RICE UNIVERSITY

Progressive Haptic Guidance for a Dynamic Task in a Virtual Training Environment

by

Joel Carlos Huegel

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE

Doctor of Philosophy

APPROVED, THESIS COMMITTEE:

Marcia K. O'Malley, Chair
Assistant Professor of Mechanical
Engineering and Materials Science

Pol D. Spanos
Lewis B. Ryon Professor of Mechanical &
Civil Engineering

Andrew J. Dick
Assistant Professor of Mechanical
Engineering and Materials Science

Michael D. Byrne
Associate Professor of Psychology &
Computer Science

Houston, Texas

February, 2009

Progressive Haptic Guidance for a Dynamic Task in a Virtual Training Environment

Joel Carlos Huegel

Abstract

This thesis presents the motivation for and implementation of a novel progressive haptic guidance scheme designed to improve the efficiency of a virtual training environment used for skill acquisition. A detailed expertise-based analysis of the dynamic human motor task identifies the key skills required for success and motivates the progressive haptic guidance scheme. The thesis compares the effectiveness of the scheme to similar visual guidance, written guidance and no-guidance. The experimental training protocol presents a target-hitting training task in a virtual environment that utilizes an LCD display for visual feedback and a force feedback joystick for haptic interactions. This protocol lasts eleven sessions over a two-month period, thereby ensuring the performance saturation of participants. During each session, the number of target hits obtained becomes the objective measure of performance. Two additional measures, trajectory error and input frequency, are defined and implemented to calculate the performance of participants in two key skills. The guidance scheme then employs these last two measures as gain inputs to the guidance controller, which in turn progressively diminishes the forces that display guidance as virtual walls. The haptic controller design initially restricts a participant's motion to a preferred task path, but increased performance results in decreased guidance from one trial to the next. In addition to these measures, the protocol also presents the computerized version of the NASA Task Load Index (TLX) to all participants at each session, thereby providing cognitive workload measurements throughout the entire training period. The results demonstrate that this progressive haptic guidance scheme, one that integrates key skills

and measures of performance, significantly outperforms three other guidance modes early on in the training and only when guidance is active. The data failed to show whether the haptic guidance scheme has significantly higher performance when the guidance is inactive. This scheme also generates less frustration and mental workload than visual guidance. Possible applications for these findings include virtual training environments designed for surgery and rehabilitation.

Contents

Illustrations

Tables

Acknowledgments

I especially wish to thank Dr. Marcia O'Malley for her guidance, insight, and encouragement in conducting the research for this thesis. I also wish to express my appreciation to Dr. Andrew Dick who provided valuable feedback and discussions regarding the methodology and analysis. Moreover, I thank Dr. Pol Spanos and Dr. Michael Byrne for suggestions and critiques of the manuscript. I am grateful to my laboratory collaborators especially Ozkan Celik for continual feedback throughout my research and Dr. Yvonne Li for providing the data from her research for my initial analysis of expertise. I thank Dr. Andrew Dick, Dr. Timothy Warburton, and Dr. Devika Subramanian for their assistance in recruiting subjects for the human-user studies. Dr. Allison Okamura from Johns Hopkins University provided a second piece of hardware permitting completion of the human-user studies in much less time.

This research was supported in part by a grant from the National Science Foundation (IIS-0448341). The *Instituto Tecnologico y de Estudios Superiores de Monterrey* (ITESM - Guadalajara, Mexico) graciously granted, through the leadership of Dr. Javier Quezada Andrade, the academic leave that permitted my residence at Rice University.

I wish to thank Prof. Joe Gaiser of LeTourneau University who inspired me to pursue teaching as a profession. My mother, Yvonne Huegel, assisted with data capture and my brother, David Huegel, assisted with stylistic improvements to the manuscript. I especially wish to thank, my mother in law, Rosa Maria Cruz de Munoz who graciously came several times to visit so that Joel, Elizabeth, and Carlos never felt my long absences during research deadlines.

Finally, but most deeply, I wish to thank and dedicate this work to my wife, Dr. Rosa Deliz Munoz, who has unwaveringly supported me throughout this endeavor.

Chapter 1

Introduction

This thesis presents the motivation for and implementation of a novel progressive haptic guidance scheme designed to improve the efficiency of a virtual training environment (VTE) used for motor skill acquisition. The effectiveness of the scheme compares favorably to similar visual guidance, written guidance and no-guidance schemes. A detailed expertise-based analysis of the dynamic human motor task identifies the two key skills required for success. This analysis also motivates the progressive haptic guidance scheme.

The human-user training protocol presents to participants a target-hitting training task in a virtual environment. The eleven sessions of the protocol, over a two-month period, provide the data for comparison. During each session of 25 trials, the number of target hits obtained provides a measure of performance. Two additional measures, trajectory error and input frequency, are defined and implemented to quantify the performance of participants in two key skills. The values of these two skill measures become the gain inputs to the guidance controller, thereby progressively diminishing the forces that display the guidance as haptic virtual walls. The haptic controller design initially restricts a participant's motion to a preferred task path, but increased performance results in decreased guidance from one trial to the next.

In addition to these skill measures, the computerized version of the NASA Task Load Index (TLX) was administered to all participants during each session, thereby providing cognitive workload measurements throughout the entire training period. An exit questionnaire also provides subjective data. The results show the differences between the four guidance schemes in terms of the three measures of performance and in terms of workload. Moreover, I conducted analysis of variance (ANOVA) and post hoc analysis of the data to reveal the significant differences between the four guidance schemes and the sessions of the protocol in terms of performance and workload measures.

1.1 Motivation

Virtual training environments (VTEs) offer great opportunities for the future, opportunities to reduce costs and risks in the training of humans in motor skill acquisition. These VTEs evolved from computer simulations which became prevalent in flight training beginning in the 1970s. More recently, medical researchers have successfully developed VTEs for surgical and laparoscopic procedures. These VTEs initially offered only visual and auditory feedback; however, the development of faster computer processors and digital motor controllers for the teleoperation field during the past 25 years has provided the necessary hardware to add haptic feedback to cutting-edge VTEs.

The term "haptics" describes both feedback through cutaneous and force feedback interaction. While loop rates on the order of 10 to 100Hz effectively display visual feedback to users, haptic systems must typically operate in excess of 1 kHz to ensure that they adequately simulate real environments. In addition to their prior use in flight and medical simulators, haptics-enabled virtual environments are now being used in stroke rehabilitation and in gaming – the field where many computer technologies have their commercial genesis. In the research community, haptic interface design and development is a relatively new field of science, forged at the intersection of mechanical, electrical, and computer engineering with cognitive psychology and neurobiology. These are the primary areas of ongoing research: hardware and software technologies, basic human haptics, and domain-specific applications. Researchers are applying newly developed virtual training environments to robotic rehabilitation as well as to flight, surgical, and sports simulators. Novel haptic interface designs reproduce the real-world task being simulated, and either do so as accurately as possible or augment skill acquisition by assisting or guiding the trainee in some way.

1.2 Problem Statement

This thesis reports the results of two user studies that address three problems in the development of VTEs with haptic guidance augmentation for guidance. The first of these problems is the identification of the key skills required for training success. The second problem is the development of quantitative performance and cognitive skill acquisition measures which will help ascertain the effectiveness of the guidance. The third problem this thesis addresses is the design haptic guidance that provides effective assistance in facilitating motor skill acquisition by either accelerating or improving training outcomes that go beyond no guidance at all as shown in Figure 1.1.

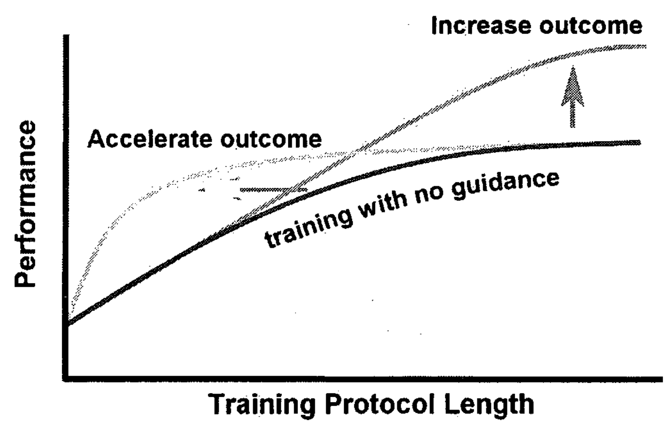


Figure 1.1 : The goal for the research reported in this thesis is to design a haptic guidance scheme that provides effective assistance in facilitating motor skill acquisition by either accelerating or improving training outcomes that go beyond no guidance at all.

1.3 Objectives

The objectives of this research are twofold. The first is to design and develop an effective progressively-diminishing haptic guidance scheme that employs measures of key skills, thereby augmenting motor skill acquisition training. The second objective is to implement this novel guidance scheme in a human-user training protocol, testing its effectiveness by comparison to similar visual guidance, written guidance and no-guidance schemes.

I meet the first objective by analyzing and comparing the performance of *experts* and *novices* as they execute the specific dynamic human motor task, by identifying the key skills and developing dynamic measures for them, and by providing the updated inputs to the guidance augmentation controller for display to the user. I meet the second objective by comparing the final results to those produced by other schemes.

The block diagram shown in Fig. 1.2 illustrates a basic haptics-enabled virtual training environment. The user applies a force or torque to the haptic interface which in turn provides position and velocity inputs to the virtual environment. The physics model of the task at hand computes output forces based on the input of the device states and the controller applies additional forces or torques to the haptic interface in order that these are felt by the user.

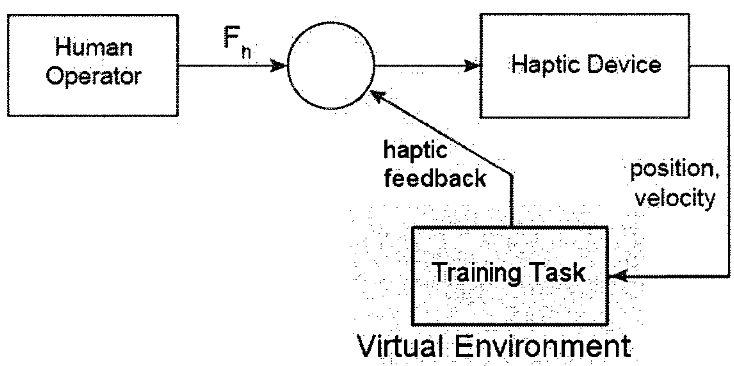


Figure 1.2 : Block diagram of a basic haptics-enabled virtual training environment with no guidance augmentation.

The block diagram shown in Fig. 1.3 illustrates a haptics-enabled virtual training environment with haptic guidance augmentation. In this scenario, the states of the virtual environment are transmitted to the haptic guidance augmentation controller. This controller computes guidance forces based on the VTE states and with the guidance scheme being employed. The controller sums the guidance forces to the VTE system dynamic forces before they are applied to the user.

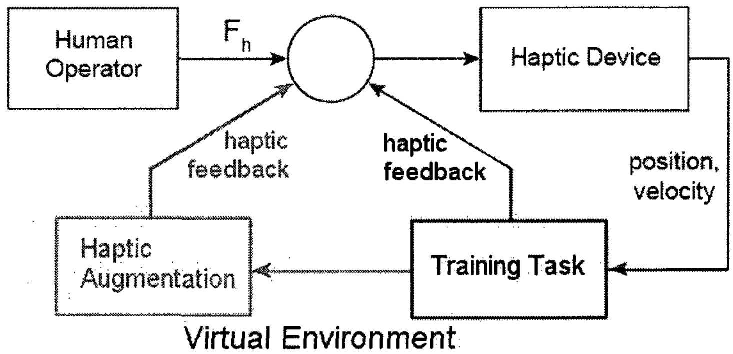


Figure 1.3 : Block diagram of a haptics-enabled virtual training environment with haptic guidance.

The block diagram illustrated in Fig. 1.4 shows a haptics-enabled virtual training environment with visual guidance. In this scenario, the states of the virtual environment are transmitted to the visual augmentation controller. This controller computes guidance overlays based both on the VTE states and on the guidance paradigm being employed. The visual interface displays the overlay to the user.

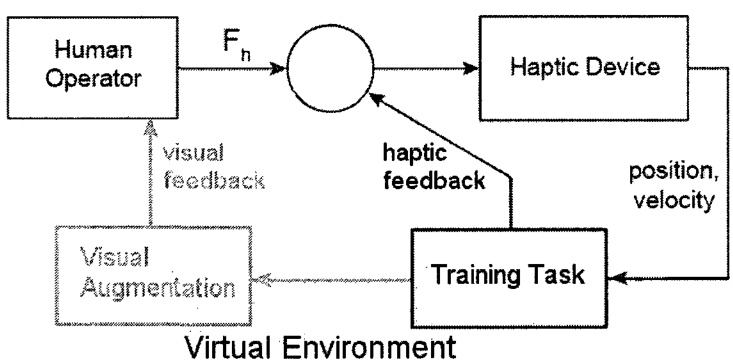


Figure 1.4 : Block diagram of a haptics-enabled virtual training environment with visual guidance.

1.4 Contributions

This thesis makes five significant contributions to the field of haptics-enabled human motor training:

The first contribution is an observation of how *experts* perform by analyzing the data regarding their performance, and by comparing that data to the performance data of *novices*. The results of the comparison validate the present approach to haptic guidance design as previously reported [35].

The second contribution is an improvement over my prior work in collaboration with Li, Patoglu, and O'Malley that showed that progressive haptic guidance designed in an ad hoc way results in no significant improvement over no guidance at all [44]. The progressive haptic guidance I design utilizes the expertise-based analysis mentioned above as a motivation for using virtual walls and a proportional-derivative (PD) controller to supply auxiliary forces to the user, thereby demonstrating the appropriate control motion for the task. Furthermore, the two independent measures of performance relate to the two key skills required for successful task completion. These measures serve as gain-adjustment inputs to the guidance controller. I evaluate this guidance design in a pilot study [37].

The third contribution is a demonstration that this performance-based progressive haptic scheme significantly outperforms nonguidance at the time that active guidance is engaged. Performance data for post-guidance subsessions fail to demonstrate significant differences between the guidance and nonguidance groups. These results confirm the general trend in augmented haptics training research that indicates that VTEs enhance performance but do not accelerate training. Nevertheless, for this particular skill acquisition, the guidance scheme here presented is the first and only guidance scheme in a series of proposed guidance schemes where haptic guidance has significantly outperformed no-guidance at any time period during the protocol.

The fourth contribution is the utilization of minimum hand jerk criteria in the design of the haptic guidance controller. In Chapter 4, an initial experiment verifies and validates the minimum hand jerk criteria for a multi-mass system [36]. Chapter 5 describes how I have integrated those criteria into the haptic guidance controller design.

The fifth contribution is a demonstration that haptic researchers should not divorce motor skill performance measures from cognitive load measures, as these may be appropriate for a given application. My research employs a cognitive workload assessment to measure the workload of each participant as each receives the assistance of varied guidance schemes. The different workload results between the guidance schemes are significant enough to suggest the advisability of including measures of cognitive load in a determination the effectiveness of any haptic guidance scheme.

1.5 Thesis Structure

This thesis is structured as follows: Chapter 1 introduces the motivation, problem statement, objectives, and significant contributions of this research. Chapter 2 reviews the literature associated with haptics and virtual training environments (VTEs). The chapter also reviews the requirements for experimental tasks and guidance schemes. An overview of expertise-based analyses as a means to study differences in performance precedes a review of measures of skill and cognitive loading that could be used to quantify training improvements. Chapter 3 fully presents the background and motivation of this research. Chapter 4 introduces and describes an initial experiment on movement smoothness, presenting the methods, results, and discussion of the experiment. Chapter 5 describes the implementation of movement smoothness as the basis for the input frequency guidance scheme and documents the overall design of the progressive haptic guidance scheme along with the methods used to test and evaluate it. Chapter 5 also reports the results of the human-user study and closes with a discussion of the findings. Finally, Chapter 6 discusses overall findings, conclusions, and directions for future research.

Chapter 2

Literature Review

This chapter reviews the literature associated with haptics and virtual training environments (VTEs) in general. It also reviews the requirements for experimental tasks and guidance schemes, followed by an overview of expertise-based analyses as a means to study differences in performance. Finally, the chapter closes by reviewing measures of skill and cognitive loading that will be used to quantify training improvements in the subsequent experiments conducted in this research.

2.1 Haptic Interfaces

This section provides an overview of haptic interfaces, basic human haptics, and application domains for haptics technology. The term "Haptic" is derived from the Greek word *haptesthai* meaning the sense of touch or the act of touching. Burdea extended the definition of haptics to include not only tactile interactions but also kinesthetic interactions pertaining to a sense mediated not on the skin surface but rather within the muscles, tendons, and joints [11]. The notion of presenting a virtual environment that includes "haptic" interaction as well as audio and visual feedback can be attributed to Ivan Sutherland, the creator of SketchPad, the first computer graphics program [74]. In 1965, Sutherland proposed *the ultimate display*: "a room within which the computer can control the existence of matter itself" [75]. This would be a room where virtual handcuffs would actually constrain and where one could actually sit on virtual chairs. After Sutherland's proposition, most of the development of computer interfaces in the 1970s and 1980s was focused on the graphic interfaces. This focus was due in part to limitations in hardware having to do with requirements of human-perception. Visual displays need only refresh at around 30

Hz to ensure adequate simulation. Since haptic interfaces require update rates in excess of 1 kHz, however, these were not possible until the advent of faster computers and digital motor controllers in the 1990s.

There is a decided difference between haptic interactions and visual or auditory feedback. The haptic interaction between the user and the virtual environment contains a bidirectional transfer of energy due to changing forces and positions. Figure 2.1 illustrates an overall virtual environment with the bi-directional haptic interactions. The burgeoning field of haptics research includes three broad categories as defined by the Association for Computing Machinery (ACM): human haptics, haptics technology, and haptics applications. While haptics does refer to both tactile and kinesthetic feedback, in this thesis the focus is on the kinesthetic feedback with little discussion of tactile feedback.

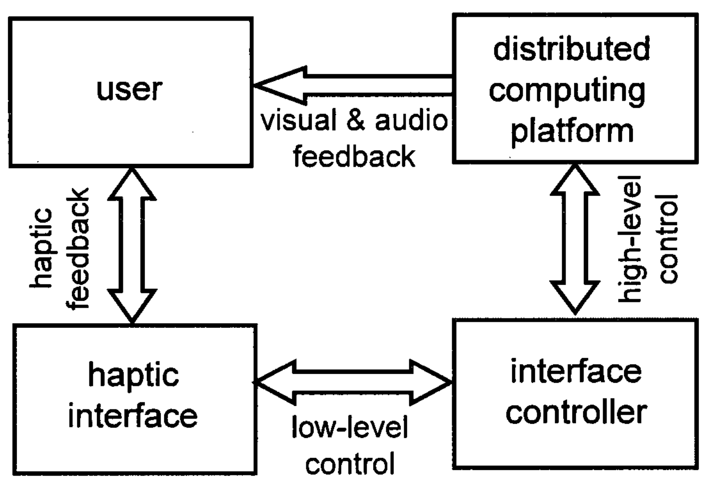


Figure 2.1 : The system architecture for haptics-enabled virtual environments. Note that visual and audio feedback to the user is uni-directional while haptic interaction is bi-directional (adapted from [11]).

2.1.1 Human haptics

Basic human haptics research involves studying human attention, biomechanics, cognition, human factors, ergonomics, human performance, neuroscience, perception, psychophysics, and social communication. While these are all mature fields of science, new developments in haptic interfaces have afforded new insights in each. Studies have sought both to gain new understandings of the senses and to develop novel forms of interaction with virtual environments.

2.1.2 Haptic devices

Three classifications describe haptic interfaces: the number of degrees of freedom (DOF) of the interface, the type of control scheme used, and the input and output capabilities of the interface. The degrees of freedom (DOF) refer to the number of variables that are required to fully represent the position of the device. Most haptic devices utilize rotational joints, although translational and spherical joints have also been employed. In order to represent a point interaction in 3-D space a 3 DOF device is required. Researchers often use 1 and 2-DOF devices in order to reduce the complexity of the interactions. Figure 2.2 depicts three different haptic devices. The Immersion Impulse Engine 2000 utilized in the experiments reported in this thesis is an example of a 2-DOF device. The Sensable PHANToM is a 3-DOF device, while the MIME-RiceWrist is actually a pair of devices that have a total of nine degrees of freedom when combined [51, 56]. The representation of multiple contact points with the user, as is the case in rehabilitation applications, requires a device with more than 3 degrees of freedom.

Each degree of freedom will typically require both sensors and actuators. Sensors such as encoders, resolvers, tachometers or accelerometers provide state information to the control system. The device may have force/torque sensors as well. Actuator technologies include pneumatics, hydraulics, and (the most prevalent) electromechanics in the form of motors. To be considered an effective and high quality interface, the haptic device must meet several requirements: it should have a high power to weight ratio, high force/torque

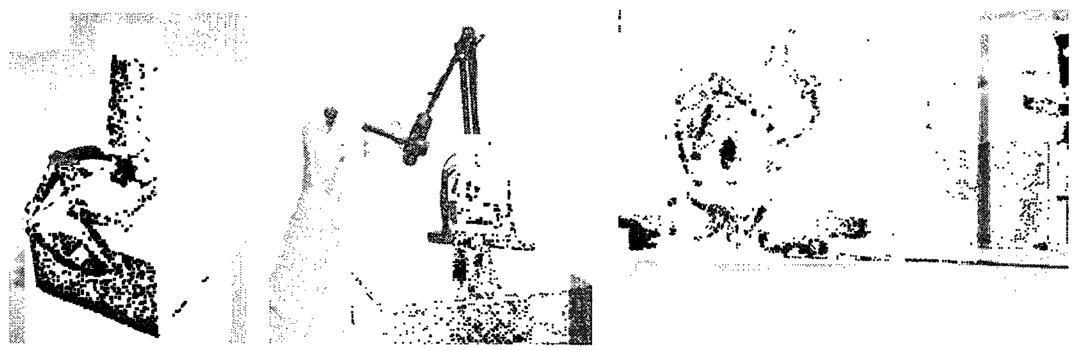


Figure 2.2 : Three haptic devices categorized by degrees of freedom (DOF) include the 2-DOF Immersion Impulse Engine 2000, 3-DOF Sensable PHANToM, and 9-DOF MIME-RiceWrist. The first two and the RiceWrist are impedance controlled while the MIME system is admittance controlled.

output, and high bandwidth [59]. The bandwidth refers to the range of the output frequencies attainable by the system. Typical haptic devices have low friction and are back drivable. These device also often have direct drive transmissions to further reduce inertial forces.

The second classification of haptic devices has to do with which one of two rendering control schemes is employed. In the impedance (force feedback) rendering scheme, the user determines the position and velocity of the device interface. The device states could be represented in workspace or joint-space coordinates. The state input is sent through signal processing and conditioning and delivered to the real time operating system. The physics model resident in the control code calculates the associated output forces and delivers current commands to the motor controller/amplifier that in turn delivers the corresponding torque to the appropriate motor of each DOF (or joint). The impedance rendering method can be summarized as:

$$F_e = Z_e X_h \tag{2.1}$$

where F_e is the force output of haptic interface, Z_e is the virtual environment impedance, while X_h is the human input position. In the admittance (position feedback) rendering scheme, on the other hand, the user applies a force or torque to the device interface, and one or more force/torque sensors detect the user's action. A data acquisition card (DAC) conditions a force or torque signal and delivers it to the controller which in turn computes the associated positions and velocities to be delivered to the motor controllers. The admittance rendering method can be modeled as:

$$X_e = F_h \, Y_e \tag{2.2}$$

where X_e is the position output of haptic interfaces, F_h is the human input force, while Y_e is the environment admittance. Depending on the application, one or the other of the haptic rendering control schemes will be integral part of the interface design and will affect the choice of hardware, software and sensors. Implementation of the admittance control scheme is, in general, more costly [11]. The MIME RiceWrist system shown in Fig. 2.2 incorporates both control schemes. The PUMA industrial robot of the MIME system has a 6 DOF force/torque sensor at the interface to provide the input to the admittance controller. The RiceWrist, on the other hand, utilizes optical encoders on all DOF to provide the inputs to its impedance controller. The two devices communicate only high-level commands with each other through a serial port connection [56]. Kotoku *et al.* also utilized both control schemes. They designed a position-force-control switching mode. Force control delivers zero feedback during motion in free space. The device switches to position control upon collision detection [41]. Most desktop haptic interfaces, including the joystick used in the experiments reported in this thesis, employ impedance control because of the lower sensor and actuator cost and low inertia of the transmission. The disadvantage of impedance control, however, is its inability to represent hard surfaces, although state-of-the-art impedance systems are able to represent "believable" interactions. For a haptic device to capture and represent "believable" kinesthetic interactions, it must operate within human perception and excitation ranges.

2.1.3 Application domains for haptics

Haptic systems developed and diversified rapidly in the past twenty years, in part due to the rapid development and decreasing cost of the requisite hardware and software. There has also been a growing demand for the technology in the private sector. These are some, though not all, of the most prevalent application areas for haptic systems:

Education

The field of psychology has shown that students have different learning styles. In the past, multi-sensory approaches to education had used only the audio and visual sensory channels. Haptics-enabled educational tools are providing deeper understanding of topics that can be learned best through the tactile and kinesthetic sensory channels. At Rice University, haptic paddles provide students the opportunity to interact and readily modify virtual mechanical systems in an undergraduate course in system dynamics [10].

Medicine

Medicine, and more specifically laparoscopic training, is possibly the most active application domain for haptics. Since this type of surgery involves fine motor control, as well as small workspaces and tools, it necessitates the use of robotic assistance. Since laparoscopy also involves obstructed vision, it also requires the use of alternative means of feedback. Moreover, the high risk of training someone to perform surgery on a live person offsets the currently high costs of haptics-enabled training simulators. As the field matures, some medical schools are already requiring residency students to train on these systems. As demand for these simulators increases and the price for them drops, they will become more commonplace [76].

Rehabilitation and assistance for the disabled or impaired

Another developing use for haptics technology is robot-mediated neurorehabilitation. Researchers are coupling advances in robotics, virtual reality (VR), and haptic interfaces with neuroscience and physical therapy to design new treatments for neurological injuries such as stroke, spinal cord injury, and traumatic brain injury. Further work will identify the most effective methods for delivering treatment in home and hospital settings [31,65].

Military simulations

Haptics-enabled VR telepresence simulations allow personnel in different locations to participate together in military training exercises. Branches of the US military test ground vehicles under simulated battlefield conditions. For example, by means of the use of force-feedback gloves to manipulate 3D components, researchers enabled workers at remote locations to simulate the reconfiguring of a vehicle chassis with different weapons. Operators of aircraft and other complicated and dangerous machinery can be safely trained with haptics-enabled VTEs [25, 48].

Entertainment

Haptic interfaces are a natural fit for video games because they allow the user to feel and manipulate virtual solids, fluids, tools, and avatars. One example is a stock XBox controller powered by Immersion's force feedback technology. Game players experience the rapid-fire vibrations from a machine gun and a heavy recoil effect when firing a rocket launcher. As is the case with so many novel computer technologies, haptics may most quickly find commercial applications in video gaming [14].

2.2 Virtual Training Environments

Haptics-enabled virtual environment (VE) technologies have applications in helping to train skills in each of the domains previously mentioned: vehicle control, medical procedures, sports training and rehabilitation [6, 14, 27, 65]. These VTE technologies provide for reliable data acquisition, analysis, feedback, and evaluation of motor skill task performance while also providing a comparatively low-cost and low-risk training platform. Virtual environments used for training are designed to reduce risk, improve and accelerate skill acquisition over traditional training schemes, and to transfer what is learned in the simulation environment to the equivalent or targeted real world task. Virtual training environments (VTEs) are designed either to provide an environment for practice that is as similar as possible to the real task or to act as an assistant by augmenting the feedback in some way during training. Commercial examples of these augmented systems include heads up displays (HUDs) for pilots and simulators for surgery residents [48, 76]. Haptics can play an important role both in matching the VTE to the targeted environment and in providing VTE augmentation during training. Researchers in haptics have proposed three broad approaches to implement haptics-enabled virtual training schemes, thereby exploiting the augmentation capabilities of the interfaces. One scheme is first to present the performance of an *expert* (human or robot) to a trainee via visual and haptic feedback and then to allow the trainee to practice the task unassisted [32] [73]. A second approach requires the trainee to perform the task with enforced restrictions or reductions of the degrees of freedom of the task as proposed by Bernstien and more recently implemented as *virtual fixtures* by Rosenberg *et al.* and Abbott *et al.* [1, 9, 67]. A third approach, shared control, modifies the dynamics of the system so as to encourage the correct behavior from the trainee [18, 27, 60]. A comparative study of these last two approaches performed by Srimathveeravalli *et al.* showed slightly better performance from the shared control approach over the virtual fixture approach [72]. Although VTEs are already in use, whether or not VTEs with haptic guidance augmentation show measurable improvement over real or virtual practice in dynamic task training is still being debated in the haptics research community. This thesis compares the performance of a progressive haptic guidance scheme to three other schemes: no guidance at all, written guidance, and a visual guidance scheme in a VTE protocol to train for a dynamic human motor skill task.

For the purposes of this thesis, I define "performance" to be a measurement of output or ability in the task being studied, while "training" is the protocol designed to increase performance over a period of time. I draw from the brain research of Karni *et al.* to declare that dynamic human motor skills require multiple-session training protocols with the sessions placed a couple of days apart to allow for consolidation of the skill acquisition [40]. The present study, therefore, implements a multi-session training protocol. Previous studies have shown that the addition of haptic feedback to VEs during training can provide benefits over against visual and auditory displays for performance enhancement, increasing dexterity and the sensation of realism and presence [18, 27, 57, 69]. While performance can be improved at the time haptic feedback is provided, there exist only a limited number of published studies aimed at determining the efficacy and outcomes of VTE protocols with haptic guidance augmentation [60]. The studies that do exist show inconsistent results.

2.3 Experimental Task and Guidance Schemes

The development of a haptic guidance training protocol presents three issues: first, the task to be studied must be difficult enough to require multiple sessions for mastery, enabling the observation of changes in performance throughout training; second, the guidance must be removed progressively as performance improves to avoid the participant's dependence on the guidance; and third, the amount of guidance must be based on measurements derived from the progressive mastery of the key skills themselves.

The first issue is that the task must present sufficient difficulty so as to require multiple sessions across various days to successfully achieve asymptotic performance improvements. Otherwise, the results will not be adequate to observe statistically significant changes across multiple trials and sessions. Yokokohji *et al.* implemented a task for moving virtual boxes, while Adams *et al.* designed a building block task with a cognitive component, but both recognized that their tasks were too simple to observe learning effects of training [82], [5]. Other studies by Reinkensmeyer's and Salisbury's groups and by Feygin *et al.*, present tasks that may be difficult enough to require multiple sessions for adequate training but they chose experimental protocols that lasted only one session, thereby limiting their results to performance assessment and not training [19,49,53]. Morris *et al.* suggested that their experiment may have been confounded because the haptic condition was novel for all participants, and Feygin *et al.* stated that a longer-term protocol would be left to future work [19,53]. Furthermore, according to Todorov *et al.* and Adams *et al.* , the value of virtual training environments (VTEs) will be demonstrated when they are used for relatively complex tasks rather than for simple tasks [5,79]. For these reasons I implemented a task similar to one previously studied by O'Malley *et al.* and later by Li *et al.* [44,46,60]. Their task was difficult enough to require multiple sessions to master and saturation was not observed until after seven to ten sessions. Based on Li's and Karni's works, the protocol for the current experiment is defined as eleven sessions over a two-month period; *i.e.* one evaluation session, nine training sessions spaced two days apart for roughly four weeks, and one retention session four weeks after that.

The second issue one faces when designing a human motor training task experiment has to do with participant dependence on the guidance. When the guidance is provided on the same sensory channel as the skill training that is sought–in this case the haptic channel–dependence can occur. The trainee actually learns the system dynamics of the augmented task rather than the targeted task. In early attempts to use haptics for training, such as the *record and replay* strategies, the dynamics of an *expert* performing the task are recorded and are then played back to the *novice* to assist learning [19, 24, 32, 82]. The record and replay training scheme does not account for differences due to user-specific dynamics and restricts the *novice* to the *expert's* performance without consideration of possible alternate strategies for completing the task [46]. Results from studies on effectiveness of record and replay techniques for motor skill training are inconclusive.

To overcome the deficiencies of the record and replay models, Bayart *et al.* proposed a four-step scheme similar to the stages in learning to ride a bicycle [7]. First, the trainee observes the teacher performing the task. Then, the trainee is guided along as the teacher pushes the bicycle and rider. Next, the rider performs the task with restrictions such as training wheels and finally, the rider successfully performs the dynamic task without any assistance. In Bayart's implementation, the stages were fixed levels that had to be switched manually by the experimenter, thereby preventing a truly gradual and automated *progressive* scheme.

Ideally the progressive model should adapt to the current performance of the participant and gradually diminish as performance improves or increase if performance worsens. Bell *et al.* showed benefits from a performance-based progressive guidance scheme for self-learning of a radar-tracking task but again they limited the length of their "training" protocol to one session and it did not include haptics [8]. In a robot-assisted rehabilitation simulation, Reinkensmeyer *et al.* measured adaptation to a dynamic environment via trajectory error [64]. The control gains of the guidance robot were then adjusted at each trial based on the measurement of error. The simulation results suggest that providing guidance only when needed is more effective than a fixed amount of assistance. In order to reproduce Reinkensmeyer's simulation and to test his hypothesis, Li *et al.* first compared a fixed-gain shared control scheme to no-guidance at all in a dynamic target-hitting task (similar to the one implemented in this study) and showed that the fixed-gain scheme had negative efficacy both during and after guidance [46]. Then, Li *et al.* compared a progressive shared control scheme to the same fixed-gain scheme and showed significant improvement over fixed-gain but no significant differences from no-guidance. This was true both at the time the guidance was active and after the guidance was deactivated [44]. Li's discussion motivated the research of this thesis by alluding to the need for guidance scheme designs to be based on the significant components of the task.

The third issue that the development of a haptic guidance training protocol presents is this: the guidance scheme inputs must be based on measures of performance that are derived from the key skills required for success in the task. The next section will address this issue in detail.

2.4 Measures of Skill Acquisition

While these virtual training schemes have demonstrated effectiveness in enabling improved task performance, they have not yet conclusively demonstrated effectiveness in accelerating developmental progression (learning) or to in increasing overall task performance after a period of training. Sutherland et al., for example, reviewed thirty studies utilizing simulation (or VTEs in some form) for surgical training [76]. In all thirty studies, VTEs did not outperform traditional training schemes, and in fact VTEs only outperformed control groups who received no training at all. Similarly, Adams *et al.* found no significant learning benefit from training for their simple pick and place assembly task in a virtual environment [5]. Furthermore, in a manual target-hitting task, Li *et al.* showed how a haptic guidance VTE designed in an ad-hoc fashion resulted in negative efficacy when compared to the non-guidance that the control group received [46]. In subsequent analyses of alternate haptic guidance schemes, Li *et al.* found that performance-based progressive haptic guidance resulted in training outcomes that were better than fixed-gain assistance but only as good as no guidance at all [44]. In contrast, Morris *et al.* found that participants could more accurately recall force profiles as a result of visual and haptic training than from visual or haptic training alone, but noted that the haptic feedback was unfamiliar to all participants [53]. In another experiment, Feygin compared visual and haptic feedback in the performing of a 3-D path-following training task [19]. They found that while visual training was significantly better for teaching the trajectory shape, dynamic aspects were more effectively learned from the haptic guidance. Feygin *et al.* qualified their findings by stating that the experiment was too short to arrive at firm conclusions about overall training outcomes [19]. A common conclusion of Feygin, Li, Morris, and their colleagues is that the best types of guidance are those that are tailored to present specific or primary skills required for the task at hand.

Once the key skills of a particular task are identified, VTE developers must define measures that can quantify the acquisition of the skills. Numerous measures have been proposed, investigated, and validated. Total movement time is the most commonly employed measure. It has been validated through Fitts' law, a well-known and robust experimental psychology movement model that predicts the total movement time from the task's index of difficulty (ID) [20]. The original Fitts' task involved an arm movement to reach a target. The user was asked to move from an initial position to a fixed target position. Specifically, Fitts' law is expressed as:

$$MT = a + b\, log_2 \frac{2A}{W} \tag{2.3}$$

where MT is the total movement time, A is the distance between the initial position and target position, W is the target region tolerance and a and b are empirically derived constants. Thus, a trade-off exists between the speed and accuracy associated with this kind of task. This law has been applied to and validated in many areas of movement research including human computer interaction (HCI). The original Fitts' task requires zero order position control only and has been used for over 50 years [20,71]. Other researchers more recently have extended the law to apply to tasks requiring higher order control but the skill measure is still a form of the "total movement time" measure. Obviously these completion-time measures cannot be used for tasks with fixed durations.

Error measures are another broad category of measures available for quantifying performance. These measures work well when the task requires a specific movement trajectory. They conveniently draw from statistical techniques to measure deviation and provide validation. In the robotic rehabilitation field, several researchers including Celik *et al.* and Colombo *et al.* have sought to correlate robotic based error measures of performance to the clinical measures that therapists have used for years [13, 15]. Celik compared a trajectory deviation measure to the Fugl-Meyer impairment measure and to the Motor Activity Log (MAL). In skill training, Li used a time-independent error measure instead of a time-dependent error measure as used in similar work by Gillespie *et al.* and Patton *et al.* [24,43,62].

Flash and Hogan initiated another category performance measures related to speed smoothness. They showed that the tangential speed profile of the hand during point-to-point reaching movements of healthy subjects can be accurately represented by an optimally smooth speed profile that minimizes jerk, the time derivative of acceleration [22]. Later, Hogan derived the optimally smooth speed profile for a rhythmic movement (like the one under investigation) [33]. Since then other researchers have used movement smoothness as a measure of movement quality. Celik also compared a movement smoothness measure to the Fugl-Meyer and to the Motor Activity Log (MAL) measures [13].

Still other researchers have looked at force or torque as measures of performance. Morris et al., for example, studied human ability to replicate force patterns [53]. Srimathveeravalli *et al.* implemented force profiles in their "haptic attributes" techniques [72]. Other researchers have investigated frequency based measures [34,38].

Finally, another broad category of performance measures is the task-specific measures of success. These measures are as varied as the tasks being represented. In surgery, for example, a common measure is the suturing force required to avoid tears. In flight training, pilots are evaluated by measuring landing location, forces, and distances. The main drawback to the task-specific measures is that they rarely transfer to other application tasks and domains.

In this research, I designed, implemented and demonstrated a progressive haptic guidance scheme for training participants to carry out a non-trivial dynamic task where the amount of guidance is adjusted by decreasing gain algorithms that utilize both error and speed profile performance measures.

2.5 Measures of Cognitive Workload

The advent of robotics and automation has relieved the human operator from much of the tedious physical work that historically characterized manual labor. Consequently, human operators are experiencing a shift from physical to cognitive demands. For example, while pilots previously invested most of their time in physically keeping the airplane on course, they are now principally occupied in mentally monitoring the computer systems that control the aircraft. For this reason, researchers find it imperative to assess the cognitive and mental workloads being placed on human operators and trainees. The human factors literature outlines four techniques for assessing mental workload: physiological measures such as heart rate and breathing rate, subjective measures, secondary task measures and primary task measures [52].

Human factors engineers most commonly use subjective workload assessment techniques because these techniques are easy to use, are non-intrusive, are low cost, and have a known sensitivity. Subjective mental workload can be defined as the subject's personal estimation or comparative judgment of the mental or cognitive workload experienced at a given moment [63]. Some popular unidimensional and multidimensional measures include the Cooper Harper scale, direct scaling and consumer mental workload scale [50]. The two most common multidimensional techniques, however, are the Subjective Workload Assessment Technique (SWAT) developed by Ried and Nygren [63] and the National Aeronautics and Space Administration – Task Load Index (NASA-TLX) developed by Hart and Staveland [30].

The SWAT scale has three dimensions: mental effort load, time load, and psychological stress load. In addition to performing the task itself, participants prioritize cards representing the three dimensions of the SWAT scale and they also score their own workload after completion of the task along the three dimensions. There are 27 cards to rank in order, and this produces a tedious procedure in order to obtain the workload ratings. Moreover, the SWAT has been criticized for a potentially low sensitivity at low mental levels of workload. Several alternative methods with more sensitivity but still based on the SWAT dimensions have been proposed in the literature [50].

