AN EXPLORATION OF THE UTILITY OF AUGMENTED HAPTIC FEEDBACK FOR LEARNING A CURVE-TRACING TASK

by

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A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
Rehabilitation Sciences Institute
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Abstract
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Technology for the field of robot-assisted rehabilitation (and haptic training, in general) is rapidly advancing. However, there is some concern among the rehabilitation community that the outcomes, in terms of motor recovery, have fallen short of expectations. One reason for this may be that—despite the understanding that motor learning is a key component of motor recovery—motor learning scientists are not always involved in the design, development and deployment of these systems. In this dissertation, I explored optimization of haptic feedback from a motor learning perspective.

In the first study, I compared learning outcomes after participants practised a curve-tracing task with assistive, error-augmenting or no haptic feedback. In study two, I investigated whether learning outcomes were affected by the bandwidth (i.e., error tolerance) at which each of the two forms of haptic feedback were provided. For the third study, I explored whether and how self-controlled or experimenter-imposed assistive haptic feedback schedules influenced motor learning. In all experiments, motor learning was assessed using a composite measure of performance efficiency (the speed accuracy cost function) on retention tests conducted immediately (10 min) and 1 day after skill acquisition.

Results showed that error-augmenting haptic feedback was the most effective for learning (study 1) but its superiority was not observed with a wider bandwidth (study 2). When learners could self-control their assistive haptic feedback schedule, a lower frequency of feedback across practice blocks appeared to enhance learning (study 3). This final study also showed that whether learners had self-control over their feedback frequency was associated with their views about the utility of assistive haptic feedback for performing and learning the task. Additionally, these expressed views were significantly associated with both self-chosen feedback frequency and motor learning outcomes.
This research demonstrates that error-augmenting haptic feedback is indeed beneficial for tasks which rely on error-based learning mechanisms but that this effect is bandwidth-dependent. Further, it highlights the importance of and need for continuing research to explore how learners’ views about the training environment impact motor learning. These principles are useful for researchers and practitioners using haptic training in both basic and applied domains.
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“Go at it boldly, and you’ll find unexpected forces closing round you and coming to your aid.”

—Basil King (1859—1928), *The Conquest of Fear*
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Chapter 1

General Introduction

1.1 Motivation

As technological advances continue to permeate more areas of our lives, we must consider whether these advances are being carefully directed and designed by the best scientific knowledge available or whether we have allowed our technical abilities to direct the purported goals and purposes of technology. One such area of concern is the incorporation of robot-assisted devices into training programs in domains such as surgical education, health professions education (e.g., acupuncture and physiotherapy), sports, and physical rehabilitation. The goal of any training program must be to facilitate effective and lasting changes in skill among the target group of trainees/learners/clients, using strategies that are both cost- and time-efficient. As a movement scientist, my primary concern is whether these robot-assisted technologies take advantage of current knowledge of human motor behaviour to achieve this goal.

As an example, studies of robot-assisted rehabilitation are typically not explicit in their treatment of motor learning principles, despite the fact that (re)learning is a key element of the process of motor recovery (Dipietro et al., 2012; Hatem et al., 2016; Krakauer, 2006). Recent reviews of robot-assisted rehabilitation have shown that high intensity and repetitive approaches with functional exercises and active participation of the client seem to be best for improving function (Basteris et al., 2014). Fortunately, the idea of functional, repetitive actions (i.e., practice) is a basic and well-studied feature of human motor learning. However, there is no evidence to suggest that robot-assisted therapy is superior to standard rehabilitation treatment for the upper extremity after stroke (Hatem et al., 2016). Instead, it appears that robots can facilitate an enhanced rate of functional recovery but not achieve the maximum level of recovery (V. S. Huang & Krakauer, 2009). Importantly, however, there currently exists a large variety of rehabilitation devices and protocols. It is possible that this diversity is obscuring more positive functional outcomes and making it difficult to understand which components of each device and protocol
are (in)effective for functional motor recovery (Basteris et al. 2014).

Although robot-assisted rehabilitation is only one of many applied fields in which robot-assisted or haptic training is developing, it represents an important one. With the worldwide incidence of disability currently at over 1 billion people (World Health Organization & The World Bank 2011), there is a great demand for rehabilitation services. Consequently, governments and health systems, particularly in developed countries, will be seeking tools and programs that can reduce the cost of rehabilitation and increase access to services while alleviating the burden on therapists and other rehabilitation care providers. Any developments in the effectiveness of robot-mediated training in this field will necessarily influence developments in other domains such as health professions education and sports training. This dissertation is an effort to examine a single but key element of robot-assisted or haptic training—haptic feedback—within the context of motor learning. To begin, I will present some key theories from motor learning followed by a more detailed explanation of how some concepts from motor learning may provide insights into the burgeoning field of haptic training.

1.2 Theories of Motor Learning

A few detailed, testable theories of motor learning have been proposed since the development of the field of motor control and learning. Adams’ (1971) closed loop theory and Schmidt’s (1975) schema theory of learning for discrete motor skills are probably the most influential and extensively tested. While Adams’ theory has mostly been archived, schema theory (though incomplete and limited) still offers many useful concepts for researchers today. Recent reviews of schema theory (Schmidt 2003; Shea & Wulf 2005; Sherwood & Lee 2003) have highlighted aspects of the theory that have stood the test of time and areas yet to be developed. In contrast to these two theories that emphasize the importance of information processing on motor performance and learning, the most recently proposed theory of motor learning is based on mounting evidence that motivation and attention influence performance as well as learning (Wulf & Lewthwaite 2016). This new theory—Optimizing performance through intrinsic motivation and attention for learning (OPTIMAL)—incorporates the motivational and attentional factors (e.g., social-cognitive, affective) that have typically been overlooked or downplayed as transient in the motor learning literature.

Nonetheless, there is currently no widely accepted, single, grand theory of motor learning. As such, all three of the above mentioned theories will be briefly described to provide a background for the models, hypotheses and principles which guide and challenge the work of researchers in the field, and are mentioned throughout this dissertation.
1.2.1 Adams’ closed-loop theory of motor learning

Adams developed his theory against the backdrop of empirical work based on Thorndike’s “Law of Effect,” proposed in 1898 (Adams, 1971). The “Law of Effect,” based on Thorndike’s studies of animal learning, stated that if a learner’s response was closely followed by a reward, it will lead to repetition of the response. In contrast, a response followed by a punishing event will lead to extinction of that response. However, the application of this law to the study of human behaviour did not always produce the same results as those observed in animals. In particular, the “Law” did not account for observations of humans improving their performance by correcting errors instead of simply repeating the previous performance (Adams, 1971). Based on this and other observations, Adams identified a number of components that a new theory of motor learning should entail and used these to guide the development of his closed-loop theory, which was described in the context of (though not limited to) a simple, self-paced positioning task. The three primary components of Adams’ new theory of motor learning were: knowledge of results (KR), an error-correction mechanism for moment-to-moment guidance of behaviour (the perceptual trace), and a separate response activation mechanism for initiating a response (the memory trace) (Adams, 1971).

In Adams’ theory, feedback was viewed as a source of information that facilitated the correction of errors, leading learners to a correct response. This correct response was represented by the perceptual trace—a reference or memory of past movement, used in conjunction with KR regarding errors, to adjust the next movement. It was responsible for determining movement extent and its strength was thought to increase with feedback (e.g., proprioception) on each trial. The perceptual trace was central to the theory’s error detection and error correction processes, which were absent from “Thorndikian” conceptualizations of learning. However, before the perceptual trace could function, it would need to be selected. This was the role of the memory trace—to select and initiate the response. As an open-loop program, the memory trace determined the direction of movement and its strength increased as a function of practice.

There are major criticisms of Adams’ theory (see Schmidt & Lee, 2011, p. 440, for an overview). Importantly, while Adams’ theory suggests that practice away from the target is detrimental to the strengthening of the correct perceptual trace, research shows that variable practice, i.e., movements different from the target action, are just as good as or better than practice with the target action only (e.g., Sherwood, 1996). Furthermore, central to the topic of this thesis, the theory proposes that the learning process is positively impacted by KR acting as guidance since repeated correct movements strengthen the perceptual trace. In a similar vein, learning would be negatively impacted by errors produced during training. This view of the roles guidance and errors in learning implies that haptic
feedback that guides learners towards and keeps them on target should be beneficial for learning.

1.2.2 Schema theory of discrete motor skill learning

A few years after the proposal of Adams’ closed-loop theory, Schmidt put forth a schema theory, specifically considering discrete motor tasks (both rapid and slow) and meant to address some of the gaps and inconsistencies in Adams’ theory (Schmidt 1975). Building on existing ideas about movement control, schema theory defined a generalized motor program (GMP) as a pre-structured sequence of motor commands governing a class of movements, and parameters as the specifications that fine-tune the GMP for a particular response scenario (Schmidt 1975). The theory also proposed two memory states: a recall memory for movement production, and a recognition memory for movement evaluation. After movement completion, the following types of information were proposed to be available for storage in short-term memory: (i) the initial conditions of the body and environment; (ii) parameters applied to the GMP; (iii) the sensory consequences of the movement; and (iv) augmented information about the movement outcome (Schmidt 1975). These sources of information are supposedly integrated to form the recall and recognition schemas which are stored in long-term memory and used for future movements. Importantly, schema theory predicted that learning should be degraded if any of the four sources of information are missing and, in contrast to Adams’ theory, variable practice and errors committed during training should be beneficial for learning because they supply data to help refine the schemas.

There are three major areas of empirical research that are inconsistent with the predictions of schema theory (Sherwood & Lee 2003). First, schema theory provides no framework for explaining observed learning effects in the absence of movement and due to cognitive processes such as observational learning and mental practice (e.g., Blandin & Proteau 2000). Second, while the theory suggests that learning should be enhanced by relatively higher frequencies of KR, empirical evidence shows that reducing relative KR frequency can be just as good or better for learning (e.g., Winstein & Schmidt 1990). Finally, research has shown that while variable practice can be beneficial for learning (as predicted), the way in which that variability is scheduled matters; however, schema theory made no predictions about how variability should be scheduled within practice.

Given these limitations, it has been suggested that most researchers no longer consider schema theory to be a “viable theoretical perspective” (Shea & Wulf 2005, p. 96) and efforts have been underway to develop a new theory that builds on the basic assumptions and predictions of schema theory that have stood the test of time, while incorporating new ideas that account for the more recent and reliable findings in motor learning research.
1.2.3 The OPTIMAL theory of motor learning

In the face of mounting evidence for the roles of motivation and attention on motor performance and motor learning, but the absence of these effects in any current theories of motor learning, Wulf and Lewthwaite (2016) have developed and proposed a new theory of motor learning. This theory steps away from the prevailing information processing perspective of motor learning to not only consider, but bring to the fore, motivational factors associated with various practice conditions that affect learning.

