# Determining the Benefit of Human Input in Human-in-the-Loop Robotic Systems

by

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## ABSTRACT

This work analyzes human-in-the-loop robotic systems to determine where human input can be most beneficial to a collaborative task. This is accomplished by implementing a pick-and-place task using a human-in-the-loop robotic system and determining which segments of the task, when replaced by human guidance, provide the most improvement to overall task performance and require the least cognitive effort. The first experiment entails implementing a pick and place task on a commercial robotic arm. Initially, we look at a pick-and-place task that is segmented into two main areas: coarse approach towards a goal object and fine pick motion. For the fine picking phase, we look at the importance of user guidance in terms of position and orientation of the end effector. Results from this initial experiment show that the most successful strategy for our human-in-the-loop system is the one in which the human specifies a general region for grasping, and the robotic system completes the remaining elements of the task.

We extend this study to include a second experiment, utilizing a more complex robotic system and pick and place task to further analyze human impact in a human-in-the-loop system in a more realistic setting. In this experiment, we use a robotic system that utilizes an Xbox Kinect as a vision sensor, a more cluttered environment, and a pick-and-place task that we segment in a way similar to the first experiment. Results from the second experiment indicate that allowing the user to make fine tuned adjustments to the position and orientation of the robotic hand can improve task success in high noise situations in which the autonomous robotic system might otherwise fail.

The experimental setups and procedures used in this thesis can be generalized and used to guide similar analysis of human impact in other human-in-the-loop systems performing other tasks.

# CHAPTER 1

# INTRODUCTION

This chapter provides background information and motivation for this thesis topic. The concept for human-in-the-loop robotic systems is discussed, and the need for analyzing their effectiveness is discussed. The objectives of this thesis, experimental results, and an outline of the remaining sections are also provided.

## 1.1 Human-in-the-Loop Robotic Systems

For systems requiring human and robot collaboration, the natural problem of balancing the control between both parties occurs. Human-in-the-loop systems offer a solution to this problem by sharing controls between the human and the robot to best leverage each other's strength and carry out work successfully in tasks that would be difficult for either of them alone. The topics of human-robot collaboration and human-in-the-loop systems are not new, and numerous works have been published detailing the design of human-in-the-loop robotic arms and wheelchairs [1] [2] [3], detecting and preventing machine error, and analyzing the effectiveness of human-in-the-loop systems [4] [5].

Autonomous systems are improving rapidly and becoming part of our daily lives. While autonomous systems have the potential to aid humans in daily life activities, this is not yet the reality. There is room for improvement in autonomous robotic systems; humans can complete some decision making and portions of the tasks more reliably and accurately than current autonomous systems [6], [7] with minimal effort. Human-in-the-loop systems provide the best of both worlds by combining the cognitive capabilities of the user and the physical advantages of the robotic system. Humans also gain a greater sense of empowerment from being involved in the decision making process, showing that it is both advantageous and desirable to include the user in the loop [8].

### 1.2 Motivation for Analysis of Human-in-the-Loop Robotic Systems

Human-in-the-loop robotic systems can be used in many situations and can greatly aid people in their daily lives. For example, human-in-the-loop robotic systems are being used in rehabilitative settings in which persons with limited extremity motion utilize a robotic system to assist in activities of daily living [9]. In such a case, it is neither desirable nor practical to remove the human entirely from the system.

For such reasons, analyzing the effectiveness of human-in-the-loop systems is important. Understanding and determining the effectiveness of a human's role in the human-in-the-loop robotic system are the first steps to improving the overall performance of the collaborative system and decreasing strain on the human operator.

### 1.3 Thesis Objectives

The objective of this thesis is to establish a method for determining the best placement for human input in a human-in-the-loop robotic system. This can be accomplished by performing two experiments involving participants and human-in-the-loop robotic systems. For the first experiment, we propose and perform an experiment that is implemented on a simple, straightforward robotic system and a task that is relatively not complicated. Results from this experiment can be used in future systems.

The purpose of the second experiment is to refine the methods used in the initial experiment and to test conclusions found in the initial experiment in a more complex and realistic environment.

By designing and performing these experiments, the most successful strategies for the human-in-the-loop system can be determined. The proposed experimental setups can be generalized for use in other robotic human-in-the-loop systems.

### 1.3.1 Hypothesis

We believe that allowing the human to control segments of the pick-and-place task that do not require a lot of precision will result in the most successful human-in-the-loop combination, and will also be the most desirable situation for the human.

## 1.4 Experimental Overview

This work is divided into two experimental sections. Both experiments were designed with the intent to analyze human-in-the-loop robotic systems.

We segmented the pick-and-place task for both experiments in a similar way: approach to a rough approximation of the goal object, fine positioning of the hand in regards to the goal object, fine tuning the orientation in relation to the goal object, grasping, and relocation. In our experimental testing, we analyze these segments by allowing a human operator to step in at these defined points during the autonomous pick-and-place task. By doing this, we can learn which aspects of the pick-and-place task are best controlled by the human and which are best controlled by the robotic system. We can also set up a general framework for determining the best blend of human and robot control for other tasks and robotic systems.

### 1.4.1 Comparison Between the Two Experiments

The initial experiment involves the use of an industrial robot and participants to complete a pick-and-place task. In this experiment, the pick-and-place task was divided into two main segments: the approach towards the goal object and the fine picking of the goal object. The picking phase is broken down further to look at the effects of controlling both position and orientation of the end effector. These task segments will be further described in later sections. We used a robotic system without sensors to conduct the pick-and-place task, and used a Phantom OMNI haptic device for user input. To make our system more realistic, we added four levels of Gaussian noise to the position and orientation of the goal object to simulate four levels of noisy sensors in the robotic system. Six participants were used to test out several human/robot collaborative pick-and-place tasks. We tracked the number of collisions and task failures for each testing strategy, as well as collected subjective results from the participants.

For the second experiment, we aimed to make both the robotic system and the pick-and-place task more complicated and realistic. We do this by utilizing an Xbox Kinect as a vision sensor and software to determine the position and orientation of the goal objects involved in the task. The OMNI is replaced by a 3D mouse to simplify participant input in an attempt to simplify the experience for the participant. We also strive to make the pick-and-place task used in the experiment more complicated and realistic by including multiple objects in the environment. These objects vary in shape (a sphere, a rectangle, and a cup). We discovered through trial and error that these shapes represent various levels of grasping difficulty due to the limitations of our vision sensor, and represent noise in the second experiment. This will be expanded on in later sections. We segmented the task for this experiment in a similar way to the first: approach to a rough approximation of the goal object, fine positioning of the hand in regards to the goal object, fine tuning the orientation in relation to the goal object, grasping, and relocation. But this time, we test on ten participants. We also simplified the user questionnaire and trained the participants on the robotic system before testing began in an effort to eliminate problems with inconclusive data that we encountered in the first experiment.

## 1.5 Overview of Experimental Results

To summarize our results from the initial testing, our research indicates that without human in the loop, the robot has much lower success rate compared with having a human in the loop at any one segment of the task when the robot's perception is noisy. In terms of both efficiency and cognitive effort, the best placement for the human in this human-in-loop-system is in the approach to goal phase in which the participant specifies a general placement for the gripper, and the autonomous robotic system completes the rest of the task. Users reported feeling the best about participating in this strategy, and concrete results indicate that having the person participant in this phase will result in fewer collisions than other shared methods. There was no significant preference or efficiency benefits for the other strategies.

The initial study reveals that the fine positioning and picking is the most difficult part of the task for humans to carry out in both the time and the cognitive effort. Surprisingly, reducing the degrees of freedom for users to control doesn't reduce the cognitive effort, and the efficiency comparison is inconclusive.

Results from the second experiment indicate that allowing the user to make fine tuned adjustments to the position and orientation of the robotic hand can improve task success in high noise situations in which the autonomous robotic system might otherwise fail.

## 1.6 Thesis Outline

The thesis is outlined as followed: Chapter one provides the reader with an overview of the experiment. Chapter two gives an outline of previous work that serves as a foundation for this study.

Chapter three gives insight into the design of the initial human-in-the-loop experiment. This chapter is broken up into sections that define the system design, the experimental procedure used to gather data, the metrics used to measure success and participant involvement, the statistical methods used to analyze the data, and the experimental results.

Chapter four outlines the second human-in-the-loop experiment, and includes details about the system design, experimental procedure, metrics, and results.

Chapter five summarizes conclusions drawn from each experiment. This chapter also contains discussion about our findings and how they can be built on in the future.

# CHAPTER 2

# RELATED WORK

Many ideas have served as the basis for this work. This chapter presents major research findings in the areas of human-in-the-loop robotics, human-robot interaction, and previous participant studies in these fields.

## 2.1 Human-Robot Interaction

The field of Human-Robot Interaction describes research involving all types of human and robot collaboration. Due to the increasing usage and acceptance of robots in a number of different applications, this is a large field that impacts many different areas of study.

A natural place for robotic systems is in an industrial setting. Robots thrive in the structured, predictable environment that can be found in some manufacturing applications. However, work has been done to show that combining the strengths of the robotic system with the knowledge of human operators can lead to advances in manufacturing in certain conditions [10].

Robots and autonomous systems often struggle in unstructured environments in which the terrain and other conditions result in a dynamic conditions. In these scenarios, human guidance can often supplement the robot's sensor information to increase overall success. [11]. Improving the effectiveness of robotic systems in natural and varied environments has large implications in many areas of robotics.

With robots and humans working together, the issue of trust arises. In military applications, robotic systems are often used to increase the effectiveness of human based forces.

In these situations, the autonomous systems may have a direct impact on human safety. Studies have been conducted on systems like this to measure the levels of trust that the human operator places in the robotic system and can help with the development of future robotic systems [12]. This work also has implications in domestic areas. One study showed that different motion planning and approach techniques (such as a frontal approach or an approach from the side) made a big difference in how positively some domestic robots were percieved by seated humans in a domestic setting [13]. Another study describes a robotic system that uses the idea of intention expression to allow the robot to visually broadcast its intentions to nearby users. This study showed that participants viewed the system as reliable and trustworthy, and felt at ease with this system [14]. Humans often perceive robotic systems as being humanoid. This unconscious tendency to anthropomorphize robots has been studied, and it is possible that findings from these studies can be used to create robotic systems that are more likely to be accepted by humans [15]. Other studies have studied the way humans treat robots when working as a team. Humans often use gestures and phrases that would be meaningful to another human team member, but are lost on the robot. The study looks at these ideas and attempts to incorporate some of the human measures into the robotic system. The results indicated that the changes improved the communication between the human and the robotic system [16]. Being able to understand and incorporate human intention into a human-robot collaborative system has also been studied [17].

Humans can also interact with robotic systems to better improve functionality. One study describes a framework for robotic grasping that relies on human participants to demonstrate a grasp by picking up and manipulating an object. The grasping algorithm described in this paper can use the data from human participants to effectively teach the robotic system appropriate grasping techniques for various shapes and objects [18].

It is clear that the field of human-robot interaction is large and varied. As robotic systems improve, more and more uses for human and robot collaboration present themselves.

## 2.2 Human-in-the-Loop Robotic Systems

Numerous studies have looked at the significance of human-in-the-loop robotic systems. Some practical applications of the human-in-the-loop system are in the fields of rehabilitation and wheelchair robotic systems, and in assistive technologies [2] [19]. In both of these situations, the user and the robotic system must be involved to form a complete task, and it is not appropriate for the robotic system to be fully autonomous. Recently, work has been done to determine the best strategies for grasping in a human-in-the-loop system [6]. The study utilized teleoperation techniques to test the effectiveness of several human/robot shared control grasping strategies. They were able to determine that ultimately, strategies in which the autonomous segments played a larger role in the task were more successful.

