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Chapter 1

EFFECTS OF FEEDBACK MAPPING ON HUMAN CONTROL OF ROBOTIC SYSTEMS IN INDIVIDUAL AND COOPERATIVE TASKS

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ABSTRACT

In this chapter, we discuss how humans learn to interact with robots with different types of feedback. Specifically, we examine human-robot interaction during reversed control situations and how two humans can jointly control a single robot. In learning to work with unmanned aerial systems, endoscopic surgery tools, or industrial robots, one of the many challenges to humans is mapping the secondary control rapidly and accurately. Three of the studies included in this chapter extend what is currently known about cooperative human-human robot control and individual human-robot control. We focus on control of a randomly moving object, cooperative dyads working via separate master robots to

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cooperatively control a single robot, and humans having her/his own pair of robotic arms attached to opposite sides of an object when doing a cooperative task. Depending on the interaction and the number of humans in control, the controls can have a one-to-one correspondence, be partially reversed (remotely controlled plane flying toward the operator) or have the fulcrum effect where all motions are reversed. The combined discussion of these research areas reveals the effect of different types of feedback and suggests extensions of current methods for testing feedback conditions with respect to theory in engineering and human factors. This chapter also discusses how the forces are affected, how humans are able to mediate their interactions through a haptic device, and how performance time is affected. The results of these studies help inform how humans use feedback to adapt to the controls required in many types of robot systems and add additional information on human limitations during adaptation and learning.

Keywords: Human-robot interaction, controls, fulcrum effect, control reversal, haptic, cognitive mapping

INTRODUCTION

Human users and robots are increasingly interacting and working cooperatively. To make the interaction more effective, the human must be able to perceive the robot's actions, manipulate the controls, interpret the robot's actions, interpret the control information and make decisions on what to do next. These interactions are partially mediated by a person’s ability to internally represent the actions of a nearby person (and presumably a robot) when working on a complementary action (Sebanz, Knoblich, and Prinz, 2003). Each robot differs in its controls, actions, and feedback provided to the human operator, which requires different actions to be completed by each member of the team.

According to Wolpert, Diedrichsen, and Flanagan (2011) each sensorimotor task relies on several individual components that include: task relevant sensory information, judgment and decision making, strategy selection in predicting the next action, and reacting to errors in action. Sensorimotor judgment in humans is less prone to cognitive biases as the human determines what feedback to use, when to make the next movement, what movement should be made and how to compensate for errors during the control of a robot. Two people (a dyad) can conduct optimal operation of a single robot sooner than a single human (Burstedt, Edin, and Johansson, 1997;

Reed, Peshkin, Hartmann, Grabowecky, Patton, and Vishton, 2006; Braun, Ortega, and Wolpert, 2009).

One of the reasons for increased cooperation in dyads lies in the operation of the human sensorimotor system. The human's sensorimotor learning and cooperation rely on the human musculoskeletal system (MSS) and the way in which it anticipates control. Wolpert et al. (2011) suggest that there are three ways in which humans optimize MSS control and achieve optimal MSS performance: predictive control, reactive control and biomechanical control. Predictive control is observable as humans anticipate the amount of strength and force needed to move an object or manipulate a control. Reactive control addresses the correction of movement error. Biomechanical control includes the structure of the human musculoskeletal system. The feedback interpretation and judgment is further refined to apply only to the current task and the intervention necessary to accomplish the intended goal.

In addition to the feedback provided by the robot, the human's musculoskeletal system (MSS) also interacts with the robot. Several models of how the MSS processes feedback exist in the literature. Grush (2004) suggests three models: (1) Feed forward; (2) Feedback control (Desmurget and Grafton, 2000); (3) Forward/emulator (Kawato, 1999; Wolpert, Ghahramani, and Flanagan, 2001). In both the feed forward model and feedback control theory, the human control process of the MSS breaks down into two components: (1) forward mapping and (2) an inverse mapping. The forward mapping estimates the MSS configuration from the current state to the future state that will result when the motor movements have been accomplished. Inverse mapping takes the future state and determines the motor movements required to attain that state. In the feed forward model and the feedback control model, the time in which the motor plan is developed defines the models.

In the feed forward model, the entire plan is determined before movement begins. In the feedback control model, the plan emerges as the action happens (Desmurget and Grafton, 2000).

The third model, the forward emulator model, considers the movement plan in terms of an emulator which can produce a copy of the feedback signal and produces preliminary plans (Kawato, 1999;Wolpert et al., 2001). In this model, the MSS dynamics are emulated and refined through a continuous stream of feedback (Desmurget and Grafton, 2000; Wolpert, Ghahramani, and Jordan, 1995). The emulator system must be able to monitor the input/output signal and compensate for changes in the physical system such as pregnancy, limb growth, and aging.

Within the forward emulator model's system is a Kalman Filter that processes noise (unpredictable external) and driving force (predictable external) to create an optimal estimate of the real state of the MSS without noise. The Kalman Filter can estimate gain (how much the prediction deviates from real over time), measurement update (how much the prediction deviates from the real in a single or series of instances), and when the sensors are expected to be unreliable and when the signal will be more accurate than the estimation. Wolpert et al. (1995) measured human estimates of the position of their own hands after movements of varying lengths without visual feedback and during three types of external force: assistive, resistive, and no force. The patterns of over-estimation increased in each participant until one second elapsed and then decreased. This is taken as support for the idea of a Kalman filter to stabilize MSS approximations (Blakemore, Goodbody, and Wolpert, 1998; Kawato, 1999; Wolpert, Ghahramani, and Flanagan, 2001; Krakauer, Ghilardi, and Ghez, 1999; Houk, Singh, Fischer, and Barto, 1990; Mehta and Schaal, 2002).

Extensions to all three models (the feed forward model, the feedback control theory, and the forward emulator model) by Slaughter (2004) advance the previous abstract model of the body schema originally discussed in Poeck and Orgass (1971). Body schema refers to how humans perceive their body and was the abstract model for the MSS. The emulator idea discussed is a significant departure from the body schema theory as it incorporates a cognitive structure that represents the body as it moves and acts within the environment. These models contribute to our understanding of the MSS in humans and why the human MSS complicates the control of robots.

Understanding joint control has implications beyond benefits to shared control. Sebanz et al. (2006) state in a review of coordinated interaction that studying humans working individually may not fully reveal how they fundamentally operate. Much like the behavior of ants that shows five ants can carry significantly more than five times what one ant can carry (Moffett, 1992), cooperative behavior between humans and robots has the potential to generate great benefits by using the best abilities of the human and the robot.

The remainder of this chapter will focus on studies that explore two different sides of human robot cooperation related to the above literature: haptic mapping and cognitive mapping. In the first two experiments on haptic mapping, two humans worked in a team task in which they had to cooperatively control a single robot and a bimanual planar task in which each person had her/his own pair of robotic arms attached to opposite sides of the object while looking at the same view.