In short, OPTIMAL theory posits that enhanced motivation, facilitated by autonomy-supportive practice environments and enhanced expectancies for future performance, in concert with an external focus of attention, activate neurological goal-action coupling mechanisms involving dopamine (Wulf & Lewthwaite, 2016). Goal-action coupling increases focus on the task goal and simultaneously decreases self-focus. These conditions serve to optimize motor performance, which further enhances expectancies and also optimizes learning.

Interestingly, the theory makes twelve very specific predictions, the testing of which will require diverse expertise in motor behaviour, psychology, and neurophysiology to name a few (Wulf & Lewthwaite, 2016). Additionally, by the authors’ own admission, research methods required to test some of the predictions are very new or yet to be developed. Consequently, it is unclear how many researchers are equipped to test the theory and it will be interesting to observe how many and which of the predictions are tested in coming years. Nonetheless, despite the complexity of the neurological mechanisms underlying the theory, its power probably lies in its simplicity: the idea that simple changes in the verbiage of task instructions and the nature of feedback can change a learner’s social-cognitive and affective experience of the training environment and, consequently optimize learning.

1.3 Motor Learning Perspectives on Haptic Training for the Upper Extremities

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1http://ieeexplore.ieee.org/document/6701132/
1.3.1 Introduction

Much of neurorehabilitation is centred around movement as a means for achieving goals or solving problems (Higgins, 1991). Motor skill can then be understood as the degree of effectiveness with which a movement is carried out (Higgins, 1991), that is, one’s ability to plan and execute a movement goal (Krakauer, 2006). The underlying assumption of neurorehabilitation is that practice or repetition of movement(s) will lead to improvement in skill or ability after a stroke (Krakauer, 2006) and the therapist’s job is not simply to ‘facilitate’ a certain pattern of movement but to get clients to use that pattern in the daily execution of functional activities (Gordon, 1987). While the precise definition of motor learning varies by scientific field and context, it is generally understood as a process of improvement in skill or ability and may include skill acquisition, motor adaptation, and decision-making (Krakauer, 2006)—all of which are relevant to the client and clinician in the neurorehabilitation setting. In fact, V. S. Huang and Krakauer (2009) assert that neurorehabilitation is based on the assumptions that principles of motor learning apply to motor recovery and that clients can indeed learn. It then follows, that principles of motor learning, derived from the behavioural sciences, can be useful in clinical settings (Crutchfield & Barnes, 1993) and further, that clients should be considered as learners who actively participate in the rehabilitative process (Carr & Shepherd, 1989). This view is supported by findings that damage caused by stroke impairs the control and execution of motor skills but spares the ability to learn motor skills (Winstein, Merians, & Sullivan, 1999). Despite this, motor control and learning theory has not always been incorporated into the practice of rehabilitation or the education of rehabilitation professionals, many of who essentially teach motor skills to their clients (Crutchfield & Barnes, 1993, Winstein, 1991) suggested that, in an effort to delineate its scope of practice, the physical therapy profession turned its focus inward and dissociated itself from other related but non-clinical fields. Similarly, Poole (1991) remarked that occupational therapy has ignored or overlooked the teaching-learning process in an effort to avoid being labelled as “teacher” in favour of the more prestigious “therapist” label. However, recent developments in neurorehabilitation have brought motor control and learning to the forefront of rehabilitation practice. In particular, the introduction and proliferation of rehabilitation robots as a means to facilitate recovery from various neurologic conditions has piqued the rehabilitation community’s interest in the underlying mechanisms of motor skill acquisition. This interest stems from attempts to fully understand how rehabilitation robots provide some of the therapeutic benefits that have been observed (Kahn, Rymer, Lum, & Reinkensmeyer, 2006).

In traditional rehabilitation contexts, many therapeutic approaches are based on physical contact between the therapist and the client. However, with the evolution of technology, there is a move towards
supplementing some of these human-to-human interactions with robot-to-human interactions. Initially, robots were used to assist people with disabilities; this idea eventually expanded to include the provision of physical therapy. In the field of rehabilitation, “robot” is considered to be interchangeable with “haptic interface.” However, haptic interface refers more specifically to a “robot used to guide or restrict the movements of a person who is in direct contact with the robot end effector” (Harwin, Patton, & Edgerton 2006, p. 1717). The robot or haptic interface is usually used in combination with a computer interface or virtual reality system to complete the therapeutic tool. The high rate of expansion in robotic neurorehabilitation can be credited to:

1. The emergence of more advanced hardware for haptics and robotics (Harwin et al. 2006);
2. A decrease in the cost of producing prototypes and commercializing products (Harwin et al. 2006);
3. Increased awareness of the potential for robotic approaches to advance scientific understanding of the rehabilitation process (Harwin et al. 2006; V. S. Huang & Krakauer 2009; Kahn, Rymer, et al. 2006); and
4. Increased awareness of the demands of caring for an ageing population (Harwin et al. 2006).

Despite the proliferation of research in the area of rehabilitation robotics, the evidence regarding such training remains inconclusive and it is important that further developments are guided by motor learning principles as well as contribute to the advancement of theories in motor control and learning.

Though the need for effective rehabilitation techniques has provided a powerful driver for the development of technology and knowledge creation in this area, rehabilitation is not the only field in which this type of research is taking place. Rehabilitation robotics may be considered a specialized application of the more general field of haptic training. Haptics refers broadly to the sensation of touch, which includes both tactile and proprioceptive (kinaesthetic) sensation. Haptic training can then be defined as the use of hardware and software that provide access to or manipulate such computer-controlled and programmable sensations for the purpose of improving a particular skill or ability. Though continued studies with clinical populations will be critical for determining the types and schedules of training that provide optimal rehabilitative benefits, it is also important to look to other applications of haptic training to discern the basic principles underlying motor learning with haptic interfaces. It is difficult to outline such basic principles using the body of rehabilitation robotics literature because:

1. Even though the majority of work for robotic neurorehabilitation has focused on patients with stroke (Brochard, Robertson, Médecé, & Rémy-Nériss 2010; Krakauer 2006), it is not clear how lesion location affects the type and extent of motor learning (Gordon 1987; Krakauer 2006).
2. With clinical populations, training programs are often individualized to maximize the chances of recovery and it can be difficult to deduce generalizable principles that would advance basic motor learning theory.

3. Many studies do not differentiate genuine motor recovery (presumably, motor learning) from recovery due to adoption of compensation strategies, due to the fact that outcomes in rehabilitation focus on function (e.g., activities of daily living).

The purpose of this review is to discuss how motor learning concepts could be of benefit in the interpretation of results from haptic training studies with the goal of identifying some future directions for the continued development of haptic training paradigms that are rooted in motor control and learning theory. In order to get a broad perspective on haptic training, we will look at studies beyond the boundaries of rehabilitation. If, as we have discussed previously, motor learning principles apply to motor recovery (neurorehabilitation), then it stands to reason that general principles addressing how to optimize haptic training will also be applicable to rehabilitation as well as other contexts requiring the development of motor skills. To maintain potential application to the majority of currently investigated robotic training strategies, we will limit our discussion to studies that include robotic, force-feedback haptic interface systems, particularly those for the upper extremities. While there is also a growing literature exploring haptic training strategies for skills of the lower extremities, including balance and gait, the majority of these occur in the context of rehabilitation (for reviews, see: Belda-Lois et al., 2011; Hussain, Xie, & Liu, 2011; Pennycott, Wyss, Vallery, Klamroth-Marganska, & Riener, 2012), which as we have explained, can be challenging for identifying more general principles of motor learning, and may rely on models of motor control that are different from those governing the upper extremities. As such, we will focus on the upper extremities and also exclude studies that have focused on person-to-person manual guidance, i.e., guidance using the hands as opposed to a robot, such as in gymnastics (e.g., Heinen, Pizzera, & Cottyn, 2010) and conventional rehabilitation (e.g., Sidaway et al., 2008), or guidance provided by tools for support or psychological security (e.g., Wulf, Shea, & Whitacre, 1998).

In sections 1.3.2, 1.3.3, 1.3.4 and 1.3.5 we will discuss four important concepts in motor learning: the distinction between performance and learning, feedback, observational learning and functional task difficulty. Throughout the discussion, we will make reference to haptic training studies to highlight the potential impact of motor learning theory on the work. We will conclude the review with a discussion of terminology in the haptic training literature (section 1.3.6) and propose a taxonomy of haptic training that we believe will help to clarify procedures and protocols and facilitate more accurate and meaningful comparisons between studies and training paradigms.
1.3.2 Performance versus learning

In order to meaningfully discuss motor learning in haptic training (or any context), there must be a clear operational definition of learning [Winstein, 1991]. This is particularly important because in motor learning, there is a critical distinction between performance during skill acquisition (practice performance) and learning. We will discuss learning as a set of processes associated with practice or experience that lead to relatively permanent changes in the ability to perform a skill [Schmidt & Bjork, 1992; Schmidt & Lee, 2011]. Experimental manipulations applied during training can therefore have immediate and usually temporary effects on performance as well as relatively permanent effects on the ability to perform a skill [Schmidt & Bjork, 1992]. We contend that learning is best inferred from these relatively permanent changes. It then follows that when attempting to measure motor learning, researchers should measure outcomes with a retention test administered some time after the skill acquisition phase (i.e., practice) has concluded. A delay between practice and the measurement of performance from which learning is inferred allows for time-dependent memory consolidation that underlies motor skill [McGaugh, 2000; Shadmehr, 1997]. Although there is no universally appropriate retention interval (time between end of practice and the retention test), intervals of at least 24 hours are commonly used [Schmidt & Lee, 2011]. Retention tests administered on the same day as skill acquisition are generally thought to demonstrate short-term retention while long-term retention is demonstrated by tests administered days, weeks or months after skill acquisition. Researchers may also make the distinction between retention (testing the same task as practised in acquisition) and transfer or generalizability (testing a variation of the practised task or context) [Schmidt & Bjork, 1992]. It is important that the retention and/or transfer tests are administered to all practice groups under a common level of the independent variable [Schmidt & Lee, 2011] and in the absence of augmented feedback (discussed below; Salmoni, Schmidt, & Walter, 1984) so that the transient effects of practice conditions do not obscure the relatively permanent effects of the training experience.