## 2.3 Pick and Place Task

The picking-and-placing of an object are fundamental aspects of human motion [20], and are therefore natural choices for use as fundamental tasks for a robotic system. For this reason, they are a popular choice for use as a benchmark. Despite being the basis of many human tasks and motions, the pick and place task is not simple to define. The definition of the task relies heavily on the environment, the shape and style of the object being picked up, the constraints and restrictions of the gripper being used, and other characteristics of the robotic system.

Numerous studies have been performed using the pick-and-place task, and there are many opinions in literature regarding the segmentation of the pick-and-place task. Sanchez et al [21] break down the task into the following segments: selection of goal object from image space, calculating the distance between goal object and arm location, moving arm to object location, choosing pick position and grasper pose, grasping. For the task oriented approach found in [22], the authors chose the following steps: defining the task, analyzing the task and planning for motion of the arm, performing calculations for the actual motion of the arm, and choosing joint poses and gripper poses for completion of the task. Some studies include obstacle avoidance strategies in their segmentation evaluation [7], [23], [24]. Other authors include steps beyond grasping including relocation of the object and re-grasping strategies [25] [23].

Based on these studies, we chose to study a pick-and-place task in our experiments. We chose to segment the task in the following way: a coarse approach to the goal object, a fine tuning of the position of the robotic hand, a fine tuning of the orientation of the robotic hand, grasping, and relocation. We did not include grasping strategies or obstacle avoidance in our system.

### 2.4 Metrics

Choosing how to measure success in a human-robot interaction studies can be a challenge due to many factors. When looking at a collaborative task, components that must be considered include the environment in which the experiment is taking place, the navigational methods being used by the robot, whether or not obstacle avoidance is necessary, and the accuracy and efficiency of the robot. In a human-in-the-loop robotic system it is also important to take the human user's opinions and feelings into account. Measurements such as level of trust, engagement with robot, and cognitive load on the user can be useful for making judgments regarding the user's experience with the robotic system [26].

In one study attempting to classify the effectiveness of grasping scenarios in a human-in-the-loop system measures the success of the task (whether or not the object was actually picked up and moved), and major or minor collisions that occurred during grasping. To measure the human's contribution to the task, the authors of the study had participants fill out a NASA-TLX scale to measure the cognitive load of the participant, and a 5-pt Likert scale to measure the participant's experience (such as how easy, boring, or complicated the participant felt the task was) [6]. Other studies in the field of Human-Robot Interaction have also employed the NASA-TLX scale to measure the workload of the participant [27].

# CHAPTER 3

# INITIAL EXPERIMENT

## 3.1 System Design

In this chapter, we describe the process used for replacing segments of the pick-and-place task with human guided segments. The experiments designed in this section look to determine which segments of the autonomous pick-and-place task can lead to a performance improvement in overall task when substituted with human guided input.

For this initial experiment, we utilized a FANUC LR Mate 200iC robotic arm with six axes. The FANUC arm has been equipped with a BarrettHand three fingered programmable pick-and-place. The arm and hand combination can be seen in both figure 3.1 and figure 3.2. We wrote software for each testing strategy using Visual C++.

A Phantom OMNI haptic device was utilized as the user interface for controlling the arm and hand, although force feedback features were not implemented in this experiment. The OMNI device was chosen due to its compact design and intuitive positional abilities that make the device a good choice for the teleoperation of the robotic arm. Our experiment involves switching between human and robotic control, where the haptic feedback features of the OMNI would not be used. When mapping the Phantom OMNI's range of motion to the robotic arm system, care was taken to limit the arm's workspace so all allowable positions were safe and reachable without the potential to cause harm to the end effector, environment, or participant.

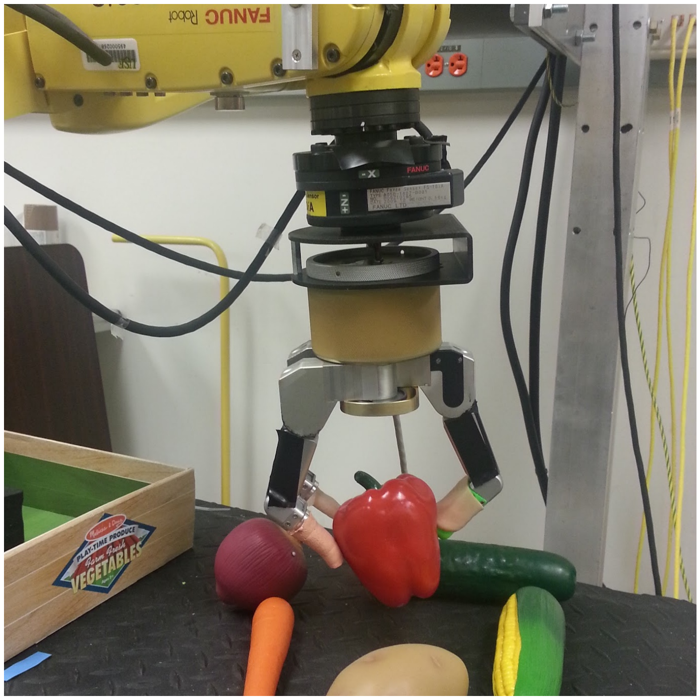


Figure 3.1: Fanuc LR Mate 200ic with BarrettHand attachment used in the first experiment. It is shown here grasping the goal object.

The FANUC arm and BarrettHand are connected to the same computer with the Phantom Omni. This configuration can be seen in figure 3.1. The manipulator is teleoperated at a position-based and unilateral mode, for which no force feedback is provided to the user. The OMNI stylus operates with a position control strategy. The positions and gimbal angles of the OMNI stylus are continuously transmitted to the PC server in real time. The workspace of the PHANTOM Omni is $160mm \times 120mm \times 70mm$, and the workspace of the robot arm is constrained to $144mm \times 60mm \times 108mm$. The dimensions of the OMNI's workspace are scaled so the robot will not collide with the environment when teleoperated by untrained subjects. The position and orientation of the OMNI stylus are thereby transformed to the corresponding position and orientation of the robot end-effector in its feasible workspace. We only allowed one degree of freedom for the orientation of the robotic hand. The robot arm and robotic hand incorporate their own motion controllers. The position commands are streamed from the PC server to the robot controller, so the manipulator is able to follow the OMNI motion in real time.

The experiment took place in a laboratory setting. Several objects were placed near each other on a flat, grippy surface within reach of the arm and hand. Children's play vegetables were chosen because they mimic real, everyday objects. Their irregular, natural, and non-constrained shapes make them desirable for a pick-and-place task. Objects were placed in the same position on the table for each trial. Participants sat at a table within visual range of the task environment, where they used the Phantom OMNI device to control the arm when necessary. Figure 3.2 depicts the environment used in the study. A complete pick-and-place task was considered to be an approach towards the goal object, grasping of the goal object, and relocation of the object to a defined area nearby. For safety, the speed of the robotic arm was constrained up to a feed rate of 30% of the maximum speed. Maximum speed for the FANUC arm for each of the six joints are as follows: J1: 350 degrees/s, J2: 350 degrees/s, J3: 400 degrees/s, J4: 450 degrees/s, J5: 450 degrees/s, and J6: 720 degrees/s. [28]

Six participants were recruited through local contacts and ranged in age from 21 to 38. There were three male participants and three female participants. Three of these participants were very familiar with the robotic system, one participant was somewhat familiar with the robotic system, and two participants were not at all familiar with the robotic system. Two participants were very familiar with the OMNI haptic device, two participants were somewhat familiar with the OMNI haptic device, and two participants were not at all familiar with the OMNI haptic device.

## 3.2 Experimental Procedure

We studied six pick-and-place scenarios in the first experiment. These scenarios are:

- Fully Autonomous
- Manual Control Using OMNI

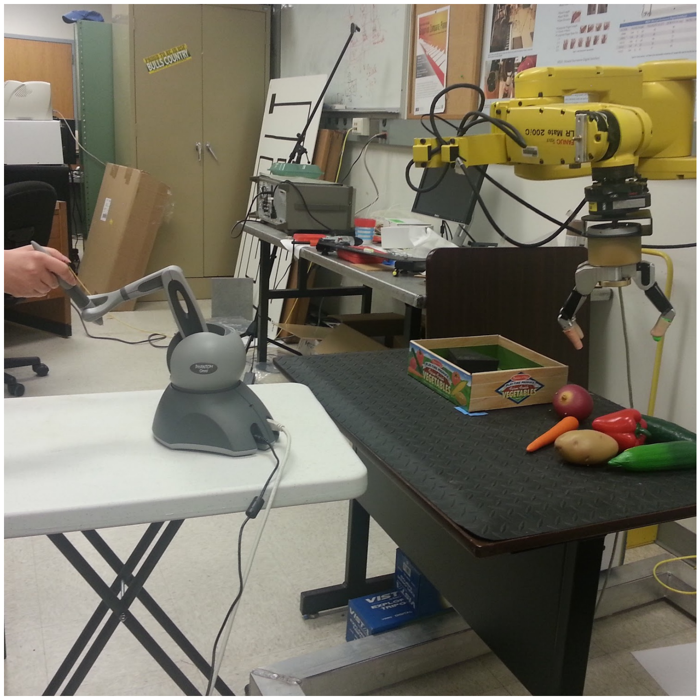

Figure 3.2: Environment used in the first experiment. The participant sat near the arm and controls actions using a Phantom OMNI haptic device.

- Human Controls the Coarse Approach to Object
- Human Controls the Position of the Robotic Hand
- Human Controls the Orientation of the Robotic Hand
- Human Controls both the Position and Orientation of the Robotic Hand

Each participant was asked to complete the pick-and-place task four times for each strategy (once per noise level), and fill out a portion of the questionnaire after each strategy. This took approximately 90 minutes per participant.

### 3.2.1 Fully Autonomous

To serve as a point of comparison in the study, the complete pick-and-place task was run 16 times autonomously. We chose to use the fully autonomous task as a baseline because it represents the most extreme end of the human-robot collaboration scale that we are looking to analyze. The autonomous task was completed using waypoints to guide the arm to the necessary positions, and the grasping pose was predetermined. Our system did not use external sensors to guide towards the goal object.

#### 3.2.1.1 Simulating Sensors Through Noise

To make our system seem more realistic, we simulated various levels of potential noise in the robot's perception. We added white Gaussian noise to the goal position and orientation of the robotic hand in relation to the goal object to give the impression of noise from a sensor. We used four randomly generated levels of white Gaussian noise, with each level corresponding to a rate of task failure. The first level, with a power of 1 dB, resulted in task failure 0% of the time, the second noise level, with power of 7 dB, resulted in failure 25% of the time, the third level, with a power of 20 dB, resulted in failure 75% of the time, and the fourth level, with a power of 25 dB, caused task failure nearly 100% of the time. The highest level of Gaussian noise for this system represents a very noisy sensor. Noise of any higher level risked positional errors sizable enough to potentially damage the BarrettHand. Four autonomous runs were completed using each level of noise.

### 3.2.2 Manual Control Using OMNI

Participants were used to test five of the six pick-and-place scenarios (the autonomous mode does not require human input). In this human-in-the-loop scenario we asked participants to complete a full pick-and-place task using a direct control strategy. The represents the other extreme case of the pick-and-place scenarios. The participants used the OMNI interface to guide the arm from a fixed starting position to the goal object, then to the final relocation area. One OMNI button was programmed to close or open the robotic hand when clicked. This experiment was run four times per participant.