In the third experiment focusing on cognitive mapping, different participants used a joystick to control an icon of a plane on a computer screen as the X coordinates of a joystick control changed in relation to the plane icon that it was controlling. Both the haptic mapping and the cognitive mapping experiments help inform how humans use feedback to adapt to the controls required in many types of robot systems.

This chapter will be separated into two main topics: haptic and cognitive mapping. After a brief discussion of the salient literature for each, we will discuss the three experiments that were conducted and how the results contribute to our understanding of haptic and cognitive mapping.

Haptic Mapping

Interacting with a robot is very different than interacting with another human because of the limitations of feedback available to the human when learning to control the robot. Research has examined the most suitable human characteristics that allow for cooperative work between two humans. This literature demonstrates that two humans are faster when working together (Reed, 2012), human groups can temporally specialize their motions (Rizzolatti, Fogassi, and Gallese, 2001; Reed and Peshkin, 2008; Ueha, Pham, Hirai, and Miyazaki, 2009), the two members will typically exert a small force against the other person (Reed, Peshkin, Hartmann, Colgate, and Patton, 2005), and the coupling stiffness affects the performance of the interaction (McAmis and Reed, 2013). This interaction has then been used to design robots that are capable of smooth, human-like movements (Bakar, Yuichiro, Ikeura, and Mizutani, 2006; Feth, Groten, Peer, Hirche, and Buss, 2009) and robots that naturally assist the human (Corteville, Aertbelien, Bruyninckx, Schutter, and Brussel, 2007). However, the quality and the type of feedback a robot must give a human in order to inspire human-robot interaction is not yet known.

When humans provide feedback to one another, two people can interact by speaking, changing facial expressions or body posture, shaking hands or hugging, and through the written word. Initially, it was thought that the role that the human plays in the interaction was the critical portion. In some two-member teams, the two members divide the roles into an executer and a conductor (Evrard and Kheddar, 2009; Stefanov, Peer, and Buss, 2009). The role of the executer is primarily contributing to the execution of the task, while the role of the conductor is to make decisions and to control the motion.

In a human-robot team, the human user is typically the conductor and the robot is typically the executer. However, when more than one conductor is using a robot or when the conductor does not make clear and decisive movements, the executer is unsure of which action to take. This happens often when groups cooperate on a physical task, such as moving a large object (Lacquaniti and Maioli, 1992; Karniel, Meir, and Inbar, 1999). One example is the design of the flight controls in airplane cockpits; in some flight controllers, the command given to the airplane control surfaces is the result of the average position from the two pilots' flight controls (Summers, Shannon, White, and Shiner, 1987). Averaging is a simple strategy, but not necessarily the best combination. Each pilot can perform independently with only a partial control of the resulting motion. A better solution likely consists of a strategy that can exploit the redundant abilities of the group (Knoblich and Jordon, 2003). In a study with relatively simple dynamics, Glynn, Fekieta, and Henning (2001) examined several methods of combining the forces from two members of a dyad cooperatively moving a cursor through a virtual maze. During force control, the added force feedback increased errors while the added feedback decreased errors during position control. With two people directly interacting, they are able to communicate both on position and force, thus there should be no detrimental interaction like there was in the force control experiment. They also showed that using the average of the commands without haptic interaction resulted in faster and more accurate task execution than one person alone.

EXPERIMENT 1 – BIMANUAL COOPERATIVE INTERACTION

Individuals frequently interact through touch when cooperatively moving or exchanging objects, much of it done without dropping the object. In many of the previous studies on physical interactions, both partners are given the same view in relation to their controls when performing the task. In this experiment, we examine the interaction that occurs when one participant has a control reversal and the other participant does not.

Experimental Setup

We used a set of four Phantom Omnis (Geomagic) that can provide fast and accurate force feedback, allowing them to easily render complex virtual objects and environments. Figure 1 shows the complete experimental setup.

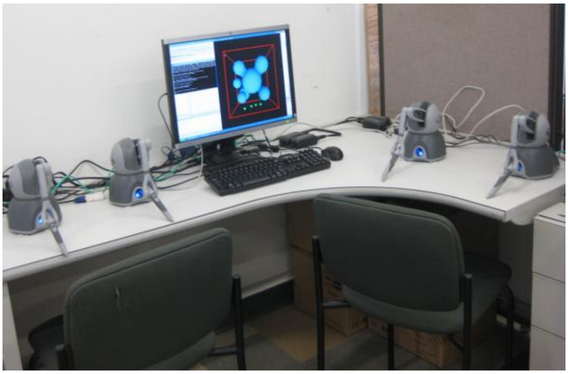

Figure 1. The complete experimental setup during the experiments. In this photo, the practice simulation has just begun, and all four haptic devices are activated and are seen hovering above the table as they are in fact resting on the floor of the virtual environment.

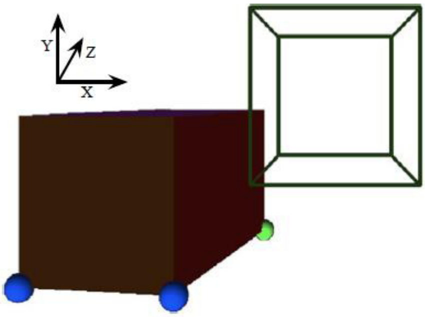

Figure 2. The box interaction in progress. This experiment measures the ability of two human participants to work together in a virtual environment through a robotic device.

The Omnis were attached to the table using double-sided tape so that they would not slide around during the experiments. Throughout these experiments, the Omnis had to be calibrated often since three and four Omnis in series is not a supported configuration.

The Omnis could become uncalibrated after as little as ten minutes, causing jerky motions and poor force feedback.

By calibrating every five minutes, there were very few calibration errors during the experiments themselves. To calibrate them, the experiment was paused, the Omnis recalibrated, and then resumed starting at the same point where it was interrupted.

The visual feedback included the virtual box in which the Omnis were virtually attached to using virtual springs and dampers. One participant's circles representing the two Omnis were colored green and the participant's circles representing the other two Omnis were colored blue. Each participant held one Omni stylus in each hand. Figure 2 illustrates the Box Interaction Experiment interface (coordinate system not shown during the experiment).

The two participants intentionally shared a single display so that each participant would have a different view relative to their virtual handle position. In the case of the participant represented by the blue circles, the view would start without control reversal, whereas the other participant, represented by the green circles, would start out with control reversal in the left/right and rotation directions.

Participants

Twenty individuals (fourteen men; six women) participated in these experiments. Ten of the participants had worked with a robotic device of some kind before, while the other ten had not.

This study was IRB approved and each participant signed an informed consent form prior to the experiments being conducted.

Practice Environments

There were a total of three parts to the first experiment: first were two simple "practice" environments in which the participants were introduced to the Omnis, force feedback, virtual object interaction, and the Box Interaction Experiment.

The participants first interacted with two simulations to reduce learning effects and familiarize them with virtual environments and force feedback. The first virtual environment was the outside of a virtual cube and the second was a simulation of moving spheres in a virtual haptic interaction simulation.