Most studies of haptic training evaluate learning by: (i) using recall trials that are interspersed among training/practice trials, that is, a presentation-test paradigm [Hagman, 1983], e.g., Feygin, Keelner, and Tendick (2002); Liu, Cramer, and Reinkensmeyer (2006); Liu, Emken, Cramer, and Reinkensmeyer (2005); (ii) using post-tests that are administered immediately after training, e.g., Bluteau, Coquillart, Payan, and Gentaz (2008); Garcia-Hernandez and Parra-Vega (2009); Marchal-Crespo and Reinkensmeyer (2008); Srimathveeravalli and Thenkurussi (2005); Teo, Burdet, and Lim (2002); or (iii) a combination of the two testing paradigms, e.g., Lewinston (2009); Milot, Marchal-Crespo, Green, Cramer, and Reinkensmeyer (2010). Even though the premise of all these studies was to determine whether or
not a skill had been learned, we propose that none of these experimental designs are optimally suited to make such conclusions. It is particularly important to understand this distinction between transient performance effects and learning because research has shown that there is often a performance-learning paradox whereby factors that enhance performance during practice (under augmented feedback or test trial conditions) are detrimental to learning, and factors that degrade performance during practice are beneficial for learning (Schmidt & Bjork, 1992). In fact, in a study explicitly investigating the effect of the relative frequency of presentation trials and test trials on acquisition and retention of distance and location, Hagman (1983) found that repeated presentation trials led to quick and extensive forgetting over a 24-hour retention interval while repeated testing led to poor performance during acquisition but enhanced recall over the same retention interval. One possible explanation for this effect is that learners are better able to develop a motor programme (schema) from the variability experienced with repeated test trials as opposed to repeated and identical presentation trials. Similar results have been observed in other studies with various forms of guidance (e.g., Armstrong, 1970). It is therefore possible that researchers have incorrectly made conclusions about or missed more permanent effects of their interventions by omitting a retention interval/test or only using a retention test immediately or very shortly after practice has concluded.

1.3.3 Feedback

When discussing the control of movement, feedback or movement-induced feedback typically refers to sensory information received as a result of performing an action (Schmidt & Lee, 2011). Of course, sensory (or afferent) information is also present in the absence of movement but we consider such cases under the broader categories of sensation and perception. Feedback may be inherent—a natural result of the movement, e.g., observing whether or not you sink a putt, or it may be augmented—supplemental information about the movement, e.g., comments from a coach about your last swing. However, when referring to haptic systems, many researchers also use “feedback” to indicate any haptic information produced by the system for a variety of purposes including delivering messages, alerts and warnings (such as with vibrating cell phones), representing some aspect of the user’s interaction with the system (such as in games), or replacing the interaction that would be experienced with a real object in virtual reality systems (Hayward & Maclean, 2007). In these situations, haptic feedback, which includes both tactile and proprioceptive sensory information, may not be movement-induced, as it is normally understood in motor control and learning. Furthermore, the term “haptic feedback” is often incorrectly used interchangeably with “force feedback” which specifically relates to replicating the proprioceptive sensations.
of interacting with real objects in a virtual environment (e.g., contact, friction, stickiness, dragging and texture) [Hayward & Maclean 2007] or using a haptic system to deliver other information (e.g., learning cues, warnings) via felt forces (e.g., D. Morris, Tan, Barbagli, Chang, & Salisbury, 2007). We will use the term “feedback” to refer specifically to augmented (i.e., externally provided) movement-induced feedback since this review is focused on situations where task requirements typically include kinematic changes.

Augmented feedback is an important variable in the learning context as it can have both positive and negative effects on performance and learning, depending on how it is delivered [Swinnen 1996]. While it is possible to learn motor skills without augmented feedback, research has shown that it can improve skill retention in persons with and without a disability [Molier, van Asseldonk, Hermens, & Jannink 2010; Thorpe & Valvano 2002; van Vliet & Wulf 2006]. Augmented feedback is generally categorized as knowledge of results (KR) or knowledge of performance (KP). Knowledge of results usually refers to verbalizable, terminal augmented feedback provided about the outcome(s) of performing an action in reference to a particular goal while KP refers to feedback information about movement patterns that can contribute to the correction of said movement patterns. It should be noted however, that this distinction is not always clear [Schmidt & Lee 2011]: for some movements, and often in haptic training, the goal of the movement is a particular movement pattern and other times, KR can indicate the changes necessary to improve performance of the pattern [Weeks & Kordus 1998]. Even though KP is more often utilized in applied, non-laboratory environments (e.g., comments from a coach about form), KR has been more widely studied because it is relatively easy to obtain terminal, outcome-based information in the laboratory. Despite this imbalance in research, studies suggest that learners use various forms of augmented information in similar ways [Schmidt & Lee 2011; Weeks & Kordus 1998]. As such, the principles governing the use of KR for learning are probably also applicable to KP and we will discuss both forms of augmented feedback using this assumption.

Based on our description of augmented feedback, the reader may begin to realize that many haptic training paradigms are based on the manipulation of movement-induced haptic feedback. In fact, haptic training paradigms that provide performance information during movement execution, based on active movement from the learner, are utilizing concurrent KP [Howard 2003; J. Lee & Choi 2010]. We will now discuss two main categories of such training paradigms.

1.3.3.1 Haptic feedback that enhance performance

Haptic guidance is probably one of the most prevalent terms used to describe haptic training procedures. However, the meaning of the term may not be as straightforward as it seems. The term guidance refers to
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A variety of procedures aimed at helping a learner move through a sequence of movements by physically pulling or pushing the learner through the sequence, verbally providing direction, or utilizing physical barriers or limitations to direct movement (Poole, 1991; Schmidt & Lee, 2011). The common element among these procedures is that guidance tends to prevent the learner from making errors (Holding & Macrae, 1964) or limits the extent or severity of errors (Harwin et al., 2006; Macrae & Holding, 1965; Schmidt & Lee, 2011). Historically, researchers in the field of motor learning have implemented guidance through one of two methods: forced-response or response restriction (Holding & Macrae, 1964; Macrae & Holding, 1965). Under forced-response conditions, a guiding mechanism or the experimenter moves the learner’s limb(s) or body through the desired movement and the learner is a passive participant in the process such that the speed, timing and extent of movement are all specified (Holding & Macrae, 1964; Macrae & Holding, 1965). Under response restriction conditions, the learner is allowed to move actively but within certain limits set by the training apparatus such that only the extent of movement is specified (Holding & Macrae, 1964; Macrae & Holding, 1965).

Results from more recent studies that have described a haptic training system as “guidance” suggest that while haptic guidance can be beneficial for skill learning, the types of tasks for which it is most useful and the conditions under which it is effective are still debatable. Haptic guidance systems have been proposed for tasks such as recalling spatio-temporal patterns (Feygin et al., 2002; Teo et al., 2002), musical motor learning (Grindlay, 2008; Lewiston, 2009), and visuomanual trajectory tracking (Bluteau et al., 2008). Feygin et al. (2002) utilized a paradigm whereby the haptic interface physically guided learners through a complex three-dimensional motion that they were to later recall. Similarly, Grindlay (2008) used a paradigm in which learners were “physically moved through the motions required to perform the task rhythm” by an actuator (p. 399). The training system used by Lewiston (2009) was implemented by “dynamically controlling the user’s key presses” (p. 11) via active magnetic forces to facilitate ordinal and temporal learning; learners were instructed to passively observe the target sequence. In a study by Bluteau et al. (2008), where participants were required to manually track a visually presented trajectory, the authors used two training paradigms: haptic guidance in position and haptic guidance in force. Haptic guidance in position minimized the trajectory error by pulling the stylus’ tip towards the next point on the desired trajectory, and haptic guidance in force, based on the idea that a particular pattern of forces (force profile) will produce a particular trajectory, delivered to the learners the sensations that would be felt by an expert correctly executing the task.

Feygin et al. (2002), Grindlay (2008) and Lewiston (2009) all found that training improved performance on test trials during acquisition for a particular aspect of training: in the case of Feygin et al.’s (2002) three-dimensional task, this aspect was timing; in the case of Grindlay’s (2008) rhythmic task,
it was velocity information; and in case of Lewiston’s (2009) key pressing task, it was ordinal learning. Bluteau et al. (2008) did not find that their haptic guidance in position training was beneficial for producing desired trajectories in immediate post-tests; however, their haptic guidance in force training improved the visuomanual tracking of trajectories on a post-test administered immediately after practice.

The term haptic demonstration is sometimes used interchangeably with haptic guidance to imply that a robot or other haptic system physically displays how a task should be performed so that the learner, in physical contact with the robot, can proprioceptively experience the goal movement. Liu et al. (2005) used both terms (demonstration and guidance) to describe a procedure in which a robot constrained the movement of the user’s hand to follow the desired path by implementing a virtual haptic channel (i.e., a channel that was not physically real but computer generated and perceived by users). Although the authors did not note the specific instructions to participants in this study they noted that participants were able to control their progress along the virtual channel’s path (Liu et al., 2005). In their subsequent study, the authors again use both terms; however, this training program required that participants hold the end effector of the robot as it moved through the desired trajectory and participants “were instructed to…move along with the robot” (Liu et al., 2006, p. 23). In this case, participants were not required to actively move during haptic training. It should be noted, however, that based on measurements of forces applied by the robot to move itself, the authors concluded that participants did not oppose nor passively rely on the robot. Overall, results of these two studies showed that participants’ ability to trace the path repeatedly without the robot quickly degraded. Lütgen and Heuer (2012) performed an experiment in which their haptic demonstration mode moved participants through the desired velocity profile and participants were instructed to “let their hand be guided by the robot” (p. 4). Their results showed that while the haptic demonstration training facilitated some improvement in performance immediately after practice (particularly for temporal aspects), there were group differences at the beginning of training that persisted throughout.

Most of the studies described above utilized guidance paradigms where feedback regarding the movement was provided concurrently (during movement execution) and frequently (via the system’s constraints on movement). Of course, viewing the sensory information received in these cases as feedback is predicated on the assumption that participants were able to interpret the difference between their movement and that of the robot/haptic system as feedback.