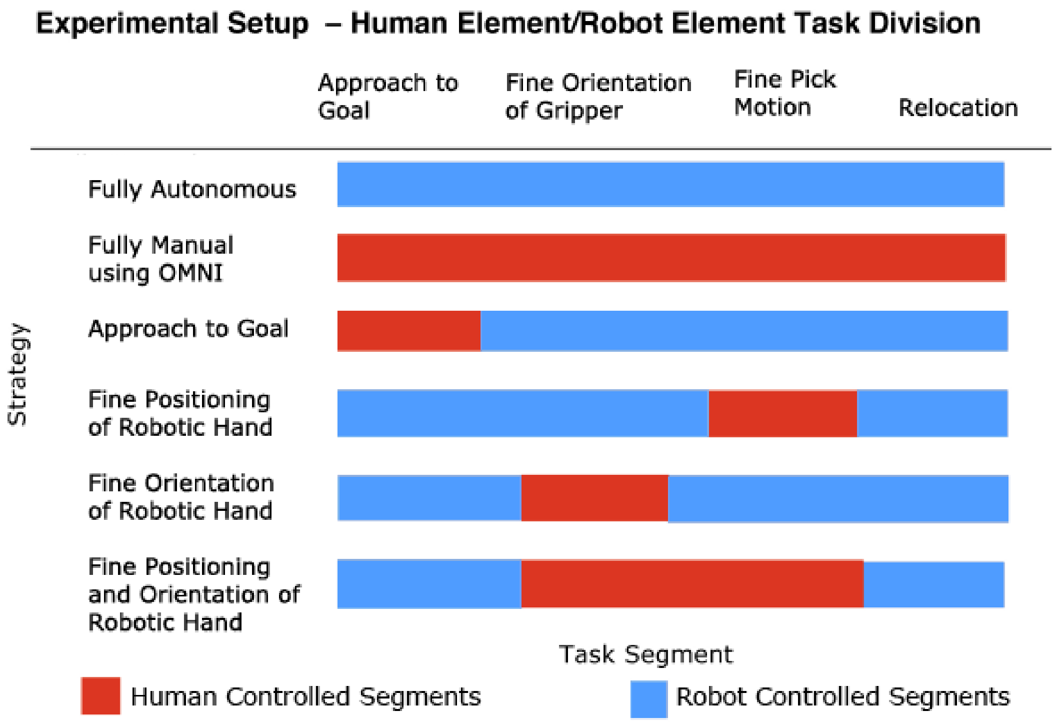


Figure 3.3: This figure depicts the level of collaboration for the pick-and-place task between the human input and the robotic system for each experimental strategy.

### 3.2.3 Human Controls the Coarse Approach to Object

The next human-in-the-loop scenario employed a shared control strategy that required participants to control the coarse approach toward the goal object. In this scenario, the participant used the OMNI device to drive the arm from the initial position to a position of their choosing near the top of the object without too much care for the precise orientation and fine tuned position of the robotic hand. The participant's coarse position was used as the initial position for an autonomous run. The two parts of the task were combined to form a full data set for the run. The "Coarse Approach" row seen in Figure 3.3 depicts the human/robotic system blend for this scenario. We ran this experiment four times with each participant, recording four total coarse positions from each participant. The total autonomous task was then completed four times for each participant recorded position - one time for each of the four noise levels. This resulted in ninety-six data points for this scenario.

### 3.2.4 Human Controls the Position of the Robotic Hand

In this human-in-the-loop scenario, the robot makes the coarse approach to the goal autonomously. The user then is able to control the fine positioning of the robotic hand in regards to the goal object, but not the orientation of the robotic hand. Once the participant is satisfied with the position of the robotic hand, they can click the OMNI button to close the robotic hand and trigger the autonomous completion of the task by the robotic system. The robotic system closes the robotic hand around the object and brings it to a predefined area. The human's role in this task can be seen in the "Human Controls Position" row in Figure 3.3. We ran this trial four times per participant, once for each of the four noise levels.

### 3.2.5 Human Controls the Orientation of the Robotic Hand

The next scenario is similar to the previous In this scenario, the robotic system autonomously performed both the coarse approach to the goal and the fine positioning of the robotic hand in relation to the object. The participant was then required to choose the appropriate orientation for the robotic hand. Once the participant is satisfied with their orientation selection, a button on the OMNI is pressed to signal the autonomous completion of the task. The grasping and relocation of the object was completed autonomously by the robotic system. The role of the human in this phase can be seen in the "Human Controls Orientation" row in Figure 3.3. This trial was run four times per participant, once for each noise level.

### 3.2.6 Human Controls both the Position and Orientation of the Robotic Hand

The last scenario was constructed similarly to the previous two scenarios, but required the participant to control both the fine position and orientation of the robotic hand before triggering the autonomous relocation of the object. The participant's role can be seen in the row labeled "Human Controls Pos. and Or." in Figure 3.3. We ran this trial four times for each participant, one trial for each noise level.

### 3.3 Metrics and Data Analysis

When determining what information would be relevant to the experiment, we were primarily interested in how well the task was completed during each scenario, and how mentally demanding each scenario was on the participant. To determine this, we measured the following metrics during the participant trials:

- Completion time: The time it takes to complete a full pick-and-place task from beginning to end, regardless of the success of the task, or if major or minor collisions occurred.
- Success of a task: We define a successful task as one that succeeds in approaching, grasping, and relocating the goal object in the designated area, regardless of collisions with other objects.
- Major collisions: A major collision is an event in which an object becomes displaced fully from its original position.
- Minor collisions: A minor collision is an event in which an object is touched or nudged without consequence.

We also had participants complete a questionnaire describing their experiences. We utilized a Likert scale to measure feelings such as perceived difficulty and boredom, and a NASA-TLX scale to measure the following self reported perceptions for each task:

- Mental demand
- Physical demand
- Temporal demand

- Performance
- Effort
- Frustration

For both the objective and self reported results, we used a one-way analysis of variance model (ANOVA) to determine the significance of relationships. For the analysis of efficiency, we not only count in the run time, but also add in half and quarter of the averaged run time as a penalty for major and minor collisions respectively and a half time penalty for not fully completing the task. The run times are weighted in this way to reflect the effects of collisions and task completion on overall task success. This relationship can be seen in equation 3.1, where E = the total efficiency score, r = run time for the task, s = the success of a task (with a value of 0 for a successful task and a 0 for an unsuccessful task), c = collisions (either a 0, 1, or 2, corresponding to no collisions, a minor collision, or a major collision), ps = the success penalty (value is the average run time of all trials divided by 2), and pc = the collision penalty (equal to the success penalty divided by 2).

$$E = r + s * ps + c * pc \tag{3.1}$$

A summary of the efficiency values calculated for each scenario can be seen in figure 3.9. After running the analysis, we looked at the mean values (M) for each run, and the p-values (p) for each relationship between the data sets. We used a threshold of 0.05 to determine the significance of a relationship. A threshold of 0.05 is a commonly used level of significance [29] that we chose to use for this experiment. If a p-value of a particular relationship among two of our tested scenarios was less than 0.05, we consider the two values to be significantly different.

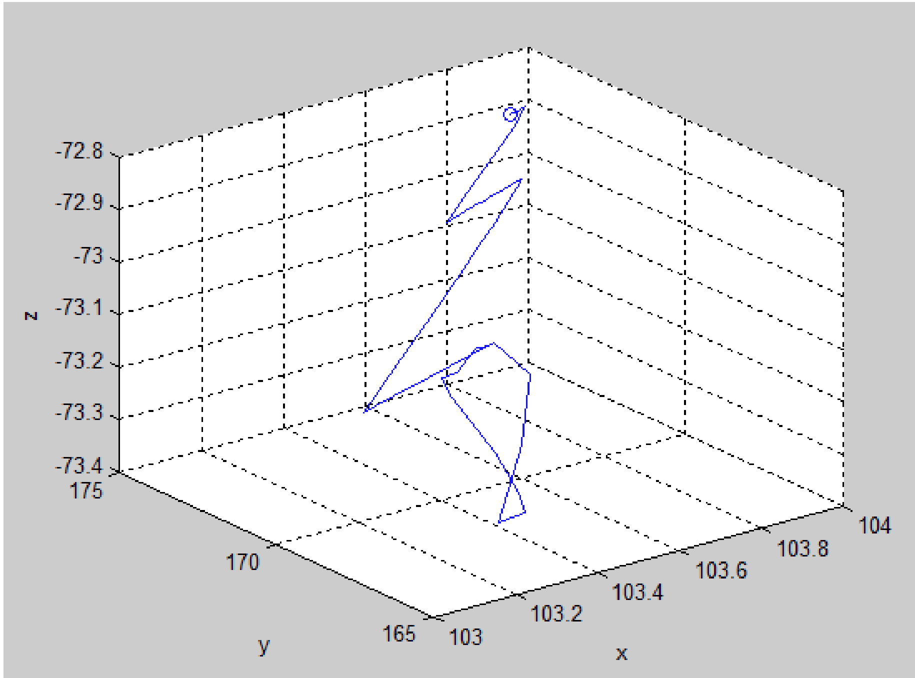

Figure 3.4: Motion data depicting the first few seconds of the transition between a robot controlled segment and a human guided segment. This data represents the participant's first time controlling this segment. We believe the zig-zag shape may indicate struggle and high cognitive load.

## 3.4 Experimental Results

This section outlines the results we have collected from our participant studies. We first look at results regarding the efficiency of each collaborative trial. This section includes an analysis of run time, task success rate, and major and minor collisions. The section outlines cognitive effort and includes an analysis of participant recorded data.

### 3.4.1 Participant Training

We did not train the participants prior to the beginning of testing. This may account for some inconsistencies with data, such as low success rates on most first trials despite low noise.

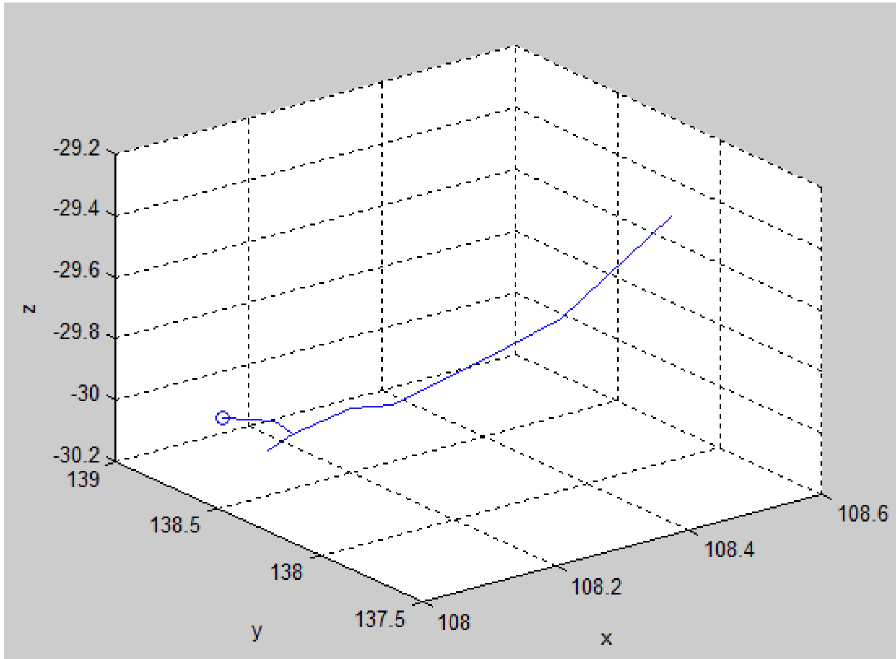

Figure 3.5: Motion data depicting the same transition between the robot and human guidance on the participant's third trial. The zig-zag pattern is much less noticeable, leading to the conclusion that training the participant before a trial begins can lead to lower levels of cognitive load.