Many of the participants had never used an Omni before, so this practice helped to introduce the participants to the virtual environment before the experiments started.

The practice interactions lasted no more than five minutes.

Procedure

The objective explained to the participants was to jointly move a virtual box into a set of ten target boxes. All of the trials required translational and rotational motion of the box. The simulation began with the box positioned in the center of the Omnis' workspaces, and the first target box was in the upper right hand corner. There were four directions in which the box could move: left and right, up and down, forward and backward, and rotation about the vertical axis. Rotations about the other two axes were left out because this research focused primarily on planar motions.

In order to reach the target box, the participants had to position the virtual box within 20 millimeters from the target with an offset angle of no more than 30°. In setting up the experiment, it was found that these constraints set a moderate difficulty level on the experiment.

Any stricter, and some of the dyads may not have been able to complete the simulation. Any more lenient, and the dyads would have reached most of the targets far too quickly to analyze their level of cooperation.

Once the first box was reached, the second appeared, and once it was reached, the third appeared, and so on, until all ten target boxes had been reached. Each box rotated 90° from the orientation of the previous box, ensuring that the participants had to apply both forces and torques to the box in order to reach the next target. Torques could only be applied by generating a moment from two inputs as the torques could not be directly applied with only one hand. Once all ten target boxes had been reached, the simulation was complete. The participants then completed the entire simulation a second time after a three-minute break.

Acquiring the Target

The target box was acquired when both the angle and distance were close enough. In this experiment, the required distance was 20 mm and the required angle was 30°. These choices were chosen by what felt like a good balance between the difficulty of each requirement, but this choice is semi-arbitrary. There are no studies that quantify a relationship between the difficulty of a rotational task compared to the difficulty of a related translational task, particularly in the realm of cooperative motion; we leave this for future work. However, one study has used Fitts' Law to compare the motions of a translational task to the motions of a combined rotational and translational task for individuals (Stoelen and Akin, 2010). Using our values of 20 mm and 30°, the distance was found to be the leading constraint in reaching the target box in 82% of the trials; the offset angle was rarely the leading constraint.

There is no statistically significant difference between the offset distances in the first and second simulation. Due to the distance constraint being reached most often, the average angle when the target was acquired was 15.3° with a standard deviation of 4.2°.

Force Analysis

The positions were recorded at 1,000 Hz and the graphics were updated at 60 Hz. The forces were calculated based on the distance of the measured Omni position and the position of the corner on the virtual box times a spring constant of 200 N/m. This is the force that each participant felt during the interaction and the force that was used to calculate the translational and rotational dynamics of the box.

Preferred Locations

The setup imposed no specific requirement on how the participants acquire the targets – the box and setup was symmetric. However, the participants preferred to stay in the same relative locations in the virtual world when returning to targets with the long axis into the screen. The individual that started out without control reversal maintained the straightforward control and the other partner maintained a control reversal position throughout the experiment in all cases. This persisted throughout the first and second rounds for all participants. There was no statistically significant difference on the direction of rotation between targets.

Redundancies

When two people cooperate on a task, there are many new force combinations available in which they can perform the task than an individual has available (Lacquaniti and Maioli 1992; Karniel et al., 1999). In this planar task, there are eight force inputs: four in the X and Z directions from each person.

However, the motion of the box only has three directions: X, Z, and a rotation. The box could also move up and down in the Y direction, but our analysis focused on the planar motions only, so the Y motion was excluded. At a high level, forces can be divided into bimanual forces, those that occur within the individual, and cooperative forces, those that occur between the individuals. If it is assumed that there could only be two forces present at a time, there are 16 possible force combinations as shown in Figure 3. There are many more combinations when three or more forces are involved.

The majority of these combinations are cooperative, or joint forces, which require both individuals to generate half the force. Note that an X direction motion cannot be created with only two forces from one individual without also rotating the box, but can when combined with an opposite direction torque. Obviously the individuals will use more than two forces, but this is a reasonable simplification for an example of the complexity involved in analyzing the forces during this task.

To reduce the interactions to an understandable level, we analyzed the eight forces using a principle components analysis in two reference frames. The forces from each individual can be analyzed in the world frame or in the movable frame of the box, as shown in Figure 4.

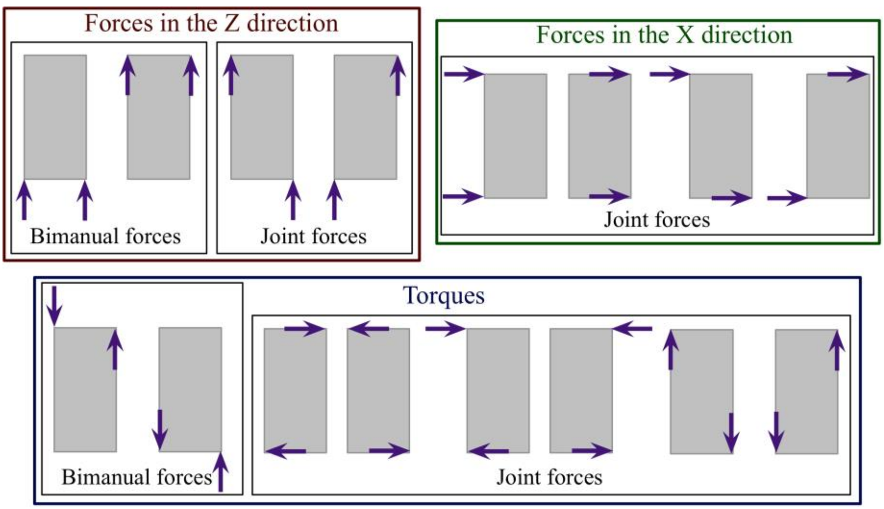

Figure 3. An example of the 16 redundant combinations that four forces from two people can create. Higher numbers of input forces leads to many more redundant combinations. These forces can be divided into bimanual forces/torques, which are those that arise from only one person, and joint forces/torques, which are those that arise from the interaction of the two individuals.

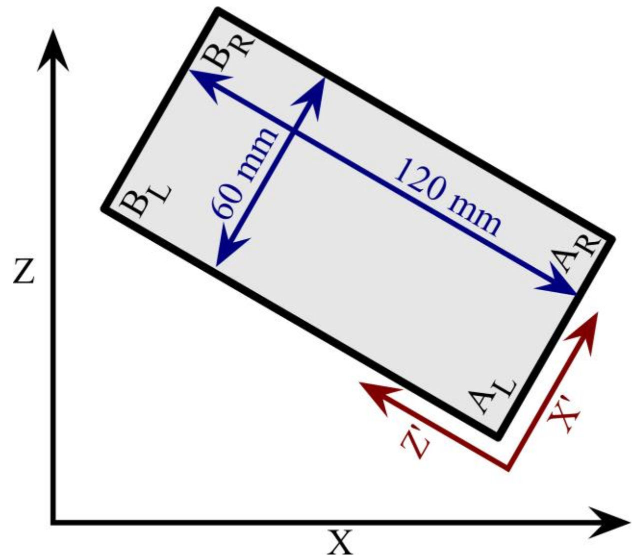

Figure 4. Two reference frames are used to analyze the planar interaction forces. One is the world frame, which is the view of the computer monitor and of the Omnis. The second is the boxframe, which is the moving frame attached to the box, indicated by X' and Z'. A_L, A_R, B_L, and B_R correspond to the left and right hands of members A and B, respectively.

