ABSTRACT

CLAMANN, MICHAEL PETER. Adaptive Haptic Forces in a Virtual Environment Improve Fine Motor Skill Training. (Under the direction of David B. Kaber).

Investigations of technological interventions to retrain motor skills using haptic control have included techniques that guide the patient (e.g., virtual fixtures) or challenge the patient (e.g., error amplification). Virtual fixtures are force fields or channels presented by a haptic device that prevent participants from deviating from a defined path based on expert performance. Error amplification increases the magnitude of errors when participants deviate from the desired path; that is, haptic forces are applied away from the desired path when errors occur.

Other training systems have incorporated adaptive aiding with haptic guidance. With adaptive aiding the intensity of virtual fixtures is modified (decreased) as operator performance improves. There is evidence that providing guidance when needed is more effective than a constant or fixed amount of assistance. Although haptic guidance has been found to enhance performance when engaged, it may not accelerate learning. To date, studies on learning effects of haptic guidance have not included adaptive aiding and haptic control using error amplification.

This research prototyped and evaluated a system that combined error amplification with adaptive aiding to determine the extent to which performance in a progressive error amplification condition transfers to an unassisted condition (i.e., a measure of skill learning).

Data collection included two phases, including: (1) unassisted drawing with a haptic device; and (2) drawing with a form of haptic guidance. In both phases participants were trained to draw a series of letter-like designs (letters from a foreign alphabet) with the non-dominant hand. Phase 1 was used to determine learning rates for participants drawing the letters without guidance in order to inform adaptive aiding schedules for Phase 2. In Phase 2, each participant received one of four forms of haptic guidance, including adaptive virtual fixtures, static virtual fixtures, adaptive error amplification or static error amplification (following a between-subjects experiment design). As participant performance improved under adaptive conditions, haptic aiding was modified; virtual fixtures were reduced and error amplification was increased. Improvements were measured objectively with comparisons of motion trajectories to a template (accuracy) and task time (speed). An unassisted test was presented after multiple training sessions. Performance was compared among the four guidance conditions to determine how training with virtual fixtures compared to error amplification with and without adaptive aiding, once haptic guidance is no longer engaged.

Results of the study were mixed. Task accuracy when training with virtual fixtures was greater than the error amplification condition, but improved virtual fixture accuracy did not transfer to the test scenario. Test accuracy following error amplification training was greater. However, task speed improvements were higher for virtual fixtures than error amplification. The error amplification condition provided more constant feedback, which caused participants to more frequently evaluate their progress, especially at greater difficulty levels.

These findings are expected to advance the design of VR systems for fine motor skill training. Future writing tutors as well as training programs for occupational domains where fine motor skills are required could benefit. Low level performance and learning data from the experiment could be used as a basis for developing a motor capability classification algorithm that could quickly assess a person's level of fine motor skill. This algorithm could be used in healthcare for determining appropriate therapy regimens for people recovering from impairment or in industry for identifying training levels for jobs requiring fine motor control.

Adaptive Haptic Forces in a Virtual Environment Improve Fine Motor Skill Training

by
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BIOGRAPHY

Michael Clamann was born in Washington DC to H. Peter and Eva Clamann. He is the grandson of Hans-Georg Clamann, a pioneer in the field of aerospace medicine.

Mr. Clamann received a dual degree in International Business and German from James Madison University in Harrisonburg, Virginia. After graduation, he worked as a software developer and designer until leaving the industry in the fall of 2000 to attend graduate school at North Carolina State University in Raleigh North Carolina.

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1 Introduction

1.1 Haptics for fine motor skill training

As innovation in computing power continues to advance, so does the sophistication of modern input and output devices. In the past 40 years, the technology market has seen computers grow from loud, room-filling devices requiring input from punch cards and providing output on rolls of paper fed through dot matrix printers, to immersive virtual environments (VE) with a variety of control devices such as wireless remotes with accelerometers and gesture-based interfaces controlled by the operator's movements (e.g., Microsoft Kinect). Haptic controls are another category of human-computer input devices that have received substantial attention in recent years. In the context of VEs, haptic systems include controls that combine sensing and motion capabilities to support user input and provide feedback (Kern, 2009). Haptic systems can vary in complexity and capability. A simple example of haptics is the vibration implemented in most cell phones that alerts us to incoming messages and warns us when the battery needs to be recharged. More complex implementations include virtual reality (VR) systems with haptic controls for surgical training (Banerjee, Luciano, Lemole, Charbel & Oh, 2007; Liu, Tendick, Cleary & Kaufmann, 2003) and teleoperations (Rosenberg, 1993).

Haptic systems also have tremendous potential for rehabilitation of fine motor skills following injury or stroke. Past studies show that the brain's motor planning and control system can reorganize with the application of motor practice in the form of physical therapy (Reinkensmeyer, Emken & Cramer, 2004). In traditional physical therapy following a loss of fine motor skills, a therapist will work with a patient to develop a customized regimen to help him or her redevelop occupational or personal skills that are of value to the patient. Due to this individual approach and the variety of goals and degrees of disability among patients, regimens can vary greatly from one patient to another. A therapist may employ a variety of low and high tech tools (manual and computer-based) to help patients achieve their rehabilitation goals.

Demand for advanced rehabilitative technologies to help patients redevelop fine motor skills is expected to continue. According to Reinkensmeyer and colleagues (2004), 80% of stroke survivors will experience a near-term loss of motor control, while 50% will have some form of long-term loss. In 2004, such loss was observed in 2 million people (Reinkensmeyer et al., 2004). As survival rates following strokes and traumatic brain injuries continue to increase due to ongoing improvements in the medical field (Harwin et al., 2006), there is increased demand for rehabilitative technologies. Ongoing technical innovations and reductions in computer costs encourage the integration of automated aids in the medical industry and present the possibility of enhancing resources available to therapists. One option is to translate and augment physical rehabilitative technologies to systems with haptic controls designed to help patients redevelop fine motor skills following an injury.

There are numerous immediate advantages to augmenting traditional rehabilitative therapy tools with a computer-based system featuring haptic controls. First, automated systems offer data recording and analysis, precision and endurance features that are beyond the capabilities of a human therapist (Patton et al., 2001). These systems can serve as tireless agents for the therapist with accuracy and objectivity remaining unchanged even after countless therapy sessions with a variety of patients. Furthermore, the scenarios and properties of objects used within the system can be changed instantly with limited or no setup and breakdown time. Virtual object surface friction, texture, resistance, size, etc. are all parameters that can be modified by system commands. Haptic systems are also valuable in medical environments because they can be used to precisely track and record patients' recovery progress. With the increasing interest in electronic medical records (EMR), such data recording capabilities may also be of particular value to clinicians.

In addition to the inherent enhancements provided as a component of a computer-based system, a VR system with haptic controls can provide other practical benefits for motor training. According to Cesqui et al. (2008), motor learning improvements occur when individuals perform a regimen of prescribed movements, identify errors and correct them in subsequent movements (Cesqui et al., 2008). This cycle of actions (within a feedback loop) can be implemented with a haptic system. Consistent with these observations, incorporating haptics in training system design has been shown to benefit sensorimotor task learning (MacLean, 2008). Related to this, there are numerous types of haptic devices that can be used for motor training. Selection should be based, in part, on training requirements such as the task, body part being used to manipulate the device, and forces. The next section provides an overview of different types of available haptic devices and features that can be considered as bases for selection.

1.1.1 Types of haptic systems

Iwata (2008) categorized haptic devices as *full-body haptics*, *tactile displays*, and *force displays*.

Table 1.1 provides a summary of the categories and some examples of each.

Table 1.1. Examples of haptic devices (adapted from Iwata, 2008)

Category	Examples
Full body haptic display	Treadmill, sliding device, moving footpad
Tactile display	Vibration display, micropin array
Force display	Exoskeleton, object-oriented, tool-handling

Full body haptic devices have been developed to study locomotion and facilitate walking in VEs. Examples include treadmills, sliding devices and moving footpads (Kaber & Zhang, 2011). Tactile displays are the most widely used haptic devices because they include vibration displays, as implemented in most mobile phones. Tactile displays include simple vibration displays as well as more complicated micropin arrays that simulate fine textures. These interfaces typically communicate information (e.g., messages) and are implemented as part of larger systems or other types of controls. According to Iwata (2008), a force display is a “mechanical device that generates a reaction force from virtual objects” (p. 194). Force displays can be controlled by or attached to different parts of the body, including the hand, and are, therefore, most applicable for fine motor tasks. Iwata provides an overview of three categories of force display summarizing available hand-operated devices. These include *exoskeletons*, *object-oriented devices*, and *tool handling* devices. Exoskeletons are collections of sensors and actuators attached to the operator's body. They are often used in telerobotic applications due to their advantage of being able to reproduce grasping forces. The CyberGrasp by CyberGlove Systems (Figure 1.1, left) is a widely-used example of an exoskeleton haptic device.

Figure 1.1. Examples of haptic interfaces including (from left to right) the CyberGrasp (photo: Wired), FEELEX (photo: University of Tsukuba), and Phantom Desktop (photo: SensAble Technologies)

Object-oriented haptic devices move or change form to communicate the shapes of virtual objects. Most haptic interfaces restrict contact to a single point or small collection of points that reproduce the sensation of interacting with a tool, but do not accurately communicate dimension or texture. Object-oriented haptic interfaces, in contrast, allow the operator to interact with the display using the whole hand. Iwata describes these devices as "robotic graphics" (2008). An example of an object-oriented device is the FEELEX (Figure 1.1, middle), developed at the Department of Intelligent Interaction Technologies at the

University of Tsukuba, Japan. Another device includes the "tactor" displays built into clothing (Kern, 2009) and seats of automobiles and airplanes that communicate warnings to an operator by stimulating the skin (O'Malley & Gupta, 2008).

The last category of haptic control described by Iwata is tool-handling haptic devices. These are the easiest to implement, which also makes them the most common. A simple example includes force-feedback joysticks and game controllers. One of the more popular examples of a tool-handling device is the pen-like Phantom by SensAble Technologies (Figure 1.1, right). Phantom implementations are restricted to operations that can be communicated through a single contact point using a haptic stylus or a thimble, so unlike the exoskeleton and object-oriented devices, it can be challenging to implement grasping motions. However, the Phantom provides 6 degrees of freedom of control and 3 degrees of freedom of haptic feedback, and it is a very versatile device that can be used to simulate operations that utilize tools like pens, scalpels or screwdrivers (O'Malley & Gupta, 2008). A variation on the Phantom device was employed in the present research due to the nature of the test task (letter drawing) and the characteristics of the haptic device.

1.2 Motor skill training

There are several general approaches to enhancing motor skill training. Two of those approaches, described by Wickens, Lee, Liu and Gordon-Becker (2004), include *simplifying* and *guiding*. The idea behind simplifying is to promote ease of individual learning of correct behaviors by moderating the complexity of a task so as to reduce cognitive load and performance errors. An example of this is learning to operate a vehicle in an empty parking lot before driving in traffic. This allows the student to learn the dynamics of vehicular control without having to keep track of traffic rules and the risk of surrounding traffic. Guiding approaches intervene so only correct behaviors can occur and prevent certain errors from ever occurring. Citing Carroll & Carrithers (1984), Wickens et al. refer to this as a "training wheels" approach in reference to the way these accessories can prevent a bike and individual from falling over (p. 484). Both of these techniques can be effective early in the training process (Wickens et al., 2004). As individual skills improve, simplification and guidance can be reduced or eliminated; the novice driver may leave the parking lot, and the training wheels can be removed from the bike.

However, these approaches also have potential problems. The use of simplified versions of tasks in training may not transfer to real-world task performance. In addition, some learners may become overly dependent on guidance, learning the dynamics of the guidance system instead of the task itself. Wickens et al. (2004) suggest this occurs when the individual does not acquire the skills replicated by the guidance during training. However, there are strategies to prevent this from occurring. For example, instead of removing the aiding all at once, the authors recommend an adaptive reduction in aiding that gradually shifts the performance responsibility to the individual. Through this process, the trainees should also be allowed to make errors so they can learn how to correct them. In fact, research on error amplification suggests increasing some types of errors during training can reduce learning time (Milot, Marchal-Crespo, Green, Cramer & Reinkensmeyer, 2010).

1.3 Classification of haptic aiding

According to MacLean (2008), there are two key methods for implementing haptic control in fine motor training systems, both of which borrow from the general simplification and guidance approaches described in the prior section. One is to provide leading forces that pilot the user along a trajectory, and the other is to orient the user's attention by applying force at specific locations. The two methods as well as some more recent approaches will be described in the following sections. Unfortunately, the current literature varies in the terminology used to describe these different methods. In an effort to use consistent terminology throughout this work, the terms used in the following subsections may not exactly match those used by the original authors, although the underlying conditions share similar properties.

1.3.1 Guidance

Systems that lead the user along a path following an expert or teacher's actual, transmitted, recorded or simulated movements are referred to as *guidance* systems. In these systems the control supplies the forward forces, and the user assumes a mostly passive role while motions are physically played back through the control device. This technique presently represents the most common form of automation-assisted therapy (Cesqui et al., 2008; Reinkensmeyer et al., 2004).

1.3.2 Virtual fixtures

Virtual fixtures (VF) represent the other key method for implementing haptic features in VR systems. Virtual fixtures help guide a task by correcting or assisting user input to maintain motions within specified boundaries (MacLean, 2008; Prada & Payandeh, 2009). When implemented, VF constrain participants within boundaries that replicate expert performance, but, in contrast to guidance schemes, the user still provides the force for forward motion. The concept of VF was first proposed by Rosenberg (1993) for improving operator performance in telerobotic systems. He described VF as “overlaying abstract information on top of a workspace” (p. 76). This is analogous to using a French curve in a manual drafting task or (using Rosenberg’s example) using a ruler to draw a straight line. Rosenberg suggested that VF can improve precision and reduce mental workload by freeing up resources normally used for fine motor coordination. In fact, since the time of Rosenberg’s research, VF have been shown to improve task performance by increasing speed, increasing precision and reducing mental workload (Prada & Payandeh, 2009).

Virtual fixtures can improve performance because although human operators are generally not skilled at absolute judgment (Wickens et al., 2004), such as identifying a specific point in space without a landmark, they are very good at sensing and modifying small changes in force (MacLean, 2008). Therefore, by providing the user something seemingly solid as a reference point, VF are effective aids for facilitating precision in task performance.

Virtual fixtures that result in simple resistive forces or forces opposing user input are often referred to as *reactive forces* (Prada & Payandeh, 2009). More recently, VF with *attractive forces* have also been tested (Prada & Payandeh, 2009). In these systems, when the user moves within the VF’s field, the resulting forces advance the progress of the user and return the control input to a trajectory defined by expert performance. Attractive force VF, therefore, include characteristics of conventional VF and guidance systems.

In addition to employing VF to aid task performance, several researchers have also incorporated VF with training tools for developing new skills (Dinse, Wilmzig & Kalisch, 2008; Srimathveeravalli, Gourishankar, Kumar & Kesavadas, 2009; Teo, Burdet & Lim, 2002). For example, Teo et al. (2002) developed a system to train novice and expert participants to write Chinese calligraphy. In addition to the 2-dimensional drawing component, the researchers included a force component to control the thickness of each line. Drawing performance was evaluated in terms of accuracy, timing, force and smoothness. Three novices with no background in Chinese and three experts in Chinese writing received training using the system. All participants received two types of aiding including attractive force and VF. Novice participants received guidance forces first and the expert participants used VF followed by guidance forces to draw the characters. Both groups showed improvement during training. However, the novice participants only showed improvements in smoothness. Expert participants showed improvement in timing (i.e., changes in speed within a single stroke). These results suggest that the type of haptic aiding and skill level may affect task performance; however, since the experiment design did not test other combinations of skill level (i.e., novice, expert) and aiding type (i.e., guidance, VF), it is unclear what aspects of the conditions led to the results.

1.3.3 Adaptive aiding

One problem with implementing guidance or VF in training systems is that the forces do not change over time. Despite their broad appeal, both systems may create a dependency where the individual learns the dynamics of the haptic interface instead of the task. This means that performance benefits achieved while using the system may not carry over to unassisted conditions. Furthermore, experts and novices will perceive the same haptic features unless there is some intervention or the task is discontinued. One recommendation is to implement training programs that introduce strong haptic features initially and reduce them over time as performance improves (MacLean, 2008). This strategy has been referred to as *adaptive aiding*. Adaptive aiding strategies distribute the responsibility of force application between the operator and the device, or, more specifically, the intensity of haptic feedback is modified as individual performance improves (Huegel, 2009; Li, 2007). In these systems, motor learning is encouraged by gradually reducing the participant's dependency on the automation as much as possible (Harwin et al., 2006). There is evidence that providing haptic guidance when needed is more effective for task performance than implementing a constant fixed amount of assistance (Li, Huegel, Patoglu & O'Malley, 2009, Reinkensmeyer et al. 2004, Srimathveeravalli et al., 2009). The efficacy for implementing adaptive aiding as a fine motor training strategy is also encouraging as the results of recent experiments show learning with strategies that schedule increases in task difficulty over time are at least comparable to VF alone (Srimathveeravalli et al., 2009). However, additional investigation incorporating strategies that adapt based on individual skill improvements (as opposed to increases based on a predefined schedule) is required to determine the degree of advantage achievable by adaptive VF.

Huegel (2009) investigated the learning effects of haptic guidance in a video game by having participants perform a point-to-point reaching task using a joystick for position and velocity control. Performance was recorded in terms of absolute error (i.e., path deviation) and frequency of control input. Each participant completed 11 sessions of 42 trials each over a one month period. Participants received either haptic, visual or no assistance from the interface. Haptic assistance in the form of VF was reduced over time to coincide with participant performance improvements. Exponential reductions in control gain were applied when participants showed improvement across three successive trials. Using the experimenters' force calculations, this would translate into a maximum of 50% reduction in force following 12 trials of increasing performance. Results revealed participants in the performance-based adaptive aiding condition to significantly outperform those receiving no guidance. However, performance improvements did not transfer to a post-test scenario in which haptic assistance was not available. Huegel suggested that participants learned the system dynamics of the augmented task instead of the target task and concluded that haptic guidance that enhances task performance may not necessarily accelerate learning.

1.3.4 Error amplification

Another alternative to conventional VF for training motor skills is *error amplification* (EA). While VF generally apply forces opposite to user input, EA applies additional forces inline with user input. In other words, haptic forces increase errors when participants deviate from a desired path. Error amplification has been shown to be a successful training approach because it maintains the attention of the participant and increases the signal-to-noise ratio for constructive sensory feedback (Cesqui et al., 2008). Furthermore, it has been hypothesized that the motor system may adapt more rapidly and completely when performance error is increased during training (Milot et al., 2010). There is also evidence that EA may provide greater training benefits to unimpaired individuals by setting task difficulty to levels that challenge individuals. Error amplification has also been identified as a viable approach for motor skill training for patients recovering from brain injuries (Cesqui, et al., 2008).

Milot et al. (2010) performed a study where they compared learning effects of haptic guidance and EA in a timing task. In their task, participants had to press a button using a wrist motion to activate a flipper in a computer-based pinball simulation. The goal was to hit a target with the ball, which required pressing the button at a precise time to achieve an accurate trajectory. In the haptic guidance condition, the simulator would correct for errors by speeding-up movements when the participants struck the button late and slowing them down when they struck it early. The EA condition had the opposite effect; early attempts were sped-up and late attempts were slowed down. Participants performing the task were also classified based on their skill level at baseline. The results of the study showed that both haptic guidance and EA provided similar learning improvements. Milot et al. results also provided evidence that training may be more effective if the difficulty of a task is set based on participant skill level. When divided into two groups, more skilled participants benefited more from training in the EA condition and less skilled participants benefited more from haptic guidance. The authors attributed this result to Guadagnoli and Lee's (2004) proposal that motor learning is related to the difficulty of the training task as well as the performance level of the trainee. As individual training performance improves, so does the ability to process information along with the ability to handle greater task demands. Therefore, more highly skilled participants benefit more from more demanding task conditions.