Figures 3.4 and 3.5 represent motion data gathered during a trial from the initial experiment. Figure 3.4 depicts the first few seconds of the transition between a robot controlled segment and the user controlling FANUC robot with the Phantom OMNI. This is the person's first time controlling this segment of the task.

Figure 3.5 shows the same transitional data of the same participant on their third try controlling the same segment.

We believe that the zig zag pattern seen in figure 3.4 visually represents struggle and a state of higher cognitive load than in surrounding areas of the data. This transitional cost is most noticeable on the participant's first use of the system and are less noticeable on subsequent runs.

Because the patterns become less noticeable with increasing familiarity with the system, we believe that thoroughly training a participant on the use of the system can reduce the cognitive load and possible time costs associated with these transitional costs. Observations from the initial experiment indicate that training may lessen the transitional costs associated with switching between a robot controlled segment to a human controlled experiment.

### 3.4.2 Efficiency

#### 3.4.2.1 Fully Autonomous

We ran a full pick-and-place task using the fully autonomous system without participants for use as a benchmark. The results for these trials show a low run time compared to the human-in-the-loop strategies. Task success decreased steadily as noise level increased, and few collisions occurred. Human-in-the-loop scenarios were able to achieve higher success rates than the fully autonomous system in high noise situations, leading to a conclusion that having a human-in-the-loop will help achieve reliable success rates in systems with sensors that are not ideal.

#### 3.4.2.2 Human Controls the Coarse Approach to Object

Using the fully manual task controlled by the OMNI as a benchmark ($M=44.33$), the scenario utilizing the participant to control the approach towards the goal object then allowing the robot to complete the task ($M=16.58$) was much faster, $p<0.00$.

The manual coarse approach to the goal was faster than the scenario in which the human controlled the position of the robotic hand ($M=16.58$ and $M=35.38$), $p<0.01$, the scenario in which the human controlled the orientation of the robotic hand ($M=16.58$ and $M=30.46$), $p<0.00$, and the scenario in which the human controlled both position and orientation ($M=16.58$ and $M=30.27$), $p<0.00$.

This strategy seemed to result in similar collision rates to the fully automatic approach. Major collisions occurred during this strategy only when major noise was present. Task success for this strategy was also dependent on noise. Since the majority of this task was

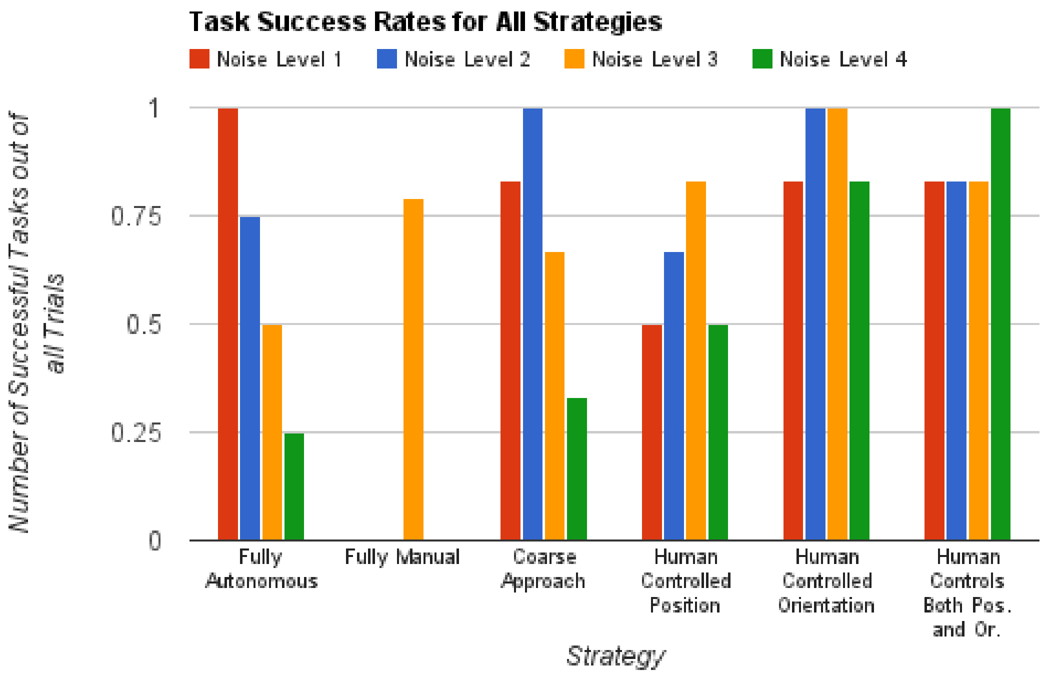


Figure 3.6: This chart depicts the task completion rates for all scenarios in the first experiment. A complete task includes a success approach, grasp, and relocation of an object, regardless of collisions. The figure shows completion rates for the fully autonomous mode, fully manual scenario using OMNI, and the four other human-in-the-loop control scenarios. All scenarios except the fully manual scenario using OMNI were tested using various noise levels to simulate potential noise in sensors.

under control of the robotic system, task completion results are similar to the autonomous task runs. This trend can be seen in Figure 3.6. However, since the robotic hand is much closer to the object, if there is a sensor mounted on the robotic wrist, the robot should have less perception noise, which may result in better performance.

#### 3.4.2.3 Human Controls the Position of the Robotic Hand

The scenario in which the human controlled the position of the robotic hand (M=35.38) was accomplished faster than the fully manual scenario (M=44.33), $p<0.01$.

The human controlling the position of the robotic hand scenario appeared to result in the fewest successful grasps, with noise level not playing a large role. This scenario resulted in more minor collisions and major collisions than the human controlling the coarse approach to object scenario. Major and minor collisions can be seen in Figures 3.7 and 3.8. The increase in collisions could be due to the robot choosing an incorrect orientation for the hand, and the human not being able to correct it. However, if the perception sensor on the robot is more accurate in measuring orientation than position, this approach might result in fewer grasping errors.

#### 3.4.2.4 Human Controls the Orientation of the Robotic Hand

The scenario in which the human controls the orientation of the robotic hand (M=30.45) yielded faster completion times than the fully manual scenario in which the user controls all aspects of the task (M=44.33), $p<0.00$.

This scenario resulted in a higher number of successful grasps than both the fully autonomous scenario and the fully manual scenario, but also resulted in a higher minor collision rate and a higher major collision rate than the fully autonomous scenario and the fully manual scenario. The high number of successful grasps in this scenario could be due to the goal object (a toy bell pepper) being tolerant of a wide range of orientations.

#### 3.4.2.5 Human Controls both the Position and Orientation of the Robotic Hand

The scenario in which the user was allowed to control both the position and orientation of the robotic hand (M=30.27) was completed faster than the fully manual scenario (M=44.33), $p<0.00$.

Similar to the human controlled position scenario, allowing the user to control both the position and the orientation of the robotic hand resulted in a higher number of successful grasps than the fully autonomous scenario and the fully manual scenario. This scenario also resulted in fewer major and fewer minor collisions than the human controlled orientation scenario. However, the frequency of both types of collisions were greater during this scenario than the coarse approach to object scenario. These trends can be seen in Figures 3.7 and 3.8.

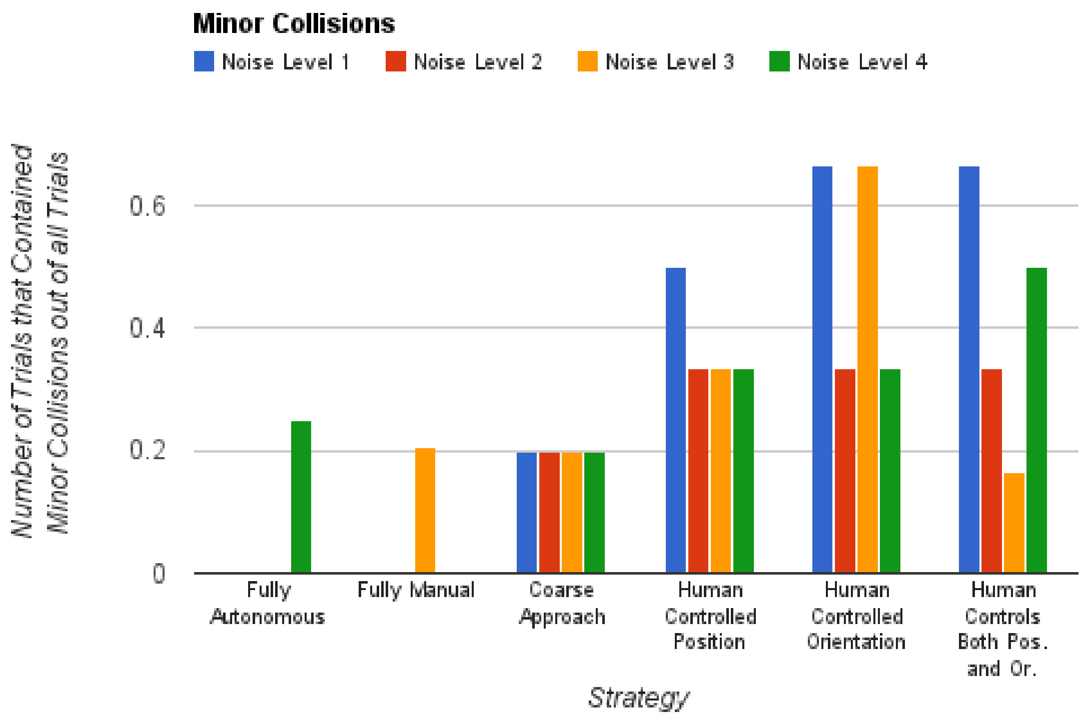


Figure 3.7: This figure displays the frequency of occurrence of a trial containing minor collisions out of all trials for all four human-in-the-loop control scenarios plus the fully autonomous and fully manually driven scenarios for comparison. A minor collision was noted without regard to the actual completion of the task. All four noise levels are represented.

#### 3.4.2.6 No Penalty for Collisions

If we consider the situation in which collisions are not important to the task, another significant relationship can be uncovered. The scenario in which the robot controls the orientation of the robotic hand (M=30.59) was completed faster than the scenario in which the robot controls only the position of the pick-and-place (M=24.61) with a p value of $p<0.02$.

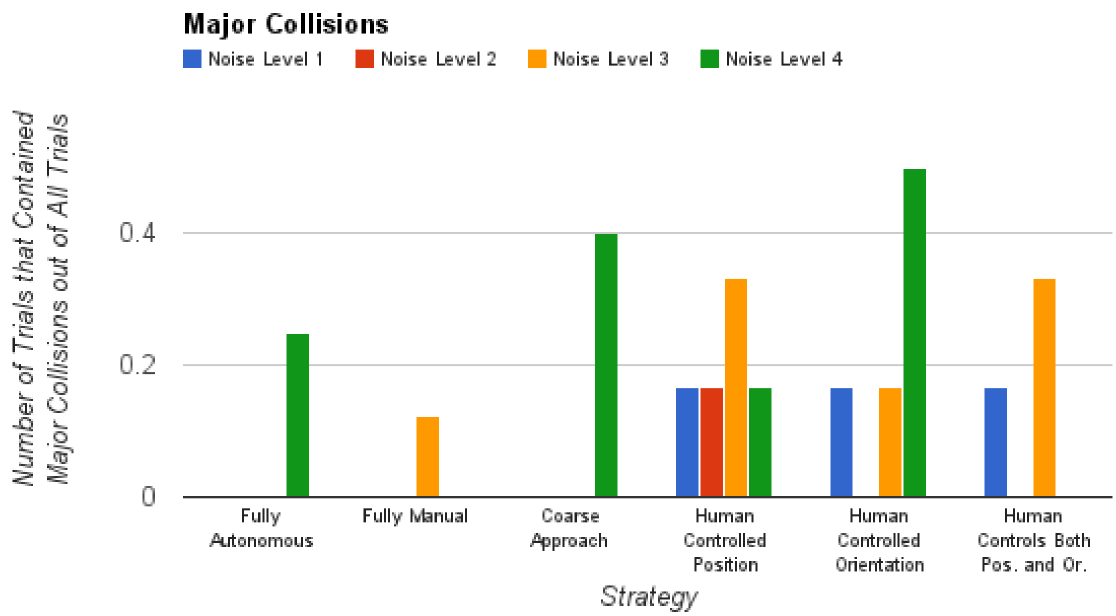


Figure 3.8: Trials containing major collisions with objects in the environment compared to all trials of a certain scenario are represented in this graph. A major collision is considered to be a collision that fully displaces one or more surrounding objects regardless of task success. All four human-in-the-loop scenarios are represented along with their corresponding noise levels, as well as the full autonomous and fully manually driven control scenarios for a benchmark.