The boxframe forces are the forces that the participants exerted on the Omni that were transformed into the moving reference frame of the box. This moving boxframe was determined by calculating the relative position of the box in box coordinates from the absolute position in world coordinates. The relative position was calculated by multiplying the world coordinates by the appropriate sine or cosine of the box angle. The principle components analysis is conducted on both of these frames for comparison.

Principle Components Analysis

The fundamental combinations of forces employed by the dyad can be examined by looking at the principle components of the forces from each individual. A principle components analysis (PCA) allows the eight forces (i.e., X and Z from all four hands) to be transformed into a new set of axes that are ordered in terms of the variance they represent. The first axis accounts for the most variance possible and each subsequent axis is orthogonal and represents the degrees of variance in the original data in descending order.

By analyzing the interaction forces with a PCA, one can quickly determine the type of interaction. PCA is frequently used in image compression as a means of quantifying the image and has also been used to quantify walking patterns (Huang, Harris, and Nixon, 1999). Here, we are doing the same, but with forces instead of pixels. Figures 5 and 6 show the correlations of the eight forces from each hand of each member in the X and Z directions. The darkness of each square represents the weighted average based on the force vector magnitude in a given direction multiplied by the percentage of variance explained by that vector. The 64 correlations, $C_{i,j}$, are determined by

$$C_{i,j} = \sum_{n=1}^{8} l_n * abs(P_{i,n} * P_{j,n}) \qquad (1)$$

where *i* and *j* - indices over the eight forces,

p is an 8 by 8 matrix where the columns are the vectors of the principle components

l_n represents the amount of variability explained by the nth principle component

$p_{i,n}$ and $p_{j,n}$ are the values of the nth principle component in the i^{th} or j^{th} direction.

The absolute value is taken to measure the correlation between the magnitude of the two values since we are not concerned with the sign of the relationship. Note that the red squares on the diagonal represent the self-correlated forces, which would necessarily be perfect, so those are ignored.

Although there are many interactions shown in Figures 5 and 6, several interactions are quickly apparent. Each quadrant of sixteen squares represents either an interaction within the individuals or between the individuals. The top right and bottom left are within individuals (bimanual) and the top left and bottom right are between individuals (joint forces/torques).

It is quickly apparent from the figures that much of the forces in the world frame are in the forward backward (Z) direction and are mostly bimanual motions. Bimanual motions can be coordinated in many different patterns (Swinnen and Wenderoth, 2004; Malabet, Robles, and Reed, 2010; McAmis and Reed, 2011) and incongruent bimanual feedback can have a detrimental impact on performance (Cooper, Wernke, and Reed, 2012). The large amount of Z direction motion is likely caused by the difficultly of determining the Z direction depth based on a 2D monitor display, whereas the X and Y direction motions can be easily determined.

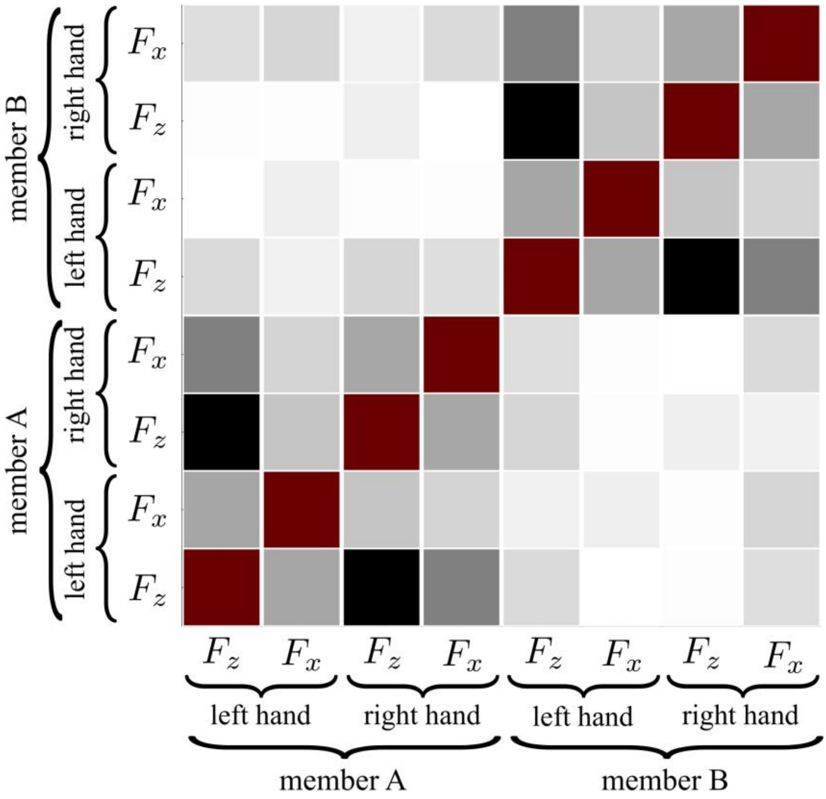

Figure 5. A principle components analysis performed in the world frame. Most of the interaction in the world frame occurs in the bimanual mode and, in particular, in the forward/backward Z direction. Very little interaction occurs between the two members of the dyad.

Previous research indicates that the position of the monitors can have a significant effect on the performance of teleoperation (DeJong et al., 2006), partially due to the control reversal issue. In a dyadic interaction, giving each member a different view of the system could increase the performance of the system, particularly if the handle arrangement was different. For example, if one member was aligned perpendicular to the other, then one of the members could focus on the Z motions and the other on the X motions. In the interaction here, the available forces were the same, only the relative view was different, which does not give any additional benefit to performing the task.

We compared the forces generated by the individuals on the control reversal side and the non-control reversal side and found no significant difference.