1.4 Design of haptic writing tasks

As discussed earlier, rehabilitation programs aimed at recovering fine motor skills need to be customized according to individual patient needs and goals in order to maximize learning. This makes developing general approaches to fine motor skill rehabilitation challenging. However, Yancosek and Mullineaux (2011) showed that a vast majority of patients retraining fine motor skills (90%) performed daily handwriting tasks, and they urged that writing should be addressed as part of any rehabilitation plan. This suggests writing may be a suitable training task for investigating the efficacy of different strategies for implementing haptic forces and retraining fine motor skills since it may be applicable to a larger percentage of patients. Although writing is neither an Instrumental nor a Basic Activity of Daily Living (IADL; BADL) by itself, it is listed as a component of a person's ability to handle financial matters independently, which is an IADL (Lawton & Brody, 1969).

In addition, writing tasks require the highest degree of unilateral motor skill that most people will ever need to achieve (Plakins, 1996). Therefore, techniques used to refine handwriting skills may also have occupational training implications for tasks requiring high degrees of unilateral motor skill, such as surgical and fine assembly tasks. If a VR system with haptic control can be used to retrain deficient skills, it may also be feasible to train unimpaired users to develop new fine motor skills or augment existing ones for occupational tasks.

Many investigations of technological interventions to retrain motor skills using techniques that assist the patient (e.g., VF) or challenge the patient (e.g., EA) have incorporated writing as the test and/or training task. Several researchers have also used these strategies to develop haptic tools for refining the fine motor skills specifically required for writing tasks. For example, Mullins, Mawson and Nahavandi (2005) developed an early low-cost haptic handwriting aid that generated assistive forces through a haptic stylus to help participants form letters displayed on a conventional 2-dimensional computer monitor. Template letters, words or sentences were input with a keyboard and played-back to the user in the form of a Comic Sans MS font through a haptic device. Users could vary the speed of the guidance as performance improved. Vishnoi, Narber, Duric and Gerber (2009) used a guidance approach to develop a more sophisticated haptic interface to train writing skills. Their system recorded the 3-dimensional motions of unimpaired individuals during a writing task and translated them to a haptic workspace. The recordings could then be played-back to guide individual movements along the correct 3-dimensional path, which included lifting the stylus from the writing surface to draw characters combining multiple strokes. The strength of the applied forces could be reduced according to user needs as writing performance improved.

Solis, Avizzano and Bergamasco (2002) used adaptive aiding incorporating VF, referred to as “reactive robot” technology, to develop a system to train users to write

Japanese characters (p. 221). Similar to Vishnoi et al. (2009), characters were first drawn by experts to define template strokes. When in use, their system introduced opposing forces along 2-DOF of a custom haptic device with five linked segments in order to return to users to the correct path when they deviated from the template. A key contribution of their work was the real-time recognition of characters performed during the drawing task, allowing individuals to draw characters on a horizontal surface without first entering them into the system using another device. As introduced in a previous section, Teo et al. (2002) developed a 6-DOF haptic system for teaching Chinese calligraphy to novice and expert users. Their system was capable of guiding the participants through the entire character or producing VF that would restrict movements but allow the participants to draw at their own pace. A study testing the efficacy of the device for training unimpaired participants showed that learning occurred across training trials for both systems, in particular for novice users. However, because an unassisted condition was not included, it is not clear if there were any carry-over effects from the training, and only 6 people participated in the study.

Although there are numerous examples of systems using VF or EA to train fine motor skills, examples of studies comparing the two directly are limited, particularly for writing tasks. A comparison of two haptic systems using a simple drawing task was performed by Cesqui, et al. (2008) to help patients recover motor skills following a stroke. Their task included tracing multiple straight lines from the center to the outward edge of a virtual fan using active guidance ("active assistance") and EA. Performance was evaluated using several measures, including the number of velocity peaks, smoothness of movement, and deviation from an optimal (i.e., straight line) trajectory. All participants received both forms of training, but one group received the active assistance followed by EA and the other received the conditions in the opposite order. Participants were assigned to each group based on their ability to complete a simple reaching task using the experiment apparatus without haptic assistance. The degree of force applied during experiment trials was calibrated separately for each participant following a clinical assessment of individual upper limb impairment in order to ensure all participants could complete the reaching task. The results varied due mostly to the differences in level of disability among the participants, however, all participants showed some degree of improvement on the three performance measures (i.e., velocity peaks, smoothness and deviation). There was also evidence that EA followed by active guidance was a more effective training regimen than active guidance preceding EA, overall. However, the researchers noted that this may have been due to a fatigue effect brought about by assigning to the same group all participants who had difficulty performing the task without haptic assistance. In addition, condition presentation order had an effect on the results when participants were grouped according to three levels of impairment severity (mild, moderate severe) based on the Chedoke Stroke Assessment score (Gowland et al., 1993). Participants with more severe disabilities (i.e., lower Chedoke scores) benefited from active guidance provided prior to the EA condition. These results were also consistent with Milot et al. (2010) finding that participant ability determines the best form of training.

1.4.1 Measuring handwriting performance

The majority of previous systems incorporating writing and haptic guidance were designed as performance aids and system success was based on writing accuracy (e.g., Mullins, et al., 2005; Vishnoi et al., 2009; Solis et al., 2002). In these cases, accuracy was measured by comparing completed drawings to templates drawn by experts. However, prior research on motor skill acquisition shows that training to automaticity should be evaluated using multiple parameters, as some performance measures (e.g., speed) continue to improve after accuracy improvements reach a plateau (Wickens & Hollands, 2000, p. 270). Therefore, multiple measures should be used to evaluate changes in handwriting skill over time. Teo et al.'s (2002) results incorporating accuracy, timing, force and smoothness suggest that different performance measures may be influenced differently by various levels of participant ability (e.g. expert, novice) and types of haptic aiding. Unfortunately, specific conclusions cannot be drawn from their work because the experiment design was not balanced. However, results did show that performance differences can be measured using variables other than accuracy (i.e., smoothness and speed).

Chowriappa, Subrahmaniyan, Srimathveeravalli, Bisantz and Kesavadas (2009) tested expert handwriting behaviors to develop models of automatic handwriting performance. Using a WACOM™ Intuos tablet, the researchers collected coordinate, pressure and pen orientation data from 22 experts writing a series of Latin and Tamil characters. They determined that performance varied significantly among participants across all performance measures; however, patterns were very similar. Deviations from model characters tended to occur in the same locations among participants and they applied the lowest and highest forces in the same locations. The researchers also observed that both speed and force increased together while drawing a character segment, and then decreased. These results imply that expert handwriting strategies are similar.

Previous work evaluating the efficacy of handwriting training using haptic devices has evaluated performance following training but testing was limited to a single session. Research results do not provide information on changes in performance over time (cf., Srimathveeravalli & Thenkurussi, 2005). Therefore, the question remains of how to model handwriting performance changes during training and which aspects of performance can be used to control adaptive aiding. To this end, one objective of the present research was to identify and test suitable performance measures for these purposes.

1.5 Summary

Previous research demonstrates that systems using VF with adaptive aiding have shown to be effective for improving fine motor task performance and as a tool for psychomotor task training. There is also evidence favoring the use of EA in haptic training systems, in particular for achieving greater levels of recovery more rapidly (Milot et al., 2010). However, there is limited empirical work on the efficacy of EA to train writing skills, and the efficacy of VF and EA with adaptive aiding as a training tool for a complex fine motor task, like writing, requires additional investigation.

Table 1.2 provides a summary of the combinations of haptic training types tested in the studies reviewed above in which participants received training in a writing task. While prior research has sought to quantify the learning effects of haptic aiding in the form of guidance, VF and EA, very few have incorporated adaptive aiding (e.g., Solis et al., 2002), and none were identified that compare VF and EA.

Table 1.2. Summary of writing training studies and haptic aiding types

Reference	Guidance	VF	EA	Adaptive
Mullins et al. (2009)	Yes	No	No	No
Vishnoi et al. (2009)	Yes	No	No	No
Solis et al. (2002)	No	Yes	No	Yes
Teo et al. (2002)	No	Yes	No	No

The literature reviewed for the present study shows that while haptic writing systems have been designed with customizable speed (Mullins et al., 2009) and force parameters (Vishnoi et al., 2009), researchers have not identified performance-based conditions for adjusting levels of haptic guidance. Furthermore, while the haptic writing system developed by Solis et al. (2002) was adaptive in the sense that it could modify guidance directions based on predictions of user intent, it was designed to assist users during task performance. It was not evaluated as a training tool. Based on the present review, learning effects of combining adaptive aiding with a writing task have not been investigated.

While adaptive aiding has been shown to complement VF when used as a training tool, the added value of adaptive aiding with EA in fine motor task training remains to be investigated. Furthermore, although there are numerous studies including VF or EA, there is limited information to compare the two techniques. A direct comparison of the two methods could be used to inform future VR and haptic guidance design for training systems. The goal of this study was to investigate the static and adaptive EA and to make comparisons with VF training methods.

Both impaired and unimpaired individuals can benefit from effective training systems with haptic control for training and retraining fine motor skills, including those needed for writing tasks. Patients recovering from a stroke or traumatic brain injury (TBI) may seek to retrain fine motor skill to an affected hand, or they may wish to transfer existing skills to the non-dominant hand. Unimpaired individuals performing occupational tasks requiring fine motor skills such as medical procedures (e.g., surgeons, dentists, nurses), drafting (e.g., architectural, cartography, engineering), fine assembly and repair (e.g., jewelry, electrical appliance), and precision machine operation may also benefit from additional vocational training to improve work performance. In either case, it is also important to develop training programs that are appropriate for a trainee's skill level so the trainee realizes maximum benefit from the training program.

In this work, the above areas were investigated, including a comparison of the effectiveness of VF and EA with adaptive aiding relative to static VF and EA. During experiment trials, participants learned to draw characters from a foreign alphabet using a custom training apparatus and software. Representative models of fine motor learning were developed to determine how to adaptively modify the degree of haptic aiding over time. Each participant received one of four types of haptic features, including adaptive VF, adaptive EA, static VF and static EA (i.e., between-subjects experiments were conducted). Comparisons were made between tests administered both prior to and following training in order to assess learning differences among the four haptic feature types. Details of the experiment tasks and results are provided in the following sections.

2 Methods

2.1 Apparatus

The haptic interface used in this study was designed to simulate a pen drawing directly on a surface. Hardware included a Dell XPS 420 PC and a custom workstation featuring a 19-inch flat screen monitor embedded in a tabletop (Figure 2.1). The embedded monitor served as a virtual drawing surface. A haptic device featuring a stylus placed immediately beyond the monitor was used to draw on the surface.

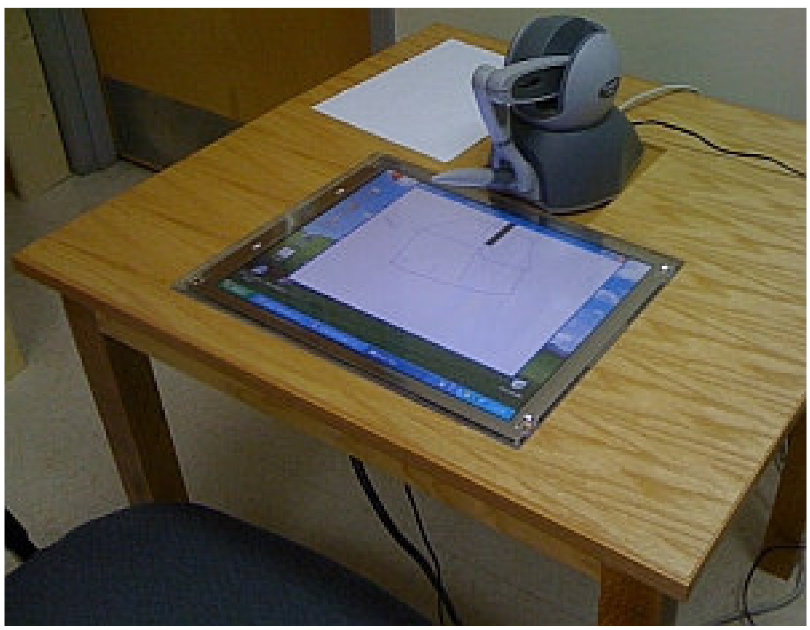

Figure 2.1. Workstation layout

The Sensable Technologies PHANTOM® Omni® haptic device (Figure 2.2) was selected for use in this study because it meets the criteria established for an active haptic device (MacLean, 2008) suitable for fine motor tasks (Iwata, 2008). Active haptic interfaces include five basic components: (1) power sources and electronics, (2) sensors to measure the position of the haptic device, (3) actuators to produce haptic forces, (4) drivers to facilitate communications between the haptic device and its controlling computer, and (5) software to control the haptic device (Robles De La Torre, 2008). The Phantom Omni has also been used in previous studies investigating haptic control for training handwriting and fine motor skills (e.g., Mullins et al., 2005; Vishnoi et al., 2009; Li et al, 2013). The Omni's backdrive friction (0.26N) has also been shown to be comparable to the friction produced by a pen on paper (Chigira, Fujii & Valera, 2004); therefore, no additional friction forces were added to the haptic interface to support the drawing task.

Figure 2.2. Sensable Technologies PHANTOM® Omni®

Although it provides an ample range of motion (160 mm wide by 70 mm deep) and precision (0.055 mm), the Phantom Omni is mechanically different from a pen. The stylus is connected to a fixed-base by two articulating arms and three gimbals and is, therefore, not identical in weight or movement to a lightweight pen. Another limitation of systems that incorporate the Phantom Omni is that they implement a simplified contact model, which is not strictly identical to pen on paper (Robles De La Torre, 2008). Similar observations were made by Srimathveeravalli et al. (2009), who also pointed out that writing in the virtual world still represents a fine motor task.

The software application for the present study was developed using a Microsoft Visual C++ environment, OpenGL for the graphical user interface (GUI) and Sensable's OpenHaptics® Software Development Kit (SDK) for haptic control. Sensable Technology's native drivers provided the communication links between the Phantom Omni and the software. The Phantom Omni features a calibration utility that is executed automatically when the stylus is connected to its base. Device calibration was confirmed following each test trial using this technique.

2.1.1 Task and interface

The task required right-handed participants to replicate different characters from the Georgian (Khutsuri) alphabet using the left hand only. Use of the non-dominant hand in a writing task has been used in the past to simulate disability (Andree & Maitra, 2002) and promote task difficulty in order to increase training effects (Srimathveeravalli et al., 2009). Furthermore, it has also been verified that participants can gain proficiency in a repetitive writing task when training with the non-dominant hand (Yancosek & Mullineaux, 2011). The analysis of results in this study was focused observing differences in motor performance in a test following training; therefore, it was important to design a task of sufficient complexity to ensure learning would take place. Related to this, Huegel (2009) recommended that a complex task should be used to quantify performance differences between a haptic training condition and an unassisted condition.

Drawing characters from a foreign language, as form of novel task, has also been used in other studies, such as Andree & Maitra (2002). Use of a foreign alphabet is intended to normalize participant experience levels, increase the task challenge and reduce the effect of lateral transfer (Andree & Maitra, 2002), in which training performed with one hand transfers to the other. This means that the vast majority of U.S.-based right-handed participants will have some left-handed proficiency when writing Latin characters due to any existing handwriting experience. Use of the Georgian alphabet was intended to ensure all participants had the same level of experience. Therefore, individuals familiar with the Georgian alphabet were not permitted to participate in data collection. Each Georgian letter was adapted from the Unicode Standard (The Unicode Consortium, 2012) to ensure consistency. Five characters were included in the handwriting training program. Table 2.1 shows the character templates included in the training software. These characters were selected for their similar complexity. Four of the characters were similar in size and could be drawn using three curves. The fifth character consisted of four curves and was presented once following training as an assessment of near skill transfer (Haskell, 2001).

Table 2.1. Sample characters from Georgian Khutsuri alphabet (The Unicode Consortium, 2012)

Unicode	**Symbol**
10E0	რ
10EA	ც
10F0	ჰ
10E6	ღ
10E3	უ

Each test character was adapted from Georgian characters in the default font available in Microsoft Office. Use of a standard vector font allowed the five characters to be scaled to a large size without pixilation. Once their size was increased sufficiently using Microsoft Word, they were converted to Bitmap (bmp) format and imported into the training software at a size of 300x300 pixels. Figure 2.3 depicts a screenshot of the drawing interface for each completed letter. The gray character in the drawing frame is the template of the character copied by the participant. The starting position is indicated by a red circle. Use of a fixed starting position is consistent with Teo et al. (2002) and Solis et al. (2002) research and helps participants orient a character so it can be completed within the workspace and reduces error marks.

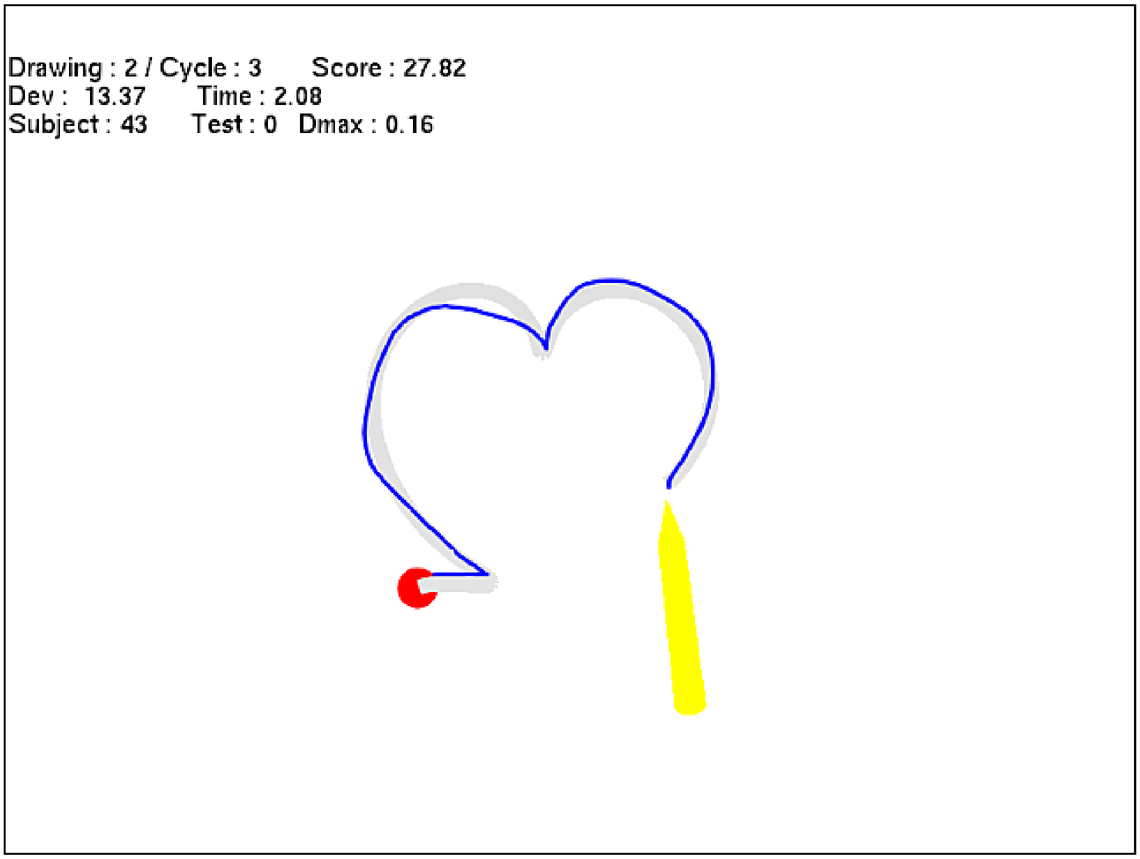

Figure 2.3. Reduced scale screenshot of the drawing interface with a completed character

The goal was for the participant to use the drawing frame to trace the character template as accurately and quickly as possible. The Omni haptic stylus controlled a yellow pencil-like cursor (see Figure 2.3), which indicated the relative location of the stylus on screen. A haptic plane representing the drawing surface was rendered slightly above and parallel to the surface of the monitor. This elevated drawing surface allowed participants to apply a variable level of force to the stylus, which was recorded automatically during each trial. The elevation was kept to a minimum, however, to maximize the reach of the haptic stylus and to minimize the parallax resulting from the separation of the stylus point from the monitor's surface. An adjustment utility was added to the interface allowing the cursor to be moved on the x and y axes to reduce the parallax occurring between the cursor and stylus point as a result of the vertical distance of the haptic plane from the monitor.

