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Exploring the Human Interactivity with a Robot to Obtain the Fundamental Properties of Materials

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to Obtain the Fundamental Properties of Materials

by

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Abstract

This research studies the way in which humans and robots interact with each other. When two humans are working together through a set of robotic devices, do they tend to work together or fight with each other more? In which Cartesian direction do they have the most difficulty? Does fighting drastically affect the performance of the team? Finally, what measures can be taken to promote better cooperation between humans and robots to ultimately allow humans to work just as comfortably with a robotic partner as with a human partner? This research answers these questions and provides an analysis of human-robot interaction.

It was found that significant fighting between the subjects does have a negative impact on the performance of the team. Out of the three Cartesian directions, the up-down direction was found to be the most difficult to cooperate in. Although the level of fighting varied greatly among different dyads, two things which greatly assisted in completing the experiments were force feedback and visual feedback. Different methods of feedback were tested, and subject performance in each was compared.

Chapter 1. Introduction

The general purpose of this research was to test the ability of two human subjects working together with a set of robots to interact with different virtual environments, perform materials testing, and acquire and analyze data. Over the last few decades, it has become commonplace for robotic devices to exist in our world. Through the development of these devices, humans must learn to work with and interact with robots in an efficient and effective way.

Interacting with a robot is very different than interacting with another human, so it crucial that we study the ways in which humans interact with each other and try to mimic those behaviors through a robotic device. As the field of robotics has developed, robots have been developed to perform more and more complex tasks. However, most robots are autonomous, and are developed to work on various simple tasks independently, without much, if any human interaction. However, one of the greatest goals in the field of robotics engineering is to develop robots which are able to work and interact with humans using some degree of intelligence and skill.

There are several difficulties in achieving this. First of all, a robot has no natural intelligence. It cannot think for itself the way a human can. In fact, even the most sophisticated robots can only do exactly what they are programmed to do. If they are not programmed for something, they cannot do it. However, some degree of artificial intelligence can be achieved by programming the robot to know what to do in multiple situations it might encounter, or by programming adaptive control into the device. Adaptive control allows for the fact that some of the system parameters slowly change over time or are random, and allows the device to compensate for it.

Another difficulty is that humans naturally work differently with another human than they do with a robot. When working with another human, there are social factors involved. For instance, a person would not want to embarrass themselves in front of their friends. However, this human factor is typically removed when working with a non-human entity.

Yet another difficulty arises because the experience of working with a robot is quite different than working directly with another person. There is a very different feeling involved when performing a task virtually through a robotic device than when performing a similar task in real life. Even the simple task of two humans using a robotic device to move a virtual object is drastically different than the task of two humans moving a physical object of the same size across a room.

When working with a robot, it is common to encounter virtual objects. A virtual object is an object that a human user can touch, feel, and interact with through a robotic device, even though it is not a physical object. There are several ways that this is achieved. The most common is through the use of force feedback. When a subject touches the virtual object with the robot's stylus, he will feel a force pushing him back out of the object, just as he would if it were a real object. This allows him to feel the shape, stiffness, and texture of the object and interact with it.

Another way to create a virtual object is through visual feedback. It is common for visual feedback to be used along with force feedback, although this is not always the case. In this research, visual feedback was used so that the subjects could see the objects they were interacting with in a 3-D view on the computer screen. This is extremely beneficial when interacting with complex virtual environments because it allows the subjects to see the entire environment and their position within it.

Yet another way to create a virtual object is through auditory feedback. This can be used with visual or force feedback, but it does not have to be. The basic concept is that the subject will hear a sound that increases in volume or pitch as he gets closer to the virtual object and decreases in volume or pitch as he gets farther away from it. Also common is the use of sensory substitution, in which one sense is substituted for another sense. For instance, the sense of touch and position may be substituted with the sense of hearing. However, auditory feedback was not used in this research.

Depending on one's research objectives, multiple feedback modes can be used simultaneously. In this research, the desired combination was to use force and visual feedback together because it allowed the subjects to see and feel the objects they were interacting with, which is the closest to real life interaction.

In this research, each subject was able to practice with two basic virtual environments before completing the first experiment, which involved moving a virtual box towards a set of targets. Then, they completed the second experiment, which involved the testing of five real materials through the robotic devices, using force feedback to guide them, with the objective of measuring the materials' Brinell hardness values. In the virtual environments, both force and visual feedback were used, and in the materials analysis experiment, only force feedback was used. After measuring a set of hardness values for each material, the subjects had to try and identify them given a table of ten materials and their hardnesses.

A total of 20 subjects participated in this research, working in two-member pairs called dyads, for a total of ten independent experiments performed over a five week period. Of the 20 subjects tested, 14 were male and six were female. Ten of the subjects stated in the pre-experiment survey that they had worked with a robotic device of some kind before, while the other ten stated that they had not. Through observation during the experiments, it was noticed that those who had not worked with a robotic device before approached the virtual environments slightly more cautiously than those who had.

This research demonstrated how well humans and robots interact with each other in performing experiments and acquiring data. The subjects had to adjust to the idea of working with each other through a series of robotic devices. The robots used were a set of four Phantom Omnis, developed by SensAble Technologies. The Omnis are excellent haptic devices, and can provide fast and accurate force feedback, allowing them to easily render complex virtual objects and environments (SensAble Technologies, 2010).

Robotics technology has many applications in the scientific community. One field of study where robotics has greatly enhanced the scope of knowledge is in space science and engineering. Space probes have been sent all over the solar system to study other worlds. These robots must be programmed to think through the many complications and problems that will commonly arise throughout their journey.

Materials science can also benefit from robotics technology. In fact, the two go hand in hand. Robots can go places that no human can go, allowing them to perform tests on materials that no human could ever get near. Humans can then remotely operate the robots and interact with them from a distance. In some cases, humans must program the robots in advance and allow them to work on their own if the time lag becomes too great for real time interaction. For example, if a Mars rover discovers an interesting rock, it must be able to identify the object of interest and then perform tests on it to determine what materials it is made of and how it formed, completely on its own, using commands sent by mission control several hours earlier. In fact, the Mars rovers Spirit and Opportunity have already explored a combined 24 kilometers of the Martian surface over the last six years, analyzing rocks and other interesting materials (Bentley, 2009). This demonstrates that the success of a mission such as this one depends on the simultaneous use of the fields of robotics and materials science.

The ultimate goal of this research is to learn how a human-robot team could someday travel in space and cooperatively study materials of extraterrestrial origin. Whether it involves studying an asteroid, a comet, or rocks on the Moon or Mars, the fields of robotics and materials science play a vital role in the success of such a mission.

Scientists are always building more and more complex robots which can study complicated materials and alloys. In the future, humans will be able to travel to other worlds with these robots. Humans will work directly with them, drastically increasing the speed at which discoveries are made. However, before this can occur, we must learn how humans and robots interact, and to determine their strengths and weaknesses. Then, the weaknesses can be corrected and the strengths can be amplified. In turn, this research is very interesting and has a lot to offer to the scientific community.

Chapter 2. Background Research

The application of robotics in today's world is enormous. Two major applications in this field are to study the way that a human-robot team can interact with virtual objects in a virtual environment and how a human-robot team can interact with a set of materials, perform tests on them, acquire data, analyze that data, and ultimately determine their identity. This chapter discusses the history of the fields of robotics and materials science, some theory behind these fields, and some current research in them.

2.1. The History of Robotics and Materials Science

Over the last few decades, machines have greatly enhanced the speed and efficiency at which tasks can be performed. As better, faster, and smarter machines have been developed, it has become possible to study things which were not possible to study in detail previously. Eventually, the technology was developed to build a programmable machine which was capable of independently performing a task and relaying the results back to a human user. This was the beginning of the field of robotics.

The Czech playwright Karel Capek first used the word "robot" in his 1921 play titled "Rossum's Universal Robots", in which he illustrated robots as mechanical machines which on the outside looked similar to humans, but could work endlessly and tirelessly, eventually turning against their masters to rise up and destroy the human race

(Murray et al., 1994). This has been a popular science fiction concept over the years, and has been used in many books and movies.

Real robots are indeed mechanical machines which can work endlessly and tirelessly, at least until the materials composing the robot fail due to fatigue or overheating. However, they do not typically resemble humans, although there is some element of artificial intelligence in which robots can exhibit. However, a robot will only do exactly what it is programmed to do, and that is it. If it makes any decisions on its own, it does that because it is programmed to do so.

During the 1940s and 1950s, the simplest of true robots were developed. These early robots consisted of what was essentially a mechanical manipulator, otherwise known as a teleoperator, or a telemanipulator. In essence, a teleoperator is an electronic and/or mechanical system made up of a master robot and a slave robot. The master user completely controls the slave robot using a master robot or controller and a communications device. The slave robot then uses the information sent from its user to work within its environment, providing feedback to the user through the master robot (Misra, Okamura, 2006).

The first of these teleoperators was developed at Argonne and Oak Ridge National Laboratories. They were very simple linkage mechanisms which were built for the purpose of handling radioactive materials. By the late 1950s, the first computers had been developed to the point where computer numerically controlled (CNC) machines had been developed for manufacturing purposes. With this technology, CNC lathes and CNC milling machines were in research and development.

CNC technology was then developed in the field of robotics as well. The master and slave teleoperators could then be replaced with reprogrammable CNC controllers. Once CNC robots had been developed, they could be programmed to perform simple tasks. Then, it was necessary to develop a programming language which could be used for programming CNC robots. The first such language, called WAVE, was developed at Stanford in 1973. This language formed the basis for programming a robot with more sophisticated commands (Murray et al., 1994).

Now that a programming language had been defined, robots were able to perform more and more difficult tasks and experiments. Throughout the 1980s and 1990s, more sophisticated programming languages were developed. The C language was eventually developed, and then C++, both of which allowed for the programming of robots to perform very complicated tasks, making them very useful to the scientific community. Today, C++ is one of the most common programming languages used in robotics.

Just as the field of robotics has advanced greatly over the last 100 years, the field of materials science has as well. We have discovered many more elements, and learned a great deal about their properties. We have learned about the way in which atoms interact with each other, and how to modify compounds to improve their properties.

As we have learned more about materials, we have discovered that the strength of a material is not constant. The strength of the same alloy can vary tremendously, even by more than an order of magnitude, depending on a variety of factors. Some of these factors include the size and shape of the alloy, the type of loading, and the cracks, voids, or other imperfections present (Pitchumani et al., 2004). For instance, a very long and very sharp crack produces a large stress concentration factor, which can cause the material to fail even at a relatively low stress. As the crack continues to propagate, the stress concentration factor can rise as high as 100 or even greater. Therefore, if the ultimate tensile strength without the crack was 50,000 psi, with the crack present, failure could occur at 500 psi or even less.

Another major factor which contributes to the strength of a material is how it was formed, and what processes were used to make it. For example, a cast iron part will be much weaker than a forged iron part. Furthermore, an annealed part will be weaker, although more ductile, than a strain-hardened part. The strain-hardened piece will be stronger, although more brittle. As a result, the annealed part will actually have the higher fracture toughness (Pitchumani et al., 2004).

In recent years, robots have been used to study materials to learn of their properties and how to manipulate them. A robot can test a material for its yield and ultimate tensile strengths, obtain a stress-strain curve, and find material properties such as elastic modulus and Poisson's ratio. This can be done by applying a set of known forces to the material by the robot, and then reading a strain gauge attached to the material to get the strain. The stress can then be calculated from the force, allowing for calculation of the elastic modulus. With two strain gauges, Poisson's ratio can be calculated as well. There are many significant properties which can be obtained by a robot, many of which can then be used to calculate other properties or determine important characteristics of the material. Table 1 summarizes these properties, the hardware necessary to test them, and some general notes on what they are and how they are useful.

Table 1. Interesting material properties and the hardware necessary to experimentally test for them.

Desired Property	**Necessary Hardware**	**Notes**
Hardness	Hardness Tester	A robot can test softer materials much easier than harder materials, so this property is essential to obtain.
Density	Scale and Beaker	A water-filled beaker can be used to find the volume and a scale can be used to find the mass. Then, $\rho = {}^{m}/_{V}$.
Stress	Tensile Tester	For a known applied force and cross-sectional area, $\sigma = {}^{F}/_{A}$.
Strain	Strain Gauge	The strain can be measured directly with a strain gauge.
Elastic Modulus	Strain Gauge	Once you know the stress and strain, $E = {}^{\sigma}/_{\varepsilon}$.
Poisson's Ratio	2 Strain Gauges	A strain gauge in the x-direction and another in the z-direction will give you Poisson's ratio. $\nu = -\varepsilon_x/\varepsilon_z$.
Yield Strength	Tensile Tester, Strain Gauge	The point at which the material begins to yield. For brittle materials, fracture occurs shortly hereafter.
Tensile Strength	Tensile Tester	The highest point on the engineering stress-strain curve.
Fracture Stress	Tensile Tester	The point on the engineering stress-strain curve in which fracture occurs.

Table 1 shows that there are many different material properties which can be experimentally found by a robot, or by a human-robot team. For this research, hardness was the desired property to be measured by the robot. This property is good for narrowing down the possibilities of an unknown material's identity, as the subjects were able to correctly identify the materials more often than not from a hardness test and haptic interaction with them.

However, robotics can be useful for more than simply finding a material's properties. For instance, a robot can also examine a material at the point of fracture. In recent years, tests have been performed on the failure of materials from several different causes. Robotic compression testers have been developed which are capable of testing materials which have failed due to fracture, fatigue, attrition, abrasion, peeling, chipping, and corrosion (Pitchumani et al., 2004).

Now that the field of robotics has developed as far as it has today, many experiments have been done in this field over the last decade, many of which involved a combination of robotics and materials. However, one aspect of robotics which is still growing is the haptic interaction between humans and robots, which involves the subject and the robot working together as a team to accomplish the defined task.

2.2. Current Research in Robotics and Materials Science

In their initial stages, robots were very simple machines which could be programmed to perform a single simple task. However, over the years they have advanced greatly. They have been designed to perform more complicated tasks, run precise experiments, acquire data, and even compute results. This has occurred because over the past couple of decades, there have been significant advancements, changes, and developments in the field of robotics. This has opened up the opportunity for robots to become involved in a diverse range of scientific fields, including medicine, healthcare, logistics, manufacturing, and material analysis. It is becoming more and more apparent that robotics will greatly influence the world over the next 50 years, and there will be many exciting new inventions along the way (A Roadmap for US Robotics, 2009).

As robots have advanced, they have begun to greatly influence the field of materials science. It has become possible to test materials using robots, to determine their properties, their history, and to learn of their imperfections. With this data, we have learned how different materials behave when put under stress, and further developed our knowledge base on how to manipulate and form them with other materials to make stronger, tougher, and more durable alloys.

One area of materials research which has recently involved robotics has been in the study of human tissues. Since tissues are very soft materials, a robot can measure their properties relatively easily, by only applying a very small amount of force. It is convenient to work with soft materials because it requires a smaller force to deform these materials by a measurable amount, and many robots can easily deliver this range of force without deforming themselves or overheating their motors.

One such experiment involved comparing the force feedback for linear dynamic tissue models versus nonlinear dynamic tissue models. Up until this point, most researchers generally assumed a linear elastic behavior for the modeling of tissues under stress (Misra et al., 2007). This seemed to be a reasonable assumption, because most other materials have an approximately linear stress-strain curve in the elastic region.

In Misra's research, robotic manipulators were used to test soft tissues using a nonlinear dynamic model. When the nonlinear model was applied, it was found that the Poynting effect developed when a shear force was applied to the tissue. The Poynting effect is the creation of large differential normal stresses or strains as a result of shear stresses applied to a highly strained material. These normal stresses were not present in the linear model. As a result, there was a significant measurable difference in the force feedback for the linear and nonlinear models. The largest difference in the maximum reaction forces between the two models was 51.2%. This demonstrated that soft tissues do not behave linearly in the elastic region (Misra et al., 2007).

Another experiment involving robotics in the testing of human tissues studied a robotically assisted teleoperated surgery. In this experiment, the surgeon manipulated a master robot, which in turn allowed a slave robot to mimic the master robot's movements while performing tests on patients, using the da Vinci surgical system (Yamamoto et al., 2008). The robots were able to extract the necessary data about the patient's tissues, and relay that information back to the surgeon through various methods of force and visual feedback. Yamamoto's research may eventually allow a surgeon to perform an operation at a distance (Yamamoto et al., 2008).

During the teleoperated surgery experiment, various elastic tissue properties were measured, including elastic deformation and reaction to applied stresses, and were then compared to a general model. However, it is extremely difficult, if not impossible, to create a perfect mathematical model for a real human tissue, although there are several good models that can approximate the dynamic behavior of tissues under stress. One of the major difficulties in performing this experiment was the lack of adequate haptic feedback to the surgeon. As a result, the surgeon had to rely too heavily on visual cues such as tissue deformation to make a guess as to how much force the robot was actually exerting on the tissue (Yamamoto et al., 2009).

Misra and Yamamoto's research has taught us a lot more about soft human tissues, and how organic materials react to applied forces. However, there has also been a significant amount of research dealing with nonorganic materials as well. For the case of nonorganic materials, temperatures, forces, and pressures which could never be withstood by any organic material are commonly dealt with.

For nonorganic materials at high temperatures, a very significant deformation over time occurs. This deformation is called creep. At high enough temperatures, typically at least one-third the melting point in absolute temperature, an applied force which is smaller than the yield strength at that temperature can cause the material to creep. When a material creeps, its strain increases by a certain amount per unit time, until it eventually fails. As the temperature of the material increases, the creep rate increases exponentially.

Creep can occur in nearly all materials, including ductile and brittle solids, polymers, and amorphous solids. Brittle solids will fail much quicker when creep occurs, while ductile solids may creep for a very long time before failure occurs. Even ceramic matrix composites can undergo creep if left at an elevated temperature for a long period of time (Sodanapalli, Coon, 2002).

There are other significant methods of failure over time as well, including fatigue and corrosion. Fatigue failure can occur after a certain number of stress cycles. The number of cycles, called the fatigue life, can range from less than 1,000 to more than 500 million. Corrosion occurs due to the chemical reactions of a material with its surroundings. For instance, water and oxygen will cause iron to rust, which is a very common form of corrosion.

As a result, it can be very difficult to predict the properties and behaviors of materials with reasonable accuracy. Typically, models in the form of regression trees must be used to find a good approximation of how a material will behave. This is because material behavior is so complex that few linear models work, so nonlinear regression techniques must be used (Li, 2006).

Nevertheless, robotics has made the testing process much easier. This has resulted in a significantly increased amount of data which can be obtained. A robot can test how a material reacts to applied stresses at defined initial conditions by performing tensile tests, compression tests, bending tests, and torsion tests. The initial conditions themselves consist of how the material was formed, such as by annealing, cold working, casting, forging, etc., and what defects are present in the material, such as voids, cracks, dislocations, or vacancies. Varying the initial conditions can drastically change the material properties, even though the material itself remains the same (Tryland et al., 2000).

Another interesting experiment which has recently been performed involved using nano-robots to manipulate nanomaterials at the nano-scale. During these experiments, a three degree of freedom nanomanipulator was used to manipulate extremely small samples of material with extremely high precision. These nanomanipulators are quite impressive, able to move a linear distance of 12 millimeters with a precision of 0.25

nanometers. They are also able to move an angular distance of 120° with a precision of 0.02 seconds of arc (Saeidpourazar, Jalili, 2008).

One method of testing these nanomanipulators involves force scaling, in which general tests are scaled to larger dimensions before the very small scale tests are performed. Such precise robots can contribute significantly to the field of nanomaterials and nanotechnology. They may even be able to develop nanomaterials which may someday be used to produce alloys of enormous strength, which could then be used to build structures which are nearly unimaginable today.

There has been and is currently a significant amount of research being done in the fields of robotics and materials. However, in order to make the most out of robotics technology, a human user must be able to work directly with a robotic device. Many of the experiments discussed in this section involved direct human interaction, especially when the human user worked with a teleoperator system, either at the macro scale or at the nano scale.

Human-robot interaction is therefore very important in robotic materials analysis, and the field of robotics in general. Due to this, there is also a lot of research exploring human interactions with robots. Much of this research consists of examining the behavior of human-human teams and comparing them to human-robot teams. Some of these experiments involve materials testing, while others are more focused on haptics research, although all of the experiments contribute to the ultimate goal of improving the interactions between humans and robots.

2.3. Human Interaction with Robots

It is very important in the field of robotics that the human user and the robot are able to interact with each other and to work together as a team. This applies for any robotics testing, including materials research. The user must be able to give a series of commands to the robot, the robot must then collect the appropriate data, make some basic interpretations of that data, and then relay the data and the interpretations back to the user.

In order for this to be done effectively, the human user must be able to successfully work with a robot as a member of a human-robot team. Often, several humans are working with several robotic devices, so cooperation between all members is essential. It is important that the robots themselves are designed to be as human-like as possible. They must have sensors which can detect applied forces and motion. Then, they must be programmed to respond to the human users based on their sensors and the data that they collect.

It is also important in research to determine the most suitable human characteristics which allow for cooperative work between two humans, and then use these characteristics to design a robot which is capable of smooth, humanlike movement (Baker et al., 2006). One of the original projects of this nature is the work of Reed and Peshkin. Reed and Peshkin performed research testing the physical collaboration of human-human teams and human-robot teams, and then comparing the results (Reed, Peshkin, 2008).

Reed and Peshkin state that most human-human interactions are controlled by vision and sound. Humans tend to mimic the actions they see done by another person.