The NASA-TLX has six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration as shown in Fig. 2.3. A computerized version of the NASA-TLX exists that reduces the time it takes to score the six dimensions, to compare the fifteen pairs created by all possible combinations of the six dimensions, and to rank each of the six in order [54]. Like the SWAT, the comparisons are tedious, but the TLX only requires 15 comparisons. The TLX provides additional information about the task that is not available from the SWAT. This task information, along with the rapid assessment the computer version affords, were the main reasons for selecting the NASA-TLX for this study.

Currently, very few published studies have investigated the cognitive workload effects of haptic guidance or assistance during long-term training despite Rosenberg's suggestion that mental workload could be reduced, a suggestion he made when he introduced the concept of virtual fixtures. He did not, however, investigate workload further [68]. Gillespie, who introduced the *virtual teacher*, later, with Griffiths, investigated secondary task workload while participants performed a vehicle steering task. Whereas the presence of a secondary task adversely affected ability to stay in a lane without haptic assistance, when haptic assistance was provided, the presence of a secondary task did not adversely

Measure Title	Endpoints of the scale	Descriptions
Mental Demand	Low - High	How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, looking, searching, remembering). Was the task easy or demanding, simple or complex, exacting or forgiving?
Physical Demand	Low - High	How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand	Low - High	How much time pressure did you feel due to the rate or pace at which the task elements occurred? Was the pace slow and leisurely or rapid and frantic.
Performance	*Good - poor*	How successful do you think you were in accomplishing the goals of the task set by set by the experimenter? How satisfied were you with your performance in accomplishing these goals?
Effort	Low - High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration	Low - High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Figure 2.3 : Six dimensions of the NASA-TLX described (from [30])

affect the participants in terms of steering performance or obstacle avoidance. This finding suggests that haptic guidance designed for enhancing performance reduces the overall cognitive workload during performance of the task but no firm conclusions about training can be derived from this study since Griffiths and Gillespie limited their investigation to single-session performance [28].

Kalawski *et al.* provided a top-down systems engineering overview to the understanding of the role of human factors in virtual environments in general but did not specifically address haptic guidance [39]. The seminal work by Tan *et al.* on human factors in the design of haptic interfaces describes the psychophysical measurements of human kinematics and forces but not subjective measurements of workload [78]. Ongoing work by Tan and her collaborators has continued to concentrate on the psychophysical aspects of haptic interactions. Zhou *et al.* recently investigated spare cognitive capacity of surgeons, at the moment that they were training with haptic feedback in a laparoscopic procedure [83]. The participants were asked to solve two digit multiplications in their mind while performing the surgical skill on a simulator. Zhou found that the participants tended to pause to solve the math problem and simply took longer to complete the surgical task. This cognitive loading of a primary with a secondary task was easier and faster for both *novices* and *experts* when haptic feedback was provided. This result suggests that haptic feedback does indeed reduce workload. Although this study included haptic feedback, it did not include haptic guidance per se. In one experimental condition, however, the haptic feedback was exaggerated in a way similar to an augmentation. Zhou was interested in cognitive capacity rather than the workload of the task itself. For extensive discussions regarding performance and workload see work by P.A. Hancock [29, 42]. Hancock has addressed such issues as the effects of control order, input device types, and augmented feedback [29]. While Hancock did extend the research to encompass both augmentation and training, to my knowledge there has not been an investigation of workload and haptic guidance during long-term training. With these considerations in mind, I decided to use the NASA-TLX for assessment of subjective workload [30]. The NASA-TLX has been used extensively worldwide because of the design of the assessment tool it uses and because it measures multiple dimensions simultaneously. Thus, this thesis records and analyzes measures of both human motor skill performance and subjective workload and investigates both, concurrently, in a multi-session user study.

2.6 Expertise-Based Analysis

In an effort to determine key skills that are critical to success, some researchers have chosen to observe complex tasks in which there are clear and significant differences between high performing *experts* and inexperienced *novices* [4, 81]. Researchers have a preference for studying training domains that are closely related to equivalent real world tasks, such as vehicle control, medical procedures, sports training and rehabilitation [6, 14, 27, 65]. In practice, *expert* is understood to mean an individual displaying exceptional levels of performance in the task of interest. In the surgical domain, Rosen *et al.* analyzed expert and novice surgeon performance during a typical laparoscopic procedure, finding significant differences between the groups in fourteen interaction types [66]. In a survey of surgical simulation for training, Gallagher *et al.* insisted on the need to define and categorize *expert* performance clearly for the purpose of establishing proficiency criteria to evaluate surgery trainees objectively regardless of the simulation used [23]. Thus the criteria for objectively categorizing an *expert* is as important as the degree of realism of the VTE. In fact, Tzafestas *et al.* state that any haptic surgical simulator must be assessed in two ways: not only as a training tool but also as a skill assessment tool [80]. O'Toole *et al.* provided evidence that the performance of two groups, experts with more than 1,000 procedures performed and novices with no experience, could be differentiated using their simulator's metrics [61]. Other fields that require similar objective measures of motor performance are flight training [47], sports [2], and rehabilitation [13, 15].

Chapter 3

Background and Motivation

As previously mentioned, when researchers design any virtual training environment (VTE) experiment to study training in a human motor task, the task must present enough difficulty so as to require multiple sessions across various days in order to successfully master the task and to achieve asymptotic performance improvements. In this chapter, I summarize and then analyze prior research in the Mechatronics and Haptic Interfaces (MAHI) Lab, research that investigated a target-hitting task which presented sufficient complexity. Prior experiments employed the target-hitting task and demonstrated performance improvements and skill acquisition over several sessions. They measured performance via a hit count score and a trajectory deviation measure, but the researchers did not use any cognitive measures. One of the guidance schemes employed actually had negative efficacy on skill acquisition while another did not demonstrate significant differences from the nonguidance control group [43, 46]. This result provided the opportunity to study the unguided performance of a group of seventeen participants. Based on prior work in the field and drawing on expert performance in sports, I conducted an expertise-based analysis of the performance data that revealed key skills required to complete the task. I report the results of this data analysis in this chapter. I then investigated measures that would adequately quantify performance in the key skills. The chapter concludes with the motivation of the expertise-based guidance scheme that I propose in the following chapter.

This chapter is organized as follows: Section 3.1 presents the VTE used in the Mechatronics and Haptic Interfaces lab. Section 3.2 presents the methods used including the experiment procedure, expertise-based grouping, performance measures and data analysis. Section 3.3 presents the results of my analysis while Section 3.4 discusses the findings, contributions and alternate measures. Section 3.5 draws the conclusions of this analysis and motivates the design of the progressive expertise-based haptic guidance described in Chapter 5. Although I was not a major contributor to conducting the experiment referred to in this chapter, I conducted the entire expertise-based research, analysis and results here reported. A major portion of this chapter is under revision for publication in a journal [35].

3.1 Dynamic Target-Hitting Task VTE

In 2003, O'Malley and Gupta first reported investigating machine-mediated training using a two-mass underactuated dynamic system as the virtual training environment experimental setup [57]. They noted the advantages of the task they had chosen: novelty, complexity, and application to real world dynamic tasks. Since then, several collaborators in the MAHI lab have used the same task and have extended the guidance designs to virtual fixtures, shared control, and progressive schemes [44–46, 58, 60]. This study extends this line of research by adding four components: an expertise-based analysis of the task, a guidance scheme that utilized measures of performance in key skills, integration of the movement smoothness model to the guidance scheme, and the inclusion of a cognitive workload assessment. Since the progressive guidance scheme proposed in Chapter 5 is designed and implemented for the same task that the previous MAHI researchers used, the present section revisits the setup, apparatus, virtual environment, and dynamic task that they employed. The experimental setup as shown in Fig. 3.1 included physical blinders around the test site to mitigate visual distractions. During all trials, all participants donned noise canceling headphones playing pink noise (equal energy in all octaves) loud enough to mitigate interference from such audio stimuli as the surrounding environment and sounds of the joystick moving during the execution of the experimental task.

3.1.1 Visual and Haptic Apparatus

The experimental apparatus, illustrated in Fig. 3.2, was comprised of a nineteen inch LCD video display and a high fidelity two degree of freedom (DOF) force feedback joystick

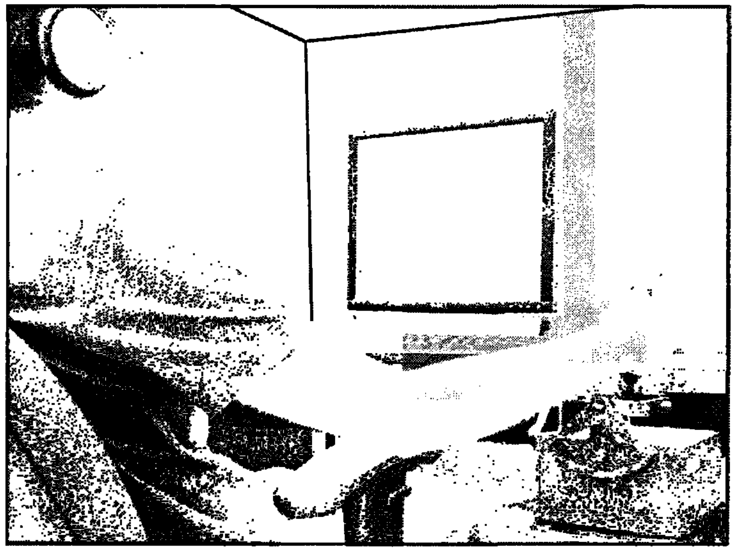


Figure 3.1 : The experimental setup includes visual blinders and audio muffing with pink-noise to mitigate visual and audio distraction from the physical environment (adapted from [44]).

(Immersion Impulse Engine IE2000). The joystick workspace limits were ± 45 deg on both axes. The arrangement and placement of the joystick relative to the the participant allowed one axis of the joystick to correspond roughly to wrist flexion/extension and the other axis to forearm pronation/supination. The ± 45 deg polar workspace of the joystick was mapped to ± 400 pixels on the video display that corresponded to a 210mm x 210mm Cartesian coordinate space. Thus the conversion from joystick rotation to visual movements was 1 deg joystick rotation = $2.333mm$ on the video display. The device exhibited low friction ($< 0.14N$) and displayed zero backlash due to the cable and capstan drive design. The fine encoder resolution along with the placement of the encoder directly on the motor shaft created a 0.002 joystick radians/encoder count rotational resolution at the joystick handle. All haptic simulations ran on a 2 GHz computer in such a way that updates occurred at the sampling frequency of 1 kHz. The system bandwidth for the apparatus was 120 Hz and it displayed a maximum force of 8.9 N in the workspace. The virtual environment graphics were created using OpenGL in the C++ programming language. The visual feedback control loop rate operated at 58Hz. The software recorded the states of the dynamic system to a data file at 50Hz for documentation and subsequent analyses.

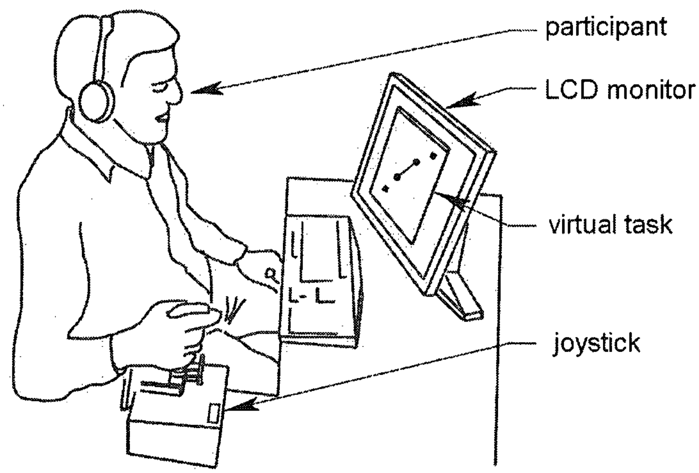


Figure 3.2 : A participant is sitting at the virtual training environment. The interface includes a visual feedback display and a haptic joystick for force feedback, both of which provide feedback of the system dynamics to the participant.

3.1.2 Dynamic Under-Actuated Task Rendering

The rendered virtual environment (VE) (recall the basic VE with haptic feedback shown in Fig. 3.3) is a planar second-order system modeled as two point masses connected by a spring and damper in parallel as shown in the inset of Fig. 3.4. This two-mass system has four degrees of freedom, namely the planar motion of each of the point masses, m_1 and m_2. Therefore, it is under-actuated since the only control inputs are the planar motions of m_1, corresponding to the joystick position. All participants receive visual feedback of the targets and moving masses via the LCD display. Additionally, all participants receive haptic feedback from the VE in the form of the mathematically-computed force interactions of the dynamic system. In other words, they feel the mass inertia and spring and damper forces as the device motors apply those force to the joystick. The participants attempt to overcome

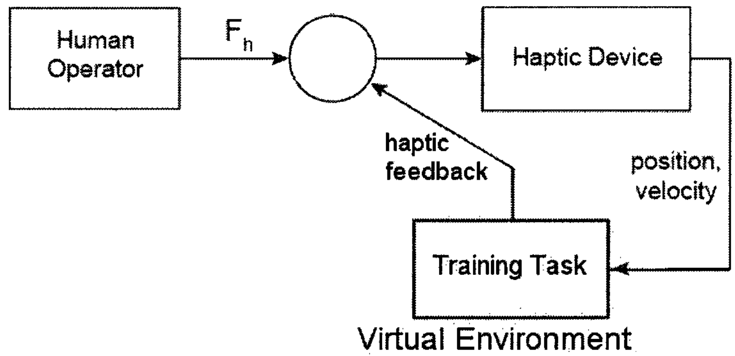


Figure 3.3 : The block diagram for haptic feedback shows how the system states were input to the virtual environment. Forces were computed based on the system dynamics and fed back to the device handle for display to the user.

the motor-generated forces to acquire the targets as illustrated in the block diagram of the haptic control loop (Fig. 3.3). The typical torque computed by the dynamics model and exerted by the motors of the joystick on the handle and therefore on the participant's hand are 1 Nm with the maximum allowable torque set to 2 Nm. These levels are set based on a similar experiment with the same virtual environment, conducted by Li *et al.* because at those levels participants did not complain of fatigue throughout the experiment [46].

The environment is rendered using an impedance control mode, where user motion is measured via optical encoders on the joystick, and forces are computed and commanded according to the equations of motion of the system and shared controller. This open-loop impedance controller is illustrated in Fig. 3.5.

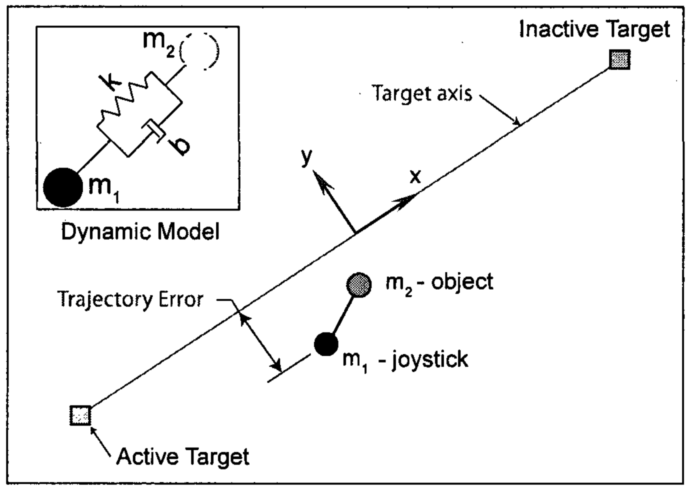


Figure 3.4 : Underactuated dynamic target-hitting task. The participant controlled the position of the force feedback joystick (m_1) in order to cause the object (m_2) to hit the desired target. Inset shows the virtual underactuated system. Trajectory error was defined as the deviation of the joystick (m_1) from the target axis (adapted from [44]).

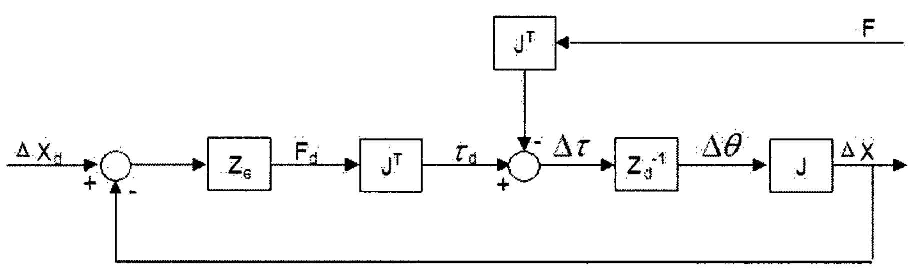


Figure 3.5 : Block diagram for the open-loop impedance controller utilized to render the VTE (adapted from [12]).

In the figure, Δx_d denotes the deviation of desired position x_d from nominal position x_0, Z_e is the virtual environment impedance, F_d is the desired force command, τ_d is the desired torque command, $\Delta\tau$ denotes the deviation of total applied torque from the nominal torque τ_0, Z_d is the impedance of the haptic device (the linearized haptic device dynamics), J is the Jacobian of the haptic interface while J^T is the transpose of Jacobian, F is the force applied by the participant, $\Delta\theta$ is difference between the actual joint angle with the nominal joint angle θ_0, and Δx is difference between the actual position with the nominal position x_0. The closed-loop impedance of this controller (Z_{cl}) is computed with Eq.3.1:

$$Z_{cl} = Z_e + Z_d \tag{3.1}$$

The linearized dynamics Z_d can be derived from Eq. 3.2:

$$M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) = \tau \tag{3.2}$$

where $M(\theta)$ is the inertia term of the haptic device, $C(\theta, \dot{\theta})$ is the coriolis effects of the device, and $G(\theta)$ is the effect of gravity, and τ is the torque commanded to the device motors. The impedance of the haptic device, Z_e, is neglected in this study since $Z_e << Z_d$, thus $Z_{cl} \approx Z_e$. This approximation can be attributed to several reasons: first, the device has relatively low inertia, therefore $M(\theta)$ is small. Second, the human motion input velocities are relatively low, so $C(\theta, \dot{\theta})\dot{\theta}$ is small. Third, the gravity compensation term $G(\theta)$ is small since the task motion is almost horizontal. Moreover, the haptic interface used in the experiments has low friction, is free of backlash, and is highly backdriveable. Therefore, the impact of the inherent dynamics of the haptic device is neglected, as is commonly done for high fidelity impedance type haptic displays [12]. The task, illustrated in Fig. 3.4, is to manipulate the motion of the point mass (m_1) via the 2-DOF haptic joystick, and thus indirectly, through the system dynamics, to control the movements of the object (m_2) in order to hit as many of the diagonally placed targets as possible during each 20-second trial. The targets are located 100mm apart on the visual display representing 76deg of joystick rotation. Once a target is hit, the current target becomes inactive and the opposite target becomes active thus the active target alternates positions.

The dynamic second-order VE task is described by the following equations of motion:

$$Fs_x = m_2\ddot{x} + b_s\dot{x} + k_s x \tag{3.3}$$

$$Fs_y = m_2\ddot{y} + b_s\dot{y} + k_s y \tag{3.4}$$

where Fs_x and Fs_x are the forces generated by the system dynamics, b_s is the damping, and k_s is the spring constant of the modeled second-order system (see Fig. 3.4 and system 1 in Table 3.1). The total force computed and delivered to the motor controllers for display on the haptic device is computed by the following sum:

$$F_D = \sum(F_h + F_w + F_c + F_s) \tag{3.5}$$

where F_h is the force applied by the participant's hand, F_w is the force created by the virtual wall guidance, F_c is the force created by the PD tracking guidance, and F_s are the forces generated by the system dynamics.

Three sets of system parameters increased the task complexity by presenting a different one of the three sets of parameters at each trial. The set to be presented in a particular trial is selected in a uniformly random fashion. The parameter sets include a specific mass of m_2, spring stiffness, and damping to provide unique resonant frequencies (f_r) as shown in Table 3.1. There is no information about f_r provided to the participants, hence they have to identify the changes based on the behavior of the virtual system (displayed on both visual and haptics channels). All three systems are under-damped since the damping ratio (ζ) is less than unity for each system. The training data for in this task are used in the expertise-

Table 3.1 : The system parameters of the target-hitting task generate unique resonant frequencies.

Parameter Set	m_1 (kg)	m_2 (kg)	k (N/m)	b (Ns/m)	ζ	f_r (Hz)
1	0	5	100	3	0.0671	0.709
2	0	2	80	1	0.0395	0.490
3	0	5	50	5	0.158	1.000

based analysis. Then, in the experiment to be presented in Chapter 5, the system parameters are maintained constant with values equal to the system parameter set 1 listed in Table 3.1.

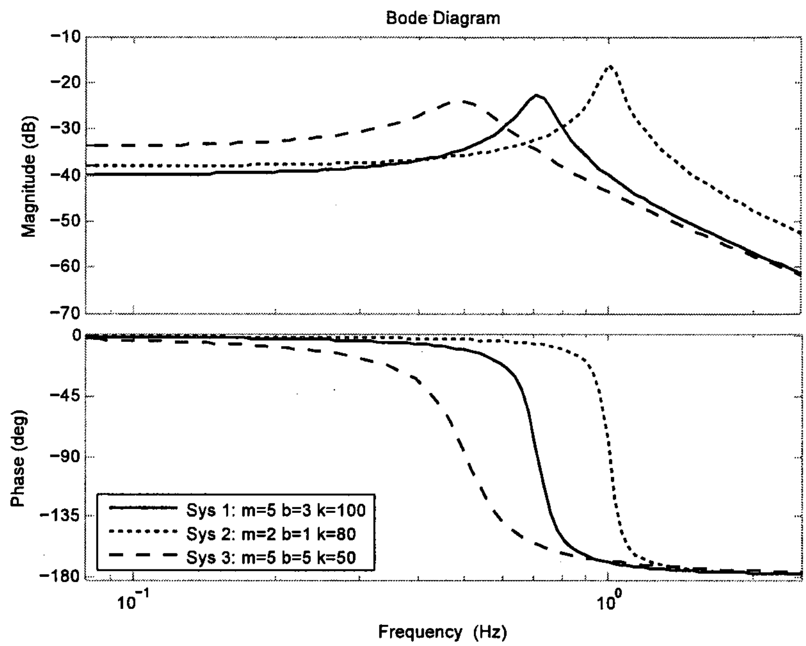


Figure 3.6 : Bode diagrams for the three systems utilized in Li's experiment.

Figure 3.6 illustrates the Bode diagrams of the three systems with their responses across a range of frequencies. The figure also shows the peak amplitudes at the resonant frequencies of the three systems.

3.2 Expertise-Based Analysis

Li, Patoglu, O'Malley and myself in the MAHI lab conducted a month-long human-user study where participants trained for the virtual target-hitting task. The virtual environment and task were described in Section 3.1. The results of the guidance was previously reported by Li *et al.* [44,46]. Those two studies aimed to determine the efficacy of an error-reducing shared controller (ERSC). The fixed-gain ERSC scheme showed negative efficacy compared to no guidance at all while the progressive (performance-based) shared control scheme showed no significant difference compared to no guidance at all but did outperform the fixed-gain scheme [44, 46].

In light of these results, I called into question the validity of error-reduction as the sole basis of Li's haptic guidance scheme. Thus, Li's findings motivated my research to identify the key skills needed to perform the target-hitting task, skills that could be measured and integrated into the design of an effective guidance scheme. Subsequently, I analyzed the performance and motion data of the experiment which Li *et al.* conducted, first to gain insight into the strategies adopted by participants who were adept at the task, and second to identify and measure key skills needed to perform the task. I analyzed the data from only those participants who trained in the VTE with unguided practice.

As a first step toward designing progressive haptic guidance schemes, I analyzed individual and unassisted performance data from the virtual environment training protocol in order to identify the key skills required for successful performance. The data was compiled from seventeen participants in a VTE experiment with unguided practice conducted in the MAHI laboratory and documented by Li *et al.* [44, 46]. As previously stated, the primary objective of Li's work was to determine the efficacy of an error-reducing shared controller (ERSC). In the two studies, the fixed-gain ERSC scheme showed negative efficacy compared to no guidance at all [46], and the progressive (performance-based) shared control scheme showed no significant difference compared to no guidance at all [44]. These results called into question the validity of error-reduction as the sole basis of Li's haptic guidance scheme. Li's findings motivated the research reported in this thesis for the purpose of understanding key skills in performing the target-hitting task in order to design an effective guidance algorithm.

To assist the analysis, the participants were divided into two groups based on their performance before training in the target-hitting task. One of the two groups was further subdivided at the end of training for a total of three groups. The analysis of the group performance presents insights into the skills that *experts* consistently execute to achieve their level of performance. The scores of these groups show significant correlations between the target hit count and two other performance measures - the space dependent *trajectory error*

(e_{traj}) and the frequency dependent *input frequency* (f_{input}) measures. I hypothesize that an understanding of the key skills and related performance measures like e_{traj} and f_{input} can be used to design performance-based visual and haptic guidance schemes that will accelerate and improve training.

Based on the performance of seventeen participants in an initial evaluation session of a VE target-hitting experiment, the participants fell into two groups: *experts* and *novices*. As a result, I gained insight into and identified the two key skills that *experts* were consistently executing to achieve their level of performance. In this chapter I define measures for these two key skills and correlate them to the task objective measure. I propose that the identification of the key skills and the employment of related performance measures in progressive guidance schemes will accelerate and improve training outcomes in virtual training environments.

3.2.1 Description of Experiments

The analysis is based on the performance data of eight participants from the nonguidance control group and nine participants who received guidance from the ERSC on only 4 out of 42 daily trials and for whom the data failed to show significant differences from the nonguidance control group throughout the entire protocol (for further explanation of the groups, see [46]). Even though the experiment was to study guidance via a shared controller, a control group was included that completed the entire protocol with no guidance provided. This was a very important component of my study. A second group of nine (called *strategy* group) received guidance in only 4 trials out of 42 trials from each session. The motivation for the reduced number of trials with assistance was based on work by Reinkensmeyer *et al.* and also work by Li *et al.* which suggested that a smaller dose of assistance could improve skill acquisition [45, 64]. These assistance forces were combined with the system dynamic forces before being presented to the participant at the joystick interface on the haptic channel during the first four trials of the guidance subsession. During the remaining ten trials of the guidance subsessions, in addition to the 28 trials total of

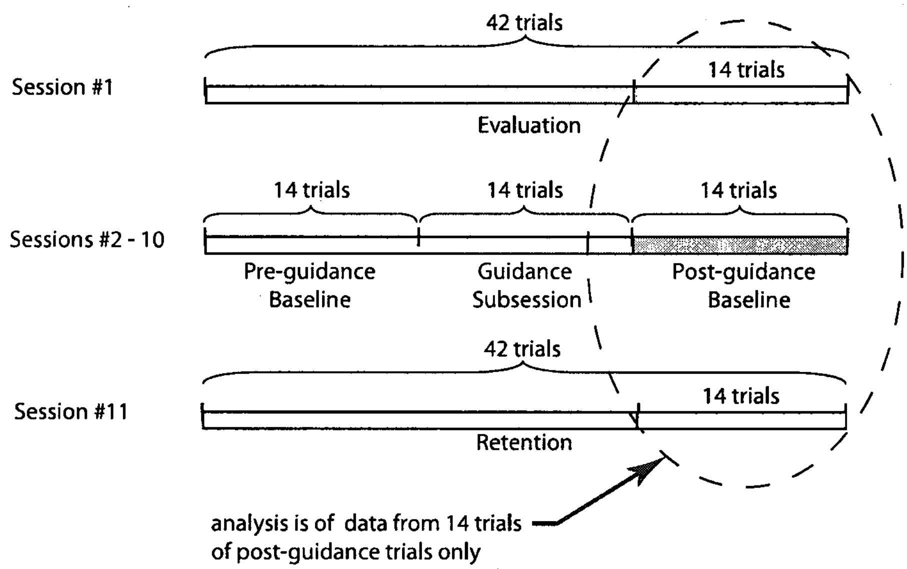


Figure 3.7 : The experiment design included an evaluation session (Session 1), nine training sessions, and one retention session (Session 11). The data was extracted from the last fourteen trials of each session as shown (adapted from Li *et al.* [44]).

pre-guidance and post-guidance baseline subsessions, the strategy group received no assistance. The statistical analysis reported by Li *et al.* demonstrated that this strategy group was in effect practicing with no augmentation. While this result with the strategy group was insignificant for that study [44], it provided me with important unassisted performance data from seventeen subjects. I decided to base my analysis specifically on the last 14 trials of each of 11 sessions where none of the participants received any guidance, thereby further ensuring homogeneity of the seventeen participants. The experiment design is illustrated in Fig.3.7 and highlights the trials that were incorporated to this data analysis.

The participants, who took part in the two month-long study (1 evaluation session, 3 sessions/week for 9 sessions followed by 1 retention session after 30 days [46]), were all right-handed undergraduate students, and had no previous experience with haptic devices. A university Internal Review Board (IRB) approved form was used to obtain informed written consent from all participants prior to incorporation. The seventeen participants were ranked by preliminary performance in the evaluation session and then randomly placed in one of the two groups for the remainder of the protocol. This placement becomes insignificant in the current study because they were re-arranged based on their level of performance in the evaluation session as the next section describes.

3.2.2 Expertise-Based Grouping

I sought to identify and measure the key skills required to perform the manual target-hitting task in order to improve the design of guidance schemes that can be conveyed in a virtual training environment augmentation. In order to identify the key skills, I chose to investigate the differences between *expert* and *novice* performers in a quantitative and systematic way. In lieu of a standardized method to determine a participant's level of expertise and recognizing the broad range of definitions for expertise in the literature (see the seminal work by Fitts [20] and recent work by Dreyfus *et al.* [17]), in this study I chose to use a statistical divider after the initial evaluation session to differentiate *experts* from *novices* in the VTE with unguided practice. After conducting the experiment, another statistical divider at the end of training further divided *novices* into fast-learning *novices* and slow-learning *novices* in the last session.

To determine the expertise of the participants, I analyzed the number of target hits for each of the seventeen participants – 8 in the "no-assistance" (N) group and 9 in the "strategy" (S) group – in the initial evaluation session as shown in Figure 3.8. Any participant whose performance was greater than one standard error above the mean of all participants was deemed to be an *expert* (Participant IDs: N6, N7, N8, and S8 as designated by Li *et al.* [46]). The remaining participants were considered *novices* ; those who performed worse than one standard error above the mean.

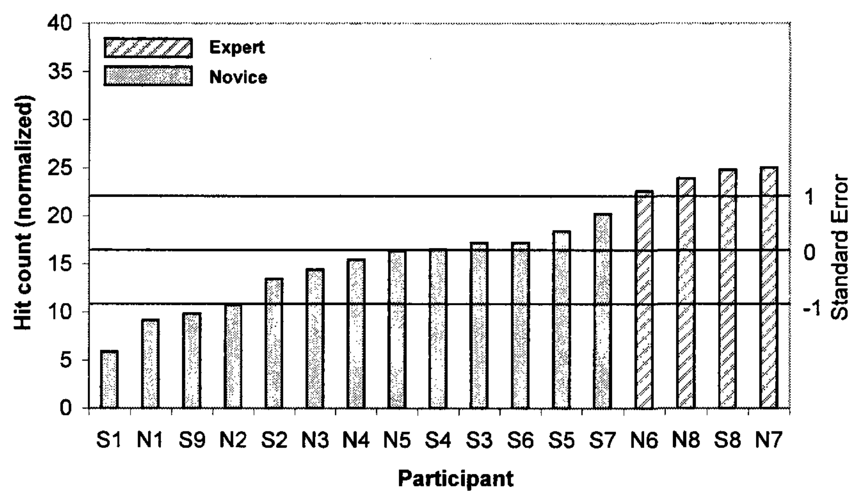


Figure 3.8 : Hit count performance rankings of all participants in the initial evaluation session (prior to training) shows designation of *experts* one standard error above the mean. Hit count was normalized by one of three possible natural frequencies of the system as presented in this section.

Having thus divided all the participants into two groups, some differences emerged as a result of observation. Figure 3.9 shows representative position trace plots from training in the task. Some participants, like Participant A, began with erratic and slow motion, and continued to be erratic throughout training. Others, like Participant B, began erratically but, during training, learned to excite the system along the target axis. Still others, like Participant C, excited the system along the target axis from the very beginning of training. These data emphasized the need to follow the target axis to achieve a high number of hits, and were the motivation for the error-reducing shared control (ERSC) algorithm. Li's ERSC algorithm used a time-independent error measure instead of a time-dependent error measure as used in similar work by Gillespie *et al.* and Patton *et al.* [24, 62]. A time dependency along the axis between the targets, exists, however, such that the input excitation frequency of the dynamic system must increase to obtain an increased hit count.

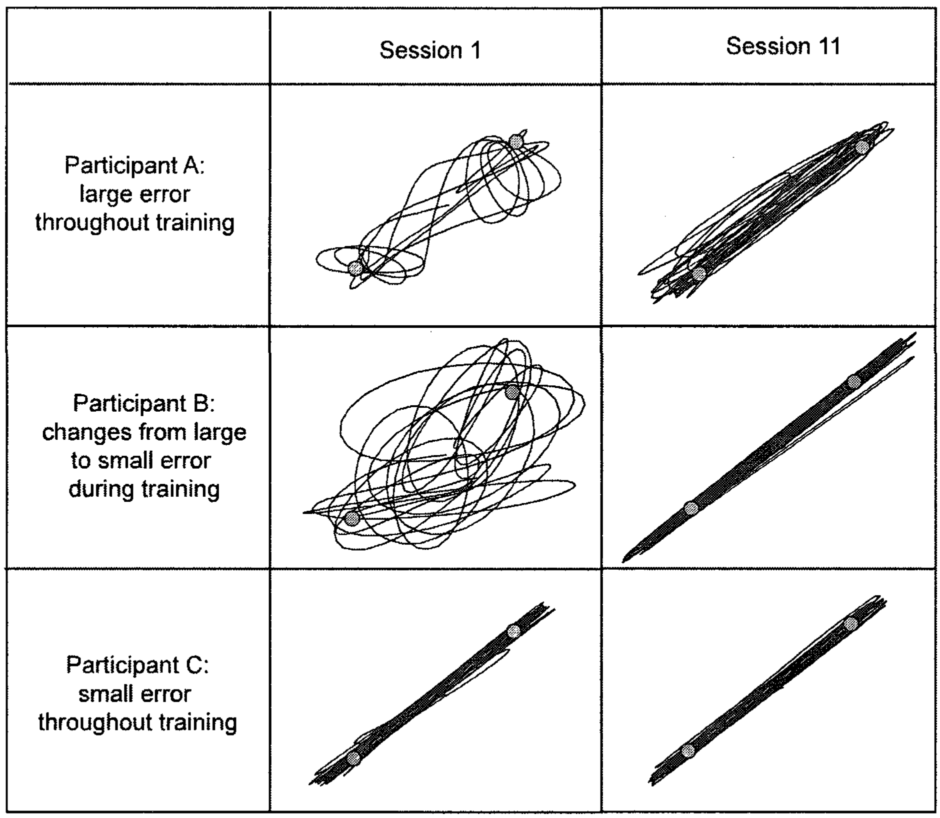


Figure 3.9 : Sample traces for three typical participants shows varying improvements and performance differences.

3.2.3 Performance Measures

From initial observations the two key skills for performing the task are first, to not deviate from the target axis and second, to excite the system at the resonant frequency so that the system response is also at the resonant frequency. A thorough investigation of the literature presented various measures that might be utilized to quantify the performance of participants. What follows is an analysis of each of these types of measures.

Time to completion

As described in the previous chapter, "Time to completion" based measures are irrelevant for this experiment since the task has a fixed length of time.

Hit count

The first measure to be included was, in fact, the objective measure of the task (The word "objective" is used in terms of this being the stated objective of the task.). The participants were instructed to "hit as many targets as possible in each 20 second trial." Although this measure has only integer values, it has enough resolution to register variations in performance over trials and sessions. For this analysis, then, the same objective measure of performance is utilized as the one defined by Li *et al.* [46]. A hit was registered whenever the center position of m_2 was detected to be within 4 mm of the target center.

In order to compare performance regardless of the virtual system parameters (mentioned in section 3.1), the total hit count per trial (count/Hz) is normalized by the following equation:

$$n_{hit} = \frac{1}{f_r} \times (hitcount) \tag{3.6}$$

Trajectory Error

The next category to be looked at is the error measures. As observed, deviation from the target axis will result in missing the target. If m_1 (see Figure 3.4) is excited such that it does not deviate from the target axis throughout the trial, the transient response of m_2 will diminish and guarantee a target hit at every pass. Therefore, any measure that quantifies the deviation of either mass from the target axis will be a valid and useful measure of performance. In prior work collaborating with Li, we utilized the RMS error of m_2 [45]. For this task, an error measure along the target axis is irrelevant because m_2 only need pass though the target, but not stop on it. Trajectory error is defined as the absolute magnitude of the deviation from the target axis of the input joystick position at each sampled instant summed for the entire trial (n = 400 samples). The target axis, shown in Fig. 3.4, is the diagonal line passing through both targets and along the oriented x-axis. Since the trial duration is always the same, trajectory error does not need to be averaged. Thus, trajectory error is expressed in units of millimeters. Mathematically,

$$e_{traj} = \sum_{i=1}^{n} abs(y_i) \tag{3.7}$$

I choose to use the error of the joystick (m_1) rather than the object (m_2) because I am analyzing the performance of the participant. Because prior analysis showed negative efficacy of the fixed-gain error reducing shared control (ERSC), I questioned the validity of error reduction as the sole basis for the task's guidance scheme [35]). Analysis of individual participant data for the target-hitting task reveals the need for additional measures of performance that are dependent on time or the phase plane. Figure 3.10 shows position traces for the tenth trial of the fourth session (approximately midway through the training protocol) for three different participants. The trajectory error (e_{traj}) as previously discussed is represented by the area from the zero reference to the thin black line. The solid thick line is the position of the mass m_1 (system input) while the dashed line represents the position of the point mass m_2 (system output) along the x axis. Figure 3.10(a) illustrates the typical low performance of a participant who has yet to learn the task and has high e_{traj} (22.9 mm) resulting in a low n_{hit} score (6 hits). The performance of another participant in Fig. 3.10(b) shows the ability to maintain low e_{traj} (14.7 mm). The participant achieves, however, only a moderate n_{hit} score (16 hits) because of an apparent inability to leverage the dynamics of the controlled system and excite the system near its resonant frequency. In contrast, the participant in Fig. 3.10(c) shows good performance by being able to maintain low e_{traj} (5.55 mm) as well as provide a consistent input excitation frequency of 95% of the resonant frequency, resulting in a high n_{hit} score (33 hits).

Velocity Profile Consistency

Velocity profile consistency was reviewed, in an attempt to obtain a measure that would capture a type of trajectory error in the target axis direction. Consistency in the velocity profile is defined as the average variation of the velocity within one trial. To make a reasonable comparison, the average excitation frequency is used to parse the trial into segments which are then overlapped. In Figure 3.11 the sample trial with high performance shows low variation for both joystick (m_1) and disc (m_2) profiles. Only the joystick variation, rather than the disc variations can be used because the dynamics of the system act as a filter to the input excitation.