The participant's trajectory while drawing was indicated by a blue line overlapping the gray template. Both accuracy and speed were emphasized in the instructions provided to the participants. Consequently, the two measures of performance were expected to improve together. Each trial was initialized when the cursor contacted the starting position (i.e., the cursor could touch and navigate the worksurface prior to initialization, but no line was drawn until the cursor contacted the red circle). This approach allowed participants to comfortably position the haptic stylus without penalty before writing. Contacting the starting position communicated that the participant was ready to draw the character. The trial (drawing) began when the cursor moved from the starting position and ended when the cursor was lifted from the worksurface. During each trial, only the grey template, the participant's drawing, the red circle and the yellow cursor were visible. A score representing the product of task completion time (sec.) and total deviation (in.) was presented to the participant at the end of each trial to emphasize the speed and accuracy goals (see Figure 2.3). The score was cleared with the initiation of each new trial and did not appear during a drawing. The score feedback was also intended to motivate participants to further learning during trials under all conditions. Each starting position was defined by the software. If a participant lifted the cursor from the worksurface without completing the character, the drawing would be discarded and the task restarted. This feature was explained to participants as part of the experiment protocol. Requiring a character to be redrawn due to lifting a haptic stylus prematurely is consistent with Wang et al. (2006). Each character was intended to be drawn completely as a continuous line, similar to a written word without the letters i, j, t or x. Incorporating letters composed of continuous lines is consistent with Srimathveeravalli et al. (2009) and reduced the possibility of vibration at the haptic device due to instability in hand motion (Wang, Zhang & Yao, 2006).

2.1.2 Haptic feature design

The VF and EA conditions in the training task were implemented using different haptic features available in the OpenHaptics SDK. The VF condition implemented the *forcefield* function. When the participant deviated from the template beyond a threshold value (described later), cursor movement was blocked by reactive forces (in the form of a rectangle) rendered parallel to a point on the character immediately opposite the cursor. Forces increased based on forces applied to the haptic stylus, up to 3N (the maximum force available to the Phantom Omni). From the participant's perspective, the VF rendered a haptic stencil that constrained writing within a specific threshold.

The EA condition used an adaptation of the OpenHaptics SDK "gravity well," which attracts a cursor toward a defined point in the interface, leading the user with positive forces. Applied to the current study, the gravity wells provided attractive forces toward a distant point parallel to the drawing template when the participant deviated beyond a threshold value (also described later). In the EA condition, deviations from the template resulted in the stylus being pulled further away from template with increasing force.

The software included five separate templates for the characters that were traced by participants during data collection (Table 2.1). Each template included a collection of approximately 300 reference points placed at regular intervals along the character. The reference points were invisible to participants. As the participant drew the character, the software calculated the cursor's distance from the template. Forces were applied when the participant deviated from the reference points. Figure 2.4 illustrates the design in reduced fidelity. The dashed line inside the template designates the ideal path traced by the participant. The black circles represent various reference points, with the starting point in red. The solid blue line represents a possible partial path drawn by a participant. As the participant draws the character, the software tracks each reference point crossed by the cursor. If the participant does not deviate from the template beyond a defined threshold (called d_{MAX}), no forces are applied. If the deviation goes beyond the threshold, the cursor is blocked at the threshold point (VF) or the participant's motion is repelled perpendicular to the template (EA). Figure 2.4 shows a sample drawing that is fairly close to the template until the cursor passes the second reference point. The dotted arrows labeled "EA" and "VF" depict the direction of applied EA and VF forces as a result of the deviation. Both haptic features apply forces perpendicular to the segment between the second and third reference points. The VF apply forces toward the template equal to the forces applied through the stylus until the cursor is returned within the threshold. The EA condition applies forces at a variable level away from the template, based on the magnitude of the deviation.

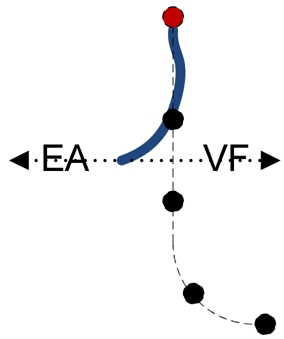

Figure 2.4. Haptic force directions

The magnitude of the EA forces increased linearly with greater deviations. The forces produced by EA followed the following formula, based on Hooke's Law:

$$F_{\mathrm{f}} = k_{\mathrm{p}} \times \left(\sqrt{(x_{\mathrm{s}} - x_{\mathrm{r}})^2 + (y_{\mathrm{s}} - y_{\mathrm{r}})^2} - d_{\mathrm{MAX}}\right) \tag{1}$$

where k_p represents stiffness and x and y represent the participant's (current) and nearest reference coordinate positions. The s and r subscripts specify the participant and reference values, respectively. d_{MAX} represents the threshold deviation at which forces are applied. Therefore, the degree of force (F_f) applied is proportional to the extension beyond the error threshold, which is dependent on the magnitude of deviations from reference points on the template character and the maximum baseline deviations by the individual participant. The precise application of forces was unique to each participant.

The formula shows that the reactive forces increase linearly until the maximum level of force is reached. Some degree of free movement is also allowed before haptic forces are perceived by the participant, which means responsibility for the highest level of accuracy (i.e., lowest deviation from the template) can still be assigned to the participant when haptic features are engaged. Maximum force output was limited to approximately 3N, based on the Phantom Omni's technical specifications. Stiffness (k_p) was set to a constant value of 4, identified through pilot testing. This value was determined to sufficiently perturb the stylus during a deviation, but still permit corrections. (Specific details on force changes implemented as part of the adaptive aiding during training are provided in Section 3.2.)

The main difference between the VF and EA conditions was in the direction of the force. Virtual fixture forces moved toward the template. Error amplification force was directed away from the template. The adaptive aiding condition increased the distance from the template at which forces were engaged over time, which is consistent with the recommendation that haptic training systems should provide strong guidance at first, and reduce it over time until the user maintains most of the control (MacLean, 2008). The EA condition, in contrast, reduced the distance at which forces were applied over time.

2.2 Experiment design

Data collection included two phases. In Phase 1, participants repeatedly traced the Georgian characters using the experiment apparatus without haptic guidance in order to identify learning curves for the dependent variables (see Section 3.1). These learning curves were used to determine the incremental changes in the sensitivity of the haptic features enabled in the second phase. The goal of Phase 2 was to compare the learning effects of adaptive VF and EA. The Phase 1 and Phase 2 procedures were kept as similar as possible to facilitate comparisons between the two phases following data collection. The main difference between the two phases was the absence of haptic aiding during Phase 1 and its presence during Phase 2. The details of the two phases are provided in the following sections.

2.2.1 Participants

Nine participants were recruited to participate in Phase 1, and 32 participants were recruited for Phase 2. A test of statistical power using the Phase 1 results (β=0.2) comparing differences in speed and accuracy between the first and last trials was used to confirm the sample size for Phase 2. Participants were not permitted to participate in both phases in order to prevent training effects (learning of the Georgian letters) between phases. All participants were required to be between 18 and 30 years old, have 20/20 or better vision (either corrected or uncorrected), and exhibit right hand dominance with full mobility of both hands while seated. Age was reported in a demographic questionnaire (Appendix A). The upper limit of 30 years was selected to account for the decreasing sensitivity in the sense of touch in older adults that can occur due to a reduction in the density of Meissner corpuscles in the skin over time (Thornbury & Mistretta, 1981). Previous work has also confirmed that sensitivity to vibrations in the fingertips does not tend to vary due to age between 18 and 30 years (Pongrac, 2008). Visual acuity was confirmed prior to data collection with a Snellen eye test. Right hand dominance was also reported by participants through the demographic questionnaire and confirmed using the Edinburgh Handedness Inventory (Oldfield, 1971;

Appendix B) administered using an online survey form prior to the first experiment session. Participants were required to score a 90 or above on the Handedness Inventory in order to participate in the study. The demographic questionnaire also included questions to screen out participants familiar with the Georgian alphabet. Participants rated their familiarity with five different alphabets (1 = not familiar; 5 = very familiar). Participants who self reported a 2 or greater on the scale for the Georgian alphabet were not permitted to participate in the study. No candidates were dismissed based on alphabet familiarity, however.

Participants were administered the Purdue Pegboard Test (Tiffin & Asher, 1948) to ensure they could perform right and left-handed manual dexterity tasks within 1-standard deviation of population norms (Lafayette Instrument Company, 1985). This test was conducted to ensure that no participants had a functional impairment of the arms or hands.

2.2.2 Conditions

No independent variables (IV) were manipulated in Phase 1. In Phase 2, IVs included the types of adaptive haptic features (2 levels; VF, EA) and aiding strategy (2 levels; adaptive aiding, static aiding). The distribution of conditions and participants for the Phase 2 experiment is summarized in Table 2.2.

Table 2.2. Summary of number of participants assigned to conditions

	Haptic Feature	
	VF	EA
Adaptive	8	8
Static	8	8

Dependent variables

According to Srimathveeravalli and Thenkurussi (2005), “an expert’s skill in a virtual environment can be represented using temporal position, velocity and force information” (p. 452). Consistent with this observation, past studies assessing handwriting and pattern reproduction have used several types of performance measures including deviations from a template or model (Cesqui et al., 2008; Chowriappa et al., 2009), task completion time (Harwin, Patton & Edgert, 2006), number of peaks in vertical force (Teo et al., 2002; Chowriappa et al., 2009) and number of velocity peaks in the speed profile (Cesqui et al., 2008; Huegel 2009; Harwin et al., 2006; Teo et al., 2002; Vishnoi et al. 2009). For the present study, the dependent variables (DV) included (1) total deviation from the template, (2) time to task completion (TTC), and (3) average vertical force. The DV were calculated and recorded for each trial (drawing) and averaged across trials. Participants were also asked to complete a brief survey (Appendix D) following training to identify subjective preferences among the four conditions.

Deviation from the template was used to control haptic forces applied during each trial, as discussed above. This parameter was also recorded at regular intervals (i.e., 300 points per character) to calculate the root mean square error (RMSE) for each trial according to the following formula:

$$\sqrt{\sum_{i=1}^{n}(d_i)^2 / n} \qquad (2)$$

where n represents the total number of reference points in the character and d is the Euclidean deviation recorded at the reference point. Time to task completion represented the elapsed time between moving the cursor from the starting position and lifting the cursor from the worksurface and was expected to decrease with practice. Vertical force is a system variable available within the OpenHaptics SDK (HD_CURRENT_FORCE), which was recorded at regular intervals. The force profiles were expected to decrease with increased practice (Teo et al., 2002). (These expectations were intended to provide a sense of how the various response measures would trend through the two training phases as part of the research. The major research hypotheses are identified in Section 2.4.)

In addition to the DVs, several additional pieces of information were recorded automatically by the computer systems used during experiment trials. This information was collected to support the data analysis effort and to provide a basis for deriving additional response measures for use in future studies. Table 2.3 lists the additional information collected during each trial. Each data field was recorded at a rate of 100Hz, producing files of approximately 300 records per trial, or 35,000 per participant.

Table 2.3. Data fields recorded automatically by the simulation software

Field	**Description**
Task	The trial number (1-8) within each of the 6 cycles
Subject	A unique ID assigned to each participant
Feature	The type of haptic feature assigned (adaptive EA, static EA, adaptive VF, static VF, control)
Letter	The Georgian character traced during the trial
Mode	Identifier indicating a test (without haptic features) or training trial (with haptic features)
Cycle	The experiment cycle (0=Baseline, 1-4=Training, 5=Post-Test)
Stiffness	k_p applied during EA training (set to a constant value of 4)
X	X position coordinate
Y	Y position coordinate
Z	Z position coordinate
Deviation	Deviation (in.) from the character template
Force	Amount of force (N) applied at the haptic stylus by the participant
HapticForce	Amount of force (N) applied to the stylus by the simulation
Time	Elapsed time from the beginning of the trial
Status	A code indicating the stage for the drawing (idle, initialized, in process, complete)
Dmax	The amount of deviation (in.) from the template at which forces will be applied

The DV were calculated for each test and training trial. The DV were normalized for each participant by comparing training and test scores to baseline performance. This was intended to account for variations in absolute performance among participants (e.g., precision, handwriting style). Lower RMSE deviation, lower vertical force profiles and shorter trial times were all considered representative of improved performance. Use of multiple DV was expected to increase the fidelity of the training and test results, with the response measures possibly improving at different rates. Previous work on psychomotor task performance shows that individuals continue to refine strategies after speed and accuracy improvements approach an asymptote (Clamann & Kaber, 2012). Past studies comparing visual and haptic guidance training methods also suggest that visual training is effective for teaching the trajectory shape while haptic guidance is more effective for teaching temporal aspects of the task (MacLean, 2008). Likewise, the two forms of haptic guidance were expected to have different effects on the various response measures.

As an extension of the of the data analysis effort, participant results were split into two performance-based classifications (i.e., high and low) following the examples set by Cesqui et al. (2008) and Milot et al. (2010). Performance classifications were identified using results from the baseline test speed and accuracy measures. Participants above the 50^{th} percentile in RMSE deviation and task time were included in the high performance group, and the remaining participants were included in the low performance group. Additional post-hoc analyses were performed to observe whether high or low performing individuals may have benefited differently from the two conditions, in terms of training and/or test performance. The results of these analyses were collected to provide further insight toward the development of learning models for each training condition. Previous research has combined similar motor performance measures to develop preliminary models of expert handwriting performance (Chowriappa et al., 2009); however, these models have not included observations of how the measures change over time as a result of continued training. The learning models developed based on the Phase I research were expected to support specification of appropriate levels of adaptive aiding throughout training.

2.3 Procedures

2.3.1 Phase 1 procedures

The goal of Phase 1 was to identify the trend in TTC (speed) across multiple character drawings. Participants repeatedly drew four characters from the Georgian alphabet using the experiment apparatus (i.e., custom workstation and Phantom Omni). The number of characters and participants was selected in order to ensure sufficient observations for the results to approximate a normal data distribution. Phase 1 was conducted over two days. The procedures are described in the following subsections. The instructions and script used during data collection appear in Appendix E.

Orientation. On the first day, participants completed an informed consent form (Appendix C) and received a brief orientation to the procedures. Following the orientation, participants received basic instruction on use of the haptic interface. While seated at the workstation, participants used the Phantom Omni to trace a simple figure (i.e., a Latin capital letter "S") using the experiment software without haptic aiding until they were comfortable (by self-report) with the drawing interface.

Baseline. Following the orientation, participants were asked to draw each of the four Georgian characters once using their non-dominant hand as a basis for a performance baseline.

Training. The structure of the Phase 1 data collection sessions followed a repetitive tracing model, a typical method for handwriting instruction (Srimathveeravalli et al., 2009).

Participants drew each character 32 times in succession using the Phantom Omni and the horizontally-mounted monitor. Participants were instructed to complete each drawing accurately and quickly. Neither performance measure was emphasized over the other as part of the instructions; instead, participants were asked to focus on the "score" combining the speed and accuracy measures. No reference points were provided to participants to assess performance; instead, they were asked to reduce the score values over time. The order of presentation of the characters was the same for each participant during testing and training trials. Presentation of characters was held constant because the sample size was not sufficient to assign an equal number of participants to the possible random character orders. Phase 1 training concluded after the participant repetitively traced each of the four characters.

Post-training testing. Each participant returned the day after completing training and participated in a test in which they drew each character one time without haptic assistance. Each participant also traced a fifth character not presented during baseline testing or training. The purpose of tracing the additional character was to assess the extent to which learning was transferred from the training context to a "near transfer" context (i.e., tracing but with a different character; Haskell, 2001). Performance differences between baseline and post-training testing represented motor learning as a result of the training. The comparison of baseline and post-test scores to measure motor learning was based on procedures used in a previous study (Kaber et al., 2013).

Improvements in motor skill training programs are based on personal goals, which are highly individual (Schmidt & Wrisberg, 2000). Depending on the complexity of the goal and the ability of the individual, improvement goals can be realized from training durations ranging from minutes to weeks or months (Dinse et al., 2008). Previous studies examining the effects of haptic control on healthy individual motor learning have also ranged broadly in duration. For example, Teo et al. (2002) had participants repeat characters 24 times each in a single session, while Huegel (2009) required participants to complete 10 training sessions over the course of a month. For the present work, the number of repetitions of each character was chosen to ensure sufficient training of participants for general proficiency in drawing and accuracy in character reproduction. The repetitions were also to facilitate recording of changes in the dependent variables at intervals that could be used to identify motor learning profiles.

According to Andree and Maitra (2002), tracing a character six times is sufficient for a person to learn to accurately draw a foreign letter with the non-dominant hand. Additional repetitions were required for participants to improve task speed. Time-to-task completion was expected to decrease proportionally with the logarithm of the number of repetitions (Niebel, 1993; Wickens & Hollands, 2000). Previous research using a similar setup in which participants used a Phantom Omni without haptic assistance to manipulate cubes in an assembly task resulted in a 21% decrease in TTC at each doubling of task repetitions, up to 8 trials (Kaber et al., 2013). Therefore, 32 repetitions were expected to be sufficient to verify consistent TTC improvements at the 2nd, 4th, 8th, 16th and 32nd repetitions. The experiment protocol stressed both accuracy and speed to participants in order to promote similar improvements in both responses across trials.

2.3.2 Phase 2 procedures

The Phase 2 experiment procedures were based on the Phase 1 design, including baseline testing, training and post-training tests. Baseline and post-training test procedures were identical to Phase 1, including the number of characters and absence of haptic aiding. The key differences were the addition of four forms of haptic guidance (according to condition) to the training trials as well as an additional unassisted test trial performed after every 8^{th} training trial.

In Phase 2, baseline testing was used to assess each participant's ability to use the haptic device to write characters with the non-dominant (left) hand without haptic guidance. The testing was also used to and establish initial d_{MAX} values. The training session included four cycles of character drawing with haptic guidance featuring static or adaptive forms of VF or EA. Each training cycle concluded with a performance evaluation in which the participant drew each character without haptic guidance. Finally, participants returned to the lab one day after the end of the training cycles for the post-training test. This test had a format identical to baseline testing (i.e., draw each character once without haptic guidance), except that, as in Phase 1, a fifth character not included during training was also introduced as a measure of near-transfer. Figure 2.5 presents a summary of the two days of procedures, from orientation to the post-training test. Each step of the procedure is summarized in the following subsections.

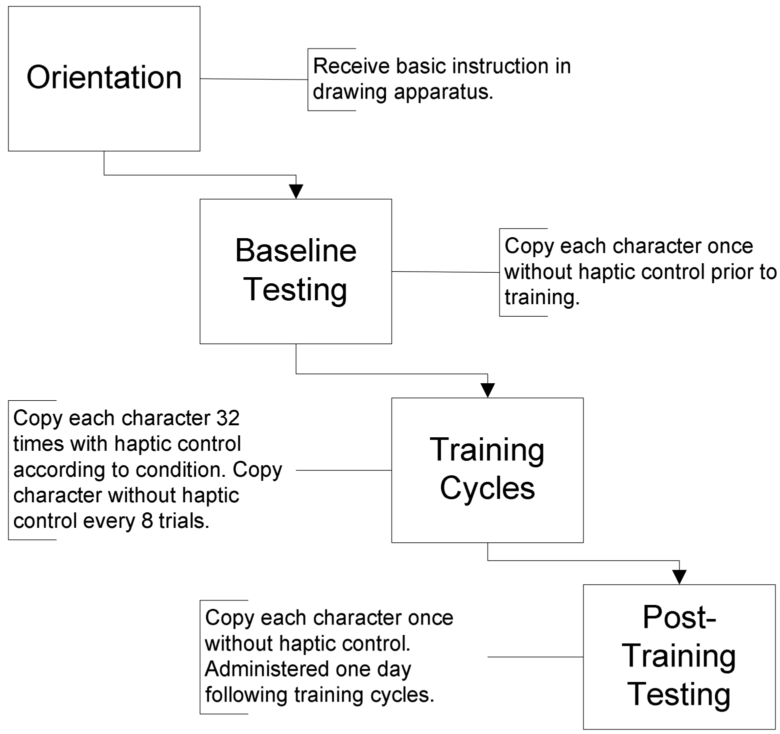

Figure 2.5. Summary of Phase 2 procedures

Orientation. On their first visit, participants completed an informed consent form (Appendix C) and received a brief orientation to the procedures. Following the orientation, participants received basic instruction using the haptic interface. While seated at the training workstation, participants were required to use the Phantom Omni to draw the Latin capital letter “S” using the training software with and without haptic aiding until they were comfortable (by self-report) with the drawing interface. The type of haptic feature was based on the participant’s assigned condition and set to a low difficulty level. Based on the Phase I results, the distance from the desired motion path to the haptic feature was 0.05 in. under the VF condition and 0.20 in. for the EA condition.