They also state that humans are very capable of adjusting to changes in their environment (Reed, Peshkin, 2008). Also significant is the physical interaction between humans and robots. Whenever two members interact with each other, whether it is two humans or one human and one robot, some level of fighting will occur. This is because it is impossible for perfect cooperation to occur, as there is always some element of resistance or human error.

The level of cooperation can be increased by designing the robot to be more human-like. To do this, the robot must possess many of the same qualities as humans. However, a major challenge is in designing a robot which is capable of adjusting to the changes in its environment through adaptive control. It must have force sensors with a fast sampling rate, and be programmed to react quickly when an applied force changes.

Another challenge arises from redundancies in the motion. Redundancies occur when there is more than one way to perform a task, and always exist in any haptic interaction involving two or more members. Furthermore, one would expect that the more members present in the group, the more prone to fighting the group is. When the human members and the robotic members are fighting with each other, the efficiency of the interaction is greatly reduced.

In Reed and Peshkin's research, their setup consisted of a circular table with a curtain in the middle. One person operated each side of the table. The two participants had to move a lever towards a projected target in a one degree-of-freedom environment, and their performance was measured by the time it took them to successfully reach the target. The two participants could not speak to or see each other, so communication was restricted to the forces and motions transmitted through the handles (Reed, Peshkin, 2008).

In their first experiment, a single individual operated the device alone, with nobody on the other side of the table. In the second experiment, two humans operated the table, one on each side. In the third experiment, one of the humans was replaced with a robotic partner. In some cases, the remaining human was told he was working with a robot, while in other cases, he was led to believe he was still working with a human (Reed, Peshkin, 2008).

The human-human teams performed the task 8.5% faster than the solo individuals, even though many of the human-human teams believed that their partner actually slowed them down. However, the human-robot teams where the human believed he was working with another person performed 0.9% faster than the solo individuals, while the human-robot teams where the human knew he was working with a robot performed 3.9% slower than the solo individuals (Reed, Peshkin, 2008).

The results of Reed and Peshkin's research illustrate that there are significant psychological issues which must be addressed in the human-robot teams. When the human user knew he was working with a robot, he performed slower than when he thought he was working with another human, even though all other variables remained the same.

These results demonstrate that, as mentioned in chapter one, there are important social factors involved in the human-human teams which are not present in the human-robot teams. These social factors exist primarily because humans naturally want to perform better if they think they are being watched and evaluated. It can be easy for someone to not care quite as much if they know their partner is a nonhuman entity. This is known as social facilitation, where an individual is motivated to perform better on simple tasks when being watched by someone else than if they were alone, and is a social obstacle which must be overcome if humans are to work with robots on a regular basis.

Even more recently, there have been some further experiments which have expanded upon the work of Reed and Peshkin. Another recent experiment by Kelso involved virtual partner interaction, which is the study of the real-time interactions between a human and a robot. This research explored how humans coordinate with human-like robots, with a primary focus of studying the continuous dynamics of interaction between a human-robot team, where the robotic member's coordination dynamics were very similar to that of a human (Kelso et al, 2009).

In Kelso's research, ten human subjects were involved in a simple test which measured their performance in working with a virtual partner. It consisted of two initial scaling trials, lasting 200 seconds each, and 32 experimental trials, lasting 100 seconds each. The human subjects were told to make smooth, rhythmic movements with their right index finger for the duration of the experiment, and to not stop this motion at any time until the tests was complete. Their motion was rather slow, so that fatigue would not have a strong impact on the results (Kelso et al., 2009).

The data collected during Kelso's experiments was then relayed to a virtual partner. The effectiveness of the information flow between the human subject and the virtual partner was measured. It was noted that there was a weakness in the coupling of the virtual partner with the human subject (Kelso et al., 2009).

Another recent experiment involved the collaboration of a human-robot team in the precise positioning of a three-dimensional flat object on a target. Both the human and the robot could exert forces and torques on the object in a six degree of freedom environment. However, due to the lack of range sensors on the robot, the human had to be the primary decision maker during the object manipulation. In a three-dimensional, six degree of freedom working environment, it is generally more challenging to properly position the object on the target than in a one-dimensional, one degree of freedom environment. However, the robot was able to assist in the human-robot interaction in order to successfully accomplish the task (Wojtara et al., 2009).

It has also been of research interest to study the roles played by each member of a human-human team and a human-robot team. In two member teams, or dyads, there is an executer and a conductor. 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 (Stefanov et al., 2009).

All of these research studies have demonstrated that it is possible for humans and robots to interact with each other successfully. Therefore, it must also be possible for a human-robot team to be able to work together to evaluate material properties as well. The field of robotics is one of the most exciting branches of science to develop over the last 50 years, and successful human-robot interaction is crucial for its success. Therefore, it is crucial that human-robot teams function just as well as human-human teams. With humans and robots working together, the possibilities are limitless, and the discoveries made will be great.

2.4. The Past, Present, and Future of Robotics in Space

One of the most exciting applications of robotics is the use of robots in space exploration. For decades, robots have been sent out into the solar system far beyond where humans could possibly go. These robotic pioneers have been sent to other worlds to study them, test their materials, and look for signs of life. The first robot to travel into space was the Soviet satellite Sputnik I, which launched in October 1957. Today, there are hundreds of satellites in Earth orbit. There have been dozens of robotic explorers sent to other worlds. In fact, robots are the only manmade objects which have ever travelled beyond the Moon. However, someday, humans will accompany these robots on their adventure, and successful human-robot interaction will be very important to the success of the mission.

One major characteristic which all robots used for space exploration must possess is mobility. If a space probe in not mobile, then it is essentially stuck on the same surface forever, and has very limited scientific potential. However, if it is mobile, then it can move around and study a much larger area. As a result, mobile robots are extremely important in planetary exploration. They are capable of taking measurements over a large area, and they can go wherever the human scientists want them to go. For instance, if there are some interesting foothills one hundred meters away, mission control can simply program the robot to drive over there and begin performing some research (Schilling, Jungius, 1996).

However, Schilling and Jungius state that there are several challenging design requirements for space faring robots which are not present in industrial or commercial mobile robots. The reason for this is that space probes must work in extremely harsh conditions, including working in a vacuum, dealing with low or zero gravity, and dealing with temperature extremes not seen here on Earth. Furthermore, the robot must be as lightweight and compact as possible, be able to work for months or years at a time on a very limited power supply, deal with communication time lags of anywhere from a few minutes to several hours, and endure a hibernation period of anywhere from a few months to several years during interplanetary travel (Schilling, Jungius, 1996).

Nevertheless, these problems have been more or less overcome in the last 50 years. There is nothing which can be done about the harsh working conditions these robots have to face, so we just have to deal with them. Due to the long time lag, the human scientists typically send a series of commands to the robot at a time, which gives the robot work to do for several more hours. However, this means that the human-robot interactions are even more critical. Since a real-time teleoperator system is not possible, the scientists must fully understand the robot and its capabilities. Fortunately, most space probes have a camera, so they can see their surroundings and take pictures, providing visual feedback to the scientists operating them. They all have force and range of motion sensors, allowing them to facilitate the exploration of the new world around them.

Today, there are several robotic space missions underway, including the Mars rovers Spirit and Opportunity, the Saturn orbiter Cassini, and the Pluto fly-by probe New Horizons, which is currently in route, and will arrive at Pluto in July 2015. However, as exciting as the prospects of robotics on other worlds is, another very important prospect in the application of robotics on the International Space Station.

The International Space Station is a massive space-based research facility in low Earth orbit. However, there are many engineering limits and cost constraints which limit the amount of payload, communication bandwidth, and number of astronauts the space station is able to carry. As a result, automated robots will be essential for smooth application of the space station in the near future. An advanced type of robonaut, which is a humanoid type of robot specifically designed to perform more delicate tasks on the space station, could be implemented for such operations (Bluethmann et al, 2003).

As the space station nears completion, there is a large amount of external maintenance which needs to be done, much of which is too dangerous to safely perform or would simply place an overbearing workload on the astronauts. Robotic assistants, or robonauts, could drastically cut back on the number of human spacewalks necessary. Spacewalks are quite dangerous and expensive to perform. However, with several robonauts in place, the astronauts on board the station could directly interact with them in a human-robot team in order to get the job done, from safely inside the station (Pippo et al., 1998).

It is clear that the field of robotics plays a vital role in solar system exploration and beyond. This is partly due to the rapidly advancing field of electronics. While the earliest spacecraft had extremely limited computing power, today's spacecraft are equipped with modern technology and computers. This is one reason why robotic space exploration has been so popular over the years. It is much cheaper and far less dangerous to send a robotic explorer to another planet than to go ourselves, even though current space probes must deal with large time lags when interacting with human scientists back on Earth (Launius, McCurdy, 2007).

However, one day, humans will travel beyond the Moon, and it will be direct human-robot teams exploring other worlds together. A full-scale mission to Mars may very well consist of a team of six astronauts and as many as a dozen robonauts. These robots will be able to work out in the environment when radiation or temperature levels do not permit the astronauts to go outside. Each astronaut may have two robonauts who assist him in performing experiments, acquiring data, and making discoveries (Bluethmann et al, 2003). The majority of the work done will be in the field of materials science. Whether it involves testing new alloys, testing soil and atmospheric samples, or looking for signs of life, the principles of effective materials testing must always be utilized. When this occurs, who knows what amazing discoveries are waiting to be made?

The field of robotics has been very significant indeed to the modern world. There have been all sorts of research in this field, from studying the collaboration of human-robot teams, studying how robots can be used in the analysis of materials, and even sending robots to other worlds to perform research where no man has gone before. There are also many unexplored parts of the Earth, such as the deep ocean, where humans and robots will go to study. There will be many fascinating new materials to study, and many exciting discoveries waiting to be made.

Therefore, it is my goal to expand upon the current research, and to learn how to improve human-robot interactions in different ways. It may prove extremely valuable someday when humans and robots travel in space together, and must work together to make discoveries. It will be the beginning of the development of a human-robot partnership which will last throughout the century, and will allow us to grow, to develop, and to explore.

Chapter 3. Devices and Design Parameters

The most important device for any robotics research is, of course, the robots themselves. To get the best results in a human-robot interaction, it is wise to select a robotic device which has a fast servoloop frequency, preferably around 1,000 hertz, which is necessary in accurately rendering a haptic environment. It is also wise to select a device which is user-friendly, comfortable, and one that is not capable of exerting dangerous levels of force back to the subjects.

Furthermore, to make the experiments themselves practical, it is a good idea to select a robot which is small enough to sit comfortably on a desktop. There are several reasons for this. First of all, large robots are very expensive, require considerably more power to operate, and can generally apply large forces back to the subjects. There are many research applications in which large robots are essential, but for this research, a small desktop device is better. Furthermore, a large stylus is going to be much heavier, causing fatigue in the subjects much more quickly.

The robot selected for this research was the Phantom Omni, developed by SensAble Technologies (SensAble Technologies, 2010). This selection was made due to availability of the devices, cost, and the abilities of the Omnis in haptic interaction. They are small and lightweight enough to be safe and reliable for human-robot interaction, have a fast servoloop frequency of 1,000 hertz, and can be programmed using the C++

language to render virtually any small-scale haptic environment or force feedback simulation.

3.1. A Robotic Haptic Interface

A total of four Phantom Omnis were used, creating a six-member human-robot team consisting of two human subjects and four robots. The Omni is actually a member of the SensAble Phantom set of haptic devices. It is capable of allowing its user to simulate many different haptic interfaces. It has many specialized features, including motion in six degrees of freedom, a compact, portable design, a rubber stylus and inkwell for convenient and easy calibration, and two switches on the stylus which can be programmed to input or output data from the Omni (SensAble Technologies, 2010).

The Phantom Omni is an impedance device (SensAble Technologies, 2010). There are two different types of robotic devices, which are impedance devices and admittance devices. An impedance device can read positions, velocities, and accelerations, and output a force back to its user. This allows them to be backdrivable and to generate inertia, making it possible for them to render very realistic force feedback. This is a major advantage in haptics, as impedance devices can easily determine from their position if they are interacting with a virtual object or not. If they are not, no force is applied back to the user. If they are, then a force pushing the user back out of the object is applied (Siciliano, Khatib, 2008).

An admittance device is just the opposite of an impedance device. It can read forces, but outputs a position back to its user. Due to this, an admittance device can easily be programmed to follow a predefined path based strictly on the positions involved. Programming them to follow a parabolic path, a circular path, or a series of more complex paths is therefore very straightforward. Although it is possible to program an impedance device to follow a predefined path, it must be done by applying a force in the direction of the desired position, set up like a spring between the actual and desired positions. This moves the stylus toward the desired position. The motion is fairly smooth and accurate for slower velocities, but it is still not nearly as good at this task as an admittance device would be.

Admittance devices have the major disadvantage in haptics in that it is difficult for them to render virtual objects or to generate adequate force feedback. The only way it could be done would be to program the device to respond to applied forces by moving to a new position that would feel similar to interacting with a virtual object. Even still, the effect would not be nearly as realistic as that which could be generated by an impedance device (Siciliano, Khatib, 2008).

Fortunately, the Omni is an impedance device, which makes it an excellent tool for generating a haptic environment. For instance, consider the most simplistic type of virtual object, a wall positioned at the x = 0 axis. The user is “trapped” in the positive-x region of his virtual world. As long as the stylus’ x-position is greater than zero, no force is applied. As soon as the x-position reaches zero, the device begins to apply a force in the positive x-direction pushing the user out of the wall. If the user continues to push into the negative x-direction, this force will increase proportional to the penetration into the wall, until the robot reaches its maximum possible force pushing the user back out of the wall.

The Omni has a maximum workspace of 320 mm x 240 mm x 140 mm. It has a good position resolution (0.055 mm) and is fairly lightweight (1.786 kg), which adds to its portability. It is capable of exerting a maximum force on the user of 3.30 Newtons (0.742 lb), although a continuous force in excess of 0.88 Newtons (0.198 lb) for an extended period of time can cause overheating or even damage to the motor and the device. Finally, it can produce a maximum stiffness of 1,260 N/m in the x-direction, 2,310 N/m in the y-direction, and 1,020 N/m in the z-direction. 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 (SensAble Technologies, 2010).

The only real limitations to the Omni are the small workspace in which it can work within, its maximum force limit of 3.30 N, and that more than two Omnis in series is an unsupported configuration, which could theoretically lose calibration after an extended period of time. However, due to its default servoloop frequency of 1,000 hertz, the Omni refreshes its force rendered every millisecond, allowing for smooth and continuous feedback, and frequent calibration during the experiments will prevent unwanted losses of calibration. This allows it to simulate realistic virtual surfaces and environments (SensAble Technologies, 2010).

These features make it perfect for this application and many other interesting haptics research projects. However, before any experiments could be done, extensive C++ programming had to be done to actually create the virtual worlds that the subjects would interact with. It is this that would command the Omnis to generate the force feedback necessary for the simulations.

3.2. Programming and Force Feedback

Before one can begin programming the Phantom Omnis to render virtual environments, he must first understand the workings of the C++ programming language, more specifically how to call up an Omni and tell it to render a certain force function. There are several parts to a successful program. First of all, in the center of any C++ program is the main function. The main function is the first function called, so it is crucial that the instructions for initializing the Omnis be placed within it (Schildt, 2003). Generally, the main function will initialize each Omni, enable them to render forces, start the servoloop scheduler, display instructions on the screen for the users, run the callback function and main application loop, and finally shut down and turn off the Omnis when the program is terminated by the user.

There are two more separate functions necessary, which are the main application loop and the servo callback function. The general purpose of the main application loop is to detect and interpret keypresses. Keyboard instructions can be programmed in this function as well. The servo callback function is called upon each servoloop tick, or every one millisecond. This function explicitly defines the force function for the Omnis to apply back to the user. It is within this function where the programmer must actually "create" the virtual environment. The position and force data are updated each millisecond when this function is called.

Fortunately, C++ is an object-oriented programming language, so it has the power to generate more complex environments with multiple virtual objects. To take advantage of the object-oriented nature of C++ to create several of the same type of object, it is best to create a class for that object. In C++, a class is simply a template that defines the form of the objects, or the members within it. Once a class and all of its member function have been created, the construction of new objects of that type is very straightforward through the use of a constructor function (Schildt, 2003).

One simulation used as a trial virtual environment simulation involved the subjects interacting with ten virtual spheres in a dynamic environment. The spheres had a virtual size and weight, and moved based on the amount of force applied to them by the subjects. Because the spheres all had the same dynamics, they were all objects of the sphere class, which contained all of the necessary data, equations, and functions to simulate their motion. The use of the sphere class was very advantageous because it allowed for the creation of new spheres very easily. This simulation could easily be expanded to include more and more spheres until the entire virtual world is filled up with spheres.

Another element of a Phantom Omni C++ program that is also very useful is the inclusion of open GL graphics. The graphics add several more functions to the program. However, they give the subjects visual feedback as well as force feedback when working within their environment. In a typical open GL display window, a three-dimensional view of the entire virtual environment is presented, including all active Omnis and all virtual objects present at the current time. The window updates itself at approximately 30 frames per second, allowing it to accurately show the state of the environment in real time.

Once a C++ program is successfully completed, tested, and debugged, then proper force feedback can be rendered back to the users. As it turns out, there are many ways to generate force feedback. Each way has some advantages and disadvantages. During the materials analysis experiment, three different modes of force feedback were used and compared, and it was found that the human-robot interaction with the materials varied quite a bit based on which feedback mode was active at the time. This proved to be true for both the softer materials as well as the harder materials. The subjects also interacted with each other differently depending on the feedback mode currently being applied back to them.

3.3. Forces, Work, and Motion Redundancies

In any robotic haptic interaction, the human subjects must apply forces to the virtual objects, and in turn, the robot applies forces back to them. When applying forces to a virtual environment, work is being done. Even with only one human subject interacting with a virtual environment through one robotic device, a combination of positive and negative work can be done if the human and the robot are fighting with each other. However, when you have more than one human or more than one robot, the concept of forces and work become a little more complicated, and motion redundancies are introduced.

Motion redundancies are always present when two or more members are working together, whether it is one human and one robot, two humans, two humans and four robots, or any other combination. This is because motion redundancies occur when there is more than one way to perform a task, or when a particular motion can be performed by either member of the team. Take for example, two humans carrying a table across a room. One person could push back, or the other could. If both are pushing back, then the motion is redundant, but they are sharing the workload. However, if one is pushing forward and the other is pushing back, then they are fighting with each other, which complicates the interaction.

In the example of the two humans carrying the table, let's assume that the table has a weight of 100 N and must be moved a distance of ten meters. It would then require a total of 1,000 J of work being done to move the table, neglecting the small height the table must be picked up off of the floor. If both humans cooperate perfectly, then each would do 500 J of work. This would be represented as person one doing 50% of the work and person two doing 50% of the work. Now, assume that person one was doing nearly all of the work while person two was passively holding the table above the ground. The work analysis may now show person one as doing 95% of the work and person two as only doing 5%. Going further, what if person two were not actually helping move the table at all, but were instead pushing back in the direction of person one? In this case, the two subjects would be fighting with each other.

For the case of both subjects fighting, the work analysis may show person one as doing 2,000 J of work and person two as doing -1,000 J of work, for a net total of 1,000 J. This concept of negative work arises because the two people are not working together, but are instead fighting with each other. Due to this, it took three times more energy between both people as was necessary to move the table. This is because person one had to work twice as hard as he would have if he were moving the table by himself to overcome the fighting of person two.

Now, take for example, a virtual box in which all four Omnis are attached to a different bottom corner. Subject one is responsible for the Omnis on the left side of the box and subject two is responsible for the Omnis on the right side of the box. The goal is for them to cooperatively move the box towards a target box. This is similar to moving the table across the room. The only difference is that there is one more degree of freedom in the system. For the case of moving a table across the room, there is likely to be significant motion in the x and z-directions, as well as rotational motion. For the box, significant motion in the y-direction will occur as well. Another difference is that, since the Omnis are positioned at a corner and not at the center of a bottom edge, pushing with only one Omni will apply a torque to the box causing it to spin due to the offset distance between the corner and the box's center of mass.

During this box interaction experiment, the subjects were instructed to work together as much as possible, and their level of cooperation was measured by first recording all of the positions of each Omni to a data file. Then, MatLAB analyzed this data and calculated the individual and joint forces and torques by each subject. A higher percentage of joint forces and joint torques indicates better cooperation between the subjects. Then, MatLAB calculated the work done by each subject for forces and for torques, based on the forces and torques themselves, distances and angles involved, and the total force work and total torque work for each target box throughout the entire simulation.

Although the detailed analysis of this experiment is presented in chapter 5, it is important to note that the percentage of work indicates how well the subjects were cooperating with each other. One very good result would be each subject contributing approximately 50% of the work for both forces and torques. This would indicate that the subjects were cooperating very well in dividing up the workload to move the box towards the target. Another very good result would be to see one subject contributing most of the work for the forces and the other subject contributing most of the work for the torques. In this case, the subjects are still cooperating very well with each other, although one is focusing on properly positioning the box while the other is focusing on properly orienting the box at the correct angle.

Another, less ideal result which sometimes arose was to see one subject dominating both forces and torques. This indicated that one subject was doing nearly all of the work to reach the target while the other subject was passively holding on to their styluses to keep the box stable. This is not ideal because the subjects did not equally spread the workload amongst each other. When negative work occurred, it indicated that the subjects were fighting more than they were working together to reach the target. The more negative a subject's work became, the more they were fighting. A few extreme cases even showed the percentages to be more than 1,000% and -900%, indicating that the subjects were not working together at all.