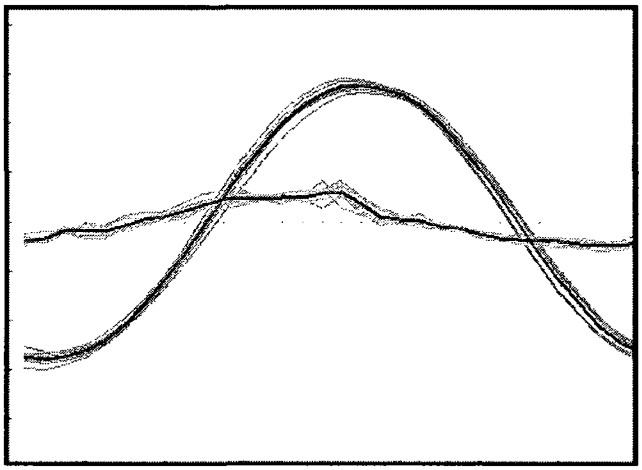
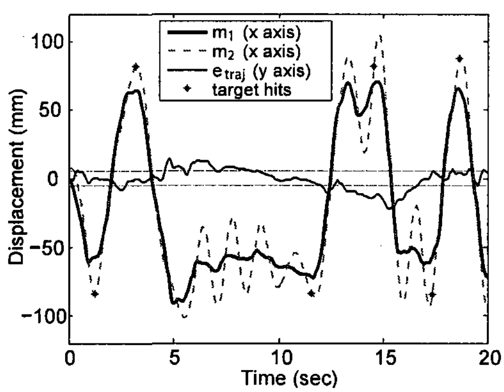
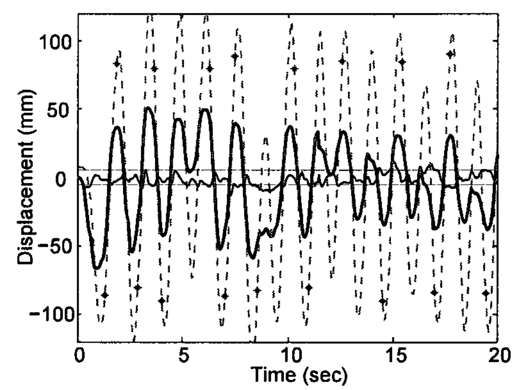


Figure 3.11 : Velocity profile consistency for both m_1 and m_2 attempt to capture variations in the velocity along the target axis.

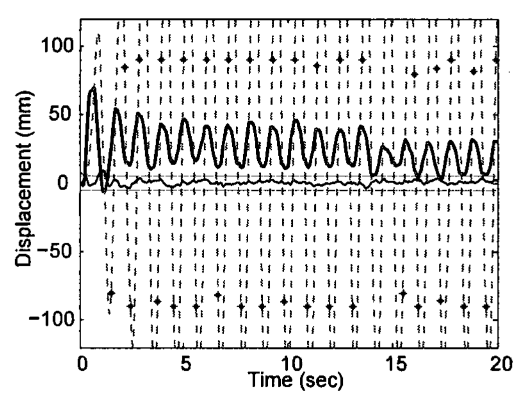
At low or irregular velocities, however, this measure was not consistent or dependable. Thus I sought another measure that could capture the periodic nature of the excitation along the target axis.



(a) low performance



(b) moderate performance



(c) high performance

Figure 3.10 : Displacement time traces from trial 10 of session 4 for three typical participants. (a) shows the high e_{traj} and irregular input motion of a low performer. (b) shows the low e_{traj} but inconsistent input motion of a moderate performance example and (c) shows a high performer's low e_{traj} and consistent excitation.

Input Frequency

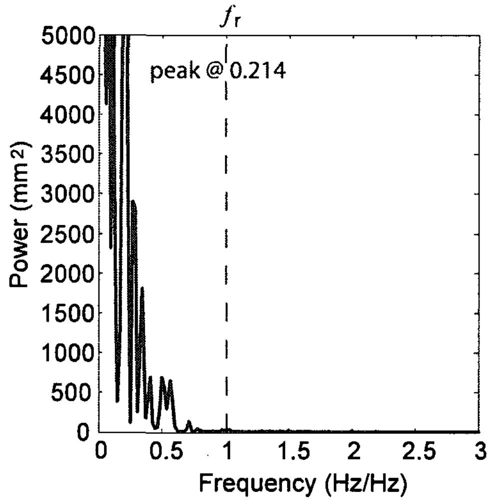
An observation of the performance periodicity indicated the importance of input excitation frequency, I propose *input frequency* (f_{input}), as a measure of excitation performance in a trial. The Fast Fourier Transform (FFT) is computed from the x axis position data of the joystick (m_1). The FFT power spectrum is a convenient way to determine the amplitude and frequency of the motion that is being applied to a system and was used by Huang *et al.* in a similar task to quantify performance [34]. Figure 3.12 shows three typical FFTs of the same three data sets represented in the displacement versus time traces shown in Fig. 3.10. Figure 3.12(a) shows the tenth trial from the fourth session of a participant who is inconsistently exciting the system and shows wide spectral variability. In contrast, Fig 3.12(b) shows a participant who is exciting the system in a fairly consistent manner. Figure 3.12(c) shows a small, but very clear, spike at 95% of the resonant frequency of the virtual two mass system. The challenge for the first participant is to increase their input frequency such that it equals the system resonant frequency. The participant must identify the resonant frequency and then provide consistent input motion commands near that frequency to the joystick m_1 in order to achieve a significant increase in n_{hit} score. To clarify, even though the FFT plot is called a "power spectrum," in this particular case it has units of mm^2. Because the experiment used three separate parameter sets, my definition includes a normalizing coefficient. The equation for the second performance measure f_{input} is given in units of (Hz/Hz) as follows:

$$f_{input} = \frac{1}{f_r} \times f(arg(max(FFT))) \tag{3.8}$$

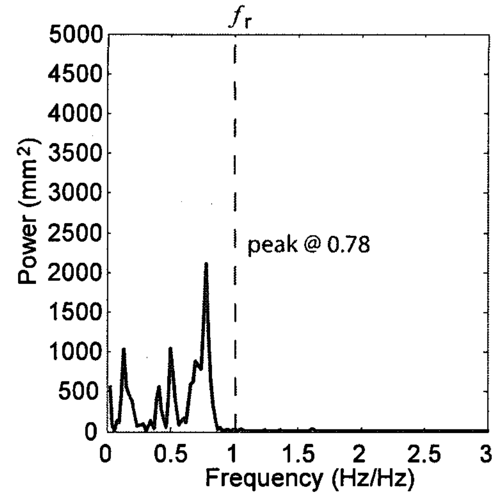
Therefore, exciting the system at the resonant frequency will give a value of $f_{input} = 1(Hz/Hz)$ regardless of the system parameter set.

Movement Smoothness

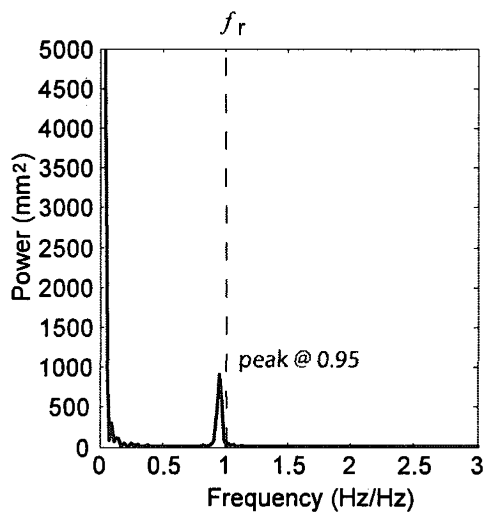
Movement smoothness was also considered and will be analyzed and discussed further in Experiment 1 in Chapter 4. For the present, and for this experiment, let it be assumed that



(a) low performance



(b) moderate performance



(c) high performance

Figure 3.12 : Two-dimensional FFT position power spectra for three participants for Trial 10 during session 4. (a) shows the erratic input spectrum of a low performing slow learner, (b) shows the fairly consistent but slower f_{input} of a moderate performance example and (c) shows the extremely consistent and low power of a high performer.

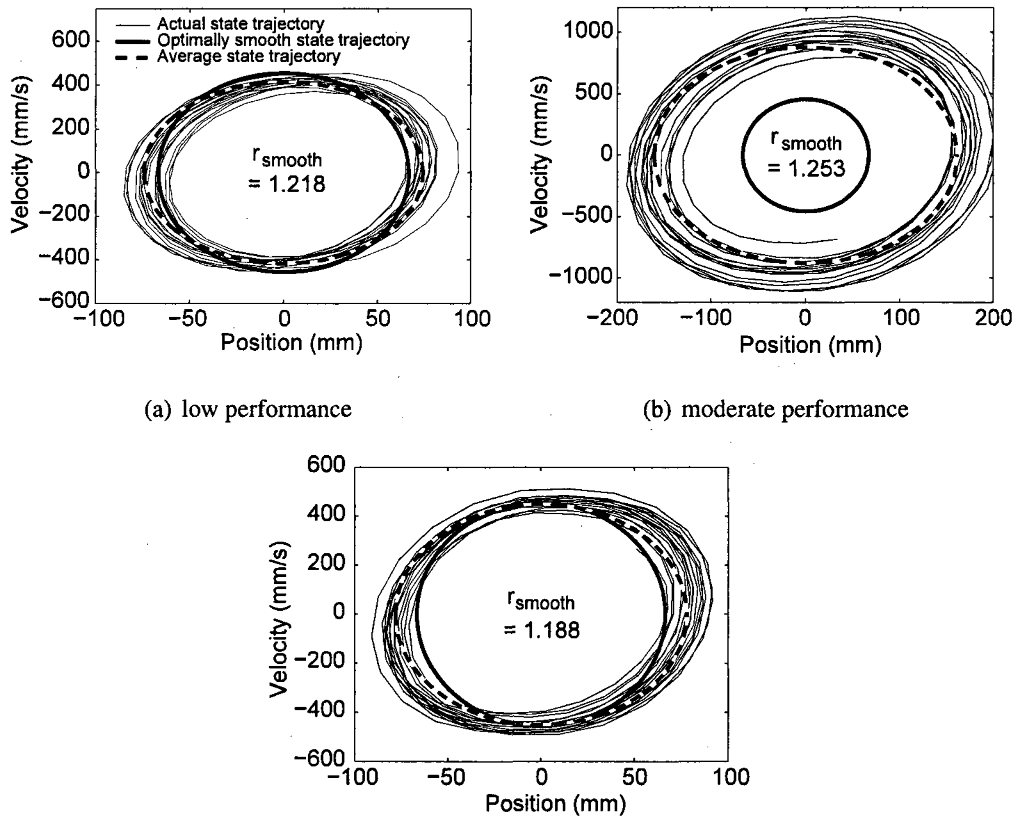
an optimal full-cycle smooth speed profile can be accurately approximated by a sinusoid with appropriate amplitude and frequency [33]. Thus I define a *smoothness ratio* measure (r_{smooth}) using the recorded state-space (position vs. velocity) trajectory of m_2 and an optimally smooth trajectory. A rhythmic movement in this state-space appears as an ellipse. There are many ways to compare two ellipses: for example, the area of each ellipse that is not common to both can be considered as an error. The nature of the task at hand, however, makes it possible to overshoot the targets, causing a wider (greater amplitude) and taller (higher velocity) ellipse than the optimally smooth ellipse and yet one could also be successful (see Fig. 3.13(b) as an example). Hence I opted for a shape comparison of the state space trajectories. The smoothness ratio is defined as

$$r_{smooth} = \frac{a_{actual}/b_{actual}}{a_{nominal}/b_{nominal}} \tag{3.9}$$

where a_{actual} and b_{actual} represent the major and minor axes of the average ellipse calculated from the recorded data by considering the points of intersection with the axes (points of zero velocity and zero position). An initial portion (1.75 seconds) of each 20 second trial is trimmed from the data before calculating a_{actual} and b_{actual}. Then $a_{nominal}$ and $b_{nominal}$ are calculated from the optimally smooth rhythmic movement that has a duration equal to the inverse of the resonance frequency of the system (f_r). When the sinusoid approximation for the speed profile is used, the movement amplitude does not need to be specifically defined, since it gets canceled when calculating the ratio $a_{nominal}/b_{nominal}$. After the simplifications, this ratio becomes

$$\frac{a_{nominal}}{b_{nominal}} = \frac{1}{2\pi f_r}. \tag{3.10}$$

With this definition of r_{smooth}, the measure approaches unity, since the state trajectory of m_2 approaches an undistorted but scaled version of the optimally smooth ellipse. As it can be easily deduced from equations 3.9 and 3.10, r_{smooth} effectively becomes a measure of the actual average period of the movement normalized by the period of the movement at the resonant frequency of the system. Therefore, one would expect to see a high correlation of r_{smooth} with f_{input}. In conclusion, the r_{smooth} measure, which describes the smoothness



(a) low performance

(b) moderate performance

(c) high performance

Figure 3.13 : Actual, average and optimally smooth state trajectories for the three participants for Trial 10 during session 4.

of a movement, is an equivalent measure of the consistency and correctness of the input or the output frequency for a rhythmic task using an underactuated linear system. Thus either measure (f_{input} or r_{smooth}) could successfully determine performance of the excitation skill required for this task. Each measure might have certain benefits depending on one or more of the following: access to either the input or output state variables, computation in real time or off-line, and types of disturbances in the system. I chose to use f_{input} in keeping with the objective to analyze the actions of the participant.

Force and Energy-Based Measures

The dynamic second order system has a theoretical minimum input energy trajectory if there exists a output amplitude requirement. Since participants were not specifically asked to minimize energy, varying input and output amplitudes could give an equal number target hits. The frequency might stay the same but the velocity would increase and thus the energy input to the system is greater. For this reason both force and energy measures were not considered.

3.2.4 Data Analysis

Based on the evaluation of measures of performance in the preceding section, this study introduces, defines, and utilizes two measures which enable the quantification of participants' performance in the two key skills: trajectory error (e_{traj}) and input frequency (f_{input}). Additionally, hit count is employed as a measure of success. For all participants, values for n_{hit}, e_{traj}, and f_{input} for each session were determined by averaging the scores of 14 trials per session. Thus each of the seventeen participants has a data point for each of the eleven sessions of training resulting in a total of 187 observations (17 participants and 11 sessions) of each measure. A performance group average score for each measure was determined from the participants' session scores to give one value per session per group. The data were fit with linear and exponential curves using MATLAB^{TM} and the best fit curves were determined from the R^2 values. Analysis of variance (ANOVA) was used to determine significance among groups. Finally, correlation coefficients were computed for each pair of measures.

3.3 Results of the Expertise-Based Analysis

After a preliminary analysis of the hit count performance of all seventeen subjects throughout the eleven sessions of the training protocol, I observed that the *novice* group could be further subdivided into slow-learning *novices* and fast-learning *novices*. This result is in keeping with expertise groups defined in the literature as follows:

- ***Expert:*** one who is able to perform the task well at the beginning of the training and therefore improves only marginally throughout training – also called masters, teachers, or autonomous in the literature ([3, 21, 23, 32, 55, 81])

- **Slow learning *novice:*** one who performs the task in a superficial way doing poorly at the outset and only marginally improving throughout training – also called novices, beginners, or students in the literature ([3, 21, 23, 32, 55, 81])

- **Fast learning *novice:*** one who begins poorly but improves rapidly early in training until he/she is as good as, or better than, the *expert* – also called intermediates, competent, or proficient in the literature ([3, 21, 23, 81])

In a way similar to the way I defined the *expert* group, those who performed better than one standard error above the mean in the initial evaluation session, any participant with a n_{hit} score less than one standard error below the mean of all participants during the last training session is considered a slow learning *novice* (Participant IDs: N1, S1, S4 and S9). Furthermore, those who performed worse than one standard error above the mean in the first session (to differentiate them from the *experts*) and better than one standard deviation below the mean in the last session (to differentiate them from the slow-learning *novices*) are called fast-learning *novices*. Figure 3.14 shows the distribution of performance for each participant, classified by their group assignment, at the end of the training protocol. Interestingly, the *experts* identified in Session 1 are not necessarily achieving the highest n_{hit} scores in Session 11 but are intermixed with the fast learners. Thus the groups were comprised of four *experts*, four slow learning *novices* and nine fast learning *novices*. These three groups (*experts* and fast and slow learning *novices*) are used in the remainder of this chapter as the basis for comparison in terms of the three performance measures (n_{hit}, e_{traj}, and f_{input}).

Next, I present and compare the results of the data analysis of the three performance measures by estimating the parameters of the learning curves for each measure and by

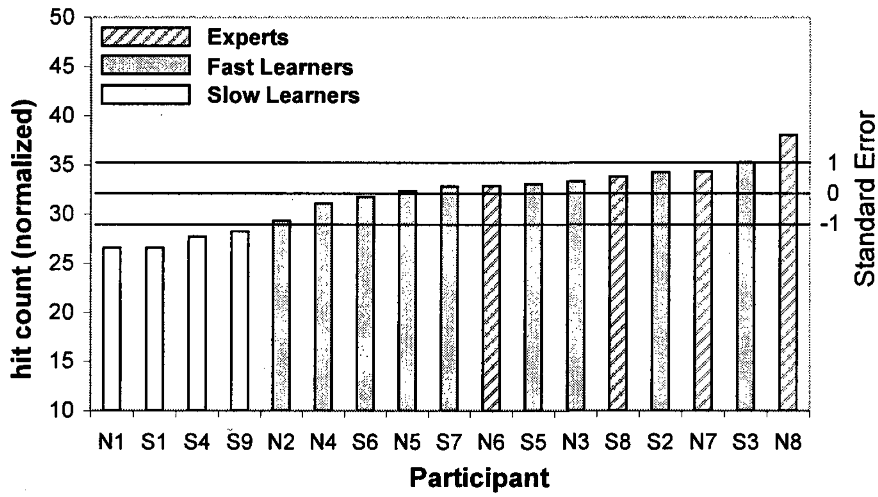


Figure 3.14 : Hit count performance rankings of all participants in the retention session show the designation of slow-learning *novices* who performed worse than one standard error below the mean and fast-learning *novices* who performed better than one standard error below the mean in the evaluation session and worse than one standard error above the mean in the retention session.

computing correlation coefficients between measures. Figure 3.15 shows the n_{hit} scores as a function of session for the three participant groups (*experts*, fast learning *novices* and slow learning *novices*). Each data point is the n_{hit} average for any given group at the corresponding session, with error bars indicating standard error from the mean. Straight line and exponential functions were fit to the data in order to visualize learning effects as a function of session. A summary of the curve fitting results, including estimated parameters and correlation coefficients from goodness of fit for each of the three groups of participants are shown in Table 3.2.

The *experts* initially had the highest n_{hit} scores and improved slowly until reaching a saturation level of approximately 36 hits (parameter c of exponential function, see Table 3.2). Fast learners began with lower n_{hit} scores than that of the *experts* (evidenced by the 95% confidence bound of parameters $c - a$) and reached saturation at a significantly faster rate than that of the *experts* (evidenced by 95% confidence bound of parameter b).

Table 3.2 : Summary of the curve fitting procedures for the performance measure data of each expertise group.

Participant Group	measure	Goodness of fit				
		DOF	Function type	Function expression	R^2	Parameters
	n_{hit}	8	Exponential	$-ae^{-bx}+c$	0.95	$a=14.6, b=0.18, c=36.6$
Experts	e_{traj}	8	Exponential	$ae^{-bx}+c$	0.65	$a=3.60, b=0.28, c=8.18$
	f_{input}	9	Straight Line	$ax+b$	0.68	$a=0.006, b=0.93$
	n_{hit}	8	Exponential	$-ae^{-bx}+c$	0.99	$a=25, b=0.37, c=33.15$
Slow Learners	e_{traj}	8	Exponential	$ae^{-bx}+c$	0.94	$a=16.4, b=0.74, c=10.6$
	f_{input}	8	Exponential	$-ae^{-bx}+c$	0.99	$a=0.53, b=0.42, c=1.03$
	n_{hit}	9	Straight Line	$ax+b$	0.98	$a=1.81, b=7.84$
Fast Learners	e_{traj}	9	Straight Line	$ax+b$	0.88	$a=-1.96, b=30.0$
	f_{input}	9	Straight Line	$ax+b$	0.96	$a=0.04, b=0.47$

The 95% confidence bound for the saturation level (parameter c) of the fast learners coincides with that of the *experts*, indicating that both groups reached the same performance level towards the end of the experiment. Additionally, the fast learners reached 90% of the saturation level slightly after the sixth session. The slow learners started with lowest n_{hit} scores and improved linearly with significant slope (parameter a), hence failing to reach saturation during the experiment. The average e_{traj} and f_{input} are shown in Fig. 3.16 and Fig. 3.17 respectively (results are over the eleven sessions of the protocol). Error bars show standard error of the group mean. Figure 3.16 shows decreasing trends of mean e_{traj} while Fig. 3.17 shows increasing trends of mean f_{input} as training progressed. Analysis of both the e_{traj} and f_{input} measures of performance by group showed similar trends to the performance by group in terms of n_{hit}. In other words, slow learners had the worst performance, *experts* showed the best performance, and the fast learners started out somewhere in the middle, yet achieved performance comparable to the *experts* at some point during training. Straight line and exponential curves were fit to the data, with details included in Table 3.2.

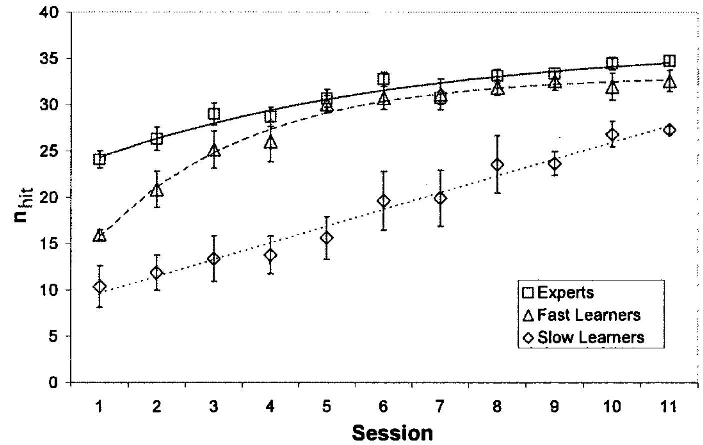


Figure 3.15 : Average n_{hit} as a function of session for the three groups of participants. Error bars indicate standard error from the mean.

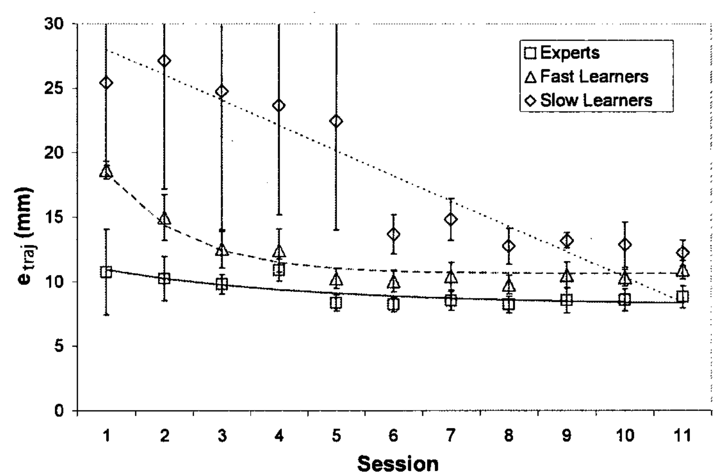


Figure 3.16 : Average e_{traj} as a function of session for three groups of participants. Error bars indicate the standard error from the mean. *Expert* and fast learner data are best fit by exponential functions while slow learner data are best fit with a straight line function. The error bars for the slow learners are especially large in the first 5 trials due to one participant who attempted to perform the task by exciting the system in a circle with a diameter equal to the distance between targets. In session 6, this participant, began to use the common oscillatory pattern.

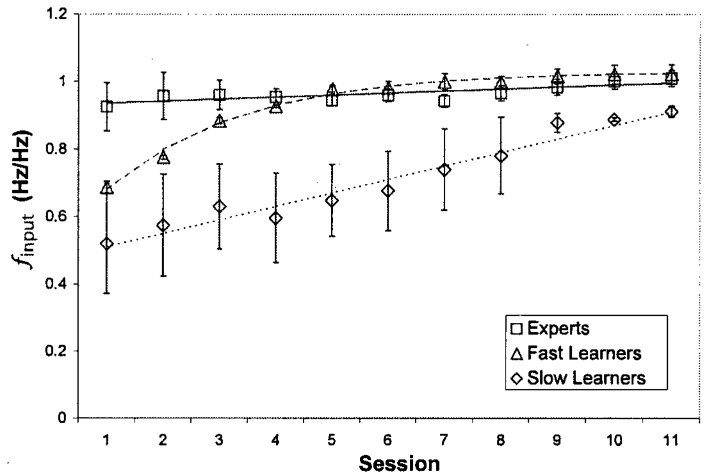


Figure 3.17 : Average f_{input} as a function of session for the three groups of participant (Error bars indicate standard error from the mean) Fast learner data are best fit with an exponential function while *experts* and slow learners are best fit by straight line functions.

For e_{traj}, data for *experts* and fast learners exhibited exponentially increasing trends, while the slow learner data was better characterized by a straight line function. For f_{input}, data for *experts* and slow learners showed linearly increasing trends, while fast learners demonstrated an exponentially increasing trend.

Each performance measure was further analyzed using a two-way ANOVA in order to highlight significant effects of group and session. For all three performance measures, the main effects of group and session were significant. For n_{hit} the effects of group and session were significant (group: $F(2,154) = 180$, $p < 0.001$; session: $F(2,154) = 41.4$, $p < 0.001$). For e_{traj} the effects of both group and session were also significant (group: $F(2,154) = 23.5$, $p < 0.0001$; session: $F(2,154) = 3.49$,$p < 0.0001$). Finally, for f_{input} the effects of both group and session were also significant (group: $F(2,154) = 51.3$, $p < 0.001$; session: $F(2,154) = 7.8$, $p < 0.001$). The interaction effect of group and session was significant for n_{hit} ($F(20,154) = 2.03, p < 0.0086$) but was not significant for either e_{traj} ($F(20,154) = 1.36, p < 0.152$) or f_{input} ($F(20,154) = 1.30, p < 0.190$). The analysis indicates that the performance measures were significantly different among groups and

Slow Learners vs. Experts	Measure	1	2	3	4	5	6	7	8	9	10	11
	n_{hit}	*	*	*	*	*	*	*	*	*	*	*
	e_{traj}		*			*	*	*				
	f_{input}	*	*	*	*	*	*	*		*	*	

Slow Learners vs. Fast Learners	Measure	1	2	3	4	5	6	7	8	9	10	11
	n_{hit}	*	*	*	*	*	*	*	*	*	*	*
	e_{traj}				*	*						
	f_{input}			*	*	*	*	*	*	*	*	*

Fast Learners vs. Experts	Measure	1	2	3	4	5	6	7	8	9	10	11
	n_{hit}	*	*									
	e_{traj}											
	f_{input}											

Legend:
- [*] Significant Difference Between Groups with 95% confidence ($p<0.05$)
- [*] Significant Difference Between Groups with 90% confidence ($p<0.1$)
- [ ] Failed to show Significant Difference with 90% confidence ($p>0.1$)

Figure 3.18 : Summary of statistical analysis of performance group differences

the performance improved along sessions. In order to show all instances of significant difference in performance between the three groups in each session, a post hoc Scheffe test was performed on the data in each session and results of the analysis are presented in Fig 3.18. The figure shows three tables for the comparison of the three participant groups. Each table has rows corresponding to each of the three performance measures and eleven columns for the sessions. Cells with asterisks indicate an instance of significant difference between groups. Dark shading indicates significance with a 95% confidence level and light shading indicates 90% confidence level. Light shaded cells with no asterisk indicate that the data failed to show significant differences with a 90% confidence level. The results here indicate that the n_{hit} measure is significantly different throughout training when comparing *experts* and slow learners as well as when comparing fast learners and slow learners. The performance of *experts* compared to fast learners was statistically different in the first two trials, but no significant differences were observed in the later sessions. This results indicates that after just two session fast learners approach the performance of the experts. The analysis also indicates similar significant trends throughout training between n_{hit} and f_{input} but not between n_{hit} and e_{traj}. To determine the relationship between n_{hit} and the two other performance measures, coefficients are computed for the correlations shown in Fig. 3.19 Strong correlation exists between n_{hit} and f_{input} evidenced by $r(185) = +0.75$

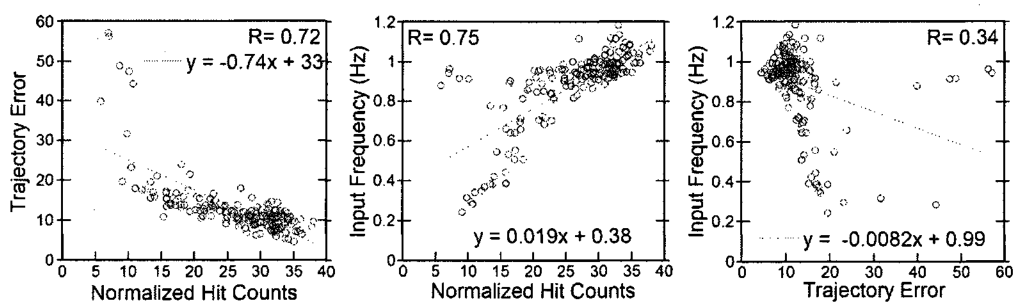


Figure 3.19 : Correlation plots for e_{traj} and f_{input} versus n_{hit} demonstrate the good correlation of the secondary measures to the objective measure of performance but not to each other.

($p < 0.01$). Correlation between n_{hit} and e_{traj} is $r(185) = -0.72$ ($p < 0.01$), indicating a slightly better correlation between n_{hit} and f_{input}. Multiple regression in the form:

$$n_{hit} = a + b_1(e_{traj}) + b_2(f_{input}) \tag{3.11}$$

where $a = 12.6$, $b_1 = -154$ and $b_2 = 22.76$ demonstrates that both secondary performance measures are significant ($r(185) = 0.90$, $p < 0.001$). Although both measures showed a good correlation with the objective measure (n_{hit}), the correlation coefficient between f_{input} and e_{traj} indicates a poor correlation ($r(185) = -0.34$) between the secondary measures, thereby suggesting the measures are independent.

3.4 Discussion of the Expertise-Based Analysis

The task used in this study demonstrated sufficient complexity, as required by Todorov to ensure differences in the levels of performance of the participants [79]. In contrast, tasks chosen by Yokokohji *et al.* and Adams *et al.* as the basis for testing virtual environment training were found to be too simple to be able to draw conclusions from them regarding the efficacy of the virtual training [5, 82]. The analysis found statistically significant differences in performance between the three expertise-based groups. By evaluating *expert* performance and comparing it to the performance of fast and slow learning *novices*, a method suggested by Williams [81], I determined two key skills for the target-hitting task.

The first key skill required for the target-hitting task is the minimization of the trajectory error. The second key skill is related to the excitation frequency of the system input. I concentrated my analysis of performance on the motion of m_1 measured in the underactuated dynamic system, which corresponds to the motion of the human via the joystick. The analysis directly assessed the participants movements and performance of the task. The trajectory error measure was based on the motion of m_1 relative to the target axis. In my prior work with Li, we analyzed the error of the output of the second order dynamic system [44]. Such analysis of performance based on trajectory is important for tracking tasks such as those studied by Feygin *et al.* [19]. Due to the dynamics of the system in this target-hitting task, the motion of the output (m_2) is directly coupled to the motion of the input (m_1). Therefore, similarly decreasing trends are noted in the trajectory error measure over the course of training. For the input frequency measure described, I based my calculations on the motion of m_1, which directly corresponds to the motion of the input joystick and human participant. Others have focused on input frequency as have I (e.g. Israr *et al.* and Huang *et al.* [34, 38]). Conversely, some groups have approached the measurement of rhythmic task performance by analyzing the smoothness of the system output but I showed that when the optimally smooth state-space trajectory is defined based on the resonant frequency of the system, a comparison of the shapes the actual trajectory with the optimal trajectory coincidentally becomes a comparison of average movement frequency with resonant frequency. Hence movement-smoothness-based measures and frequency-based measures have an inherently close relationship for rhythmic tasks.

3.5 Motivation for Progressive Haptic Guidance

I propose that haptic guidance schemes for virtual environment training must be based on key skills that are critical to successful task completion. The performance of each of three expertise-based groups who completed a virtual target-hitting task was analyzed in this chapter to determine the key skills necessary for success, measured by the number of target hits during a trial. Two key skills of the virtual target-hitting task were determined, namely minimization of trajectory error and excitation of the virtual dynamic system near resonance. Correlation between these measures and the objective hit count measure was verified for seventeen participants of varying skill level. Participants were grouped by their hit count performance into three distinct groups (*experts*, fast learning *novices* and slow learning *novices*). These groupings were determined to be consistent for the key skills as well. The measures, e_{traj} and f_{input} have high correlation to the objective measure of n_{hit} yet have low correlation between each other, suggesting independence. The performance-based progressive guidance scheme designed in the Chapter 5 enhances the effectiveness of a VTE over unguided practice and visual guidance schemes by incorporating mechanisms for emphasizing these two key skills. The next chapter investigates and develops one specific component of the guidance scheme, an optimal excitation trajectory for guiding the participant.

Chapter 4

Movement Smoothness Model: Experiment I

This chapter presents the experiment design, results, and analysis of a human-user study that tests and validates the minimum hand jerk (MHJ) model implemented in the progressive haptic guidance controller for input frequency guidance. This experiment pertains specifically to a human forearm reaching task while simultaneously manipulating a multi-mass object. This work validates and extends prior work that demonstrated the MHJ criteria, a mathematical approach to human movement modeling, more accurately represents movements with multi-mass objects than the alternative optimally smooth transport (OST) model. To validate the prior work, I developed a visual and haptic virtual environment with a five-mass system with friction and connected by springs and viscous dampers. The point to point reaching task I implemented required participants to move their hand with the set of masses to a target position, thereby generating movement profiles for analysis. The experimental design uniquely extends the application of the MHJ criteria to forearm pronation movements and my results show that the MHJ model holds. The extension of the model to forearm movements and the MHJ criteria for human movements generally provide inexpensive models of human movements applicable to fields such as computer animation and virtual environments. Portions of this chapter have been accepted for publication in the Proceedings of the *IEEE* 11th International Conference on Rehabilitation Robotics [36].

4.1 Introduction to Movement Smoothness

This chapter presents the experiment design, results and analysis of a human-user study that tests and validates the minimum hand jerk (MHJ) model for a human forearm reaching movement when manipulating a multi-mass object. The MHJ model is a mathematical optimal control model of human reaching movements that can be used for analysis. Analysis of human movement is achieved via two broad computerized approaches which in turn serve to capture and represent these movements precisely. The two approaches are *motion capture* and *mathematical modeling.* In the motion capture approach, a human subject must perform the motion under consideration in the presence of a motion capture device, such as dedicated cameras or electromechanical position sensors. Typically, the captured position data must be merged across trials or subjects to obtain some type of average or representative movement. Intensive post-processing into a 3-D representation is often required as well. While these systems do allow movement researchers to access and utilize reliable and detailed data, the method relies on expensive equipment and software and thus limits the implementation of the technology. Furthermore, if a modification to the represented trajectory is desired, the modified motion must be re-captured and processed again.

Mathematical modeling is another approach to represent human movement. In this approach, an equation represents a family of movements. Movements can be modified by changing the equation parameters. The primary benefits of modeling are the ease with which it modifies trajectories as well as its low processing costs. The disadvantage of this approach is difficulty in developing representative equations that are accurate enough for a range of applications. Numerous researchers have chosen to develop these mathematical representations via optimal control theory. More specifically, hand reaching movements are excellent candidates for the application of optimal control theory. The movement paths tend to be straight and smooth, despite the fact that revolute and spherical joints generate the movements. These joints create a redundancy that allows many different state trajectories for a given reaching task. In general, however, the path taken by the hand tends to be a straight line with smooth bell-shaped velocity profiles [22]. Current research in the functioning of the central nervous system (CNS) indicates that the path of the hand is planned in the coordinate system defined by the eye and the target location [70]. The CNS then computes the smoothest trajectory based on a cost function. Flash and Hogan proposed to quantify the smoothness of a human reaching movement via the minimization of the jerk function, one that they defined as the third derivative of position [22]. My work extends the validity of the MHJ model to forearm pronation movements in the presence of a multi-mass system.

The minimum hand jerk (MHJ) model, experimentally confirmed by Flash and Hogan, was limited to point to point reaching movements in free space. Dingwell *et al.* proposed the optimally smooth transport (OST) method (also called minimum object crackle) as the model of choice for reaching movements with a two-mass system [16]. Dingwell suggested that people adopt the external end effector as an extension of their own limb [16]. Recent work by Svinin *et al.* broadened the original MHJ model to include dynamic constraints, namely the equations of motion of the multi-mass system. In the same work, Svinin *et al.* compared the two criteria and found that the OST representation does not adequately apply to multi-mass systems . The MHJ model, on the other hand, can sufficiently represent any multi-mass system as long as it has an added dynamic constraint [77]. In the case of a multi-mass system, Svinin and his collaborators showed that the end effector's velocity is limited by an upper bound when using an MHJ model but not when using the OST. In this chapter I first replicate the results of Svinin *et al.* Then, I present and resolve two significant deficiencies in their experiment. Finally, I arrive at the same result that MHJ is a more accurate representation than OST of upper extremity reaching movements. My work extends their model to forearm pronation reaching movements and the results show that the MHJ mathematical model matches experimental data while the OST model does not.

4.2 Methods

I conducted a user study in human performance to record data for comparison analysis of the two mathematical movement models. Similar to the work of Svinin and his collaborators, I chose to represent the dynamic task in a haptic virtual environment rather than build a physical model for motion capture. In the user study, I demonstrate smooth output profiles and I use viscous damping, both of which are absent in Svinin's experimental setup. Additionally, my experiment featured a forearm pronation movement rather than a compound shoulder, elbow, and wrist movement, like the one Svinin *et al.* tested. I chose forearm pronation because it better matched the virtual environment presented in Section 3.1 and, for simplicity, limited my analysis to only one joint. Position and velocity data were captured from the virtual environment during task performance for later analysis.

4.2.1 Participants

Seven participants (all healthy males, ages 18-39, 5 right-handed and 2 left-handed who both chose to perform the task right-handed) completed the experiment. A university IRB-approved form was used to obtain informed written consent from all participants. The data from the first two participants were used as pilot trial data for further refinement of the experiment and therefore were not included in the analysis. The remaining five participants (ID's 3 through 7) took part in the three-session study comprised of one familiarization session, one training session, and one evaluation session. Each session lasted approximately 10 minutes. The first two sessions were separated by a time period of 10 minutes to 4 hours, while the last two sessions were separated by a time period of anywhere from 2 hours to 24 hours. Only data from the evaluation session (the third session) were used in the analysis of human movements in the virtual environment.

4.2.2 Apparatus and Virtual Environment

The experimental apparatus and virtual environment used in this experiment are shown in Fig 4.1. The physical apparatus included a nineteen-inch LCD display with a 60 Hz graphics software loop rate for visual display and a force feedback joystick (Immersion IE2000) for haptic interaction. Participants interacted in a visual and haptic enabled virtual environment providing both position and velocity inputs to the joystick by rotating the forearm in pronation and simultaneously receiving feedback via both the visual display and the haptic force display. The environment was a sufficiently accurate virtual representation of the multi-mass system and did not demonstrate chatter on the output or any instabilities.

Figure 4.1 : The experimental setup for the participant to interact with the task in a virtual environment included position input as well as haptic force and visual feedback. The participant provided both position and velocity inputs to the virtual environment via the joystick encoder. An LCD display provided visual feedback to the participant while a haptic joystick provided force feedback.

While the force feedback joystick is a two degree of freedom (2-DOF) device, the experiment required only 1-DOF. Therefore, I mechanically restricted the rotation of the joystick in ulnar/radial deviation. With the flexion deviation of the wrist restricted by the shape of the fixed joystick handle, the only motion allowed was the pronation and supination of the participant's forearm. The setup was different from Svinin's planar setup that allowed participants to move shoulder, elbow and wrist. I chose the 1-DOF rotational setup in order to limit the analysis to one-joint human movements rather than three joint movements that allow an infinite set of kinematic configurations for the reaching task.

The hardware and simulation were controlled by a 2 GHz Pentium computer operating the haptic loop at 1kHz while movement data was stored at 50Hz. The virtual multi-mass system was modeled as a linear second order system on one axis of movement with five point masses: m_{hand}, m_2, m_3, m_4, and m_5 as shown in Fig 4.2. The location of the first mass, m_{hand}, was the joystick encoder position, thereby transferring the hand states directly to the

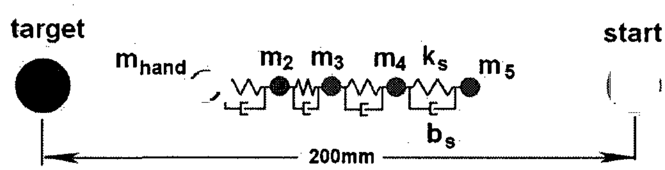


Figure 4.2 : The virtual environment included the joystick location and four equal masses linked by springs (k_s) and viscous dampers (b_s) connected in parallel. The experimental task presented to the participants was to move all five masses and their hand from the start position to the target position 200mm away within a specified time.

the virtual environment. The remaining four masses were connected to m_{hand} via parallel spring and damper links (k_s and b_s in Fig 4.2 respectively).