Baseline. Following orientation, each participant copied the series of four foreign characters from Phase 1 using their non-dominant hand without haptic guidance. Results were recorded as the baseline performance values that determined the maximum allowable deviations (d_{MAX}) from character templates during training.

Training. The structure of the Phase 2 data collection sessions also followed a repetitive tracing model (Srimathveeravalli et al., 2009). However, the visual tracing aspect of the task was reinforced with haptic feedback, as originally described by Rosenberg (1993). That is, participants were guided in the character reproduction by haptic cues similar to how they would have been guided by line segments in visual training. During training, participants traced each character 32 times for a total of 128 drawings (32 repetitions of 4 characters) with one type of haptic guidance (VF or EA, adaptive or static). Repetitions occurred one letter at a time (i.e., participants drew one letter 32 times, followed by the next letter 32 times, etc.). The order of presentation of the four letters within each set of trials was the same for each participant. Presentation of characters was held constant because the sample size was not sufficient to assign an equal number of participants to the possible random character orders. As in Phase 1, participants were instructed to complete each drawing accurately and quickly. Neither performance measure was emphasized over the other as part of the instructions; instead, participants were asked to focus on the "score" combining the speed and accuracy measures. No reference points were provided to participants to assess performance; instead, they were asked to reduce the score values over time.

The type of haptic guidance was manipulated between participants. Equal numbers of participants were presented with adaptive VF, static VF, adaptive EA, or static EA (according to

Table 2.2). For participants assigned to the adaptive conditions, the haptic guidance was manipulated following each block of 8 trials in order to increase task difficulty.

Intermediate Testing. After each block of 8 training trials, participants drew a character once without haptic aiding. Training resumed until the participant completed a total of four training cycles (128 assisted plus 16 unassisted drawings per participant). A 10-minute rest was provided after each hour of training, when applicable, as recommended by Robles De La Torre (2008) when training in a system with haptic control. Participants also completed a usability survey (Appendix D) following training to assess subjective differences among conditions.

Post-training test. Participants returned a day after training for one additional session of test trials, nearly identical to baseline testing. Each of the characters presented during training were drawn once without haptic aiding, along with a new fifth character not included in the training trials. The latter character was introduced as a test of near transfer (Haskell, 2001). The results of the post-training test trials were compared to the baseline results to evaluate learning due to the training trials.

2.4 Hypotheses

The following research hypotheses were formulated based on the previous research in the area of haptic guidance for motor skill training:

Hypothesis 1: Participants performing the training tasks under VF conditions were expected to perform better, in terms of drawing accuracy and speed, compared to EA participants.

Hypothesis 2: Participants performing under EA conditions vs. VF were expected to show greater improvements in accuracy and speed across intermediate (unassisted) test trials, between baseline and the post-training test.

Hypothesis 3: Participants performing with adaptive aiding vs. static were expected to show greater improvements in accuracy and speed across intermediate (unassisted) test trials, between baseline and the post-training test.

Hypothesis 4: Participants with greater drawing skills (in terms of both DV) were expected to show greater improvements in accuracy and speed following training in the EA condition, while less-skilled participants were expected to show greater improvements following training in the VF condition.

2.5 Data Analysis

The results for each participant were automatically written to text files at the end of each experiment session (see Table 2.3 for data definitions). All text files were subsequently combined into a single Microsoft Access database for post-processing. Post-processing included normalizing TTC, deviation and force data for each participant as a percent change from baseline using the following formula:

$$\text{Percent Change} = (\text{Baseline Value} - \text{Current Value}) / \text{Baseline Value} \qquad (3)$$

Normalization was performed to account for differences in performance levels for participants.

Post-processing also included identifying skill levels by ranking participants within condition according to the product of their baseline deviation and TTC. This product was also the "score" communicated to participants after each drawing, which represented their primary performance measure during testing and training. The top 50% of participants were identified as "High" performers, and the remainder were identified as the "Low" performing group.

Several statistical analyses were performed for the results. First, a multivariate analysis of variance (MANOVA) was conducted, as it was suspected that there might be inter-correlations among the various types of response measures (accuracy, force, speed). The MANOVA also accounted for potential inflation in the Type I error rate as a result of conducting multiple independent analyses of variance (ANOVAs) in order to identify any influence of haptic aiding on each measure. The MANOVA model applied was as follows:

$$Y = \mu + \text{Condition} + \varepsilon$$

Second, a series of repeated measures ANOVAs was conducted, including analysis of each of the three types of responses in order to account for any time dependence of test results across the five test cycles. The following ANOVA model was applied:

$$Y = \mu + \text{Condition} + \text{Cycle} + \text{Condition*Cycle} + \varepsilon$$

Subsequently, a series of matched pairs tests were performed for each DV to compare baseline performance (Cycle 0) with test performance after each subsequent training cycle, as well as the final post-training test. Given the number of matched pairs tests conducted on the results for each training condition, the criterion p-value for significance of any test statistic (0.05) was adjusted accordingly by dividing the p-value by the number of tests (i.e., $p = 0.05 / 5 = 0.01$). These analyses were performed to identify significant improvements recorded during intermediate and post-training tests as a result of each condition.

Finally, a series of ANOVAs was conducted to identify significant differences in responses at each test cycle due to condition. The following ANOVA model was applied:

$$Y = \mu + \text{Condition} + \varepsilon$$

An additional ANOVA was conducted on the DV to identify differences in test performance resulting from the training strategy; i.e., the adaptive, static or control conditions. The ANOVA model was structured as follows:

$$Y = \mu + \text{Strategy} + \varepsilon$$

After participants were ranked according to skill levels (“Low”, “High”), an additional ANOVA was performed on the DV using the following model:

$$Y = \mu + \text{Condition} + \text{Skill} + \text{Condition*Skill} + \varepsilon$$

For each significant ANOVA result, Tukey’s Honestly Significant Difference (HSD) tests were used to compare the speed, accuracy and force responses within cycle and among the training conditions (including multiple levels). Correlation analyses using Spearman’s ρ

were conducted to identify any statistical significant associations of the DVs with the subjective confidence and fatigue ratings.

At the outset of the statistical analyses, diagnostics were conducted on the response measure data distribution by using the simple main effects ANOVA models on the untransformed responses. Unfortunately, these diagnostics revealed violations of the normality assumption of the F-test. Shapiro Wilk tests of goodness of fit returned significant results for the normalized time ($W=0.861$, $p<0.0001$), deviation ($W=0.915$, $p<0.0001$) and force data ($W=0.783$, $p<0.0001$). Consequently, a log transformation was applied to the three response measures; however, subsequent Shapiro-Wilk tests revealed the transformed DV to also be non-normal (TTC: $W=0.962, p<0.0001$; Deviation: $W=0.944, p<0.0001$; Force: $W=0.959, p<0.0001$). Therefore, in order to address the non-normal response data distribution, rank transformations were performed on the speed, accuracy and force observations as a basis for the MANOVA and repeated measures ANOVA tests. In addition, the one-way ANOVA models and F-tests were substituted with Kruskal-Wallis tests. Beyond this, the matched pairs tests were replaced with Wilcoxon Signed-Rank Tests on the identified dependent measures.

3 Results

3.1 Phase 1

The purposes of Phase 1 were to: (1) represent a control condition for comparison with the four haptic conditions, investigated in Phase 2; and (2) inform the levels of change in haptic forces under the two adaptive conditions. This section describes the design of the adaptive aiding levels. A comparison of the Phase 1 and Phase 2 results will be covered in Section 3.3.

Time-to-task completion was expected to decrease proportionally with the logarithm of the number of character repetitions (Niebel, 1993; Wickens & Hollands, 2000). As previously mentioned, research using a similar apparatus and requiring participant manipulation of cubes in an assembly task found a 21% decrease in TTC at each doubling of task repetitions (Kaber et al., 2013). Therefore, the 32 repetitions performed in Phase 1 were expected to be sufficient to verify consistent TTC improvements at the 2nd, 4th, 8th, 16th and 32nd repetitions.

As expected, participant speed (measured by TTC) improved following the first trial. Figure 3.1 shows the average TTC across trials.

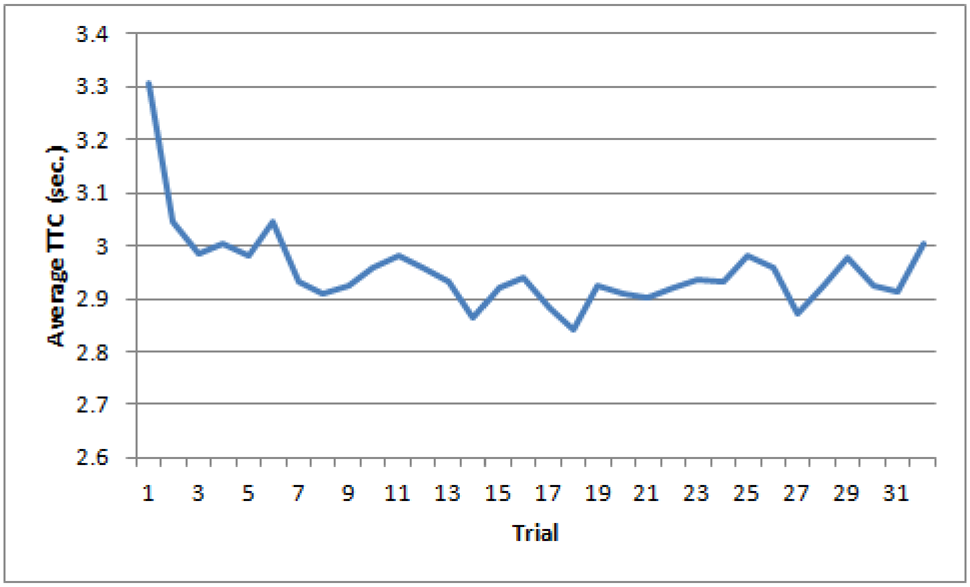

Figure 3.1. Average Phase 1 drawing speed (sec.) by trial

As Figure 8 suggests, participants improved until approximately halfway into the total number of trials, at which point performance seemed to asymptote or degrade (possibly due to fatigue). Consequently, only the first 16 trials were used to calculate proportional decreases in TTC (i.e., 2^{nd}, 4^{th}, 8^{th}, $16^{th)}$. Since TTC was used to model training improvements as a basis for scheduling adaptation of task difficulty in the Phase 2 experiment, it was determined that the Phase 1 performance decreases would not be included in the model.

Figure 3.2 shows the average TTC at trials 2, 4, 8 and 16. During Phase 1, improvements in TTC approximately followed a logarithmic relationship:

$$y = -0.126\ln(x) + 3.2163 \ (R^2=0.7587)$$

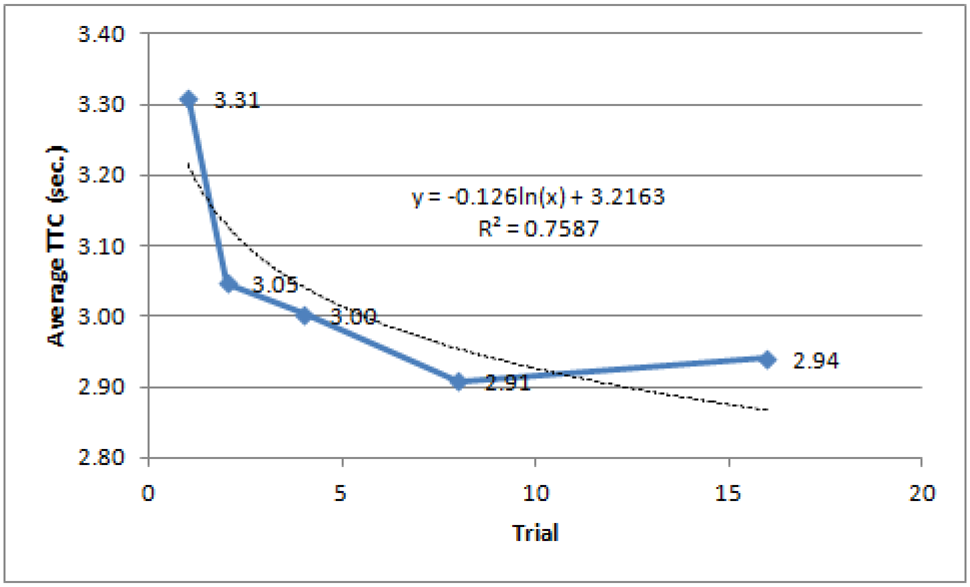

Figure 3.2. Average completion time at trials 2, 4, 8 and 16 including trendline showing a 12% logarithmic improvement

On the basis of this analysis, a 12% learning rate was adopted for determining levels of adaptive aiding in Phase 2 through the VF and EA haptic features. The level of haptic guidance under the VF condition was reduced at a rate of 12% across all 32 training trials performed in Phase 2. The level of haptic challenge posed by the EA condition was similarly increased at a rate of 12% across trials. It was expected that the haptic assistance would sustain or exceed the 12% learning rate beyond the 16 trials observed in Phase 1.

3.2 Haptic feature modeling

3.2.1 Adaptive

Speed, as measured by TTC, improved at a consistent rate, as attentional demands decreased with practice (Wickens & Hollands, 2000). The experiment protocol stressed both accuracy and speed to participants in order to promote similar improvements in the response measures across trials. Consequently, by using the speed improvements as a model, the haptic aiding also enforced accuracy improvements at a 12% learning rate across trials.

The maximum Euclidean deviation from the template for each character was calculated for each of four drawings produced by participants at the Phase 2 baseline. The average of these four deviations represented the extent of deviations addressed by the two haptic conditions (d_{MAX}) as follows. For VF, the average maximum deviation represented the distance from the template at which the opposing force (3.0 N based on Phantom Omni specifications) was applied during the *final* 8 trials of the Phase 2 training. VF at the beginning of training were set to maintain participant hand motion along the template trajectory without deviation. For EA, the maximum deviation represented the distance at which parallel forces were applied at the *beginning* of training. Error amplification at the end of training was set so deviations that were ~55% of the average maximum baseline deviation from the template trajectory produced haptic forces. (The derivation of the final EA deviation value (~55%) is explained in detail later in this section.) Figure Figure 3.3 shows an example of the target level of improvement during training, measured by a 50% change in d_{MAX} when drawing a single character.

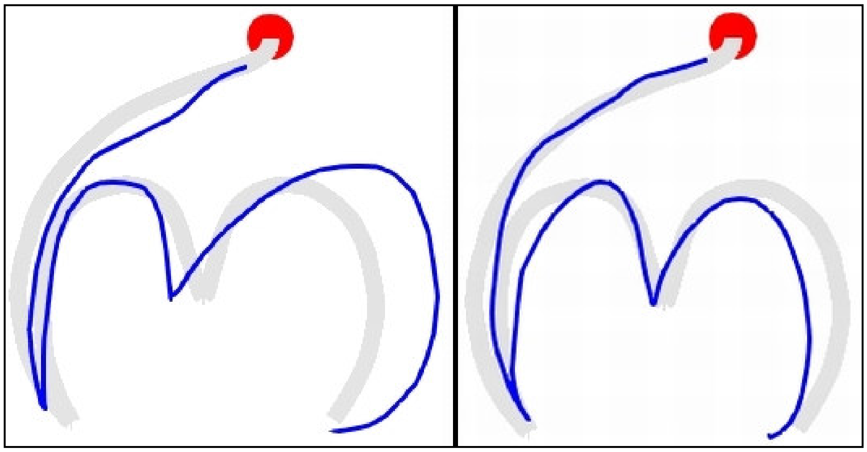

Figure 3.3. Example of a 50% d_{MAX} improvement for a single character. The figure on the left reflects a 0.44 in. d_{MAX}, and the d_{MAX} for the figure on the right is 0.22 in.

During training trials with adaptive haptic features, the level of haptic force was adjusted every eight trials (following each of the intermediate test trials). Haptic force presentation was designed to help participants perform at higher levels of precision than those recorded during Phase 1. This was achieved by training participants to perform at a higher accuracy level than would be expected without haptic assistance (according to Phase 1 results). Accuracy levels were enforced by modifying d_{MAX} at regular intervals.

d_{MAX} was updated every 8 trials according to a ratio (c_i) comparing average TTC to baseline TTC established during Phase 1 at the i^{th} trial. c_i was calculated for VF and EA using the following formula:

$$c_i = l^{\log(i) \div \log(2)} \tag{4}$$

where l is the learning percentage identified in Phase 1 and i is the number of completed trials. The learning percentage is expressed as a decimal in the equation, and the log function is base 10. Table 3.1 shows how c_i was applied to the VF condition for the 12% TTC improvement (i.e., $l = 0.88$) across the four training cycles.

Table 3.1. Examples of average to baseline TTC ratios (c_i) within trial cycles

Trials	i	c_i
1-8	1	1
9-16	8	0.681
17-24	16	0.600
25-32	24	0.556

The maximum allowable deviations (d_{MAX}) under VF was increased every 8 trials according to Table 3.1. Error amplification maximum deviations, in contrast, were decreased according to the same scale. That is to say, the VF became wider, and the range of EA implementation became narrower. These adjustments represented increases in task difficulty for both types of haptic aiding. For VF, the change meant that as training progressed, responsibility for accuracy shifted from the fixtures to the participant. For EA, increases in difficulty forced the participant to closely monitor drawing accuracy to avoid further deviations from the template.

Figure Figure 3.4 shows examples of how VF and EA forces for one participant changed over time, assuming a 12% improvement with each doubling of trials and the participant's maximum average deviation recorded at the Phase 2 baseline being 0.25 inches. The figure shows that during Cycle 1 (i.e., the first 8 trials), the VF force was applied at very short distances from the drawing template, limiting participant deviations to 0.05 inches. The 0.05 inch width for VF was identified as the narrowest field that did not restrict forward movement of the stylus. Cycle 4 (i.e., trials 25-32) shows VF applied only when deviations from the template were equal to the average maximum deviation recorded at baseline. During these trials, the VF feature was relaxed to its maximum, placing the responsibility for task completion almost completely on the participant.

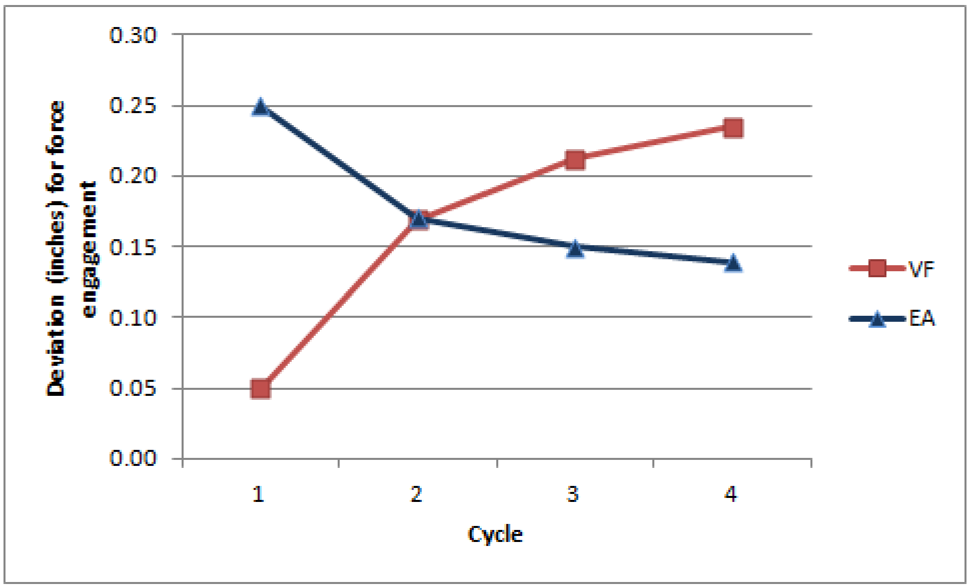

Figure 3.4. Example of VF and EA force applications across cycles when d_{MAX} at Baseline was 0.25 in.

Figure Figure 3.4 shows a narrowing of EA forces at higher trial numbers. During Cycle 1, forces were not applied unless the average maximum deviation from the Phase 2 baseline testing was exceeded. By Cycle 4, forces were applied for smaller deviations.