There are many different types of human-robot interactions present in this simulation, which brings up the concept of the "fighting factor", which will be discussed in detail in section 5.2. More details on how MatLAB was programmed to calculate the fighting factor is also discussed in detail in section 4.5. The fighting factor is an integer between 1 and 5 which indicates how the subjects interacted with each other. Once the fighting factors had been determined for each target box for each dyad, the target boxes were compared to determine which had the highest or lowest fighting factors, how much the fighting factor affected the time required to reach the target box, and whether the first or second time running the simulation affected the fighting factor.

The box interaction experiment was only the first of two experiments. Extensive analysis was done on this experiment to determine whether translational motion or rotational motion caused the most fighting, and to determine whether there were any correlations between the time to reach the target and the fighting factor for that target. However, the concept of fighting between the subjects was looked into even further on the second experiment performed, which was the materials analysis experiment.

3.4. Robotic Interaction with Materials

In the materials analysis experiment, the fighting distances and fighting velocities in each Cartesian direction of the world frame were calculated and compared. With increased fighting come negative work, wasted energy, and hindered performance. Therefore, the objective is to learn when and why members of the human-robot team fight with each other so that measures can be taken to better enable them to cooperate more.

When interacting with the materials, the Omnis were set up as a three Omni teleoperator system with two master robots and one slave robot. Each of the two subjects controlled one of the master robots, while the slave robot mimicked the average position and velocity of the two master robots. The fourth Omni was deactivated during the materials analysis experiment.

The objective was for the two subjects to work together as much as possible to move the slave Omni towards the target material and perform a series of hardness tests on it. Each subject would feel a force applied back to them, which, depending on the current active force feedback mode, was based on either the hardness of the material the slave Omni was in contact with, the amount in which he was fighting with his partner, or both.

In the materials analysis experiment, three force feedback modes were used. For all three, the slave Omni averages the position and velocity of the two master Omnis, mimicking the combined motions of the two human subjects. The fighting position and fighting velocity were calculated for each of the three Cartesian directions by writing to a data file the x, y, and z-positions of each Omni every millisecond. Then, MatLAB could read this file and calculate the fighting distance. By differentiating, the fighting velocity could be calculated as well. The following eight equations were used to calculate the fighting distance and velocity for each Cartesian direction. Remember 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.

$$\text{fight\_pos\_x} = \text{mean}\ [\text{abs}\ (x_1 - x_2)] \quad (1)$$

$$\text{fight\_pos\_y} = \text{mean}\ [\text{abs}\ (y_1 - y_2)] \quad (2)$$

$$\text{fight\_pos\_z} = \text{mean}\ [\text{abs}\ (z_1 - z_2)] \quad (3)$$

$$\text{fight\_pos} = \text{sqrt}\ [(\text{fight\_pos\_x})^2 + (\text{fight\_pos\_y})^2 + (\text{fight\_pos\_z})^2] \quad (4)$$

$$\text{fight\_vel\_x} = \text{mean}\ [\text{abs}\ (\text{vel},x_1 - \text{vel},x_2)] \quad (5)$$

$$\text{fight\_vel\_y} = \text{mean}\ [\text{abs}\ (\text{vel},y_1 - \text{vel},y_2)] \quad (6)$$

$$\text{fight\_vel\_z} = \text{mean}\ [\text{abs}\ (\text{vel},z_1 - \text{vel},z_2)] \quad (7)$$

$$\text{fight\_vel} = \text{sqrt}\ [(\text{fight\_vel\_x})^2 + (\text{fight\_vel\_y})^2 + (\text{fight\_vel\_z})^2] \quad (8)$$

For example, assume that the x-position of the first master Omni is -50 mm and the x-position of the second master Omni is 50 mm. In this case, the slave Omni would be at the average x-position of 0 mm, but the fighting distance in the x-direction would be 100 mm. Now, assume that the first master Omni is moving upward at 50 mm/s and the second master Omni is moving downward at 50 mm/s. In this case, the slave Omni would remain stationary in the y-direction, but the fighting velocity in the y-direction would be 100 mm/s.

However, one of the greatest difficulties in this experiment was accurately rendering the stiffness of the material, felt by the slave Omni, back to the subjects through their master Omni. One reason for this was the small maximum force of 3.30 N for which the Omnis are capable of producing. Another reason is that there are always differences between the way a virtual surface feels as opposed to the way a real surface feels. Therefore, three different force feedback modes were used and compared, to see which resulted in the better interaction between the subjects, the Omnis, and the materials. These modes were System Force Feedback, Social Force Feedback, and Dual Force Feedback.

The general concept between the three force feedback modes is as follows. In System Force Feedback, each master Omni feels a spring force between its position and the position of the slave Omni (equations 11 and 12). In Social Force Feedback, each master Omni feels a spring force between its position and the position of the other master Omni (equations 13 and 14). This mode has the advantage that it is easy to tell if you are fighting with your partner, but has the disadvantage that you cannot obtain any information on the object the slave Omni is interacting with based on the force feedback provided.

Both of these modes have been used to some degree before (Glynn et al., 2001). However, a new type of force feedback, called Dual Force Feedback was also used in this research. The general concept here is that both master Omnis feel the exact same force, equal to a spring force between the average position of the two master Omnis and the position of the slave Omni (equations 15 and 16). This mode tends to bring all three Omnis towards a stable equilibrium position.

Dual Force Feedback has the advantage that both subjects feel the same force, so each subject knows that his partner feels the same force as he does, but it has the disadvantage that it is very difficult to know whether the forces experienced are due to the slave Omni interacting with a material or from the two subjects fighting with each other. The following nine equations were used to calculate the force to be rendered back to each of the three Omnis for each of the three force feedback modes. Note that for all three modes, both the position and velocity differences were used to calculate the magnitude of this spring force.

Desired Positions and Velocities:

$$desiredPos = 0.5 * (pos_{Omni\_1} + pos_{Omni\_2}) \quad (9)$$

$$desiredVel = 0.5 * (vel_{Omni\_1} + vel_{Omni\_2}) \quad (10)$$

System Force Feedback:

$$F_{system,\ Omni\_1} = -k * (pos_{Omni\_1} - pos_{Omni\_3}) - b * (vel_{Omni\_1} - vel_{Omni\_3}) \quad (11)$$

$$F_{system,\ Omni\_2} = -k * (pos_{Omni\_2} - pos_{Omni\_3}) - b * (vel_{Omni\_2} - vel_{Omni\_3}) \quad (12)$$

Social Force Feedback:

$$F_{social,\ Omni\_1} = -k * (pos_{Omni\_1} - pos_{Omni\_2}) - b * (vel_{Omni\_1} - vel_{Omni\_2}) \quad (13)$$

$$F_{social,\ Omni\_2} = -k * (pos_{Omni\_2} - pos_{Omni\_1}) - b * (vel_{Omni\_2} - vel_{Omni\_1}) \quad (14)$$

Dual Force Feedback:

$$F_{dual,\ Omni\_1} = k * (pos_{Omni\_3} - desiredPos) + b * (vel_{Omni\_3} - desiredVel) \tag{15}$$

$$F_{dual,\ Omni\_2} = F_{dual,\ Omni\_1} \tag{16}$$

Slave Omni:

$$F_{Omni\_3} = k * (desiredPos - pos_{Omni\_3}) + b * (desiredVel - vel_{Omni\_3}) \tag{17}$$

From equation 17, it is clear that the slave Omni was drawn to the average position and velocity of the two master Omnis. Also, all of the force feedback modes were based on a spring-mass-damper system, where "k" was the spring constant and "b" was the damping coefficient. In two of the force feedback modes, System Force Feedback and Dual Force Feedback, the subjects felt a force when the slave Omni was interacting with the material in a similar manner to if they were interacting with a virtual material through their Omni. In the other force feedback mode, Social Force Feedback, the subjects could not feel anything that the slave Omni was encountering.

These three modes will be discussed in greater detail with the results presented in sections 6.1 and 6.2, but it is important to note that the human-robot interaction with the materials was very different in each of the different feedback modes. However, the fighting distance and velocity did remain fairly consistent for each of the five materials, indicating that feedback mode and Cartesian direction have a much larger impact on performance than the actual material being tested.

Now that all of the theory behind the experiments has been defined, the next chapter focuses on the details of the actual experiment itself, from the time the subjects entered the laboratory until they left. It then goes on to discuss how the calculations were performed, any problems which were encountered along the way and the solutions which were found to solve them.

Chapter 4. Experimental Protocol

Before any of the actual experiments could be run, the C++ codes for generating the virtual environments had to be written and tested, and IRB approval had to be granted for this research. Then, all of the necessary hardware had to be obtained, formed, and set up. It was crucial that everything be tested, checked, and rechecked before bringing in the subjects so that everything goes as smoothly as possible when running the actual experiments.

4.1. The Necessary Hardware

There were several different items necessary for setting up and running the experiments. First and foremost is a medium-sized workstation containing the computer, four SensAble Phantom Omnis, and two chairs, one for each subject. The experiment operator stood during the experiments. Also necessary was a copy of the IRB consent form and survey for each subject, and a device for backing up and storing the data collected. Figure 1 shows the complete experimental setup with the sphere interaction simulation running.

Figure 1. The complete experimental setup during the experiments. In this photo, the sphere interaction simulation has just begun, and all four Omnis are activated and are seen "hovering" above the table as they are in fact resting on the "floor" of the virtual environment. The subjects sit in the chairs and each control two of the Omnis during this practice trial. During the materials analysis experiment, the two subjects control only the left two Omnis, the third acts as the slave robot and actually interacts with the materials, and the fourth is deactivated.

The next item needed was a 6" x 6" x 6" open cardboard box, painted black, for the materials to be placed inside of during the materials analysis experiment. The next items necessary were the five materials themselves, which included a small block of soft foam, styrofoam, cardboard, soft wood, and aluminum. All of the materials were painted black to make them appear similar. The box was also painted black, so that the subjects could not easily determine the identity of the materials from sight alone. The box was also placed about one meter away from the subjects, further reducing this possibility, which was possible since the subjects interacted with the materials through a teleoperator system.

4.2. Experimental Setup

Once all of the necessary hardware had been obtained, the experiments could actually be set up and conducted. There were a total of four parts to the entire experiment, two simple "practice" environments in which the subjects were introduced to the Omnis, force feedback, and virtual object interaction, as well as the two actual experiments themselves. During the experiments, the Omnis were taped to the table using double sided tape so that they would not slide around during the experiments.

Once the Omnis were set up, the next step was to calibrate them often. A set of four Omnis in series is an unsupported configuration, so the Omnis can easily become uncalibrated after as little as ten to fifteen minutes, causing jerky motions and poor force feedback, so it was essential to recalibrate them as often as possible during the experiments. By calibrating often, there were very few calibration errors during the experiments themselves.

Table 2 presents a general minute-by-minute outline of the experimental procedure for the subjects. Sometimes the experiments finished in as little as 30 minutes if the subjects were quicker in the box interaction or materials analysis experiments, but the goal was to not let them run longer than 45 minutes, as to not take up too much of the subject's time.

Table 2. The basic scheduled timeline that the subjects followed when taking part in the experiments. The total time involved for each subject pair, or dyad, was approximately 45 minutes.

Time	**Current Activity**
0 min	The subjects enter the laboratory, IDRB 114, and I introduce myself to them.
1 min	Give both subjects the IRB consent form and allow them 5 minutes to read over it, sign it, and ask any questions they may have at the time.
6 min	Survey the subjects to get their subject number (1 through 20), gender, and whether they have ever worked with a robotic device before. It is made clear in the consent form that this data will not be attached to their name and will only be used for statistical analysis purposes only.
7 min	Begin the first practice run, which is the simulation of the outside of a box. The subjects have up to 2 minutes to practice with this simulation.
9 min	Begin the second trial run, which is the sphere interaction simulation. The subjects have up to 3 minutes to practice with this simulation.
12 min	Explain the box interaction experiment instructions.
13 min	Perform the box interaction experiment twice, recording the data for each trial. The subjects should be able to complete each simulation in 4 minutes or less, allowing up to 8 minutes for this experiment.
21 min	Give a 5 minute break from the Omnis, allowing the subjects to rest. At this point, it is time to set up the materials analysis experiment and to explain the instructions and procedure for it. It is also necessary to explain the three force feedback modes to the subjects at this time.

Table 2. Continued

26 min	Begin the hardness tests on the first material. One minute will be allotted for each of the three force feedback modes, for a total of 3 minutes.
29 min	Set up the experiment for the second material.
30 min	Perform the hardness tests on the second material.
33 min	Set up the experiment for the third material.
34 min	Perform the hardness tests on the third material.
37 min	Set up the experiment for the fourth material.
38 min	Perform the hardness tests on the fourth material.
41 min	Set up the experiment for the fifth material.
42 min	Perform the hardness tests on the fifth material.
45 min	Save all of the data to a disk. Give the subjects the post-experiment survey and thank them sincerely for participating in this research project.

Table 2 presents the general timeline followed throughout the experiment and all four simulations involved with it. The next section goes into greater detail on each of the simulations and what was actually being done, studied and measured for each of them.

4.3. Conducting the Experiments

Once the subjects entered the laboratory, their first task was to carefully read and fill out the IRB paperwork as I explained the fundamentals of robotics and haptics to them. Then, each subject got to practice with two virtual environments, each involving four Omnis. The first of these environments involved simulating the outside of a virtual cube. The cube passively floated in midair, in the center of the Omni's workspace.

The cube did not move, deform, or change in any way as the subjects interacted with it. Each Omni had its own independent cube. This interaction only had force feedback, no visual feedback was presented. The cubes were perfectly smooth and frictionless. The purpose of this simple interaction was to get the subjects used to force feedback and the concept of interacting with a virtual object. The cubes were soft, and if enough force was applied, one could actually push straight through the cube and come out the other side.

After a couple of minutes interacting with the cubes, the subjects were ready for a more interesting virtual environment. The second practice simulation involved simulating moving spheres in a virtual haptic interaction simulation. This was a dynamic environment, ruled by Newton's second law, $F = m * a$, where 'F' is the force vector applied to a particular sphere by a subject's Omni or by another sphere, 'm' is the virtual mass of that sphere, and 'a' is the resultant acceleration vector of that sphere. The acceleration was then integrated up to the new velocity vector and position of the sphere. A total of ten spheres and four Omnis were present in this virtual environment. The Omnis can interact with each other as well, feeling like hitting a bump when one Omni "runs into" another Omni.

The feature that distinguished this simulation from the first one was the visual feedback included. Through the use of open GL graphics, the subjects could see the position of all ten spheres as well as their positions in real time on the screen. This was extremely beneficial in a more complex virtual environment such as this one because without it, the subjects would have had no idea as to the actual position and velocity of the spheres and the other Omnis.

However, with the visual feedback, the subjects were easily able to visualize the virtual environment they were working within. All 20 subjects stated in the post-experiment survey that the open GL visual feedback was useful in the sphere and box interaction simulations. Figures 2 and 3 illustrate the virtual environment itself and the actual visual feedback available to the subjects during the simulation.

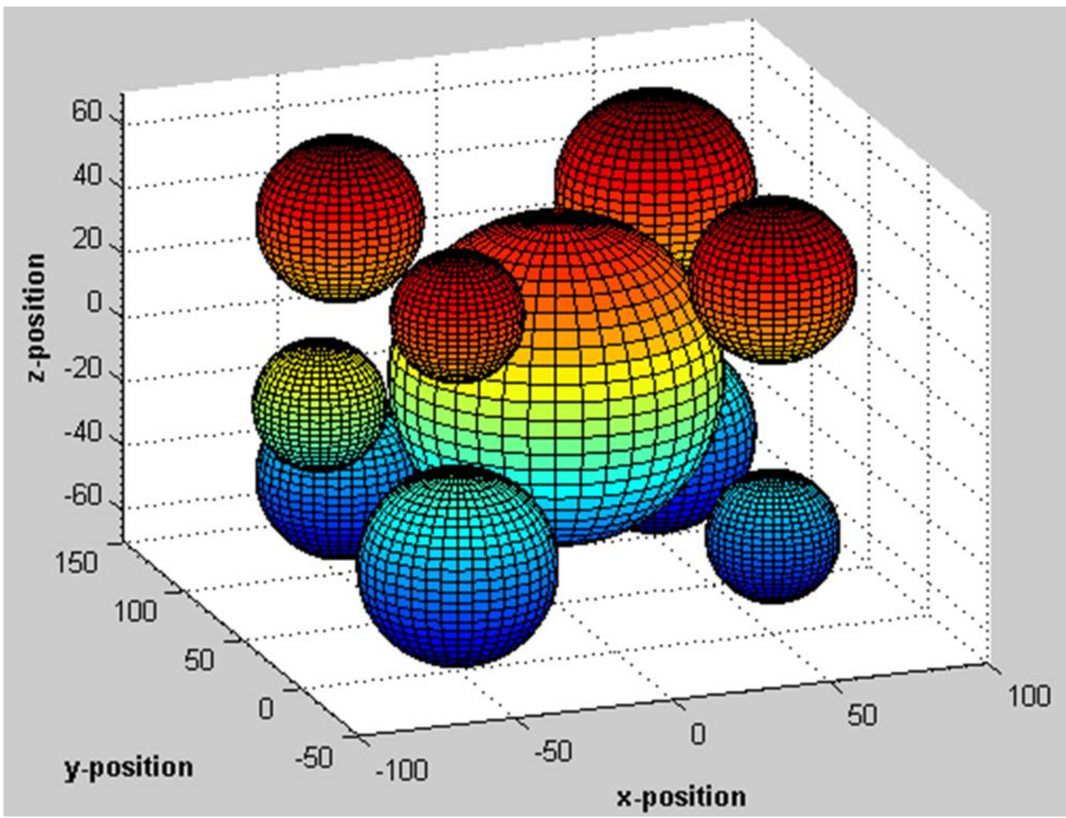

Figure 2. A 3-D MatLAB representation of the initial position of all ten spheres in the sphere interaction simulation.

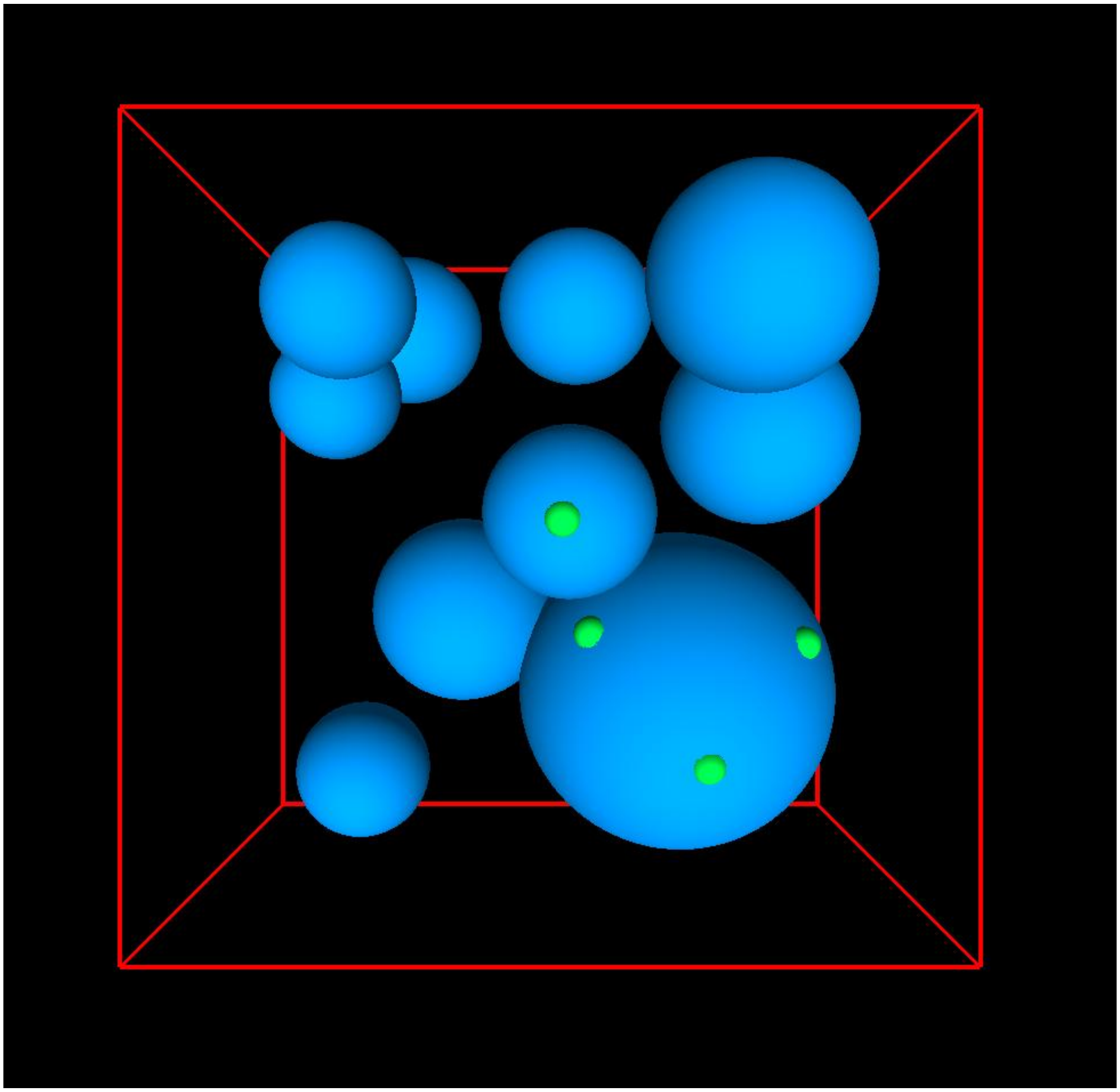

Figure 3. The sphere interaction simulation in progress. This was the second of two practice environments the subjects work with before the actual experiments begin.