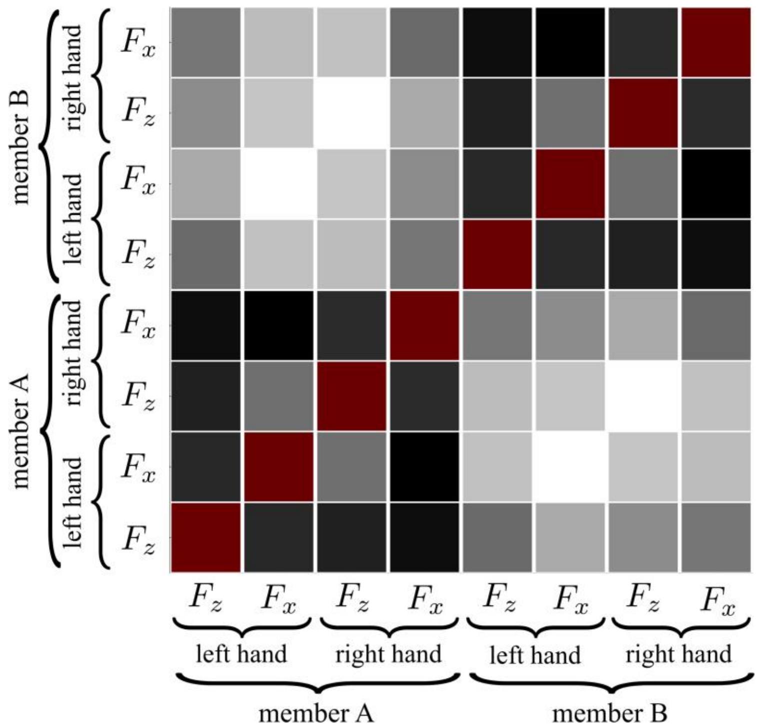

Figure 6. A principle components analysis performed in the moving box frame. Significantly more of the interaction can be seen between the two members of the dyad. This indicates a cooperation and/or negotiation that is done in this reference frame.

We expected some difference in the motions due to control reversal of one member of the dyad, but the participants apparently learned how to perform the task within either of the viewpoints and continued that interaction throughout. Thus, for the comparisons, we combined all twenty participants so that the forces shown are symmetric. Thus, the correlations are a representation of how similar the directions of the components are.

There are noticeable differences between the world frame and the moving box frame. Significantly more of the interaction is occurring between the two members in the moving box frame. The percentage of the cooperative interaction that occurs in the box frame is 31.5%, whereas the cooperative interaction is 16.5% of the motion in the world frame. These values are statistically significantly different (p (199) < .001).

This suggests that nearly one-third of the motions involved in moving the box are occurring cooperatively between the individuals.

EXPERIMENT 2 – COOPERATIVE MANIPULATION OF A SINGLE MANIPULATOR

In contrast to interacting through a single object, this experiment aimed to understand how to combine teleoperation interfaces for two humans working cooperatively to control a single manipulandum. Such a task is commonly done with flying an airplane (copilot and pilot), when training individuals to use machines, and during some teleoperation tasks.

Unlike the box interaction experiment, the individuals tested here have the same relative force inputs and view of the procedure.

The aim of this experiment is to examine different methods to mediate the interaction between the two individuals.

This experiment was performed in the context of analyzing a material's properties, but the main goal was to examine the cooperative behaviors of the two individuals.

Setup

The setup was similar to that shown in Figure 1, but only three Omnis were used. Participants each controlled one Omni with their dominant hand, while the third Omni was the slave robot, which interacted with the material to be tested. The participants had to work together to determine the material's hardness, which was calculated based on the deflection and forces applied by the third Omni.

A force was applied to each participant based on the position of the slave and the two masters. The third Omni position and velocity were controlled by one of three controllers based on the position and velocity of the first and second Omni. The participants worked with three different force feedback modes, which were System Force Feedback, Social Force Feedback, and Dual Force Feedback. These three interaction modes are demonstrated in Figure 7.

In the System Force Feedback mode, the user feels a force proportional to the difference between his position and the position of the slave robot. This has the advantage that the participant can feel the stiffness of an object the slave robot is interacting with in a position-exchange feedback mode, but has the disadvantage that it is difficult to distinguish whether the participants are fighting with each other or if the slave robot is restricted by interacting with a material.

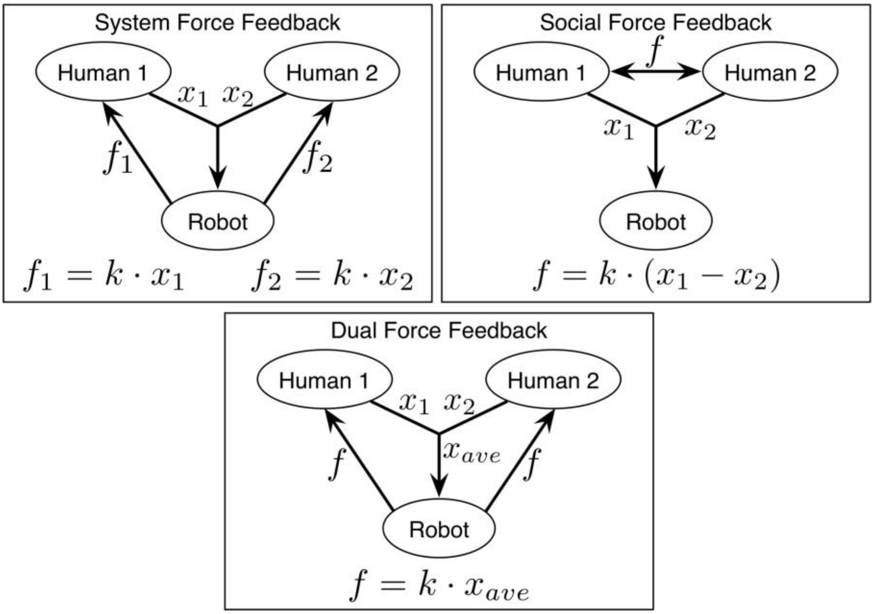

Figure 7. The three force feedback modes used in this cooperative interaction experiment. Each mode controls the slave to be the average of the two master robots. System Force Feedback is based on the individual position of each master. Social Force Feedback is based on the difference of the two master positions. Dual Force Feedback provides the same feedback to each user based on the average position of the two masters.

In the Social Force Feedback mode, the user feels a force proportional to the difference between his position and the position of his partner. This has the advantage that the participants are less likely to fight with each other since they feel a resistive force if they do. However, it has the disadvantage that the participants are unable to feel any restrictions of the slave robot, so they cannot feel the material they are interacting with. This is beneficial for training purposes when position information is most important.

In the Dual Force Feedback mode, both users feel the same force, proportional to the difference between the average position of the two master robots and the position of the slave robot. This has the advantage that both participants feel the exact same force.

However, it has the disadvantage that it is nearly impossible to distinguish whether you are fighting with your partner or if the slave robot is restricted.

Furthermore, if the participants are fighting with each other, the force feedback will not easily guide them back into equilibrium.

Therefore, this mode is the most likely to cause significant fighting between the two participants, but allows identical forces to be felt by each user, which could be beneficial during teaching/learning tasks.

Participants

The same twenty participants performed this study as the box interaction experiment during the same session. This materials experiment was always performed after the practice and box experiments, described above.

Materials Analysis

The hardness of a material is an easily obtainable, yet fundamental property. There are many hardness testers out there that are more suited to the task of finding a material's hardness than the Phantom Omni, yet they do not have the haptic interaction between the user and the device, nor do they allow two participants to cooperate in a human-robot interaction when performing the experiments. One limitation of the Phantom Omnis is that they are only able to perform these experiments on softer materials. Soft materials require a smaller force to deform by a measurable amount, and many robots are unable to deliver larger amounts of force, such as the Omni. Due to the limited force, it was observed that the harder the material, the less accurate the results and the more common repeat hardness measurements became due to the Omni slipping on the hard surface. Five materials ranging in hardness (soft foam, styrofoam, cardboard, soft wood, and aluminum) were used to test how the two participants interacted when trying to identify the hardness of a material. The three softest materials did not suffer from this issue as much as the two hardest materials.