It is thought that augmented feedback motivates learners, calibrates the motor system in relation to the outside world and also serves a guiding role whereby the learner uses feedback to produce more accurate performance on subsequent trials (Salmoni et al., 1984). However, research on scheduling of augmented feedback suggests that the largest learning effects are observed when augmented feedback
is delivered less frequently and/or delayed (terminal or summary). These observations are explained by the guidance hypothesis, which postulates that when augmented feedback is provided too frequently it becomes part of the task. When this happens, learners come to depend on the guiding feedback and their performance suffers when it is removed (Salmoni et al., 1984; Schmidt & Bjork, 1992) because they have essentially learned to perform a different task—one where the feedback is intertwined with the task dynamics (Reinkensmeyer & Patton, 2009; Weinstein, Pohl, & Lewthwaite, 1994). One view is that frequent feedback may inhibit information processing, particularly processing of inherent (proprioceptive) feedback, which limits error-detection capabilities required for retention and transfer performance (Schmidt & Bjork, 1992). Thus, it appears that haptic training with guidance is poised to be an ineffective training method if too much support is provided to the learner.

We have previously suggested that most haptic training can be considered manipulation of concurrent feedback and it has been shown that concurrent (and more frequent) feedback can be beneficial for learning more complex tasks (Wulf & Shea, 2002). Therefore, it may be possible to utilize haptic interfaces for training complex movements involving the hand/arm and these types of movements may benefit more from haptic guidance than less complex movements. Additionally, this line of research suggests that for less complex movements, haptic guidance paradigms that reduce the frequency and/or immediacy of augmented feedback may be more effective.

How then can researchers reduce the frequency of concurrent feedback and reduce the likelihood that learners will develop dependence? To test the predictions of the guidance hypothesis and identify potential solutions, researchers have devised training paradigms that are adaptive or responsive to the learner’s performance. Such training programs often begin with very restrictive or hard guidance which gradually decreases, either on a fixed schedule (J. Lee & Choi, 2010; Marchal-Crespo, Furumasu, & Reinkensmeyer, 2010) or in response to performance improvements (Marchal-Crespo, McHughen, Cramer, & Reinkensmeyer, 2010; Marchal-Crespo & Reinkensmeyer, 2008). These methods alter the frequency of feedback presentation within and/or across trials for each learner. An initial study with a steering task comparing fixed guidance and performance-based guidance (guidance-as-needed) paradigms found that the benefit of the guidance-as-needed paradigm was short-lived—both groups demonstrated similar performance on the tenth trial of a retention test administered immediately after practice (Marchal-Crespo & Reinkensmeyer, 2008). In a follow-up study, the authors utilized a 1-week retention interval and found that guidance-as-needed facilitated learning of some or all aspects of steering performance as compared to practice without any form of physical guidance (Marchal-Crespo, McHughen, et al., 2010). Interestingly, they also found that training with guidance was more beneficial for participants who were initially less skilled at the steering task (i.e., at the beginning of training). Another way to reduce frequency of KP is
to deliver augmented feedback within a bandwidth such that correction is only provided for movements outside a set tolerance for error (Garcia-Hernandez & Parra-Vega, 2009; Liu et al., 2005; Teo et al., 2002). Results from these studies show that participants improve their performance for some, if not all, aspects of performance. However, none evaluated learning with retention tests so it is difficult to make conclusions about long-term effects of this training method.

1.3.3.2 Haptic feedback that degrade performance

Haptic error-augmentation or error-amplification is a relatively new concept in haptic training. As such, there are few studies examining it in the context of skills training for the upper extremities. Error-augmentation paradigms provide augmented feedback that is directly related to the participant’s movement and so constitutes movement-induced feedback. It is believed that error-augmentation should be beneficial for learning because: (i) error drives learning (Kawato, 1990; Wolpert, Ghahramani, & Jordan, 1995) and therefore larger errors could speed up the learning process; and (ii) exaggerating small errors may increase motivation for learning as well as the likelihood that errors will be noticed and a response will be triggered (Wei, Patton, Bajaj, & Scheidt, 2005). There are few studies exploring this type of training in healthy participants and so we describe here some of the studies that examine error-augmentation using visual (not haptic) error-augmentation, studies using motor adaptation paradigms, and/or studies involving stroke survivors.

Visual error-augmentation may be accomplished by increasing the error gain (displaying an error that is a multiple of the performer’s actual error) or using an error offset (displaying an error that is the sum of a constant error value and the performer’s actual error) (Wei & Patton, 2004; Wei et al., 2005). Necessarily, in order to utilize visual error-augmentation, vision of the limb is blocked during movement. Researchers pursuing this line of inquiry in relation to motor learning note that there is some evidence to suggest that mechanical and visuomotor adaptation involve similar neural mechanisms (Wei et al., 2005). The implication is therefore that knowledge gained from visual error-augmentation studies will transfer (at least to some extent) to mechanical or haptic error-augmentation. For example, one study compared a control condition (gain = 1) with three visual error-augmentation methods (gain = 2; error-offset; gain = 3.1) for making target-directed movements along a straight line trajectory while experiencing a visuomotor distortion (Wei et al., 2005). While all conditions facilitated motor adaptation (reduction of trajectory errors on catch trials interspersed during the learning phase), the error-offset method demonstrated the greatest overall amount and fastest rate of learning (Wei et al., 2005). In another study, Cesqui et al. (2008) compared two forms of therapy for training stroke survivors with mild to severe impairments to produce aiming movements to targets on a semi-circle. All participants
experienced two therapy conditions: active assistive therapy, whereby the robot provided assistance when the client was unable to complete the movement independently; and divergent force field therapy, whereby the client experienced forces perpendicular to the movement direction and proportional to the error in their movement trajectory. Participants with mild impairment (judged by their ability to complete the tasks independently before training) were assigned to the group that experienced the divergent force field first while participants who were unable to complete the tasks independently experienced the assistive therapy first. Results showed that the divergent force field produced better results for mild to moderately impaired patients while the active assistive therapy was better for patients with more severe disabilities. In another motor adaptation study, Patton, Stoykov, Kovic, and Mussa-Ivaldi (2006) involved both healthy participants and stroke survivors to explore whether robotic training forces that enhanced or reduced errors would better improve motor adaptation. The direction of error-augmenting forces experienced on each trial was a function of the movement’s instantaneous velocity vector. Results showed that error-augmentation was more effective than error reduction for correcting the hand’s initial movement direction through motor adaptation.

While adaptation studies such as the ones described above are able to provide insight into how the central nervous system adapts to novel learning situations, it may be premature to draw conclusions for skill learning and rehabilitation. This is because it is possible that motor adaptation is in fact distinct from motor skill learning (V. S. Huang & Krakauer, 2009). This view is supported by observations that after-effects are short-lived (V. S. Huang & Krakauer, 2009) and the proposition that motor adaptation may actually be a process of movement re-optimization where the goal is simply to “maximize performance in that environment” (Izawa, Rane, Donchin, & Shadmehr, 2008).

In a study involving only healthy participants, Milot et al. (2010) compared the effects of haptic guidance and error-amplification on the learning of a timing-based motor task. They found that error-amplification training improved performance but only for individuals who were initially more skilled during baseline testing. This is similar to results of a study we have previous discussed (Cesqui et al., 2008) that showed differential benefits of error-augmentation by skill (or impairment) level. J. Lee and Choi (2010) extended the error-amplification concept to propose two training protocols that they describe under the umbrella term “haptic disturbance.” In their study, haptic disturbance was presented as either repulsive forces dependent on the learner’s current performance (movement-induced feedback) or random feed-forward forces that disturbed the learner’s movements at irregular intervals. Results suggested that noise-like, random disturbance was better for learning a two-dimensional tracking task than both fixed progressive guidance and repulsive haptic disturbance (feedback), as measured on a 24-hour retention test.
While the utilization of haptic feedback that degrade performance is relatively new, the results thus far are promising. However, as with studies of haptic guidance, more studies that include delayed retention tests are needed to make more conclusive statements about learning. Furthermore, additional studies utilizing haptic error-augmentation, as opposed to visual error-augmentation, are required to confirm that these findings transfer to the haptic sensory modality.

1.3.4 Observational learning

Observational learning involves learning from an individual who provides a physical demonstration of a skill so that learners can observe the elements of the action directly (Schmidt & Lee, 2011). The term “modelling” is sometimes used interchangeably with “observational learning” but more specifically refers to the use of a display (the model) which selectively depicts some aspect(s) of task performance (e.g., spatial or temporal details) (Shea, Wulf, Park, & Gaunt, 2001). The display usually consists of computerized visual and/or auditory presentations. There is a growing body of literature in support of observational learning, showing that movement strategies (e.g., Hayes, Ashford, & Bennett, 2008), discrete spatial information (e.g., Steffens, 2007; Weeks, Hall, & Anderson, 1996), spatial sequences (e.g., Heyes & Foster, 2002; Kelly, Burton, Riedel, & Lynch, 2003), timing (e.g., Andrieux & Proteau, 2013), and even dynamic movements such as dance (Gray, Neisser, Shapiro, & Kouns, 1991) and surgery (Custers, Regehr, McCulloch, Peniston, & Reznick, 1999) can benefit from observational learning.

A common form of observational learning is by visual demonstration of a skill. Guadagnoli and Lee (2004) compared three studies that used a timed key press task with varying levels of complexity determined by the timing requirements. They explained that under more challenging practice conditions (random practice), providing a model (visual demonstration) of the task was more beneficial for performance and learning of the more complex task. They proposed that the information provided by the model facilitated the learners’ action planning—a key component of skilled performance.

The concept of modelling during practice is closely related to the idea upon which many haptic training programs are developed: providing a correct kinaesthetic demonstration of the desired movement. As such, it is tempting to immediately draw parallels between visual demonstration and haptic demonstration; however, successful use of visual demonstration does not imply that all forms of demonstration will be equally beneficial. In fact, many studies in the haptic training literature have been designed to compare the efficacy of visual demonstration and haptic demonstration for learning a novel motor skill. These studies have reported no differences between visual and haptic demonstration conditions (Liu et al., 2006) or that haptic demonstration was superior only for particular (e.g., temporal) aspects of
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Interestingly, the observational learning literature has shown that observation of a model who is also learning the goal movement can be just as good (McCullagh & Meyer, 1997) or even better for learning than observation of an expert model only (Laguna, 2008), because learners are able to observe errors in action with appropriate feedback. A recent study also showed that observation of a novice and an expert model produced better retention than observation of either two novice or two expert models (Andrieux & Proteau, 2013). Furthermore, observational learning followed by or interspersed with physical practice of the task, as compared to observational learning alone, leads to superior learning (Andrieux & Proteau, 2013; Blandin, Lhuisset, & Proteau, 1999), and importantly, physical practice provides an advantage over observational learning alone (Black & Wright, 2000). These findings raise some interesting questions regarding haptic training.