Once the subjects had adequate time to practice with these first two simulations, they were ready to begin the actual experiments. The first of these was the virtual box interaction experiment. In this experiment, the objective was for the subjects to cooperate as much as possible to move the virtual box toward a set of ten target boxes, all of which required translational and rotational motion of the box.

This simulation began with the box positioned in the center of the Omnis' workspaces, and the first target box in the upper right hand corner. There were four directions in which the box could move, which were left and right, up and down, forward and backward, and rotation about the y-axis. Rotations about the x-axis and the z-axis were left out because this research focused primarily on planar motions.

In order to reach the target box, the subjects 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 properly 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 subjects had to apply both forces and torques to the box in order to reach the next target. Once all ten target boxes had been reached, the simulation was complete. The subjects then completed the entire simulation again, and their performance was compared between the first and second time. Quantities which were compared include the time to reach each box, the offset angle when each box was reached, and the fighting factor for each box.

For this experiment, open GL graphics were also utilized just as in the sphere interaction simulation. The visual feedback included the virtual box in which the Omnis were attached to, the current target box, and the Omnis themselves. The subject on the left's Omnis were colored green and the subject on the right's Omnis were colored blue.

This interaction would have been nearly impossible without visual feedback. Figure 4 illustrates the box interaction experiment as the subjects are approaching the tenth target box. To reach this box, the subjects must move the virtual box up and to the right, as well as straighten out the box angle slightly.

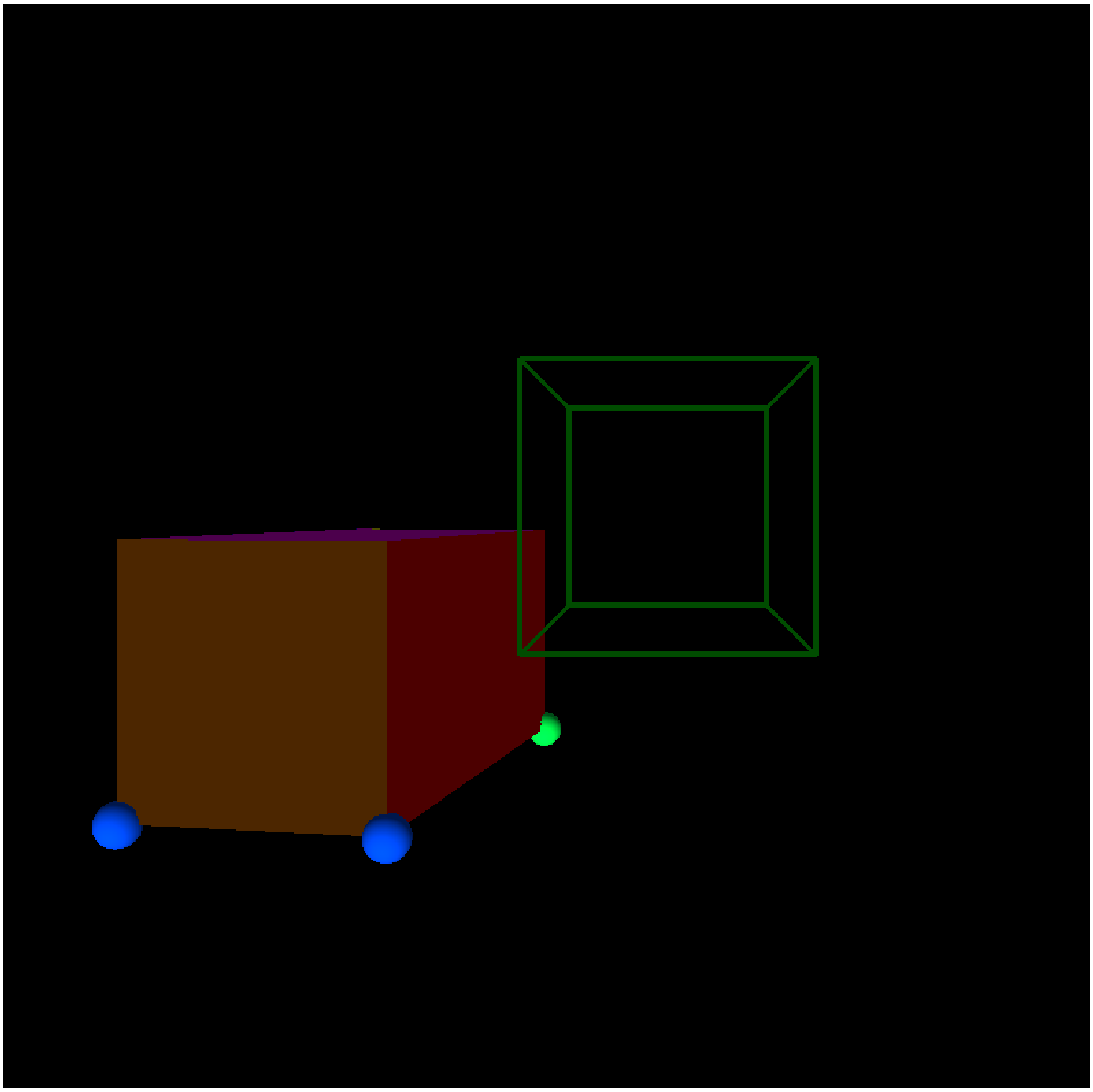

Figure 4. The box interaction experiment in progress. This is the first of two experiments which is designed to measure the abilities of two human subjects working together in a virtual environment through a set of robotic devices.

After the box interaction experiment was completed two times, a five minute break was given to allow the subjects to rest and to allow for the setup of the second experiment, which was the materials analysis experiment. During this experiment, a total of five materials were tested using the three force feedback modes described in section 3.4, which were System Force Feedback, Social Force Feedback, and Dual Force Feedback (Glynn et al., 2001).

During the materials analysis experiment, the hardness of the material was calculated in the C++ program based on the deflection of the material and the forces applied to it by the third Omni. As mentioned in section 4.1, the materials were all painted black and placed inside of a black box approximately one meter away from the subjects so that their identity was not revealed too soon. Figure 5 shows the left, front, and right-side view of the third Omni interacting with a block of soft wood, performing a hardness test on it.

Figure 5. The materials analysis experiment in progress, as seen from the left, front, and right side. This is the second of two experiments which measures the ability of two human subjects to interact with a robot to perform an actual experiment and acquire data. All of the materials are painted black and are placed inside of a black box so that the subjects cannot easily determine the material's identity from sight alone.

As you can see in figure 5, the stylus of the third Omni is taped up. This is because the stylus is not motor-controlled and would otherwise flop around, making the hardness tests impossible to accurately perform. Figure 5 is seen peering down into the box. However, the subjects were encouraged not to peer into the box and were strictly not permitted to touch the materials or interact with them in any way except through the third Omni. This kept the experiments fair and unbiased, as the final task for the subjects was to try and figure out the identity of the materials using a table of known material hardnesses. The table contained ten materials, five of which were the five they tested. After the experiment, the subjects filled out the post-experiment survey and were sincerely thanked for participating in this research study.

4.4. Problems and Solutions

Throughout the research process, there were a few minor problems which arose and had to be dealt with. The main issue was that, although the Omnis are excellent haptic devices and are well suited for this type of research, a set of four Omnis in series can lose calibration after about 10 to 15 minutes of continuous force feedback. This is because only dual Omni setups are supported in a series configuration, while three and four-Omni setups are not. When a miscalibration occurs, callback errors become more common, and eventually, the uncalibrated Omni stops properly rendering force feedback and can even start vibrating or moving around uncontrollably.

To prevent this problem from arising, the Omnis had to be recalibrated as often as possible throughout each experiment. They were calibrated a total of six times throughout the entire process, once at the very beginning, once after the first virtual box interaction, once after the sphere interaction simulation, once after each of the two box interaction simulations, and once after the materials analysis experiment. To calibrate, the subjects were instructed to place the stylus of each Omni back into the inkwell and the Phantom Test Calibration tool was run (SensAble Technologies, 2010).

Another issue which arose on one occasion was overheating of the motors. The box interaction simulation is very demanding on the motors, and is often applying the maximum force of 3.30 Newtons back to the subjects. Most of the simulations were completed in less than 4 minutes, so overheating did not occur. However, in one case, the time taken to complete the first simulation was 9 minutes and 27 seconds and the time taken to complete the second simulation was 4 minutes and 59 seconds, the longest at which the box interaction simulation had ever been run continuously for.

Towards the end of the second simulation, a warning message appeared on the screen that the second Omni had warm motors. This caused this Omni to immediately lose calibration, so the simulation had to be aborted and a ten minute break was mandated to allow the motors to cool. After ten minutes, the second simulation was resumed on target box 7, which was where the issue first arose, and the simulation was finished without further problems.

One possible solution for future work with simulations such as this one would be to limit the maximum force rendered. A force of 0.88 Newtons can be rendered continuously for 24 hours without causing overheating or other stresses on the device, so for a ten minute simulation, the maximum force could be limited to somewhere between 0.88 Newtons and 2.00 Newtons, depending on how much of a safety factor you are striving for. However, other than these two issues, the experiments ran very well and the data collected was very interesting. The next section discusses how MatLAB was used to calculate the interesting quantities from the original data files.

4.5. Post-Experiment Analysis and Calculations

For each dyad tested, three data files were generated by the Omnis. The first two were from each box interaction experiment, and included the time, target box number, and the actual and desired x, y, and z-positions of all four Omnis each millisecond throughout the simulation. The third was from the materials analysis experiment, and included the time, material number, force feedback number, and the x, y, and z-positions and forces for all three Omnis each millisecond throughout the simulation.

For the box interaction experiment, the time taken to reach each target and the offset distance and angle when each target was reached was written to a separate data file. The MatLAB analysis was only applied to the positions file for this experiment. The first task was to calculate the individual forces and torques and the joint forces and torques.

First, the boxframe forces were summed up for each time step. The boxframe forces are the forces that the subjects exerted on the Omni that were transformed into the moving reference frame of the box. This moving reference frame was determined by calculating the relative position of the box in box coordinates from the absolute position in world coordinates. This relative position was calculated by multiplying the world coordinates by the appropriate sine or cosine of the box angle. The concept of the boxframe forces on the box are illustrated in figure 6.

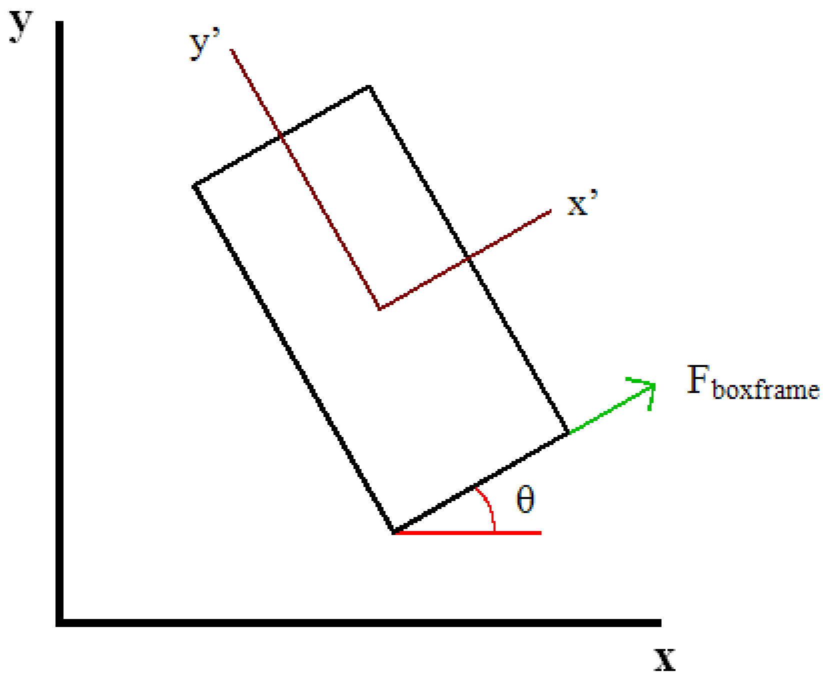

Figure 6. An illustration of the relative position of the box in box coordinates, the absolute position of the box in world coordinates, and the boxframe forces. In this figure, the x-y axis represents world coordinates, the x'-y' axis represents box coordinates, and the box's offset angle is $\theta = 30°$.

Then, the self forces and self torques were then calculated based on subject A using Omnis 1 and 2, and subject B using Omnis 3 and 4. Then, the total forces and total torques were added up for each target box. The percentages of individual forces and torques were then calculated by dividing the self force for each subject by the total force and dividing the self torque for each subject by the total torque and multiplying each value by 100%. The following eight equations were used to calculate these quantities.

$$\text{instant\_force} = 2 * \min[\text{abs}(L, R)], \quad \text{when sign}(L) = \text{sign}(R) \tag{18}$$

$$\text{instant\_torque} = d * \min[\text{abs}(L, R)], \quad \text{when sign}(L) = -\text{sign}(R) \tag{19}$$

$$\text{self\_force}_n = \text{sum}(\text{instant\_force}) \tag{20}$$

$$\text{self\_torque}_n = \text{sum}(\text{instant\_torque}) \tag{21}$$

$$total\_force = sum\ [abs\ (boxframe\_forces)] \tag{22}$$

$$total\_torque = sum\ [abs\ (d * boxframe\_forces)] \tag{23}$$

$$individual\_force_n = (self\_force_n / total\_force) * 100\% \tag{24}$$

$$individual\_torque_n = (self\_torque_n / total\_torque) * 100\% \tag{25}$$

In equations 18 and 19, instant_force and instant_torque are the individual force and torque quantities for each time step. The individual forces and torques are those contributed solely by one subject, and not jointly by both subjects. They are based on the force component, or boxframe force, of either translation or rotation of each of the four Omnis. L was the boxframe force for a subject's left Omni and R was the boxframe force for a subject's right Omni. The minimum absolute value of L and R was computed, since the Omni with the lowest boxframe force produced the self force or torque. If L and R were applied in the same direction, then a force was applied, and if they were applied in opposite directions, then a torque was applied. This concept is illustrated in figure 7.

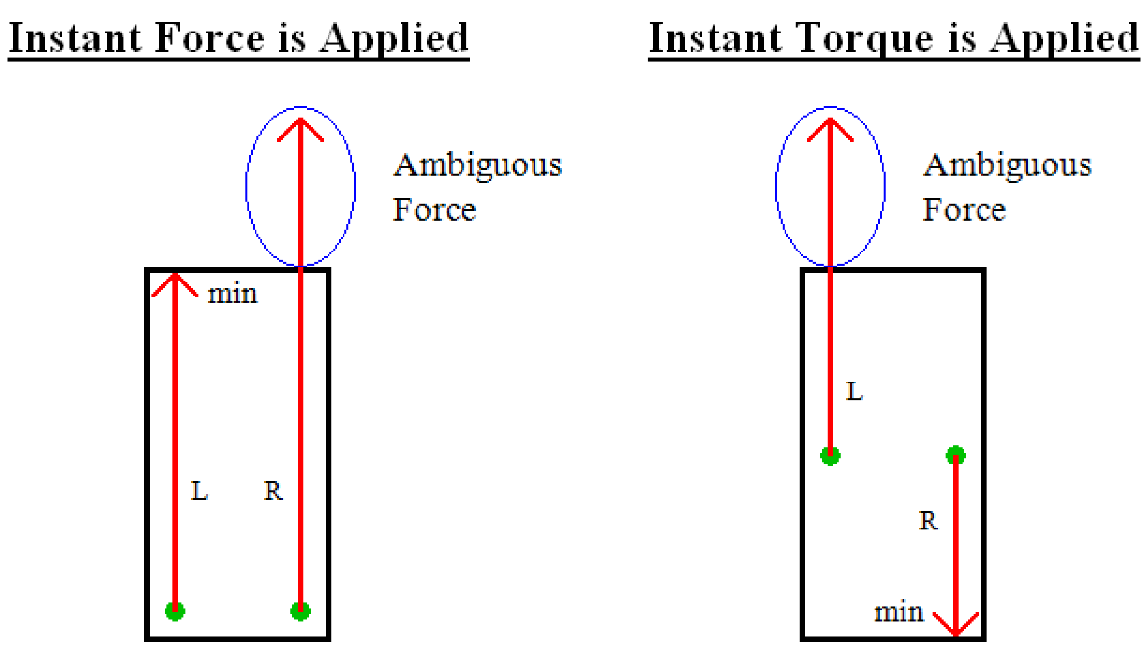

Figure 7. An illustration of the instant forces and instant torques.

In figure 7, the concept of the L and R forces are shown, as well as why the minimum of these forces was used in the calculation. The portion of the larger force which exceeded the magnitude of the minimum force was an ambiguous force. This force, shown within the blue circles, is ambiguous in terms of what the user wants it to do, either moving the box or rotating the box.

In equations 20 and 21, the instant_force and instant_torque quantities were summed up for each millisecond that the target box was active. Note that the subscript "n" refers to the subject number, either one or two. The variable "d" in equations 19 and 23 was the distance between the box's center and the corner for the Omni currently being solved for, and is either equal to half of the box's x-dimension or half of the box's y-dimension, depending on the case. The individual forces and torques were then calculated using equations 24 and 25 by dividing the self force by the total force or by dividing the self torque by the total torque.

Once the individual forces and torques had been calculated, the joint forces could be calculated by making the assumption that the rest of the forces and torques not contributed solely by one subject or the other must have been contributed jointly by the pair. Therefore, equations 26 and 27 were used to calculate these quantities.

$$\text{joint\_force} = [1 - (\text{self\_force}_1 + \text{self\_force}_2) / \text{total\_force}] * 100\% \qquad (26)$$

$$\text{joint\_torque} = [1 - (\text{self\_torque}_1 + \text{self\_torque}_2) / \text{total\_torque}] * 100\% \qquad (27)$$

The general concept for the joint forces and torques is as follows. Let's assume that, for a particular target box, the total force was 1,000 N and the total torque was 100 N*m. Let's also assume that subject A individually contributed 150 N of force and 8

N*m of torque, and subject B individually contributed 200 N of force and 7 N*m of torque. From equations 26 and 27, the joint force would be 650 N and the joint torque would be 85 N*m. Therefore, the individual forces for subjects A and B would be 15% and 20%, the individual torques for subjects A and B would be 8% and 7%, the joint forces would be 65%, and the joint torques would be 85%.

Once the joint forces and torques had been calculated, the next step was to calculate the self components of work for both forces and torques for subjects A and B. Then, the total work done by the translational forces and the total work done by the rotational torques was calculated. The percentages of individual work for forces and torques were then calculated by dividing the individual work done by each subject by the total work for that target box for both forces and torques and multiplying each value by 100%. Note that the force work was calculated based on the difference in the relative position of the box, and the torque work was calculated based on the difference between the box angle from the current time step to the previous time step. The following six equations were used to calculate these quantities.

$$\text{self\_work\_force}_n = \text{sum}\,[\text{instant\_force} * (\text{r\_pos}_{\text{time\_loop}} - \text{r\_pos}_{\text{time\_loop - 1}})] \tag{28}$$

$$\text{self\_work\_torque}_n = \text{sum}\,[\text{instant\_torque} * (\theta_{\text{time\_loop}} - \theta_{\text{time\_loop - 1}})] \tag{29}$$

$$\text{total\_work\_force} = \text{sum}\,[\text{boxframe\_forces} * (\text{r\_pos}_{\text{time\_loop}} - \text{r\_pos}_{\text{time\_loop - 1}})] \tag{30}$$

$$\text{total\_work\_torque} = \text{sum}\,[\text{boxframe\_forces} * (\theta_{\text{time\_loop}} - \theta_{\text{time\_loop - 1}})] \tag{31}$$

$$\text{force\_work}_n = (\text{self\_work\_force}_n \,/\, \text{total\_work\_force}) * 100\% \tag{32}$$

$$\text{torque\_work}_n = (\text{self\_work\_torque}_n \,/\, \text{total\_work\_torque}) * 100\% \tag{33}$$

In equations 28 through 33, the quantity "$r\_pos_{time\_loop} - r\_pos_{time\_loop\ -\ 1}$" is the magnitude of the distance between the relative position of the box in the current time step and the relative position of the box in the previous time step. The quantity "$\theta_{time\_loop} - \theta_{time\_loop\ -\ 1}$" is the difference between the box's offset angle in the current time step and the box's offset angle in the previous time step. Just like for the individual forces and torques, the individual force work and torque work were calculated using equations 32 and 33 by dividing the self work force by the total work force or by dividing the self work torque by the total work torque.

When summing up the force work or torque work for subjects A and B, you get 100%. However, this does not mean that the individual percentages themselves are between 0% and 100%, as they were for the individual and joint forces and torques. In fact, the individual work component for one subject can be greater than 100%, meaning that the individual work component for the other subject is negative.

As discussed in section 3.3, negative work indicates that there was more fighting than cooperation between the subjects for that particular target box. However, it was often seen that, even though there may have been immense fighting for translational forces, there was quite a bit of cooperation for torques, or vice versa, indicating that the two are not directly related to each other. A direct comparison, however, showed that there was consistently more cooperation in applying torques to the box than there was in applying translational forces to the box, which will be discussed in more detail in sections 5.1 and 5.2, along with the discussion of the fighting factor, which is derived directly from the force work and torque work calculated here.

For the materials analysis experiment, the level of cooperation between the subjects was measured a bit differently. For this experiment, the measured hardness values were written to a separate data file. Just like for the box interaction experiment, the MatLAB analysis was only applied to the positions file. For each material, the fighting distance and velocity was calculated for each force feedback mode and for each Cartesian direction.