Since the participant could only directly manipulate m_{hand}, the 5-DOF system was under actuated, thereby differentiating the task from a simple reaching task in free space that Fitts's Law is based on and that Flash and Hogan originally studied [21, 22]. The parameters of the system dynamics were masses $m_{2-5} = 3.0Kg$ and spring stiffness $k_s = 120N/m$ as modeled by both Dingwell *et al.* and Svinin *et al.* [16, 77]. In order to ensure settling, I added both viscous damping $b_s = 10$ and viscous friction $c_f = 0.1N/m$. The mass of the hand (m_{hand}) depended on the mass of the joystick and the dynamics of the participant which are assumed to be much larger than the masses of the virtual task. Each spring-damper link force is computed solely from the positions and velocities of the attached masses as follows:

$$F_{disp} = k_s(x_2 - x_h) + b_s(v_2 - v_h), \tag{4.1}$$

$$F_i = k_s(x_{i+1} - x_i) + b_s(v_{i+1} - v_i), \tag{4.2}$$

$$F_5 = k_s(x_5 - x_4) + b_s(v_5 - x_4). \tag{4.3}$$

In Eq. 4.1, F_{disp} is the force displayed to the participant via the DAC output current to the haptic joystick motor. F_i in Eq. 4.2 is the force across the ith spring and F_5 in Eq. 4.3 is the spring force acting on the 5th mass which is the end effector. At each haptic iteration, the acceleration, velocity, and position of the end effector (x_5, v_5,a_5), were computed according to Newtonian dynamics as follows:

$$x_5 = v_5 t + \frac{1}{2} a_5 t^2, \tag{4.4}$$

$$v_5 = a_5 t, \tag{4.5}$$

$$a_5 = \frac{F_5}{m_5} - v_5 c_f. \tag{4.6}$$

The end effector mass is m_5 and c_f is the coefficient of viscous friction applied to all of the masses except m_{hand}. The positions, velocities and accelerations of the intermediate masses were computed in a similar fashion and in the same order. In this same way, all kinematic and dynamic information was updated within three iterations of the haptic loop during performance of the task.

4.2.3 Experimental Multi-mass Task

The experimental task consisted of the participant moving all masses from a start position to a target position as shown in Fig 4.2. The start position was located at 45° of forearm supination. The rotational distance from the start position to the target location was 60° of forearm pronation. The 60° rotation mapped to 200*mm* of linear travel on the 2D visual display. The task presented to the participants was to move all five masses and their hand from the start position to the target 200mm away. At the start position the five masses were colocated. Position, velocity, and time constraints had to be met at the target location for the trial to be successful. The task had three conditions (A, B, and C), each with its own set of constraints as listed in Table 4.1. Having three different conditions of the task permitted the participants to complete the task in a single oscillation or multiple oscillations as Svinin *et al.* reported. I obtained the constraints both from pilot tests and by matching the success rates that Svinin *et al.* reported. The constraint values chosen show both single oscillation solutions (Condition C) as well as multiple oscillation solutions (Condition A).

Table 4.1 : Successful Completion Tolerances for the three timed conditions of the task where T was the base completion time, ΔT was the time tolerance, Δx was the final position tolerance, and Δv was the final velocity tolerance.

Parameter	Condition A	Condition B	Condition C
T	2.25s	1.35s	1.00s
ΔT	$\pm 0.5s$	$\pm 0.5s$	$\pm 0.5s$
Δx	$0 \pm 6mm$	$0 \pm 12mm$	$0 \pm 12mm$
Δv	$0 \pm 6mm/s$	$0 \pm 12mm/s$	$0 \pm 24mm/s$

4.2.4 Data Collection and Analysis

Point to point reaching data was obtained for the five participants over three sessions. The first session consisted of 90 familiarization trials without any time requirement. This session permitted success in every trial. The second session, used for training in the task, consisted of all three timed conditions (A, B and C), with 50 trials for each and presented to all participants in the same order from the slowest to the fastest condition as listed in Table 4.1. The third session, identical to the second session, was the evaluation session. Only the successful trials of the evaluation session were used for analysis. In other words, only those trials that met the constraints for all parameters in the current condition were kept for analysis (see Table 4.1). Filtering out the unsuccessful trials ensured comparable velocity profiles for each condition. A wider tolerance in the completion times would have allowed participants to complete the trial successfully more often; however, the raw data had to be normalized for trial matching. Also, if the time tolerance were kept small, it would ensure that the profiles being compared were similar. During the pilot testing I observed, as did Svinin and his collaborators, that when longer completion times are permitted, participants may use either a single oscillation or a double oscillation velocity profile to complete the task, thereby making comparison difficult.

By choosing small time tolerances for all three conditions and ensuring single oscillation patterns, the only post processing required was to time-shift the peak velocity in order to normalize the trial. One participant's joystick (m_{hand}) and end effector (m_5) velocity profiles for Condition B are shown in Fig. 4.3 to illustrate the data shifting. Once the data were shifted, the velocity profiles were consistent enough for analysis and comparison to the mathematical models. The MHJ model of the end effector trajectory used was:

$$x(t) = x_o + (x_o - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \tag{4.7}$$

where $\tau = t/t_f$, x_o is the initial object position and x_f is the final position [22]. The OST model of the end effector trajectory used was:

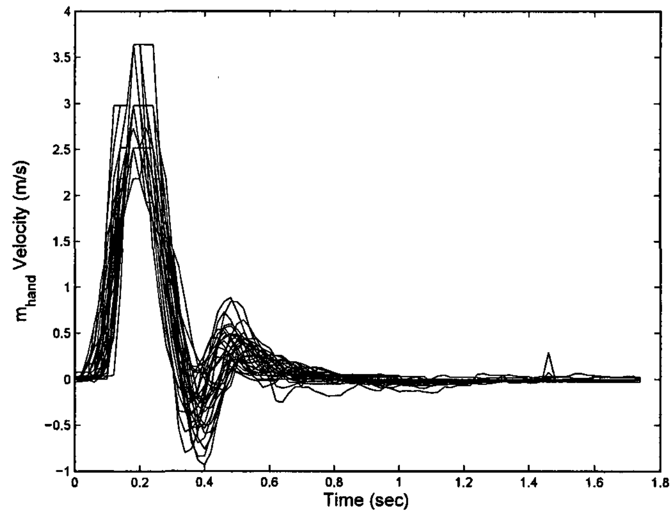
$$x(t) = L\tau^5(126 - 420\tau + 540\tau^2 - 315\tau^3 + 70\tau^4) \tag{4.8}$$

where $\tau = t/t_f$ and L is the length of the trajectory [16]. The inverse dynamics of the system were used to compute the theoretical hand trajectories for both models.

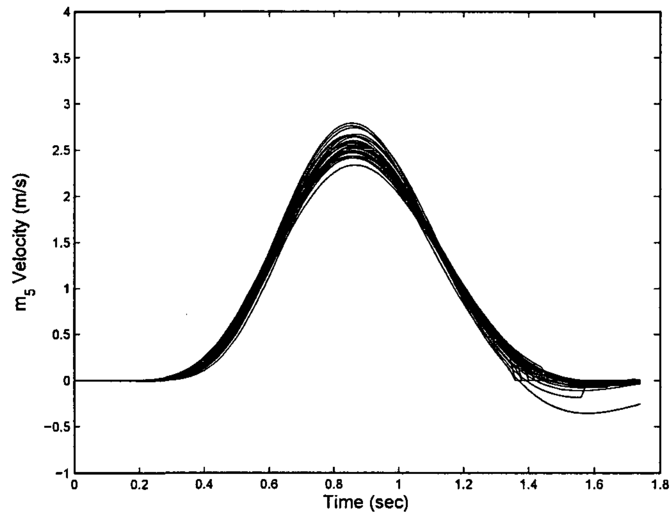
4.3 Results of the Movement Smoothness Experiment

All five of the participants completed all three conditions. During the third session, the worst success rate was 55% while the best success rate was 98% as listed in Table 4.2. As previously stated, the pilot data from participants 1 and 2 were not included in this work. The success rates were comparable to the rates obtained by Svinin *et al.* , namely 25% to 93% success. My success rates are higher than Svinin's in part because all of my participants had previous experience with force feedback haptic devices whereas theirs did not.

To achieve a comparison of all participants, each participant's average velocity profile is presented in one plot per condition as shown in Fig. 4.4(a), (c), and (e). Joystick data represents the hand motions and provides a reasonable estimate of velocity and position of the multi-mass system. The end effector velocity profiles are emphasized in this experiment in order to compare them with the theoretical MHJ and OST models. Joystick and end effector velocity variances decrease as the time requirement of the condition decreases. In fact, under Condition A the joystick velocity average for each participant shows the



(a) Joystick (m_{hand}) velocity profiles.



(b) End effector (m_5) velocity profiles.

Figure 4.3 : Velocity profiles of successful trials in Condition B for Participant 5, a typical participant. Profiles are peak velocity shifted for time normalization of the data. The end effector velocity profiles shown in (b) are consistent. The hand velocity profiles shown in (a) are also consistent and smooth.

Table 4.2 : Success rates in percentages for each participant during the evaluation session.

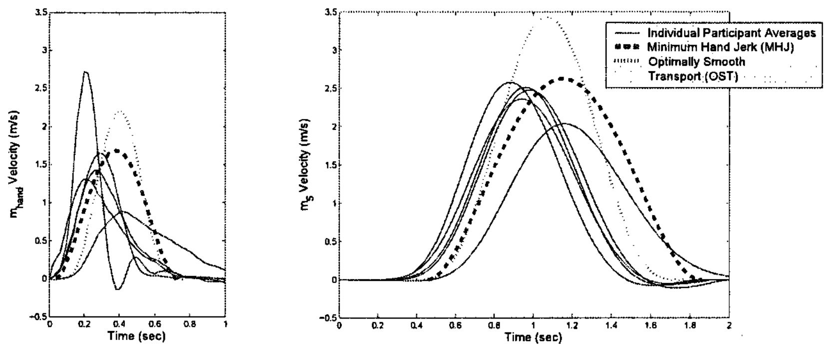
Participant	Condition A	Condition B	Condition C
3	92	55	96
4	94	98	98
5	90	90	90
6	82	55	63
7	86	92	90

most variance due to Condition A's slower completion time permitting a wider range of successful trajectories. Because Condition C has the fastest completion time, it requires a trajectory pattern that approaches optimal in order to have success.

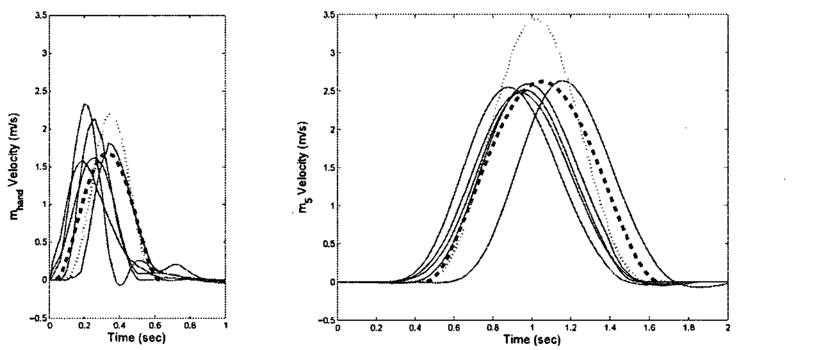
The end effector velocity profiles for the three movement conditions are shown in Fig. 4.4(b), (d), and (f). As the task increases in speed, the MHJ theoretical curve with an amplitude of 2.5m/s aligns closely with the experimental end effector velocity profiles with amplitudes between of 2m/s and 2.5m/s. Condition A is the slowest condition and has the largest envelope of time to complete the task. Therefore, the theoretical profiles for Condition A have a visibly greater difference from the experimental end effector velocities. The optimally smooth transport (OST) trajectories with amplitudes of 3.5m/s do not match the experimental end effector velocity data with amplitudes of 2.5m/s for multi-mass systems.

4.4 Discussion of Movement Smoothness

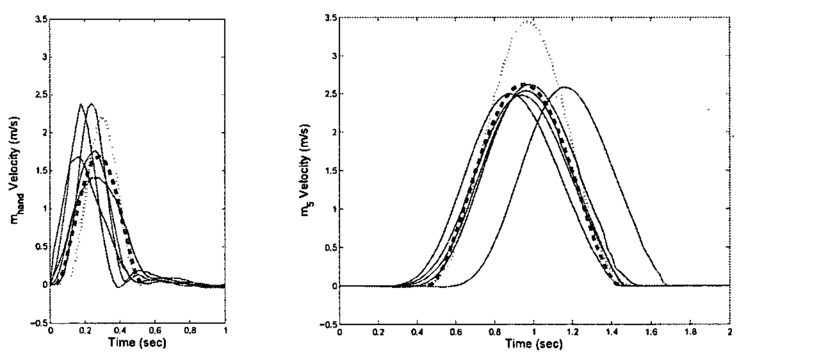
The experiment results show that the MHJ model with a dynamic constraint represents human reaching movements with a multi-mass system closer than the OST model. While these results are the same as Svinin's, there are three noteworthy differences between the studies: the physics model, the apparatus, and velocity differences. The first difference is in the physics model of the virtual environment. Svinin and his collaborators reported using



(a) Joystick (m_{hand}) velocity (b) End Effector (m_5) velocity profiles Condition A.



(c) Joystick (m_{hand}) velocity (d) End Effector (m_5) velocity profiles Condition B.



(e) Joystick (m_{hand}) velocity (f) End Effector (m_5) velocity profiles Condition C.

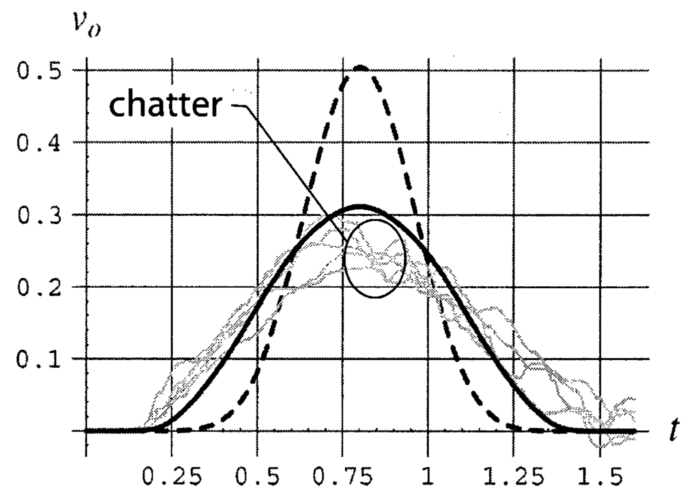
Figure 4.4 : The thick dashed line represents the theoretical MHJ model. The thin dashed line represents the theoretical OST model. The thin solid lines are the experimental averages. The MHJ model more accurately represents experimental data of the end effector velocity profiles.

a simple mass-spring system model [77]. In a simple mass-spring system, once energy has been input to the system, the end effector settles by oscillating around the joystick. Svinin's data do not show such oscillations [77]. However, even for an over-damped system, the settling time is too brief to obtain completion times similar to Svinin's. Therefore, I include viscous friction between the masses and a modeled virtual surface under the masses to further reduce the settling time. For these reasons, my model of the dynamic system explicitly includes viscous damping and friction. By matching all the other system parameters to the Svinin *et al.* model, I then varied the damping in an attempt to approach the success rates and times presented in their work.

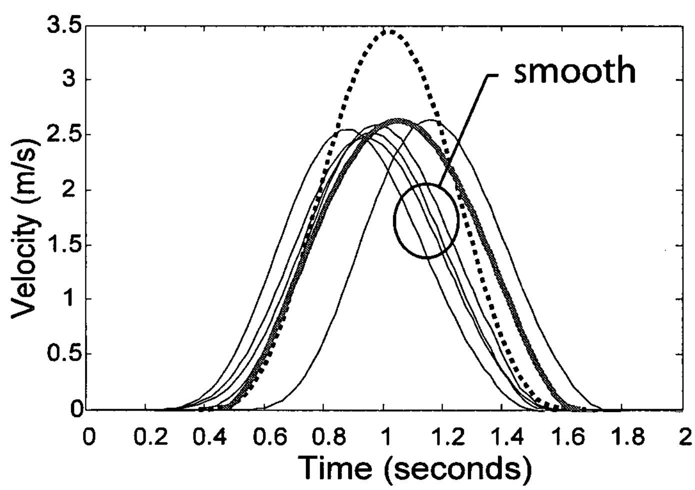
The second difference between my work and Svinin's is the choice of apparatus and virtual environment implementation. Svinin and his collaborators implemented the haptic virtual environment on a PHANToM 1.5 with 3 DOF. Therefore, they had to implement virtual walls in the directions orthogonal to the movement line [77]. Interactions with these orthogonal forces may be the cause of chatter in Svinin's experimental data as shown in the end effector velocity profiles such as the one in Fig. 4.5(a). In my implementation of the virtual environment, I use a 2-DOF device and further simplify the environment by mechanically securing one of the axes of the device. One axis limits movements of the handle along the task axis, thereby avoiding the need for virtual walls. As can be seen from Fig. 4.5(b) the experimental end effector velocity has no chatter.

The last significant difference between my work and Svinin's regards the results with peak variations of the velocities across each of the three conditions. The peak velocity of the end effector is directly related to the system dynamics through its natural frequency. Thus, regardless of the completion time and velocity profile of the hand, the maximum velocity of the end effector should remain constant [26]. Svinin's data showed different peak velocity for each condition while my peak velocities are constant across all three conditions.

The results from the experiment reported in this chapter show that a sinusoidal velocity movement pattern models an optimal way to perform the task at hand. Since the task is



(a) Condition B end effector velocity profile shows chatter (from [77]).



(b) Condition B end effector velocity profile is smooth.

Figure 4.5 : Comparison of Svinin et al.'s results in (a) and my results in (b) show first that the experimental data from both works match the MHJ criteria much closer than the OST criteria. Secondly, the end effector chatter evident in the Svinin result is not present in my results.

under-constrained it is not possible to consider unique optimality. Nevertheless, the conclusion afforded by the movement pattern can also be defended by resorting to experimental data as presented in the expertise based analysis in Chapter 3. The data clearly shows that *experts* performing this task tend to excite the system in patterns that are approximately rhythmic and sinusoidal in the velocity dimension. For these reasons, the guidance design described in the next chapter will be based on a sinusoidal movement pattern.

Chapter 5

Progressive Haptic and Visual Guidance: Experiment II

This chapter presents the expertise-based design of the proposed progressive haptic guidance scheme as well as the methods and results of implementing the scheme for training in a previously designed dynamic task. This is the main contribution of this thesis. The chapter begins with the experimental methods used to design and implement the guidance scheme based on the background and motivation presented in Chapter 3. The chapter also includes a description of the human-user study designed to test the haptic guidance scheme against similar visual guidance, written guidance and no-guidance in both skill performance and cognitive workload measures. Section 5.2 presents the results of the experiment while section 5.3 discusses the findings.

5.1 Methods

A two-month human-user study was conducted to evaluate the performance and workload effects of training with haptic, visual or written guidance and to compare each guidance scheme to no guidance at all. The haptic and visual guidance schemes were motivated by the conclusions from the expertise based performance analysis described in section 3.2. The training was conducted in the virtual environment (VTE) described in Chapter 3.1 with participants performing the dynamic target-hitting task illustrated in Fig. 5.1. Prior work by Li in a similar task helped determine the duration of this training experiment to be eleven sessions spaced over one month in order to saturate the participant performance [44, 46]. This section will cover the design of the guidance controller, experiment protocol, and the implementation of the cognitive workload questionnaire (NASA-TLX).

The expertise analysis in Section 3.2 showed that there exist two key skills required for

Figure 5.1 : A participant is sitting at the virtual training environment. The interface includes a visual feedback display and a haptic joystick for force feedback. The training task is shown on the visual display with the visual guidance activated.

success [35]. First, the participant should not deviate from the target axis so as to ensure that the object (m_2) passes through the targets. Second, the participant should excite the system close to its resonant frequency in order to generate rhythmic oscillations of the object (m_2). Thus, in addition to hit count presented to the participants as the objective of the task, I use the two additional measures, trajectory error e_{traj} and input frequency f_{input}, to determine performance in the two key skills and suggest that they can be used as inputs to a progressive guidance controller [35]. The dependent variables of experiment II are the following three measures of performance:

Hit count

The objective of the task was for the participant to hit as many targets as possible in each 20 second trial. A hit was registered whenever the center position of the object (m_2) was detected to be within 4 mm of the target center. Hit count (n_{hit}), the objective measure of performance, is defined as the number of target hits occurring in each trial.

Trajectory Error

Trajectory error (e_{traj}) is defined as the absolute magnitude of the deviation (y direction as shown in Fig. 3.4) of the input joystick position (m_1) at each sampled instant (50Hz sample rate) summed for the entire trial (n), and expressed in units of millimeters. Mathematically,

$$e_{traj} = \sum_{i=1}^{n} abs(y_i), \tag{5.1}$$

where y_i is the deviation of one sample.

Input Frequency

Based on the observation of the importance of input excitation frequency for this task, input frequency (f_{input}) is a measure of the rhythmic performance in a trial. The fast Fourier transform (FFT) of the position data of the joystick (m_1) provides a frequency spectrum of the input signal. For clarification, even though the FFT plot is called a "power spectrum," in this particular case it has units of mm^2. To simplify the understanding of the measure, the definition includes a normalizing coefficient. The equation for the second performance measure f_{input} is given in units of (Hz/Hz) as follows:

$$f_{input} = \frac{1}{f_r} \times f(arg(max(FFT))), \tag{5.2}$$

where f_r is the resonant frequency of the system. Therefore, exciting the system at the resonant frequency will give a value of $f_{input} = 1(Hz/Hz)$ regardless of the system frequency. The system parameters and resonant frequency are kept constant in order to eliminate interactions with the experimental conditions.

While the participants were explicitly told that hit count (n_{hit}) was the objective way of measuring performance, e_{traj} and f_{input} measure the participants' performance in the two key skills of the task. The analysis in section 3.2 showed that these two measures correlate well with hit count but not with each other suggesting independence. This fact drove the design of the guidance scheme for this work to represent the two measures independently and orthogonally.

5.1.1 Guidance Scheme Design

As stated in Chapter 1 the first objective of this research is the design of a progressive haptic guidance scheme that integrates performance measures of key skills, thereby augmenting human motor skill training. The block diagram shown in Fig. 5.2 describes the haptics-enabled virtual training environment with haptic guidance augmentation. The trajectory error guidance is in the form of augmenting forces modeled as virtual walls. The input frequency guidance is in the form of a PD tracking controller moving in a sinusoidal pattern at the resonant frequency of the system.

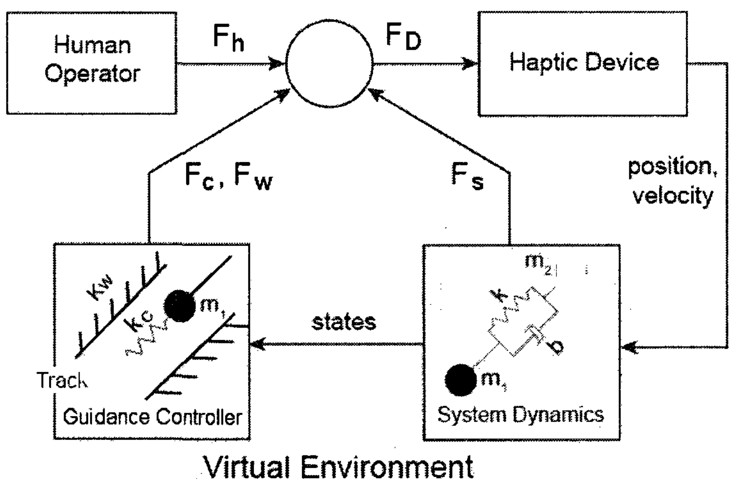


Figure 5.2 : Block diagram of the haptics-enabled virtual training environment with haptic guidance augmentation. The guidance is in the form of virtual walls to mitigate deviation from the target axis and in the form of a PD tracking controller.

As described in Section 3.1.1 the dynamics attributed to the haptic device are neglected in this study due to the selection of a high-fidelity haptic interface. Such a device exhibits negligible friction, very low effective inertia, and the velocities and accelerations that the haptic device experiences in this VTE are relatively low. Therefore, the dynamics of the device (specifically its mass) are neglected during the implementation of the controller. Parasitic forces due to the existence of the haptic device and modeling errors exist, but these forces are negligible when compared with the forces rendered through the task dynamics [43].

After completing the initial evaluation session, participants were ranked by n_{hit}. The ranked participants were then randomly assigned to one of three groups: *haptic guidance*, *visual guidance* or *no-guidance*. The written guidance group data used in this study was from a first attempt of this same experiment by the author . In that experiment, the haptic and visual guidance controllers were flawed and only the written guidance group data could be rescued. While all effort was made to mitigate external effects, the written guidance results reported here should be taken in consideration with this caveat: this group received verbal and written instructions regarding the two skill necessary to successfully complete the task.

The nonguidance control group replaced the written guidance group in the second run of the experiment. The session 1 mean scores of all four groups were compared to ensure that the groups were balanced at the beginning of the training protocol. The haptic and visual guidance groups received a form of guidance during the guidance subsession of each of the nine training sessions. Appendix A documents the hints provided to each participant at the beginning of Session 2, the first training session, depending on their assigned guidance scheme. At the end of each 20 second trial, the performance of the participant was computed in terms of e_{traj} and f_{input} which then automatically adjusted the inputs to the guidance controller. The corresponding adjustments to the level of guidance were then presented to the participant in the next trial. One group received its guidance via the haptics channel while the other received it via the visual channel. The guidance was in the form of two orthogonal regions as shown in Fig. 5.3 and as proposed in the previous section to demonstrate the best performance in the two key skills. The first region (shown in a dark shade in Fig 5.3) indicates the maximum allowable deviation from the target axis that will still result in a target acquisition, thereby reducing e_{traj}. This region does not move in either the visual scheme or the haptics scheme. The second region (shown in a light shade in Fig 5.3) oscillates at the resonant frequency of the system and with an amplitude that, if tracked, will ensure sufficient output amplitude to acquire the targets. The oscillations are presented as a cosine which generates a sine wave velocity profile and closely approximates an optimally smooth velocity profile as presented in Chapter 4.

For the visual guidance scheme, the two regions are represented by colored areas whose intensities diminish independently as performance improves in each of the two measures. Similarly, in the haptic scheme, the edges of the regions are represented by stiff virtual walls (see Rosenberg *et al.* [68]). The minimum force required to penetrate the walls is progressively reduced as performance improves thus gradually shifting primary control from the robot to the trainee as the training protocol progresses. Both the visual and haptic guidance schemes employ exponentially diminishing gains that are controlled by the two measures of performance e_{traj} and f_{input}. In the case of haptic guidance, the guidance forces are calculated and then combined with the system dynamic forces before being presented to the user at the joystick interface on the haptic channel. The trajectory error region is represented by two stiff and fixed virtual walls only 2mm apart creating a channel for the joystick to travel in. Due to the high initial stiffness, the walls must be modeled as bi-cubic splines so that motor torques can ramp smoothly as the joystick enters the wall face. The wall forces are computed based on three equations depending on whether the joystick is outside a wall, completely inside a wall, or on the wall face (with a 0.95mm tolerance). If the joystick is outside the walls, then the equation for the wall force is simply:

$$F_w = 0 \tag{5.3}$$

If the joystick position is inside the wall, then the wall force is:

$$F_w = k_w \tag{5.4}$$

where k_w is the maximum gain for the wall. Finally, if the joystick is on the wall face within ± 0.05mm of the wall face, then the following equation is used to compute the wall force:

$$F_w = k_w(2t_w^3 - 3t_w^2) \tag{5.5}$$

where k_w is the maximum gain for the wall, and t_w is the parametric position on the wall face (from 0 to 1 where 1 is the wall depth required to reach maximum force. Figure 5.4

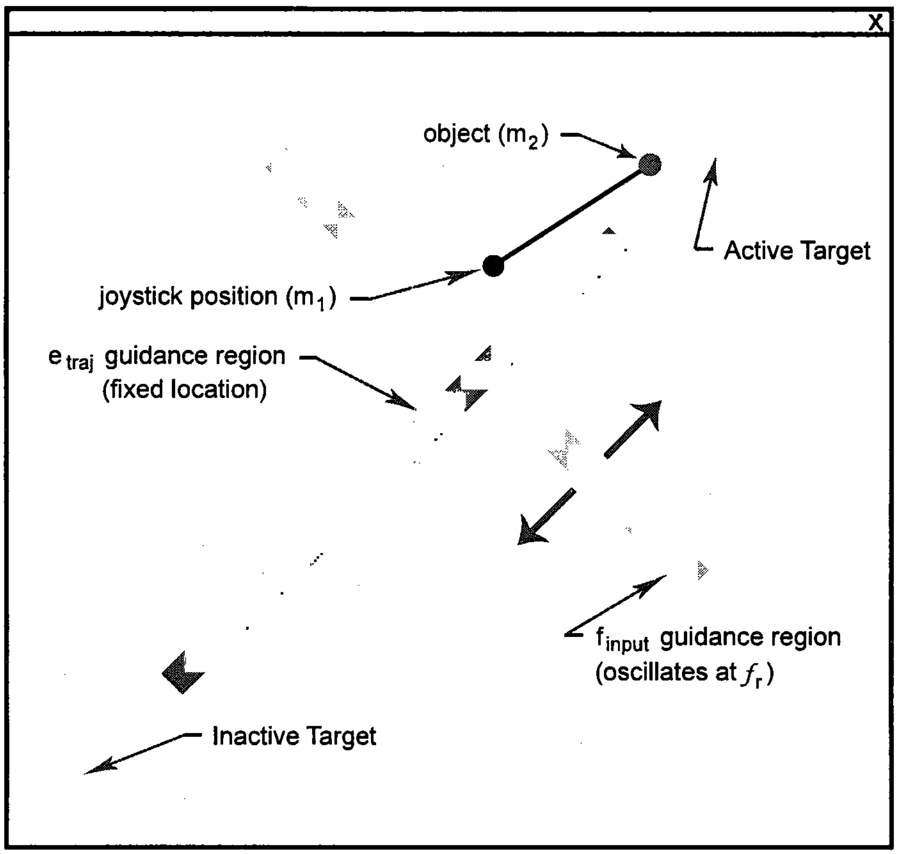


Figure 5.3 : Guidance schemes designed from the measures of performance in the dynamic task show both input deviation and frequency key skills to the trainees. In addition to a nonguidance control group, a second group received progressive guidance only through the visual display while a third group received equivalent progressive guidance only through the haptic joystick display. A fourth group was given written instructions regarding the two skills necessary to successfully perform the task.

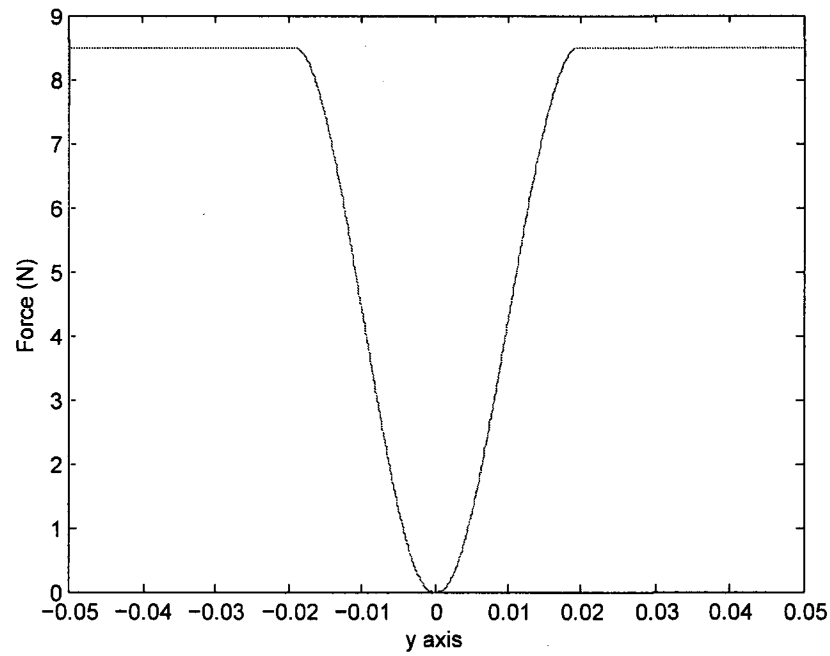


Figure 5.4 : Virtual walls are designed such that the force displayed is related to the position of the joystick. At the wall interface, the force is displayed as a bi-cubic spline to avoid chatter that might occur due to high wall stiffness.

shows the force profile for the trajectory error guidance on the y-axis. At the beginning of training k_w is set to the maximum force value allowed by the software limits of the motor torque outputs.

The input frequency region is represented by a 1 DOF proportional-derivative (PD) controller that tracks the position of a reference along a sinusoidal pattern assumed to be an optimal path as developed in Chapter 4. The frequency of the sinusoid pattern is the same as the resonant frequency of the system (see Table 3.1). The equation for the PD controller is:

$$F_c = k_c(\hat{x}_t - \hat{x}_1) + k_d\hat{\dot{x}}_1 \tag{5.6}$$

where k_c is the position gain, k_d is the derivative gain, $\hat{x}_t$ is the position of the reference at time t, and $\hat{x}_1$ and $\hat{\dot{x}}_1$ are the joystick position and velocity at the current time. The hat denotes that these values are in the rotated coordinate frame of the target axis. The position gain, k_c, is initially set to the maximum value allowed by the software motor torque limits. The derivative gain, k_d was set by experimentation to be as small as possible and still prevent chatter. A PID control scheme was considered but deemed unnecessary because there is no need avoid lagging behind the track. The source code included in the haptic loop for the controller can be found in Appendix C

The progression of the guidance gains vary according to the three conditional statements of the control algorithm: *increase, decrease,* and *no change*. The *decrease* condition occurs when three successive trials show improvement in one of the two measures of performance resulting in a gain decrease of the corresponding guidance. The *increase* condition occurs when three successive trials show degrading performance in one or both of the measures, thereby resulting in an increase in the gain of the corresponding guidance. Finally, the *no change* condition occurs when fluctuating performance trends occur resulting in no change in the gain. The size of the step was determined from the following exponential equation:

$$k_w = F_{max}\frac{1}{2^{(step-1)}} \tag{5.7}$$

where step = [1, 1.25, 1.5, . . 8]. Thus 4 steps are required to reduce the max force of the wall by 50%. The first 20 steps are illustrated in Fig. 5.5. As shown, this step design ensures a smooth and almost imperceptible change between steps and also ensures that the walls can be completely removed in less than three sessions.

A pilot study was administered to two trainees prior to the experiment to verify the functionality of both the visual and haptic guidance schemes. The changes of both gains for both trainees are graphed in Fig. 5.6 and show exponentially diminishing trends with some occasions where the gains remained the same or increased, thereby verifying the functionality of the guidance schemes. These two trainees did not participate in the main study.

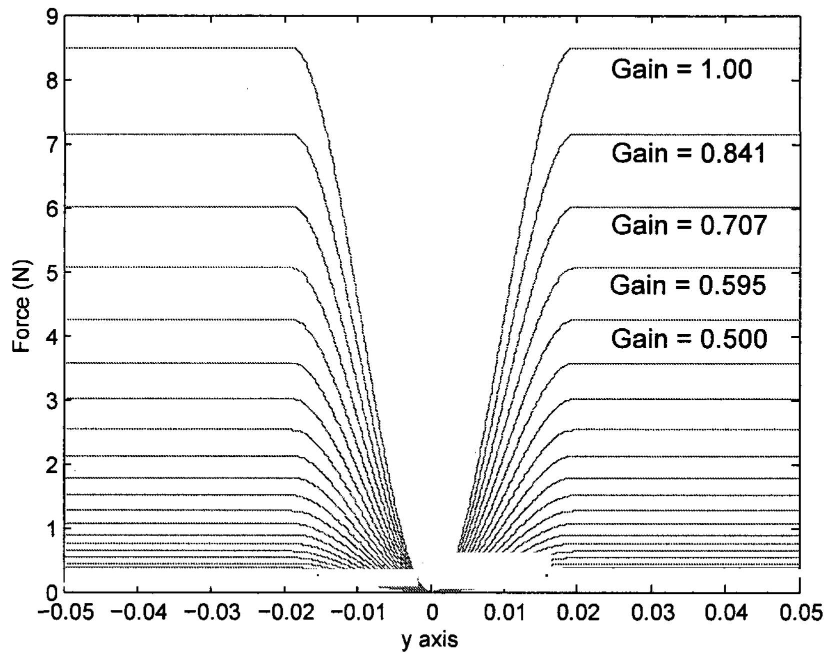


Figure 5.5 : Virtual wall maximum force is progressively and exponentially reduced as long as performance in trajectory error improves.

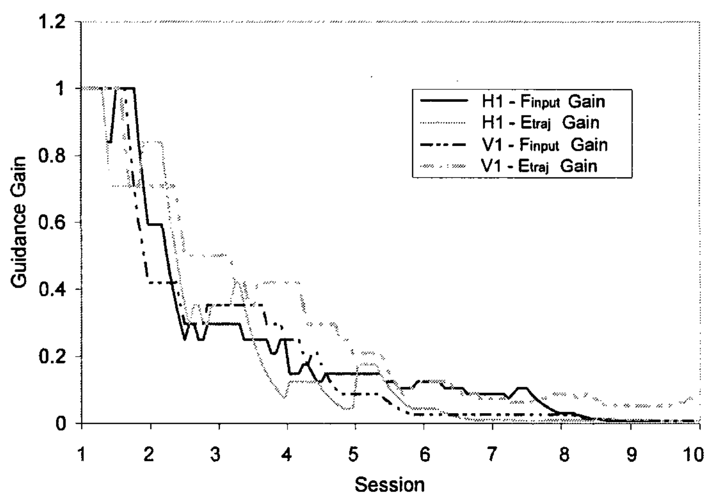


Figure 5.6 : Both visual and haptic guidance gains, based on the measures of performance e_{traj} and f_{input}, diminish throughout training in the dynamic task for both haptic (H1) and visual (V1) guidance trainees. This suggests that the designed guidance schemes are functional.

5.1.2 Experiment Protocol

The experiment protocol consisted of one evaluation session, followed by nine training sessions (two or three sessions per week), and one retention session after thirty days for a total of eleven sessions as shown in Fig. 5.7. The nine training sessions were spaced two to five days apart. The retention session was at least 30 days, but no more than 45 days, after the last training session. The protocol was similar in length and structure to one implemented by Hancock to study both performance and workload effects [29]. One of the factors of the experiment was session (guidance mode was the other factor). Each training session contained three subsessions: first, a pre-guidance baseline with five trials; second, a guidance subsession with fifteen trials; and third, a post-guidance baseline, again with five trials. Each trial lasted 20 seconds for a total duration of approximately nine minutes active baseline and guidance time per session. Participants were given the specific objective of hitting as many targets as possible in each 20 second trial. Each trial began with the two point masses 0.1 mm apart at the center of the screen and ended at precisely 20 seconds from the start signal. At the end of both the pre-guidance and guidance subsessions, participants completed the computerized version of the NASA Task Load Index (TLX). The questionnaire typically took about three minutes to complete. At the end of each training session, all participants filled out a paper questionnaire self-evaluating and comparing the daily performance to the previous session's performance (see Appendix A for the questionnaire). Thus the total time required was 16 to 20 minutes per participant per session for a total of under four hours over the two-month period.