Firstly, does haptic demonstration provide a sort of observational learning with the self (in collaboration with the robot) as an expert model? In some instances of haptic demonstration, vision of the limb and/or end effector is blocked to avoid a confound between visual and haptic demonstration (e.g., Feygin et al., 2002). In this situation, self-observation in the visual sense is not possible. In any case, if we consider haptic demonstrations that allow only proprioceptive observation, it becomes clear that there is a difference between visual and haptic demonstrations with respect to the focus of attention. Visual demonstration draws the learner’s attention outward, toward the model, whereas haptic demonstration (without vision) turns the learner’s attention inward toward the feel and experience of the model movement. Research examining the impact of attentional focus on motor skill performance suggests that an internal focus is more beneficial for novices while an external focus is more beneficial for skilled performers (Beilock, Bertenthal, McCoy, & Carr, 2004; Beilock, Carr, MacMahon, & Starkes, 2002; Perkins-Ceccato, Passmore, & Lee, 2003). Furthermore, it has been demonstrated that an external focus (particularly on the effects of movement) can enhance motor learning, possibly as a result of a learner’s progression from cognitive to autonomous stages of learning (Wulf & Prinz, 2001). (See Marteniuk, 1979 and Anderson, 1982 for discussions of the classical stages of learning.) This may help to explain findings that haptic demonstration is not superior to visual demonstration for learning visuomotor skills: While learners may benefit from haptic demonstration in the initial stages of training, if the training method does not change or progress to methods that encourage a more external focus of attention, learners may become stagnant in earlier stages of learning.

Secondly, are the benefits of haptic error-augmentation and observation of a learning model due to the same underlying processes? Comparisons of haptic guidance and haptic error-augmentation paradigms
provide some preliminary evidence that, in the context of haptic training, practice with (exaggerated) errors can be beneficial. Perhaps similarly, observation of a learning model allows a learner to observe the commission (and possibly correction) of errors. These findings are further supported by the notion that conditions in practice are as effective as the extent to which they engage processes appropriate for performance on retention and transfer tests. This concept, known as transfer-appropriate processing, is one type of practice specificity that leads to skill learning through the deliberate design of practice conditions that engage learners in the same problem-solving processes that are required for retention and transfer performance (C. D. Morris, Bransford, & Franks 1977; Schmidt & Lee 2011).

Observational learning and modelling can be useful in reducing task demands and/or facilitating cognitive processing, especially for novices performing complex tasks. However, the skill level and source of the model (external performer, self/robot end effector) has an impact on learners’ focus of attention, which further impacts the learning process. Modelling utilized for haptic training should promote problem solving and information processing required for performance under retention conditions.

1.3.5 Functional task difficulty

The challenge point framework is a well-known motor learning framework for understanding the effects of various practice conditions on learning (Guadagnoli & Lee 2004). A key concept in the challenge point framework is that of functional task difficulty: how challenging a task is in relation to the skill of the performer and the conditions under which the task is performed (Guadagnoli & Lee 2004). The authors contend that learning is hindered in the presence of too much or too little information. As such, low levels of functional task difficulty are optimally challenging for those with low skill levels, who stand to gain much new information from training, whereas higher levels of functional task difficulty are optimal for highly skilled individuals. Consequently, very simple tasks may present high functional task difficulty for novices or lesser skilled individuals, and given the right conditions, very complex tasks may present low functional task difficulty for highly skilled individuals.

With this in mind, we can reconsider some of the motor learning concepts we have previously discussed. Haptic error-augmentation may be viewed as one instance of the implications of the challenge point framework, as the process of augmenting errors does indeed make task completion more difficult. In fact, the challenge point framework’s conceptualization of functional task difficulty fits nicely with the results we have mentioned whereby skill level or degree of impairment was directly related to the amount of benefit received from haptic guidance (Marchal-Crespo, McHughen, et al. 2010) or haptic error-augmentation training (Cesqui et al. 2008; Milot et al. 2010; Patton et al. 2006). In addition to
issues of how learners are instructed to interact with haptic training systems and the absence of retention tests we have discussed previously, haptic guidance paradigms may also be suffering from an inappropriate level of challenge for learners. This appropriate level of challenge is no doubt difficult to identify since task complexity is not easily defined. However, it would be useful for haptic training researchers to begin acknowledging this concept in their reports of training strategies and perhaps assessing initial skill levels through pre-tests or proxy evaluations (e.g., spatial ability tests) as some researchers have done (Marchal-Crespo, McHughen, et al., 2010; Milot et al., 2010). With regard to observational learning, training programs that only require learners to observe a model, with no (or little) active participation, offer very little challenge, even for unskilled learners. This may partially explain the results of Liu et al. (2006) and Lüttgen and Heuer (2012) where both training programs consisted of proprioceptive observations of model movements.

The feed-forward haptic disturbance utilized in J. Lee and Choi (2010) is a good example of the utilization of functional task difficulty: random perturbations during movement execution definitely increase task difficulty. Readers will recall that this haptic training method actually proved superior to two feedback-based haptic training strategies (progressive haptic guidance and repulsive haptic disturbance) (J. Lee & Choi, 2010). Another implementation of increasing challenge for learners is the use of resistive forces that oppose the learner’s movements. This method actually has roots in physical therapy (Voss, 1967) and was utilized in a preliminary study with stroke survivors (Stein et al., 2004). The study compared the use of haptic resistive training to active-assisted exercise and found no differences in patients’ outcome measures; however, the authors note that clients’ skill at baseline predicted the amount of improvement observed with robot training.

1.3.6 A note on terminology

We have discussed four concepts in motor learning that may help to contextualize some of the results from recent studies of haptic training. The studies described above highlight the fact that the nature of the haptic training protocol is a function of not only what the haptic system does (i.e., what haptic information is provided to learners) but also how the learner is instructed to interact with the system. Is the learner active or passive? Are they moving along with the system or allowing themselves to be moved by it? Furthermore, while some studies utilized condition-specific instructions in an attempt to manipulate the learner’s activity/passivity during training (e.g., J. Lee & Choi, 2010), it is also possible that the learner’s level of activity changes within each trial, especially when there are no explicit instructions about how to interact with the system.
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Figure 1.1: Proposed taxonomy for classifying haptic training paradigms for skills involving movement of the upper extremities.

We have noted that there is quite an extensive vocabulary of terms relating to haptic training, some of which may be redundant. Often, this does not facilitate comparisons among the multiple haptic training paradigms presented in the literature (Powell & O’Malley, 2012). We (and others: Powell & O’Malley, 2011, 2012) propose that there must first be a common understanding of what types of training are implied in order to have meaningful discussions about the efficacy of training interventions. Based on the studies discussed here, and the way in which we have discussed them, we propose a classification of haptic training strategies (Figure 1.1) that we hope will help researchers more clearly define their interventions and more readily draw connections between studies, between the fields of haptic training and motor learning, and finally between experimental haptic training and applied fields such as rehabilitation.

We acknowledge that the proposed taxonomy is not the first, nor is it completely novel. Powell and O’Malley (2011, 2012) proposed a taxonomy for haptic training (the authors use the term “haptic guidance”) paradigms. Their discussion occurs mainly in the context of shared-control whereby novices receive real-time feedback from a real or virtual expert and their taxonomy is based on three dimensions of
classification: (i) whether the paradigm assists or resists the novice user; (ii) how the paradigm combines presentation of task forces (forces inherent to the task’s dynamics) and training forces; and (iii) whether the paradigm adjusts the relative contributions (weights) of the task forces and training forces in response the user’s performance. From the concepts we have discussed, the reader should recognize the relevance of the first (compare sections 1.3.3.1 and 1.3.3.2) and third dimensions (section 1.3.3.1). With respect to the second dimension, the authors note that most guidance paradigms combine task forces and training forces using a simple weighted average, and present the combined forces simultaneously via a single haptic channel. They contend that this usually leads to the user being unable to distinguish the two as the training forces alter the perceived dynamics of the task, which leads to impaired learning (Powell & O’Malley, 2012). These concerns are similar to ones we discussed above regarding the frequency of augmented feedback presentation.

Powell and O’Malley’s classification system led to the description of the following types of haptic training paradigms.

1. Gross assistance: combines presentation of task and training forces.

2. Temporally separated assistance: displays task forces and guidance forces in temporal succession via a single haptic device.

3. Spatially separated assistance: displays task forces and guidance forces simultaneously with two haptic channels (by using two body areas or two haptic devices).

4. Gross resistance: increases the difficulty of the task or resists optimal task completion in some way (e.g., resistive forces or error-augmentation).

Our review has not considered the specific cases of temporally or spatially separated assistance. As such, we encourage interested readers to explore these methods further, especially in relation to the potential challenges presented by asymmetries in: proprioception (Adamo & Martin, 2008), utilization of proprioceptive feedback for movement (Goble & Brown, 2007), and force matching and sense of effort (Adamo, Scotland, & Martin, 2012).

Though there are some similarities between our categorization (Figure 1.1) and that of Powell and O’Malley (see Powell & O’Malley, 2011, 2012 for a detailed discussion of the categories), we believe that our taxonomy brings motor learning principles to the forefront of the discussion. Consequently, it is clear that training typically thought of as “haptic guidance” actually exists on a continuum: from scenarios where participants are fully active and receive occasional feedback on performance (Haptic Assistance), to scenarios where participants are completely passive during training (Haptic Demonstration). Therefore,
because Haptic Assistance is based on feedback, it should, by definition, be progressive or adaptive (assuming that the learner is improving). Furthermore, it is nonsensical to consider the provision or scheduling of augmented haptic feedback in haptic training paradigms that utilize Haptic Demonstration because the entire movement is predetermined and there can be no movement errors on which to report.

Additionally, we note that our taxonomy identifies some forms of haptic training that were not explicitly discussed in the present review. For example, D. Morris et al. (2007) utilized a haptic training condition that consisted of applying to the learner the opposite of the desired force pattern (a haptic display) such that the learner would successfully apply the desired force by opposing the haptic force profile delivered by the system. Results showed that visual display of the force profile was superior to haptic display for immediate recall of the target forces. It should be clear to the reader that the training paradigm described here did not really utilize haptic feedback (the term used by the authors) since the haptic display of forces was not based on the learner’s movements. Instead, we would classify this training paradigm as Haptic Cueing. If we also consider that similar paradigms (e.g., error-augmentation, noise-like perturbation and resistive training) are sometimes lumped together (e.g., Powell & O’Malley, 2012), our classification, which attempts to differentiate them, may encourage researchers to focus on their differences and explore whether underlying mechanisms are also differentiable (e.g., error-detection capabilities, motivation for learning and attention to training). Finally, while we have named six training paradigms, we acknowledge that there are others (already existing and yet to be developed) that we have not classified. In particular, we have indicated this by listing Haptic Resistance as one example of training paradigms that degrade performance but do not specifically increase movement error.