#### 3.4.2.7 Summary

To summarize efficiency results, using the participant to control the coarse approach to the object resulted in the fastest completion times when compared to the fully manual task controlled by participant using the OMNI. Since this scenario depends a great deal on the autonomous robotic system, task success rate and frequency of major and minor collisions closely resemble the results from the fully autonomous task and are dependent on the accuracy of the robotic system. Trials using noise level 1 were often less successful and more created collisions than other noise levels within the same scenario, contrary to expected results. We believe this may be caused by the participant's lack of familiarity with the OMNI controller and may also have to do with these trials being performed first. A summary of efficiency results can be seen in Table 3.1.

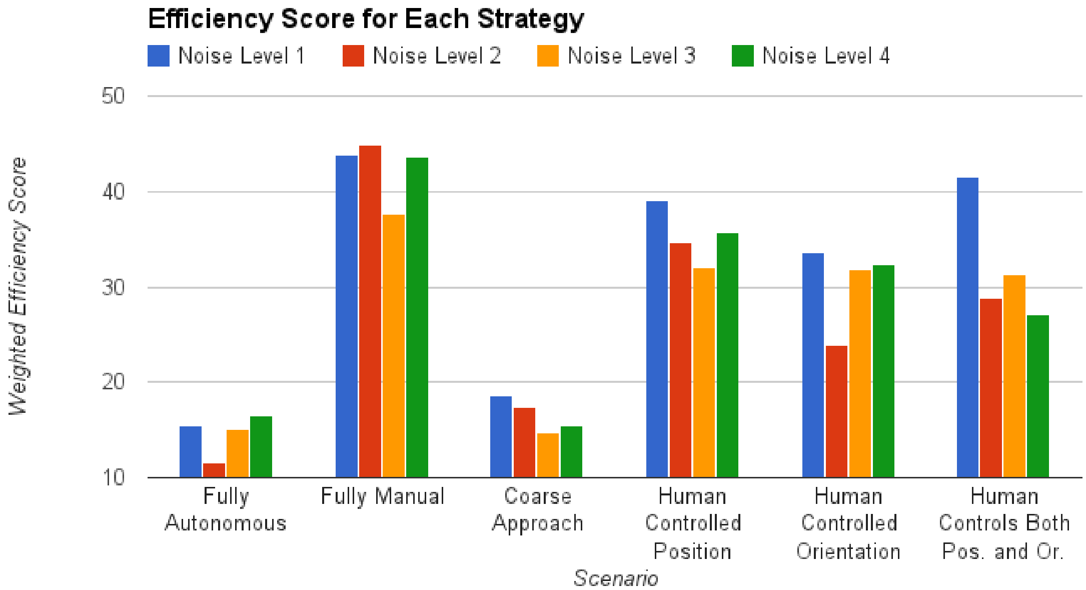


Figure 3.9: Summary of efficiency scores for each scenario and noise level. The efficiency score was calculated using equation 3.1.

### 3.4.3 Cognitive Effort

Participants felt that controlling the task manually using the OMNI (M= 3.00) was more tedious than both the manual approach towards object scenario (M= 1.50) and the strategy in which the human controlled the orientation of the robotic hand(M=2.00), $p<0.00$ and $p<0.03$ respectively. The fully manual task (M=3.50) was also considered to be more difficult than the coarse approach towards object (M=1.00), $p<0.00$, and more difficult than having the human controlled orientation of the robotic hand (M=2.17), $p<0.05$. The fully manual scenario (M=11.50) was considered to be harder to accomplish than the scenario in which the human controlled the orientation of the robotic hand (M=4.83), $p<0.01$.

Results were inconclusive regarding how boring or engaging a scenario was, as well as perceptions of physical demand and temporal demand on the user.

Table 3.1: Efficiency summary for all strategies and noise levels for the first experiment.

| Strategy | Mean | Major and Minor Collisions | Success Rate |
|---|---|---|---|
| Autonomous Task | 11.50 | 0.06/0.06 | 0.63 |
| Fully Manual using OMNI | 44.33 | 0.12/0.20 | 0.65 |
| Human Makes Coarse Approach to Goal | 16.58 | 0.10/0.20 | 0.70 |
| Human Controls Position | 35.38 | 0.20/0.37 | 0.62 |
| Human Controls Orientation | 30.45 | 0.20/0.49 | 0.90 |
| Human Controls Position and Orientation | 30.27 | 0.11/0.41 | 0.87 |

#### 3.4.3.1 Coarse Approach to Goal

Manually controlling the approach towards the goal object (M=1.00) was considered to be simpler than scenarios in which the human controlled the position of the robotic hand (M=2.67), $p<0.00$, scenarios in which the human controlled the orientation of the robotic hand (M=2.17), $p<0.03$, and scenarios in which the participant controlled both the position and orientation of the robotic hand (M=2.67), $p<0.02$.

Users felt that the coarse approach towards the object was more straightforward (M=1.00) than the fully manual scenario (M=2.50), $p<0.02$, the scenario in which the human controlled the position of the robotic hand (M=1.50), $p<0.05$, and the scenario in which the human controlled the orientation of the robotic hand (M=1.50), $p<0.05$.

Participants felt more successful in completing the task using the coarse approach to object scenario (M=1.67) when compared to the fully manual scenario (M=8.17), $p<0.02$, the human controlling the position of the robotic hand (M=8.00), $p<0.01$, and the scenario in which the participant controlled both the position and orientation of the robotic hand (M=7.83), $p<0.04$.

The manual approach towards the goal object was considered to be less frustrating than the fully manual scenario (M= 2.33 and M= 10.83), $p<0.02$, less effort than the fully manual scenario (M=4.17 and M=11.50), $p<0.03$, and less mentally demanding than the fully manual scenario (M=3.67 and M=10.17), $p<0.03$.

In summary, participants responded best to controlling the approach to the object, feeling that it was the least frustrating, least mentally demanding, most simple, and more straightforward than the other strategies. Users also felt like they were the most successful when using this strategy.

# CHAPTER 4

# SECOND EXPERIMENT

The initial experiment served as a way to test our experimental procedure and come to some preliminary determinations regarding the best placement for the human in our collaborative robotic system. We chose to conduct a second experiment to incorporate some of the feedback we received and some of the lessons we learned from the initial experiment. The initial experiment involved a simple robotic system conducting a simple task. For the second experiment, we chose to incorporate a new user controlled input device and an Xbox Kinect sensor into the robotic system, allowing us to implement more realistic pick and place task. We also made some improvements to the questionnaire we provide to the participants, and adjusted our methods for measuring success. The changes provide the second study with more complexity and will lend credibility to results and conclusions.

## 4.1 System Design

For the second experiment, we continued to utilize the FANUC LR Mate 200iC robotic arm with six axes as well as the three fingered BarrettHand attachment. Based on feedback from participants during the previous experiment, we decided to use a 3Dconnexion Space-Navigator instead of the Phantom OMNI used in the initial experiment as an input device for the human controlled portions of the task. The SpaceNavigator is a 3D joystick that can move with six degrees of freedom. The SpaceNavigator functions more like a traditional joystick than the OMNI, something that participants may be more familiar with. Unlike the OMNI, which used a position control strategy, the SpaceNavigator utilizes a velocity control


Figure 4.1: 3Dconnexion SpaceNavigator 3D mouse used in the second experiment.

strategy. To map the results from the SpaceNavigator to the robotic arm, we determined value passed from the SpaceNavigator, adjusted it to fit within a safe number boundary, and allowed the value to increment the current value of the robotic joint. The SpaceNavigator can be seen in figure 4.1. A program was designed to capture the positional, rotational, and button outputs from the SpaceNavigator and write them to a file. The robot system control software was configured to accept these values from the file and use them to adjust the position of the arm.

In the initial experiment, the autonomous portions of the task execution was accomplished using predetermined way points. No sensor information was used to sense the position of the goal object or to calculate an appropriate grasping strategy. To improve upon this in our second experiment, we utilized an Xbox Kinect to visualize the environment and determine the position and orientation for the objects in the environment. As in the first experiment, only one degree of freedom was used for adjusting the orientation of the robotic hand. The robotic arm and hand configuration we used can be seen in figure 4.4.

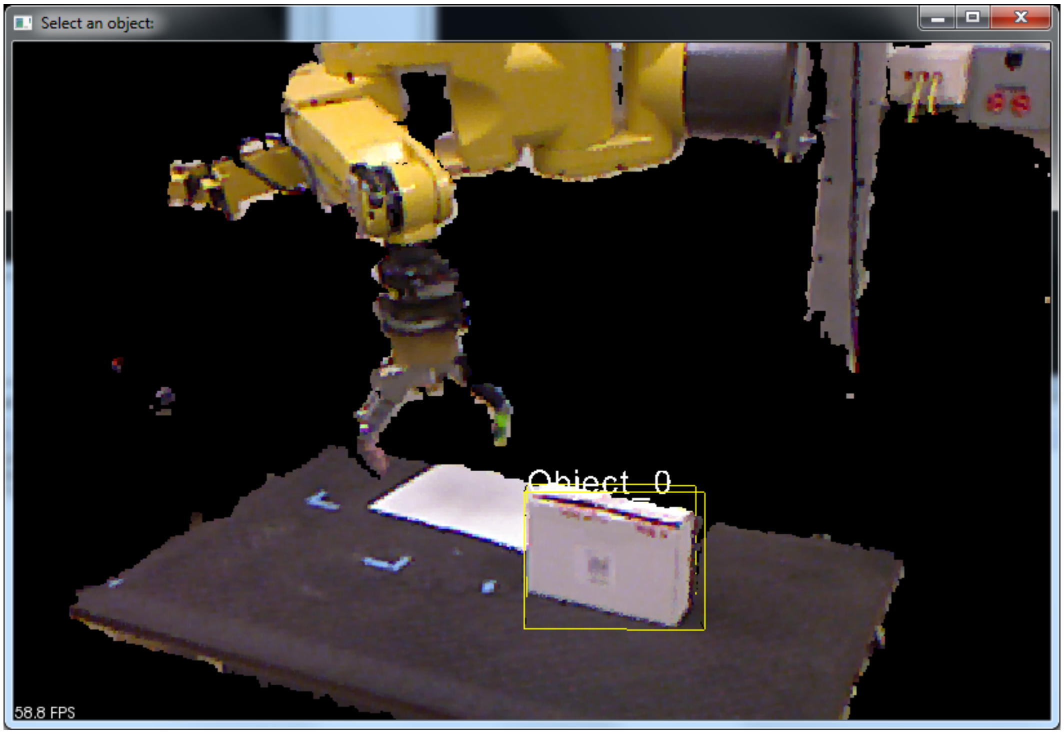

Figure 4.2: An example of the view of the testing environment as shown by the Kinect sensor. The size, location, and pose of the objects are determined by fitting superquadratics to the 3D point cloud generated by the Kinect. This allows the objects in the scene to be "discovered" and their positional and rotational characteristics to be determined.