5.1.3 Cognitive Workload Assessment

Subjective cognitive workload was assessed using the NASA Task-Load Index (NASA-TLX), developed by Hart and Staveland [30] and later implemented in a computer based questionnaire [54]. Prior to the beginning of the first evaluation session, each participant was provided with a one-page description of the NASA-TLX and descriptions of the six scales to be used during the assessment. The computerized version of the NASA-TLX was

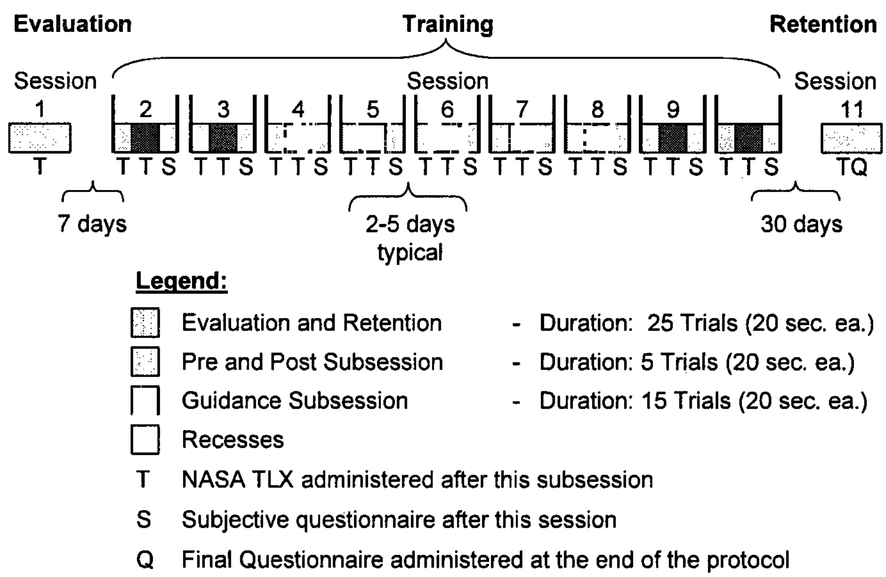


Figure 5.7 : The training experiment design consists of eleven sessions including one evaluation session and one retention session (shown in light gray above). Only during guidance subsessions (shown as dark shaded boxes above) do the haptic and visual guidance groups receive the corresponding progressively diminishing guidance. Rest periods between sessions are indicated with braces and their duration is noted. The NASA-TLX (T) is administered after the pre-guidance subsession (shown in light shading above) and once again after the guidance subsession (shown in dark shading above). A subjective questionnaire (S) is administered after the post-guidance subsession. A final demographic survey (Q) is administered after the last session.

integrated to the dynamic task testing such that as soon as the participant finished a subsession, the first of the two-step procedure of the NASA-TLX appeared on screen. In the first step, participants rated from low to high (with 20 subdivisions) their perceived workload demand on each of the six scales: mental, physical, temporal, performance, effort and frustration. Then, in the second step, the participants were asked to pairwise compare all six scales to generate a 'weighting' for each scale with a value from 0 to 5. The total overall workload score was computed by multiplying each raw scale score with the appropriate weighting and then dividing the sum of the six products by fifteen (the number of pairwise comparisons). Percentage scores for the six scales were then computed from the total score.

5.1.4 Participants

Initially, 57 healthy participants, primarily undergraduate engineering students, were recruited for the experiment: 27 for the first run of the experiment and 30 for the second run. Recruitment was conducted via classroom announcements with sign-up sheets to subsequently e-mail further information. The incentives included snacks after each session, cash prizes for top performers, extra credit in the particular course (depending on professor approval and depending on the relation of this experiment to the course content), and altruistic support of research. As mentioned in section 5.1.1 the data from the visual and haptic groups in the first run had to be discarded because of an error in the code that caused the guidance to diminish immediately at the beginning of the protocol with no regard to the participants' performance. Therefore, of the first run, only the written guidance group could be salvaged. Of the nine participants that were ranked and assigned to the written group, one did not complete the experiment for personal reasons. The performance of this participant in the first session was roughly equal to the average of the whole group. For the second run of the experiment, 30 participants were recruited. Two participants had equipment failures in the seventh and eighth sessions respectively and did not immediately report the problem to the investigator. The investigator detected the failure during daily data download and questioned the participants about the problem at the next session. Both commented that they had felt something awkward in the previous session. The hardware failure was a loose cable in the capstan drive system, causing the joystick position to slip to the edge of the screen. The entire data for those two participants was ultimately removed from the analysis. In order to preserve an equal number of participants per group, the data of two other participants was removed. The participants whose data were chosen to be removed were determined by their having an identical ranking in their own groups as the two whose hardware failed. Hence, the data included in the experimental results is from 32 participants (7 female and 25 male; 30 right-handed and 2 left-handed; ages 18 to 51) primarily undergraduate engineering students with no previous experience with haptic devices. Despite these changes to the data, initial performance evaluation in terms of hit count still presented no significant differences between groups as shown in Fig. 5.8. All 32 participants completed the protocol. A university IRB approved form was used to obtain informed written consent from all participants. To allow for simultaneous testing, two experiment stations were assembled. Participants were assigned to one station for the duration of the training protocol to mitigate effects due to differences in the stations. The visual displays and force feedback joysticks were equivalent for the two stations. One of the stations could be adapted for left-handed participants by moving the joystick to the opposite side of the display. Moreover, a mirrored version of the task was implemented in the software so that the task continued to be from lower flexion to upper extension.

5.1.5 Data Analysis

For all participants, values for n_{hit}, e_{traj}, and f_{input} for each subsession are recorded: five trials for pre-guidance and post-guidance subsessions and fifteen trials for the guidance subsession. Thus each of the 32 participants has five data points (or fifteen during guidance) for each of the eleven sessions of training resulting in a total of 1760 observations of each measure for pre-guidance and post-guidance subsessions (5 trials, 11 sessions, and 32 participants) or 5280 observations for the guidance subsessions (15 trials, 11 sessions, and 32 participants). The data were also averaged by guidance mode to be fit with ex-

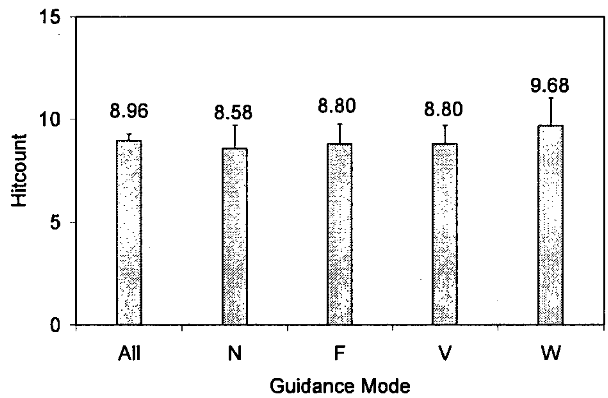


Figure 5.8 : Formation of groups after completing the evaluation session. Participants were rank ordered by performance in terms of hit count and then randomly placed in one of the three groups: no-guidance (N), haptic guidance (H), and visual guidance (V). The written guidance (W) group data was transferred from the first run of the experiment. The means and standard errors of the means fail to show significant difference between the four groups.

ponential curves using MATLAB^{TM} and the best fit curves were determined from the R^2 values. Analysis of variance (ANOVA) was used to determine significance of the factors between groups. The guidance mode factor had four levels, namely *haptic guidance, visual guidance, written guidance*,and *no-guidance*. Furthermore, guidance mode was a between-subjects factor since eight different subjects were used for each one of the modes. Session was a within-subjects factor (also called *repeated measure* because the measure was repeatedly taken on each participant for each session) since the same subjects were used for all 11 sessions. Thus the experiment was a factorial design with guidance mode (4) and session (11) as factors. A post hoc test performed on the data of each session identified the significant differences in performance between the three guidance modes and during each session.

For the subjective workload analysis, each participant completed the computerized version of the NASA TLX after both the first and second subsessions resulting in two data points per session averaged over the eight subjects per group for a total of 88 observations (2 subsessions, 11 sessions, 4 groups) for each of the six workload measures. An analysis of variance analysis (ANOVA) was conducted on the total workload as well as the six workload measures. Finally, at the end of each of the nine training sessions (see Fig. 5.7 the participants completed a short subjective questionnaire with three or five questions depending on the group assignment. The questions asked participants to compare their performance in both the guidance and post-guidance subsessions to the previous session. It asked, "Did your performance improve? Y/N and why?" The third question asked if in the current session the participant had had any new insight that helped improve performance. For the visual and haptic groups a perception question asked: "which of the two skill guidance methods did you still receive." Finally, these same two guidance groups were asked if they thought that the guidance helped and if so, how. The results of the subjective questionnaire are documented in Appendix B. The the performance and cognitive results are reported in the next section.

5.2 Results

The data analysis and results are obtained from the two-month human-user study. A total of 32 participants completed the protocol. Section 5.2.1 includes comparisons of guidance modes in terms of performance, estimations of skill acquisition rates, analyses for significant factors, and differences at the experimental and session levels. The next subsection reports comparisons of guidance modes in terms of cognitive workload and the final subsection reports analysis of the subjective questionnaire administered after each session.

5.2.1 Measures of Performance

The results and data analysis are presented for the four guidance groups in terms of performance. Figures 5.9 through 5.14 show the performance of the four groups (no-guidance, haptic guidance, visual guidance and written guidance) across the three measures (n_{hit}, e_{traj}, and f_{input}) for both the guidance subsessions and the post-guidance subsessions. The pre-guidance subsession results are not included in the analysis because the data fail to show significant differences in performance between guidance modes during those subsessions. The scores of the fifteen guidance trials (or of the five post-guidance trials) for the eight participants of each mode are averaged to obtain one mean score per subsession in each performance measure. The data points plotted in Figs. 5.9 through 5.14 represent the mean of the subsession scores of each guidance mode with error bars indicating the standard error of the mean. The n_{hit} scores for all participants show increasing trends across all sessions as training progressed with saturation at about 22 hits per trial. Scores for e_{traj} show decreasing trends with a saturation around 30mm while f_{input} scores show increasing trends across all sessions with saturation just below 1 Hz/Hz. In order to visualize trends that suggest skill acquisition, in performance from session to session power functions are fit to the data according to the following equation:

$$y = ax^b + c \tag{5.8}$$

where a, b, and c are the parameters of the equation and have R^2 values in excess of 0.95 except for the haptic guidance group in the guidance subsession that had an e_{traj} curve fit of $R^2 = 0.85$. The fit curves are also plotted in Figs. 5.9 through 5.14 along with the mean subsession scores and associated error bars. A summary of the curve fitting results, including estimated parameters and goodness of fit for each of the four groups of participants are shown in Table 5.1. During both guidance and post-guidance subsessions, all guidance modes reach saturation in terms of the measures of performance. During the guidance subsession, the haptic group reaches saturation at a significantly faster rate (parameter b) than the other three groups in terms of all three measures performance as shown in Figs 5.9, 5.11, and 5.13. In other words, during the guidance subsession, the haptic guidance mode increases in performance at a faster rate. This performance rate increase, however, is not observed during the post-guidance baseline as shown in Figs. 5.10, 5.12, and 5.14. The visual guidance group also appears to perform slightly better than no guidance during the training subsessions. Moreover, the visual and written guidance groups appears to outperform the other groups early in training (sessions 2 and 3) in terms of e_{traj} and f_input in the post-guidance subsessions suggesting that being given the instructions visually and in writing was beneficial.

Table 5.2.1 summarizes the statistical analysis of performance as measured by the three dependent variables, n_{hit}, e_{traj}, and f_{input}. Each guidance group is analyzed using a two-way analysis of variance (ANOVA) in order to highlight significant effects of group and session. For all three measures of performance in both subsessions, the effects of session are significant as shown in Table 5.2.1. With respect to guidance mode, the guidance subsessions show significant differences, while the post-guidance subsessions fail to show significant differences. The interactions between guidance mode and session fail to show statistically significant differences.

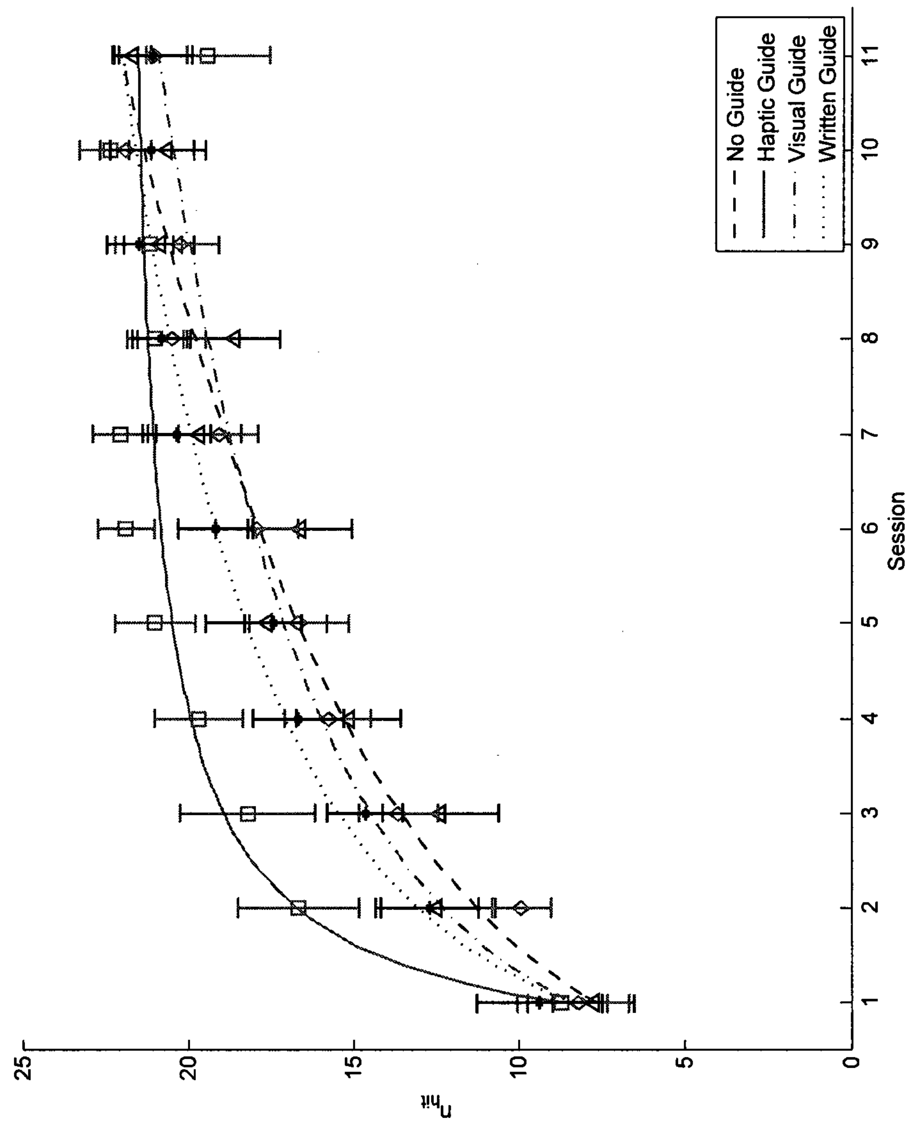


Figure 5.9 : Performance in terms of hit count during the guidance subsessions. The haptic group appears to demonstrate a higher performance in sessions 2-6 and a higher rate of skill acquisition. The other groups do not appear from the curve fits to be different from each other.

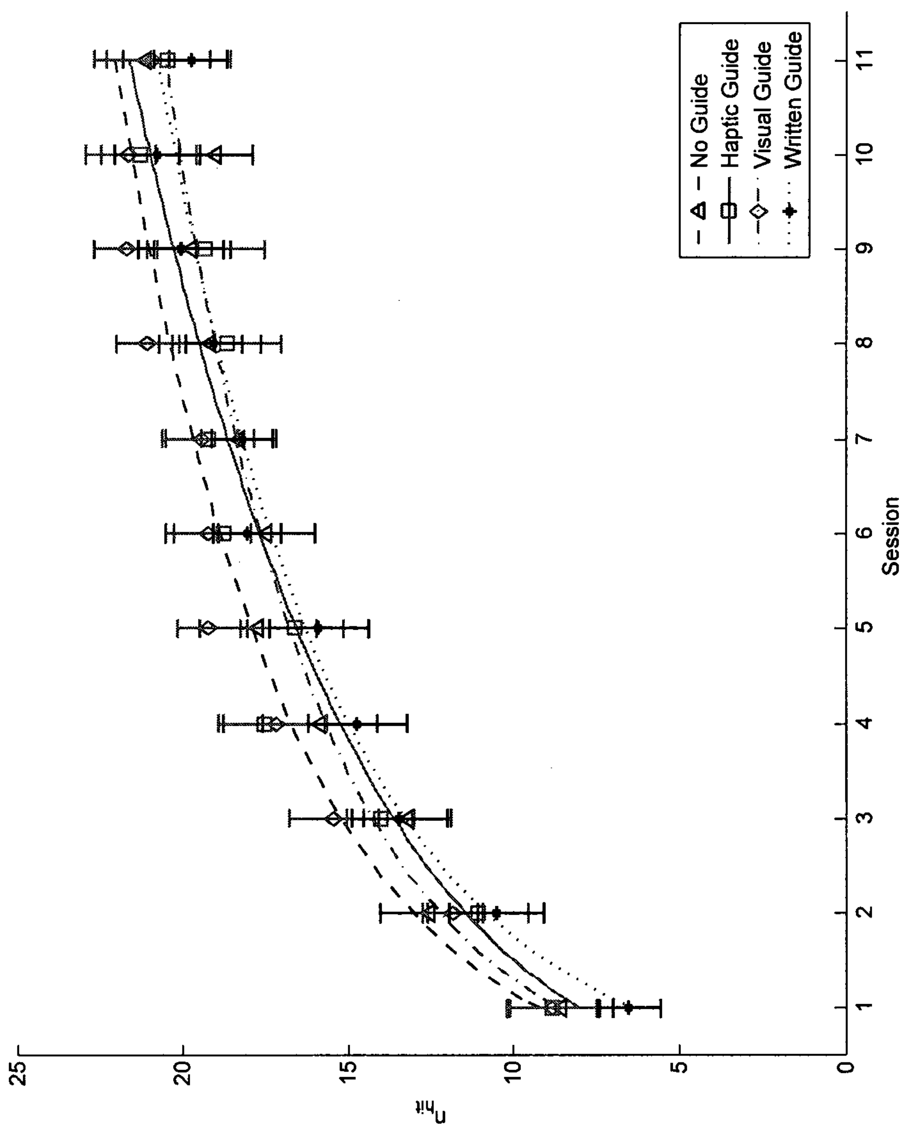


Figure 5.10 : Performance in terms of hit count during the post-guidance subsessions. No obvious differences between groups are immediately visible.

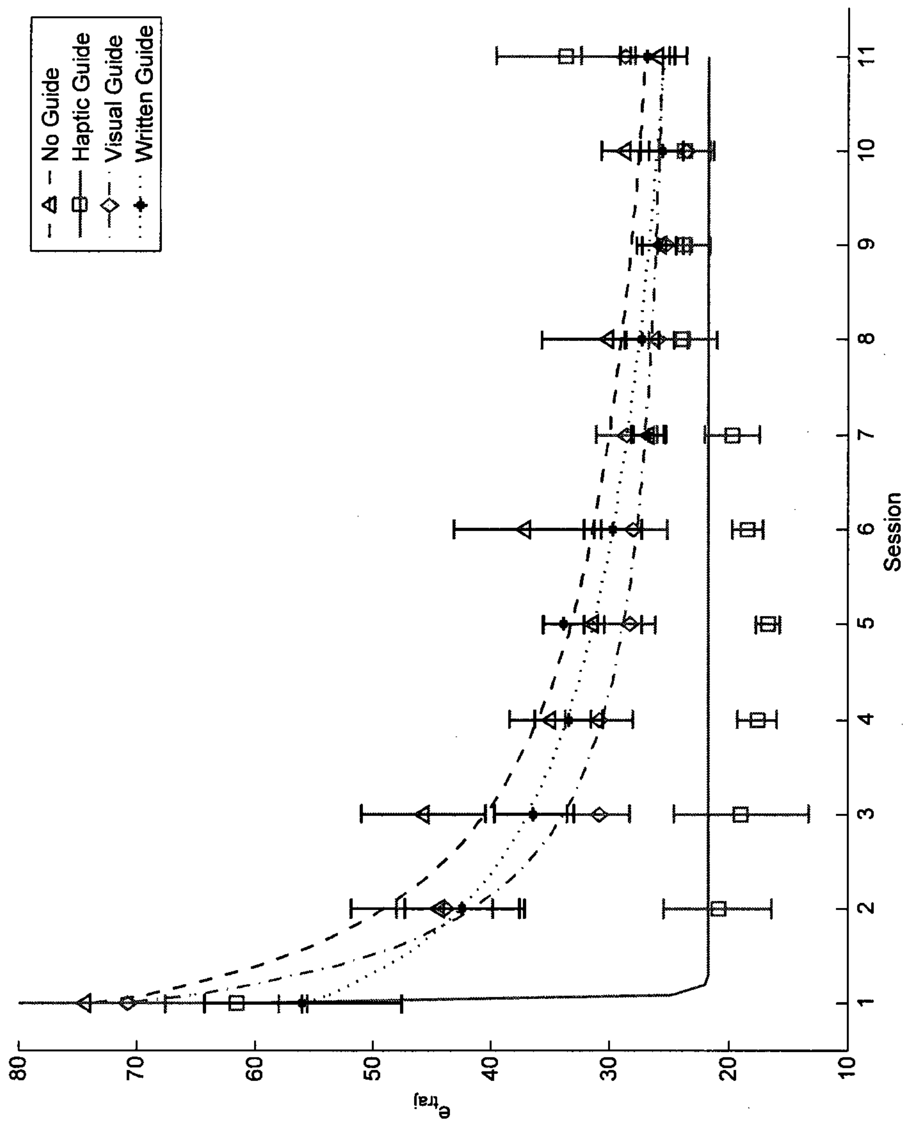


Figure 5.11 : Performance in terms of trajectory error during the guidance subsessions. The haptic guidance group appears to have significantly smaller e_{traj}. Both visual and and written guidance groups also appear to have lower e_{traj} early in the training protocol.

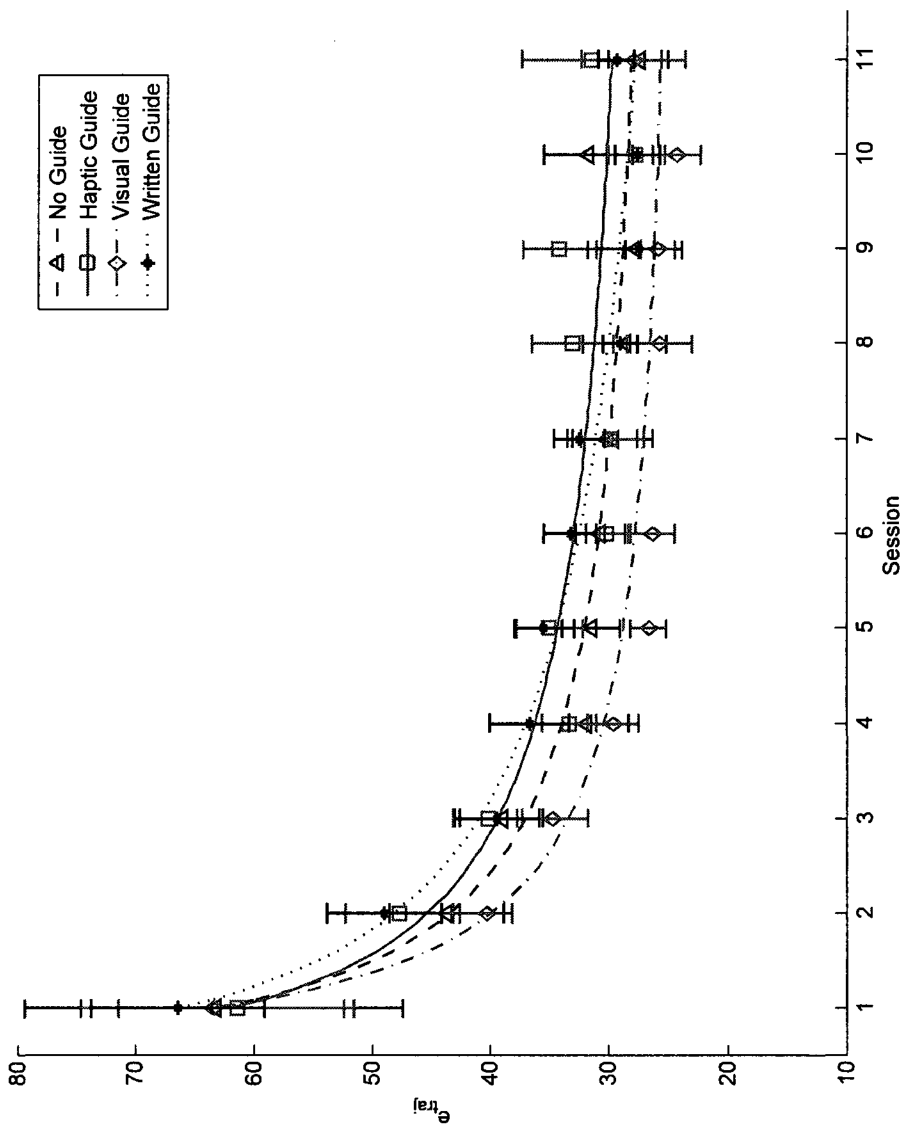


Figure 5.12 : Performance in terms of trajectory error during the post-guidance subsessions. Visual guidance group appears to have a lower error than the remaining groups.

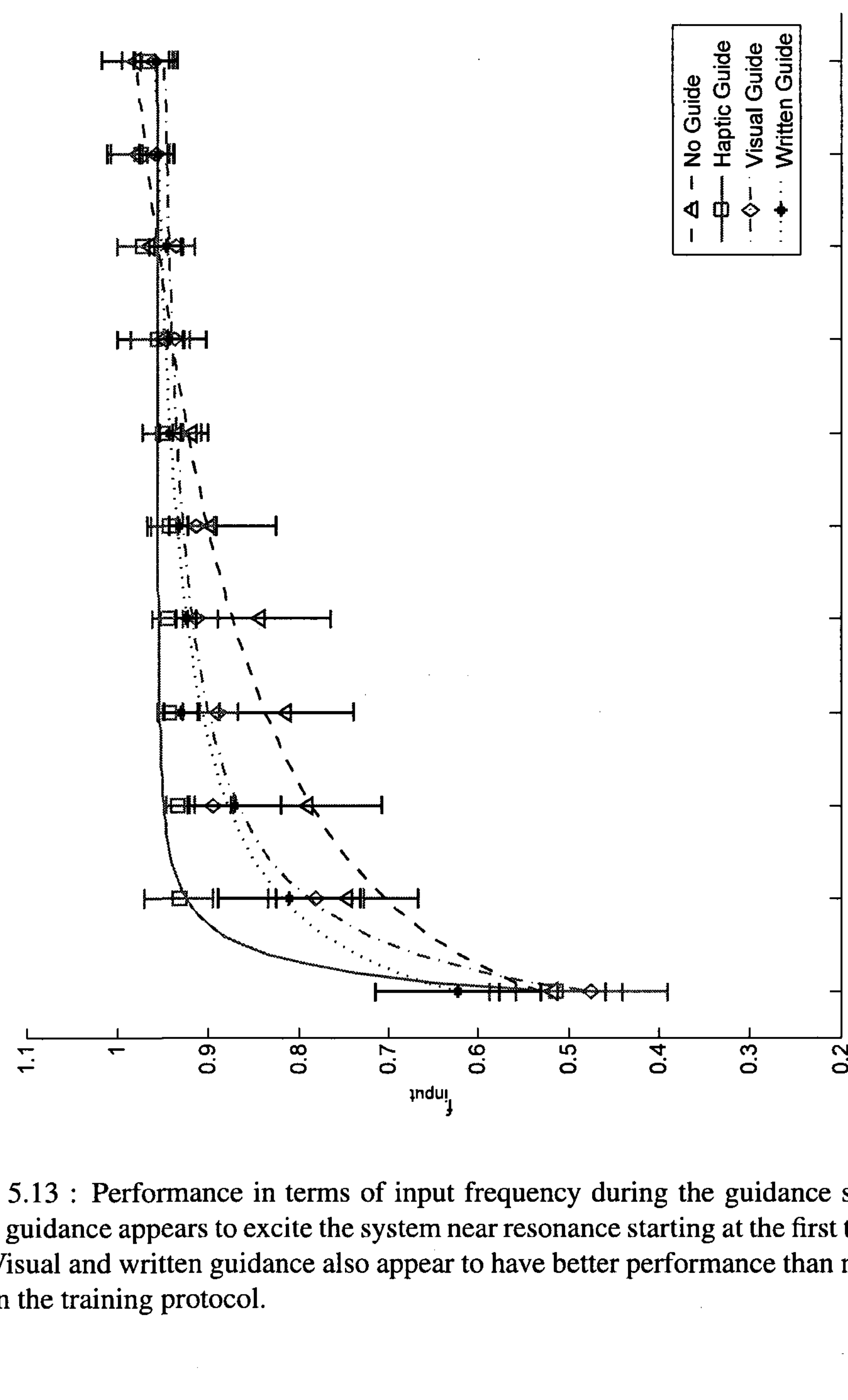


Figure 5.13 : Performance in terms of input frequency during the guidance subsessions. Haptic guidance appears to excite the system near resonance starting at the first training session. Visual and written guidance also appear to have better performance than no-guidance early in the training protocol.

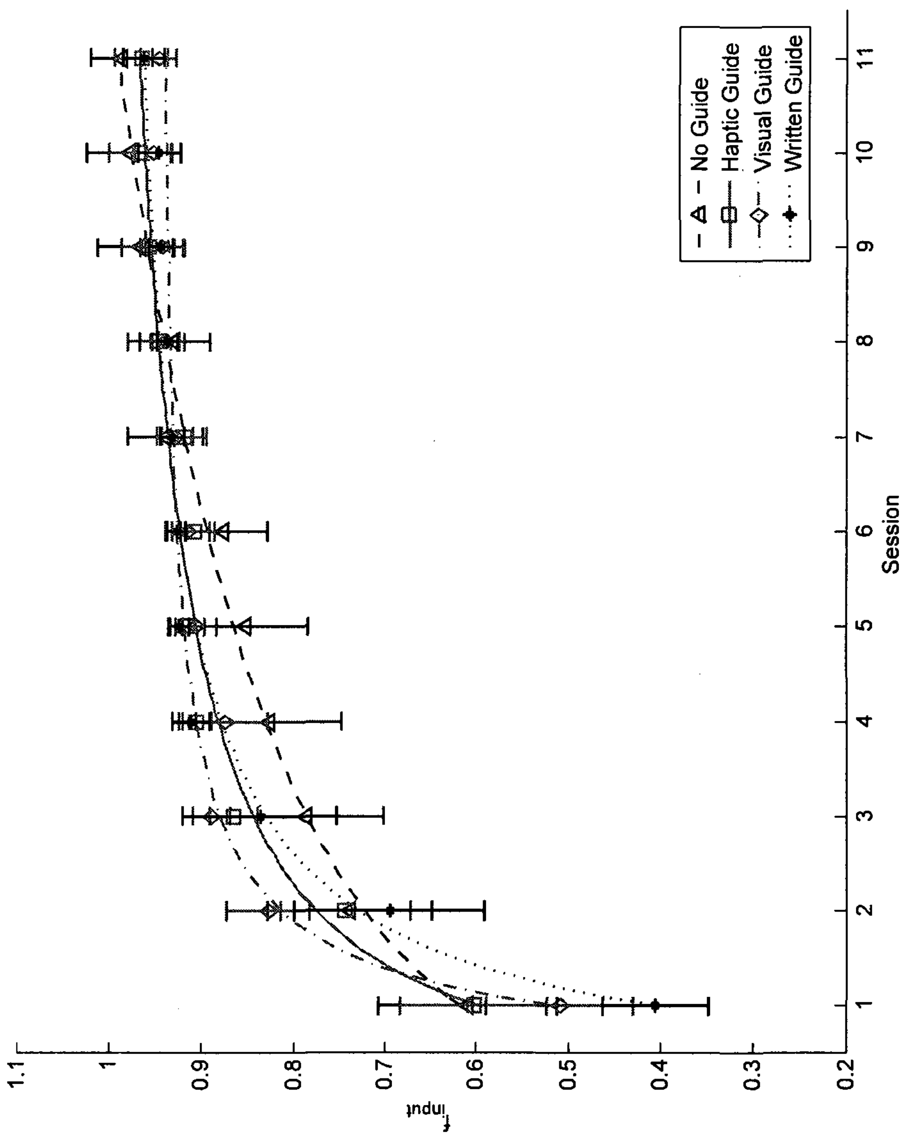


Figure 5.14 : Performance in terms of input frequency during the post-guidance subsessions. Visual guidance may slightly outperform the other groups in sessions 2 and 3.

Table 5.1 : Summary of the curve fitting procedures for estimating guidance mode skill acquisition rates.

		Goodness of fit Guidance		Goodness of fit Post-Guidance	
Guidance Group	**measure**	R^2	Fit Parameters	R^2	Fit Parameters
No-Guidance	n_{hit}	0.96	$a = 31.7,\ b = 0.15,\ c = -23.8$	0.97	$a = -85.0, b = -0.06,\ c = 93.6$
	e_{traj}	0.95	$a = 52.8,\ b = -0.90,\ c = 20.8$	0.98	$a = 38.5,\ b = -1.06,\ c = 25.0$
	f_{input}	0.98	$a = -0.76, b = -0.37,\ c = 1.29$	0.99	$a = 5.69,\ b = 0.03,\ c = -5.07$
Haptic Guidance	n_{hit}	0.95	$a = -13.5, b = -1.33,\ c = 22.1$	0.95	$a = -56.6, b = -0.11,\ c = 65.0$
	e_{traj}	0.87	$a = 39.9,\ b = -26.8,\ c = 21.7$	0.95	$a = 37.1,\ b = -0.87,\ c = 25.1$
	f_{input}	0.99	$a = -0.44, b = -3.83,\ c = 0.96$	0.98	$a = -0.45, b = -0.73,\ c = 1.04$
Visual Guidance	n_{hit}	0.98	$a = 33.0,\ b = 0.15,\ c = -25.4$	0.97	$a = -34.3, b = -0.21,\ c = 42.7$
	e_{traj}	0.98	$a = 47.1,\ b = -1.42,\ c = 24.0$	0.98	$a = 39.8,\ b = -1.30,\ c = 23.9$
	f_{input}	0.99	$a = -0.49, b = -1.49,\ c = 0.94$	0.99	$a = -0.44, b = -1.71,\ c = 0.95$
Written Guidance	n_{hit}	0.98	$a = -85.0, b = -0.08,\ c = 91.4$	0.99	$a = -164,\ b = -0.03,\ c = 173.3$
	e_{traj}	0.98	$a = 41.1,\ b = -0.57,\ c = 14.9$	0.99	$a = 47.8,\ b = -0.70,\ c = 18.8$
	f_{input}	0.99	$a = -0.36, b = -1.14,\ c = 0.98$	0.99	$a = -0.60, b = -1.14,\ c = 1.00$

Table 5.2 : Statistical analysis summary for each on the three measures of performance shows significant differences during the guidance subsession but fails to show significant difference during the post-guidance subsession

Metric	Effect	During Guidance	P value	Post-Guidance	P value
	Guidance	$F(3,348) = 9.25$	$p < 0.0001*$	$F(2,348) = 3.39$	$p = 0.0183*$
n_{hit}	Session	$F(10,341) = 39.05$	$p < 0.0001*$	$F(10,341) = 36.73$	$p < 0.0001*$
	Interaction	$F(30,337) = 0.95$	$p = 0.5505$	$F(30,337) = .31$	$p = 0.9998$
	Guidance	$F(3,348) = 10.66$	$p < 0.0001*$	$F(2,348) = 1.12$	$p = 0.341$
e_{traj}	Session	$F(10,341) = 22.85$	$p < 0.0001*$	$F(10,341) = 18.52$	$p < 0.0001*$
	Interaction	$F(30,337) = 1.20$	$p = 0.2228$	$F(30,337) = 0.33$	$p = 0.99976$
	Guidance	$F(3,348) = 4.77$	$p = .0143*$	$F(2,348) = 0.65$	$p = 0.5863$
f_{input}	Session	$F(10,341) = 26.92$	$p < 0.0001*$	$F(10,341) = 28.53$	$p < 0.0001*$
	Interaction	$F(30,337) = 0.74$	$p < 0.8657$	$F(30,337) = 0.72$	$p = .8597$

In both guidance and post-guidance subsessions all three measures of performance show significant main effects of session as documented in Table 5.2.1. The interaction effects during guidance are also all significant. The guidance mode factor shows significant main effects in terms of all measures during guidance (see Table 5.2.1). However, in the post-guidance subsession, guidance mode fails to show a significant main effect in terms of input frequency. Furthermore, the interaction effects are mixed.

In order to identify significant differences in performance between the four groups in each session, a post hoc Scheffe test is performed on the data of each set of subsessions and results for the guidance subsession are presented in Fig 5.15. The figure shows the six pairwise comparisons of the four guidance modes. Each sub figure has three rows corresponding to three measures of performance and eleven columns for the sessions. Cells with asterisks indicate a significant difference between the pair of groups. A darkly shaded cell indicates to a 95% confidence level that a significant difference exists between the pair of groups. A lightly shaded cell indicates with to a 90% confidence level that there is a significant difference. Lightly shaded cells with no asterisk indicate that the data fails to

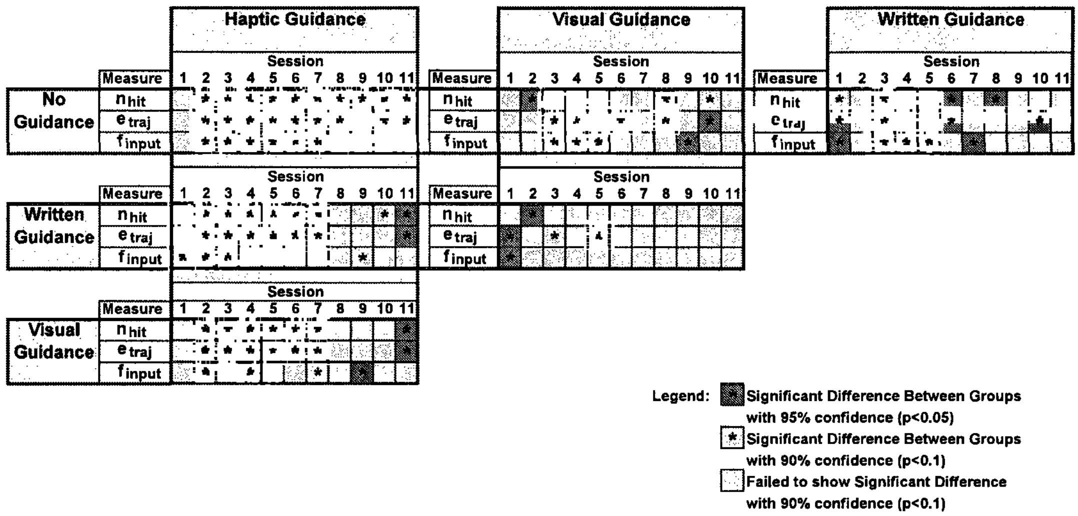


Figure 5.15 : Summary of the post hoc test to summarize differences between guidance modes during the guidance subsession. Test shows that the haptic guidance is significantly different from all three of the other guidance schemes during sessions 2 through 7.

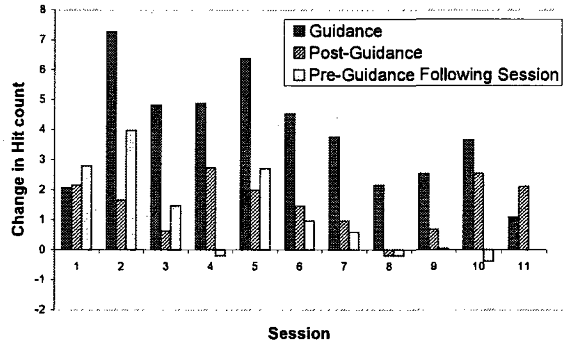
show significant differences. The test demonstrates, first of all, that the groups are balanced after session 1 in terms of n_{hit}, but written guidance is significantly different in terms of e_{traj} and f_{input}. From sessions 2 through 7, the haptic guidance is significantly different from no-guidance in terms of all three measures. Also from sessions 2 through 7, and comparing haptic guidance to both written and visual guidance, there are significant differences in terms of both n_{hit} and e_{traj}. However, differences in terms of f_{input} are mixed for the same sessions. Results of comparisons for sessions 8 through 10 are mixed. In session 11 the haptic guidance group performs significantly worse in all measures. This last result may in part be due to one participant performing much worse in session 11 having undergone surgery between session 10 and 11 and delaying to complete session 11 for almost two months.