Since our proposed taxonomy is preliminary, we invite other researchers to discuss, challenge and modify it to develop common understanding and facilitate advances in haptic training. As Powell and O’Malley (2011, 2012) explain, a taxonomy allows researchers to separate the underlying principles of a training paradigm from its specific implementation (i.e., the task and the haptic device used). This will facilitate comparisons between the paradigms themselves instead of implementation details, which can be held constant (Powell & O’Malley, 2011, 2012).

1.3.7 Conclusions

Motor learning theory is especially concerned with how people acquire motor skills. Robotic training for the upper extremities is rapidly expanding but clear conclusions on optimal training strategies are still lacking. Motor learning principles may provide some insight into training strategies currently being employed in this field. By reviewing studies of haptic training for the upper extremities with healthy
populations, we have highlighted and discussed some concepts in motor learning that will be important for advancing knowledge in the field of haptic training, including the performance-learning paradox, augmented feedback, observational learning and functional task difficulty. While we did not review studies involving the lower extremities, it is possible that some of the paradigms being explored in that field are not only relevant to the present discussion but also bear similarities to the training paradigms we have identified. Synthesis of results from these two areas of research may provide additional insights into the utility of haptic training.

Most of the studies that we reviewed attempted to make inferences about skill learning but did not differentiate between short-term and long-term learning. In fact, since most studies looked only at short-term skill retention (measured by immediate post-tests or test trials within a presentation-test paradigm), it is possible that the results observed were transient and not fully representative of learning (a relatively permanent change in ability). Additionally, motor learning research has shown that augmented feedback can be beneficial for learning if it is provided in a way such that the feedback does not become an integral component of the task and learners do not become dependent on it for performance. Many of the extant haptic training paradigms operate by providing augmented feedback during training. Researchers can therefore look to the motor learning principles governing the provision of augmented feedback in order to structure their use of this haptic information for training. Bearing this in mind, researchers are encouraged to pursue well-designed and systematic tests of feedback designs within the haptic modality before making comparisons to other modalities (e.g., vision) (Sigrist, Rauter, Riener, & Wolf, 2012).

In general, training paradigms that allow learners to make and correct errors (e.g., bandwidth feedback training) and decrease the frequency of feedback presentation should be more beneficial for learning. We have also discovered that it is important to be clear about how participants have been instructed to interact with the training system. Finally, studies of haptic training should be systematically extended to a wider variety of tasks with respect to complexity (Sigrist et al., 2012) and dynamics (Powell & O'Malley, 2012). We believe that in order for researchers in haptic training to uncover the underlying principles governing proprioceptive skill learning, research must be guided by existing principles of motor learning. In turn, researchers in applied fields such as robot-aided rehabilitation will contribute to the advancement of motor learning theories and be poised to make more impactful contributions in their own fields.
1.4 Research Goal & Objectives

In the previous sections of this chapter, I have outlined various motor learning principles and how they may be relevant to the ongoing research and development in haptic training. A fuller understanding of motor learning principles that affect learning with haptic training could serve to focus and hone the training paradigms being deployed for robot-assisted training across domains. As a first step in this process, I sought to explore the optimal parameters for provision of haptic feedback to a non-clinical (healthy) population, learning a simple laboratory task.

This overarching research goal spawned three specific research objectives, each of which is explored in one of the following chapters. The research objectives were:

1. To determine whether one of two forms of haptic feedback (assistive or error-augmenting) or no augmented haptic feedback is most effective for motor learning;

2. To determine whether the bandwidth at which two forms of haptic feedback are presented during acquisition influence their learning effects; and

3. To determine whether self-control of haptic guidance is beneficial for learning, how participants choose to schedule it and for what functional role(s) participants use it.

In this dissertation, the guidance hypothesis was used as the primary basis for optimization of haptic feedback, that is, in each case, I attempted to reduce the occurrence of and dependence on haptic feedback for performance and then further explored whether this was detrimental or beneficial for motor learning.

1.5 Overview of Dissertation

Chapter Two of this thesis outlines the first experiment in a manuscript titled “It pays to go off-track: Practising with error-augmenting haptic feedback facilitates learning of a curve-tracing task.” In this chapter, I explored two forms of haptic feedback—haptic assistance or error-minimizing haptic feedback, and haptic error-augmentation (as described earlier in 1.3.3 [Williams & Carnahan, 2014]). Other authors may describe these as convergent and divergent forms of robot assistance, respectively (Heuer & Lüttgen 2015). While haptic assistance has a strong guiding influence on performance because it moves the participant towards correct performance, haptic error-augmentation provides similar information but cannot be conceptualized as guidance. The results of this experiment demonstrated that haptic error-augmentation was the most effective strategy for learning and indicated the primacy of an error-based
learning mechanism for the task.

Chapter Three outlines a second experiment in a manuscript titled “Learning effects of practice with error-altering haptic feedback depend on bandwidth: Are there implications for rehabilitation robots.” This chapter expanded the concept of bandwidth feedback—providing feedback only when performance exceeds a pre-determined tolerance for error—to the provision of two forms of haptic feedback for learning. Feedback provided at wider bandwidths, that is, with greater tolerance for error effectively reduces feedback frequency and should reduce dependence on feedback for performance. I sought to determine whether changing the bandwidth or error tolerance at which each of the two forms of haptic feedback are provided impacts motor learning. The results indicated that, while there were no performance effects of bandwidth, learning effects did emerge: the two forms of haptic feedback had differential learning effects only at the narrow bandwidth, i.e., a smaller error tolerance. Essentially, I replicated the effect described in Chapter Two and provided evidence that at wider bandwidths, researchers may not find evidence of differences between these two training approaches.

Chapter Four outlines the third and final experiment in a manuscript titled “Enhancing haptic assistance training through self-controlled practice: Influences of feedback frequency and opinions of haptic assistance.” In this chapter, I explored how participants chose to schedule haptic assistance, whether the opportunity to self-control their haptic feedback schedule impacted motor learning, as well as the rationales and opinions of participants regarding their self-controlled or externally-imposed haptic feedback schedule. Allowing participants self-control of the haptic feedback schedule gave them the opportunity to select the number of blocks with haptic assistance (and therefore their dependence on haptic feedback) in accordance with what they believed would best serve their needs and the stated learning goals.

The final chapter, Chapter Five, provides a general discussion of the overall findings, including theoretical interpretation, limitations, future directions for research and practical implications.
Chapter 2

It pays to go off-track: Practicing with error-augmenting haptic feedback facilitates learning of a curve-tracing task

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2.1 Introduction

It is well known that the nature and scheduling of feedback is extremely important in the process of motor learning. Recent technological developments, particularly in haptics and robotics, have allowed researchers to embed novel and complex feedback presentations into training programs. Robotic training and haptics-enhanced performance are being explored in fields such as neurorehabilitation (V. S. Huang & Krakauer, 2009; Kahn, Rymer, et al., 2006), surgical training (Delorme, Laroche, DiRaddo, & Del Maestro, 2012; Prasad, Maniar, Soper, Damiano, & Klingensmith, 2002), handwriting instruction (Y.-S. Kim, Collins, Bulmer, Sharma, & Mayrose, 2013; Vishnoi, Narber, Duric, & Gerber, 2009; Xiong, Milleville-pennel, Dumas, & Palluel-Germain, 2013), and sports training (P. Y. Huang, Kunkel, Brindza, & Kuchenbecker, 2011). The most common form of robotic or haptic training is haptic guidance; however, the term

\(^1\)https://www.frontiersin.org/articles/10.3389/fpsyg.2016.02010/full
\(^2\)https://creativecommons.org/licenses/by/4.0/
is used to refer to a variety of training strategies [Williams & Carnahan, 2014], including that which delivers forces, or assistance, on the basis of movement-induced feedback about performance [Bluteau et al., 2008; J. Lee & Choi, 2010; Marchal-Crespo, McHughen, et al., 2010; Marchal-Crespo & Reinkensmeyer, 2008]. Haptic assistance most often serves to minimize errors in performance, either directly, by physically correcting or limiting movement errors, and/or more indirectly, by reducing task difficulty or highlighting the correct movement.

Error avoidance during skill acquisition seems intuitive because this is the ultimate goal of practice—acquiring the ability to perform a task with minimal errors [Johnson, 2004] and in fact, there are a couple lines of evidence that support the avoidance of errors during the learning process. The first is based on the idea that erroneous responses made during practice may be remembered and later repeated [Holding, 1970]. Consequently, correct learning of the task of interest would require, not only the acquisition of new information and skills, but also the unlearning of incorrect ones [Kay, 1951]. However, Holding (1970) found that despite some repetition of errors, there was little correlation between the errors made in early and later practice. Nonetheless, proponents of errorless learning believe that the experience of errors, especially early in learning, can lead to frustration, practice of undesirable behaviours which must later be unlearned, and lack of positive reinforcement [Singer, 1977], none of which are particularly beneficial for learning.

Although this idea first emerged with animal studies in the context of discrimination learning [Terrace, 1963], it has since been implemented using prompts and cues [Singer & Gaines, 1975], physical guidance [Armstrong, 1970; Holding & Macrae, 1964, 1966] and task constraints [Capio, Poolton, Sit, Holmstrom, & Masters, 2013; Maxwell, Masters, Kerr, & Weedon, 2001] for learning a variety of motor skills. Studies have shown that learners who experienced minimized errors, through some form of guidance or prompting during practice, performed better during acquisition than groups who experienced trial-and-error learning conditions [Armstrong, 1970; Singer & Gaines, 1975; Singer & Pease, 1976; Wulf et al., 1998]. While these learners typically experienced decrements in performance on retention and transfer tests [Armstrong, 1970; Singer & Gaines, 1975; Singer & Pease, 1976], a few studies have shown that some benefits of guided practice persist during unguided performance [Marchal-Crespo, McHughen, et al., 2010; Marchal-Crespo & Reinkensmeyer, 2008; Wulf et al., 1998]. Furthermore, other studies that minimized errors through the low-to-high progression of task difficulty over the course of practice, have shown that this errorless practice approach led to better retention and transfer [Maxwell et al., 2001; Poolton, Masters, & Maxwell, 2005] as well as protected against performance decrements under secondary task loading in both adults [Maxwell et al., 2001; Poolton et al., 2005] and children [Capio et al., 2013]. These benefits have been attributed to the release of working memory when learning under error-
less conditions and the continued release of working memory during subsequent performance (Poolton et al., 2005).