This was done to measure the difference in position and velocity between the first two Omnis. Since this experiment was set up in a three-Omni teleoperator system with two master Omnis and one slave Omni, the first two Omnis were the master Omnis in which the two subjects controlled. The positions data was recorded to the data file each millisecond and the velocity data each millisecond was obtained through differentiation. The difference between the two Omnis could then be easily obtained, allowing for the calculation of the fighting distance. The fighting velocity, in millimeters per second, was calculated for each Cartesian direction in the same manner. Equations 1 through 8 from section 3.4 were used to calculate these quantities for each discrete time step. The average of all time steps for a particular feedback mode of a particular material was the quantity recorded for analysis.

The purpose of this analysis was not only to measure how well a human-robot team cooperated with each other, but to also measure which force feedback mode gave the subjects the most difficulty and which Cartesian direction gave them the most difficulty for both position and velocity. The next two chapters will present the results for both experiments, and answer these questions. They will also reveal how the subjects' interpretation of the difficulty of each force feedback mode compared to the actual numerical analysis of the data.

Chapter 5. Experimental Assessment of Virtual Environments

For the box interaction experiment, the subjects were instructed to cooperatively move the virtual box towards a target box, with tolerance levels of 20 millimeters and 30 degrees. There were ten target boxes in the simulation, and the entire simulation was completed twice. For subjects who had never worked with a robotic device before, this was the first time that they had ever worked with a partner to interact with a virtual object in this manner.

It is therefore of research interest to determine the successfulness of the human-robot interaction in this environment, whether distance or offset angle was the leading constraint in reaching the target box, and the fighting factors for both horizontal and rotated target boxes, in both the first and second simulation. The force feedback mode was constant throughout this experiment. Each Omni was attached to a bottom corner of the box, and the force applied back to the subjects was a spring force proportional to the distance the Omni was from the desired corner position, as calculated by equation 34.

$$F = k * \mathrm{sqrt}\,[(x_{omni} - x_{corner})^2 + (y_{omni} - y_{corner})^2 + (z_{omni} - z_{corner})^2] \tag{34}$$

In equation 34, k is the spring constant of the virtual spring between the Omni and the box corner, F is the magnitude of the force in the direction of the corner, and x, y, and z are the positions of the Omni or corner, whichever the case may be. The constraints on the box were that it was limited to a maximum angular velocity of 1 rad/sec, and was bound to the region between +100 and -100 in the x, y, and z-directions. If one of these bounds was reached, the box simply bounced back off of a virtual wall. The box's size was 120 x 60 x 60 millimeters and its density was 4,000 kg/m^3, or 4 times the density of water, giving a virtual mass of 1.728 kilograms (3.810 pounds).

5.1. Human-Robot Interaction in the Box Interaction Experiment

Both the first and second simulations were exactly the same, although the subjects all felt as if the second time was somewhat easier. This was due to having some experience with the virtual box the second time through, versus having no experience with it the first time through. This was also indicated by the time taken to complete each simulation. The average time required to complete it the first time was 3 minutes and 49 seconds while the average time required to complete it the second time was 2 minutes and 27 seconds.

In the box interaction experiment, boxes 1, 3, 5, 7, and 9 were the horizontal boxes and boxes 2, 4, 6, 8, and 10 were the rotated boxes. The horizontal boxes had the longest edge facing the screen and the rotated boxes had the narrow edge facing the screen. This ensured that the subjects would have to rotate the box 90° after reaching a target box in order to reach the next one.

The graphs presented in figures 8 through 15 fully analyze the data in the box interaction experiment. However, it is also of interest to see which pairs are actually statistically significantly different. In order to do this, a paired t-test was run for each of the comparisons in these figures. If the p-value, or probability that the null hypothesis is correct, is less than 0.05, then the two data sets are statistically significantly different. If $p \geq 0.05$, then the null hypothesis cannot be rejected and there is no statistically significant difference between the pairs. Figure 8 shows the average time to reach each target box for each simulation. Note that for all graphs with error bars present, the range represents one standard deviation from the mean of the data collected.

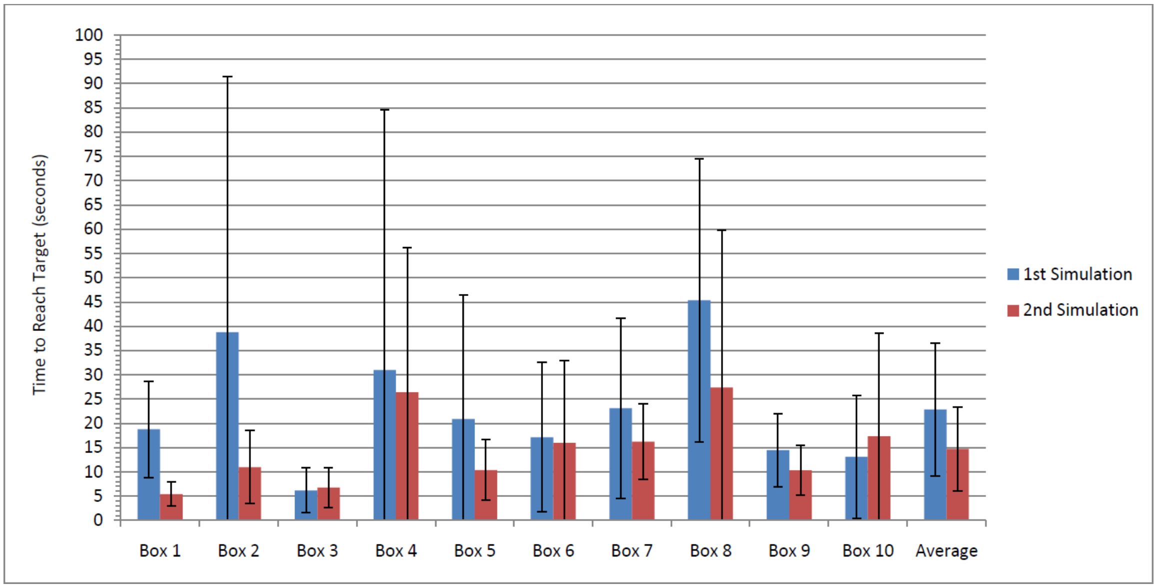

Figure 8. The average time taken to reach each target box in the box interaction experiment. The error bars represent one standard deviation from the mean.

In figure 8, it is clear that the average time for reaching each target box except 3 and 10 was less in the second simulation than in the first. However, it is notable that there are very large standard deviations for some of the boxes, in particular 2, 4, and 8. This is due to one or two dyads having great difficulty in lining up the virtual box with the target box, taking more than three minutes to reach a single box in some cases. These pairs did not actually have a large amount of fighting, they just could not get within the 20 mm and 30° limits for several attempts. Also notable is that all three of these boxes are rotated boxes. Box 5, a horizontal box, also has a fairly large standard deviation for the first simulation, although it is not nearly as large as the ones for 2, 4, or 8.

The longest time taken to reach a single box in the entire experiment was 3 minutes and 3 seconds, for target box 4 in the first simulation. The fastest a single box was reached in the entire experiment was 1.71 seconds for target box 3 in the first simulation. The longest time taken to complete the entire simulation was 9 minutes and 26 seconds in the first simulation, and the fastest the entire simulation was completed was 1 minute and 15 seconds in the second simulation.

Out of all ten dyads tested, nine completed the second simulation faster than they completed the first simulation, and one took 16.86 seconds longer to complete the second simulation than the first. This demonstrates that even a little practice can greatly increase the speed and efficiency at which a human-robot team can interact with a virtual environment. However, were the times statistically significantly different between the two simulations? When the paired t-test was run, it yielded a p-value of 0.0050. Therefore, it is safe to say that the null hypothesis can be rejected, and that the subjects did perform the second simulation statistically significantly faster than they performed the first simulation.

The next comparison made was between the average offset distances for each target box when reached. Due to the constraints on the experiment, the distance was always less than 20 millimeters. Figure 9 shows the average distance from the target box when reached, for each box in each simulation.

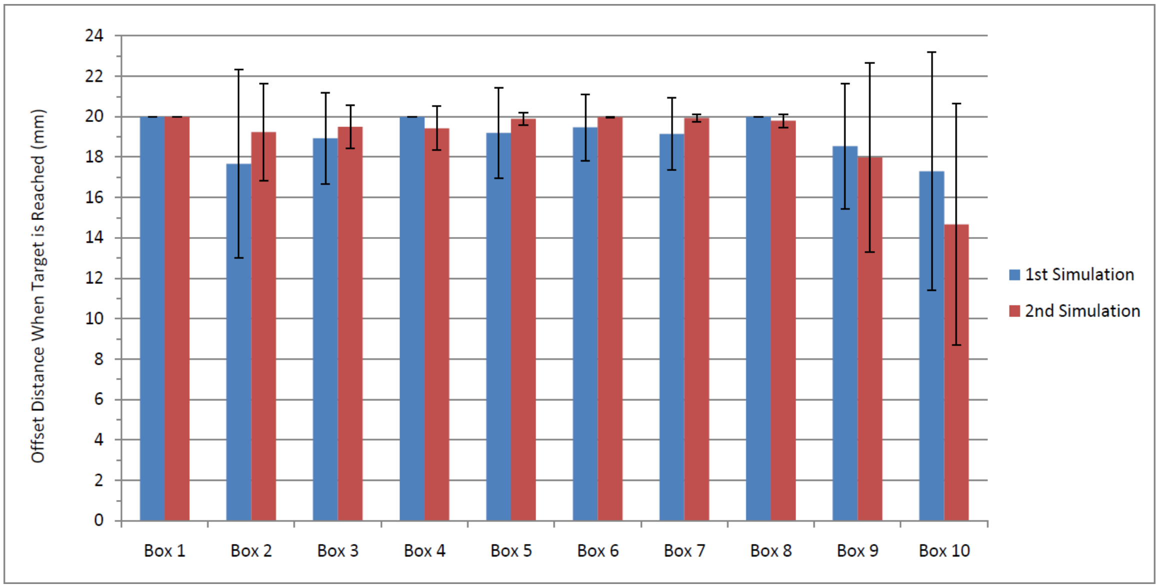

Figure 9. The average offset distance when each target box was reached in the box interaction experiment. The error bars represent one standard deviation from the mean.

As was observed in the actual data, distance was the leading constraint in reaching the target box 82% of the time in both the first and second simulations. This is verified by figure 9 as the average offset distances are quite close to 20 mm. For box 1, distance was the constraint 100% of the time. This demonstrates that, for the constraints given, it was more difficult to correctly position the box in the 3-D environment than to rotate it to the proper position. Through observation, it was common for the subjects to get the box to within 21 or 22 mm of the target, miss, and then have to try again. Perhaps if the tolerance had been increased to 30 mm, the results may have been quite different. However, for the constraints given, offset distance was proven to be more difficult to meet than offset angle.

There is no statistically significant difference between the offset distances in the first and second simulation. When the paired t-test was run, it yielded a p-value of 0.96.

This proves that there was absolutely no improvement in the offset distances the second time the simulation was run from the first time.

The next comparison made was between the average offset angles for each target box when reached. Due to the constraints on the experiment, the angle was always less than 30°. Figure 10 shows the average offset angle from the target box when reached, for each box in each simulation.

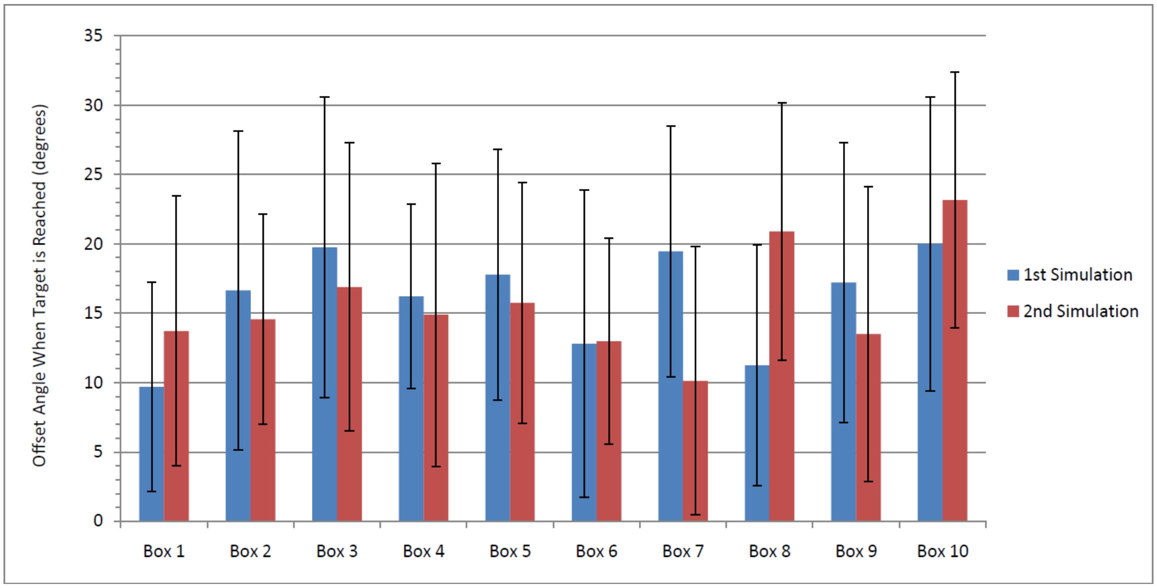

Figure 10. The average offset angle when each target box was reached in the box interaction experiment. The error bars represent one standard deviation from the mean.

In figure 10, it is clear that no box has an average offset angle close to 30°, indicating that the offset angle was rarely the leading constraint in reaching the target box. However, the large standard deviations indicate that the offset angle did vary significantly between the dyads for each box. However, there is no statistically significant difference between the angles in the first or second simulation. The t-test yielded a p-value of 0.75.

The lack of statistical significance between the first and second simulation and the data seen in figure 10 demonstrate that the offset angles were some random value between 0° and 30° when the target was reached. This makes sense since the offset distance was the leading constraint in reaching the target box for 82% of the targets.

Once the time, offset distance, and offset angles had been analyzed, the individual and joint forces and torques were analyzed to measure the level of cooperation between the subjects. Figure 11 shows the average individual and joint forces and torques for each target box in the first and second simulation. In figure 11, the individual forces and torques presented are actually the sum of those for both subjects. For example, if the individual forces for subjects A and B were 20% and 20% and the joint forces were 60%, figure 11 would show 40% for individual forces and 60% for joint forces.

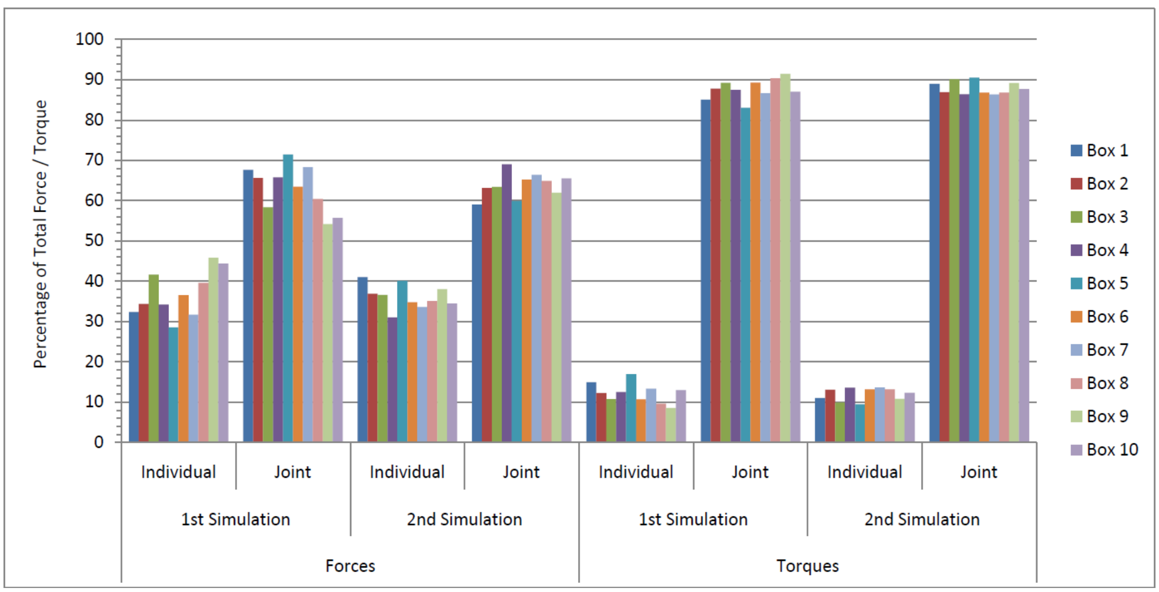

Figure 11. The individual forces and torques versus the joint forces and torques in the box interaction experiment.

As you can see, there was no statistically significant difference between the first and second simulations, but there was a statistically significant difference between the overall forces and torques, the individual and joint forces, and the individual and joint torques. There were five t-tests run on this data. Comparing the joint forces between the first and second simulation yielded a p-value of 0.68. Comparing the joint torques between the first and second simulation yielded a p-value of 0.78. However, when comparing the overall joint forces to the overall joint torques, the resulting p-value was less than 0.0001. When comparing the individual forces to the joint forces, the p-value was less than 0.0001, and when comparing the individual torques to the joint torques, the p-value was less than 0.0001. This demonstrates that there is essentially a 100% chance that the null hypothesis can be rejected for these three cases, proving that the subjects did cooperate more for rotational motion than for translational motion, and that there was a statistically significant difference between the individual and joint forces and the individual and joint torques.

On average, approximately 63.46% of the total forces were joint forces and approximately 87.85% of the total torques were joint torques. This also demonstrates that the subjects cooperated more with rotational torques than with translational forces, as was stated in section 4.5, and as is also illustrated by the offset distance being the leading constraint in reaching the target box.

The greater cooperation between the subjects for rotational torques than for translational forces is also proven by the analysis of work. Going beyond the individual and joint forces and torques, the work done by the forces and torques was obtained next using equations 28 through 33 from section 4.5. Once the force and torque work had been analyzed, the concept of the fighting factor could then be formed.

5.2. The Fighting Factor

The concept of positive and negative work was discussed in detail in sections 3.3 and 4.5. Since the percentages indicate how well the subjects worked together to move the box, the "fighting factor" could then be defined. The fighting factor is an integer value between 1 and 5 and is based directly on these percentages, with a "1" indicating a high level of cooperation and a "5" indicating a high level of fighting. Remember that subjects A and B both doing 50% of the work would indicate a perfect distribution of the work, and hence a very good level of cooperation.

A fighting factor of "1" indicates that the subjects worked very well together. There was a good deal of cooperation, and the subjects distributed the work nearly equally in order to move the box towards the target. A "1" is given if the percentages are between [50% 50%] and [30% 70%]. That is, 30% for one subject and 70% for the other.

A fighting factor of "2" is given if the percentages are between [30% 70%] and [0% 100%]. This indicates that the subjects are still working together, but one is doing most of the work. This is similar to the example given in section 3.3 where two people are carrying the table across the room, and one is passively holding the table above the ground while the other does most of the work to move it. This is also a very good result if one subject does the majority of the work for forces and the other does the majority of the work for torques, as they have still evenly distributed the work amongst each other, just in a different way as a fighting factor of "1" would indicate.

A fighting factor of "3" is given if the percentages are between [0% 100%] and [-30% 130%]. This, like a fighting factor of "2", indicates that one subject is doing most of the work. However, the difference is that the subjects are fighting with each other more than they are cooperating, hence the negative work. For fighting factors of 3 through 5, the level of fighting between the subjects increases with each step.

A fighting factor of “4” is given if the percentages are between [-30% 130%] and [-100% 200%]. This indicates that the subjects were fighting considerably, which makes it significantly more difficult and more tiring to reach the target. For this case, anywhere from 1.3 to 2 times as much work is being done than is necessary to reach the target, which is problematic because it can lead to increased fatigue in both the subjects and the Omnis.

Lastly, a fighting factor of “5” is given if the percentages are greater than [-100% 200%]. This indicates that the subjects were fighting the entire time and eventually got lucky enough to reach the target. Often in these cases, several times as much work was being done than was necessary. Also unique to this case is that both subjects have done more work than if they had moved the box by themselves.

The research interest here is to study whether horizontal or rotated boxes have the highest fighting factors, whether the fighting factor is highest for forces or torques, whether the fighting factor was less in the second simulation than the first, and how much the fighting factor affected the time taken to reach each target box. Figure 12 shows the number of each fighting factor for horizontal and rotated boxes in each simulation.