3.2.2 Static feature modeling

Haptic forces for the first 8 trials were calculated identically for the adaptive and static aiding conditions. Under static control, however, there were no increases in difficulty based on Phase 1 performance and the VF and EA features remained the same for Cycles 2-4 as for Cycle 1.

3.3 Phase 2

The Phase 2 results are divided into two main sections, including training and testing. Training covers the 32 trials administered between baseline and the post-training test, which incorporated varying levels of haptic guidance, depending on the condition. Testing covers baseline and post-training test trials as well as the four intermediate tests administered after every 8 trials (cycles) during training. The effect of the conditions on the speed and accuracy DV (i.e., TTC and total deviation) was the primary focus of these analyses. Note that the values in each of the tables were determined empirically. Additional analyses of secondary variables recorded during testing, including skill and force, were also conducted. A brief analysis of subjective measures follows the sections on training and testing.

3.3.1 Training

3.3.1.1 Adaptive feature levels

In the adaptive conditions, haptic forces were applied at varying levels according to (1) cycle and (2) each participant's average maximum deviation recorded at baseline (d_{MAX}; i.e., maximum deviation averaged across the four characters). In the VF condition, resistive forces were initially applied at 0.05 inches to eliminate all deviations during character reproductions. Forces were then gradually reduced (following a 12% learning curve) every cycle (i.e., every 8 trials) until the width of the VF equaled the participant's d_{MAX}. The maximum width was applied for training trials 25-32. In the EA condition, parallel forces were initially applied at deviations equal to the participant's d_{MAX}. In subsequent cycles, the deviation at which forces were applied was reduced following a 12% learning curve. Forces applied during static training were identical to forces applied during Cycle 1 of the adaptive conditions, but were maintained for all 32 training trials. The average deviations at which forces were applied for each cycle in the two adaptive conditions are summarized in Figure 3.5.

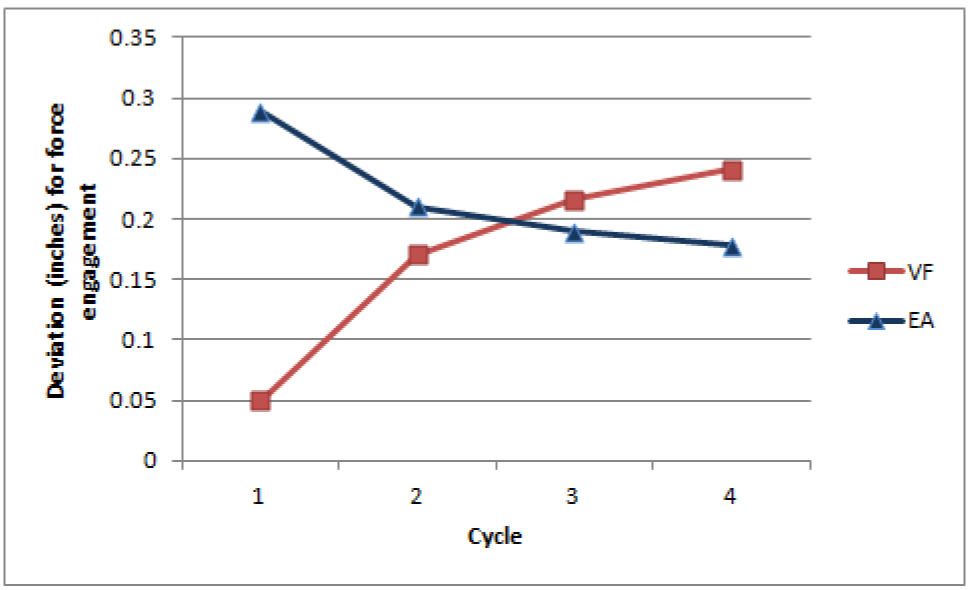

Figure 3.5. Average deviation at which haptic forces were engaged during each training cycle

Given that the Omni's maximum force output is 3.3 N, it was possible for participants to apply forces sufficient to break through the VF. In those cases, forces would be reapplied automatically when the participant corrected the trajectory. The VF condition, therefore, did not guarantee a specific performance level in terms of deviation. In fact, participants completing training in the VF conditions broke through the VF in approximately 97% of trials.

Table 3.2 and 3.3 summarize the average speed and accuracy results recorded during each training cycle. The following sections detail how performance for each DV varied by cycle and condition.

Table 3.2. Average TTC (sec.) during training by cycle and condition

	Condition				
Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
1	3.044	2.545	2.844	2.976	2.739
2	2.934	2.523	2.759	2.724	2.725
3	2.902	2.360	2.666	2.622	2.680
4	2.936	2.294	2.638	2.539	2.715

Table 3.3. Average deviation (in.) during training by cycle and condition

	Condition				
Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
1	17.283	10.433	19.407	9.489	17.779
2	16.396	16.540	18.961	8.273	16.670
3	16.799	16.870	20.334	8.494	16.118
4	16.843	17.226	18.502	8.603	16.522

An initial Kruskal-Wallis tests on the speed and accuracy scores at baseline revealed no significant differences among the five experiment conditions (speed, $\chi2=2.3362$, $p=0.5056$; accuracy, $\chi2=7.5332$, $p=0.1103$), suggesting that participants started at similar skill levels. Results revealed no significant differences in near-transfer speed ($\chi2=3.1591$, p=0.5316) and accuracy ($\chi 2$=5.8904, p=0.2075) due to condition following training. The normalized results for speed (TTC) and accuracy (deviation) during training are presented in Figures 3.6 and 3.7.

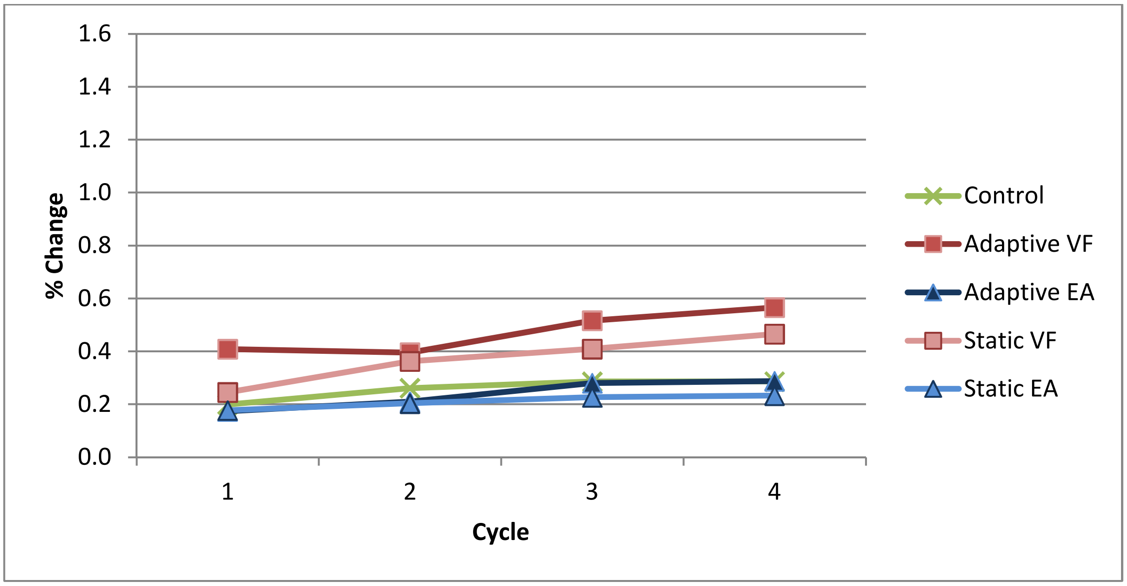

Figure 3.6. Average TTC percent change by cycle for each condition during training

Figure 3.6 suggests that speed improved gradually over time during training. In particular, speed improvements during training, as compared to baseline appeared highest for the VF conditions. A series of Kruskal-Wallis tests were performed to identify differences in speed resulting from condition. Results revealed highly significant differences (p<0.0001) among the haptic guidance conditions for all cycles. Table 3.4 provides a summary of the results.

Table 3.4. Results of Kruskal-Wallis tests comparing effects of condition on speed for each cycle during training

Cycle	$\chi2$	Prob> $\chi2$
1	11.41	p<0.0001*
2	53.00	p<0.0001*
3	70.32	p<0.0001*
4	83.32	p<0.0001*

* Significant at the p<0.05 level

Tukey's HSD tests were used to compare the speed responses within cycle and among the training conditions. Results revealed varying improvements in speed according to cycle. Participants training using adaptive VF (AVF) showed greater increases than all other conditions in Cycle 1. In Cycle 2, AVF participants showed greater improvements than the control (C) group and EA participants. In addition, static VF (SVF) participants improved more than adaptive EA (AEA) and static EA (SEA) participants. In Cycle 3 and Cycle 4 all VF participants showed greater improvements than the control group and both AEA and SEA participants. A summary of the Tukey's HSD results on the speed response during training is presented in Table 3.5.

Table 3.5. Results of Tukey's HSD tests comparing differences in speed by condition during training. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

	Group Identifiers for Condition Means				
	A	**AB**	**B**	**BC**	**C**
Cycle 1	AVF		C, AEA, SVF, SEA		
Cycle 2	AVF	SVF		C	AEA, SEA
Cycle 3	AVF, SVF		C, AEA, SEA		
Cycle 4	AVF, SVF		C, AEA, SEA		

Figure 3.7 shows the normalized results for accuracy during training. The Figure shows that accuracy improvements during training may have been higher for the VF and EA conditions, as compared to the control, but improvements under the haptic guidance conditions varied very little across most cycles. The large improvement in deviation during Cycle 1 in the AVF condition and improvement in all cycles under SVF was due to the narrowness of the VF (i.e., 0.05 in.) that facilitated near perfect drawing accuracy. The dramatic drop in AVF performance in Cycle 2 reflects the relaxing of the adaptive VF.

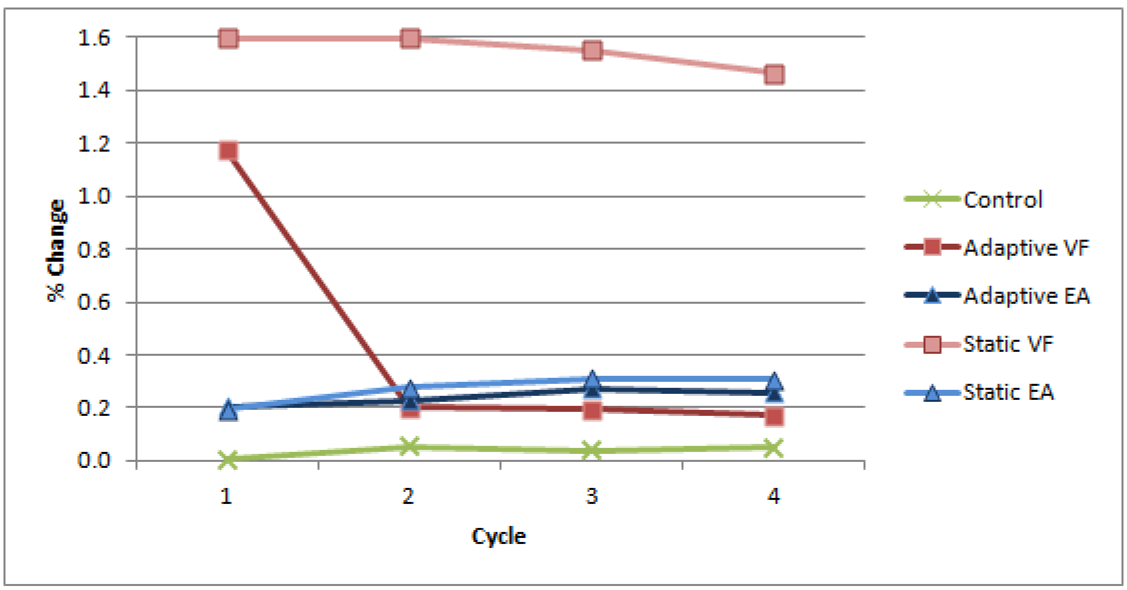

Figure 3.7. Average deviation percent change by cycle for each condition during training

According to a Kruskall-Wallis test, the different improvements in deviation were significant. Table 3.6 summarizes the p-values for differences in accuracy across the five conditions.

Table 3.6. Kruskal-Wallis results for differences in accuracy percent improvements from baseline across conditions

Cycle	$\chi 2$	Prob> $\chi 2$
1	525.02	$p<0.0001$*
2	398.95	$p<0.0001$*
3	387.04	$p<0.0001$*
4	398.66	$p<0.0001$*

* Significant at the $p<0.05$ level

Tukey's HSD tests were used to compare the accuracy responses within cycle and among the training conditions. Results revealed varying improvements in accuracy according to cycle. Static VF produced the greatest level of improvement across all cycles; differences in the remaining conditions varied according to cycle. In the first cycle, AVF accuracy improvements were higher than for the control group and both EA conditions. In Cycle 2, static EA improvements were greater than for the control group. In Cycle 3 and Cycle 4, AEA and SEA improvements were significantly higher than for the control group. Differences in accuracy during training were expected as deviations in hand motion from a template represented the basis for control of the haptic features. A summary of the Tukey's HSD test results is presented in Table 3.7.

Table 3.7. Results of Tukey's HSD tests comparing differences in accuracy by condition during training. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

Group Identifiers for Condition Means					
	A	**AB**	**B**	**BC**	**C**
Cycle 1	SVF		AVF		C, AEA, SEA
Cycle 2	SVF		SEA	AEA, AVF	C
Cycle 3	SVF		AEA, SEA	AVF	C
Cycle 4	SVF		AEA, SEA	AVF	C

The training results were in partial support of H1. Participants performing the training tasks under VF conditions were expected to perform better in terms of drawing accuracy and speed, as compared to EA participants. In Cycles 3 and 4, VF participants made greater improvements in speed, as compared to EA participants. In terms of accuracy, SVF participants consistently showed greater improvements than the other training groups. In later cycles, EA participants also outperformed control participants in terms of accuracy. Adaptive VF participants only outperformed other participants in Cycle 1.

3.3.2 Testing

In contrast to training trials, test trials did not incorporate haptic features. In this respect, differences in test performance represent carry-over effects from the training trials. Test trials were administered prior to and following training, as well as after each cycle of training trials. Tables 3.8, 3.9 and 3.10 show the average speed, accuracy and force results, respectively, for each test cycle. Figures 3.8 and 3.9 summarize the percentage improvements in speed and accuracy, respectively, across tests. In all tables and figures in this section, Cycle 0 represents baseline performance; Cycles 1-4 represent intermediate tests presented immediately following training drawings; and Cycle 5 represents the post-training test, administered following a 1-day decay period.

Table 3.8. Average speed (sec.) during testing by cycle and condition

	Condition				
Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
0	3.538	3.409	3.184	3.402	3.136
1	2.908	2.763	3.013	3.328	2.900
2	2.941	2.706	2.862	3.316	2.984
3	2.932	2.567	2.861	3.241	2.902
4	2.960	2.540	2.826	3.323	3.073
5	3.358	2.584	2.783	3.333	3.404

Table 3.9. Average deviation (in.) during testing by cycle and condition

	Condition				
Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
0	16.974	19.618	22.244	19.119	20.479
1	16.483	18.171	18.613	16.896	16.433
2	16.334	16.979	18.474	15.378	15.237
3	17.424	17.889	17.236	17.222	14.583
4	17.113	20.449	17.330	15.678	15.059
5	16.089	18.301	19.088	16.507	16.875

3.10. Average force (N) during testing by cycle and condition

	Condition				
Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
0	1.879	2.438	2.264	2.126	2.053
1	1.796	1.633	2.591	1.590	2.200
2	2.013	1.610	2.494	1.387	1.828
3	2.086	1.615	2.611	1.367	1.724
4	2.224	1.659	2.520	1.342	1.819
5	1.489	1.986	1.911	1.793	1.649

The MANOVA model used to assess the influence of the training condition across the speed, accuracy and force response measures revealed a significant main effect ($p=0.0057$) during test trials. The results of the repeated measures ANOVA models varied by response measure. The effect of condition was significant for all three responses, while cycle was not significant for any of the responses. Interaction effects were significant for speed and force, but not for accuracy. The statistical results are summarized in Table 3.11. The findings suggested that the timing of the intermediate tests (alone) did not influence performance; however, the pattern of test performance over time varied among the training conditions.

3.11. Results of repeated measures ANOVA tests for speed, accuracy and force

	Condition	Cycle	Condition*Cycle
Speed	p=0.0034*	p=0.9674	p=0.0030*
Accuracy	p=0.0008*	p=0.9989	p=0.2058
Force	p=0.0023*	p=0.9931	p<0.0001*

* Significant at the *p*<0.05 level

3.3.2.1 Speed

Figure 3.8 shows that average participant speed improved across the first 3 cycles (24 training trials) and then tended to level-off or drop. The figure also suggests that speed in the post-training test for groups not receiving adaptive aiding (i.e., the control, SVF, and SEA conditions) fell to levels near baseline, while post-training test TTC for the adaptive groups remained at levels similar to those immediately following training or was better.

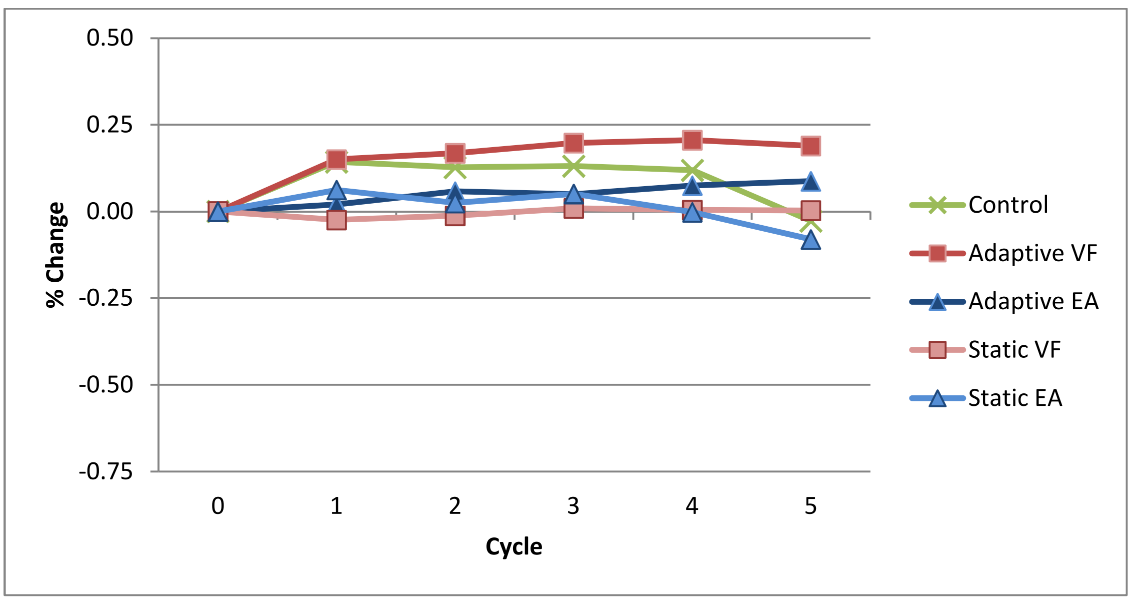

Figure 3.8. Average percent change in TTC by cycle for each condition during testing

The Wilcoxon Signed-Rank tests comparing baseline speed to speed in each of the other cycles revealed highly significant differences between baseline and all subsequent test trials (including the post-training test) for the AVF group. Results for the other conditions were mixed. In the control condition, speed improved at the intermediate tests following training Cycles 1 through 4 but did not differ significantly from baseline during the post-training test. Test performance following Cycle 1 did not differ significantly from baseline for the AEA condition; however, speed improved marginally in Cycles 2, 4 and 5. Post-training test speed also differed significantly from baseline following AEA training. Training in the static conditions (SEA and SVF) did not result in significant speed improvements over baseline levels except for a marginal improvement under SEA in Cycle 1. Table 3.12 summarizes the results of the Wilcoxon Signed-Rank tests for speed.