### 4.1.1 Kinect Object Detection and Calibration

For the experiment, we used an Xbox Kinect as a vision sensor for our robotic system. We used methods outlined by the authors in [30] to acquire the position and pose of objects in the workspace environment. The techniques used allowed for the rapid processing of shapes from the 3D point cloud data generated by the Kinect camera. A voxelization strategy is used to fit superquadratics to the 3D point cloud, allowing for the estimation of the size, shape, and pose of any objects in the cloud to be estimated [30]. An example of the Kinect sensor outputs can be seen in figure 4.2.

To determine the position of the goal object relative to the robot's coordinate frame from the information generated by the Kinect software, we utilized transformation techniques from [31] to transform the coordinates of the object as seen by the Kinect to coordinates that can

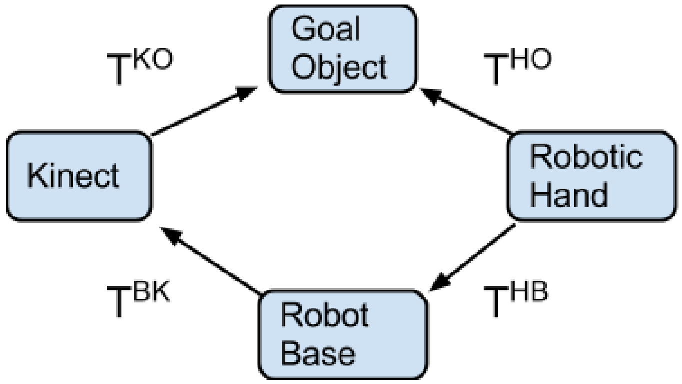

Figure 4.3: Diagram demonstrating the coordinate frame transformation between the Kinect, goal object, the robotic hand, and the robot base. More detail regarding this diagram can be seen in equation 4.1.

be used by the FANUC robotic arm controller. We collected the position and orientation of an object several times from the perspective of the Kinect sensor. We also collected the robotic hand's position and orientation corresponding to the object for each data set. Using this information we were able to construct a transformation matrix to map the position and orientation of the object the Kinect sensor frame to the robot's coordinate frame [31]. We completed a similar calculation to transform the coordinates and pose of the object from the robot's base to the end effector coordinate frame. This relationship can be seen in figure 4.3 and is described in equation 4.1, where $T^{HO}$= transformation from the robotic hand to the goal object, $T^{HB}$= transformation from the robotic hand to the robot base, $T^{BK}$= transformation for the robot base to the Kinect, and $T^{KO}$= the transformation from the Kinect to the goal object.

$$T^{HO} = T^{HB}T^{BK}T^{KO} \tag{4.1}$$

### 4.1.2 Pick and Place Task and Segmentation

We continued to use the pick and place task for the second experiment, and split the task up in a similar way. We consider a complete pick and place task to consist of an approach to the approximate location of the goal object, a fine tuning of the hand's position and orientation, grasp, and relocation.

### 4.1.3 Environment

The environment in which the experiment took place was in a lab setting. Three objects (a ball, a box, and a cup) were placed on the same flat, grippy workspace table as used in the initial experiment placed near the FANUC robotic arm. This setup can be seen in figure 4.4. These objects were chosen because they are common shapes and could realistically be found in most typical settings. Their various shapes also present different grasping challenges for the robotic system. Even though the robotic system being used in this experiment includes a Kinect camera to determine the position and orientation of the objects, the objects were placed in roughly the same place for each experiment to keep trials consistent. The Kinect sensor was mounted on a tripod and placed nearby, overlooking the table and the robotic arm. The participant was seated with the SpaceNavigator input device within visual range of the table and faced the objects from a similar angle as the Kinect sensor. As in the first experiment, the workspace of the robotic arm is constrained to $144mm \times 60mm \times 108mm$ to ensure that the robot would not collide with the environment when operated by untrained participants. The speed of the robot was lowered to 5% of it's maximum speed as well to ensure safety. The speed was lowered from the first experiment to decrease the likelihood of damming collisions with the environment. This speed was held constant across all testing strategies to maintain consistency.

### 4.1.4 Kinect Sensor Noise

In the initial experiment, we ran trials at various levels of Gaussian noise on the position of the goal object in an effort to simulate the success rate of various sensors. We did this to expand the experiment and make it applicable to more general robotic systems and

Figure 4.4: Environment used in second experiment. The FANUC LR MATE 200ic robotic arm was fitted with BarrettHand attachment. Three objects were placed on the table, and the Kinect sensor was positioned in such a way as to fully view the scene. The participant sat near the Kinect with the SpaceNavigator controller in order to see the environment from a similar angle to the Kinect.

configurations, and not limited to our own robotic system. For the second experiment, we chose to utilize the Kinect sensor in combination with various objects in the environment. Due to limitations in the image processing software we utilized in the experiment, we were able to make accurate estimates of object position for certain shapes, while other shapes were not as accurately modeled. We chose three objects to represent various success levels in our tests. Several autonomous tasks were run to determine the accuracy of these three objects. When the autonomous task was run using a rubber ball as a goal object, our system was able to successfully complete the task 90% of the time, major collisions occurred 0% of the time, and minor collisions occurred 20% of the time. When run using a small cardboard box, the task was completed 100% of the time, major collisions occurred 10% of the time,

Table 4.1: Error distribution for the Kinect sensor in terms of object position and orientation

| | Ball | Box | Cup |
|---|---|---|---|
| X | Mean=1.245<br>stdev=0.002 | Mean=1.289<br>stdev=0.003 | Mean=1.284<br>stdev=0.005 |
| Y | Mean=0.079<br>stdev=0.001 | Mean=-0.016<br>stdev=0.001 | Mean=0.062<br>stdev=0.001 |
| Z | Mean=-0.226<br>stdev=0.001 | Mean=-0.211<br>stdev=0.002 | Mean=-0.196<br>stdev=0.002 |
| Yaw | Mean=2.389<br>stdev=2.086 | Mean=3.000<br>stdev=1.113 | Mean=6.164<br>stdev=2.452 |
| Pitch | Mean=0.028<br>stdev=0.724 | Mean=-1.676<br>stdev=1.456 | Mean=-0.330<br>stdev=0.335 |
| Roll | Mean=-0.494<br>stdev=1.159 | Mean=0.297<br>stdev=1.659 | Mean=-0.318<br>stdev=1.673 |

and minor collisions occurred during 30% of the trials. When the autonomous mode was tested using a plastic drinking cup, the task was completed only 50% of the time, major collisions occurred 50% of the time, and minor collisions occurred 10% of the time.

Table 4.1 shows the error distribution in terms of position and orientation for the Kinect sensor. We took ten samples of data from the Kinect for each object. The object was not moved between each sample. We then took the mean and standard deviation of the results, to indicate how consistent the Kinect is at estimating the position and orientation of each object. This data tells us that the Kinect sensor is fairly consistent in reporting position data from trial to trial. The orientation data is less consistent. Even though the Kinect sensor can consistently provide data, this does not reflect on any errors in calibration that may ultimately effect the position of the hand in terms of the goal object. The shape of the goal object can also influence success, as a shape, such as a sphere, may be more tolerant to small errors in position or orientation than another shape, such as a cup or rectangular box.

### 4.2 Experimental Procedure

This section describes the procedures used for this experiment. We tested six human-robot collaborative scenarios, each consisting of a full pick and place task. The scenarios we investigated are as follows:

- Fully Autonomous
- Manual Control Using SpaceNavigator
- Human Controls the Coarse Approach to Object
- Human Controls the Position of the Robotic Hand
- Human Controls the Orientation of the Robotic Hand
- Human Controls both the Position and Orientation of the Robotic Hand

With the exception of the coarse approximation to the object scenario, the human participant is responsible for the relocation of the object in each case. This is a change from the first experiment, in which the robotic system completed the relocation of the object. We do not believe this makes a difference in the overall results from the two experiments.

The participants were asked to complete each scenario a total of three times (one trial per goal object). The ordering of the scenarios was randomized from participant to participant. Once the participant had completed all scenarios, they were asked to fill out the questionnaire. This took approximately 60 minutes per participant.

Ten participants were recruited for the second experiment. They ranged in age from 22 - 38. Six of these participants were males and four were females. Five participants considered themselves to be not familiar at all with the robotic system, two considered themselves to be slightly familiar with the robotic system, and three considered themselves to be very familiar with the robotic system.

### 4.2.1 Fully Autonomous

To serve as a point of comparison, we had the robot complete the pick and place task using the autonomous program using the Kinect as a sensor for determining the position of the goal object. As in the initial experiment, we record data from the autonomous task because it represents an extreme case of our human-robot collaborative task that we are analyzing in this experiment. We ran the autonomous mode a total of 30 times, 10 times for each of the three testing objects.

### 4.2.2 Manual Control Using SpaceNavigator

In this scenario participants were asked to control the robotic arm using the SpaceNavigator to complete the full pick and place task from beginning to end. The SpaceNavigator buttons had been programmed to correspond to the closing and opening of the robotic hand. This experiment was run three times per participant, once for each of the goal objects.

### 4.2.3 Human Controls the Coarse Approach to Object

We asked participants to control the coarse approach to the object in this scenario.The participant used the SpaceNavigator to direct the arm and robotic hand to a rough approximation of the location of the goal object. The participant then clicked a button on the SpaceNavigator, which triggered the robotic system to complete the task by using data gathered from the Kinect to approximate the fine position of the object and the fine orientation required by the robotic hand, grasp the item, and relocate. This test was run three times per participant, once for each goal object.

### 4.2.4 Human Controls the Position of the Robotic Hand

This scenario begins with the robotic system using data gathered from the Kinect to make the coarse motion toward the goal object. The robotic system also makes a determination on the correct orientation of the robotic hand for grasping the goal object. The participant then takes over control of the arm and hand to choose the fine position for grasping. In this case, the participant is unable to physically change the robotic hand from the chosen orientation. Once the desired position is chosen, the participant closed the robotic hand and relocated the object. Each participant completed this scenario three times, once for each goal object.

### 4.2.5 Human Controls the Orientation of Hand

Similar to the previous scenario, the robotic system autonomously completes the coarse movements toward the goal object using Kinect inputs. This time the system chooses a fine tuned position for grasping the item and moves the robotic hand to this point. The participant can then adjust the orientation of the robotic hand to better facilitate the grasp or to attempt to prevent collisions with other objects in the environment. Once the participant was satisfied with the orientation of the robotic hand, they grasped and relocated the object. This scenario was run three times, once for each goal object.

### 4.2.6 Human Controls Both the Position and Orientation of the Robotic Hand

The final test scenario also begins with the robotic system autonomously completing the coarse motion towards the goal object using position information gathered from the Kinect sensor. The participant then took over control of the system, choosing both the fine tuned position and the orientation of the robotic hand. Once the participant felt satisfied with their choices, they grasped and relocated the object. As with the other scenarios, this one was completed three times, once per goal object.

#### 4.2.7 Training

To avoid the potential for some of the errors seen in the initial experiment (such as low success rates on trials with low noise due to the participant not be familiar with the system during the first trial), the participants were briefly trained on the system before testing took place. Observations from the initial experiment indicate that training would lessen the transitional costs associated with switching between a robot controlled segment to a human controlled segment. We believe that thoroughly training a participant on the use of the system before the testing begins can reduce the cognitive load and possible time costs associated with these transitional costs. Based on these findings, incorporating training into the experiment may also lead to the generation of cleaner data. To further decrease the likelihood of false data, the order in which the trials were completed by the participant was also be randomized.

