male Female Other

3. **Have you ever been diagnosed as having a deficiency in your visual acuity**? _____(Y/N)

   a. If yes, do you have correction with you (i.e. glasses, contact lenses, etc.)? _____(Y/N)

4. **Have you ever been diagnosed as color deficient or color blind?** ______(Y/N)

5. **Which is your dominant hand?**

6. **Do you have any arm or hand injuries?** _____(Y/N)

   a. If yes, please explain? ____

APPENDIX C

VIDEO GAME AND CONTROL DEVICE EXPERIENCE QUESTIONNAIRE

Indicate the average number of *hours per week* you spend playing the following types of games. If none, indicate 0.

a. First person shooter games (e.g., Perfect Dark, Call of Duty) _______
b. Massively multiplayer online games (e.g., World of Warcraft, Age of Empires) _______
c. Flight simulators (e.g., X-Plane, ProFlight Sim) _______
d. Sports/racing (e.g., Madden NFL 10, Mario Kart Wii) _______
e. Military command/strategy (e.g., Tekken Tag, America's Army) _______
f. Fighting (e.g., Street Fighter IV) _______
g. Life/business simulations (e.g., The Sims) _______
h. Fantasy/adventure (e.g., Assassins Creed, Final Fantasy 8) _______
i. Puzzles/card games/board games (e.g., Solitaire, Settlers of Catan). _______
j. Social networking games (e.g., Mafia Wars, Farmville) _______
k. Other: Please specify ______________________ Hours: _______

8. Indicate the number of *hours per week* you spend playing games using the following controllers. If none, indicate 0.

a. Steering wheel _______
b. Keyboard and mouse _______
c. Joystick for PC (e.g., Logitech Extreme 3D) _______
d. Nintendo DS and Nintendo 3DS _______
e. Gameboy and Gameboy Color _______
f. Gameboy Advance _______
g. Touchscreen (e.g., smartphone, tablet) _______
h. Wii remote _______
i. Wii accessories (e.g., numchuck, balance board) _______
j. WiiU gamepad _______
k. Nintendo 64 controller _______
l. Nintendo GameCube controller _______
m. Xbox, Xbox 360, and Xbox One controller _______
n. PlayStation controller _______
o. PlayStation Portable (PSP) and PlayStation Vita _______
p. Xbox Kinect _______
q. Leap Motion 3D controller_______
r. Oculus Rift _______
s. Other: Please specify ______________________ Hours: _______

9. Indicate the average number of *hours per week* you spend using computers (personal and work combined): _____

10. Circle the number that corresponds to how confident you are in using computers:

1	2	3	4	5	6	7
Low			Average			High

APPENDIX D

ROBOT EXPERIENCE QUESTIONNAIRE

For the following robots, please indicate your familiarity in terms of hearing about them, using them, or operating them. Please circle only one option.

Robots	Not sure what this is$_0$	Never heard about, seen, or used this robot$_1$	Have only heard about or seen this robot$_2$	Have used or operated this robot <u>only occasionally</u>$_3$	Have used or operated this robot <u>frequently</u>$_4$
a. Autonomous Car	0	1	2	3	4
b. Domestic/Home robot (e.g., Roomba)	0	1	2	3	4
c. Entertainment/toy robot (e.g., Aibo, Furby)	0	1	2	3	4
d. Manufacturing robot (e.g., robotic arm in factory)	0	1	2	3	4
e. Military Robot (e.g., search and rescue)	0	1	2	3	4
f. Personal Robot 2 (PR2)	0	1	2	3	4
g. Remote presence robot (e.g., Texai, Anybot)	0	1	2	3	4
h. Research robot (e.g., at university or company)	0	1	2	3	4
i. Robot lawn mower	0	1	2	3	4
j. Robot security guard	0	1	2	3	4
k. Space exploration robot (e.g., Mars Rover)	0	1	2	3	4

l.	**Surgical robot (e.g., da Vinci Surgical System)**	**0**	**1**	**2**	**3**	**4**
m.	**Unmanned Aerial Vehicle (UAV)/Drone**	**0**	**1**	**2**	**3**	**4**

APPENDIX E

POST-EXPERIMENT QUESTIONNNAIRE

Please answer the following questions about yourself by circling the most appropriate response. The information you provide will be kept completely confidential and will not be linked backed to you in any way.

Please circle only one answer per question.