Table 3.12. Results of Wilcoxon signed-rank tests (Prob<S) comparing speed at baseline to subsequent test cycles (DF=31)

Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
1	S=-221; p<0.0001*	S=-159; p=0.0004*	S=-40; p=0.2315	S=1; p=0.5073	S=-95; p=0.04
2	S=-194; p=0.0007*	S=-194; p<0.0001*	S=-54; p=0.1368	S=-20; p=0.3539	S=-46; p=0.1991
3	S=-188; p=0.001*	S=-190; p<0.0001*	S=-63; p=0.0982	S=-26; p=0.3139	S=-69; p=0.0991
4	S=-183; p=0.0013*	S=-196; p<0.0001*	S=-73; p=0.0778	S=-36; p=0.2417	S=-0.5; p=0.4964
5	S=-69; p=0.1423	S=-207; p<0.0001*	S=-94; p=0.0314	S=-24; p=0.3304	S=47; p=0.806

* Significant at the $p<0.01$ level

A Kruskal-Wallis test comparing differences in TTC for each cycle revealed significant differences due to condition within all cycles. The p-values are summarized in Table 3.13.

Table 3.13. Kruskal-Wallis results for differences in speed percent improvements from baseline across conditions (DF=4)

Cycle	$\chi 2$	Prob> $\chi 2$
1	13.24	p=0.0102*
2	14.38	p=0.0062*
3	12.77	p=0.0125*
4	16.19	p=0.0028*
5	12.98	p=0.0114*

* Significant at the p<0.05 level

A post-hoc comparison of the speed responses using Tukey's HSD tests revealed speed improvements in the AVF condition to be significantly higher than SVF in Cycle 1 and Cycle 2, higher than the two static conditions in Cycle 3 and Cycle 4 and higher than the static and control conditions in Cycle 5. The results of the post-hoc tests are summarized in Table 3.14.

Table 3.14. Results of Tukey's HSD tests comparing differences in speed by condition during testing. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

Group Identifiers for Condition Means			
	A	**AB**	**B**
Cycle 1	AVF, C	SEA, AEA	SVF
Cycle 2	AVF, C	SEA, AEA	SVF
Cycle 3	AVF	C, AEA	SVF, SEA
Cycle 4	AVF	C, AEA	SVF, SEA
Cycle 5	AVF	AEA	C, SVF, SEA

3.3.2.2 Accuracy

Figure 3.9 shows that the accuracy improvements (reductions in deviation) also varied according to condition. Average deviation following training under the control condition appeared to drop slightly, but with little change over time. In contrast, following VF condition training, deviations decreased up to Cycle 2 and to Cycle 3 for participants trained under the EA conditions. Greater improvements in accuracy appeared to remain in EA post-training test performance, as compared to the control and AVF conditions, which yielded similar performance, with SVF falling in-between.

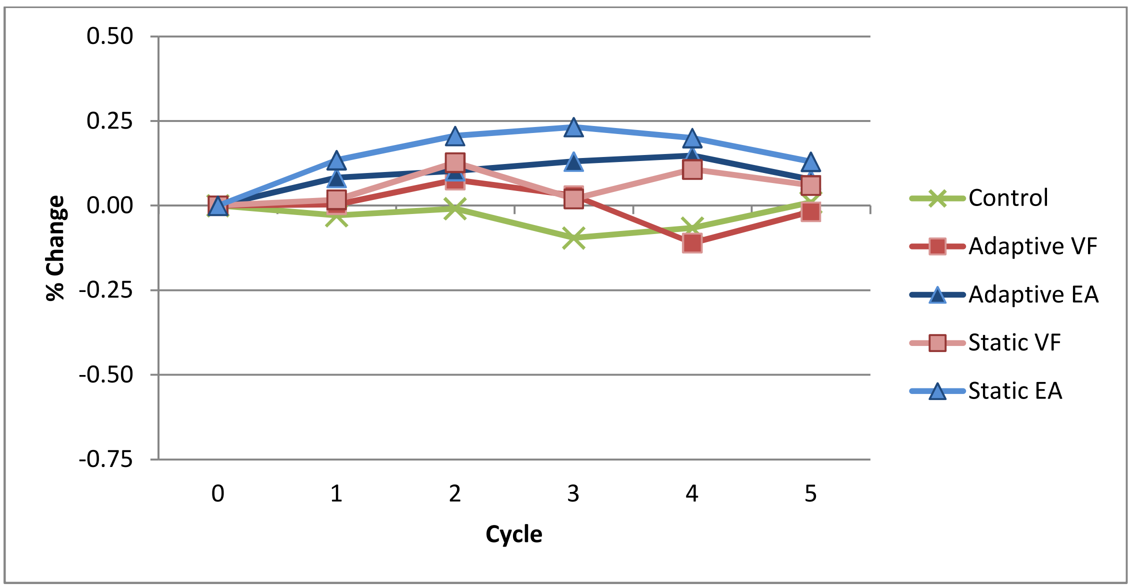

Figure 3.9. Average percent change in deviation by cycle for each condition during testing

As in the speed response analysis, the criterion p-value for judging significance of the Wilcoxon Signed-Rank test statistics was adjusted for the number of test within training condition. The tests comparing baseline performance to each of the other cycles revealed significant differences between baseline test accuracy and all subsequent test trials following training under the EA conditions, except for post-training AEA tests. Training in the AVF condition resulted in significant improvements in accuracy in Cycle 2 only, while SVF training resulted in significant improvements in Cycles 2 and 4. Training without haptic features did not result in any deviation improvements. Table 3.15 summarizes the results of the Wilcoxon Signed Rank tests.

Table 3.15.Results of Wilcoxon signed-rank tests (Prob<S) comparing deviation baseline performance to subsequent test cycles (DF=31)

Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
1	S=4; p=0.5245	S=-63; p=0.1224	S=-145; p=0.0024*	S=-61; p=0.1302	S=-183; p<0.0001*
2	S=9; p=0.4449	S=-134; p=0.0049*	S=-144; p=0.0026*	S=-164; p=0.0006*	S=-201; p <0.0001*
3	S=-24; p=0.3559	S=-73; p=0.0881	S=-173; p=0.0003*	S=-76; p=0.0792	S=-219; p <0.0001*
4	S=35; p=0.7052	S=-52; p=0.1694	S=-173; p=0.0003*	S=-150; p=0.0017*	S=-201; p <0.0001*
5	S=-53; p=0.2064	S=-36; p=0.2548	S=-120; p=0.0111	S=-111; p=0.0178	S=-191; p <0.0001*

* Significant at the p<0.01 level

A subsequent Kruskal-Wallis test comparing differences in deviation improvements for each cycle revealed significant differences in Cycles 1, 2, 3 and 4. The p-values are summarized in Table 3.16.

Table 3.16. Kruskal-Wallis results for differences in accuracy percent improvements from baseline across conditions (DF=4)

Cycle	$\chi 2$	Prob> $\chi 2$
1	9.46	p=0.0505
2	16.61	p=0.0023*
3	22.13	p=0.0030*
4	17.44	p=0.0112*
5	5.60	p=0.2314

* Significant at the p<0.05 level

A post-hoc comparison of the responses using Tukey's HSD tests revealed accuracy improvements in the SEA condition to be significantly higher than for the control group in Cycles 2 and 3 and significantly higher than the AVF and control conditions in Cycle 4. A summary of the post-hoc results is provided in Table 3.17.

Table 3.17. Results of Tukey's HSD tests comparing differences in accuracy by condition during testing. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

	Group Identifiers for Condition Means				
	A	**AB**	**B**	**BC**	**C**
Cycle 2	SEA	AEA, AVF, SVF	C		
Cycle 3	SEA	AEA		AVF, SVF	C
Cycle 4	SEA	AEA, SVF	AVF, C		

3.3.2.3 Test Summary

Table 3.18 summarizes the results of the Wilcoxon Signed Rank tests for speed and accuracy by condition.

Table 3.18. Summary of DV improvements from baseline test for all conditions

Condition	**DV**	**Result**
Control	Speed	Significant improvements in Cycles 1-4; no significant post-test differences
	Accuracy	No significant improvement
Adaptive VF	Speed	Highly significant improvements in **all cycles**
	Accuracy	Significant improvement in Cycle 2 only
Adaptive EA	Speed	Significant improvements from baseline in Cycles 2, 4 and 5
	Accuracy	Significant improvements in Cycles 1-4; no significant post-test differences
Static VF	Speed	No significant improvement
	Accuracy	Significant improvements from baseline in Cycles 2 and 4
Static EA	Speed	Marginal improvement in Cycle 1 only
	Accuracy	Significant improvements from baseline in **all cycles**

The AEA condition showed greater intermediate test results, in terms of accuracy. While there were no significant differences in accuracy following one training cycle, AEA training resulted in significant improvements over the control condition in Cycle 2 and Cycle 3, and significant improvements over the SVF and control conditions in Cycle 4. Intermediate results revealed AVF training to be superior for improving speed. In Cycle 4, AVF speed improvements were greater than in the control condition. In Cycle 5, AVF speed improvements were significantly greater than all conditions except AEA. Neither adaptive condition (VF or EA) resulted in greater post-training test improvements (in terms of speed or accuracy), as compared to the other adaptive condition.

The test results partially supported H2. Accuracy and speed were expected to improve more in intermediate test (without haptic assistance) between baseline and post-training testing for the EA conditions. Accuracy improved following both forms of EA training, but speed improved more often following AVF training. Post-training test speed improvements were also significantly higher following AVF training. However, the analysis did not reveal significant differences in post-training test accuracy improvements. Overall, training in AEA resulted in the greatest number of test improvements in terms of the speed and accuracy response measures.

3.3.3 Additional analyses

3.3.3.1 Training strategy

The Kruskal-Wallis test applied to the DV to identify differences in test performance resulting from the training strategy; i.e., the adaptive, static or control conditions revealed the effect of the training strategy to vary by cycle. The model revealed significant speed improvements due to strategy during all cycles. The results of the Kruskal-Wallis tests are summarized in Table 3.19.

Table 3.19. Kruskal-Wallis results for differences in speed percent improvements from baseline across training strategies (DF=2)

Cycle	$\chi 2$	Prob> $\chi 2$
1	6.52	p=0.0384*
2	8.90	p=0.0117*
3	6.24	p=0.0441*
4	11.21	p=0.0037*
5	11.09	p=0.0039*

* Significant at the p<0.05 level

Based on Tukey's HSD tests, speed improvements in Cycle 1, 3 and 4 were lower following static training, as compared to the adaptive training strategies. In Cycle 2, speed improvements were lower following static training compared to the adaptive *and* control strategies. In Cycle 5, adaptive training improvements exceeded the other training strategies. A summary of the post-hoc results is provided in Table 3.18.

Table 3.18. Results of Tukey's HSD tests comparing differences in speed by training strategy during testing. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

Group Identifiers for Condition Means			
	A	**AB**	**B**
Cycle 1	C	A	S
Cycle 2	C, A		S
Cycle 3	A	C	S
Cycle 4	A	C	S
Cycle 5	A		C, S

With respect to the accuracy improvements, the Kruskal-Wallis tests revealed improvements in Cycles 2, 3, and 4. The results are summarized in Table 3.21.

Table 3.20. Kruskal-Wallis results for differences in accuracy percent improvements from baseline across training strategies (DF=2)

Cycle	$\chi 2$	Prob> $\chi 2$
1	4.97	p=0.0834
2	13.82	p=0.0010*
3	10.58	p=0.0050*
4	12.72	p=0.0017*
5	2.66	p=0.2646

* Significant at the p<0.05 level

Post-hoc tests using Tukey's HSD method revealed accuracy improvements following training using static strategies to exceed control strategies in Cycles 2 and 4. In Cycle 3, accuracy improvements following static and adaptive training exceeded control improvements. A summary of the post-hoc results is provided in Table 3.22.

Table 3.21. Results of Tukey's HSD tests comparing differences in accuracy by training strategy during testing. (Note: Conditions with different grouping identifiers are significantly different at $p<0.05$.)

Group Identifiers for Condition Means			
	A	**AB**	**B**
Cycle 2	S	A	C
Cycle 3	S, A		C
Cycle 4	S	A	C

These results are in partial support of H3. Adaptive training was expected to lead to greater improvements in speed and accuracy in test trials between baseline and post-training tests.

3.3.3.2 Force changes during testing

The degree of downward force applied during each trial was tracked automatically by the simulation. An additional analysis was performed to determine if the average force applied during testing changed as a result of the training conditions. Figure 3.10 presents a summary of changes (reductions) in average force measured in test trials following baseline testing. The figure reveals greater reductions in force during test trials for the VF conditions, as compared to the EA and control conditions. It can also be noted that four of the five conditions resulted in relatively similar levels of force during the post-training test.

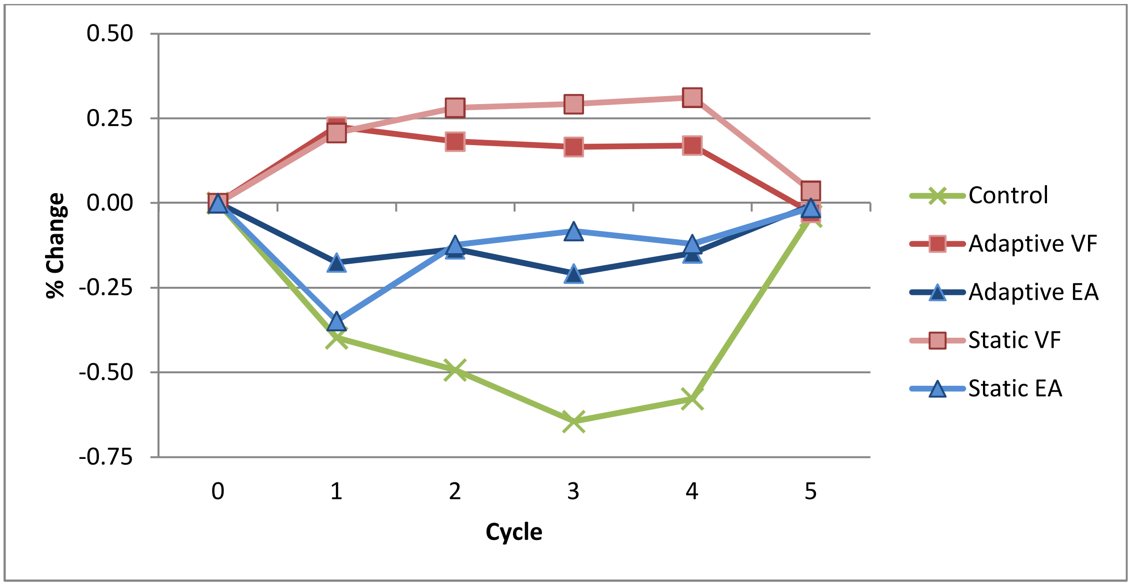

Figure 3.10. Average percent change in force by cycle for each condition during testing

Additional Wilcoxon Signed-Rank tests were conducted to compare baseline performance to the other cycles with the criterion significance level adjusted according to the number of tests within training condition. In general, results revealed significant reductions in average force in all intermediate tests following training under both VF conditions but not in the post-training test. Training in the EA condition as well as training without haptic features did not result in any significant changes in average force. Table 3.23 summarizes the results of the Signed-Rank tests.

Table 3.22. Results of Wilcoxon signed-rank tests (Prob<S) comparing force baseline performance to subsequent test cycles (DF=31)

Cycle	**Control**	**Adaptive VF**	**Adaptive EA**	**Static VF**	**Static EA**
1	S=35;p=0.713	S=-129;p<0.0001*	S=35;p=0.7393	S=-145;p=0.0001*	S=13;p=0.5938
2	S=67;p=0.8606	S=-152;p=0.0014*	S=8;p=0.5581	S=-213;p<0.0001*	S=-58;p=0.1426
3	S=85;p=0.9165	S=-166;p=0.0005*	S=18;p=0.6289	S=-226;p<0.0001*	S=-64;p=0.1186
4	S=89;p=0.9263	S=-172;p=0.0003*	S=20;p=0.6426	S=-226;p<0.0001*	S=-43;p=0.215
5	S=-98;p=0.0626	S=-36;p=0.2548	S=-98;p=0.033	S=-88;p=0.0503	S=-81;p=0.066

* Significant at the p<0.01 level

A subsequent nonparametric ANOVA comparing differences in force improvements for each cycle due to condition revealed significant differences in Cycles 1-4. The p-values are summarized in Table 3.24.

Table 3.23. Kruskal-Wallis results for differences in force percent improvements from baseline across conditions (DF=4)

Cycle	$\chi 2$	Prob> $\chi 2$
1	17.07	p=0.0019*
2	16.94	p=0.0020*
3	19.76	p=0.0006*
4	22.53	p=0.0002*
5	1.81	p=0.7702

* Significant at the p<0.05 level

However, a comparison of the force responses using Tukey's HSD tests showed varying results among the training conditions. Participants tended to show the least improvement in the Control and AEA conditions and the most in the two VF conditions. AVF tended to show greater improvements in the initial cycles, while SVF showed greater improvements in latter cycles. A summary of the post-hoc results is provided in Table 3.25.

Table 3.24. Results of Tukey's HSD tests comparing differences in force by condition during testing. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

	Group Identifiers for Condition Means				
	A	**AB**	**B**	**BC**	**C**
Cycle 1	AVF	SVF, SEA, C	AEA		
Cycle 2	AVF, SVF	SEA	C, AEA		
Cycle 3	AVF, SVF, SEA		C, AEA		
Cycle 4	SVF	AVF	SEA*	AEA	C

3.3.3.3 Skill comparison

An additional analysis was performed to determine how responses were affected by participant skill levels. To address the non-normal response data distribution, rank transformations were performed on the speed and accuracy observations. (This approach is equivalent to a non-parametric test when applied with the ANOVA.)

For the ranked speed and accuracy response measures, the model revealed a significant interaction between condition and skill only for speed during post-testing. This finding is in contrast to H4, which stated that skilled participants were expected to improve more in the EA condition and less skilled participants would improve more through VF training. With respect to main effects, the results of application of the model were mixed. The effects of skill varied for each response.

The ANOVA for speed rankings revealed a significant in all five cycles. Effect tests showed that low skill participants improved more than higher skilled participants. The results of the ANOVA for speed including skill and feature*skill interaction effects are presented in Table 3.26.

Table 3.25. ANOVA results for ranked speed response during testing, including skill and condition*skill interaction effects

Cycle	Model result	Model p-value	Skill effect p-value	Condition*Skill effect p-value
1	$F(9,154)=2.87$	$p=0.0037$*	$p=0.0061$*	$p=0.6526$
2	$F(9,154)=3.94$	$p=0.0002$*	$p=0.0004$*	$p=0.2412$
3	$F(9,154)=4.68$	$p<0.0001$*	$p<0.0001$*	$p=0.1609$
4	$F(9,154)=5.49$	$p<0.0001$*	$p<0.0001$*	$p=0.1121$
5	$F(9,154)=5.47$	$p<0.0001$*	$p<0.0001$*	$p=0.0281$*

* Significant at the $p<0.05$ level

Based on a Tukey's HSD test on the interaction effect in Cycle 5, lower skilled participants training with AVF made the greatest improvements, which were significantly larger than lower skilled participants training with SVF and higher skilled participants training with both EA features and higher skilled control participants. A summary of the post-hoc result is provided in Table 3.27.

Table 3.26. Results of Tukey's HSD tests comparing differences in speed*skill interaction effects by condition during post-testing. (Note: Conditions with different grouping identifiers are significantly different at p<0.05.)

Skill Level	**Condition**	**Group Indentifiers for Condition Means**		
Low	AVF	A		
Low	AEA	A	B	
Low	C	A	B	
High	AVF	A	B	C
Low	SEA	A	B	C
High	SVF	A	B	C
Low	SVF		B	C
High	AEA		B	C
High	SEA			C
High	C			C

The ANOVA for accuracy was consistent with previous results. The model was significant only in Cycles 2, 3 and 4. However, effect tests did not show significant differences resulting from participant skill. The results of the ANOVA for speed including skill effects are presented in Table 3.28.

Table 3.27. ANOVA results for ranked accuracy response during testing, including skill and condition*skill interaction effects

Cycle	Model result	Model p-value	Skill effect p-value	Condition*Skill effect p-value
1	$F(9,154)=1.52$	$p=0.1437$	$p=0.7044$	$p=0.5289$
2	$F(9,154)=2.72$	$p=0.0058$*	$p=0.2043$	$p=0.3100$
3	$F(9,154)=3.03$	$p<0.0023$*	$p<0.1051$	$p=0.7007$
4	$F(9,154)=2.67$	$p<0.0065$*	$p<0.0829$	$p=0.6254$
5	$F(9,154)=1.18$	$p<0.3106$	$p<0.7784$	$p=0.3206$

* Significant at the $p<0.05$ level

3.3.3.4 Near Transfer Test

During post-training tests, each participant traced a fifth character that was not presented during baseline testing or training in order to assess the extent to which learning was transferred from the training context to a near transfer context. Differences in average deviations and average TTC among conditions were analyzed directly, instead of through analysis of normalized values. Since the near transfer character was not presented at baseline, there was no baseline value available to assess the percent change used for the other four characters.