In spite of this evidence supporting error minimization during training, there are theories that suggest we should be cautious about this approach, and in fact, support the creation of training scenarios that facilitate the commission of errors in order to enhance learning. The theory of “desirable difficulties” (Bjork, 1994; Linn & Bjork, 2006) posits that introducing difficulties for the learner by, for example, varying conditions of practice, utilizing distributed practice, and reducing feedback, often lead to poorer performance during training but enhanced post-training retention and transfer performance. Effortful training conditions may lead learners to be more active and engaged in training, thereby enhancing information processing and better protecting against the forgetting of new information and skills (T. D. Lee, Swinnen, & Serrien, 1994; Schmidt & Bjork, 1992). Furthermore, as suggested by the schema theory, the detection and correction of movement errors drive motor adaptation and motor skill acquisition (Schmidt & White, 1972). Likewise, error detection and correction processes update internal models that map movements of the limb to consequences in the environment (Kawato, 1990; Lisberger, 1988; Thoroughman & Shadmehr, 2000; Wolpert & Ghahramani, 2000).

It is, therefore, logical to propose that artificial augmentation of errors may produce similar or added benefits to learning. These benefits may include: (i) increasing motivation by highlighting consequences of error; (ii) increasing the detection and correction of small errors; and (iii) boosting the signal-to-noise ratio for sensory feedback (Wei et al., 2005). A few studies have shown that error-augmentation or noise-like haptic disturbance may be just as beneficial as haptic assistance for learning path-following (Chen & Agrawal, 2013), pursuit tracking (H. Lee & Choi, 2014; Powell & O’Malley, 2012), and target-hitting tasks (Powell & O’Malley, 2012). It has also been shown that, for a golf putting task, while error augmentation had no effect on post-training performance, it did negatively impact motivation, both during and after training (Duarte & Reinkensmeyer, 2015). This is in contrast to one of Wei et al.’s (2005) hypothesized benefits of artificial error augmentation. Nonetheless, Milot et al. (2010) demonstrated that error-amplification for timing in a pinball-like game was beneficial for initially skilled, young adult learners but not for older adults (Bouchard, Corriveau, & Milot, 2015). In addition, if we look outside the realm of upper-extremity movements, studies have also shown some benefits of error augmentation in comparison to no robot assistance for a simple locomotor task, particularly for initially less skilled learners (Marchal-Crespo, Schneider, Jaeger, & Riener, 2014). However, for a more complex locomotor task, it was found that error augmentation reduced errors from baseline immediately after training for initially more skilled learners while random noise-like perturbation reduced errors for both skilled and unskilled participants (Marchal-Crespo, Lopez-Oloriz, Jaeger, & Riener, 2014).
Haptic feedback is particularly suited to providing information about or altering performance while movement is ongoing (i.e., concurrently). Consequently, we are particularly interested in understanding the relative benefits of these two forms of haptic feedback (assistance and error-augmentation) for continuous, trajectory-based tasks that require ongoing use of feedback, throughout movement execution, as opposed to recall of spatial trajectories which have also been studied (Feygin et al., 2002; Liu et al., 2006; Yang et al., 2008). Such tasks are relevant to numerous functional skills including steering—in the contexts of human-computer interaction (Accot & Zhai, 1999) as well as vehicle control (Chen, Ragonesi, Galloway, & Agrawal, 2011; de Groot, de Winter, López García, Mulder, & Wieringa, 2011), drawing (Garcia-Hernandez & Parra-Vega, 2009; Kyung, Lee, & Srinivasan, 2009), some cases of calligraphy/handwriting (Bluteau et al., 2008; Y. K. Kim & Yang, 2007; Yang et al., 2008) and surgery (Lathan, Cleary, & Traynor, 2000). Steering or tracing tasks are well-studied in the field of human-computer interaction but such studies typically involve modeling performance under various conditions or evaluating performance with different input devices without concern for any practice or learning effects that may occur. While some studies have explored haptic training for these types of feedback-dependent trajectory-based tasks, only a fraction of them (Chen & Agrawal, 2013; H. Lee & Choi, 2014; J. Lee & Choi, 2010; Powell & O’Malley, 2012) have compared the learning effects of both error minimizing and error augmenting haptic feedback.

Furthermore, these trajectory-based tasks are often externally-paced in the laboratory, i.e., presented with a target or fixed speed for performance, presumably to tease apart the effects of haptic training on the spatial and dynamic features of the task. However, many functional tasks performed outside the laboratory are self-paced and only one study, to our knowledge, has compared haptic error minimization and error augmentation for learning a continuous, trajectory-based, self-paced task (Chen & Agrawal, 2013). The results from this study suggested that both haptic feedback paradigms enhanced performance but there was no significant difference between them. Looking to the broader motor learning literature, it has been suggested that closed, self-paced skills are targeted to automation and should therefore benefit from guided practice, i.e., error minimization (Singer, 1977). However, the importance of online feedback and corrections for continuous skills suggest the primacy of an error-based learning mechanism which should benefit from error augmentation.

In the present study, we compared practice conditions with error-minimizing haptic feedback, error-augmenting haptic feedback and no haptic feedback for learning a tracing task. We hypothesized that: (i) in comparison to error-minimizing haptic feedback, error-augmenting haptic feedback would be more beneficial for learning; and (ii) in comparison to no haptic feedback, error-minimizing haptic feedback would be detrimental for learning. We utilized a transfer design (Salmoni et al., 1984), whereby, follow-
ing skill acquisition under their assigned haptic feedback condition, all participants were tested under conditions without any augmented feedback, in order to distinguish between the transient performance effects caused by our practice conditions and more permanent changes in ability, which is indicative of motor learning (Schmidt & Bjork, 1992).

### 2.2 Methods

The University of Toronto Health Sciences Research Ethics Board approved the protocol and we recruited 27 adults with normal or corrected-to-normal vision: 24 women, 3 men, aged 22 to 55 years ($M = 28.5, SD = 8.7$), 24 of whom self-identified as right-handed while 3 self-identified as left-handed. All participants gave voluntary informed consent in accordance with the guidelines set out by the 1964 Declaration of Helsinki and received gift cards valued at CAD$15 as compensation for their time.

#### 2.2.1 Apparatus

The experiment was conducted using a SensAble Phantom Omni (currently Geomagic Touch; Rockhill, SC, USA), a standard computer monitor (Dell UltraSharp™ 2209WA) and a custom software program. The Phantom Omni is a three-degree of freedom, desktop haptic interface that can exert precise forces to the user through its end effector via a hand-held stylus as well as measure the position of said end effector in space (Massie & Salisbury, 1994). The device allows users to feel and interact with virtual objects. Its maximum exertable force is 3.3 N and its position resolution is approximately 0.055 mm. The visual gain between displacements on the visual display and the haptic device was 1.48.

The haptic device was programmed to operate in one of three feedback modes: none, spring assistance, and spring disturbance. The spring assistance mode produced a linearly increasing spring-like force that pulled the user back towards the target curve if the cursor deviated beyond a specified limit (bandwidth), while the spring disturbance mode produced a linearly increasing spring-like force that pushed the user farther from the target curve, augmenting errors, if performance deviated from the curve beyond a specified bandwidth (see below). For the assistance (i.e., error minimization) and disturbance (i.e., error augmentation) modes, haptic gain, magnitude and channel bandwidth were established through pilot experimentations. The haptic gain represents the spring constant, $k$ in the spring force equation, $f = k \times x$, where $f$ is the force exerted by the device, up to a maximum specified by the magnitude parameter, and $x$ is the displacement between the cursor and its target position on the target curve. The programmable ranges for both gain and magnitude were $[0, 1]$, representing values 0–0.5 N mm$^{-1}$ for gain and 0–3 N for magnitude. The channel bandwidth parameter specified the radius of the haptic feedback-free zone.
on either side of the target trajectory where no forces were exerted on the user, regardless of the mode of operation. The gains for each of the experimental conditions were set to be equivalent in order to maintain the rate of change of feedback. During pilot studies, performing under the error augmentation condition with the same gain and magnitude as the error minimization condition made it very difficult to complete a trial. As a result, the haptic gain and magnitude for the error minimization condition were set to 0.3 N mm\(^{-1}\) and 1 N, respectively, while the gain of the error augmentation condition was kept the same (i.e., 0.3 N mm\(^{-1}\)) but the magnitude was reduced to 0.3 N.

### 2.2.2 Task

The position of the haptic device was adjusted for handedness and movements primarily took place in the vertical plane. Seated at a table, participants were required to grasp the device’s stylus to manipulate the corresponding cursor shown on the computer screen. The target curve comprised seven fixed control points, a start-point and an end-point, all of which were connected by sinusoidal curve segments (Figure 2.1). The curve was 0.8 mm wide and the invisible channel bandwidth was 0.8 mm on either side of the target curve. With respect to movement of the stylus, the amplitude of the curve was 155.6 mm from start-point to end-point, with path length 392.4 mm. With the visual gain, these measurements were 230.1 mm and 580.2 mm, respectively, on the computer monitor.

### 2.2.3 Procedure

There were three practice/acquisition conditions: (i) a control condition with no manipulation of errors using the “none” feedback mode; (ii) an error minimization condition using the “spring assistance” mode; and (iii) an error augmentation condition using “spring disturbance” mode. Using the Research Randomizer website\(^3\), participants were randomized to one of these three conditions for practice of the task, with the sole constraint that group assignments were equal in number, (i.e., nine participants in each group). Based on this random assignment, it was assumed that all groups were equal in skill prior to training; however, this was not measured with a pre-test to avoid providing additional practice, which could be problematic for this relatively simple task.

After introductory explanation of the task, participants were allowed three familiarization trials with a curve different than the one to be learned. Once participants were comfortable with the device and the task, the experimenter explained, per their group assignment, what they should expect with respect to haptic feedback when practising the task. Participants then began the practice phase: 100

\(^3\)http://www.randomizer.org/
Figure 2.1: Annotated screenshot showing the target curve along with characteristics of the curve.
trials organized as 20 blocks (5 trials/block). Once the target curve appeared on the computer screen, participants started the trial by moving the cursor to the start-point near the bottom of the screen and ended the trial by moving the cursor to the end-point near the top of the screen. The target curve and the cursor were visible for the entire trial and participants were instructed to trace the curve as quickly and as accurately as possible. After each trial, feedback regarding the tracing accuracy (a red trace of their movement superimposed over the target curve) and the movement time (a numerical value displayed in seconds to the nearest decisecond) were provided on-screen. Participants also received a numerical summary tracing error score (a numerical value, in arbitrary units [AU] where 1 AU = 0.0798 mm) after each block indicating the average tracing error for a block of trials.