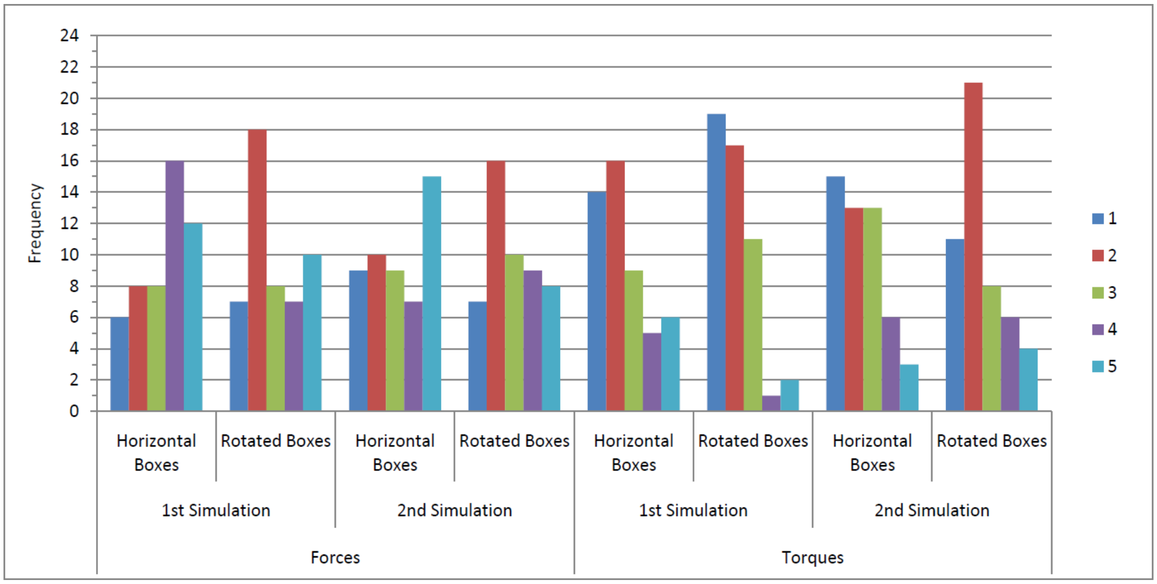

Figure 12. The frequency of each fighting factor per simulation in the box interaction experiment. Note that each simulation has a total of 100 fighting factors, since there were ten target boxes reached for each of the ten dyads.

In figure 12, the first notable observation is that there are far more 1's and 2's for torques than for forces, and far fewer 3's, 4's, and 5's for torques than for forces. This also demonstrates that the subjects cooperated better in rotating the box than in positioning the box, as was discussed in section 5.1. Another notable observation is the high frequency of 2's in the rotated boxes, for both forces and torques. This indicated that, for the rotated boxes, it was very common for one subject to do most of the work for forces and the other to do most of the work for torques.

It is also seen in figure 12 that there were a large number of 5's for the horizontal boxes in the force analysis, especially in the second simulation. This indicates that, for these boxes, the subjects had great difficulty in cooperating to move the box. This was observed during the experiments as well. It was common to see one subject push the box one way and the other push back the other way. Also common was to see the box getting very close to the target when one subject would make a strong move, causing the box to either spin around or fly away from the target, causing the subjects to have to start over in reaching that target. This brings up the next question, how does the fighting factor affect the time taken to reach the target box? Figure 13 shows the average time taken to reach each target box based on the fighting factor, for both force analysis and torque analysis.

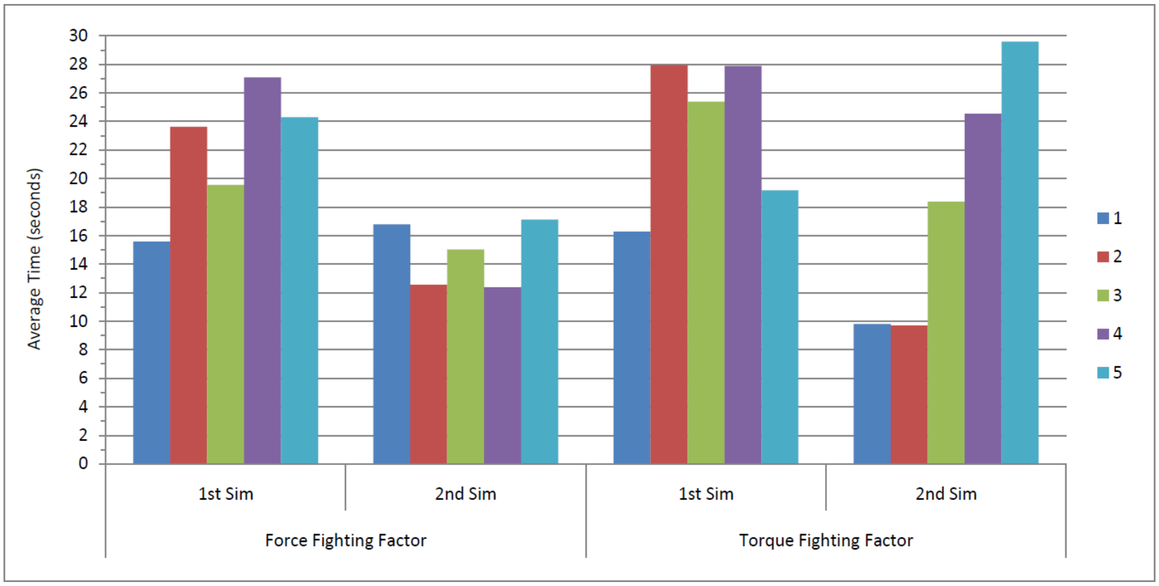

Figure 13. The average time taken to reach the target box per fighting factor in the box interaction experiment.

Figure 13 also shows that there was a statistically significant difference between the times taken to complete the first and second simulations. However, the results were somewhat unexpected. One would expect the average time to increase steadily as the fighting factor increased. However, this was only somewhat seen. For force analysis in the first simulation, the 1's were indeed completed the fastest, while the 4's and 5's took the longest. However, for the second simulation, the behavior is not what you would expect. The 5's did take the longest, but the 1's took nearly as long. It was the 2's and 4's which were completed in the least amount of time. For torque analysis in the first simulation, the 1's were completed the fastest. However, the 5's were completed nearly as fast. The 2's, 3's, and 4's took significantly longer than the 1's and 5's. In the second simulation, the analysis was exactly what one would expect. The 1's and 2's were completed very quickly, whereas the 3's, 4's, and 5's took progressively longer.

When looking at the actual data, it becomes clear why some of these discrepancies occurred. Some dyads were much quicker at completing the simulation than others, so their 5's may have not taken any longer than another dyad's 1's. Also, there were not that many 1's and 2's in the force analysis and there were not that many 4's and 5's in the torque analysis, so one target which took an unusually long time to reach could greatly skew the results shown in figure 13. However, figure 13 still shows that, for most cases, the 1's and 2's were completed somewhat quicker than the 3's, 4's, and 5's.

Yet another analysis regarding the fighting factor is the actual fighting factors themselves for each individual target box. Figure 14 shows the average fighting factor for each of the ten target boxes in both the first and second simulation.

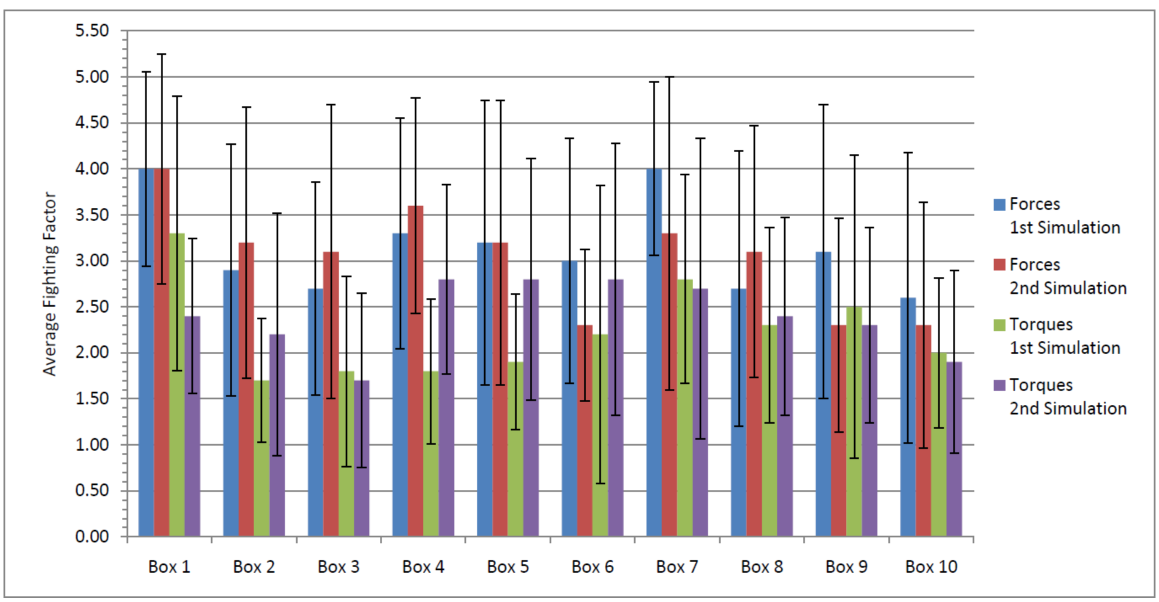

Figure 14. The average fighting factor per target box in the box interaction experiment. The error bars represent one standard deviation from the mean.

Figure 14 reiterates that there was no statistically significant difference between the fighting factors in the first and second simulations, but that there was a statistically significant difference between forces and torques. However, it also indicates which boxes were easiest for the subjects to cooperate on and which were the most difficult. For force analysis, boxes 1 and 7 promoted the most fighting while box 10 promoted the least fighting. For torque analysis, box 1 promoted the most fighting while boxes 2, 3, and 10 promoted the least fighting. However, an interesting observation was that for boxes 4, 5, and 6, the second simulation had a much higher average torque fighting factor than the first simulation. This may have been due to the subjects rushing more in the second simulation, thinking that they were more skilled than they actually were.

The standard deviations are also quite large for the fighting factors, indicating that some subject teams had a much higher level of cooperation than others. However, the first target box in the first simulation had a higher average fighting factor than the other boxes, which was likely due to this being at the very beginning of the experiment, so the subjects were just getting used to the force feedback and the task at hand.

When performing the statistical analysis for this data, the results were exactly what was expected. Running a t-test to compare all of the fighting factors for both forces and torques between the first and second simulation yielded a p-value of 0.80, so, just as predicted, there was no statistical significance between the first and second simulation. However, running a t-test to compare the force fighting factors to the torque fighting factors yielded a p-value of less than 0.0001, which demonstrates that there is essentially a 100% chance that the null hypothesis can be rejected for this case and that the torque fighting factor is statistically significantly less than the force fighting factor.

The final analysis regarding the fighting factor is the actual correlation between the work percentages themselves for forces and torques. The theory is that if a subject has a higher work percentage for forces, then they would have a lower work percentage for torques, as each subject would specialize on a separate portion of the task. Figures 15 illustrates this concept. Each subject's work percentage is plotted on an x-y plane, with the x-axis representing the force work percentage and the y-axis representing the torque-work percentage.

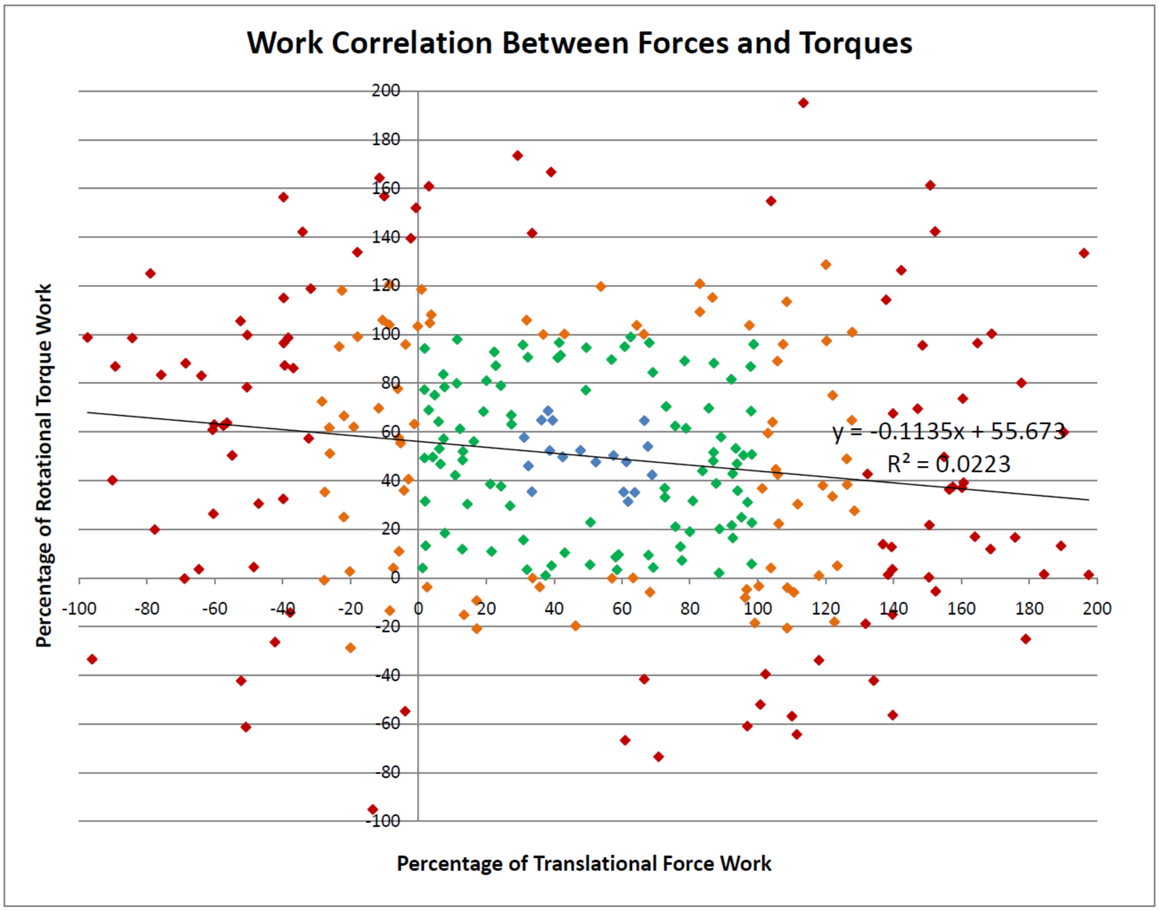

Figure 15. The force work vs. torque work scatter plot for all subjects of fighting factors 1 through 4 in the box interaction experiment.

Figure 15 presents all of the individual force work and torque work data for fighting factors 1 through 4 in a scatter plot. All points with a fighting factor of 1 are colored blue, all points with a fighting factor of 2 are colored green, all points with a fighting factor of 3 are colored orange, and all points with a fighting factor of 4 are colored red. The data for fighting factors of 5 were not analyzed here because the subjects were fighting too much to get any meaningful data in this analysis.

As seen in figure 13, the trendline has a negative slope, indicating that the theory of a subject having a higher percentage of torque or work, but a lower percentage of the other, is at least somewhat true. It is difficult to prove this theory, however, since the data points are greatly scattered, which is indicated by the very low value of R^2, and since the slope of the trendline is so shallow. However, this trendline and R^2 value is only for all data points with fighting factors 1 through 4. Table 3 lists the best fit trendline and R^2 value for seven different combinations of fighting factors.

Table 3. The best fit line and R^2 values of the force work vs. torque work data.

Fighting Factors	**Best Fit Trendline**	**R^2 Value**
1	y = -0.2800x + 63.998	0.1141
2	y = -0.1213x + 56.067	0.0180
3	y = -0.0793x + 53.966	0.0089
4	y = -0.1216x + 56.079	0.0290
1 and 2	y = -0.1257x + 56.285	0.0194
1 through 3	Y = -0.0934x + 54.670	0.0118
1 through 4	y = -0.1135x + 55.673	0.0223

In table 3, it is clear that there is not a large difference in the slope of the trendline or in the R^2 value for different combinations of fighting factors. The slope is negative in all seven cases, giving some element of proof to the force vs. torque correlation. However, an ideal correlation would result in the trendline y = -x + 100, with an R^2 value of at least 0.50.

The shallow slope of the trendline demonstrates that the subjects did not cooperate in this way as well as they could have in this experiment. This is also supported by the large amount of fighting and negative work seen in the analysis. For improving the human-robot interaction in an experiment such as this one, the ultimate goal would be to eliminate the fighting factors of 3, 4, and 5 altogether. For the best human-robot interaction, the fighting factors need to be 1 or 2, and the points on the scatter plot need to be as close to the line y = -x + 100 as possible. However, this is quite difficult to achieve. It would take considerably more practice on the part of the subjects, as well as better force feedback and visual feedback. However, if it is achieved, then the human-robot team could be capable of working with a much higher level of efficiency and speed by each member focusing on separate parts of the task.

5.3. Force Feedback vs. Visual Feedback

The concepts of force feedback and visual feedback were introduced in chapter 1, but now it is time to expand on them to improve their beneficence. The box interaction experiment was programmed such that only one method of force feedback and one method of visual feedback were used. However, better methods of feedback could certainly improve the fighting factor between the subjects.

While all 20 of the subjects stated that the visual feedback was useful, there was definitely some room for improvement. Future versions of this experiment could include two open GL windows. The first would show the virtual box and the target box from the perspective of subject A and the second would show it from the perspective of subject B.

Another possibility would be to have the open GL window be based on a moving coordinate frame associated with the box's position and angle. In the experiment, the window remained fixed in the same absolute reference frame, so the box moved within it. Yet another possibility would be to have two windows, one being the absolute reference frame as was in the actual experiment, and the other being based on the moving coordinate frame described above.

Future expansions of this project could include running this experiment with different types of visual feedback and then comparing the results. Another type of future expansion could be to try different types of force feedback for the box. One possibility for this could be to instead have the force feedback based on the level of cooperation between the two subjects, similar to Social Force Feedback in the materials analysis experiment. The general concept here is that the subjects would feel a spring force keeping them attached to the box corner, just as they did in the experiment, but they would also feel an additional force pulling them slightly in the direction of their partner.

This method would be a very good teaching method, in that it would promote one subject "leading" the simulation and the other subject "following" his partner. The leader would be someone who is highly experienced in haptic interactions such as this, and the student would be someone who is new to haptic interactions, and is seeking some practice in human-robot interactions. After all, the best way to improve the cooperation between the subjects would be for them to practice with several virtual environments such as this one. Improved methods of force feedback and visual feedback may help, but overall, the best way to improve these skills is to practice.

More future expansions and developments will be presented in section 7.1, but it is significant to note that, even during the 30 – 45 minutes the subjects spent participating in this research, they all showed significant improvements in their robotic interaction skills and confidence by the end of the experiments. Most of the subjects, especially those who had never used a robotic device before, approached the experiments with a fair amount of caution and shyness in the beginning. However, by the end of the materials analysis experiment, they all showed significantly more confidence and comfortability in using the Omnis and interacting with their partner through them.

5.4. Subject Feedback vs. Numerical and Statistical Analysis

The statistical analysis performed for the box interaction experiment proved that there was indeed a statistically significant difference between the level of cooperation between the subjects for translational motion and rotational motion of the box. The subjects cooperated significantly more in rotating the box than in moving it in space, as was demonstrated by the analysis of the forces, torques, work, and the fighting factor. The percentage of joint torques was much higher than the percentage of joint forces, and the average fighting factor was significantly lower for torques than for forces.

The statistical analysis also proved that the subjects performed the simulation significantly faster the second time than the first time, indicating that practice does improve performance and efficiency by a statistically significant amount. However, what did the subjects have to say about this? Did their perception match the numerical results?

Interestingly enough, in the post-experiment survey, 55% of the subjects stated that rotational motion was in fact the most difficult to control. The other 45% stated that translational motion was the most difficult. This is in contradiction to the numerical and statistical analysis, which demonstrated that the subjects had an easier time controlling the rotational motion than the translational motion.

Some of the reasons stated by subjects who felt that rotation was more difficult to control were that it was difficult to know which way your partner is turning the box, that there was a limited frame of reference in viewing the box while it was rotating, and that it was difficult to see your Omnis when you are in the back of the open GL window. All of these issues would be corrected by the implication of some of the visual and force feedback methods described in section 5.3.

Some of the reasons stated by subjects who felt that translation was more difficult to control were that it required extensive coordination with your partner, the box position would often place the Omnis in their extreme positions, at which they placed unwanted torques on the box, and that the box sometimes felt too heavy or had too much momentum to be moved easily. These issues could be corrected by slightly reducing the size of the field in which the box can move within and reducing the density of the box. Other than that, more practice would be required to master the coordination issues in this human-robot interaction.

As stated previously, the box was bound to the region between +100 and -100 in the x, y, and z-directions, and had a density of 4,000 kg/m^3. By limiting the region to between +70 and -70 in the x, y, and z-directions, reducing the density to 1,000 kg/m^3, improving the force and visual feedback available to the subjects, and allowing the subjects to practice for a substantial amount of time with this and other similar haptic environments, an average fighting factor of between 1 and 2 for all target boxes may easily become obtainable.

Good subject cooperation is essential in using human-robot teams to perform actual experiments, such as the materials analysis experiment. Chapter 6 will discuss the results of this experiment, and provide a detailed analysis of the cooperation between the subjects in a three dimensional Cartesian space between three different force feedback modes.

Chapter 6. Results and Observations of Materials Analysis

The hardness of a material is an easily obtainable, yet fundamental property. There are many hardness testers out there which are more suited to the task of finding a material's hardness than the Phantom Omni, yet they do not offer what the Omni offers. They provide no haptic interaction between the user and the device, nor do they allow two subjects to cooperate in a human-robot interaction in performing the experiments.

One limitation to the Phantom Omnis is that they are only able to perform these experiments on softer materials. As discussed in section 2.2, it requires a smaller force to deform these materials by a measurable amount, and many robots are unable to deliver larger amounts of force, the Omni being one of them. With that, 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 or getting an erroneous value.

The five materials tested were soft foam, styrofoam, cardboard, soft wood, and aluminum. The hardness values recorded for soft wood and aluminum were slightly higher than the actual values, although this was due to the Omnis being unable to get as accurate of measurements on these two harder materials. However, the most interesting aspect of this experiment was not the hardness values themselves, but how the subjects worked together to obtain them. They worked with three different force feedback modes to obtain the results.