The near transfer speed and accuracy data violated the normality assumptions; therefore, a nonparametric Kruskal-Wallis test was performed to identify differences in speed and accuracy means. Results revealed no significant differences in near transfer speed ($\chi2=3.1591$, $p=0.5316$) and accuracy ($\chi2=5.8904$, $p=0.2075$) due to condition following training. That is, all VF and EA haptic guidance as well as adaptive and static training strategies were comparable in terms of learning to support novel character reproduction.

3.3.3.5 Subjective measures

Following training, participants completed a brief subjective questionnaire evaluating (1) confidence during testing, (2) confidence during training, and (3) fatigue following training. Responses were scored from 1 to 10 ranging from "not at all" to "completely." Mean confidence during testing was 5.19. Training confidence was slightly higher at a mean of 6.88. Fatigue was low, overall, with a mean of 3.23. A series of Kruskal-Wallis tests for differences in the three subjective responses revealed significant differences in training confidence ($\chi2=11.41$, $p=0.0097$) and testing confidence ($\chi2=9.27$, $p=0.0259$). Figures 3.11 and 3.12 summarize the average training and test confidence scores for each condition. Note that test confidence was not rated for the control condition because the training and test trials were presented without additional haptic forces. In other words, control participants experienced no differences between test and training trials.

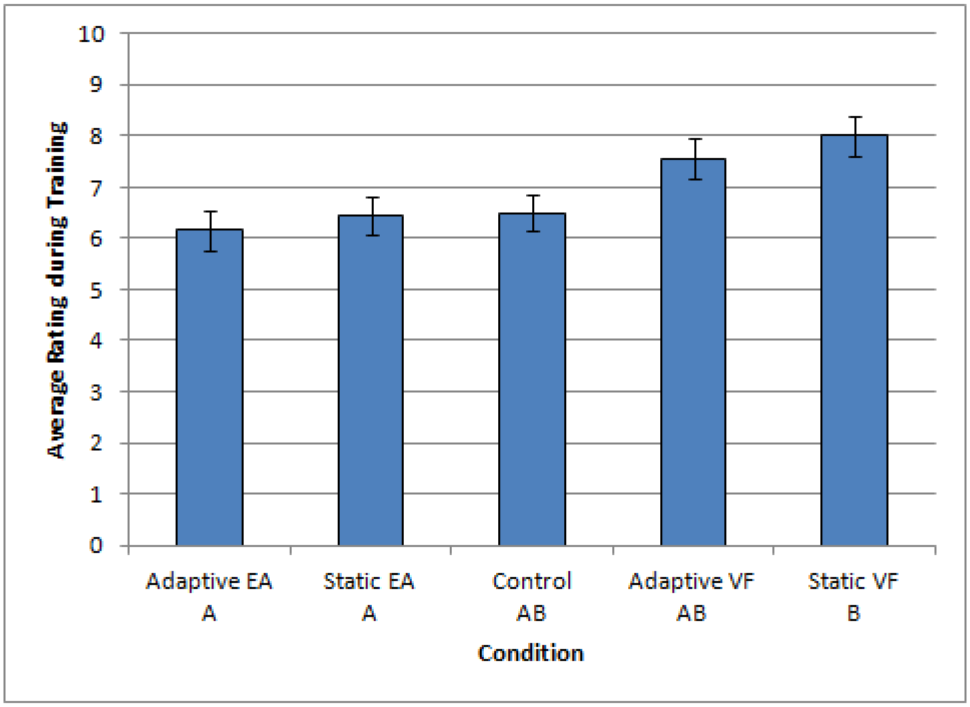

Figure 3.11. Average confidence rating for training trials by condition including groups of means identified by Tukey's HSD tests. Error bars represent standard error.

The figure suggests that participants had the greatest confidence in performing the training task under the VF conditions and the least under EA, with small advantages attributable to the static conditions compared to adaptive. This was expected as the SVF condition represents the highest degree of aiding while AEA represents the highest challenge. Post-hoc tests using Tukey's HSD method showed that, during training, participants reported less confidence in their performance under the two EA conditions compared to static VF.

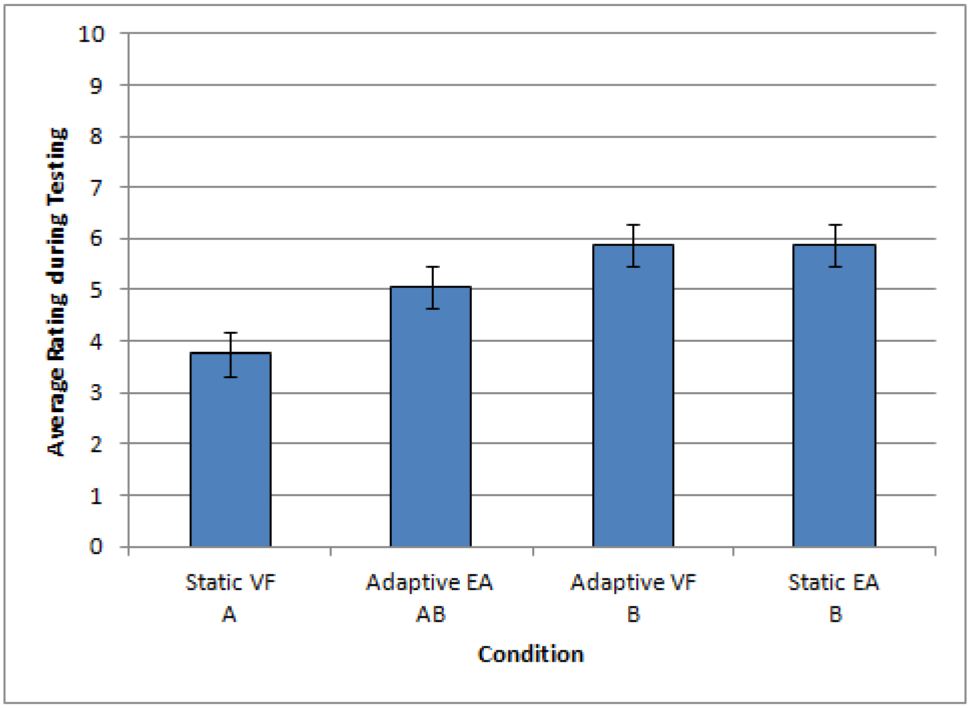

Figure 3.12. Average confidence rating for test trials by condition including groups of means identified by Tukey's HSD. Error bars represent standard error.

While static VF resulted in the highest reported confidence during training, it also resulted in the lowest confidence during testing, as shown in Figure 3.12. The highest confidence resulted from training under AVF and SEA. This finding may be due to the common deviation threshold of the haptic forces under these two conditions. Haptic forces were activated at similar deviations during the final eight training trials for AVF and SEA. Post-hoc tests using Tukey's HSD method revealed that, during testing, participants reported less confidence in their performance under the SVF condition compared to AVF and SEA conditions.

Correlation analyses using Spearman's ρ were conducted to identify any statistical significant associations of the subjective confidence and fatigue ratings with the DVs collected during testing. The correlation results are summarized in Table 3.29.

Table 3.28. Spearman's ρ results comparing DVs on testing with subjective ratings for each condition

Dependent Variable	Subjective Measure	Feature	ρ	p-value
Accuracy	Confidence	AVF	-0.1637	0.0233*
		AEA	-0.2879	<0.0001*
		SVF	0.1899	0.0083*
		SEA	-0.0897	0.2251
	Fatigue	AVF	-0.0316	0.6638
		AEA	-0.1243	0.0858
		SVF	0.1442	0.0460*
		SEA	-0.0658	0.3642
Speed	Confidence	AVF	.4382	<0.0001*
		AEA	.4230	<0.0001*
		SVF	-0.0938	0.1957
		SEA	0.1001	0.1672
	Fatigue	AVF	-0.3452	<0.0001*
		AEA	0.0306	0.6739
		SVF	-0.3434	<0.0001*
		SEA	-0.1892	0.0086*
Force	Confidence	AVF	0.1400	0.0528
		AEA	-0.0108	0.8817
		SVF	0.1680	0.0199*
		SEA	-0.1487	0.0396*
	Fatigue	AVF	-0.4324	<0.0001*
		AEA	-0.4083	<0.0001*
		SVF	-0.0272	0.7080
		SEA	0.5015	<0.0001*

* Significant at the $p<0.05$ level

The table reveals highly significant correlations between force and subjective fatigue and between speed and subjective confidence. Increases in force in the writing task (i.e., performance decrements) led to higher fatigue ratings, which can be expected. The SVF condition was, however, an exception. It is likely that this situation occurred because SVF was the only feature that required participants to use a consistent amount of light force.

There was also a small, but significant, correlation between speed and subjective ratings of fatigue, with reduced speed improvements leading to greater fatigue ratings. This correlation may be due to participants experiencing greater fatigue when spending more time on drawings.

The correlation table also suggests that speed may be a better predictor of confidence than accuracy under the adaptive conditions. In general, it appears that participants tended to provide higher test confidence ratings with the AVF and AEA conditions when speed improved, as compared to accuracy improvements. This result may also explain the small negative correlations between accuracy and confidence. Given a tradeoff between speed and accuracy, a strong positive correlation between confidence and speed would reduce the chances for positive correlations between confidence and accuracy.

4 Discussion

Table 4.1 lists the haptic features that led to the greatest test improvements in speed, accuracy and force during training and testing, based on the results of the Kruskal-Wallis and post-hoc tests. The table confirms that VF conditions resulted in the greatest speed and accuracy improvements during training. During testing, AVF training generally led to greater speed improvements compared to the other conditions, although training in the control condition was comparable in the first two cycles. AVF training also resulted in high levels of force improvements in Cycles 1 through 3. In Cycles 2 and 3, force improvements following SVF training were comparable to AVF, and exceeded the other conditions in Cycle 4. Accuracy improved the most as a result of SEA training, but only in Cycles 2 through 4. SEA training also led to high levels of force improvements in Cycle 3.

Table 4.1. Haptic features leading to greatest training and test improvements in speed, accuracy and force by cycle

		Speed	Accuracy	Force
Training	Cycle 1	AVF	SVF	•
	Cycle 2	AVF	SVF	•
	Cycle 3	AVF, SVF	SVF	•
	Cycle 4	AVF, SVF	SVF	•
Testing	Cycle 1	AVF, C	•	AVF
	Cycle 2	AVF, C	SEA	AVF, SVF
	Cycle 3	AVF	SEA	AVF, SVF, SEA
	Cycle 4	AVF	SEA	SVF
	Cycle 5	AVF	•	•

4.1 Training

4.1.1 Accuracy

It was expected that training using VF with static or adaptive aiding would improve performance, in particular in terms of task completion times (Hypothesis (H) 1), as speed was expected to continue to improve following a plateau in accuracy. Results were generally consistent with expectations. Participants training using SVF consistently outperformed the other participants during training. During static training, the VF restricted deviations to 0.05 inches, which was well below the abilities of any of the unassisted participants. This increased level of assistance was also resulted in a high level of participant confidence compared to the other conditions, as reflected in the results of the subjective measures. The same was true for Cycle 1 of AVF training; however, AVF accuracy fell sharply to levels similar to the two EA and control conditions during Cycles 2-4 when the VF were relaxed. Training with EA also showed improvements over time. In Cycle 1, when EA allowed the largest deviations from the template, accuracy was similar to the control condition. By the end of Cycle 3 (24 training trials), EA participants were drawing with significantly greater accuracy improvements than control participants. This performance continued through Cycle 4. Improved accuracy was likely due to participants being more attentive to deviations to avoid EA penalties (Cesqui, et al., 2008).

4.1.2 Speed

Performance in speed during training was consistent with expectations. The corrective forces of VF required less effort to be devoted to accuracy. This allowed participants to devote more resources to speed improvements. Speed improved across training cycles and was consistently greater than the EA and control conditions. In contrast to the accuracy results, EA and control condition speeds were similar throughout training. This result is noteworthy as it suggests that EA participants did not need to compromise speed to achieve accuracy improvements during training, compared to control participants whose accuracy was significantly lower than EA participants at the end of training.

4.2 Testing

The improvements observed during VF training were not expected to transfer to an unassisted condition due to overreliance on the assistance, which is consistent with previous research (Huegel, 2009). In contrast, the EA condition was expected to have a longer initial learning time, due to the additional complexity of the task dynamics, but task learning (unassisted performance) was expected to be greater (H2; Milot et al., 2010). Although the results show greater accuracy improvements in unassisted trials as a result of training in SEA, these differences did not carry-over into post-test trials, where the analysis revealed no significant differences among conditions in terms of accuracy. In fact, the only significant learning effects revealed during post-training tests occurred following AVF training, which resulted in greater speed improvements from baseline as compared to all the conditions except AEA. These results did not support H2.

Subjective confidence ratings of test trial performance did not follow the performance measures. Participants felt more confident during test trials following training under SEA and AVF, as compared to SVF. This finding may be due to the amount of participant autonomy from the haptic features preceding the final test trials. Under SVF, accuracy was generally the responsibility of the haptic features for all training trials. For SEA and AVF, d_{MAX} was greatest during the last eight training trials. This situation meant the two conditions were most similar to the test trials (compared to the other conditions) during the final training cycle. It is, therefore, possible that this similarity contributed to the higher degree of confidence, as compared to SVF.

Although the differences among conditions were not always significant, training using haptic features was generally favorable to training without haptic features. Training under the control condition did not result in any post-training test improvements (speed or accuracy), as compared to baseline. Training in SEA resulted in post-training test accuracy improvements, while post-training test speed improved following training under AEA and AVF. The latter result revealed an advantage of adaptive training for improving speed, which was in partial support of H3. Furthermore, training under AEA was the only condition that resulted in multiple test improvements in both speed and accuracy.

When the results were analyzed based on participant skill level classification, it was also expected that the more skilled participants would show greater benefits in the unassisted condition following EA training, as compared to VF (H4) due to the higher motor demands being more appropriate for participants with higher skill levels (Guadagnoli & Lee, 2004). This expectation was consistent with Cesqui et al. (2008) and Milot et al. (2010) findings. Participant skill did affect test performance; however, there were no significant interaction effects between skill and condition (in contrast to H4). Lower performing participants tended to show greater improvements in speed than higher performing participants. This finding is likely due to a ceiling effect for the higher performing participants. In other words, the low-performing participants had more opportunity to improve than the high performing ones. This result is consistent with Teo et al. (2002), who found that experts and novices can show different speed-related improvement levels in a haptic training task. Participant skill did not affect improvements in accuracy during test trials.

Significant differences were also not identified for the near-transfer task. This finding may be due in part to differences among the participants. Because the near-transfer character was not administered at baseline, it was not possible to calculate percent improvement using the same method as the other characters. The design of the transfer character may have also affected the outcome. All the characters included in the training trials had a common number of curves (i.e., three). The transfer character, in contrast, was unique in that it included four curves and an “S” bend. It may be that the homogenous nature of the training characters was not sufficient to facilitate training for drawing such a novel character.

In general, the results suggest that the ideal form of haptic features for motor skill training may depend on the training goals. For tasks where the goal is to improve speed, AVF is the ideal choice. Error amplification (static or adaptive) should be selected if the goal is to improve accuracy. If the goal is to improve both speed and accuracy, then AEA may be the best choice. Figure 4.1 provides an overview of the test results for speed and accuracy, according to condition. Each axis represents the number of tests (0 to 5) that resulted in a significant DV improvement over baseline. An “X” marker indicates a significant post-training test improvement in accuracy; a "+" marker indicates a significant post-training test improvement in speed.

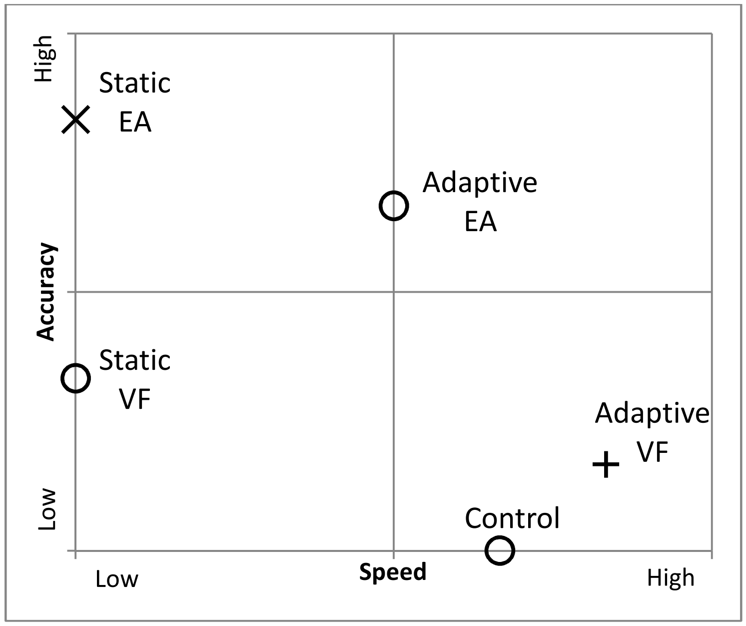

Figure 4.1. Speed and accuracy tradeoff resulting from the training conditions

The figure shows that any of the haptic training methods combined with the visual template resulted in more accuracy improvements than the visual stimulus alone. The results also suggest that accuracy may benefit from a consistent presentation of haptic forces. In the EA conditions, deviating beyond the d_{MAX} threshold resulted in the participant drawing a figure with a large error (and a reduced score). This condition likely caused participants to evaluate their progress more often in order to prevent application of haptic forces (Cesqui et al., 2008), especially at greater difficulty levels. Adaptive VF and control conditions, in contrast, provided limited feedback of deviation errors. Feedback applied during AVF training also did not impose a penalty on participant scores. Participants may have been less motivated to improve accuracy, as a consequence.

Figure 4.1 also shows that conditions that led to fewer increases in accuracy yielded more speed improvements. Specifically, while the control and AVF conditions produced the lowest accuracy improvements, they yielded the greatest improvements in speed. The narrow channels implemented in the SVF condition limited drawing speed, to a degree. Therefore, SVF participants may not have been able to practice higher speed drawings during training trials as much as AVF and Control participants, which may explain the lack of speed improvements. Control and AVF participants were required to attend to the haptic features less often and, therefore, had more opportunity to improve speed. This result is inconsistent with Srimathveeravalli et al.'s (2009) statement that training using AVF should be at least as effective as SVF training. However, the results are consistent with Huegel's (2009) findings that AVF did not contribute to improvements in an unassisted condition beyond SVF training.

The results on average force across trials further demonstrated the value of incorporating multiple performance measures for evaluating handwriting performance (Chowriappa at al., 2009; Teo et al., 2002). Unlike speed and accuracy, training in both VF conditions contributed to consistent reductions in average force compared to baseline. This finding is likely the result of successful VF trials requiring participants to yield to the restrictive forces. Applying too much force during VF training increased friction at the haptic stylus and could, if applied beyond 3N, result in breaking through the VF and large deviations from the template. Therefore, participants receiving training with VF likely learned to apply less force, overall, to the haptic stylus compared to the EA and control conditions. These results did not carry-over to the post-training test trial, however.

This work includes many significant results for each of the various performance measures. However, the improvements realized by the participants were fairly small. The highest-performing conditions resulted in accuracy improvements up to 13% (SEA condition) and speed improvements up to 19% (AVF condition) between baseline and post-testing. For speed, this equates to about 0.8 seconds; for accuracy it means 0.012 inches of deviation, on average, across the length of each character. As a point of comparison, previous work investigating handwriting improvements in healthy participants following intermanual transfer training also resulted in 13% accuracy improvements, on average, following three days of training with the non-dominant hand (Basteris, Bracco & Sanguineti, 2012). While these values were statistically significant, the practical significance of the results depends of the application and the needs of the individual. As with other types of motor skill training, the overall success of handwriting training is highly subject-dependent (Pereira, Raja, & Gangavalli, 2011; Yancosek & Mullineaux, 2011).