1. This experiment was time consuming.

Disagree strongly Disagree Neutral Agree Agree Strongly

2. This experiment was confusing.

Disagree strongly Disagree Neutral Agree Agree Strongly

3. I did not feel like I had a good grasp on the instructions for this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

4. I feel like I performed well on this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

5. I feel like I performed poorly on this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

6. This experiment was easy to understand

Disagree strongly Disagree Neutral Agree Agree Strongly

7. This experiment was enjoyable.

Disagree strongly Disagree Neutral Agree Agree Strongly

8. I did not enjoy this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

9. I am glad that I participated in this experiment

Disagree strongly Disagree Neutral Agree Agree Strongly

10. I felt engaged in the tasks for this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

11. I felt like I received adequate time to train and get comfortable with the experimental task before beginning the actual experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

12. I felt like I did not receive adequate time to train and get comfortable with the experimental task before beginning the actual experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

13. I felt motivated to perform to the best of my ability in this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

14. I did not care how well I performed in this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

15. I tried my best to perform well on this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

16. I did not try my best to perform well on this experiment.

Disagree strongly Disagree Neutral Agree Agree Strongly

17. Overall, I would recommend this experiment to other students.

Disagree strongly Disagree Neutral Agree Agree Strongly

18. Did you have a strategy for responding to the experimental task?

Yes No

If yes, please describe

____

____

____

19. Do you have any other thought, feelings, or comments about the experiment?

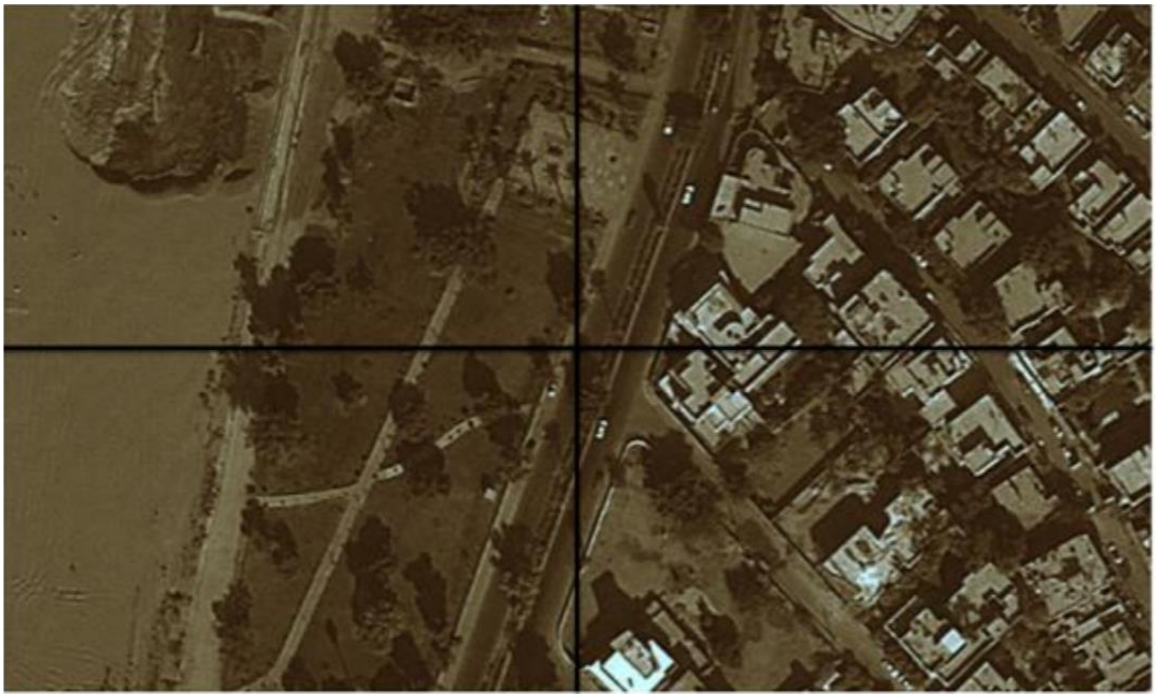
____

____

____

APPENDIX F

EXAMPLE OF AERIAL IMAGE



APPENDIX G

DESCRIPTIVE STATISTICS FOR FULL DATA SET

		Leap	Xbox
Speed (s)	Low	537.30 (89.55)	463.65 (179.06)
	High	461.45 (161.08)	474.45 (164.67)
Number of errors	Low	16.80 (6.77)	5.60 (5.08)
	High	14.55 (7.32)	4.90 (3.92)
Number of tasks shed	Low	1.05 (1.36)	1.25 (1.65)
	High	1.25 (1.55)	0.90 (1.37)
Completion rate (0-1)	Low	.187 (.197)	.038 (.092)
	High	.113 (.172)	.075 (.143)

Note. Descriptive statistics for mixed ANOVA for all participants (N = 40). Standard deviations are in parentheses. Time included is speed, errors, and completion rate does include participants who task shed.