With regard to the post hoc test of post-guidance subsessions, significant differences are mixed and sporadic. Visual guidance is significantly different from written guidance in terms of e_{traj} in sessions 5 and 6. Visual guidance is also significantly different from haptic guidance in terms of error in sessions 5,8 and 9 and significantly different in terms of hit and error from no-guidance in session 10. Haptic guidance is significantly different in terms of error from all three other groups. All of these post-guidance subsession comparisons are made to a 95% level of confidence.

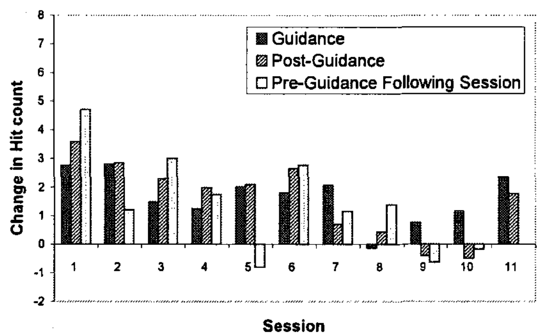
To further analyze differences in learning patterns changes in performance from one subsession to the next were computed for the three groups (This discussion does not include the written guidance group from the first run of the experiment as explained in Section 5.1.1.). Figure 5.16 illustrates the differences utilizing the pre-guidance subsession as a reference and then computing the differences. In Fig. 5.16(a) the black bars indicate that the greatest change in performance for the haptic group occurs between the pre-guidance and guidance subsessions. The improvement is then lost as the gray bar comparatively shows when the haptic guidance is removed in the post-guidance subsession. There is some increase in performance in the first five sessions when the participants come back the next day as shown by the white bars. Figure 5.16(b) shows the nonguidance control group learning effects to be gradually increasing from subsession to subsession and somewhat consistent across the training protocol. This group serves as a baseline for expected improvement from subsession to subsession and from session to session. The final sub figure 5.16(c) shows improvements for the visual group occurring not only between pre-guidance and guidance but also between the guidance and post-guidance subsessions suggesting that this group improves the most after having been shown the guidance but are undisturbed by the guidance scheme when they are again in the unassisted post-guidance subsession.

5.2.2 Cognitive Workload Measures

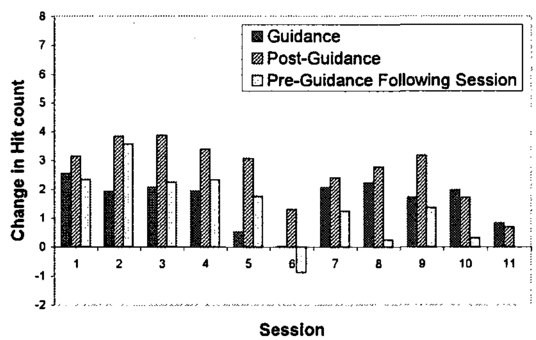
The subjective workload tested via the NASA Task Load Index (TLX) also presents significant results. Figure 5.17 shows the overall workload computed across all pre-guidance and guidance subsessions for the four groups. The visual guidance group reports significantly greater workload than both the nonguidance and written guidance groups. The haptic guid-



(a) Haptic guidance group subsession differences in terms of hit count.



(b) Nonguidance control group subsession differences in terms of hit count.



(c) Visual guidance subsession differences in terms of hit count.

Figure 5.16 : Differences in subsession performance. The Pre-guidance of each trial is the base score. Bars represent: guidance subsession minus pre-guidance shown in black, post-guidance minus pre-guidance shown hatched, and pre-guidance of the next session minus the current pre-guidance session)

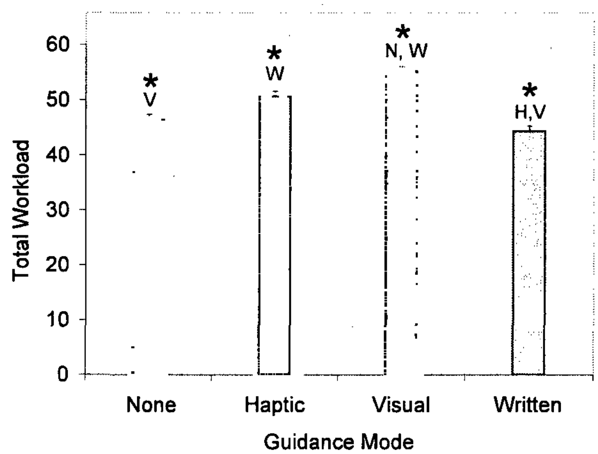


Figure 5.17 : Total subjective workload computed via the NASA-TLX for the four groups: nonguidance (N), haptic guidance (H), visual guidance (V), and written guidance (W). Significant differences (with a 95% level of confidence) are shown above the mean with the initials of the modes that are different. Error bars indicate standard error of the means. Visual guidance mode records the highest workload and is significantly different from the written and nonguidance groups. Data fails to show significant difference between the haptic guidance and the visual guidance groups.

ance group also has a significantly higher score than the written group but the data fails to show any significant differences by comparison to the other two groups.

Upon analyzing the six scales separately, more details emerge. Figure 5.18 shows individual subplots for each of the six scales. Each subplot presents the four guidance groups as vertical bars. The error bars indicate standard error of the means of the eight participants per guidance mode. Significant differences with a 95% level of confidence are listed above each bar. The visual guidance group reports significantly higher mental workload than the haptic group, but both fail to show significant differences from the no-guidance and written guidance groups. The visual group presents significantly higher frustration than all three groups. This particular result is further confirmed by the subjective questionnaire administered after each session and reported in Section 5.2.3. The nonguidance control group displays significantly less frustration than all three guidance groups. As might be expected,

Table 5.3 : The six scales of the NASA TLX cognitive workload assessment show significant main effects of guidance mode for both the guidance and the post-guidance subsessions. Asterisk * indicates $\alpha = 0.05$ confidence interval.

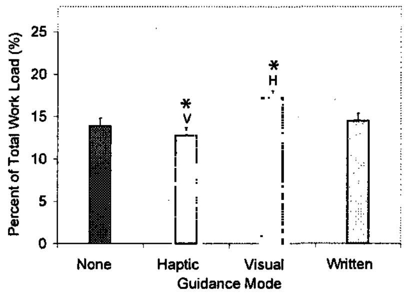
TLX Scale	Pre-Guidance	Guidance
Mental	0.024*	0.025*
Physical	$< 0.0001*$	$< 0.0001*$
Temporal	0.25	0.032*
Performance	$< 0.0001*$	0.0037*
Effort	0.002*	0.0002*
Frustration	$< 0.0001*$	$< 0.0001*$

the haptic group reports significantly higher physical workload than visual but not different from no-guidance. The the visual group reports significantly less physical demand than the other three groups. In terms of the temporal workload, both haptic and visual groups report greater workload than the no-guidance group. The written guidance group reports significantly greater effort than both visual and haptic guidance, while the no-guidance group has a significantly higher performance demand over visual and written guidance but failed to show a difference from haptic guidance.

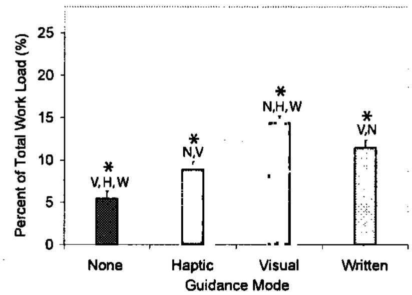
Analysis of variance on the six cognitive workload scales indicated a significant main effect of the guidance mode in both the pre-guidance and guidance subsessions but failed to indicate a main effect of session in any of the six measures. These results are summarized in Table 5.3.

5.2.3 Subjective Questionnaire Analysis

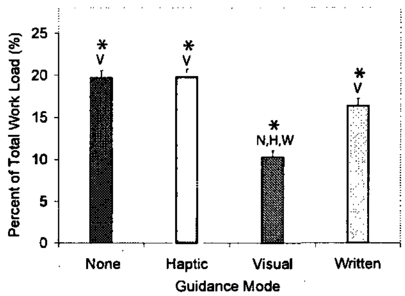
Two subjective questionnaires were administered, one at the end of each session and another longer one at the end of the training protocol (see Appendix A for copies of the questionnaires). All participants completed a short questionnaire at the end of each training session (see Fig. 5.7). The questionnaire included three questions that everyone answered



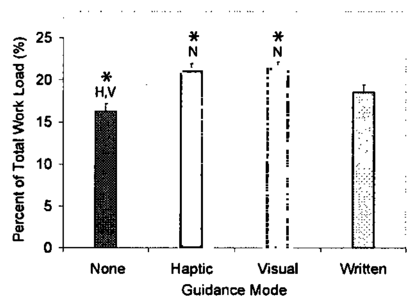
(a) Mental workload index



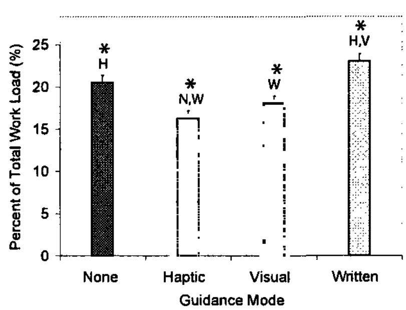
(b) Frustration workload index



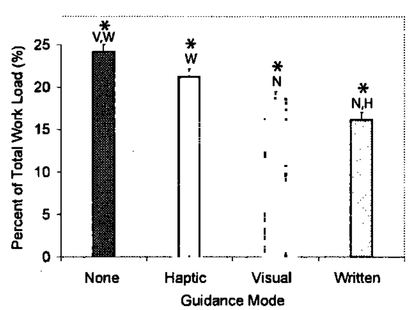
(c) Physical workload scale



(d) Temporal workload scale



(e) Effort workload scale



(f) Performance workload scale

Figure 5.18 : NASA Task Load Index. The six workload scales show the differences of the mean scores of the four guidance modes: no-guidance (N), Haptic (H), Visual (V), and Written (W) guidance scheme. Error bars indicate standard errors. Significant differences are indicated with an asterisk (*) and the initials (N, H, V, or W) of the different groups. For bars not indicated with asterisks, the data failed to show significant differences.

and two additional questions that only those in the three guidance groups answered regarding the guidance itself. The first two questions asked of everyone compared participant perception of current session performance to that of the previous session. The third question asked of everyone had to do with skill learning. Those who received guidance were asked about it and whether or not the guidance helped. The answers to this questionnaire are documented in Appendix C.

5.3 Discussion

This chapter presents the implementation of a novel progressive haptic guidance scheme designed to improve the effectiveness of a virtual training environment used for motor skill acquisition. The scheme integrates the measurements of key skills as input gains as proposed in Chapter 3. Depending on the participant's performance from trial to trial, the guidance gains progressively diminish, thereby reducing the level of guidance. The functionality of the progressive scheme is demonstrated via a pilot experiment showing the general diminishing trend of the guidance gains over the duration of the training protocol. The results of this methodology confirm prior work that had suggested that providing guidance when needed is more effective than a fixed amount of assistance [44, 64].

Furthermore, because saturation does not occur until after the sixth session, this task provides sufficient complexity to be able to study the effects of guidance as recognized by Todorov et al., Yokokohji et al., and Adams *et al.* [5, 79, 82]. The analysis of variance showed, as expected, that session is a significant factor and demonstrates that skill acquisition is occurring from session to session. The trends are approximated well by power curves in all three measures of performance: hit count n_{hit}, trajectory error e_{traj}, and input frequency f_{input}, indicating skill acquisition "learning rates." The haptic guidance mode has the greatest rate of $b = -1.33$ (parameter b of the curve fit equation 5.8) compared to $b = 0.15$, $b = 0.15$ and $b = 0.08$ for visual, written, and no-guidance respectively. This "learning rate" difference does not hold for the post-guidance subsession, suggesting a lack of transfer to the un-guided task. Nevertheless, at least the guidance group does not perform significantly worse than no-guidance in the post-guidance subsession as Li reported for a fixed-gain guidance scheme [46]. Dependence on the proposed haptic guidance is to be expected since the guidance drives the participant at the beginning of training. Toward the end of training, however, as the participant's performance improves and the guidance diminishes, the dependence is eliminated. The post-guidance data from each session fails to show significantly worse performance that might indicate the adverse effects of dependence.

The post hoc Scheffe pairwise test exposes significant differences between guidance modes within the sessions (see Fig 5.15). The results show that from sessions 2 through 7, the haptic guidance mode is significantly different from no-guidance in terms of all three measures. Comparing haptic guidance to both written and visual guidance, also from sessions 2 through 7, there are significant differences in terms of both n_{hit} and e_{traj}; however, differences in terms of f_{input} are mixed. These results are true for the guidance subsession but not for post-guidance, indicating that the proposed haptic guidance can be applied early in training without affecting the training outcome and it does not significantly improve performance in the post-guidance session. Interestingly, the performance gains obtained by the haptic guidance are not obtained by either visual or written guidance.

These results suggest that haptic guidance, based on key skill measurements, is effective early in the training protocol when participants are beginning to understand the skills required for the task but should be progressively removed to avoid possible dependence as suggested in prior work [46]. The resolution of the experiment design may be too coarse to capture the changes in performance occurring in the first three sessions. An experiment with finer resolution may be required. During the post-guidance baseline subsessions the data fails to show significant differences between the haptic guidance group and the nonguidance group suggesting that the skill acquired during haptic guidance does not transfer to the post-guidance unassisted condition. Further insight, however, is obtained from the results of the cognitive workload assessment.

The results of the NASA-TLX, administered during each session, show that the haptic guidance scheme generates less frustration and mental workload overall as shown in Fig. 5.18. This result, that haptic guidance reduces mental workload, confirms prior findings by Griffiths and Gillespie that had the same result utilizing secondary task technique [27]. The visual guidance group reports significantly higher mental workload than the haptic group, but both fail to show significant differences from the no-guidance and written guidance groups. The visual group presents significantly higher frustration than all three groups. This particular result is further confirmed by the subjective questionnaire administered after each session and reported in Section 5.2.3. The control group displays significantly less frustration than all three guidance groups. As might be expected, the haptic group reports significantly higher physical workload than visual but no different from no-guidance. The visual group reports significantly less physical demand than the other three groups. In terms of the temporal workload, both haptic and visual groups report greater workload than the no-guidance group. The written guidance group reports significantly greater effort than both visual and haptic guidance. Although the no-guidance group has a significantly higher performance demand over visual and written guidance, it failed to show a difference from haptic guidance.

A trade off between performance and workload may exist. In some cases, the addition of guidance schemes may be warranted if the workload is reduced, even if the performance, or rate of improvement, does not increase. On the other hand, guidance schemes that generate an improvement in performance may not be acceptable if the workload in a particular category is unduly increased. Therefore, it is important that haptic guidance schemes used for training be evaluated not only according to performance improvements but also according to changes in workload. Quantitative measures as the NASA-TLX, subjective workload assessment technique (SWAT), or physiological measures of workload should be used if practical. This recommendation is in keeping with the interdisciplinary nature of haptics research, bridging the gaps between mechatronics engineering, cognitive science, and neurobiology.

Chapter 6

Conclusions and Future Work

Novel haptic interface designs attempt to reproduce real-world tasks as accurately as possible or to provide virtual environment augmentation that will assist or guide the trainee in some way during skill acquisition. This thesis presents the implementation of a progressive haptic guidance scheme designed to improve the efficiency of an augmented virtual training environment to be used for skill acquisition. Based on a detailed analysis of the performance of *experts* and *novices* executing a dynamic motor skill task, I identified the key skills required for success and motivated the progressive haptic guidance scheme. The modification of a previously-developed virtual environment target-hitting task accommodates the guidance controller for investigation. The research compares the effectiveness of this scheme to a visual guidance that presents the same information in an exclusively visual way rather than using haptics. The research also compares this same scheme to written guidance and to no guidance at all. The user study is a training protocol that lasts eleven sessions over a two-month period. During each session, target hit count, trajectory error, and input frequency quantify performance. The latter two measures indicate the level of proficiency in the two key skills; by feeding their values into the controller, it updates the level of guidance offered to the participant. In addition to these measures, the computerized version of the NASA Task Load Index (TLX) was administered to all participants during each session, thereby providing workload measurements throughout the entire training period. An exit questionnaire also provided subjective data. The analysis of the experimental results demonstrates that during the time the guidance is active, the haptic guidance significantly outperforms visual guidance, written guidance, and no guidance at all in all three measures of performance until late in the protocol when all four groups of participants converge at approximately the same level of performance. After each active guidance subsession, participants complete a short no-guidance baseline test. During these baseline subsessions the data failed to show significant differences between any of the groups. These data suggest that the level of proficiency acquired during haptic guidance does not transfer to the unassisted condition. The results of the cognitive workload assessment, however, show that the haptic guidance scheme tends to generate less frustration and mental workload than the visual and written guidance schemes overall. Haptic guidance tends to produce greater physical workload than the visual guidance scheme. Visual guidance is significantly lower than the other schemes on this count. The no-guidance group is significantly less frustrated than the others but reports the same high physical workload as the haptic group. The written guidance group reports significantly greater effort than either guidance group and is significantly more frustrated than the no-guidance group. The group's performance data, however, failed to show any significant differences from the no-guidance group, a result that suggests that the advantage of being shown a skill – either via the visual or the haptics channel – over being told how to perform the same task does not reside in improved performance but in reduced frustration.

The results of two user studies here presented address three problems in the development of haptic guidance in virtual training environments. The first problem is to identify the key skills required for training success. The second problem is to develop quantitative performance and cognitive skill acquisition measures, which will help ascertain the effectiveness of the guidance. The third problem is to design haptic guidance to provide appropriate and timely assistance in facilitating skill acquisition by either accelerating or improving training outcomes that outperform no guidance at all. The design of the haptic guidance scheme integrates measures of performance of key skills by comparing and analyzing the execution of the dynamic human motor task by both *experts* and *novices*. This design also incorporates a preferred state trajectory validated by a movement smoothness model described in the first experiment.

Previous shared-control experiments by other colleagues have included the presentation of three sets of system parameters to participants and followed by the random alteration of those parameters from trial to trial. The change in parameters modified the resonant frequency of the two-mass system, causing participants to require more sessions to achieve performance saturation. This study maintains the system parameters constant, thereby reducing the number of significant experimental factors. This reduction itself, by reducing the complexity of the task allows participants to saturate their performance sooner than in previous experiments. One future direction of research would be to again increase the complexity of the task to ensure slower rates of skill acquisition. This could possibly demonstrate further improvements in the effectiveness of haptic guidance. Another method to increase the task complexity would be to require the excited mass to stop on the target rather than allowing overshoot. In addition to raising the complexity of the task, this requirement would open up the opportunity to analyze the task with optimization techniques. This change, in turn, would allow the development of alternate performance measures that are task-independent. Findings suggest that if the early part of the training protocol presents multiple conditions, it will initially affect performance adversely but will ultimately result in better overall performance. This is another possible direction of research. Since the progressive guidance scheme is an essentially different training condition from the nonguidance task, there is a possibility that it may produce better results in participants facing a third experimental condition. Another line of research that follows from the results of this thesis is to develop "smart" progressive guidance schemes. In this study, the gains of the guidance were varied by fixed amounts. Better results may come from guidance that can recognize not only an improvement in performance but also how much of an improvement has been observed and adjust the level of guidance based on that. Input frequency is a reliable measure of rhythmic motions such as the one here studied, but it fails in typical point-to-point reaching tasks. Trajectory error is an effective measure in most reaching tasks but is ineffective when task success does not depend on the path. The most important future research will apply the augmented VTE design considerations developed in this thesis within a study that would compare the effectiveness and outcomes of haptic guidance in a VTE to no guidance at all in a targeted real-world task such as pole-balancing, juggling, bicycling, or navigation of an under constrained vehicle.

These are the significant contributions of this research: First, the analysis of relative expertise thereby identifies and validates performance measures of key skills. Second, when the proposed haptic guidance scheme is active, it improves task performance. Third, the research suggests that skill performance measures should be supplemented by cognitive workload measures, such as the NASA-TLX, to more completely evaluate the effectiveness of haptic guidance schemes. Fourth and finally, the guidance scheme integrates progressive performance gains with an optimized path. The results of this thesis demonstrate that a progressive haptic guidance scheme, one that integrates an emphasis on key skills with measures of performance, is effective early in the training protocol. The haptic guidance design considerations and the findings of the analyses reported in this thesis can be applied to the development of an array of virtual training environments: surgical tasks, vehicle control, sports training, and rehabilitation.

Appendix A

Forms and Testing Documents

This appendix includes the forms and documents used in executing the experiments. The forms include:

- IRB Sample Form
- Invitational Flyer
- Experimenter Instructions for Session 1.
- Experimenter Instructions for session 2-11.
- Experiment Description for Participants
- NASA-TLX Questionnaire Description
- Hints Provided to Each Group at Session 2
- Session Subjective Questionnaire: No Guidance
- Session Subjective Questionnaire: Written Guidance
- Session Subjective Questionnaire: Visaul and Haptic Guidance
- Final Questionnaire

IRB Form

Rice University

Consent to Participate in a Research Study

Study Title: Augmented Haptic Feedback for Training

Principal Investigator: Dr. Marcia O'Malley

Interviewer: Joel C. Huegel

The purpose of this study is to determine whether adaptive assistive forces, displayed via an arm exoskeleton robotic device or a joystick robotic device and in tandem with interaction forces that arise when interacting with a virtual environment, increase efficiency, retention, and transfer of training in manipulation and assembly tasks.

You are being asked to participate in this study because you are a healthy individual with no known perceptual disabilities. You will be asked to:

- Wear/manipulate one or more of the haptic interfaces
- Interact with virtual environments that simulate the visual and haptic (force) cues the exist during manipulation (e.g., maneuvering blocks through a maze) and assembly (e.g., building objects out of component pieces) tasks
- Train to perform these manipulation and assembly tasks with and without assistive forces displayed at the same time as the interaction forces. For example, you will feel the block surface and resistance when you push it through the environment. At the same time, you may feel that there are certain paths through the workspace that are easier to move along. These paths are desired paths that we are trying to teach you.
- Sessions will be no longer than one hour.
- Repeatedly perform the manipulation and assembly tasks so that we can measure your learning rates with and without the assistive forces, your retention of training at given intervals (two to four weeks between training sessions), your ability to adapt to

different systems, your perception of differences between systems, and your ability to transfer that training to a similar real-world task.

You may be asked to test for several sessions under different simulation conditions.

You may find the following risk(s) or discomfort(s) from participating in this study: First, there are minimal risks of injury to you due to the hardware. There are safety shut-offs and hardware limits for each of the haptic interfaces. All interactions with the devices will be closely supervised by the PI or the research assistant. There is also the risk of fatigue of the arm due to the weight of the exoskeleton device and repeated arm motions with all of the haptic interfaces.

Personal benefits you may receive from this Study are the chance to interact with state-of-the-art virtual environment technologies and receive extra credit for certain courses in which you are enrolled (pending instructor approval).

Neither your name nor information that could identify you personally will be used in the data analysis and publication/ presentation of this study. Your identity will be kept confidential by: You will be assigned a number and your name will not be recorded. Your participation is completely voluntary. You may refuse to participate or withdraw your consent or discontinue your participation in the study at any time without penalty or loss of benefits or rights to which you might otherwise be entitled.

If you have any questions about this study, you should feel free to ask them now or anytime throughout the Study by contacting Dr. Marcia O'Malley, Department of Mechanical Engineering at Rice University at 713/348-3545 or by email at omalleym@rice.edu.

If you believe that your rights have been violated in any way, please contact Nancy Nisbett, Director of the Office of Sponsored Research at Rice University at 713/348-6200. or by email at nnisbett@rice.edu.

By signing this consent form, you are indicating your consent to participate in this study.

Signature Date

Invitational Flyer

The flyer used to invite participants is shown in Figure A.1 describing the experiment in very simple terms, presenting the time commitment required and the incentives offerred to motivate participation. When visiting a classroom by professor invitation, students were invited to put the name and email address on a form that was passed around. These classroom visits were followed up by an eamil with a more detailed task description and invitation to participate and how to proceed. This permitted the investigator to send several emails until the students either signed up or asked to be removed from the list. Thus the emails were not unsolicited.

mahi

Experiment Description

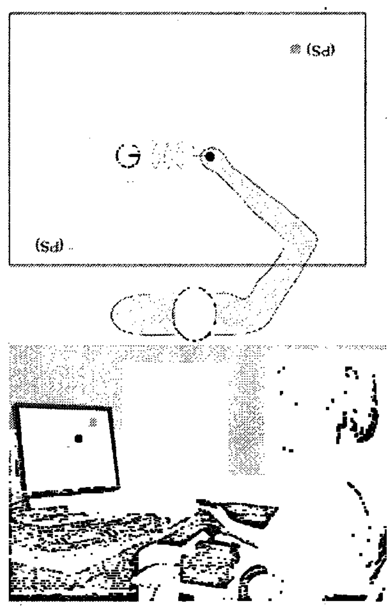
- Goal: to design the training paradigm to accelerate human motor learning in virtual environments
- Participants will interact with an underactuated dynamic system via a 2 DOF haptic joystick

Time Commitment

- 20 minutes per session
- 11 sessions total over 2 month

Incentives

- Simple and interesting virtual reality interaction game (FUN!)
- Cookies and drinks (FREE FOOD!)
- Prizes for top performance (CASH!)



Note: If you are interested, we can arrange a lab tour, here are the contacts and our lab website

Jhuegel@rice.edu / Tel: 713-348-2300 http://mems.rice.edu/~mahi

Figure A.1 : Flyer used to invite students to participate in the program.

Experimenter Instructions for Session 1

1. Welcome the participant in a friendly manner.
2. Verify the participants name and email address on the participation list.
3. Ask if they are LeftHanded or RightHanded. If Left ask if they prefer to do the task LH or RH. (they can play with the Dots example in step 7 to decide)
4. Have the participant read and sign the Consent Form.
   a Answer any questions he/she might have.
5. Provide the participant with the Instruction sheet and allow he/she to read over it.
   a Answer any questions he/she might have about the instructions.
6. Explain the experiment setup including of sessions, duration of each session and briefly describe the 6 parts of a session.
7. Show the participant the "dots" example and give the subject 3 minutes to get familiar with the device and force feedback.
   a Observe the participant and provide additional information about the device and interacting with it.
8. Ask if the participant is ready to begin.
9. Start the 2008-NFV program and ask the participant to enter their initials (in Group field), date and session number. (do not need to enter a subject number).
10. Show the participant the "Calibration Position."
11. Show the participant the "Center the Joystick" position.
12. Reiterate the "purple mass is to hit the green dot" and watch the participant perform the first trial (provide no additional verbal instruction or feedback).

13. Verify that the participant can again center the device.

14. Allow the participant to perform the Test 1 Trials without observation.

15. Assist the participant with the TLX User ID (Initials + 1).

16. When the participant is finished, offer her/him a drink and snack..

17. Have the participant select a “best” time slot and a “second” best slot for the training sessions which begin next week.

18. Thank the participant and remind them that I will email them before the first appointment.

Experimenter Instructions for session 2-11.

1. Welcome the participant in a friendly manner.

2. Verify the participants name and time slot on the schedule.

3. Verify the Group Letter and Subject Number on the participation list. Inform them of the Group Letter and Subject Number that they will use throughout the remainder of the program.

4. Provide the participant with an Instruction sheet based on the Group Letter and allow him/her to read over it.

    a Answer any questions he/she might have about the instructions especially the hints.

5. Ask if the participant is ready to begin.

6. Start the 2008-NFV program and ask the participant to enter their Group Letter (A,B,C), Subject number ID (1-9) , Session number (2). Assist them with the correct numbers.

7. If the participant is in groups A or C there will be a prompt for the Gains. Please refer to the chart. Ask the participant to enter the new gains that will be displayed after Test 2.

8. Remind the subject that there will be 5 trials followed by the questionnaire then 15 trials of training and one more questionnaire.

9. Remind the participant what group and subject number to use in the TLX questionnaire. (Group, Subject, and Session, eg: A1-2-1).

10. Ask the participant to don the headphones and verify the volume.

11. Verify that the Joystick red light is on.

12. Verify the participants use of the "Calibration Position."
13. Verify that the Joystick green light is now on.
14. Watch the participant perform the first trial (provide no verbal instruction or feedback).
15. Verify that the participant can again center the device.
16. Allow the participant to perform the remainder of the session without observation.
17. When the participant is finished, offer her/him a drink and snack..
18. Have the participant fill in the post session questionnaire.
19. Remind the participant that they should not discuss the experiment with other participants.
20. Verify the next appointment time and date.
21. Thank the participant.

Experiment Description for Participants

MAHI - Dynamic Task Training

Experiment Description

- Goal: to train participants to perform better in a manual dynamic task.
- Participants will interact with an underactuated dynamic system via a 2 DOF haptic (force feedback) joystick.

Time Commitment

- 20 minutes per session
- 10 sessions total during 1 month
- 1 follow up session 1 month later

Instructions

Each Session consists of 6 parts:

1. Test 1 - Evaluation of current performance level 5 trials each 20 seconds in duration.
2. Questionnaire 1 - Workload during the Evaluation period.
3. Test 2 - Training period of 15 trials each 20 seconds in duration.
4. Questionnaire 2 - Workload during the Training period.
5. Test 3 - Post-Training Evaluation of current performance level 5 trials each 20 seconds in duration.
6. Questionnaire 3 - End of session questionnaire (on paper).

Tests 1,2,3 Description: You will be asked to move the joystick, overcoming the dynamic forces of the system, to drive the purple dot to the active target square (indicated by being green). When you have hit the target, the active target will alternate to the opposite side of the screen (indicated by red target changing to green) and you will have to drive the purple dot to that target. Your performance will be measured based on how many targets you hit in each 20 second trial.

NASA-TLX Questionnaire Description (Scales) We are not only interested in assessing your performance but also the experiences you had during the different task conditions. Right now we are going to describe the technique that will be used to examine your experiences. In the most general sense we are examining the "Workload" you experienced. The factors that influence your experience of workload may come from the task itself, your feelings about your own performance, how much effort you put in, or the stress and frustration you felt. The workload contributed by different task elements may change as you get more familiar with a task, or perform easier or harder versions of it. Since workload is something that is experienced individually by each person, there are no effective "rulers" that can be used to estimate the workload of different activities. One way to find out about workload is to ask people to describe the feelings they experienced. Because workload may be caused by many different factors, we would like you to evaluate several of them individually rather than lumping them into a single global evaluation of overall workload.

This set of six rating scales (shown in the table below) was developed for you to use in evaluating your experiences during different tasks. Please read the descriptions of the scales carefully. If you have a question about any of the scales in the table, please ask me about it. It is extremely important that they be clear to you. After performing the task, six rating scales will be displayed. You will evaluate the task by marking each scale at the point which matches your experience. Each line has two endpoint descriptors that describe the scale. Note that "own performance" goes from "good" on the left to "bad" on the right. This order has been confusing for some people. Please consider your responses carefully in distinguishing among the task conditions. Consider each scale individually. Your ratings will play an important role in the evaluation being conducted, thus, your active participation is essential to the success of this experiment, and is greatly appreciated.

Measure Title	**Endpoints of the scale**	**Descriptions**
Mental Demand	Low - High	How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, looking, searching, remembering). Was the task easy or demanding, simple or complex, exacting or forgiving?
Physical Demand	Low - High	How much physical activity was required (e.g. pushing, pulling, turning, controlling, activating, etc)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand	Low - High	How much time pressure did you feel due to the rate or pace at which the task elements occurred? Was the pace slow and leisurely or rapid and frantic.
Performance	*Good - poor*	How successful do you think you were in accomplishing the goals of the task set by set by the experimenter? How satisfied were you with your performance in accomplishing these goals?
Effort	Low - High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration	Low - High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Figure A.2 : Description of the six dimensions of the NASA-TLX (from [30]).

Hints Provided to Each Group at Session 2

(Written Guidance group):

Hints:

1. By keeping the purple mass on an imaginary line between the two targets, you can improve the number of hits in each trial.

2. By moving the joystick at or near the natural frequency of the system you can get more hits in the same amount of time.

Visual Guidance group:

Hints:

1. By keeping the purple mass an imaginary axis between the two targets, you can improve the number of hits in each trial. During the training test, initially the computer will provide a blue bar on this axis to help you keep on the target axis).

2. By moving the joystick at or near the natural frequency of the system you can get more hits in the same amount of time.

During the training test, initially the computer will show you a green bar that is moving at the natural frequency to help you keep the joystick moving at the natural frequency.
As your performance improves, however, the computer will slowly remove the visual guides leaving you to do the task on your own without assistance.

Haptic Guidance group:

Hints:

1. By keeping the purple mass on an imaginary axis between the two targets, you can improve the number of hits in each trial. During the training test, initially you will feel the computer help you to keep the purple mass on the target axis.

2. By moving the joystick at or near the natural frequency of the system you can get more hits in the same amount of time.

During the training test, initially the computer will help you drive the joystick at the natural frequency.

As your performance improves, however, the computer will slowly remove the haptic guides leaving you to do the task on your own without assistance.

Session Subjective Questionnaire: No Guidance

GROUP ___ SUBJECT ID ___ Session ___

1. Comparing just the Test #2 (Training) with the previous sessions Test #2, do you feel your performance improved? ___ a. If yes, why? If no, why?

2. Comparing just the Test #3 (Post-Evaluation) with the previous sessions Test #3, do you feel your performance improved? ___ a. If yes, why? If no, why?

3. What did you learn or figure out (if anything) during this session that helped you improve your performance?

Session Subjective Questionnaire: Written Guidance

GROUP ___ SUBJECT ID ___ Session ___

1. Comparing just the Test #2 (Training) with the previous sessions Test #2, do you feel your performance improved? ___ a. If yes, why? If no, why?
2. Comparing just the Test #3 (Post-Evaluation) with the previous sessions Test #3, do you feel your performance improved? ___ a. If yes, why? If no, why?
3. What did you learn or figure out (if anything) during this session that helped you improve your performance?
4. What impression do you have of the hints and guidance received?

Session Subjective Questionnaire: Visual or Haptic Guidance

GROUP ___ SUBJECT ID ___ Session ___

1. Comparing just the Test #2 (Training) with the previous sessions Test #2, do you feel your performance improved? ___ If yes, why? If no, why?
2. Comparing just the Test #3 (Post-Evaluation) with the previous sessions Test #3, do you feel your performance improved? ___ If yes, why? If no, why?
3. What did you learn or figure out (if anything) during this session that helped you improve your performance?
4. Which, if any, guidance did you still receive during Test #2?

   a. none b. axis error c. excitation frequency d. both b and c
5. Did you feel the guidance helped you? If so, how? If not, why not?

Final Questionnaire

Subject number: ___ Subject Age: ___ Gender: M / F Today's Date: ___

Dominant hand for computer/videogame use: LH / RH

1. Were you experienced with haptics before this experiment? (devices such as Sidewinder, phantom, or falcon).

   a. no experience b. used once or twice before c. used on a weekly basis

2. Are you experienced with videogames that require eye-hand coordination? Rank yourself:

   a. never have played b. novice c. defend myself d. better than most e. expert

3. Is there any other activity that you are good at that requires a high level of coordination and might have helped you be better at this task? (e.g. baseball, ping pong, racecar driving, walking and chewing gum at the same time, etc.) ______

4. Do you play a musical instrument? NO / YES If YES, which one? ______

5. Throughout the sessions, what strategy did you develop for hitting the targets quicker or more accurately? ______

6. Did you change your strategy at any time? NO / YES. If YES, what was the new strategy and what prompted it? ______

7. Now that you have trained for the task for 11 sessions, please recall your experience in the first session. Which of the following statements best describes your situation upon completing session 1:

   a I mentally understood how the task should be performed to obtain high scores BUT I did not have the motor skills to perform the way I mentally wanted to.

   b I mentally understood how the task should be performed to obtain high scores AND I had the motor skills necessary to perform the way I mentally wanted to.

c I mentally did not understand how to perform the task to obtain high scores BUT I had the motor skills to intuitively perform it and obtain high scores.

d I mentally did not understand how to perform the task to obtain high scores NOR did I have the motor skills to perform it and obtain high scores.

8. Which of the statements above best describes your situation upon completing session 11 (circle one) a. b. c. d.

9. What was your all-time maximum Hitcount score: _______

10. What do you think might be the highest Hitcount score possible for this task: ____

11. What do YOU think YOU would have to do differently to achieve the maximum score? _______

12. Did you or do you have any complaints about this study? NO / YES If Yes, please describe:

Appendix B

Subjective Questionnaire Results

Question 1

Comparing just Test 2 (training) with the previous session's Test 2, do you feel your performance improved?