In general, the learning curves for speed identified during Phase 1 were adapted successfully during Phase 2 in order to determine adaptive accuracy levels when speed and accuracy were identified as goals to the participants. This strategy led to (1) greater test improvements in accuracy (AEA) and speed (AVF) compared to training without haptic features and (2) accuracy and speed improvements that continued beyond 16 training trials.

The Phase 1, results show that participants did not improve significantly in terms of accuracy, and, while speed improved beyond baseline levels, improvements tended to drop after 16 training trials. Training with AEA extended improvements up to the 24th training trial. This finding suggests that participants may have become fatigued or lost motivation after completing multiple drawing trials, and 32 training trials may be excessive for handwriting training. It is possible that participants may experience further benefits from additional training sessions incorporating fewer trials.

5 Conclusions

This work prototyped and evaluated several types of haptic features, in a computer-based simulation of a character reproduction task, including static and adaptive forms of VF and EA in order to determine the extent to which training under each condition transfers to unassisted handwriting.

The novel aspects of the study include:

1. The direct comparison of the efficacy of VF and EA for fine motor training
2. The application of EA for writing task training
3. The implementation of a training system incorporating individual performance-based adaptive EA
4. Validation of a haptic writing tutor using multiple training and test sessions to show learning over time.

The data collection phases of the study were designed to: (1) develop a preliminary model of fine motor skill learning, and (2) compare the various types of haptic features. Statistical results revealed the ideal form of haptic training strategy to be dependent on the training goals. Adaptive haptic features, and AVF in particular, are best for improving task speed. Adaptive and static EA are best for training accuracy. Adaptive EA was also the only training technique to show similar test improvements in speed and accuracy. In general, the present work demonstrated advantages for administering AEA for learning task accuracy, which is supported by the literature on training and EA. The advantages were due to increased task difficulty (Milot et al., 2010), which was varied over time (Li et al., 2009; Reinkensmeyer et al., 2004; Srimathveeravalli et al., 2009), and a high signal-to-noise ratio of the prototype haptic features (Cesqui et al., 2008). Beyond these advantages, the EA feature maintained the dynamics of the underlying writing task (Wickens et al., 2004), thereby providing for more comprehensive task training compared to the VF feature, which removed user responsibility for accuracy. Counter to expectations, participant skill did not influence the efficacy of any of the training types.

5.1 Applications

The results of this study are expected to advance the design of computer-based haptic systems for fine motor training. Future writing tutors, as well as training programs for occupational domains where fine motor skills are required, could also benefit. Table 5.1 lists a brief sample of possible applications for the various forms of haptic aiding included in the present work. In guidance systems, the user assumes a mostly passive role and the system supplies the forward motion. While not effective for task training, per se, these systems can be effective in rehabilitation settings for improving mobility and flexibility (Cesqui et al., 2008). Static VF were somewhat effective for training in accuracy but not at all effective for training in speed. However, if static VF can be used for task performance, they are highly effective (Prada & Payandeh, 2009). Based on the present work, AVF appear effective for training task speed, while SEA is effective for training accuracy. Adaptive EA provides the best balance for simultaneous training in speed and accuracy.

Table 5.1. Applications for haptic features

Haptic Feature	Application
Guidance	Mobility training
Static Virtual Fixtures	Task performance
Adaptive Virtual Fixtures	Speed training
Static Error Amplification	Accuracy training
Adaptive Error Amplification	Accuracy and speed training

5.2 Caveats and future research

The present work demonstrated that training with haptic features can extend training benefits beyond those provided by systems providing only visual feedback. Participant training effectiveness peaked after approximately 16 unassisted training trials, while it peaked after about 24 with EA engaged. However, test performance tended to drop again in the last test cycle (trials 25-32), independent of the condition. This suggests that additional work is needed to identify an optimal duration for haptic training to optimize the level of effort for benefit. Further comparisons can be made between the present training durations and multiple shorter-duration sessions spread across several days. Training sessions with multiple visits may reveal different results for the various haptic features and make speed and accuracy differences more pronounced.

The procedures used for the present work in which individual letters were drawn separately may also be expanded to train writing whole words or sentences. In this context, the present procedures represent elements of *part-task* training (Wickens & Hollands, 2000).

Future transfer tests could evaluate performance improvements in writing multiple letters in the context of words ("whole-task" testing) as a result of part-task training.

The duration of training can also be investigated. The present work investigated retention periods of 1 day or less. While this is longer than previous work on haptic training systems, it is still fairly brief in terms of evaluating training efficacy. Longer training periods lasting weeks or months combined with longer retention periods would provide additional insight toward the benefits of the different training types. This work could also investigate the influence of overtraining (Wickens & Hollands, 2000) on learning retention.

It is possible that the analysis of trainee skill did not reveal significant results because differences in task difficulty were not sufficient to affect performance. Additional studies can be performed to compare different task difficulty levels. For example, more challenging EA levels with narrower deviation tolerances may have different effects on training performance. The present work also investigated one stiffness level for presenting EA. High stiffness levels prevent participants from recovering from errors. Low stiffness levels allow recovery, but may be insufficient for communicating smaller errors. Future work could investigate variable stiffness levels to increase or decrease training task difficulty. Furthermore, in the present study, it was determined that imposing restrictions on accuracy through adaptive VF had significant effects on speed. Likewise, training with performance-based increases in drawing speed (e.g., Mullins et al., 2006) may also improve accuracy.

The different benefits attributable to the different types of haptic features also motivate investigation of hybrid approaches to training with haptic features. Speed and accuracy improvements following haptic training that combines adaptive forms of VF and EA may exceed training with either of the individual training types. This would be consistent with Wickens et al. (2004) guidelines that state VF are most effective when presented early in a training process.

Finally, the procedures described in this work can be adapted for other domains requiring fine motor skills, such as laparoscopic surgery (McColl, Brown, Lim & Alsaraia, 2006). Simulations similar to the prototype described in this work would allow clinicians to practice procedures without a patient present. Not only would this facilitate increased training frequency, but it would provide the opportunity for practicing at increased difficulty levels (e.g., narrower areas, reduced time requirements) designed to improve real-world performance.

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APPENDICES

Appendix A – Demographic Survey

Welcome to our experiment. Let's start with some introductory questions to help us understand your background.

1. Please provide your personal information in the spaces below.

   Age (in years):

   Gender [Circle one answer]:

   - Male
   - Female

2. Which is your dominant hand? [Circle one answer]:

   - Right
   - Left

3. Do you wear glasses or contacts? [Circle one answer]:

   - Yes
   - No

4. Please rank your familiarity with the following alphabets from 1 to 5 by circling the corresponding number, with 1 meaning "not at all familiar" to 5 meaning "very familiar."

	Not Familiar		Somewhat Familiar		Very Familiar
Armenian	1	2	3	4	5
Cyrillic	1	2	3	4	5
Georgian	1	2	3	4	5
Greek	1	2	3	4	5
Latin	1	2	3	4	5

Appendix B – Edinburgh Handedness Inventory

Please indicate your preference in the use of hands in the following activities *by putting + in the appropriate column*. Where the preference is so strong that you would never try to use the other hand unless absolutely forced to, *put* + +. If in any case you are indifferent, *put + in both columns*.

Some of the activities require both hands. In these cases the part of the task, or object, for which hand preference is wanted is indicated in brackets.

Please try to answer all the questions, and only leave a blank if you have no experience at all in the object or task.

		LEFT	RIGHT
1	Writing		
2	Drawing		
3	Throwing		
4	Scissors		
5	Toothbrush		
6	Knife (without fork)		
7	Spoon		
8	Broom (upper hand)		
9	Striking Match (match)		
10	Opening box (lid)		
i	Which foot do you prefer to kick with?		
ii	Which eye do you use when using only one?		

L.Q		Leave these spaces blank	DECIL E	

Appendix C – Informed Consent

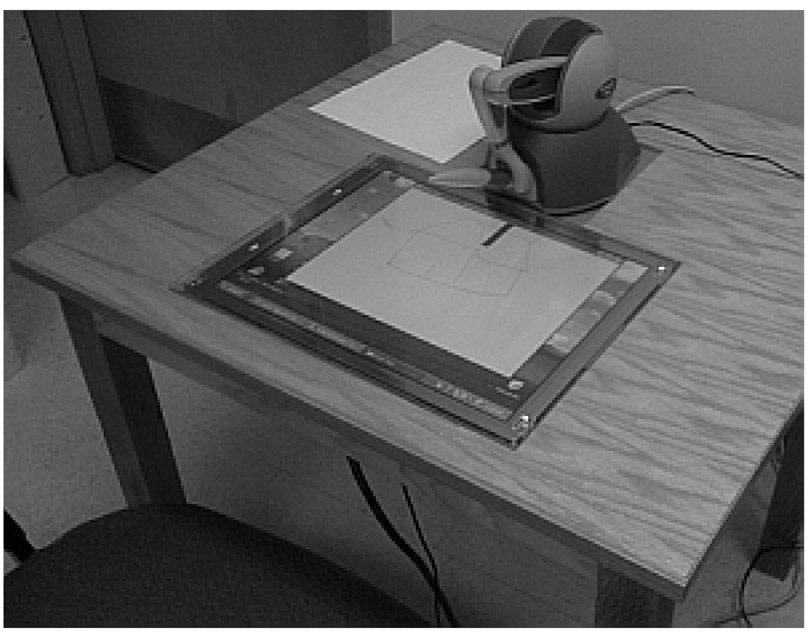
North Carolina State University
INFORMED CONSENT FORM for RESEARCH

Title of Study: Comparison of adaptive haptic forces for fine motor skill training in a virtual environment

<u>Principal Investigator:</u> Michael Clamann　　　　　　　<u>Faculty Sponsor:</u> Dr. David Kaber

General Information
You are being asked to take part in a research study. Your participation in this study is voluntary. You have the right to be a part of this study, to choose not to participate or to stop participating at any time. The purpose of this research is to gain a better understanding of how haptic simulations may help develop fine motor skills. You are not guaranteed any personal benefits from being in this study. Research studies like this may also pose risks to those that participate. In this consent form you will find specific details about the research in which you are being asked to participate. If you do not understand something in this form it is your right to ask for clarification or more information. A copy of this consent form will be provided to you.

Purpose of this study
The purpose of this study is to learn more about using virtual reality (VR) simulations to improve fine motor skills. The VR simulation to be used in this study involves a visual display on a horizontally-mounted monitor (see image below). Your control of the VR will be through a hand-held stylus (similar to a joystick; again, see image below) that provides force-feedback (when a virtual cursor contacts a virtual object). The tasks to be performed in this study involve simulated drawing. Your performance while using the VR system is expected to provide insights into VR design features and approaches to best develop fine motor skills.



Procedure
If you agree to participate in this study, you will be asked to read and sign this consent form once you understand the research. After completing the form, you will be asked to complete two different experimental

sessions to use the VR system. The first visit will last approximately 2 hrs., and the second visit will last approximately 15 minutes. The sessions will involve training and testing on the VR system in several trials. During these experiment sessions you will draw simple figures on a virtual drawing surface. The experiment sessions will be conducted s follows:

(a) Session 1 will include the informed consent, training and testing on the VR system for a total of approximately 2 hours;
(b) Session 2 will be scheduled approximately 1 day following Session 1 and will include approximately 15 minutes of testing on the VR system.

Risks

Risks from this research include: general fatigue due to (1) attending to the VR displays during the test trials; and (2) completing the drawing task with the computer systems. Rest periods will be arranged between trials. There is no time limit for your drawing task performance; however, the number of task trials will be limited.

Benefits

There are no direct benefits to you from this research. Knowledge gained from this study will help researchers understand how haptic systems can help people with motor skills impairment.

Eligibility

You must be 18 years or older on the date of the first session to participate in this research study. You must also be right handed, as defined by the Edinburgh Handedness Inventory, and have no major upper extremity impairments affecting either hand. You will be provided an opportunity to complete the handedness inventory before beginning the experiment training and test sessions.

Confidentiality

The information in the study records will be kept strictly confidential. Information such as your gender, age, etc. will be collected only for demographic statistics. Data will be stored securely in the Cognitive Ergonomics Lab in the Edward P. Fitts Department of Industrial and Systems Engineering and will be made available only to the persons conducting the study. No reference will be made in oral or written reports which could link you to the study.

Compensation

For participating in this study you will receive an honorarium of $10 per hour, up to maximum of $25 (2.25 hours at $10.00 per hour), if you complete the entire study. If you withdraw from a session prior to its completion, you will receive compensation at a rate of $5 per hour for any time that you provided. If you withdraw from a session, your participation in the full study will be terminated.

Contact

If you have questions at any time about the study or the procedures, you may contact Michael Clamann by visiting Room 475, Daniels Hall, Department of Industrial and Systems Engineering or mpclaman@ncsu.edu. If you feel you have not been treated in accordance to the description in this form, or your rights as a participant in research have been violated during the course of this project, you may contact Mr. Matthew Ronning, Assistant Vice Chancellor, Research Administration, Box 7514, NCSU Campus (919-513-2148).

Consent to Participate

"I have read and understand the above information. I have received a copy of this form. I agree to participate in this study with the understanding that I may withdraw at any time."

Subject's signature____ Date _________________

Investigator's signature____________________________________ Date _________________

Appendix D - Post Training Questionnaire

Subject # ______

Post-Training Questionnaire

Place an "X" on the charts below in the locations that best describe your experience in the following aspects of the experiment:

Level of **confidence** using the stylus during **training** (with force feedback):

| | | | | | | | | | | |

Not at all confident — Completely confident

Level of **confidence** using the stylus during **testing** (without force feedback):

| | | | | | | | | | | |

Not at all confident — Completely confident

Level of **fatigue** at the end of training:

| | | | | | | | | | | |

Not at all fatigued — Completely fatigued

Appendix E – Experimenter Instructions

Experimenter Instructions: Comparison of adaptive haptic forces in a virtual environment for fine motor skill training

Introduction	*Thank you for participating in this experiment. Today and tomorrow you will be trained to write several foreign characters. The results will help develop future handwriting training procedures. Training will take place today and testing will be scheduled for tomorrow. Training will last an hour, and testing will only take a few minutes.* *Before we start handwriting training, you will perform a brief motor skill test. This task should take you about 5 minutes.* *After the motor skill test is complete, you will get instructions on how to use the experiment apparatus, complete a brief test of handwriting speed and accuracy, and participate in a one-hour handwriting training session. Tomorrow you will also complete a final speed and accuracy test.* *Please understand this experiment is not to test your personal ability or skills. The goal of this study is to assess the impact of various training methods on drawing performance, independent of ability level.*
Informed consent	Prepare the **informed consent** form and a pen. *This form summarizes information you need to know about the experiment. Please read it. If you have any questions, feel free to ask me. Please note that in order to participate in this study you should be at least 18 years old, have 20/20 vision (with or without correction, glasses or contact lenses are OK) and be right handed. You will receive $15/hour for your participation. If you consent to participation, please sign and date the form.* After signing the form, seat the participant at the testing station for the Purdue Pegboard test and begin with the instruction. *Before we start I need you to turn off your cell phone. You will be able to take breaks, but in order to prevent distractions it needs to be off during testing and training.* Have subject fill out the **demographic form** if it was not already completed online.
Purdue Pegboard	*Before we can start handwriting training, I need to see how quickly and*

	accurately you can work with your hands. Administer this test using the Purdue Pegboard instructions for the 'Right Hand' and 'Left Hand Tests' only. The subject's score should be within 1 SD of the mean for 'Male and Female Applicants for Production Work.' This is between 15 and 20 points for the right hand and between 15 and 19 for the left. If the score is not within this range, thank the subject for his/her time and sign the payment form for 30 minutes. If the score is within 1 SD, continue with the experiment.
Start	*Today you will learn how to trace 4 characters from the Georgian alphabet. You will need to reproduce a series of letters on a computer screen with a Phantom Omni haptic device.* Show the participant the test station, and seat him/her in front of it. *You will first complete 4 test trials and then several training trials using your **left hand.** The whole process will take about 40 minutes.*
Orientation (All conditions)	**Lift the stylus** and open the Haptic Writing Tutor to the demonstration character ("S"). *This is the drawing interface that allows you to trace a letter with the haptic device like this.* Demonstrate how to use haptic device to trace the S. *The haptic device simulates drawing on paper. At first, nothing happens when you move the stylus around* **[Demonstrate]**. *To initialize the drawing, you have to put the point of the stylus in the red circle* **[Demonstrate]**. *After you are in the red circle, you can trace the letter* **[Demonstrate]**. *A timer starts automatically when the point leaves the circle and stops when you lift the stylus.* *Your goal is to trace every character as quickly and accurately as possible. After every trial, you will receive a combined speed and accuracy score. You want to make this score as low as possible.* Give the stylus to the subject. *Now you try. Please draw the S with your **left** hand as quickly and accurately as you can. Accuracy is based on keeping the line inside the letter's boundaries.* *You can draw with the stylus by pressing lightly on the surface. The pressure*

	should be about the same as you would need to write with a ballpoint pen; if the stylus touches the Plexiglas surface, you are pressing too hard. Lift the stylus when you finish each character. *I will clear the drawing when you finish. Let me know if I clear the drawing too fast.* Let the subject draw a few S. *Do you feel comfortable with the device? If so, we will continue*

Orientation (Virtual Fixtures only)	*During training, the stylus will apply forces help you trace each character.* Turn on Virtual fixtures for the demo character ("S") with a "DMax" value of 0.05. *Now try drawing the character again with assistive forces. Please draw the S with your **left** hand as quickly and accurately as you can. Try to handle the stylus gently; it is not necessary to push against the assistive forces.* Let the subject draw a few S. *Do you feel comfortable with the device? If so, we will continue*
Orientation (Error Amp-lification only)	*During training, the stylus will apply forces highlight the characters' boundaries. If you trace too far from the character, reactive forces will pull the stylus away from the character.* Turn on Error Amplification for the demo character ("S") with a "slope" of 4 and a "DMax" value of 0.2. *Now try drawing the character again with reactive forces. Please draw the S with your **left** hand as quickly and accurately as you can. Try to handle the stylus gently; however, it may be necessary to push against the forces.* Let the subject draw a few S. *Do you feel comfortable with the device? If so, we will continue*
Baseline Testing	*We can now move on to the test.* **Lift the stylus** and open the Haptic Writing Tutor to the "E0" character.

	You will now four different letters from a foreign alphabet, one time each one after the other. When I say "start" please trace the letter using your left hand as quickly and accurately as possible. The stylus will not be applying any forces during testing. *Please do not lift the stylus too early. If you lift it before the letter is done, you will need to repeat the letter. I will clear each drawing when you lift the stylus.* Repeat the process for "EA" "E6" and "F0". *Thank you for your patience, we will now move on to the next step.*

Training	*For training, you will repeat the letters you traced during testing. You will trace each letter 32 times.* If the condition is EA or VF, read the following text, in brackets: *[I will be adjusting the forces every 8 drawings. before each adjustment, you will draw the character without the extra forces; so you will draw 8 with, 1 without, 8 with, etc., until you have made 32 drawings.]* *It is important that you trace each letter as quickly and accurately as possible. You will see a speed and accuracy score in the upper-left of the screen each time you finish a trial. Try to make that score as low as possible.* *I will clear each drawing when you lift the stylus. Let me know if I clear the drawing too fast. Please do not lift the stylus too early. If you lift it before the letter is done, you will need to repeat the letter.* *You will be given a chance to take a break after you trace each letter 32 times.* *Do you have any questions?* **Lift the stylus** and open the Haptic Writing Tutor to the "E0" character. *You can start tracing when you are ready.* Every 8 trials, change the "type" setting from "training" to "test" for one drawing, then change it back to "training" for the next 8 trials. Repeat the process for "EA" "E6" and "F0". *Thank you. That completes your training and today's session. Tomorrow's session will be very short and will only take about 10 minutes.*

	Schedule the subject's test session.

1 day later…	
Baseline Testing	*For today's test you will trace five different letters from a foreign alphabet, one time each, one after the other. Four of these are the ones you trained in yesterday, and one is new.* **Lift the stylus** and open the Haptic Writing Tutor to the "E0" character. *When I say "start" please trace the letter using your left hand as quickly and accurately as possible. I will clear each drawing when you lift the stylus.* *Please do not lift the stylus too early. If you lift it before the letter is done, you will need to repeat the letter.* Repeat the process for "EA" "E6" "F0" **and** the E3 character. *Thank you. That last thing I need you to do is fill out this brief questionnaire. After you finish, I can answer questions you have about the study.* Give the subject the questionnaire.