Contrary to the first experiment, we allowed participants to become comfortable with the robotic system and the SpaceNavigator input device. We did this both to obtain consistent data and to observe the transitional period between a robot controlled task segment and a human controlled task segment. Figure 4.5 shows the robot's position in the first few seconds of the trial in which the user controls only the position and orientation of the hand. This is the user's first time controlling the robot for this task.

Figure 4.6 depicts the transition between the robot and human during the same participant's third time controlling the same testing scenario. In this case, we can see that he position of the robot varies less and is less erratic than in the first trial. The analysis of other participants showed a similar trend between the first and third attempts at the scenario. This leads us to believe that training and experience with the system results in lower cognitive stress and transitional costs. We concluded participant training after three trials, as this number of trials generally resulted in improvement in the zig-zag motion shape. Any more training would take too much time and put too much strain on the participant.

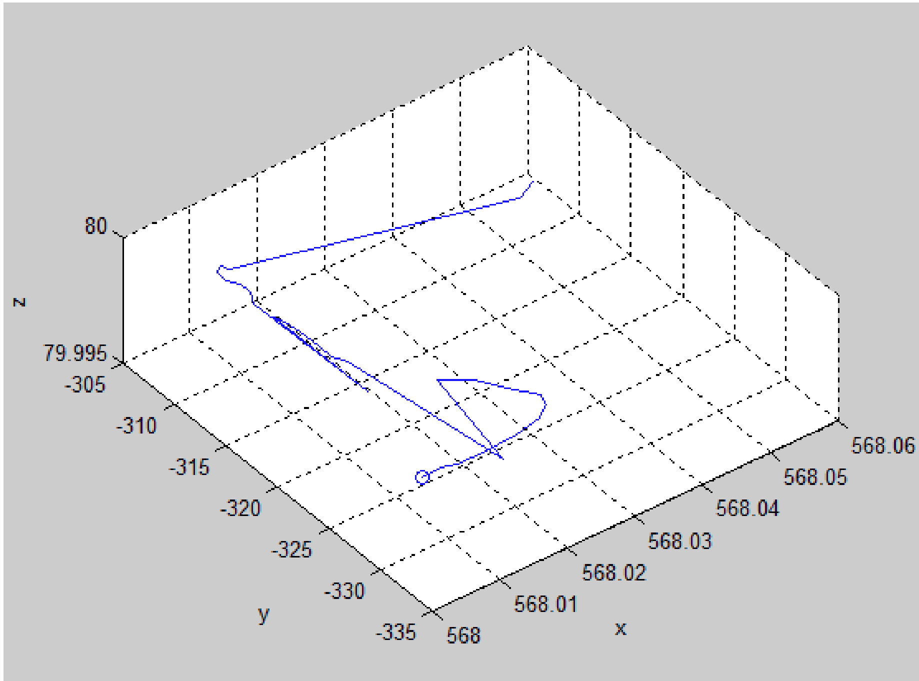


Figure 4.5: Motion data depicting the first few seconds of the transition between a robot controlled segment and a human guided segment in the second experiment. This data represents the participant's first time controlling the robot in this scenario. We believe the zig-zag shape may indicate struggle and high cognitive load.

### 4.3 Metrics and Data Analysis

As in the initial experiment, we collected data that reflects both how well the task was completed and how demanding the task was on the participant. To determine this we measured the following metrics during the participant trials:

- Completion time: The time it takes to complete a full pick and place task from beginning to end, regardless of the success of the task, or if major or minor collisions occurred.

- Task Failures: A task that does not succeed in approaching, grasping, and relocating the goal object in the designated area, regardless of collisions with other objects.

- Major collision: An event in which an object becomes displaced fully from its original position.

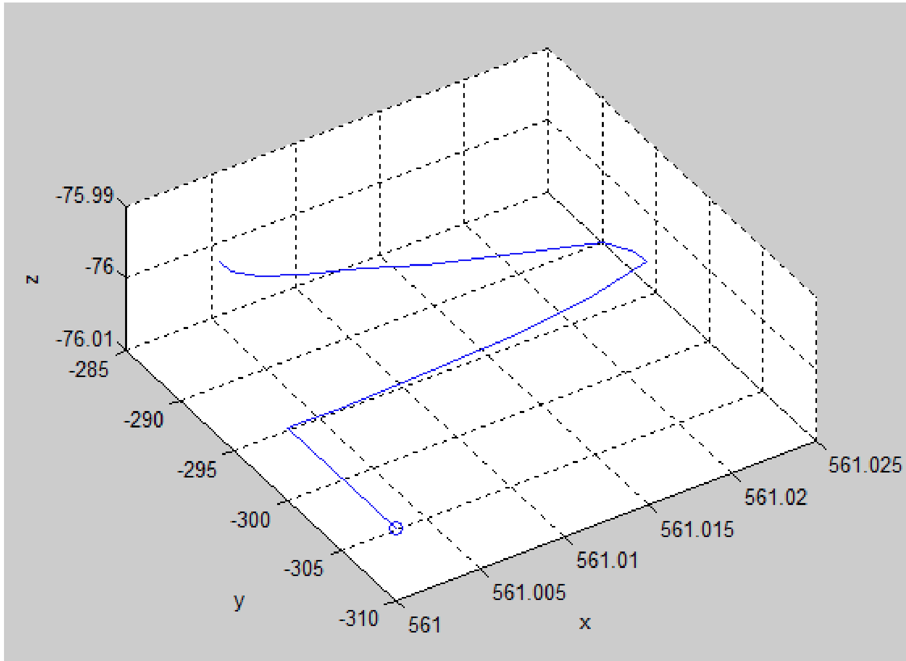

Figure 4.6: Motion data depicting the same transition between the robot and human guidance on the participant's third trial during the second experiment. The zig-zag pattern is much less noticeable in this figure than in figure 4.5, leading to the conclusion that training the participant before a trial begins can lead to lower levels of cognitive load.

- Minor collision: An event in which an object is touched or nudged without consequence.

We also had participants complete a questionnaire describing their experiences. In the second experiment we modified the Likert and NASA-TLX scales to cause less confusion and ask questions more relevant to the test scenarios. We measured the following self reported perceptions for each task:

- Mental demand
- Performance
- Effort
- Frustration

For both the objective and self reported results, we used a one-way analysis of variance model (ANOVA) to determine the significance of relationships. In order to better judge the success of a task, we use a weighted combination of run time, major and minor collisions, and task failure to come up with a number that represents the success score of each task. For the analysis of efficiency, we start with the run time, add in half or quarter of the averaged run time as a penalty for major and minor collisions and a half time penalty for not fully completing the task. We compare these success scores to each other to determine whether or not a particular scenario is more successful than another. This relationship can be seen in equation 4.2, where E = the total efficiency score, r = run time for the task, s = the success of a task (with a value of 0 for a successful task and a 0 for an unsuccessful task), c = collisions (either a 0, 1, or 2, corresponding to no collisions, a minor collision, or a major collision), ps = the success penalty (value is the average run time of all trials divided by 2), and pc = the collision penalty (equal to the success penalty divided by 2).

$$E = r + s * ps + c * pc \tag{4.2}$$

After running the analysis, we looked at the mean values (M) for each run, and the p-values (p) for each relationship between the data sets. We used a threshold of 0.05 to determine the significance of a relationship. A threshold of 0.05 is a commonly used level of significance [29] that we chose to use for this experiment. If a p-value of a particular relationship among two of our tested scenarios was less than 0.05, we consider the two values to be significantly different.

### 4.4 Experimental Results

This section outlines both the efficiency results and the user reported results from the second experiment.

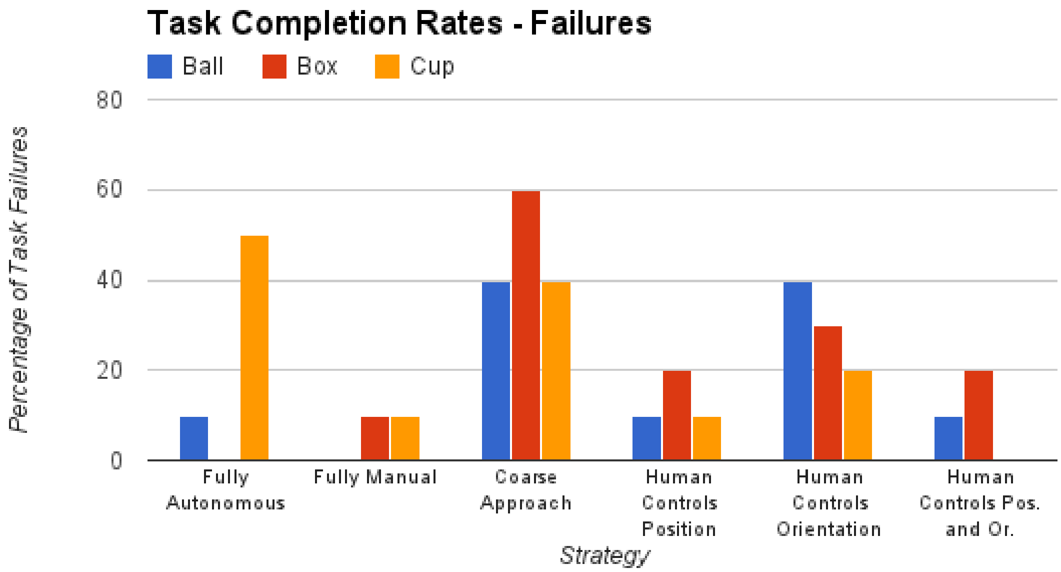


Figure 4.7: Chart showing task failure rates for all scenarios and object types. Task completion is measured without regards for collisions.

### 4.4.1 Efficiency

Using the measure of success described in section 4.3, we found that the scenario in which the participant controlled the task manually using the SpaceNavigator was more successful than the scenario in which the participant controlled only the fine position and orientation of the hand with M= 58.52 and 71.98 respectively, and p<0.03. If we consider results with a larger p value, the scenario in which is the participant controlled the full task using the SpaceNavigator (M=58.52) was also more successful than the scenario in which the user controlled only the position of the hand (M=67.34) with a p<0.09. One reason for this result could be that the autonomous system placed the hand with an incorrect orientation that prohibited the successful grasp.

The autonomous scenario, with M= 37.6, was more successful than the fully manual scenario (M=58.5), p<0.00, the manual approach to object scenario (M=62.38), p<0.00, the scenario in which the human only controls the fine position of the hand (M=67.34), p<0.00, the scenario in which the human controls only the fine orientation of the hand (M=66.09),

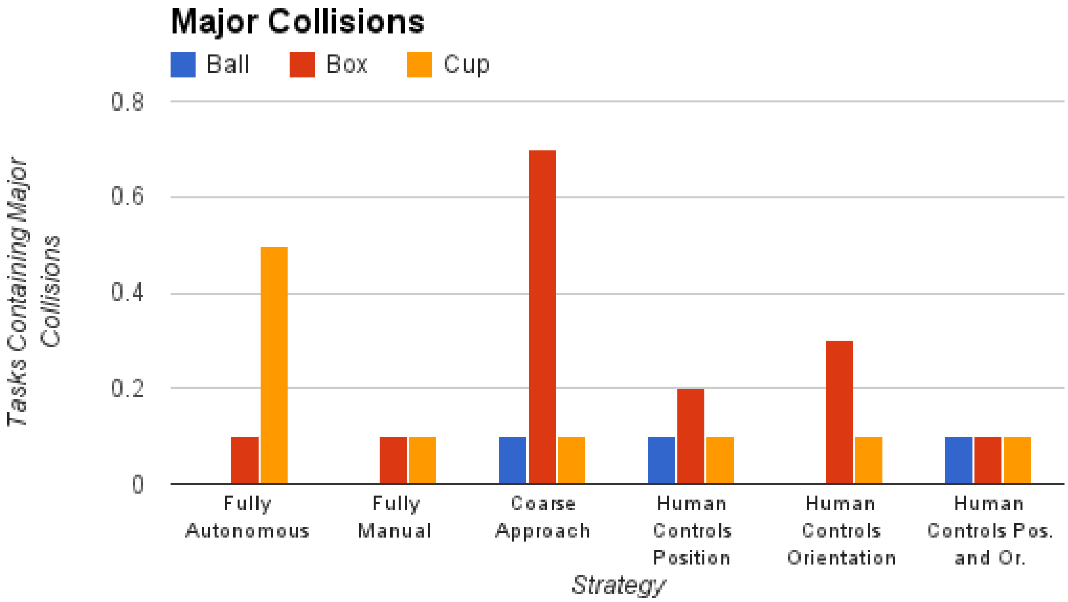


Figure 4.8: Percentage of tasks that resulted in a major collision for each of the tested goal objects.