Procedure

The participants were told to identify the materials based on the stiffness felt when interacting with it. The participants were not permitted to touch the materials directly or interact with them in any way except working cooperatively through the three Omnis. The materials were all painted black and placed inside of a black box approximately one meter away from the participants so that their composition was not revealed. Participants were allowed to touch the material through the Omni up to five times before they were asked to identify the material. The three interaction modes were each tested two times for each material. The interaction modes and materials were all displayed in a random order to the participants.

Comparing Performance in Calculating Hardness

Some of the materials were more difficult to identify than others. This was partly due to the materials themselves, and partly due to the participants being more familiar with some of them than others. The material which was the easiest to identify was aluminum, and the most difficult to identify was soft wood. Of the 20 participants who participated, 18 correctly identified aluminum, 17 correctly identified soft foam, 14 correctly identified styrofoam, 11 correctly identified cardboard, and 7 correctly identified soft wood.

Only three of the twenty participants were able to correctly identify all five materials.

Dyad Cooperation Results

When analyzing the Materials Analysis Experiment, we used the fighting distance and fighting velocity for each of the three Cartesian directions to quantify the interaction of the individuals, shown in Figures 8 and 9. The fighting distance is $F_d = \text{mean}(\text{abs}(X_1 - X_2))$ where X_1 and X_2 are the positions throughout the trial and all differences are averaged together. A larger fighting distance indicates that the participants were not cooperating in performing the hardness test. The fighting velocity is $F_v = \text{mean}(\text{abs}(V_1 - V_2))$ where V_1 and V_2 are the positions throughout the trial and all differences are averaged together. A larger fighting velocity indicates that the participants were moving in different directions or with different velocities and that the participants were not cooperating. Note that in the Omni's workspace, the x-direction refers to the left-right direction, the y-direction refers to the up-down direction, and the z-direction refers to the forward-backward direction.

There was no statistically significant difference for fighting distance ($F(4,432) = 0.53$) or velocity ($F(4,432) = 0.42$) between the five materials themselves.

This indicates that the material hardness itself does not have an impact on the fighting distance or velocity; many of the motions were similar between the different materials, so this is not surprising.

There is a significant difference between the three directions for both distance ($F(2,432) = 3.08$, $p < .05$) and velocity ($F(2,432) = 3.78$, $p < .05$). Post-hoc tests with Bonferroni corrections show that both the fighting distance and velocity is statistically significantly smaller in the z and x directions than in the y-direction. There is no statistically significant difference between the fighting distance in the x and z-directions. As expected, vertical depth is a vital part of this task. There is a significant difference between the three force feedback modes, $F(2,432) = 6.23$, $p < .005$ for fighting distance, but not fighting velocity ($F(2,432 = .77$). Post-hoc tests with Bonferroni corrections show that Dual Force Feedback produced the most disagreement in position, and then System Force Feedback, and Social Force Feedback produced the least fighting. This is as expected since Dual Force Feedback does not provide any measure of the difference between the two users, it only provides a measure of the average interaction with the environment, which could lead to an improved agreement upon the interaction with the environment.

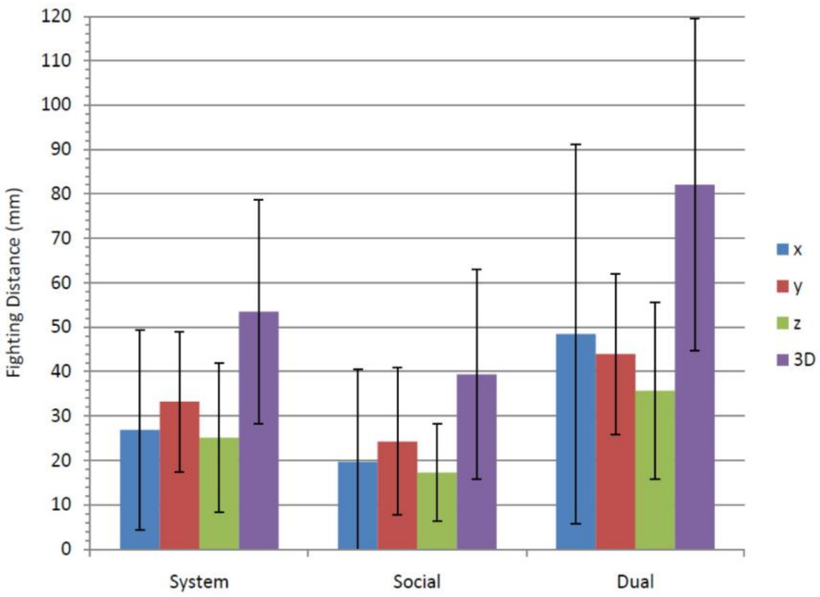

Figure 8. The fighting distance between the participants per Cartesian direction in the Materials Analysis Experiment. The error bars represent one standard deviation from the mean.

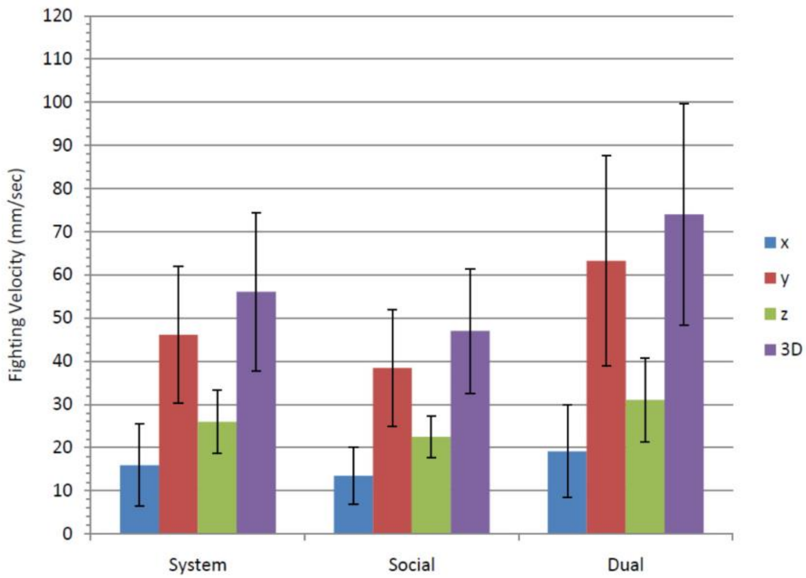

Figure 9. The fighting velocity between the participants per Cartesian direction in the Materials Analysis Experiment. The error bars represent one standard deviation from the mean.