Session 2

A1 N/R
A2 Yes, it helps me keep on a straight line (ruler)
A3 Yes, I had a better idea of how I would accomplish my goal after this session's training
A4 Yes, guided joystick help feel the needed movement
A5 Yes, I hit a new all-time high of 24
A6 Yes, the oscillation helped me find the natural rhythm
A7 Yes, joystick was physically guided
A8 Yes, once I stopped trying to control the stick, the machine did all the work for me
A9 Yes, because I had some help giving me the path motion to hit more times the two squares
AA No, I felt like I was fighting against the joystick, not being guided
B1 Yes, I'm getting more used to control the stick and the score is getting improved a lot too
B2 Not really, it was a long time between, there wasn't much advantage of having done it before
B3 Yes, I have experiences and skills
B4 Yes, simply logging more time on the sim improved my performance
B5 Yes, I used Test 2 from previous session to experiment different methods and find the best one
B6 No, I think it took me a while to get used to the opposite orientation of the targets for left-handers
B7 No, it's really hard to get a technique that works every time even when I feel I'm doing the same thing, I just miss the targets
B8 Yes, I already knew what to expect and had developed muscle memory
B9 Yes, I have improved my control of the device and also have learned techniques to increase my score
BA N/R
BB Yes, lots of practice
C1 Yes, I've had more experience with the equipment
C2 Yes, the visual aids provided an easy way to keep the black ball and consequently the purple ball in line with the targets
C3 Yes, more familiarity with the joystick, guides
C4 No, because last time I did the experiment in this way
C5 No, I had trouble conceptualizing the little and not just using arcs to try to reach the point

C6 Yes, the direction bar between the targets helped the most by giving a constant reference to how straight I was aiming
C7 Yes, natural frequency bar helped get a better rhythm
C8 Yes, I was able to get into a good rhythm with the joystick
C9 No, Feel I scored worse this session
CA No, the moving bars only distracted me from focusing on hitting the targets; I was trying to match the bars
Session 3
A1 Yes, I felt relaxed and I knew what to expect, but the joystick did feel much "stiffer" than before!
A2 Yes, experience helped
A3 No, I thought the training was very similar-I was struggling with the same things
A4 Yes, feel the rhythm better
A5 Yes, I knew what to expect with training. Let machine take control earlier.
A6 Yes, I learned to work with the guidance instead of against it.
A7 Yes, the computer provided some resistance making the joystick easier to control, but not so much that I felt as if I didn't have to do anything.
A8 Yes, I understood what was happening in test 2 from the beginning.
A9 No, because I forgot how was the proper movement in order to get to the targets.
AA Yes, I felt that I had become more used to the resistance the training provides.
B1 No, I was trying to move the ball as fast as I could. But later I figured out it didn't help much in improving the number of hits.
B2 Yes, practice
B3 Yes, I can remember the skills which I summarized last time and keep these skills in mind while training.
B4 No, I was trying to go too fast, and it took a while to realize that the feedback force is related to applied force (the harder you press the joystick, the more it pushes back).
B5 No, wasn't as consistent as before, tried a different approach
B6 Yes, I was more consistent of hitting the targets. My scores were much higher.
B7 No, today I just couldn't get into a pattern of moving the ball in a straight line
B9 Yes, but not too much. I am more familiar with the device and its response to my actions.
BA No, I tried a different technique and failed.
BB Yes, maybe a little because of practice
C1 Yes, because I was used to the moving bar and therefore less distracted
C2 Yes, the visual guides helped keep the ball between the axis because you only had to focus on keeping the black ball on the blue line instead of hitting targets.
C3 Yes, still more familiar with mechanism moving with pattern
C4 Yes, more practicemore progress
C5 Yes, I felt more comfortable with the joystick, and also more relaxed
C6 Yes, because I am becoming more experienced using the joystick to accomplish the task
C7 Yes, I think I have higher average
C8 Yes, I felt more comfortable with (less distracted by) the green bar so I was able to focus on staying on the blue
C9 Yes, followed the purple bar better
CA Yes, experience

Session 4
A1 Yes, more freedom on moving guide resulted in less "effort" and "physical demand" and consequently better "performance"
A2 Yes
A3 Yes, I think with practice my performance improves
A4 Maybe, performance seemed to be the same
A5 Yes, more comfortable with training
A6 Yes, I guess I've gotten used to the assistance now.
A7 Yes, more consistent in hitting target, able to establish rhythm faster; no computer aid
A8 Yes, more used to sensation of the testing aid
A9 No, I felt almost the same because it seems is the same help, so it's the same result
AA No, the resistance provided by the training doesn't accurately model the evaluation tests
B1 No, I couldn't control the stick as smoothly as last time. The ball on the screen didn't go in the same direction as I wanted it to.
B2 Yes, more practice
B3 Yes, I just slept for a while at noon, so I couldn't concentrate immediately on the game in the previous sessions. As far as I can remember, I broke my record in the training session.
B4 Yes, different strategy led to higher hit count.
B5 Yes, more consistent
B6Yes, I feel that I improved my consistency. I also achieved my highest score yet (26).
B7 Yes, today I was able to get a smooth pattern going. I got it to not go so circular but more straight.
B9 No, just did same thing as before
BA Yes, more consistent rhythm
BB Yes, I went faster
C1 Yes, I have learned to control the equipment (spring) better.
C2 No, I tended to concentrate more on keeping the black ball on the guideline instead of hitting the targets.
C3 No, the guides actually feel like more of a distraction
C4 No, I got some influence from the green bar.
C5 No, the numbers on average seemed lower, and I felt the training was still distracting
C6 Yes, greater experience level
C7 Yes, more consistent
C8 No, very similar to previous time
C9 Yes, better rhythm, more consistent hits
CA Yes, more experience
Session 5
A1 Yes, understanding of physical demand
A2 No, the enforced training became annoying
A3 No, I think they were about the same
A4 Yes, hit more targets with less effort-found the rhythm sooner
A5 No, not as much guidance
A6 Yes, I guess it just finally snapped into place for me. I did a lot better today, though.
A7 Yes, more accurate at hitting target, not overshooting
A8 No, last session had "target axis fixed guide"

A9 Yes, because I felt I could be more constant because I'm getting more used to the exercise.
AA Yes, I learned how to work with the guidance forces more.
B1 Yes, I'm more concentrated on the movement of the stick than last time and thus having a much more concise control on the ball.
B2 Yes, more experience
B3 Yes, at first, I can't concentrate quickly, and the joystick feeling is not very well because I didn't use it for 3 days. Then after several trials, I came back.
B4 No, less hits per turn, not sure why
B5 Yes, just a little, consistent
B6 Yes, scores were higher overall. More consistency
B7 Yes, today some of my hit counts were higher than I've ever received.
B9 No, I arrived a little late, so I was not focused completely on the task. The performance was terrible.
BA Yes, got more consistent
BB No, I feel it was about the same
C1 No, I was more frustrated than before
C2 Yes, I focused on the target rather than the guidelines
C3 Yes, more consistent, better feel with joystick
C4 No, the joystick is hsard to move. I think it's because I didn't move it correctly first to upper right
C5 Yes, hit count fairly consistently over 20. I'm pretty sure that counts as improvement. Also, hitting the targets faster. No as annoyed by the moving guide.
C6 Yes, more experience
C7 Yes, better feel for the rhythm
C8 No, a little rusty
C9 No, stayed about the same
CA Yes, more experience, familiarity with joystick
Session 6
A1 I allowed the feedback of the joystick to make the increased frequency of motion; again subtle motions still got better
A2 No
A3 Yes, I thought, in general the training was better. I was able to hit more target more consistently.
A4 Yes, not sure
A5 Yes, had higher numbers
A6 No, I did OK, but compared to the last session, it wasn't an improvement
A7 No, stay pretty much the same
A8 Yes, more used to no track (target axis guide)
A9 Yes, because I felt I was a little bit more constant
AA No, still fighting the resistance the training provides
B1 Yes, I have a more steady performance today. The speed of the ball is well controlled so that it can move in the desired direction
B2 Yes, more consistent-have more practice I guess
B3 Yes, I need some hint to get familiar with the joystick
B4 Yes, more consistent. Higher average hits/trial.
B5 No, stayed the same

B6 No, my consistency was much worse. I received scores in the teens too often.
B7 No, today was really irregular. I started off really bad but toward the end I got back to my average performance
B9 No, there was something different in today's experiment. The position of my arm was different. I had to correct its action more often.
BA No, I tried something new and it didn't work
BB No, I just couldn't seem to hit as many
C1 No, I felt more resistance from the joystick and it took more physical effort to move/complete the task
C2 No, I wasn't able to keep the black ball along the guideline so I couldn't hit as many targets
C3 Yes, more consistent, better control of the joystick
C4 Yes, I control the frequency
C5 No, I wasn't hitting as often, and I didn't feel like I had much control (I'm also exhausted, which is probably a large factor). The guides didn't help at all.
C6 No, my average hits didn't change.
C7 Yes, higher average hits
C8 Yes, felt it easier to stay in tune with natural frequency
C9 About the same, more comfortable though
CA No, it stayed the same, frustrated with improving my hit count
Session 7
A1 Yes, I continued to use the feedback and the joystick to increase the frequency of the "purple ball"
A2 Yes, much better; follow the guidance's tempo more
A3Yes, I think I was generally more consistent
A4 Yes, felt the rhythm better with minimum joystick movement
A5 Yes, more consistent
A6 Yes, I've gotten used to the way the ball moves. It seems easy now.
A7 No, stayed the same
A8 No, performance did not really change much
A9 No, I think my arm got a little bit tired earlier and I was kind of sleepy
AA No, the resistance is still too strong
B1 Yes, more hits than last time
B2 Yes, decided to try really hard
B3 Yes, in test 2 I broke my record again, 23/trial, but the average record in test 2 may not be very good. As I feel a little frustrated when I miss one hit.
B4 Yes, practice
B5 No, very sluggish today. Not enough sleep. Had trouble focusing. Required more mental demand/concentration than preceding sessions.
B6 Yes, my overall consistency improved. Also, I developed a new technique for higher scores.
B7 Yes, today was an improvement because last session was not uniform in performance. I feel I did average today.
B9 Yes, the device was different. I was in a better mood.
BA Same. Did the same technique.
BB Yes, I didn't do very well last time.
C1 No, I'm tired.

C2 No, there was too much circular movement instead of going in a straight line between the targets.
C3 No, the joystick felt slightly less firm than usual.
C4 Yes, control the direction and frequency.
C5 Yes, I wasn't completely exhausted. I hit more per session, and I felt I was moving faster. Almost feel like I'm up to speed with the guide.
C6 No, similar average hits
C7 No, not so good at staying on the line
C8 Yes, better use of natural frequency
C9 Yes, better score
CA No, a little rusty from weekend and missing Monday
Session 8
A1 No, still learning to use increased frequency of joystick movement along axis of targets
A2 Yes, feel closer to the natural frequency
A3 No, I thought they were about the same
A4 No, too early to perform at best
A5 No, lower scores
A6 No, something went wrong with the calibration. My center was far above the training space.
A7 No, a little worse. Joystick seemed stiff.
A8 No, tried new things to break plateau, sometimes didn't work
A9 Yes, because with the practice, I know how to control more easily the speed and the right path
AA Yes, just stopped trying to guide and let the training force do all the work
B1 No, performance same as last time
B2 No, wasn't as consistent
B3 Yes, at first, I didn't concentrate enough. In the training session, my average record improved, so I'm not frustrated.
B4 Yes, practice
B5 No, although I got a new ?-score of 28, twice. I was less consistent due to trying for a high score
B6 Yes, I got my highest score to date (28)
B7 No, my highest hit count value didn't improve
B9 Yes, I wanted to improve it
BA No, I tried to do it faster and failed
BB No, I did really well last time and not very well this time
C1 Yes, more practice
C2 No, I feel that my performance was about the same as last week's because I still had too much circular motion
C3 Yes, the joystick seemed a little more light, and thus I was able to move it more easily
C4 Yes, I increased the frequency
C5 Yes, I think hit count improved overall. But mentally, I felt about the same.
C6 Yes, better hit average
C7 No, about the same
C8 No, was a little rusty; took a little bit to get back in the groove
C9 No, worse scores
CA No, not at prime physical and mental condition
Session 9

A1 Still improving on increasing the frequency of motion of joystick
A2 No, the joystick was aligned well
A3 Yes, I hit more targets on average
A4 No, guide once seemed to fight what needed to be moved
A5 No, lower hit totals
A6 Yes, well, for one, the controls were working properly. I also felt more energetic today.
A7 About the same
A8 No, no guide conquered 4 incorrect, last time
A9 No, I felt it was almost the same because it's getting pretty normal to get the same help and the same results
AA No, still just as much resistance in training or at least it feels like it
B1 No, same as last time
B2 No, about the same-repetition
B3 No, this time I am trying to find a way to make the ball move faster, so I don't care about performance
B4 Yes, improvement with practice
B5 No, stayed the same
B6 Yes, I got a 28 twice and a 27 once. My scores were higher overall.
B7 Yes, In the beginning of the session my average was 20 or above. But as I started feeling confident, it went down some. But over all pretty consistent for once
B9 Yes, I was more relaxed than the last time. Also I didn't use the noise reduction headphones.
BA Yes, I tried to go faster and succeeded.
BB Yes, I did really badly last time
C1 Yes, I learned that I should focus on hitting the upper node and this will also in turn cause me to hit the bottom node. To clarify, I never looked at the bottom node and my performance improved.
C2 No, it took me longer than usual to get comfortable controlling the ball
C3 Yes, joystick seemed loose, move lightly ? tapped for precision
C4 No, the green bar influence my frequency
C5 No, hit count was down a little, but not drastically. (No real loss, just no improvement either.)
C6 Yes, more hits on target
C7 No, no real improvement in hits
C8 Yes, the green bar faded to where I could almost not see it
C9 No, same
CA Yes, because performance horrible last time
Session 10
A1 Yes, starting to have better rhythm and targeting
A2 Yes, guidance isn't as pushy as last time
A3 No, I thought they were about the same.
A4 Yes, better first movement on axis
A5 Yes, higher hit count
A6 No, last time was the best I did; this session just couldn't have surpassed it.
A7 Yes, got better at just barely reaching squares
A8 Yes, more consistent
A9 No, I don't know, I felt like I had better rhythm but it didn't seem to work
AAYes, slightly, tried to focus more on feeling the frequency and let the fixed guide do all the work

B1 Same as last time
B2 Yes, more consistent
B3 Yes, I make the ball move quicker, more quickly and more accurately
B4 Yes, practice
B5 No, same
B6 Yes, I got my highest score (31) to date
B7 No, I feel it was similar to my session 9 performance
B9 No, it should be very close to the previous. I used the same things.
BB No, there was a lot more interfering force
C1 Yes, I am getting better implementing my strategy
C2 No, I couldn't keep the ball on the middle axis so I wasn't able to hit as many targets
C3 No, had some problem with getting started into the rhythm today, due to human error.
C4 Yes, I find the frequency of the movement of the green bar can improve my performance
C5 No, again, not hitting as much (I kept careening wildly into all the wrong places)
C6 No, it's the last session. I am as good as I am going to get.
C7 No, same
C8 No, it was very similar
C9 Yes, better consistency
CA Yes, more experience-not higher hits, just more consistent

Question 2

Comparing just Test 3 (post-training) with the previous session's Test 3, do you feel your performance improved?
Session 2
A1
A2 Yes, my hand memorizes the "ruler" pattern
A3 Yes, again I had a better idea of what to do
A4 Yes, just barely-not until final trial did I seem to improve
A5 No, I was babied in Session 2 where last week Session 2 was more practice
A6 No, I think learning on my own helped the "muscle memory" more. I got thrown off when the training force was gone.
A7 No, although the guiding was effective, my hands pretty much "forgot" how to move on their own. Staying on the diagonal axis was harder.
A8 Yes, hit 20 this time, but not last time
A9 Yes, because now I have practiced more and I have known how to stabilize the motion a little more
AA Yes, knowing more what line to move on helped
B1
B2 Yes, test 3 this time was my best. Finally figured out best strategy. I guess I hadn't for 3 last time
B3Yes, based on the training improvement
B4
B5 Yes, the two sessions of training allowed me to "remember" the movement required for a high score

B6 Yes, my average was a lot (+10) higher, and I figured out how to rack up high scores
B7 No, same as above. It seems as if I'm never training. It just seems like endless test in which some I do good and others I don't
B8 No, past test 3
B9
BA
BB Yes, same reason. I feel like I have the pattern now.
C1 Yes, same as above
C2 Yes, even though the visual aids were no longer present, it was easy to keep the ball in line because it was just a continuation of the pattern from the previous trial
C3 Yes, overall more experience with the most efficient pattern to movement
C4 Yes, because I have practiced more
C5 Yes, even if I was moving in arcs, they were straighter and more accurate
C6 Yes, because of mostly more time under my belt so I was more practiced at the task
C7 Yes, better training with bars
C8 Yes, better familiarity with the joystick and the movement of the two dots
C9 Yes, scored better
CA Yes, more experience
Session 3
A1 Yes, again I felt relaxed except this time I physically felt at ease
A2 Yes, it helped me recall the technique
A3 No, I don't think there was a significant improvement between this session and the previous one because I'm still trying to learn the best way to accomplish the task.
A4 Yes, could remember the feeling of joystick movement from training
A5 Yes, more familiar with motion/strategy, more practiced
A6 No, learning to work with guidance throws me off when I have no assistance
A7 Yes, finding the correct rhythm was easier
A8 No, the adjustment to receiving no aid took longer today than it did last week
A9 No, I think it was similar to the last one
AA Yes, this session's training I focused mostly on the first motion of the ball
B1 Yes, I slowed down my speed a little bit and felt that it's easier to control the movement of the ball
B2 Yes, practice
B3 Yes, based on the training, I'm more familiar with the skills
B4 Yes, improvement with time/experience
B5 No, about the same, new approach reduced physical effort but affected speed/accuracy
B6 Yes, again consistency was much better, and the effort I exerted was lower
B7 No, same as above
B9Yes, practice
B3 Yes, based on the training, I'm more familiar with the skills
B4 Yes, improvement with time/experience
B5 No, about the same, new approach reduced physical effort but affected speed/accuracy
B6 Yes, again consistency was much better, and the effort I exerted was lower
B7 No, same as above
B9 Yes, I am familiar with the response of the device to different levels of strokes

BA No, same reason
BB No, I messed up a few times
C1 Yes, but I attribute this to luck and chance
C2 Yes, having the training period twice improved my performance because it reiterated the targeted motion
C3 Yes, same reason as 1
C4 Yes, I control the method
C5 Yes, I felt more comfortable, I guess
C6 Yes, level of experience
C7 Yes, higher average
C8 Yes, felt better at keeping black dot on axis between squares
C9 Yes, scored better with more accuracy
CA Yes, feel more consistent in hitting targets
Session 4
A1 Yes, muscle memory. Also, my "performance" encouraged my "mental demand."
A2 Yes
A3 Yes, this training session was easier than the last. It helped me focus on improving rather than trying to deal with the guidance.
A4 Yes, seemed to move joystick with less effort to keep on axis
A5 No, I was on fire last time
A6 Yes, I'm starting to remember exactly how to move so that I get more hits.
A7 Yes, same as above, more consistent and able to establish rhythm more quickly
A8Yes, quicker adjustment to lack of aid
A9 Yes, here I felt that I had a little better performance because of the practice.
AA Yes, better control of initial motion
B1 No, same reason as above
B2 Yes, more practice-post-evaluation seems to not matter as much
B3 Yes, my average record has been increased. Based on the training, I am more confident about my performance.
B4 Yes, same reason
B5 Yes, got a high score of 26, in one trial, didn't miss a target, first time this has happened B6 Yes, again my consistency improved-all of my scores were above 20
B7 Yes, I slowed down how quick I tried to begin each run and this allowed for better control of the ball
B9 No, I just did the same thing as before
BA No, I tried new techniques, they didn't work
BB Yes, I used the same technique as the Test 2
C1 Yes, I've had more practice
C2 Yes, I was able to keep the ball on the axis between the two targets and increase the natural frequency instead of just one or the other
C3 Yes, more practice with the joystick, better with the pull
C4 Yes, I have control over the direction and frequency
C5 Yes, relief that the training guides were gone? Or maybe just used to the controls by now. Seemed to get more hits in a row.
C6 Yes, more experience

C7 No, lower average hits
C8 Yes, I did feel like I fared better on staying between squares
C9 Yes, higher scores
CA Yes, more experience
Session 5
A1 No, my mental demand had lowered! Less focus starting out and really had to improve in Test 3
A2 Yes, stimulated by the training frustration and learned from making mistakes
A3 No, I thought they were about the same, too.
A4 Yes, some-found the rhythm sooner
A5 No, not as high of hits
A6 Yes, the lesson I learned from the training session actually carried over this time.
A7 Yes, same as above
A8 Yes, more consistent
A9 No, because it took me longer to get the hand of it on my own
AA Yes, more on line between dots
B1 Yes, the general score gets improved, but the performance is not very stable. Sometimes I can get a high score while sometimes the score is very low.
B2 No, same
B3 Yes, after the training, I became familiar with the joystick and can concentrate easily on the performance
B4 No, I must be having an off day.
B5 Yes, higher score, new high score! 27!
B6 Yes, I reached my high score (26) 3 times
B7 Yes, I feel an improvement but not much. With only 5 sessions in Test 3, it doesn't allow you to mess up on too many and still make up for it
B9 No, I think the final performance was still influenced by the ? conditions. I "forgot" how to deal with the device in order to get higher scores.
BA Yes, same reason
BB Yes, I was more ?
C1 Yes, my rhythm is better
C2 Yes, I wasn't focusing on the guide lines when I did the training, so when I got to test 3 I was already used tohitting the targets without a visual guide
C3 Yes, more consistency more experience with joystick, but my hand is a bit tired at that point
C4 No, the same reason to 1
C5 No, I wasn't doing as well as I did in practice, and the numbers seemed similar to last time's
C6 Yes, more experience
C7 Yes, better rhythm
C8 Yes, got in better sync with the natural frequency
C9 No, scored worse
CA Yes, same as above
Session 6
A1 Yes, I attempted to mimic the faster frequency of motion
A2 Yes
A3 No, I thought it was much worse. I thought the joystick was very hard to control. At first it was very difficult to move, then for the last two trials it was very loose

A4 Yes, felt more rhythm
A5 Yes, higher numbers
A6 No, same thing it was decent, but it wasn't an improvement over the previous session
A7 Yes, reached new high of 29 hits
A8 Yes, hit 20 again
A9 Yes, because I felt more relaxed and confident because of the practice
AA Yes, more relaxed
B1 Yes, same as above
B2 No, I think it was less good. Didn't put as much effort.
B3 Yes, I have some trials of Test 3. A good record, but not all I feel the duration of Test 3 is a little shorter than that of Test 2.
B4 Yes, high hits pretrial, consistently great than 15
B5 No, did a little worse, but just a little
B6 No, again my score was marginally lower
B7 No, I think it was just about the same. Nothing major changed in my performance.
B9 No, same as before. Still, the performance improved because I assume the learning process restarted.
BA No, same reason
BB No, I kinda feel like I've already peaked
C1 No, I did not learn anything which would have increased my performance
C2 Yes, I found it easier to maneuver the purple by keeping the black ball in the center of the targets and just barely changing directions
C3Yes, hand wasn't as tired due to below
C4 Yes, direction and frequency are controlled
C5 No, again I was missing the targets fairly often, and I knew I wasn't going as fast due to lack of control
C6 Not really, my hit average is still only around 23
C7Yes, higher average hits
C8 Yes, got in sync with the natural frequency and stayed on axis between squares
C9 Better feeling for purple bar when it wasn't there
CA No trying different techniques
Session 7
A1 Yes, I may have muscle memory that I received from the joystick
A2 Yes, but unstable.
A3 Yes, I think my post-evaluation was much better, I didn't have any joystick problems this time
A4 Yes, get the ball moving on the correct axis sooner
A5 Yes, higher number of hits, less effort
A6 No, for some reason, the black ball kept starting in a different place than I was used to
A7 No, about the same, a little more consistent
A8 Yes, more consistent
A9 No, because I forgot sometimes the proper movement or path and it made some circles
AA Yes, faster "swings" of the ball
B1 Yes, more hits than last time
B2 Same, in post-evaluation, combination of knowing it's the post-evaluation and arm soreness makes me do a little worse

B3 Yes, I have a new record in test 3 this time, 23/trial. My average performance in this session is better too.
B4 Yes, practice
B5 No, same reason as above
B6 Yes, I got my highest score to date (a 27)
B7 Yes, same as above
B9 Yes, see above
BA Yes, more consistent
BB Yes, I didn't do very well with test 3 last time
C1 No, I have not learned anything new that would improve my performance and I felt the joystick had more resistance than before
C2 Yes, my movements were shorter and more precise so I was able to hit more targets
C3 No, see above comment
C4 Yes, I know the frequency
C5 Yes, (I think I did better the session before last, though) Again, not completely wiped out, and better at aiming at higher speeds
C6 No, same number of hits
C7 No, same results
C8 Yes, better job of staying on axis and oscillating at natural frequency
C9 Yes, felt more comfortable
CA Yes, relaxing and bit plus motion is in "muscle memory"
Session 8
A1 Yes, I'm becoming relaxed as I use the increased frequency
A2 Not much
A3 Yes, I thought my performance was generally the same, maybe a little better
A4 No, same
A5 No, lower gain, not as many hits
A6 No, for the same reason above. At the lowest point on the joystick I was halfway up the screen.
A7 No, about the same
A8 Yes, new things worked, hit 27
A9 No, because I was trying to do it faster and faster but I lost control at a certain point
AA No, about the same
B1 No, same as last time
B2 No, same, not consistent. This time my third trial was way worse than 2nd.
B3 Yes, in test 3 I keep 2 times of 24 hits/trial. I'm very familiar with the game
B4 Yes, practice
B5 No, less consistent
B6 No, my average score was lower on average by about 2 hits
B7 No, my hit counts are not uniform. They vary a lot.
B9 Yes, same as above
BA Yes, I tried to do it faster and succeeded
BB No, I did better in test 3 than test 2, but I still did better last time
C1 Yes, more practice
C2 Yes, I was able to restrict the motion of the ball more effectively so the movement was more controlled and precise

C3 No, about the same performance-wise due to some human inconsistency in moving the ball
C4 Yes, more practice. Much better.
C5 No, I was not hitting as often as I was capable of. Couldn't get into the groove, really.
C6 Yes, better hit average
C7 No, a bit lower average
C8 Yes, consistently got over 20 hits
C9 No, worse scores
CA No, same as above
Session 9
A1 No, could not get my frequency rhythmic
A2 No, disturbed by Test 2
A3 Yes, my average number of hits was higher
A4 Yes, seemed better without the training, i.e., no forced movement
A5 No, lower hit totals
A6 Yes, I'm getting used to controlling without the guide now. This was probably the best I've done.
A7 About the same
A8 Highest score last time
A9 Yes, because I learned how to be constant in the movement
AA No, about the same
B1 No, same as last time
B2 No, about the same-repetition
B3 No, the same as above
B4 Yes, improvement with practice
B5 No, same
B6 Yes, I got my highest score to date (29)
B7 Yes, my average was higher, I believe. My results were more consistent.
B9 Yes, same as above
BA Same. I tried to go faster and failed.
BB Yes, I didn't do well last time.
C1 Yes, see answer for 1.
C2 Yes, I concentrated more on accuracy rather than speed, and I was able to hit more targets.
C3 Yes, same as above
C4 No, perhaps I am not so concentrated on it.
C5 No, I just couldn't aim properly. I don't know why, but I kept missing and going back to ellipses.
C6 Yes, more hits per section.
C7 No, same hits
C8 Yes, reached new personal best number of touches
C9 No, same
CA Yes, same as above
Session 10
A1 No, not sure, performance probably ? leveled
A2 Yes, less confused
A3 N/A

A4 Yes, better first movement on axis
A5 Yes, felt more in control
A6 No, likewise, last session's Test 3 was amazing. This session was good, but it wasn't an improvement.
A7 Yes, high score at 32. Just barely reaching squares makes a big difference.
A8 Yes, more consistent
A9 No, even with the ? of the path and the constant movement, sometimes I lost the control.
AA Hit counts were similar. No improvement in frequency which appears my limiting factor.
B1 Same as last time
B2 No, about the same
B3 Yes, I'm trying to make the ball move quickly so even I miss once or more, the score also could reach 23/trial
B4 Yes, improvement with practice
B5 No, same
B6 Yes, my scores were on average higher and the standard deviation was lower.
B7 No, same as above
B9 No, I tried new things this time. I tried to compare the usual technique with the new one (test 8)
BB No, there was a lot more interfering force
C1 Yes, I have found an effective way to hit the nodes
C2 Yes, I had more controlled movements because I didn't feel as rushed
C3 Nothing new
C4 Yes, I improve my frequency
C5 No, couldn't hit over 20. More wild careening
C6 No, same as above
C7 Nothing new
C8 Natural frequency
C9 Yes, better feel for axis
CA Same as above

Question 3

What did you learn or figure out (if anything) during this session that helped you improve your performance?
Session 2
A1 I needed to physically relax which led to less mental demand and my score escalated
A2 Body has memory as well, so performance could be enhanced by repetitive assisted practice
A3 Moving the joystick along the axis helped my performance
A4 First motion was off axis. Trying to make first motion on axis helps
A5 Loosen grip, relax hand
A6 I was moving the ball too much last time, so I was losing valuable seconds
A7 Stay exactly on the axis and oscillate back and forth
A8 Nothing; simple reinforcement
A9 How to prevent the circular motion a little
AA The direction of the first pull is the most crucial step

B1 It's better to let the purple ball move in a straight line instead of letting it circle around. In order to do this, I need to stable the position of the black ball. When the purple ball begins to circle around and being hard to control, I can slow down the movement of the black ball so that the purple ball can slow down, too.
B2 The most efficient technique
B3 Make the movement of the stick accurate and simple. The amplitude of the dot vibration on the screen should be a less as possible
B4 The joystick has its own applied forces I have to fight.
B5 I learned that the ball is unlikely to go off course given more momentum towards the target. Also, direction can easily be adjust when the ball reaches the very end of the string (farthest away)
B6 I learned that the best way to get high scores is to use an easy back-and-forth motion, on the joystick
B7 My strategy is to try to keep the ball moving in a straight line rather than in circular motion
B8 I learned to take it slow and steady and focus on trying to improve
B9 Keeping centered the black ball and harder toward the targets, measure velocity of the movement (frequency of the move) and its
BA
BB I think that by the end of the last one, I had the same pattern down that I used this time
C1 Nothing, I had already figured this out
C2 Keeping the black ball in line with the targets made the purple ball go through the targets rather than around them
C3 Nothing much, just improved on technique used last time
C4 The blue bar and the frequency are very important
C5 Straight lines really are the most efficient way to get somewhere! And not as much effect is necessary as I used.
C6 Nothing over the previous session
C7 Better feeling for natural frequency
C8 Staying on the axis between the two squares
C9 Axis and frequency
CA More mental: relax and try and find a rhythm
Session 3
A1 I learned how to make more gentle and subtle movements of the joystick; I also attempted to bring the black dot into the green square-this method often and easily caused a "strike" by the purple dot.
A2 Keep hand stable and static
A3 Nothing new
A4 Less force and movement-don't oversteer
A5 Once again, light grip, motion diagonally back and forth
A6 Nothing new since last session, I think
A7 Get the purple ball to just touch the 2 squares without overshooting too much
A8
A9 Nothing
AA
B1 It's essential to find a moderate speed so that I can control the ball movement in the most efficient way

B2 Go slow at the beginning
B3 I need to highly concentrate on the game, never miss one hit. Make the movement appropriate, not too large nor too small.
B4 To go slow and steady. Smoothly
B5 Less action=less reaction. Pull with minimum force to hit target. Thus, one feel less resistance going the other direction.
B6 I learned that I think that muscle memory is key to this exercise
B7 I just have to work on starting off smoother. If you start bad, it just goes downhill from there.
B9 Nothing new. However, the fact of knowing my score was good made me worry more about the final score of the trial.
BA I "learned" that faster rebound means more hits, with a drawback–less accuracy-sill try to master both.
BB No, I didn't learn or use anything new or different.
C1 Move the joystick in small movements
C2 Nothing new
C3 Started moving joystick in tighter oscillations to save time
C4 The blue line is very important
C5 I stopped fighting the pull of the joystick as I changed the direction of the "ball" on the string.
C6 Nothing
C7 Faster speed is not necessarily good
C8 Better at finding blue axis when bar not there
C9 Following purple really helps
CA Do not grip the joystick hard. A loose grip works best.
Session 4
A1 I'm making more subtle movements of the joystick, consistently hitting more targets
A2 Not that much
A3 Since I can hit the targets more accurately now, I was able to experiment with going faster.
A4 Use less pressure
A5 Same as before: telling myself to have loose grip
A6 The natural axis I swing the ball on is off the axis of the points
A7 Making ball barely pass through targets is not sufficient, must oscillate at certain frequency to make ball move quickly
A8 I am better at catching the square on the return bounce.
A9 I feel that with the more sessions I have, the better performance at the exercise.
AA The training makes me overcompensate (strength-wise) in the post-evaluation.
B1 Not really
B2 Go faster?
B3 I have to cope with the frustration exactly, which could influence my record. To improve my record (best record), I need to know the basic parameter of the game. Such as the elastic coefficient of the string.
B4 Minimizing movement of black dot, keeping it centered, while slinging purple dot along a linear path from square to square is the optimal method.
B5 I improved on the technique I developed in the previous session to be more consistent.
B6 I tried to keep the maximum displacement of the ball to a minimum, so I would waste time between target hits.

B7 Starting off slower gives you more control
B9 Nothing
BA Nothing
BB I was a little faster. It seemed to help a bit.
C1 Nothing
C2 Nothing new
C3 Nothing
C4 The blue bar is important
C5 I don't know if I figured anything outno great revelations today
C6
C7 Working on rhythm
C8 Stayed between squares better on Test 3
C9 Rhythm is important
CA Nothing
Session 5
A1 Relax and breathe: every time I was satisfied with my performance
A2 Instead of positive difference, I improved by learning from error-prone tendency
A3 Nothing new
A4 Just move joystick in correct direction to prevent circling
A5 Nothing
A6 I suppose I learned how to better imitate the training guide
A7 Have to start moving opposite direction before purple ball passes you
A8
A9 I felt I didn't improve my performance, but I think the training session helps you a lot.
AA Timing the frequency of the oscillations
B1 No
B2 Not really
B3 1. Feel easy if miss one hit. My best record is 22, but I can reach 21 even miss once or twice. So keeping composure can improve my average record. 2. To improve my best record, I should find out a way to make the ball move faster.
B4 No really
B5 Nothing much just did what I've been doing
B6 I tried to be more aggressive and move the joystick faster
B7 Just working to keep everything moving in a straight line between the points
B9 I need some time to focus in the task (?). The muscles of my arm seem to be used to the task, but the ? of executing the process must be clear. It's kind weird.
BA Slow and steady wins the race
BB Just starting out a little slower seemed to help
C1 Nothing
C2 Nothing new
C3 Keep the oscillations smaller, more small corrections
C4 I must do it correctly at the beginning
C5 I can move the ball a bit faster and control it better. Also, using the moving guide as a (very general) guide helped a little bit.
C6

C7 Increase speed for more hits
C8 Got closer to the natural freqauency
C9 Nothing
CA Nothing
Session 6
A1 "I ? conceded" to the feedback and the joystick! Also, I tried to strike the target in the forward stroke: big challenge
A2 Avoid unnecessary over-pull to increase accuracy
A3 N/A
A4 Starting motion is critical-take the first motion slowly
A5 move joystick very little, concentrate on one dot
A6 I was having shoulder pain from raising my arm too high, and raising the chair fixed that.
A7 Be more consistent, don't overshoot target.
A8
A9 How to correct the movement of the point when it gets out of the proper path
AA
B1 No
B2 Center the joystick as perfectly as possible, then it's easier to make the first one, and faster. Move joystick minimally.
B3 On the same condition, making the ball move in straight line is faster than making it more circularly. And the first hit is very important to improve the performance.
B4 N/A
B5 Nothing
B6 I learned to reduce the amplitude of my joystick swings
B7 Once you panic because you're messing us you tend to rush to try to make up hits but that doesn't work
B9 Position of ? right arm and even body have influence on the performance
BA Doing it in circles does not help performance. Believe more and more that slow and steady wins the race
BB Nothing new
C1 No
C2 You can hit more targets if you keep the black ball directly between the targets. The less the black ball moves the more likely it is for the purple ball to hit the targets
C3 No need to swing the joystick around or hard, controlled ? movements are easier to recover from and place less stress on the hand/wrist
C4 Frequency and strength are very important
C5 Well, I had to learn to avoid the guides all over again, since they were moving much faster than I was comfortable with today. Other than that, I'm too tired to innovate.
C6 Nothing
C7 Rhythm
C8 How to get the ball to oscillate quicker
C9 Nothing
CA Move the joystick a big faster possibly
Session 7
A1

A2 As I found the guidance being more helpful, I became more dependent on it; thus I lose focus more easily once the guidance is removed, but I recall the tempo aster a few runs.
A3 N/A
A4 First movement needs to be considered to get ball on proper axis
A5
A6 My performance depends on how quickly I can get the purple ball onto the axis
A7 Be more consistent
A8
A9 Nothing
AA
B1 N/A
B2 Not really
B3 1. The first movement of the joystick is very important. Making it straightforward to the green point in a line is a good start for me to break the record. 2. Making the ball move in a straight line is faster than in circular line.
B5 N/A
B6 Sleep deficit reduces mental focus.
B7 I learned to use a rocking motion to minimize my swing amplitude
B8 N/A
B9 I tried to use the velocity of the ? recuperative movement. It goes faster but requires more control. It can not be a good strategy.
BA The tempo can be increased by ? lunging the joystick back and forth. I will try this on my next test.
BB No, I used the same methods
C1 No, I already try to stay on the blue line even when it's not there
C2
C3 No, it's just a distraction now rather than an aid
C4 No, I have my own frequency
C5 The moving guide did, but the target fixed guide didn't do much for me. I just tried to move sort of with the moving guide. Even if I was slower than it, I'm faster than I have been.
C6 The fixed axis is useful
C7 To be led staying on the line
C8 Yes, because I was able to focus more on the natural frequency
C9 Yes, h elps me remember rhythm
CA No, just distracted
Session 8
A1
A2 Driving force ? be about out of force to the spring
A3 N/A
A4 Slow down movement if off axis then increase speed when on axis
A5
A6 I didn't learn anything this time.
A7 Be more consistent
A8 Improved travel distance of purple ball
A9 That I can improve my performance by doing it faster, but without losing the right movement

AA
B1 N/A
B2 Not really. I tried a different grip but my results were the same. My arm might have gotten a bit more sore.
B3 Find out the way to make the ball more faster.
B4 N/A
B5 I started pulling the opposite direction as the ball passes through the center of the plane. This change in ?tone is very prone to directional error, reducing my consistency. However, it allows the ball to oscillate faster and achieve higher scores.
B6 I was more aggressive with my joystick movements
B7
B9 Nothing
BA Launching the ball does work, it's just a matter of accuracy. With improved accuracy, since the speed is already there, I will improve.
BB No, not really
C1 Nothing
C2 Nothing new
C3 Nothing this time
C4 Increasing frequency plays a key role
C5 It's a bit easier to aim if you don't overshoot by 2 or 3 times the distance to the square (duh)!
C6 Nothing new
C7 Nothing
C8 I feel that I am really getting good at oscillating at the machines natural frequency
C9 No
CA Nothing
Session 9
A1 Need a rhythm!
A2 No
A3 N/A
A4 Start slower
A5
A6 Nothing that I didn't already know.
A7 Keep the rhythm steady
A8
A9 That being constant helps you to get to a higher performance
AA
B1 N/A
B2 No
B3 Moving the joystick to the opposite direction of the ball's movement would make the ball move faster. This will need a lot more physical demand and technique
B4 N/A
B5 Nothing
B6 I used a lot of force moving the ball across the screen. This led to shorter times between hits and larger scores.
B7 Don't rush because that only causes unnecessary errors.

B9 The control of the joystick. It is enough to hold the top of the device to make the ball do the movements I wanted. This improved my confidence doing the tasks.
BA
BB Nothing
C1 Yes, see answer for 1 and 2.
C2 It's better to focus on making slow but precise movements rather than less accurate fast movements because it's hard to regain control when the ball is moving that fast.
C3 Continue to u se light touch for adjustment
C4 Yes, concentration and frequency are both important.
C5 Nothing. My performance was terrible for no reason at all.
C6 The first few movements are key to getting more hits in one section.
C7 Nothing really
C8 Natural frequency
C9 Nothing
CA Same, learned not to swing the ball so far out
Session 10
A1 Sometimes my increased frequency caused the paddle to swell
A2 Focus on the temporal manipulation
A3 N/A
A4 First movement on axis
A5
A6 Nothing
A7 By barely touching squares, more targets can be hit within the time limits
A8
A9
AA
B1 N/A
B2 No
B3 Practice more to make the ball move more quickly and accurately as I did in the previous tests
B4 A great deal more concentration is necessary to get into the proper rhythm at the start of a trial than is required to maintain that rhythm.
B5 Nothing
B6 I tried to go "all out," even if that meaning making a few mistakes.
B7
B9 Nothing
BB I couldn't use the same method because of the ? force. I had to keep the black ball at the bottom and aim for the targets one at a time.
C1 Keep concentrating on only one node throughout the session.
C2 Nothing new
C3 Nothing new
C4 Improving frequency
C5 If my performance didn't improve, then I don't think I learned anything. I don't feel like I learned anything.
C6
C7 Nothing new

C8 Natural frequency
C9 Move faster back and forth
CA No

Question 5

Did the guidance help you? If so how?
Session 2
A1 No, it generated muscle tension in my elbow and bicep, and my score went down
A2 It generally helped, but when I made an error it makes it harder to get back on the right track
A3 Yes, it kept me from trying to overcompensate when I missed (which was previously causing me to waste a lot of time)
A4 Yes, helped feel the correct amount of joystick movement and frequency
A5 Yes, after I got used to it, kept me on correct axis
A6 It helped and hurt, I guess. It threw off my personal sense of the axis, but it helped me in getting the oscillation frequency
A7 Somewhat, but if I got off rhythm I felt like I was pushing against something all the time
A8 Once I realized how the guidance worked, it helped. Instead of controlling the stick, I just let it move on the path of least resistance
A9 Yes, by pushing me to do the right motion
AA Not much. I'm not convinced the increased speed is an advantage considering the extra distance it requires you to travel
C1 No, I found the excitation frequency was distracting
C2 Yes. It was easier to keep the black ball in line with the visual aid present
C3 To some extent; the frequency was useful, to make swing more efficient length-wise. The bar, not so much; I just seem to have a problem moving the stick
C4 Yes, tell me the direction where I shall move the joystick
C5 The axis error did, but the excitation frequency was just distracting (since I was trying to go for accuracy, not speed).
C6 I felt like the axis reference bar was the most helpful. I found the moving frequency bar to be distracting.
C7 Definitely helped, especially the frequency bar
C8 The bar along the axis helped to visualize the axis. The frequency bar did not help at all; in fact, it made it difficult to focus on staying on the axis.
C9 No, green didn't start delayed
CA Yes, my performance increased due to experience. The moving bars only distracted me from focusing on hitting the targets; rather I was trying to match the bars.
Session 3
A1 Not sure; the moving guide tended to restrict my attempts at a longer movement of the black dot
A2 Yes, it "rulered" my hand
A3 At first it helps but if it continues after a few seconds it makes it more difficult
A4 Not too much-didn't feel the guide was helping i.e. moving me to the correct movements of joystick
A5 Yes, it did, I was able to recover quicker in Test 3 this time too.
A6 Both; it helped my performance, but it left me confused when it disappeared.