$p<0.00$, and the scenario in which the human controls only the position and the orientation of the hand (M=71.98), $p<0.00$.

One reason for the success of the autonomous scenario is that in our autonomous trails, we used objects that resulted in a 100% completion rate, a 90% completion rate, and a 50% completion rate. This skews the autonomous data unfairly towards a high completion rate, and therefore a high overall success rate.

A summary of the overall task success rates, major and minor collisions can be seen in figures 4.7, 4.8, and 4.9.

If we consider the scenario in which we do not care about collisions, and only consider task success and failure, the scenario in which the human controls the coarse approach to the object (M=53.42) is more successful that the scenario in which the human controls only the position and the orientation of the grasper, $p<0.01$.

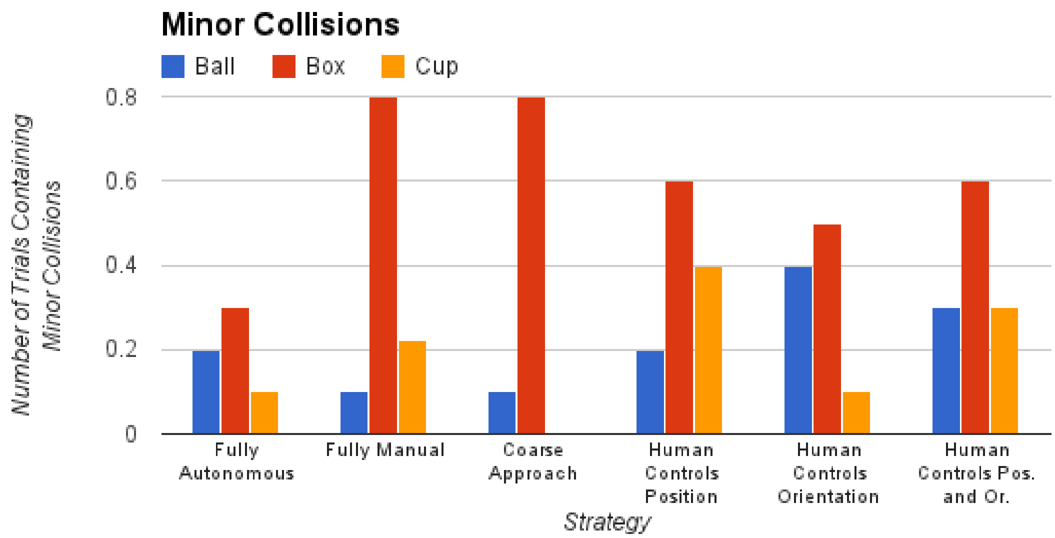


Figure 4.9: Percentage of tasks that resulted in a minor collision for each of the tested goal objects.

#### 4.4.1.1 Ball

We were also interested to look at efficiency results regarding data sets of the same noise level. Considering only tasks for which the ball was the goal object, we found that results were similar to those without considering the goal object. The fully manual task was more successful than the scenario in which the human chose only the fine position of the hand (M=51.15 and 70.73, $p<0.02$). The fully manual task (M=51.15) was also more successful than the scenario in which the human chose the orientation of the hand (M=69.42), and the scenario in which the human controlled only the position and orientation of the hand (M=80.14), $p<0.02$ and $p<0.01$ respectively. The autonomous mode was more successful than all the other scenarios.

#### 4.4.1.2 Box

Looking at the tasks in which the box was the goal object, results indicate that the autonomous mode was more successful than the other five testing scenarios. There were no other conclusive results for this object compared to the other scenarios.

#### 4.4.1.3 Cup

For tasks in which the cup was the target goal, we found that the user controlling the full task using the SpaceNavigator was more successful (M=47.65) than the scenario in which the user chose only the position of the hand (M=67.32), $p<0.02$, and that the scenario in which the user controlled only the position of hand was less successful (M=67.32) than the autonomous picking of the cup (M=43.94), $p<0.03$. Again this could be due to inaccuracies with placement in the autonomous portion of the task. The cup was the object most sensitive to errors in position and orientation, and had the most failures and major collisions in autonomous testing. Results did not indicate that the autonomous scenario was more successful than any of the other scenarios.

#### 4.4.1.4 Summary

When accounting for all goal objects, we found that the scenario in which the user controlled the full task using the SpaceNaviator accounted for the fewest task failures and the fewest major collisions. In terms of human-in-the-loop scenarios, the scenario in which the human controls both the position and orientation of the hand resulted in fewer task failures and major collisions than the autonomous task during the trials with the cup. This shows that allowing the human to intervene in fine positioning when the robotic system has difficulty can improve the success of a task.

The scenario in which the participant controlled only the approach to the goal object exhibited the fastest completion times and highest collision rates. This task relies heavily on the autonomous portion of the robotic system, and results regarding collisions and execution time are similar between the two scenarios. The human approaching the goal object scenario resulted in the highest number of task failures of the human-in-the-loop strategies, although this may be due to Kinect placement inconsistencies with the experimental setup during participant testing. It is possible that the Kinect had shifted slightly throughout the

Table 4.2: Efficiency summary for the second experiment - includes all strategies and noise levels.

| Strategy | Mean Time (s) | Major and Minor Collisions | Task Failures |
|---|---|---|---|
| Fully Autonomous | 27.36 | 0.21/0.20 | 0.20 |
| Fully Manual | 38.27 | 0.06/0.40 | 0.06 |
| Coarse Approach | 26.44 | 0.30/0.30 | 0.47 |
| Human Controls Position | 42.73 | 0.13/0.40 | 0.13 |
| Human Controls Orientation | 36.81 | 0.13/0.40 | 0.30 |
| Human Controls Position and Orientation | 45.05 | 0.10/0.40 | 0.10 |

participant testing, causing the calibration to be off slightly. This may account for some of the incongruent results between the relatively high failures rates of autonomous portions of the robotic system during participant testing when compared to the autonomous testing. A table summarizing the efficiency results for the second experiment can be seen in table 4.2.

### 4.4.2 Participant Reported Effort

#### 4.4.2.1 Mental Demand

Participants felt that controlling the full task using the SpaceNavigator (M=4.30) was more mentally demanding than controlling only the coarse motion to the object (M=2.90), $p<0.02$. Participants also felt that controlling the full task using the SpaceNavigator (M=4.30) was more mentally demanding than the scenario in which the human controlled the fine tuned position of the robotic hand (M=3.40), $p<0.01$.

#### 4.4.2.2 Effort

Participants considered the scenario in which they had to control the position of the robotic hand (M=2.50) to take more effort than the scenario in which they had to control the orientation of the robotic hand (M=3.40), $p<0.02$. They also considered controlling the full task using the SpaceNavigator (M=4.10) to take more effort than both the scenario in which the human controlled the orientation of the hand (M=3.40) and the scenario in which the user controlled both the position and orientation of the hand (M=4.00), $p<0.04$ and $p<0.01$ respectively. Users also reported that controlling the coarse approach to the object (M=3.40) took more effort than controlling the orientation of the hand (M=3.40), $p<0.04$.

Participant survey results were inconclusive regarding how easy, complicated, frustrating a scenario was, as well as participant perceptions of performance.

# CHAPTER 5

# CONCLUSIONS AND DISCUSSION

## 5.1 First Experiment

In the first experiment we studied the benefits of having a human in the loop of a typical pick-and-place task. We have split the pick and place task into several strategies combining both human and robot controls: human controls approach towards an object, human controls fine positioning of the robotic hand, human controls orientation of the robotic, and human controls both position and orientation of the robotic hand. Using an industrial robot fitted with a three fingered grasper, we tested these strategies on six participants.

The results indicate that without human in the loop, the robot has much lower success rate comparing with having a human in the loop at any one segment of the task when the robot's perception is noisy. In terms of both efficiency and cognitive effort, the best placement for the human in this human-in-loop-system is in the approach to goal phase in which the participant specifies a general placement for the robotic hand, and the autonomous robotic system completes the rest of the task. Users reported feeling the best about participating in this scenario, and concrete results indicate that having the person participant in this phase will result in fewer collisions than other shared methods. There was no significant preference or efficiency benefits for the other scenarios. This reveals that the fine positioning and picking is the most difficult part of the task for humans to carry out in both the time and the cognitive effort. Surprisingly, reducing the degrees of freedom for users to control doesn't reduce the cognitive effort, and the efficiency comparison is inconclusive.

Other works have concluded that the human benefits the human-in-the-loop system the most when the robotic system makes the decisions regarding precise movements [6] Our results agree with this finding to a point: in our system, the best human-in-the-loop performance occurred when the human was doing the least amount of precise work. However, our results indicate that there is no obvious benefit in allowing the robotic system to make precise decisions in the presence of high noise, which is not consistent with previous findings discussed in [6].

### 5.2 Second Experiment

We ran a second experiment to clarify findings and address some problems with the first experiment. For the second experiment, we continued to study the pick-and-place task and segmented it in a similar way. However, our robotic system was altered to include an Xbox Kinect as a vision sensor. We changed the way the environment was set up by testing the pick-and-place task on multiple objects of various shapes. We focused the user reported questionnaire on more relevant topics to avoid confusion, trained subjects before testing began and ran participant experiments in a randomized order to reduce inconsistent data. The tests were run on ten participants.

The results indicate that in high noise situations, allowing the participant to control fine tuned orientation and position of the hand can result in higher success rates than the autonomous robotic system. We found also that there were some inconsistencies between success rates of the autonomous systems and the success rates of the human-in-the-loop scenarios that rely heavily on the autonomous system. This could be due to inconsistencies in the experimental setup, specifically regarding the shifting of the Kinect's placement throughout the testing. Running the participant tests multiple times per user might also have provided us with a larger, more conclusive data set.

## 5.3 Concluding Remarks

We believe that this work can be used to determine where human input can increase performance for a robotic system completing a pick and place task, and can serve as a framework for analyzing human impact on any robotic system performing any robotic task. The results in this paper also suggest a robot with a human in the loop should be equipped with a close-range high accuracy sensor other than a sensor with large range but low accuracy in the close range.

### 5.3.1 Hypothesis

Our conclusion supports our original hypothesis in that allowing the human to control the coarse approach to the object (the segment that requires the least amount of precise work) yielded the highest success rates in robotic systems with good sensors. Our hypothesis did not include the finding that allowing the human to control high precision segments can achieve success in robotic systems with poor sensors.

## 5.4 Future Work

In particular, robotic systems for rehabilitation purposes can benefit greatly from this study, as it is neither practical or desirable to remove the human from the loop in this scenario. This study can be extended to look at such a system and determine the best use of the human in this setting. Improving a rehabilitative human-in-the-loop robotic system could greatly improve the success and efficiency of a person's activities of daily living and improve quality of life.

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