6.1. Three Force Feedback Modes

As discussed in section 3.4, the three force feedback modes utilized in the materials analysis experiment were System Force Feedback, Social Force Feedback, and Dual Force Feedback. Remember that System Force Feedback was based on a force proportional to the distance between the subject's position and the slave Omni's position, Social Force Feedback was based on a force proportional to the distance between the subject's position and his partner's position, and Dual Force Feedback was based on both master Omnis feeling the same force, proportional to the distance between the average position of both master Omnis and the position of the slave Omni. These feedback modes are mathematically defined in equations 9 through 17 from section 3.4.

The hypothesis is that Dual Force Feedback would cause the most fighting because it is difficult to tell if the force you feel is due to you fighting with your partner or due to the slave Omni being restricted due to its interaction with a material. Social Force Feedback was expected to cause the least fighting because all of the force feedback was based on the fighting distance between you and your partner. As the fighting distance increased, the force applied back to you increased, pulling you back towards your partner's position. In turn, System Force Feedback would be in the middle, and would then be expected to have more fighting than Social Force Feedback, but less than Dual Force Feedback.

The subjects found all three force feedback modes to be different, but useful. Each has their advantages and disadvantages. The advantage of System Force Feedback is that the force tends to pull all three Omnis toward the same position, and gives the subject the sense of how stiff the material is that he is interacting with, although the disadvantage is that it is harder to know if you are fighting with your partner, so it can be more difficult to cooperate than in Social Force Feedback.

The advantage of Social Force Feedback is that the mode makes it very easy to cooperate with your partner and reduce the fighting distance and velocity substantially. However, the disadvantage is that it is impossible to know what the slave Omni is feeling in this mode. Hence there is no way to gauge the stiffness of the material from the force feedback alone.

The advantage of Dual Force Feedback is that both subjects feel the exact same force, so each subject knows what his partner is feeling. This mode is very good if one person is trying to train another in force feedback, since the trainer could set up the system so that he feels a force in which he wants the trainee to feel, knowing that the trainee would feel that force as well. It also tends to bring all three Omnis towards a stable equilibrium position. However, the disadvantage is that it is very difficult to cooperate using this mode for an experiment such as this one because it is hard to tell whether the forces experienced are due to the slave Omni interacting with a material or from the two subjects fighting with each other. This means that this mode promotes a higher likelihood of fighting between the subjects than the other two modes, as the subjects can easily end up fighting more just trying to get the system back to equilibrium.

During the break between the box interaction experiment and the materials analysis experiment, the subjects were given a thorough explanation and demonstration of these three force feedback modes. Then, they were ready to begin the materials analysis experiment. Therefore, the next step is to analyze their interaction with the Omnis in each of the three force feedback modes in this experiment.

6.2. Human-Robot Interaction in the Materials Analysis Experiment

It was seen that in a human-robot interaction within a virtual environment, the subjects had an easier time controlling rotational motion than translational motion, even though more subjects felt that rotational motion was actually more difficult to control. However, in the materials analysis experiment, the motion involved all translational motion in a Cartesian three-dimensional space. There were five materials tested, and three different force feedback modes used for each of the materials. Figure 16 shows the average fighting distance between the subjects for each force feedback mode and for each Cartesian direction in the materials analysis experiment.

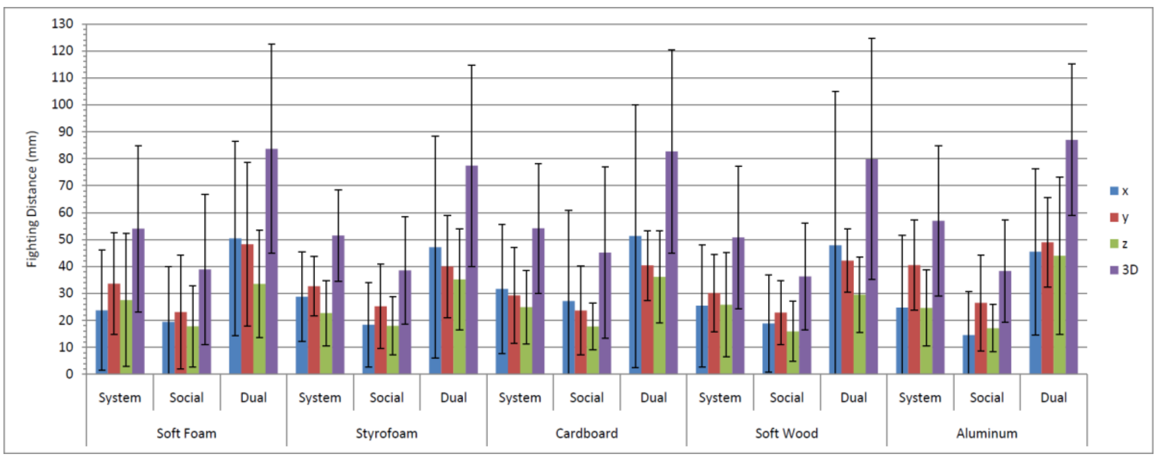

Figure 16. The fighting distance between the subjects per Cartesian direction in the materials analysis experiment. The error bars represent one standard deviation from the mean.

As seen in figure 16, there was no significant difference between the five materials themselves. This indicates that the material hardness itself does not have a large impact on the fighting distance. However, there is a significant difference between the force feedback modes. As was hypothesized, Dual Force Feedback consistently produced the largest fighting distance, then System Force Feedback, and Social Force Feedback produced the smallest fighting distance.

The average fighting distance is statistically significantly smaller in the z-direction than in the x or y-directions. There is no statistically significant difference between the fighting distance in the x and y-directions, although out of the 15 possible combinations, the y-direction had the largest fighting distance of the three Cartesian directions in 9 cases, the x-direction had the largest fighting distance in 6 cases, and the z-direction never had the largest fighting distance.

To compare the statistical significance between the three Cartesian directions, a paired t-test was run for each comparison, similar to what was done for the box interaction experiment. The comparisons made were between the x and y-directions, the x and z-directions, and the y and z-directions, independent of the force feedback mode. Then, System Force Feedback was compared to Social Force Feedback, System Force Feedback was compared to Dual Force Feedback, and Social Force Feedback was compared to Dual Force Feedback, using only the 3-D fighting vectors, so that these comparisons were independent of the Cartesian direction. This was done for both fighting distance and fighting velocity, for a total of 12 t-test comparisons.

The first six comparisons made involved the fighting distances in figure 16. Comparing the x-direction to the y-direction yielded a p-value of 0.42. Comparing the x-direction to the z-direction yielded a p-value of 0.047. Comparing the y-direction to the z-direction yielded a p-value of less than 0.0001. This confirms that the fighting distance in the z-direction was statistically significantly smaller than in the x or y-directions, but that there was no statistically significant difference between the fighting distances in the x and y-directions.

Comparing System Force Feedback to Social Force Feedback yielded a p-value of less than 0.0001. Comparing System Force Feedback to Dual Force Feedback yielded a p-value of less than 0.0001. Comparing Social Force Feedback to Dual Force Feedback yielded a p-value of less than 0.0001. This also confirms what was observed in figure 16, that Social Force Feedback produced the smallest fighting distance, that System Force Feedback produced significantly more than Social Force Feedback, and that Dual Force Feedback produced significantly more than the other two modes.

The next quantity to be analyzed was the fighting velocity. Figure 17 shows the average fighting velocity between the subjects for each force feedback mode and for each Cartesian direction in this experiment.

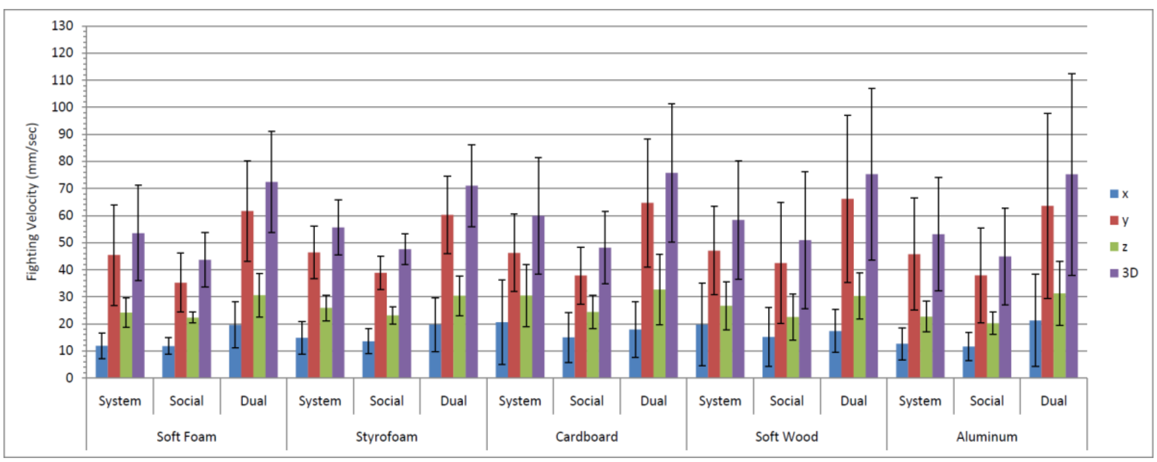

Figure 17. The fighting velocity between the subjects per Cartesian direction in the materials analysis experiment. The error bars represent one standard deviation from the mean.

As seen in figure 17, there was no significant difference between the five materials themselves, indicating that the material hardness did not have a large impact on the fighting velocity, just as it did not have a large impact on the fighting distance. Again, it is clear that, for the fighting velocity, Dual Force Feedback also produced the most fighting and Social Force Feedback produced the least.

The final six statistical comparisons made involved the fighting velocities in figure 17. Comparing System Force Feedback to Social Force Feedback yielded a p-value of less than 0.0001. Comparing System Force Feedback to Dual Force Feedback yielded a p-value of less than 0.0001. Comparing Social Force Feedback to Dual Force Feedback yielded a p-value of less than 0.0001. This also confirms what was observed in figure 17, that Social Force Feedback produced the smallest fighting velocity, that System Force Feedback produced significantly more than Social Force Feedback, and that Dual Force Feedback produced significantly more than the other two modes.

However, for fighting velocity, there was a much larger difference between the x, y, and z-directions than there was for the fighting distance. Hence, the fighting velocities in the three Cartesian directions were far more statistically significantly different to each other than the fighting distances were. Comparing the x-direction to the y-direction yielded a p-value of less than 0.0001. Comparing the x-direction to the z-direction yielded a p-value of less than 0.0001. Lastly, comparing the y-direction to the z-direction yielded a p-value of less than 0.0001.

This analysis also confirms what was observed in figure 17, that the fighting velocity in the x-direction was statistically significantly smaller than in the other two directions, that the fighting velocity in the z-direction was statistically significantly larger than in the x-direction but statistically significantly smaller than in the y-direction, and that the fighting velocity in the y-direction was statistically significantly larger than the fighting velocity in the other two directions. For all 15 cases in figure 17, the y-direction has by far the largest fighting velocity, the z-direction has the second largest, and the x-direction has the smallest. This proved that motion in the y-direction was much more difficult to match than motion in the x and z-directions.

This result indicates that, quite often during the experiment, one subject was moving his stylus up while the other was moving his down. Since most of the motion was up and down motion, it was somewhat expected that this direction might have a larger fighting velocity and fighting distance. However, the subjects were instructed to work together as much as possible in moving the slave Omni, and this data shows that they clearly were not doing so a good amount of the time. This may have been responsible for some of the repeat hardness measurements that had to be taken.

One other notable observation in both figures 16 and 17 is the standard deviations present in the data. For the fighting distance, the standard deviations were generally very large, indicating that some dyads cooperated much more than others during this experiment. This is largely due to the fact that in some dyads, both subjects had previous experience in working with robotic devices, while in others, only one had previous experience, and in others, neither subject had ever worked with a robotic device before. For fighting velocity, the standard deviations were much smaller than for fighting distance, but they were still quite large.

The best way to reduce the fighting distance and fighting velocity is, just like in the box interaction experiment, for the subjects to get substantial practice working with robotic devices in experiments such as this one. Furthermore, running the experiment in Social Force Feedback mode all the time would further reduce the fighting distance and velocity, but unfortunately, the subjects would not be able to receive haptic feedback from the material's stiffness.

Therefore, the best force feedback mode to use for this type of interaction would be System Force Feedback. This mode allows the subjects to feel the stiffness of the material, and it also allows them to feel if they are fighting with their partner. With enough practice in this feedback mode, the levels of fighting distance and velocity should be reduced greatly.

Yet another possibility would be to introduce visual feedback into this experiment. The position of both master Omnis and the material could be shown in an open GL window. That way, the subjects would see exactly how far apart they are from their partner, which would likely reduce the fighting distance by a significant amount. The fighting velocity should be reduced somewhat too, as each subject would see the motions of his partner on the screen and could more easily mimic it. These possibilities will be discussed further in section 7.1.

6.3. Obtaining the Fundamental Properties of Materials

The final objective in this research was to actually study the effectiveness in which a human-robot team could obtain the fundamental properties of materials such that they could be identified. Of the five materials tested, the property measured was the Brinell hardness. The measured hardness values were then compared to the actual hardness values, for each of the three force feedback modes. Figure 18 shows the average measured hardness value for each force feedback mode and for each material, compared to the actual hardness of that material.

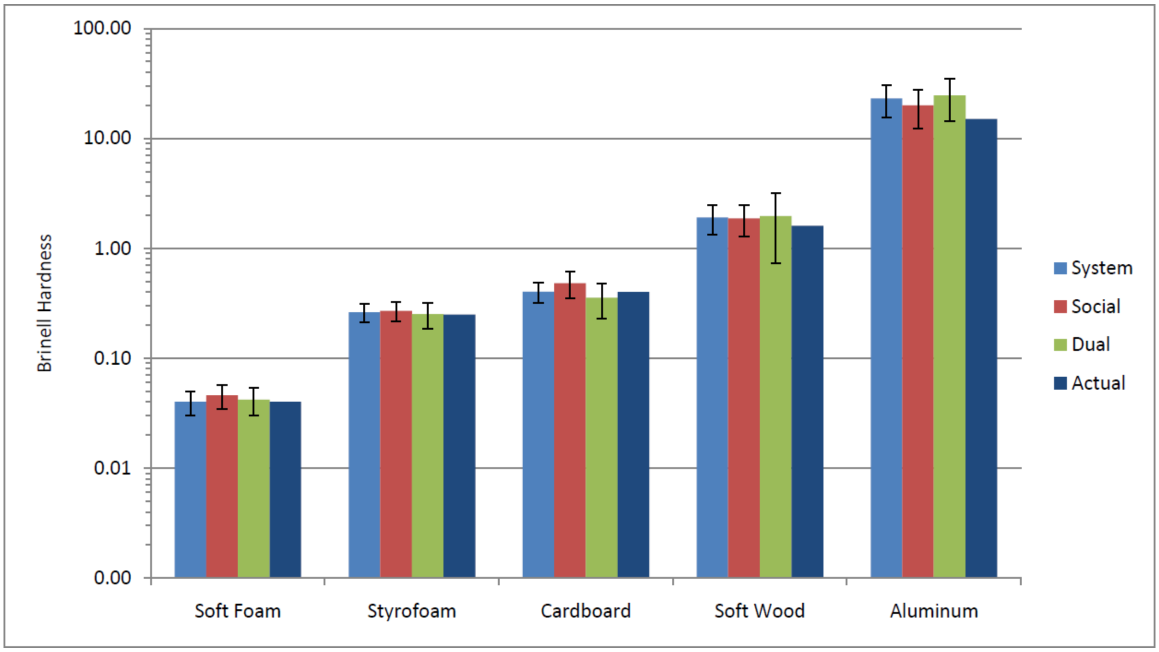

Figure 18. The actual hardness test results from the materials analysis experiment. The error bars represent one standard deviation from the mean.

As seen in figure 18, the measured hardness values are quite close to the actual hardness values, within the standard deviations. As stated earlier, the measured values for soft wood and aluminum were consistently high, but this was due to the Omni having difficulty actually measuring these harder materials.

As seen in figure 18, Dual Force Feedback produced a slightly larger standard deviation than the other two feedback modes. There is definitely a significant difference between the measured hardness values of the five materials, indicating that the methods used were fairly accurate in calculating the hardness values. There was not a significant difference between the force feedback modes, indicating that the feedback mode did not have a strong impact on the calculated hardness value.

Once the materials analysis experiment was complete, the subjects were given a table of ten materials and their actual hardness values. They were then shown all 75 hardness data points, five for each of the three force feedback modes for each of the five materials. They then used this data, the table, and the haptic feedback rendered to them during the experiments to try and figure out the identity of the materials.

It was found that some of the materials were more difficult to identify than others. This was partly due to the materials given in the table, and partly due to the subjects 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. Table 4 lists the number of subjects to correctly identify each material and the percentage of accuracy which resulted.

Table 4. The successfulness of the subjects in identifying the unknown materials in the materials analysis experiment. A total of 20 subjects participated in this experiment.

Material	**Number of Subjects to Correctly Identify**	**Percentage of Subjects to Correctly Identify**
Soft Foam	17	85%
Styrofoam	14	70%
Cardboard	11	55%
Soft Wood	7	35%
Aluminum	18	90%

Out of all 20 subjects tested, only three were able to correctly identify all five materials. For soft wood, the major factor which made identifying it more difficult was that the Omnis measured it to be slightly harder than it really was, causing seven of the subjects to incorrectly assume that it was hard wood. However, this should not have been such an issue as soft wood has an actual hardness value of 1.6 while hard wood has an actual hardness value of 4.0, and the average values measured by the Omnis were around 1.9.

Testing for more material properties, such as yield strength, elastic modulus, and Poisson's ratio, and then comparing all of these properties to a material database would likely yield better results for subject identification. However, considering that there were ten materials in the table, the rate of success by chance alone would be two subjects per material. Since the actual number of subjects to correctly identify the materials was much higher than this, it proves that just testing for the hardness can eliminate a lot of possibilities. Even if you cannot pinpoint the identity after just this test, you can often reduce the number of possibilities by a significant amount.

Once the experiments were completed, the subjects were given the post-experiment in which they analyzed the experiment. Their responses for the box interaction experiment were already analyzed in chapter 5, but they also discussed the three force feedback modes and the materials analysis experiment as well. The next section analyzes their responses and compares them to the numerical analysis of human-robot interaction in each of these feedback modes.

6.4. Subject Feedback vs. Numerical and Statistical Analysis

The statistical analysis of the materials analysis experiment proved that there was indeed a statistically significant difference between the three force feedback modes for both fighting distance and fighting velocity. For both fighting distance and velocity, Social Force Feedback was significantly less than the other two, Dual Force Feedback was significantly more than the other two, and System Force Feedback was significantly more than Social Force Feedback but significantly less than Dual Force Feedback. The statistical analysis also proved that the y-direction promoted the largest fighting velocity, while there was not nearly as much difference between the fighting distances. However, what did the subjects have to say about this? Did their perception match the numerical results?

Out of the 20 subjects tested, three stated that they liked System Force Feedback the most, ten stated that they liked Social Force Feedback the most, six stated that they liked Dual Force Feedback the most, and one stated no preference to either mode. Then, the subjects were asked to rate each mode on a scale of one to five, with one indicating that they did not like the mode or that it was too hard, and five indicating that they really liked the mode, and found it to be very comfortable and user-friendly. System Force Feedback received a mean score of 3.15, Social Force Feedback received a mean score of 3.35, and Dual Force Feedback received a mean score of 3.45. System Force Feedback had a median of 3 and a mode of 3, Social Force Feedback had a median of 4 and a mode of 4, and Dual Force Feedback had a median of 3 and a mode of 3. This indicates that the subjects as a whole liked Social Force Feedback and Dual Force Feedback more than they liked System Force Feedback.

Next, the subjects were asked which feedback mode they found to be the easiest and which they found to be the most difficult. Four stated that System Force Feedback was the easiest, ten stated that Social Force Feedback was the easiest, and five stated that Dual Force Feedback was the easiest. As for which was the most difficult, six stated that

System Force Feedback was, five stated that Social Force Feedback was, and eight stated that Dual Force Feedback was. One subject stated no preference to any of the modes.

This indicates that there was some discrepancy between the subjects on which modes were easier or harder. It seems pretty clear from the subject feedback that they liked System Force Feedback the least, even though it would be the mode of choice for this experiment. The subjects indicated that they liked Dual Force Feedback, but that it was too difficult to control and cooperate with your partner in. They also indicated that they liked Social Force Feedback because it was easy to use and easy to cooperate with your partner in. However, the biggest criticism of Social Force Feedback was that you cannot feel the material you are interacting with, which is the primary disadvantage of this mode.

With that, the subjects basically feel the same thing about the three feedback modes as the numerical analysis shows. Dual Force Feedback feels nice, but it is more difficult to control. Social Force Feedback is easy to control, but you cannot feel anything you are interacting with. System Force Feedback offers very good force feedback, but it requires a lot of practice to get used to, and can often be confusing at first. Dual Force Feedback can often be confusing at first too.

The final question on the survey asked the subjects whether interacting with their partner through a robotic device in a virtual environment, either the box interaction experiment or the materials analysis experiment, was easier or more difficult than in real life. Only three subjects felt that it was easier and 17 felt that it was more difficult. Most of the subjects who felt it was more difficult said that it was because it was a new experience, and not something they were used to doing on a regular basis. Several then went on to say that with practice, such as in the second box simulation or by the end of the materials analysis experiment, the robotic interaction seemed much easier than at first.

Of the three subjects who stated that it was easier than in real life, two had previous experience with a robotic device and one did not. The key reasons stated by the 17 subjects who felt that it was more difficult included that it was difficult to tell your position on the box from the visual feedback given, that the Omni made hand-eye coordination more difficult, and that there was an intermediate device connecting you to the object. Some possible solutions for overcoming these difficulties were presented in section 5.3 with some of the possible force and visual feedback additions. After the completion of the survey, the subjects were sincerely thanked for participating, and their portion was complete.