On the other hand, Social Force Feedback provides a feedback directly related to the interaction of the two individuals. Each of these interaction methods has a benefit and tradeoff and could be used depending on the desired interaction and purpose of the interaction.

The best way to reduce the fighting distance and fighting velocity is for the participants to get substantial practice working with robotic devices in experiments such as this one.

Figures 8 and 9 illustrate the fighting distance and velocity between the participants per Cartesian direction in this experiment.

Cognitive Mapping of Control

Controls have long been a topic of concern in regard to robot system operation, both in terms of the dyadic interaction described above and in individual interactions with an interface. Initially, Fitts explored the motorized control of tools through dials and knobs and concluded that consistent mapping resulted in the best performance (Fitts and Seeger, 1953; Fitts and Deininger, 1954).

Consistent mapping means that the tool moves in the same direction as the control. Inconsistent mappings (the tool moves in a direction contrary to the control movement) were a source of significant error. As a result of Fitts' and colleagues' work, design guidelines have successfully urged a consistent control/tool mapping and the problems have decreased substantially.

While there is a potential for many types of robotic systems with humans-in-the-loop to have the control/tool mapping problem, endoscopic surgery systems and unmanned vehicle systems are two of the most often used systems to have this challenge. Endoscopic surgery robotics enable a surgeon to complete a procedure using several small incisions in the patient and inserting a camera and the endoscopic tools. As the surgeon moves a control downward, the tool moves upward. This is typically referred to as the 'fulcrum problem'. In unmanned aircraft systems, a similar problem occurs and it is referred to as the 'control reversal problem'. As the plane flies toward the operator, the plane moves inconsistent to the control mappings. A joystick move to the right produces a plane movement to the left. The number of performance errors due to the inconsistent mappings is significant in both areas. Adding multiple users to a control problem can exacerbate the problems since the direct mapping from action to result is diminished and can generate similar inconsistencies that inconsistently mapped controls can cause.

Many computer users have been subjected to a control reversal in order to make the interaction more consistent in the long term. In Apple's OS X Mountain Lion© upgrade, the default scroll direction was reversed. The change in direction makes the interaction consistent between scrolling on touchscreen devices and computers. Historically, scrolling would change the direction of the scrollbar position, so pulling the scroll wheel towards you would move the text up (scroll bar down). On a touchscreen device, swiping toward you would be expected to generate the opposite effect, that of moving the text down (scroll bar up). This change makes the interaction more consistent between Apple computers and touchscreen devices, but has caused a slight confusion with cognitively mapping the scroll direction when switching between computers with different implementations.

Wolpert et al. (2011) discusses three types of learning: error based learning, reinforcement based learning and use dependent learning. According to Marr (1982) the learning processes may work together to produce human adaptation to the robotic controls. The types of learning are interdependent operating within the MSS independent of the human's attention. Thus, Wolpert and other researchers theorize the cognitive structure of an emulator.

In error based learning, the outcome of the sensorimotor system's actions are compared to the desired outcome. This comparison tells the sensorimotor and information processing system how, where, when, and why the intended outcome was or was not achieved. In addition to the goal achievement, the comparison provides information on error correction (Marr, 1982).

It is thought that this comparison method is the basis for the sensorimotor adaptation (Krakauer, Ghilardi, and Ghez, 1999). Error based learning seems to drive adaptation regardless of the human's desire to adapt (Donchin, Francis, and Shadmehr, 2003; Diedrichsen, Hashambhoy, Rane, and Shadmehr, 2005; Srimal, Diedrichsen, Ryklin, and Curtis, 2008) and persists until the sensorimotor system cannot further optimize the movement.

Reinforcement base learning also provides correction to the sensorimotor system through reinforcements (Wolpert et al., 2011). Little is currently known about the types of rewards, frequency needed and extinction of reinforcement based learning for the sensorimotor processes in humans. To date, studies have found that full reinforcement throughout an entire task creates human reliance on the robotic trainer and may interfere with a human’s internal motor learning (Schmidt and Wrisberg, 2008). More recent studies suggest that just-in-time reinforcement that gradually disappears is more successful and does not create reliance on the reinforcement (Crespo and Reinkensmeyer, 2008; Emken and Reinkensmeyer, 2005).

In use dependent learning, the sensorimotor system adapts simply from repetition with the robot controls (Verstynen and Sabes, 2011). Wolpert, Diedrichsen, and Flanagan (2011) state that this type of learning can occur in parallel with error based learning. Use-dependent learning does not require that the system provide feedback to the human. The lack of feedback to the human defines use-dependent learning. Motor neurons may play a role in use-dependent learning however, in all three types of learning, the human must experience the feedback and errors him or herself in order for the learning to occur (Wolpert et al., 2011).

Thus, when the controls change how the robot moves, do humans adapt to the changed controls and how long does the learning take? In order to test only this portion, we created a simulated task on a desktop computer in which the human used a joystick to control a plane icon on a computer screen. The participants were to keep the plane icon within a slowly moving box. The joystick controlled the X coordinates (right and left) and the Y coordinates (up and down) coordinates. Depth controls were not used. During the experiment, the joystick's X coordinates reversed and participants had to adapt.

In the control reversals, a right motion of the joystick would produce a left motion of the plane.

This task replicates the controls of a remotely piloted plane. When the plane approaches the operator either for landing or during the execution of a turn. It is very similar to the controls used by the MicroB manufactured by Bluebird Aero Systems (2009) or any small remotely piloted plane.

During the experiment, the distance between the plane's central point and the box's central point was calculated and recorded every 0.10 seconds and the root mean square (RMS) was calculated. The experiment lasted 36 minutes with 6 trials. The X coordinates were normal (right = right; left = left) for trials one, three and five. The X coordinates were reversed (right = left; left = right) for trials two, four and six.

Participants

The study was approved by the institution's IRB. There were 141 participants who volunteered either for course credit or for payment (74 men and 67 women). The age range was between 18 years old and 45 years old with a mean age of 19.47 years old and a standard deviation of 3.5 years. Less than five participants reported having any piloting or radio controlled aircraft experience. Of the 141 participants, 43 of them reported video game experience. Of these, 16 participants played first person shooter games (6 women, 10 men) and 21 participants played sports, puzzle, music or other types of games (14 women, 7 men).

RESULTS

When comparing all six trials by the control mappings (normal or reversed), there was a significant difference ($F(1, 53) = 6.879$, $p = 0.01$). The reversed controls were more difficult for all participants. Overall, persons who did not play first person shooter games were the least successful in keeping the plane near the center of the box. However, the standard deviation was high for all groups and in some cases the standard deviation was higher than the mean.

This indicates that some participants did very well across all of the trials and other participants struggled with the task. Participants reported that they found the experiment to be tedious and boring. Observations of the participants suggested that some participants were more attentive than others.