APPENDIX H

CORRELATIONS BETWEEN PERFORMANCE VARIABLES AND EXPERIENCE

	L Time	X Time	L Comp Rate	X Comp Rate	L Tasks Shed	X Tasks Shed	L# Errors	X# Errors	Comp Hrs	Comp Conf	Xbox Exp	Motion Exp	VGE overall
LTime	.	.280	.202	-.188	-.844**	.034	.806**	.255	-.042	-.192	.040	.	.235
X Time		.	.016	-.086	.270	-.774**	.175	.506**	-.382*	.018	-.242	.	-.240
L Comp Rate			.	.259	-.158	-.110	.190	.092	-.162	-.221	.086	.	.091
X Comp Rate				.	.061	-.059	-.198	.068	-.080	-.211	.230	.	.064
L Tasks Shed					.	.454**	-.391*	-.299	.043	.244	.015	.	-.162
X Tasks Shed						.	-.157	-.442**	.390*	.069	.171	.	.240
L# Errors							.	.142	-.051	-.242	.045	.	-.060
X# Errors								.	-.221	-.198	-.046	.	-.044
Comp Hr									.	.361*	.503**	.	.519**
Comp Conf										.	.673	.	.147
Xbox Exp											.	.	.507**
Motion Exp												.	.
VGE overall													.

* < .05; **< .01

Note. No participants reported using Motion Capture controllers on a weekly basis.

VITA

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EDUCATION

Old Dominion University, Norfolk, VA 2014 – Present
PhD, Human Factors Psychology (expected December 2020)
MS, Applied Experimental Psychology (January 2019)
Certificate, Modeling and Simulation Engineering (December 2015)

Georgia Institute of Technology, Atlanta, GA 2009 – 2013
BS, Psychology, High Honors

SELECTED PUBLICATIONS

Long, S. K. & Bliss, J. (2016). The effect of control device on performance in a robotic arm task. *Proceedings of the Human Factors and Ergonomics Society 60th Annual Meeting*. Santa Monica, California: Human Factors and Ergonomics Society.

Long, S. K., Karpinsky, N. D., Döner, H. & Still, J. (2016). Using a mobile application to help visually impaired individuals explore the outdoors. *Proceedings of the International Conference on Applied Human Factors and Ergonomics*. Berlin, Germany: Springer.

Proaps, A., **Long, S. K.**, Cowan, M., & Sandberg, H. (2015). Presence and performance as a function of teammate agency and individual differences in a video game. *Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting.* Santa Monica, California: Human Factors and Ergonomics Society.

Smarr, C.-A., **Long, S. K.**, Prakash, A., Mitzner, T. L., & Rogers, W. A. (2014). Understanding younger and older adults' needs for home organization support. *Proceedings of the Human Factors and Ergonomics Society 58th Annual Meeting.* Santa Monica, California: Human Factors and Ergonomics Society.

Olson, K. E., **Long, S. K.**, Fisk. A. D., & Rogers, W. A. (2013). *Toward understanding human trust in service robots*. Presented at ACM/IEEE International Conference on Human-Robot Interaction, Tokyo, Japan.

SELECTED HONORS & AWARDS

Department Graduate Student Service Award (2016), Patricia W. and J. Douglas Perry Fellowship (2014-2016), President's Undergraduate Research Award (2013), Alpha Delta Chi Alumnae Scholarship (2013), Psi Chi (2013), Alpha Delta Chi Service Scholarship (2012), Georgia Rotary International – Study Abroad Trip Award (2011), Georgia HOPE Scholarship (2009-2013)

PROFESSIONAL SERVICE

- **Student Coordinator**, ODU Psychology Department PhD Interview Day (2015, 2016)
- **Student Volunteer**, International Conference on Applied Human Factors and Ergonomics (2016); Human Factors and Ergonomics Society Annual Meeting (2015, 2016); Cognitive Aging Conference (2014); Strategies in Human-Technical Systems Conference (2014)
- **Session Chair**, Virtual Environments Technical Group, Human Factors and Ergonomics Society (Co-chair, 2015); Virginia Junior Academy of Science (2015)
- **Judge**, Virginia Junior Academy of Science Research Symposium (2015, 2016)
- **Panelist**, Applying to Graduate School for ODU Psi Chi (2016); Life in Graduate School for ODU Fellowship of Women in Science (2015)