A7 Yes, this time the guide was softer, so that I could move the joystick as I wanted to, but it still had resistance when I got off track.
A8 No, when the guidance was removed, adjusting took time.
A9 It reminded me again at the proper movement to hit the targets
AA I still feel that the guidance is something I'm fighting and when it goes away I'm completed thrown the first time.
C1 Maybe. It was helpful but again, it was also somewhat distracting.
C2 Having the blue line visual helped keep the ball on the axis between the two targets
C3 No, rely more on experience and trajectory analysis rather than the guides
C4 Yes, it helps me to control the frequency
C5 Target axis is still sort of useful in determining direction, but the moving guide just seems distracting
C6 Only the axis guide was actually helpful
C7 Helped keeping my hand on the "line" between targets
C8 Yes, because I was able to stay between the squares and at a better speed
C9 Yes, helped and middle line to follow
CA Yes, helped me to stay on line with the targets
Session 4
A1 Good question: I'll say "Yes" (C.F., 1 above); the moving guide allowed me more freedom or travel than I needed. That resulted in ? to make the subtle movements of the joystick.
A2 Not this time
A3 Yes, instead of distracting me it was minimal enough that I thought it helped
A4 Help feel the desired/optimum movement need for joystick
A5 Yes, although it was lighter this time (kept me on line)
A6 Yes, even though it's not as strong, I'm still getting better at swinging the ball
A7 No, guidance gave more realistic practicing environment for the actual evaluation
A8 Yes, guidance kept me on the optimal path
A9 So so, I feel that the moving guide helps me, but what I think is better, is the practice
AA No, it doesn't mimic the test situation enough
C1 No, not really. I can already mentally see a line connecting the two nodes.
C2 No, though I was able to keep the ball on the guideline, I wasn't always able to make the necessary adjustments to hit the targets because I was concentrating on the blue line
C3 No, it distracted me from just moving the ball back and forth due to movement of the guides; plus I feel I need to keep the blue ball in the target axis which is not always good
C4 Yes, it helps me to find the direction
C5 No, moving guide still distracting me-still can't get speed up that high and be accurate at the same time
C6 Just the axis guide was helpful
C7 Target axis helped
C8 Blue bar helped stay on axis
C9 Yes, line guides, green sets rhythm
CA Yes, once got used to it, but I have a different technique which doesn't match up so I have to switch
Session 5

A1 Yes, like in Session 4, the moving guide assisted me in making subtle and gentle movements of the joystick
A2 Yes, but it was a counter force
A3
A4 Yes, helped get the movement in the correct axis and prevent circling
A5 Kept me on track
A6 Yes, it gives you the best movement and teaches you how to do it yourself
A7 N/A
A8 Yes, only having the moving guide gives more transferable aid than both guidance methods together
A9 Yes, because it helps your brain and arm to get used to the proper movement.
AA The guidance still feels like too much of a handicap; when it's on, I'm not able to improve because it changes the environment too much.
C1 No, I still find it distracting and feel increased pressure to follow its lead.
C2
C3 No, it's more of a distraction at that point.
C4 I think so. But it's a pity that the joystick cannot work as normal.
C5 Target axis is still helpful, but now more in a peripheral vision sort of way. Moving guide's speed and distance are still not comfortable to me, but I could move in its general pattern.
C6 The moving guide is really just a distraction. The axis guide is helpful.
C7 Yes, both guides helped me increase hits by providing a visual guide to follow.
C8 Helped get in tune with natural frequency
C9 Yes, bar helps align still
CA Not really. It would be interesting to see if the test 2 was unguided.
Session 6
A1 Yes, the increased frequency seemed to improve my performance
A2 This time guidance helped concentrate on the temporal adjustment
A3 I think the guidance helps me most at the very beginning. It helps me start off going in exactly the right direction.
A4 Develop the feeling for the best movement
A5
A6 Yes, it corrects my weird axis when I swing the ball
A7 N/A
A8 Yes, more ? applicable to post-evaluation not to have target axis fixed
A9 It always helps me to remember which is the correct path of the moving point
AA No, it fails to mimic the testing situation. The correction is too extreme to be applicable to the post-evaluation performance.
C1 No, it's still distracting.
C2 The training session didn't really make a difference this time.
C3 No, it was a distraction.
C4 Yes, helped me to ensure the direction and frequency.
C5 No, not at all. The moving guide was too fast again, and I'm trying to hit a straight line without the target axis guide and only occasionally glancing at it. I still can't move in a straight line at the speed I need to.
C6 Target axis was useful, moving guide was distracting

C7 Not any more
C8 Focusing on staying on blue bar allowed me to focus more on my oscillations.
C9 Helped me remember rhythm and axis
CA No, just distracted me
Session 7
A1 Encouraged faster frequency of movement
A2 As said in part 3
A3 I think this helps me at the beginning. Once I get going there is little guidance but it helps me start going in the right direction
A4 Guidance helped keep the wrist motion on the proper axis-helped to feel that motion
A5
A6 Yes, even though it's faint, it still helps to stabilize my movements
A7 N/A
A8 N/A
A9 It always helps me to remember the proper movement and path
AA No, the frequency guidance isn't strong enough to help and the axis guide is too strong
C1 No, I already try to stay on the blue line even when its not there
C2
C3 No, it's just a distraction now rather than an aid
C4 No, I have my own frequency
C5 The moving guide did, but the target fixed guide didn't do much for me. I just tried to move sort of with the moving guide. Even if I was slower than it, I'm faster than I have been.
C6 The fixed axis is useful.
C7 To be led staying on the line
C8 Yes, because I was able to focus more on the natural frequency
C9 Yes, helps me remember rhythm
CA No, just distracted
Session 8
A1 Yes, reminded me to use increased frequency
A2 It helped me concentrate more on the tempo rather than straightening the path
A3
A4 Feel the on axis movement
A5 No, restricted motion, felt heavy
A6 Yes, it still found the true center, even if the positioning was off
A7 The stiffness was bad, arm got tired after 7-9 trials
A8 N/A
A9 I felt it just a little, but it was always helpful to remind you how you're supposed to do it
AA No, not similar enough to testing situation
C1 No, I've had it for weeks; I understand how it should help improve my performance.
C2
C3 No, still just a distraction
C4 Not so much because I have found the way to improve my performance
C5 Well, apparently, it did, since I became suddenly incapable of hitting things in the post-evaluation. But I still pay slightly more attention to the moving guide.
C6 By now the guides don't help much any more.

C7 No, wasn't there
C8 Helped get better at the natural frequency
C9 Yes, reminded me where axis is
CA Very little, just confused
Session 9
A1 N/A
A2 The guidance was initialized off the right track-whether it's on purpose or not, it's not helpful.
A3
A4 No, for first time felt guidance hurt performance rather than help
A5
A6 Actually, the guidance has gotten so slight I could barely feel it, so it didn't help much.
A7 N/A
A8 N/A
A9 Not much because I'm getting used to the proper movement.
A9 No, it's strong enough now I don't really do anything in training.
C1 No, it never does.
C2
C3 No, it's just a distraction.
C4 No, influence my frequency
C5 Kept me on the path, which I was apparently incapable of doing on my own today.
C6 Neither, by now I am about as good at the task as I will ever be
C7 Did not have it
C8 The blue bar helped me stay on the axis better
C9 Not really, used to it
CA Indifferent/unsure.
Session 10
A1 N/A
A2 Yes, the axis fixed guide helped me focus better.
A3
A4 Not much
A5
A6 It did help me, but only very slightly. It corrected me just a little bit when I got off course.
A7 N/A
A8 N/A
A9 It didn't help me because I didn't get anything. I'm on my own now with the knowledge of the past sessions.
AA No, the frequency (moving) guide is too difficult to interpret, so I still don't really know what the resonance is.
C1 No, I just ignore it
C2
C3 No, especially since trying to move your hand at the speed of the moving guide tires out my hand/wrist pretty quickly
C4 Yes, help me to increase my frequency

C5 It reflects badly on me that I started missing more when the fixed guide became fainter except I never looked at it (even peripherally) anyway. I think I was trying to match the moving guide, and that didn't help at all.
C6 Not really. By now I know what to do.
C7 No guidance
C8 Not really because they were very faint
C9 Yes, helped me find center
CA A bit with my rhythm

Appendix C

Source code Progressive Haptic Guidance Scheme

```
//Haptic-Function Thread   ************************************

// Updates force and position
void --stdcall Haptic-Function(void *pv)
{
//  V.a. Initialization of local variables
**********************************************
int j = numtrials/FILE_SAMPLING;
float m_tool = 1;
float target_dist;
float K_field = 400, xacc_tool, yacc_tool;
float lambda = 5;
float K_p = 70;
//float Guide_K_p = 100; // Globalized for tying to guidance
float K_d = 1;
float Guide_K_d = .2; //was 100
int assist_counter=0;

float PosTool_inline;
float VelTool_inline = 0;


if (j>snumpts)
j = snumpts - 1;

force[0] = 0;
force[1] = 0;

// V.b.  Get raw Postion and record
****************************************

// Get the current position of the device put in NewPosition
Imp_EncMultiInput(IE_DEVICE_N, 0x03, NewPosition);


NewPosition[0] *= -1; //correct sign of x-coordinate
```

```
NewPosition[0] = NewPosition[0] + 3000;  //jch added to be a
NewPosition[1] = NewPosition[1] + 3000;  //jch added

xpos_tool = slope*(float)NewPosition[0] / 3000; //adjust to
ypos_tool = (float)NewPosition[1] / 3000;


// choose one of the methods to calculate velocity
//Get the current velocity of the device and put in NewVelocity
Imp_EncMultiVel(IE_DEVICE_N, 0x03, NewVelocity);
//hardware velocity calculation
//xvel_tool = (xpos_tool - oldxpos_tool)
/ ((float)HAPTICS_UPDATE_PERIOD/1000);
//offline velocity calculation
//yvel_tool = (ypos_tool - oldypos_tool)
/ ((float)HAPTICS_UPDATE_PERIOD/1000);

xvel_tool = slope*(float)NewVelocity[0] /3000;
yvel_tool = -1*(float)NewVelocity[1] /3000;

PosTool_inline = ((1/(2*sqrt(2)))*xpos_tool)+
((1/(2*sqrt(2)))*ypos_tool);
VelTool_inline = ((1/(2*sqrt(2)))*xvel_tool)+
((1/(2*sqrt(2)))*yvel_tool);


xacc_tool = (xvel_tool - oldxvel_tool)/ ((float)
HAPTICS_UPDATE_PERIOD/1000);
yacc_tool = (yvel_tool - oldyvel_tool)/ ((float)
HAPTICS_UPDATE_PERIOD/1000);

oldxpos_tool = xpos_tool;
oldypos_tool = ypos_tool;

oldxvel_tool = xvel_tool;
oldyvel_tool = yvel_tool;

//distvector = the current position of the disc in the
//reference frame of the device
distvector[0] = discPosition[0] - xpos_tool;
distvector[1] = discPosition[1] - ypos_tool;

//distnorm = the length of distvector
```

```
distnorm = sqrt(distvector[0]*distvector[0] +
distvector[1]*distvector[1]);

//force due to spring =
forcespring[0] = spring_k * (distnorm - FREESPRING) *
distvector[0] / distnorm;
forcespring[1] = spring_k * (distnorm - FREESPRING) *
distvector[1] / distnorm;

//velvector = the current velocity of the disc in the
// reference frame of the device
velvector[0] = discVelocity[0] - xvel_tool;
velvector[1] = discVelocity[1] - yvel_tool;

//force due to damper = B * velocity
forcedamper[0] = damper_b * velvector[0];
forcedamper[1] = damper_b * velvector[1];

//forcespring_e[0]=0;
//forcespring_e[1]=0;

// V.c.  Haptic Guidance Calculations
**********************************************

if(HAPTIC_GUIDANCE)
{

//Tracker Frequency and Amplitude
float h_amplitude = .16; //.12; //tracker;
//In version 7 was set to 0.16
//float h_freq = trackfreq; // sent to a global variable
float h_track = h_amplitude * ( sin(((time_now/25)/
(2*3.1418))*h_freq)); // haptic tracking point
float posinwall = 0;
float inwall = (wall_location + wall_thickness);
float outwall = (wall_location - wall_thickness);
//jchh variables for guidance walls
float guide_thickness = .1; // 1/2 the total guide thickness
//float guide_location = .01; // still tbd but worked with .075
float posinguide = 0;
float g_loc = .03; //guide distance from haptic track
float   pt4 = (g_loc + guide_thickness);  // in guide right max
float   pt3 = (g_loc - guide_thickness); // out guide right min
float   pt2 =  (-g_loc + guide_thickness); // out guide left min
float   pt1 =  (-g_loc - guide_thickness); // in guide left max
```

```
// end jch variables


//Potential forces  to prevent deviation from desired trajectories
float angleForce[2], PosTool, VelTool;
//Potential force  to guide in the desired trajectories


// jch adding code to improve the virtual walls to be cubic with a
//maximum force
if(TARGET_SET_FLAG < 2 )
{
PosTool=((1/(2*sqrt(2)))*xpos_tool)-
((1/(2*sqrt(2)))*ypos_tool);
VelTool=((1/(2*sqrt(2)))*xvel_tool)+
((1/(2*sqrt(2)))*yvel_tool);
angleForce[0] = 0;
//angle force in line (for just virtual walls w/no guidance

// conditionals for virtual wall penetration

if ((PosTool > -outwall) && (PosTool < outwall))
//between walls
{
angleForce[1]= 0;
}
else if (PosTool <= -inwall)
// beyond penetration of neg side wall
{
angleForce[1] = wall_maxforce;
//angleForce[1] = 0;
}
else if (PosTool >= inwall)
//beyond penetration of positive side wall
{
angleForce[1] = -wall_maxforce;
//angleForce[1] = 0;
}
else if ((PosTool > outwall) && (PosTool < inwall))
// penetrating positive side wall
{
posinwall = (PosTool - outwall)/(inwall - outwall);
        angleForce[1] = -(-2*(posinwall*posinwall*posinwall) +
        3*(posinwall*posinwall))*wall_maxforce;
//angleForce[1] = 0;
```

```
}
else if ((PosTool < -outwall) && (PosTool > -inwall))
// penetrating negative side wall
{
posinwall = (PosTool - (-outwall))/((-inwall) -
(-outwall));
    angleForce[1] = (-2*(posinwall*posinwall*posinwall)  +
     3*(posinwall*posinwall))*wall_maxforce;
//angleForce[1] = 0;

}

else // between walls repeated
{
angleForce[1] = 0;
}

// moving guide conditionals


//PD Controller
angleForce[0] = ((h_track - PosTool_inline )
/guide_thickness)*Guide_K_p + VelTool_inline * Guide_K_d;

}

forcepotential[0]=((1/sqrt(2))*angleForce[0])+((1/sqrt(2))
*angleForce[1]);//*.8;  // removed .8 scale factor
forcepotential[1]=((1/sqrt(2))*angleForce[0])-((1/sqrt(2))
*angleForce[1]);//*.8;  // removed .8 scale factor
// note: version 7 error in equations:
//       was *sqrt(2) but now changed to 1/(sqrt(2))
//for correct calculation
//  had to change Guide_Kp and wall_maxforce
//from 100 to 200 to give
//  similar results as NFV2008-1.

}
//  V.c.  END OF  HAPTIC_GUIDANCE
*****************************************************************

else
{
forcepotential[0] = 0;
forcepotential[1] = 0;
```

```
}

//  V.d. New Postion and Forces calcuation
*****************************************************

//net force felt = force due to spring + force due to damper
force[0] = forcespring[0] + forcedamper[0];
force[1] = forcespring[1] + forcedamper[1];
//TotalForce[0] = forcespring[0] + forcedamper[0];


//Set up new position, velocity, and acceleration
//of disc according to Newtonian mechanics
discPosition[0] += discVelocity[0]*HAPTICS_UPDATE_PERIOD/1000 +
0.5*discAccel[0]*(HAPTICS_UPDATE_PERIOD/1000)*
(HAPTICS_UPDATE_PERIOD/1000);
discPosition[1] += discVelocity[1]*HAPTICS_UPDATE_PERIOD/1000 +
0.5*discAccel[1]*(HAPTICS_UPDATE_PERIOD/1000)*
(HAPTICS_UPDATE_PERIOD/1000);

discVelocity[0] += discAccel[0]*HAPTICS_UPDATE_PERIOD/1000;
discVelocity[1] += discAccel[1]*HAPTICS_UPDATE_PERIOD/1000;


discAccel[0] = -1*force[0]/mass;
discAccel[1] = -1*force[1]/mass;

target_dist = sqrt((discPosition[0] -
x_target[ACTIVE_TARGET_FLAG])*(discPosition[0] -
x_target[ACTIVE_TARGET_FLAG])
+ (discPosition[1] -  y_target[ACTIVE_TARGET_FLAG])
*(discPosition[1] -  y_target[ACTIVE_TARGET_FLAG]));

//  V.e.  Collision Detection
**********************************************************
if(target_dist <= (TARGET_RADIUS/100) + (DISC_RADIUS/100))
{

if(ACTIVE_TARGET_FLAG == 0)
ACTIVE_TARGET_FLAG = 1;
else
ACTIVE_TARGET_FLAG = 0;
no_of_hits++;
hit_interval=time_now-time_old;
time_old = time_now;
```

```
}


// V.f.  Write out the force to the joystick command
**************************************************************

force[1] = -force[1]; //correct sign of y-coordinate

// lastforce[0] = force[0]; //save force for debugging display
// lastforce[1] = force[1];


// Adjusting force
AssForce[0] = (forcepotential[0] + 0.5*forcecomplete[0])
* FORCEMULT;
TotalForceX= (force[0] + forcepotential[0] +
.5*forcecomplete[0])* FORCEMULT;

AssForce[1] = (forcepotential[1] + 0.2*forcecomplete[1])
* FORCEMULT;
TotalForceY = (force[1] - forcepotential[1] -
.2*forcecomplete[1])* FORCEMULT;

outforce[0] = slope*TotalForceX;
outforce[1] = TotalForceY;

if (MOTORS_ON == FALSE)
// turn off motors whenever the haptic loop is stopped
{
outforce [0] = 0;
outforce[1] = 0;
}

Imp_DacMultiOutput(IE_DEVICE_N, 0x07 , outforce);


// V.g.  Input to the file variables
*****************************************************

if(time_now!=0)
{
if((timer%FILE_SAMPLING)==0)  // this is every sample period
{
toolx[numpts] = xpos_tool; // Values to be printed to file
```

```
tooly[numpts] = ypos_tool;
discx[numpts] = discPosition[0];
discy[numpts] = discPosition[1];
numpts++;
}

}
else
{
for(int i=0; i<numpts; i++)
{
toolx[i] = 0;
tooly[i] = 0;
discx[i] = 0;
discy[i] = 0;
}

numpts=0;
}


time_now++;
timer++;

if ((timer%FILE_SAMPLING)==0)
{
if (!Practice)
{
no_of_sample++;
trial_sample++;

int assist, test;
if (HAPTIC_GUIDANCE)
assist=2; // group 4
else if (VISUAL_GUIDANCE)
assist=3;
else
assist=1;//group 1
if (Training)
{
if(Baseline)
test=1;
else
test=2;
}
```

```
else
test = 3;

data_assist[no_of_sample]=assist;
data_test[no_of_sample]=test;
data_mass[no_of_sample]=mass;
data_spring_k[no_of_sample]=spring_k;
data_damper_b[no_of_sample]=damper_b;
data_sys_set[no_of_sample]=sequence_sys;
data_trial[no_of_sample]=done+1;
data_xpos_tool[no_of_sample]=xpos_tool;
data_ypos_tool[no_of_sample]=ypos_tool;
data_discPosition_x[no_of_sample]=discPosition[0];
data_discPosition_y[no_of_sample]=discPosition[1];
data_xvel_tool[no_of_sample]=xvel_tool*3000;
data_yvel_tool[no_of_sample]=yvel_tool*3000;
data_discVel_x[no_of_sample]=discVelocity[0];
data_discVel_y[no_of_sample]=discVelocity[1];
data_x_target[no_of_sample]=x_target[ACTIVE_TARGET_FLAG];
data_y_target[no_of_sample]=y_target[ACTIVE_TARGET_FLAG];
data_TotalForceX[no_of_sample]=TotalForceX;
data_TotalForceY[no_of_sample]=TotalForceY;
data_AssForce_x[no_of_sample]=AssForce[0];
data_AssForce_y[no_of_sample]=AssForce[1];
data_no_of_hits[no_of_sample]=no_of_hits;
data_VisualControlGainX[no_of_sample] = VisualControlGainX;
data_VisualControlGainY[no_of_sample] = VisualControlGainY;
data_ForceControlGainX[no_of_sample] = ForceControlGainX;
data_ForceControlGainY[no_of_sample] = ForceControlGainY;
//data_VelocityConsistency[no_of_sample] = VelocityConsistency;
data_hit_interval[no_of_sample]=hit_interval;
data_timer[no_of_sample]= timer;
trialdata_traj_error[trial_sample]
=slope*(((1/(2*sqrt(2)))*discPosition[0])-((1/(2*sqrt(2)))*
discPosition[1]));//added slope version 9
trialdata_freq_error[no_of_sample] =
trial_freq_error[no_of_trial];
}
}
}
//   V. END OF Haptic Function Thread  ****************
```

Bibliography

[1] J. J. Abbott and A. M. Okamura. Stable forbidden-region virtual fixtures for bilateral telemanipulation. *Journal of Dynamic Systems, Measurement, and Control*, 128(1):53–64, 2006.

[2] B. Abernethy, D. Farrow, and J. Berry. Constraints and issues in the development of a general theory of expert perceptual-motor performance. In J. Starkes and K. A. Ericsson, editors, *Expert Performance in Sports: Advances in Research on Sport Expertise*, pages 349–369. Human Kinetics, Champaign, IL, 2003.

[3] B. Abernethy, R. Neal, and P. Koning. Visual-perceptual and cognitive difference between expert, intermediate, and novice snooker players. *Applied Cognitive psychology*, 8(3):185–211, June 1994.

[4] B. Abernethy, K. T. Thomas, and J. T. Thomas. Strategies for improving understanding of motor expertise [or mistakes we have made and things we have learned!!]. In J. Starkes and F. Allard, editors, *Cognitive Issues in Motor Expertise*, pages 317 – 356. Elsevier Science/North-Holland, Amsterdam, Netherlands, 1993.

[5] R. J. Adams, D. Klowden, and B. Hannaford. Virtual training for a manual assembly task. *Haptics-e Journal, IEEE Robotics & Automation Society*, 2(2):1–7, 2001.

[6] C. Basdogan, S. De, J. Kim, M. Muniyandi, H. Kim, and M. Srinivasan. Haptics in minimally invasive surgical simulation and training. In *Proc. IEEE Computer Graphics and Applications*, volume 24, pages 56–64, 2004.

[7] B. Bayart, A. Pocheville, and A. Kheddar. An adaptive haptic guidance software module for I-TOUCH: example through a handwriting teaching simulation and a 3D maze. In *IEEE International Workshop on Haptic Audio Visual Environments and their Applications*, pages 51–56, Ottowa, Canada, October 2005.

[8] B. S. Bell and S. W. J. Kozlowski. Adaptive Guidance: Enhancing Self-Regulation, Knowledge, and Performance in Technology-Based Training. *Personnel Psychology*, 55(2):267–306, 2002.

[9] N. Bernstein. *The Coordination and Regulation of Movements*. Pergamon, London, 1967.

[10] K. Bowen and M. K. O'Malley. Adaptation of haptic interfaces for a labview-based system dynamics course. In *Proc. IEEE 14th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS'06)*, pages 147–152, 2006.

[11] G. Burdea. *Force and touch feedback for virtual reality*. Wiley, New York, 1996.

[12] C. R. Carnigan and C. K. R. Close-loop force control for haptic simulation of virtual environments. *Haptics-e*, 1(2):1–14, 2000.

[13] O. Celik, M. K. O'Malley, C. Boake, H. Levin, S. Fischer, and T. Reistetter. Comparison of robotic and clinical motor function improvement measures for sub-acute stroke patients. In *Proc. IEEE International Conference on Robotics and Automation (ICRA '08)*, pages 2477–2482, Pasadena, CA, May 2008.

[14] D. Chang. Haptics: gaming's new sensation. *Computer*, 35(8):84–86, 2002.

[15] R. Colombo, F. Pisano, S. Micera, A. Mazzone, C. Delconte, M. C. Carrozza, P. Dario, and G. Minuco. Robotic techniques for upper limb evaluation and rehabilitation of stroke patients. 13(3):311–324, 2005.

[16] J. Dingwell, C. Mah, and F. Mussa-Ivaldi. Experimentally confirmed mathematical model for human control of a non-rigid object. *Journal of Neurophysiology*, 91(3):1158–1170, 2004.

[17] H. L. Dreyfus and S. E. Dreyfus. *Mind over Machine the Power of Human Intuition and Expertise in the Era of the Computer*. The Free Press, New York, NY, 1986.

[18] J. Emken and D. Reinkensmeyer. Robot-enhanced motor learning: accelerating internal model formation during locomotion by transient dynamic amplification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 13(1):33–39, March 2005.

[19] D. Feygin, M. Keehner, and F. Tendick. Haptic guidance: experimental evaluation of a haptic training method for a perceptual motor skill. In *Proc. IEEE 10th Symposium*

on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (HAPTICS'02), pages 40–47, Orlando, FL, March 2002.

[20] P. Fitts. Perceptual-motor skill learning. In A. Melton, editor, *Categories of Human Learning*, pages 243–285. Academic Press, New York, NY, 1964.

[21] P. Fitts and M. Posner. *Human Performance*. Brooks, Belmont, CA, 1st edition, 1967.

[22] T. Flash and N. Hogan. The coordination of arm movements: an experimentally confirmed mathematical model. *Journal of Neuroscience*, 5(7):1688–1703, 1985.

[23] A. G. Gallagher, E. M. Ritter, H. Champion, G. Higgins, M. P. Fried, G. Moses, C. Smith, and R. M. Satava. Virtual reality simulation for the operating room: proficiency-based training as a paradigm shift in surgical skills training. *Annals of Surgery*, 241(2):364–72, February 2005.

[24] R. B. Gillespie, M. O'Modhrain, P. Tang, D. Zaretzky, and C. Pham. The virtual teacher. In *Proc. of the ASME Dynamic Systems and Control Division*, pages 171–178, Anaheim, CA, Nov 1998.

[25] J. Glassmire, M. O'Malley, W. Bluethmann, and R. Ambrose. Cooperative manipulation between humans and teleoperated agents. In *Proc. IEEE 12th International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS'04)*, pages 114–120, March 2004.

[26] I. Goncharenko, M. Svinin, S. Forstmann, Y. Kanou, and S. Hosoe. On the Influence of Arm Inertia and Configuration on Motion Planning of Reaching Movements in Haptic Environments. In *Proc. IEEE Second Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems (WHC '07)*, pages 33–38. IEEE Computer Society Washington, DC, 2007.

[27] P. Griffiths and B. Gillespie. Shared control between human and machine: using a haptic steering wheel and aid in land vehicle guidance. In *Proc. IEEE 12th International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS '04)*, pages 358–366, Chicago, IL, March 2004.

[28] P. G. Griffiths and R. Gillespie. Sharing Control Between Humans and Automation Using Haptic Interface: Primary and Secondary Task Performance Benefits. *Human Factors*, 47(3):574, 2005.

[29] P. A. Hancock. Effects of control order, augmented feedback, input device and practice on tracking performance and perceived workload . *Ergonomics*, 39(9):1146–1162, 1996.

[30] S. G. Hart and L. E. Staveland. Development of NASA-TLX (Task Load Index): results of empirical and theoretical research. In P. Hancock and N. Meshkati, editors, *Human Mental Workload*, pages 139 – 183. Elsevier Science/North-Holland, Amsterdam, Netherlands, 1988.

[31] W. Harwin, J. Patton, and V. Edgerton. Challenges and opportunities for

robot-mediated neurorehabilitation. In *Proceedings of the IEEE*, volume 94, pages 1717–1726, 2006.

[32] K. Henmi and T. Yoshikawa. Virtual lesson and its application to virtual calligraphy system. In *Proc. IEEE International Conference on Robotics and Automation, (ICRA 1998)*, pages 1275–1280, Leuven, Belgium, May 1998.

[33] N. Hogan and D. Sternad. On rhythmic and discrete movements: reflections, definitions and implications for motor control. *Experimental Brain Research*, 181(1):13–30, 2007.

[34] F. C. Huang, R. B. Gillespie, and A. D. Kuo. Visual and haptic feedback contribute to tuning and online control during object manipulation. *Journal of Motor Behavior*, 39(3):179–193, May 2007.

[35] J. C. Huegel, O. Celik, A. Israr, and M. K. O'Malley. Expertise-Based Performance Measures in a Training Virtual Environment. *Presence: Teleoperators and Virtual Environments*, 2009 (in review).

[36] J. C. Huegel, A. J. Lynch, and M. K. O'Malley. Validation of a Smooth Movement Model for a Human Reaching Task. In *Proc. IEEE 11th International Conference on Rehabilitation Robotics (ICORR 2009)*, Kyoto, Japan, June 2009 (accepted).

[37] J. C. Huegel and M. K. O'Malley. Visual versus Haptic Progressive Guidance for Training in a Virtual Dynamic Task. In *Proc. IEEE Third Joint Eurohaptics*

Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '09), Salt Lake City, UT (in press), 2009b.

[38] A. Israr, H. Kapson, V. Patoglu, and K. O'Malley, Marcia. Effects of magnitude and phase cues on human motor adaptation. In *Proc. IEEE Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '09)*, Salt Lake City, UT. (in press), March 2009.

[39] R. S. Kalawsky, S. T. Bee, and S. P. Nee. Human Factors Evaluation Techniques to Aid Understanding of Virtual Interfaces. *BT Technology Journal*, 17(1):128–141, January 1999.

[40] A. Karni, G. Meyer, C. Rey-Hipolito, P. Jezzard, M. M. Adams, R. Turner, and L. G. Ungerleider. The acquisition of skilled motor performance: Fast and slow experience-driven changes in primary motor cortex. In *Proceedings of the National Academy of Sciences*, volume 95, pages 861–868, 1998.

[41] T. Kotoku, K. Takamune, and K. Tanie. A virtual environment display with constraint feeling based onposition/force control switching. In *Proceedings 3rd IEEE International Workshop on Robot and Human Communication, 1994. RO-MAN'94*, pages 255–260, Nagoya, Japan, 1994.

[42] J. Kozak, P. A. Hancock, E. Arthur, and S. Chrysler. Transfer of training from virtual reality. *Ergonomics*, 36(7):774–784, 1993.

[43] Y. Li. *Shared Control: Active Haptic Assistance for Motor Skill Training in Virtual Environments*. PhD thesis, Rice University, 2008.

[44] Y. Li, J. C. Huegel, V. Patoglu, and M. K. O'Malley. Progressive shared control for training in virtual environments. In *Proc. IEEE Third Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '09)*, Salt Lake City, UT (in press), 2009b.

[45] Y. Li, V. Patoglu, and M. K. O'Malley. Shared control for training in virtual environments: Learning through demonstration? In *Proceedings of EuroHaptics*, pages 93 – 99, Paris, France, 2006.

[46] Y. Li, V. Patoglu, and M. K. O'Malley. Negative efficacy of fixed gain error reducing shared control for training in virtual environments. *ACM Transactions on Applied Perception*, 6(1):21, January 2009.

[47] G. Lintern, S. N. Roscoe, J. M. Koonce, and L. D. Segal. Transfer of landing skills in beginning flight training. *Human Factors*, 32(3):319–327, 1990.

[48] G. Lintern, S. N. Roscoe, and J. Sivier. Display principle, control dynamics, and environmental factors in pilot training and transfer. *Human Factors*, 32(3):299–317, 1990.

[49] J. Liu, J. Emken, S. Cramer, and D. Reinkensmeyer. Learning to perform a novel movement pattern using haptic guidance: slow learning, rapid forgetting, and

attractor paths. In *Proc. IEEE 9th International Conference on Rehabilitation Robotics (ICORR 2005)*, Chicago, IL.

[50] A. Luximon and R. S. Goonetilleke. Simplified subjective workload assessment technique. *Ergonomics*, 44(3):229–243, 2001.

[51] T. Massie and J. Salisbury. The phantom haptic interface: A device for probing virtual objects. In *Proceedings of the ASME Winter Annual Meeting, Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, volume 55, pages 295–300, 1994.

[52] N. Meshkati and A. Loewenthal. An eclectic and critical review of four primary mental workload assessment methods: a guide for developing a comprehensive model. In P. Hancock and N. Meshkati, editors, *Human Mental Workload*, pages 251 – 268. Elsevier Science/North-Holland, Amsterdam, Netherlands, 1964.

[53] D. Morris, H. Tan, F. Barbagli, T. Chang, and K. Salisbury. Haptic training enhances force skill learning. In *Proc. IEEE Second Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems, (WHC '07)*, pages 21–26, Tsukuba, Japan, March 2007.

[54] NASA-TLX. Computerized version, 1986. http://humansystems.arc.nasa.gov/groups/TLX/computer.php. Moffett Field, CA: NASA-Ames Research Center, Aerospace Human Factors Research Division.

[55] V. Nistor, B. Allen, E. Dutson, P. Faloutsos, and G. P. Carman. Immersive training and mentoring for laparoscopic surgery. In *Proc. SPIE Nanosensors, Microsensors and Biosensors and Systems 2007*, volume 6528, pages 1–11, San Diego, CA, 2007.

[56] M. O'Malley, A. Sledd, A. Gupta, V. Patoglu, J. Huegel, and C. Burgar. The RiceWrist: A distal upper extremity rehabilitation robot for stroke therapy. In *ASME International Mechanical Engineering Congress and Exposition*, 2006.

[57] M. K. O'Malley and A. Gupta. Passive and active assistance for human performance of a simulated underactuated dynamic task. In *Proc. IEEE 11th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS '03)*, pages 348–355, Los Angeles, CA, March 2003.

[58] M. K. O'Malley and A. Gupta. Skill transfer in a simulated underactuated dynamic task. In *Proc. IEEE International Workshop on Robot and Human Interactive Communication*, pages 315–320, Millbrae, CA, Oct-Nov 2003.

[59] M. K. O'Malley and A. Gupta. Haptic interfaces. In P. Kortum, editor, *HCI beyond the GUI: Design for Haptic, Speech, Olfactory, and other nontraditional Interfaces*, pages 25–73. Elsevier, New York, 2008.

[60] M. K. O'Malley, A. Gupta, M. Gen, and Y. Li. Shared Control in Haptic Systems for Performance Enhancement and Training. *Journal of Dynamic Systems, Measurement, and Control*, 128:75–86, 2006.

[61] R. V. O'Toole, R. R. Playter, T. M. Krummel, W. C. Blank, N. H. Cornelius, W. R. Roberts, W. J. Bell, and M. Raibert. Measuring and developing suturing technique with a virtual reality surgical simulator. *Journal of the American College of Surgeons*, 189(1):114–127, 1999.

[62] J. Patton and F. Mussa-Ivaldi. Robot-assisted adaptive training: custom force fields for teaching movement patterns. *IEEE Transactions on Biomedical Engineering*, 51(4):636–646, 2004.

[63] G. Reid and T. Nygren. The subjective workload assessment technique: a scaling procedure for measuring mental workload. In P. Hancock and N. Meshkati, editors, *Human Mental Workload*, pages 185 – 218. Elsevier Science/North-Holland, Amsterdam, Netherlands, 1988.

[64] D. Reinkensmeyer, D. Aoyagi, J. Emken, J. Galvez, W. Ichinose, G. Kerdanyan, J. Nessler, S. Maneekobkunwong, B. Timoszyk, K. Vallance, et al. Robotic gait training: toward more natural movements and optimal training algorithms. In *Proceedings IEEE 26th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC 2004)*, volume 2, pages 4819–4821, San Francisco, CA, September 2004.

[65] D. Reinkensmeyer, J. Emken, and S. Cramer. Robotics, Motor Learning, and Neurologic Recovery. *Annual Review of Biomedical Engineering*, 6(1):497–525, 2004.

[66] J. Rosen, B. Hannaford, C. G. Richards, and M. N. Sinanan. Markov modeling of minimally invasive surgery based on tool/tissue interaction and force/torque signatures for evaluating surgical skills. *IEEE Transactions on Biomedical Engineering*, 48(5):579–591, May 2001.

[67] L. B. Rosenberg. The use of virtual fixtures to enhance operator performance in time delayed teleoperation. *Journal of Dynamic Systems Control*, 49:29–36, 1993.

[68] L. B. Rosenberg. Virtual fixtures: Perceptual tools for telerobotic manipulation. In *Proc. of the IEEE Annual Int. Symposium on Virtual Reality*, pages 76–82. IEEE, September 1993.

[69] E.-L. Sallnäs, K. Rassmus-Gröhn, and C. Sjöström. Supporting presence in collaborative environments by haptic force feedback. *ACM Transactions on Computer-Human Interaction*, 7(4):461–476, December 2000.

[70] R. Shadmehr and S. P. Wise. *The Computational Neurobiology Of Reaching And Pointing: A Foundation for Motor Learning*. Bradford Books, 2005.

[71] J. Shea and R. Morgan. Contextual Interference Effects on the Acquisition, Retention, and Transfer of a Motor Skill. *Journal of Experimental Psychology: Human Learning and Memory*, 5(2):179–87, 1979.

[72] G. Srimathveeravalli, V. Gourishankar, and T. Kesavadas. Comparative study: virtual fixtures and shared control for rehabilitation of fine motor skills. In *Proc. IEEE*

Second Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environments and Teleoperator Systems (WHC '07), pages 304–309, Tsukuba, Japan, March 2007.

[73] G. Srimathveeravalli and K. Thenkurussi. Motor skill training assistance using haptic attributes. In *Proc. IEEE First Joint Eurohaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, (WHC '05)*, pages 452–457, March 2005.

[74] I. E. Sutherland. *Sketchpad: A man-machine graphical communication system.* PhD thesis, Massachussets Institute of Technology, 1965.

[75] I. E. Sutherland. The ultimate display. In *Proceedings of IFIP Congress 2*, 1965.

[76] L. M. Sutherland, P. F. Middleton, A. Anthony, J. Hamdorf, P. Cregan, D. Scott, and G. J. Maddern. Surgical simulation: a systematic review. *Annals of Surgery*, 243(3):291–300, March 2006.

[77] M. Svinin, I. Goncharenko, Z. Luo, and S. Hosoe. Reaching Movements in Dynamic Environments: How Do We Move Flexible Objects? *IEEE Transactions on Robotics*, pages 724 – 739, 2006.

[78] H. Tan, M. Srinivasan, B. Eberman, and B. Cheng. Human factors for the design of force-reflecting haptic interfaces. *ASME Dynamic Systems and Control*, 55(1):353–359, 1994.

[79] E. Todorov, R. Shadmehr, and E. Bizzi. Augmented feedback presented in a virtual environment accelerates learning of a difficult motor task. *Journal of Motor Behavior*, 29(2):147–158, June 1997.

[80] C. Tzafestas, K. Birbas, Y. Koumpouros, and D. Christopoulos. Pilot evaluation study of a virtual paracentesis simulator for skill training and assessment: the beneficial effect of haptic display. *Presence: Teleoperators and Virtual Environments*, 17(2):212–229, 2008.

[81] A. Williams and K. Ericsson. Perceptual-cognitive expertise in sport: Some considerations when applying the expert performance approach. *Human Movement Science*, 24(3):283–307, 2005.

[82] Y. Yokokohji, R. L. Hollis, T. Kanade, K. Henmi, and T. Yoshikawa. Toward machine mediated training of motor skills - Skill transfer from human to human via virtual environment. In *Proc. IEEE 5th International Workshop on Robot and Human Communication, 1996*, pages 32–37, Tsukuba, Japan, Nov 1996.

[83] M. Zhou, D. Jones, S. Schwaitzberg, and C. Cao. Role of Haptic Feedback and Cognitive Load in Surgical Skill Acquisition. In *Proc. of the Human Factors and Ergonomics Society 51st Annual Meeting, 2007*, pages 631–635, Baltimore, MD, October 2007.