These results have a strong impact in the development of human-robot interactions. There are many future developments, experiments, and applications that can come from this research. Just as there was a lot learned from this research, there will be a lot more learned from future research in this field. The ultimate goal is to advance human-robot interactions to the point at which human-robot teams can perform advanced research anywhere on Earth and beyond, into the Universe.

Chapter 7. Future Developments, Experiments, and Applications

This research has demonstrated some of the ways in which humans and robots can interact with each other in a research setting. Overall, there have been many interesting observations, results, and findings. However, there are several continuations of this research which may come in the near future, which can expand upon some of the knowledge gained from it.

In general, there are two types of future developments, experiments, and applications which can come from this. The first is a set of direct expansions upon this research, many of which were briefly introduced in chapters 5 and 6. These direct expansions would serve to improve human-robot interaction and performance, as well as study some other methods of human-robot interaction not fully observed in this research.

The second type is a set of future developments that could eventually come from this and similar research, several years in the future. This set would include many of the concepts presented in chapter 2, such as a robotically teleoperated surgery (Yamamoto et al., 2008), advanced robots as material analyzers, robots as personal assistants, and space faring human-robot teams which travel beyond the Earth to study the cosmos.

Both types of future research are very interesting and offer significant contribution to the scientific community, but the first set of research must be performed before the second set can. We must learn more about human-robot interaction, develop better methods of force feedback and visual feedback, and develop the human social factors such that the subjects will naturally work just as well with a robotic device or with another human through a robotic device as they would when working with another human directly.

7.1. Future Developments and Expansions

Of the two types of future developments, experiments, and applications for this project, the first is the most straightforward to apply. As mentioned in chapter 5, there are significant improvements in the visual feedback which can be implemented for the box interaction experiment. Several of the subjects stated in the survey that it was too difficult to determine their position on the box with the visual feedback given.

In the actual experiment, the subject on the left's Omnis were color-coded green and the subject on the right's Omnis were color-coded blue. However, as the box rotated, it was common for both of one subject's Omnis to be hidden behind the box. This had the disadvantage in that it made it more difficult for someone without considerable practice with the environment to know where he was. Even more so, it was even more difficult for the subjects to be able to tell which of their Omnis on the screen corresponded to their left Omni and which corresponded to their right Omni.

A direct expansion on this research would run the box interaction experiment with two or three different visual feedback methods and then comparing the results, just as the results were compared for horizontal boxes and rotated boxes, and for the first and second simulation, in this research. Different types of visual feedback were described in detail in section 5.3.

Section 5.3 also went into the possibility of comparing different force feedback methods for the box interaction experiment as well. While this may have some advantages, it is clear that improved visual feedback would be the most advantageous, at least for the box interaction experiment. None of the subjects suggested that the force feedback available was in need of improvement, although one did say that the Omnis simply could not render enough force back to them to create the virtual environments as accurately as would be necessary to compare to real life. However, several subjects mentioned the need for improved visual feedback in this experiment.

For the materials analysis experiment, there are several direct future expansions as well. As mentioned in section 6.2, the most productive type of force feedback mode for this experiment would be System Force Feedback. Although the subjects were not too popular with this mode, it does provide the best force feedback for accurately rendering the stiffness of the materials and the fighting distance and velocity between the subjects.

In a future version of this experiment, more materials could be tested, focusing primarily on soft materials with a hardness value of less than 2.0. Visual feedback, such as that mentioned in section 6.2 could be introduced, allowing the subjects to see the position of the material in the box on the screen, as well as the position of the slave Omni and the two master Omnis. Not only would this reduce the fighting distance and velocity between the subjects, but it would also eliminate the need for the subjects to look in the direction of the slave Omni, further reducing the possibility of the subjects prematurely figuring out the material's identity. However, as emphasized previously, the only way to truly get excellent human-robot interaction with very little fighting is through practice. Therefore, in any future version of this research, it may be best to focus on just one experiment instead of two, and allow the subjects to practice with several virtual environments of increasing complexity, instead of just two.

Now that both of these experiments have been completed and their results analyzed, there are not only these direct expansions or improvements which can be done, but there are other similar research projects that can be done as well. One type of experiment which is also being done involves one subject 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 was not able to be studied in this research.

This bimanual experiment would further study human-robot interaction between one human and two robots. A variation on this would be to use one experiment operator, one subject, and two Omnis in Dual Force Feedback mode. The operator would move his Omni in a simple path and the subject would try to match the motion based on the feedback. In Dual Force Feedback, both the operator and the subject 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 very different in that it would apply force feedback to the subject, whereas the bimanual experiment does not, and it would explore the interaction of a two person, two robot team. However, there is plenty of other research in the second category of future developments, those which would include very advanced applications, often taking many years to complete, and offering incredible new inventions and discoveries along the way. The next three sections will discuss some of these possibilities, and many of the exciting new applications for which could come from them.

7.2. Robots as Material Analyzers

The materials analysis experiment demonstrated how a human-robot team can test a material for its properties. However, it only tested for one simple property, hardness. Any of the properties discussed in Table 1 in Section 2.1, as well as many other properties, can be tested for by a more advanced robotic device.

It is fairly unlikely that two people would be interacting with a series of robots in a more advanced materials analysis, as they did in this experiment. Instead, it would likely be one human scientist remotely operating either one or a series of devices. However, the general concept is the same. The human scientist must be able to respond to force feedback and cooperate with the robot to get the job done.

Even more advanced applications may involve detailed material analysis at the micro or even nano scales. Human-robot interactions could still be performed at these scales through the use of force scaling, similar to what was done in Saeidpourazar and Jalili's nano-robotic manipulation research (Saeidpourazar, Jalili, 2008). The human scientist would move the stylus, and he would see an atomic force microscope image on the screen of the nano-robot and its actual interaction with the sample. As the scientist moved the stylus, the robot would mimic the motion, with the forces and distances scaled by a factor of, say, one million. Therefore, a motion by the scientist of 10 centimeters would correspond to a motion of the nano-robot of 100 nanometers.

With this, it is clear that teleoperators play a massive role in human-robot materials analysis, in current research and in future research. Furthermore, there are many materials which are simply impossible for humans to directly access. For accessing and studying materials in places such as nuclear waste sites, the interior of volcanoes, or the bottom of the ocean, it is simply too dangerous or outright impossible to send humans to directly interact with the environment, but teleoperator robotic systems make it feasible. An advanced slave robot, specifically designed to not only survive, but work effectively in such harsh conditions is sent to the target location, while the human scientist sits comfortably in a laboratory interacting with it through a master robot and a computer (Buss et al., 2010).

While the field of robotics offers great potential in the field of materials science and analysis, robotics can also contribute greatly to the advancement of many other applications. Throughout this century, robots will likely be used to improve the life of many individuals, not just in the scientific community, but in the lives of each and every one of us.

7.3. Robotics in the 21st Century

As human-robot interaction continues to be explored and developed, robots will eventually become household items. In this research, the subjects and the robots were all in the same laboratory, sitting at the same workstation. However, it is also possible for a virtual haptic interaction to be conducted remotely, with the human subjects being hundreds or even thousands of miles apart, through the use of a Collaborative Virtual Environment (Chellali et al., 2010).

In a Collaborative Virtual Environment, two or more subjects work together with one or more virtual objects in a digital space connected through the internet. This allows the users to be located anywhere in the world. With this type of interaction, the box interaction experiment could be run using two subjects ten thousand miles apart, who would be able to feel the same force feedback, see the same visual feedback, and communicate with each other just as if they were sitting right next to each other. Another advantage is that it would allow dozens or even hundreds of users to interact with a larger, more complex virtual environment, which would not be practical in a single laboratory setting (Chellali et al., 2010).

As discussed in section 2.3, interactions involving two members, whether it be two humans or one human and one robot, typically have an executer and a conductor. However, in virtual environments involving many people, it is much more difficult to strictly define these roles, and in some cases, no member can have a distinct role. Research is already being done to study the human-robot interaction between two human subjects, where neither subject is permitted to be in either a leader or follower role. The goal is to establish a model based on this, in which both subjects work together to perform the task, instead of one person leading and the other passively following along. This concept can then be expanded to human-robot interactions involving several members (Evrard, Kheddar, 2009).

While this research focused a lot on the concept of work, another area for future development is to focus on the concept of energy. There is some research already taking place with this, studying the energy exchange in a human-human-robot interaction. This research compares the difference between human-human, human-robot, and human-human-robot teams. It was found that the performance was the greatest when two humans were involved than in any case with one human, even when the mass of the virtual object was reduced by 50% (Feth et al., 2009).

However, it would be of interest to study the energy exchange between many subjects in a large interaction, interacting with each other through a Collaborative Virtual Environment. Furthermore, it would be of interest to study the role in which the human social factors play in a typical single laboratory setting versus in a Collaborative Virtual Environment. Does remote operation affect the way in which the subjects interact with each other and with the robotic devices?

Lastly, one of the greatest potentials of the field of robotics is the use of robots as personal assistants. While a robot such as the Phantom Omni would not be capable of such a task, a more sophisticated robot may be. However, in order to achieve this, there are several things the robot must have. First of all, the robot must be programmed to understand spoken language very well, meaning that it must have voice recognition. Next, it must be programmed in how to respond to thousands of different vocal commands and in turn, complete thousands of common household tasks relatively quickly and efficiently. This will likely require complex programming algorithms, as well as a mechanical design which is very robust and adaptable.

Finally, it must be easy to clean, maintain, and service, relatively available, and affordable. Although not possible today, it is likely that later this century robotics technology will have advanced to the point where such a robot will be readily available, for a cost which is not prohibitive to the average consumer. By then, enough research will have been done regarding human-robot interaction that the robots will be as human-like in their interaction as possible, and instructing the human owners on how to effectively interact with the devices will be relatively straightforward as well.

There are many exciting applications for the future of robotics here on Earth. However, another exciting application for this field is the future of robotics out in the final frontier. Some of the greatest discoveries are waiting to be made by human-robot teams in space.

7.4. The Future of Humans and Robots in Space

While designing robots tough enough to venture to some of the most inhospitable regions of the Earth is a significant challenge, designing robots tough enough to venture into space presents a whole new league of complexity. Beyond an altitude of 100 miles, the atmosphere is so tenuous that you are essentially in a vacuum, stronger than even the best laboratory vacuums on Earth. Beyond 1,000 miles up, space is filled with high energy cosmic radiation and micrometeoroids which could disable a robotic explorer, or even kill a human astronaut (Schilling, Jungius, 1996).

Humans as well as robotic explorers travelling to other worlds must be protected from these harsh conditions, which is very difficult and expensive to do. Without adequate protection, sending humans on longer space voyages beyond the Moon, such as to Mars or beyond, would expose them to dangerous levels of radiation, which could cause them to suffer from radiation sickness, which could in turn cause cancer or other adverse health problems (Fry, 1984).

Although it is much easier to protect a small space probe than a large manned spaceship, eventually the technology will reach the point where this obstacle will be overcome. With advancements in propulsion, the obstacle of long travel times between planets will be overcome as well. With these two obstacles overcome, humans and robots will travel together throughout the solar system to perform research, study materials, and search for life.

In the future, space stations will be constructed in orbit around different worlds, and human-robot teleoperators will be necessary for repairs. It is much safer to have a robonaut perform an external repair than to have an astronaut perform a spacewalk. Furthermore, a manned mission to Mars may likely use robotic teleoperators to study the Martian environment. Just like studying harsh regions of the Earth, the human scientist can sit comfortably inside the Mars spaceport and drive the robonaut to a site of interest, at which it will take samples and perform on site research (Bluethmann et al, 2003). There will be no communications time lag since the human operators will be on Mars, and not on Earth. Furthermore, they will be able to analyze the data in real time, greatly expediting the rate at which research can be performed.

In the distant future, humans and robots may travel beyond the solar system, to distant worlds around distant suns. For a high-speed spacecraft flying through the cosmos, external repair robonauts will be essential, as will be personal assistant robots, which will aid the astronauts in basic tasks throughout their multi-year flight. There are many great discoveries just waiting to be made, and many new adventures on the horizon. The field of robotics and materials science will play a central role in these adventures throughout the 21st century and beyond.

Chapter 8. Conclusions

The field of robotics has been a rapidly growing field throughout the second half of the 20th century, and into the 21st century. It will continue to grow and develop at an accelerating pace throughout the 21st century and beyond. With that, human-robot interaction will become more and more common in the coming decades.

There has been a significant amount of research done in the fields of robotics and materials science, and there is currently a significant amount of research going on right now. This research was unique in that it combined several aspects, including virtual environments, teleoperators, and material analysis. It studied the way two humans worked with each other in a virtual environment, and which Cartesian directions are easier to cooperate in and which are more difficult.

This research set out to explore the human-interactivity with a robot to obtain the fundamental properties of materials. In doing so, there were several questions which were determined to be answered. For instance, when two humans are working together through a set of robotic devices, do they tend to work together or fight with each other more? In which Cartesian direction do they have the most difficulty with? Does fighting drastically affect the performance of the team? Finally, what measures can be taken to promote better cooperation between humans and robots, to ultimately allow humans to work just as comfortably with a robotic partner as with a human partner?

Through analysis of the fighting factor, it was found that when two humans are working together through a set of robotic devices, there is a considerable amount of fighting that occurs. However, there is also a considerable amount of cooperation as well. Out of all the trials performed, about half of the time the subjects were cooperating more than they were fighting, and about half of the time they were fighting more than they were cooperating.

It is pretty clear that the Cartesian direction in which the subjects have the most difficulty cooperating in is the y-direction. The fighting velocity was statistically significantly larger in the y-direction than in the other two directions. The fighting distance was slightly larger in the y-direction than in the x-direction, although there was no statistically significant difference. The fighting distance was, however, statistically significantly larger in the x and y-directions than in the z-direction.

It was also found that increased fighting did adversely affect the performance of the team, although not nearly as much as was hypothesized. A few of the target boxes with a fighting factor of 5 were still reached in under ten seconds, although this was more likely due to chance than skill. However, it was generally observed that the higher the fighting factor, the longer it took to reach the target and the more fatigued the subjects became.

Lastly, there are several measures which can be taken to promote better cooperation between humans and robots. First of all, improved force feedback and visual feedback such as that discussed in sections 5.3 and 7.1 can be implemented to reduce the fighting distance and fighting velocity, as well as to generate more fighting factors of 1 or 2, and reduce the number of 3's, 4's, and 5's. Also, the force feedback could be tailored to help compensate for weaknesses in the interaction, such as fighting in the y-direction. For instance, the spring force rendered back to the subjects could be larger for displacements in the y-direction than for displacements in the x and z-directions. Lastly, the subjects could be given more time to practice with several virtual environments leading up to the experiments, allowing them to become more comfortable with the devices, the virtual environments, and the overall haptic interaction.

In conclusion, there are many future applications which can come from this research and others, some of which has the potential to change the world. Someday, we will live in a world in which robots are an everyday part of life. They will be common around the house, in the workplace, and may even become like buddies in which we can interact with when no one else is around.

Further in the future, humans and robots will travel out into the cosmos together, exploring and colonizing other worlds. New material alloys will be discovered, developed, and studied. Human-robot interaction will play a major role in the research performed on them. Eventually, massive colonies will exist throughout the solar system in which humans and robots will live, work, and interact on a daily basis.

The challenges we face are great, but the rewards are even greater. The knowledge we have gained involving haptics, human-robot interaction, virtual environments, and more effective teleoperator systems will prove immensely valuable in mankind's greatest adventure. And what an adventure it will be. Someday, our descendants will live in a world in which we can only dream of. In the journey there, we will be able to dream, to inspire, and to explore.

References

"A Roadmap for US Robotics: From Internet to Robotics". 86 pages. 2009.

Bakar, SBA; Yuichiro, H; Ikeura, R; Mizutani, K. "Characteristic of a two Degree of Freedom Cooperative Task by Two Humans." ICASE Transactions on Haptics. Pages 296-301. 2006.

Bentley, M. "Humans Need not Apply." New Scientist. Pages 42-45. 2009.

Bluethmann, W; Ambrose, R; Diftler, M; Askew, S; Huber, E; Goza, M; Rehnmark, F; Lovchik, C; Magruder, D. "Robonaut: A Robot Designed to Work with Humans in Space." Autonomous Robots, Volume 14. Pages 179-197. 2003.

Buss, M; Peer, A; Schaub, T; Stefanov, N; Unterhinninghofen, U; Behrendt, S; Leupold, J; Durkovic, M; Sarkis, M. "Development of a Multi-Modal Multi-User Telepresence and Teleaction System." The International Journal of Robotics Research, Volume 29, No. 10. Pages 1298-1316. 2010.

Chellali, A; Dumas, C; Milleville, I. "Haptic Communication to Enhance Collaboration in Virtual Environments." The European Conference on Cognitive Ergonomics. Pages 1-8. 2010.

Evrard, P; Kheddar, A. "Homotopy Switching Model for Dyad Haptic Interaction in Physical Collaborative Tasks." Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. Pages 45-50. 2009.

Feth, D; Groten, R; Peer, A; Hirche, S; Buss, M. "Performance Related Energy Exchange in Haptic Human-Human Interaction in a Shared Virtual Object Manipulation Task." Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. Pages 338-343. 2009

Fry, RJM. "Approaches to Radiation Guidelines for Space Travel." Advances in Space Research, Volume 4, Number 10. Pages 121-130. 1984.

Glynn, SJ; Fekieta, R; Henning, RA. "Use of Force-Feedback Joysticks to Promote Teamwork in Virtual Teleoperation." Human Factors and Ergonomics Society Annual Meeting Proceedings, Virtual Environments. Pages 1911-1915. 2001.

Kelso, JAS; de Guzman, GC; Reveley, C; Tognoli, E. "Virtual Partner Interaction (VPI): Exploring Novel Behaviors via Coordination Dynamics." PLoS ONE, Volume 4, Issue 6. Pages 1-11. 2009.

Launius, RD; McCurdy, HE. "Robots and Humans in Space Flight: Technology, Evolution and Interplanetary Travel." Technology in Society, Volume 29. Pages 271-282. 2007.

Li, Y. "Predicting Materials Properties and Behavior Using Classification and Regression Trees." Materials Science and Engineering A, Volume 433. Pages 261-268. 2006.

Misra, S; Okamura, AM. "Environment Parameter Estimation during Bilateral Telemanipulation." IEEE Transactions on Haptics. Pages 301-307. 2006.

Misra, S; Okamura, AM; Ramesh, KT. "Force Feedback is Noticeably Different for Linear versus Nonlinear Elastic Tissue Models." IEEE Transactions on Haptics. Pages 519-524. 2007.

Murray, RM; Li, Z; Sastry, SS. "A Mathematical Introduction to Robotic Manipulation". 467 pages. 1994.

Pippo, SD; Colombina, G; Boumans, R; Putz, P. "Future Potential Applications of Robotics for the International Space Station." Robotics and Autonomous Systems, Volume 23. Pages 37-43. 1998.

Pitchumani, R; Zhupanska, O; Meesters, GMH; Scarlett, B. "Measurement and Characterization of Particle Strength Using a New Robotic Compression Tester." Powder Technology, Volume 143-144. Pages 56-64. 2004.

Reed, KB; Peshkin, MA. "Physical Collaboration of Human-Human and Human-Robot Teams." IEEE Transactions on Haptics, Volume 1, Number 2. Pages 108-120. 2008.

Saeidpourazar, R; Jalili, N. "Nano-Robotic Manipulation using a RRP Nanomanipulator: Part A – Mathematical Modeling and Development of a Robust Adaptive Driving Mechanism." Applied Mathematics and Computation, Volume 206. Pages 618-627. 2008.

Schildt, Herbert. "C++: A Beginner's Guide, 2nd Edition". Published by McGraw-Hill Osborne Media. 576 pages. 2003.

Schilling, K; Jungius, C. "Mobile Robots for Planetary Exploration." Control Engineering Practice, Volume 4, Number 4. Pages 513-524. 1996.

SensAble Technologies. Phantom Omni Haptic Device. < http://www.sensable.com/haptic-phantom-omni.htm >. 2010.

Siciliano, B; Khatib, O. "Springer Handbook of Robotics". Published by Springer. 1,611 pages. 2008.

Sodanapalli, P; Coon, DN. "Simulation of Creep Crack Growth in Ceramic Composites." Journal of Materials Science, Volume 37. Pages 4197-4202. 2002.

Stefanov, N; Peer, A; Buss, M. "Role Determination in Human-Human Interaction." IEEE Transactions on Haptics. Pages 51-56. 2009.

Tryland, T; Hopperstad, OS; Langseth, M. "Design of Experiments to Identiry Material Properties." Materials and Design, Volume 21. Pages 477-492. 2000.

Wojtara, T; Uchihara, M; Murayama, H; Shimoda, S; Sakai, S; Fujimoto, H; Kimura, H. "Human-Robot Collaboration in Precise Positioning of a Three-Dimensional Object." Automatica, Volume 45. Pages 333-342. 2009.

Yamamoto, T; Bernhardt, M; Peer, A; Buss, M; Okamura, AM. "Techniques for Environment Parameter Estimation During Telemanipulation." IEEE Transactions on Haptics. Pages 217-233. 2008.

Yamamoto, T; Vagvolgyi, B; Balaji, K; Whitcomb, LL; Okamura, AM. "Tissue Property Estimation and Graphical Display for Teleoperated Robot-Assisted Surgery." IEEE Transactions on Haptics. Pages 4239-4245. 2009.