Table 1. Summary of RMS by participant groups

	Mean RMS	SD RMS
Women (67)	54.61	56.70
Men (74)	33.90	38.93
Only First Person Shooter Gamers (16)	53.20	20.76
Only Non-First Person Shooter Gamers (21)	77.43	36.08

The participants' performance scores were segregated ordinally into thirds by participant with the most efficient (low RMS) compared to each other and the least efficient (high RMS) compared. The most efficient participants improved by 20% after the first six minutes or the first trial. The least efficient participants improved by approximately 56% within the same time period. The learning effect was stronger in the least efficient participants despite the participants self-report that they were bored and had trouble paying attention.

We were most interested in what would happen when the X coordinates of the joystick reversed. In the reversed trials (see the dark bars on Figure 10), participants performed significantly better when the first trials were compared to the last trials ($t(704) = 8.48$, $p < 0.0001$). In normal trials, participants also showed significant improvement ($t(703) = 11.807$, $p < 0.0001$). When subtracting the last RMS distance from the first RMS distance within each trial, participants improved by an average of 35 RMS. In both the normal and the reversed controls, participants improved substantially within 36 minutes. While the reverse control performance did not match the normal control performance within the 36 minutes, it was approaching equal performance.

Adaptation to a new control mapping shows learning within 6 minutes and proficiency approaching 30 minutes, consistent with Worringham and Beringer (1998).

CONCLUSION

The combination of all three experiments reveals the effect of different types of haptic and cognitive mapping of controls. In the box interaction study, the forces generated by the humans did not differ when the controls were reversed and subjects maintained their original interactions, suggesting that they are comfortable with either arrangement as long as the interface is consistent. In the third study, control reversal was quickly learned with a pronounced improvement in about a half an hour's worth of practice.

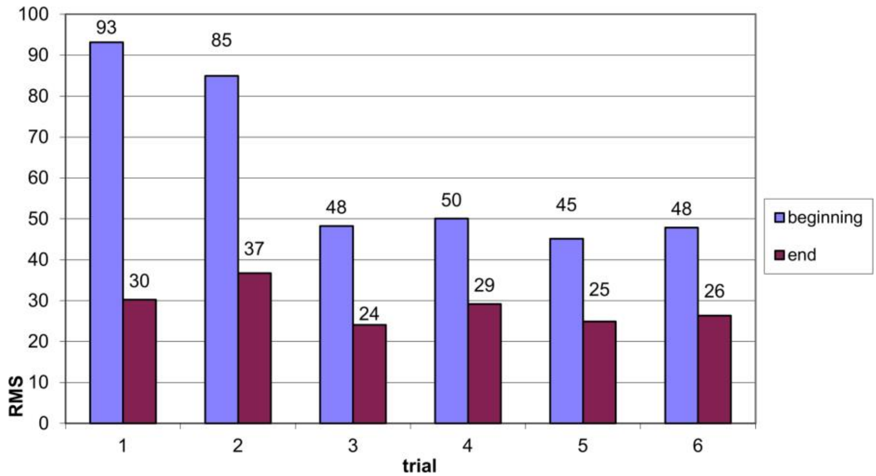

Figure 10. Median first and last RMS score by trial – (less distance is better).

The interaction between two may be beneficial for teaching control reversal when a novice first experiences it and can learn appropriate motions from an expert who guides them and possibly does not have a control reversal effect to minimize errors. In the second study, the “Social Force” feedback produced the least amount of fighting between the participants’ haptic forces, but detrimentally decreased their ability to perform the task. Methods to improve the interaction and ability to physical learn from another person are important and are not yet well developed. There are several measures that can be taken to promote better cooperation between humans and robots. First of all, improved force feedback and visual feedback could be implemented to reduce the fighting distance and fighting velocity.

Also, the force feedback could be tailored to help compensate for weaknesses in the interaction. For instance, when cooperatively controlling a single interface, the spring force rendered back to the participants could be larger for displacements in the y-direction than for displacements in the x and z-directions, which had less fighting. Furthermore, the participants could be given more time to practice with several virtual environments, allowing them to become more comfortable with the devices, the virtual environments, and the overall haptic and cognitive interaction.

A typical problem in multi-user collaboration is displaying both a position and a force to a novice at the same time. When using only one manipulator, only a force or a position can be displayed, but both cannot be simultaneously displayed.

One method to combine the benefits of Social Force Feedback with the benefits of Dual Force Feedback is to use a bimanual setup where each hand receives a different type of information (McAmis and Reed, 2012). In this implementation, one hand could receive the social (or guidance) information and the other could receive the task (environment force feedback) information. In this way, the two could more effectively cooperate while still accurately performing the task and maximizing learning effects.

The Box Interaction experiment shows the analysis of a cooperative task using a principle components analysis (PCA). PCA is used to simplify the large number of force interactions throughout a task into a representative sample of the interactions that will be used in future analyses. Using the PCA, the interaction of two people can be tracked over time and possibly modeled to predict the continued interaction. This would possibly enable teleoperation systems with large lag to estimate the interaction of two people and use a local model to interact with while the system was being updated. This study supported the results by Worringham and Beringer (1998) by demonstrating that when control reversals happen, haptic force does not experience a decrement. However, most of the participants were male and the third study demonstrated that males can perform the control reversal situation better. If the population of the interaction study had more female-female dyads, the results may have shown a difference. In particular, mixed gender teams may result in different interaction modes.

There are several related areas on which this research can expand. As discussed earlier, there are no studies that quantify a relationship between the difficulty of a rotational task compared to the difficulty of a related translational task. An extension of this work would examine the difficulty of only rotating the box into place compared to only moving the box into place. Ideally, this would be done using Fitts' Law, which is a well-established method of comparing performance in target acquisition tasks, but a relationship between translation and rotation needs to be developed. Furthermore, more experiments could be performed as a continuation of this research. One type of experiment involves one participant performing a bimanual experiment in which his left Omni generates a preset motion and he must match it as closely as possible with his right Omni. This offers an additional type of human-robot interaction that could not be studied in this research. This bimanual experiment would further study human-robot interaction between one human and two robots.

A variation on the bimanual version would be to use one experiment operator, one participant, and two Omnis in Dual Force Feedback mode.

The operator would move his/her Omni in a simple path and the participant would try to match the motion based on the feedback. In Dual Force Feedback, both the operator and the participant would feel the same force rendered back to them. This variation would be analyzed in a similar fashion to the bimanual experiment, except it would be different in that it would apply force feedback to the participant.

From the cognitive standpoint, the transfer and permanence of learning to control an object when the controls are reversed warrants further study. Within each of the six blocks (each block lasting for 6 minutes), participants improved their ability to control the plane and this effect carried over to the next trial. In addition, there seems to be a performance plateau. Participants improved dramatically within the first two blocks (12 minutes), but then additional performance gains were slower. The sensorimotor system adapts fairly rapidly. However we did not address factors such as video gaming, gender, and attention. These factors warrant further study. The type of Video Game did confer a small performance benefit consistent with Rosser Jr., Lynch, Cuddihy, Gentile, Klonsky, and Merrell, (2007) and Green and Bavelier (2007). Games that involve first person movement and spatial mapping are more effective than games that are solely hand eye coordination.

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