Ten minutes after the end of practice, participants completed an immediate retention test in which they attempted 5 trials of the task without any augmented haptic feedback and without summary or terminal feedback regarding tracing error or movement time. Solely the cursor and the target curve were visible throughout these retention test trials. After approximately one day ($M = 1.1$, $SD = 0.4$), participants returned for a delayed retention test, which was identical to the immediate retention test, and a transfer test that solely differed from the retention test by having the target curve be a mirror-reversal of the one that was practised. Prior to skill acquisition, all participants were informed that the tests following skill acquisition would not contain any augmented haptic or visual feedback about performance.

2.2.4 Outcome measures & data analyses

Performance was evaluated by calculating the tracing error, movement time, and samples outside the bandwidth. The tracing error (in mm) for each trial, similar to the mean modulus error [Poulton 1974], was calculated as follows:

$$TracingError = \frac{1}{N} \sum_{i=1}^{N} |e[i]|$$ (2.1)

Where there are $N$ samples in a trial, for each sample, the distance, $e[i]$, between the cursor and the next untraced portion of the curve was calculated; then, all these distances were averaged to produce the tracing error for that trial. Movement time for each trial was measured as the time (in seconds to the nearest millisecond) from when the cursor was moved to the start-point, to when the cursor was moved to the end-point. We then calculated a measure of overall performance efficiency, the Speed Accuracy Cost Function: $CostFunction = TracingError \times MovementTime$ [Culmer, Levesley, Mon-Williams, & Williams 2009, Raw, Wilkie, Culmer, & Mon-Williams 2012]. While we were primarily interested in tracing accuracy, the cost function variable allowed us to account for the speed-accuracy trade-offs that
participants would inevitably make when performing this task. As such, we could determine if better tracing accuracy was a result of increased skill or simply a slower movement. A large cost function indicated less efficient and overall, poorer, task performance.

In order to determine whether any effects of haptic feedback were simply due to participants having different amounts of feedback about their performance, we measured samples outside the bandwidth, expressed as a percentage of samples in a trial, to ascertain the amount of augmented haptic feedback that was provided on a given trial. This data was only relevant for the error minimization and error augmentation groups during the acquisition phase of the experiment. All these data (movement time, tracing error, cost function and samples outside the bandwidth) were averaged over each block of 5 trials to provide 20 data points for the acquisition phase and three data points for the retention/transfer phase of the experiment.

The primary outcome measure was the cost function and we conducted a mixed model ANOVA (3 group x 20 block in acquisition) with repeated measures on the block factor for the skill acquisition data and three separate one-way ANOVAs for each of the retention and transfer tests. The cost function provides a succinct and easily understood measure of performance. However, there are multiple combinations of the component factors (movement time and tracing error) that could lead to a particular outcome. For example, an increase in cost function (i.e., a decline in performance), could be due to increased movement time, increased tracing error or both. In order to fully understand the mechanisms leading to any significant effects on the cost function, we conducted similar analyses for movement time and tracing error, as appropriate. We also conducted a mixed ANOVA (2 group x 20 block) with repeated measures on the block factor on the samples outside the bandwidth data. Because we expected that performance would improve over the course of acquisition (i.e., cost function and samples outside the bandwidth would decrease), main effects or interactions involving block in acquisition were explored using contrasts with the first block as the reference category.

Main effects of practice condition or test were explored using post hoc comparisons using Tukey HSD as well as the Games-Howell procedure when there was concern about the homogeneity of variances, as determined by Levene’s test (Field, 2009). When Mauchly’s test indicated that the assumption of sphericity had been violated for repeated measures factors, Greenhouse-Geisser corrections were applied (all $\epsilon < .75$) and adjusted degrees of freedom were reported. Effects for all analyses were considered statistically significant at $p < .05$. Effect sizes associated with F-tests were estimated using partial eta-squared values ($\eta^2_p$).
2.3 Results

Results of the analysis of the acquisition and immediate retention data demonstrated the immediate effects of our error manipulations during and shortly after practice, while the results for the delayed retention and transfer tests were used to infer learning effects from our haptic feedback manipulations during acquisition.

Due to technical difficulties, one participant in the error augmentation group completed only 15 practice blocks. Consequently, this participant’s data were excluded from the statistical analyses of acquisition data (because these were repeated measures analyses). However, because three quarters of this participant’s skill acquisition trials were available, the data were included for the analyses of retention and transfer tests.

2.3.1 Amount of haptic feedback experienced during acquisition

![Figure 2.2: Average percent of Samples Outside the Bandwidth for each experimental practice group in each block of acquisition. Error bars are 95% confidence intervals.](image)

Analysis of the proportion of samples that were outside the bandwidth (i.e., percent of the movement for which haptic feedback was received) resulted in a significant block by practice group interaction, \( F(19, 285) = 2.5, \ p = .001, \eta_p^2 = .14 \) [Figure 2.2]. Neither the effect of practice group, \( F(1, 15) = 3.6, \ p = .076, \eta_p^2 = .19 \), nor the effect of block, \( F(19, 285) = 0.9, \ p = .614, \eta_p^2 = .06 \), were significant. To break down this interaction, we first performed simple contrasts with block 1 as the reference category for each
practice group. This analysis did not yield any significant differences between blocks for either practice group. Subsequently, we performed a simple effects analysis to analyze the effect of group at each level of the block factor. This analysis yielded significant results for blocks 13 \((p = .033)\), 15 \((p = .008)\), 17 \((p = .039)\), 18 \((p = .024)\), 19 \((p = .019)\), and 20 \((p = .016)\). In all cases, the number of samples outside the bandwidth was greater for the error augmentation group. This suggests that in the last quarter of acquisition, the error augmentation group received significantly more haptic feedback than the error minimization group.

### 2.3.2 Performance during acquisition with various forms of haptic feedback

![Graph showing performance metrics for different conditions](image)

**Figure 2.3:** Traces of the fifth acquisition trial from a representative participant in each practice group (black curves) alongside the target curve shown in red

Representative traces from a participant in each group are shown in Figure 2.3, along with the corresponding tracing error, movement time and cost function for those trials. Figure 2.4 summarizes the results of speed accuracy cost function for each group during skill acquisition and tests and learning. Mauchly’s test of sphericity was significant, \(\chi^2(189) = 625.6, p < .001\), so degrees of freedom were corrected using Greenhouse-Geisser estimates. There was a main effect of block, \(F(4.2, 96.7) = 7.0, p < .001\), \(\eta^2_p = .23\) (Figure 2.5) and contrasts revealed that cost function on acquisition block 1 was significantly
higher than cost function on block 3 and all subsequent blocks of acquisition (all $p < .05$).

![Figure 2.4: Mean Speed Accuracy Cost Function by group and experimental phase (block in acquisition and test in retention/transfer). Error bars are 95% confidence intervals. A = acquisition block, Imm Ret = immediate retention test, Del Ret = delayed retention test.]

There was also a main effect of practice group, $F(2, 23) = 15.4$, $p < .001$, $\eta^2_p = .57$ [Figure 2.6], and Tukey HSD post hoc comparisons showed that the error augmentation group performed worse (i.e., higher cost function) during acquisition than both the error minimization group ($p < .001$) and the control group ($p = .002$). As might be expected, the error augmentation group also exhibited greater variance than the control and error minimization groups. Consequently, we sought to confirm our post hoc comparisons by using Games-Howell post-hoc comparisons. These comparisons confirmed the group differences described above but also suggested that the control and error minimization groups were significantly different ($p < .001$).
Figure 2.5: Grand Means of Speed Accuracy Cost Function by block of acquisition. Error bars are 95% confidence intervals. Bracketed acquisition blocks represent those significantly different from block 1. *p < .05.

Figure 2.6: Mean Speed Accuracy Cost Function by practice group in each experimental phase. Error bars are 95% confidence intervals, *p < .05, **p < .001.
2.3.2.1 Contributions of movement time and tracing error to acquisition performance

To better understand the main effect of practice group for overall performance as indicated by the speed accuracy cost function, we conducted separate mixed ANOVAs on movement time and tracing error. Similar to the cost function analysis, there were main effects of practice group for both movement time, $F(2, 23) = 7.8, p = .003, \eta^2_p = .41$, and tracing error data, $F(2, 23) = 11.1, p < .001, \eta^2_p = .49$ (see Table 2.1). Tukey HSD post hoc comparisons indicated that for movement time, the error minimization group had significantly shorter movement time than both control ($p = .003$) and error augmentation ($p = .003$) groups, while for tracing error, the error augmentation group had significantly worse tracing error than the control and error minimization groups (both $p = .001$). However, the main effect of block observed for cost function was reflective only of participants’ movement time: there was a main effect of block for movement time, $F(3, 74.9) = 17.3, p < .001, \eta^2_p = .43$, but none for tracing error, $F(3, 71.4) = 1.6, p = .196, \eta^2_p = .07$ (see Table 2.2). This suggests that participants improved their performance over the course of acquisition by maintaining their tracing error but improving their movement time (i.e., tracing faster).

Table 2.1: Mean values of Movement Time and Tracing Error for each practice group during skill acquisition

<table>
<thead>
<tr>
<th>Practice Group</th>
<th>Movement Time (s)</th>
<th>Tracing Error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>95% CI</td>
</tr>
<tr>
<td>Control</td>
<td>16.4</td>
<td>[13.7, 19.1]</td>
</tr>
<tr>
<td>Error Minimization</td>
<td>9.6</td>
<td>[6.9, 12.3]</td>
</tr>
<tr>
<td>Error Augmentation</td>
<td>15.3</td>
<td>[12.5, 18.2]</td>
</tr>
</tbody>
</table>

2.3.3 Performance on retention and transfer tests

Figure 2.6 shows group means of speed accuracy cost function for each of the retention and transfer tests. Analysis of cost function for the retention and transfer tests showed that there was a main effect of group for the immediate retention test, $F(2, 24) = 4.0, p = .031, \eta^2_p = .25$, and Tukey HSD post hoc comparisons indicated that the error minimization group performed significantly worse than the error augmentation group, $p = .024$. There were no statistically significant effects of group for either the delayed retention test, $F(2, 24) = 2.9, p = .076, \eta^2_p = .19$, or the transfer test, $F(2, 24) = 1.9, p = .173, \eta^2_p = .14$. 
Table 2.2: Mean values of Movement Time and Tracing Error for each block of skill acquisition

<table>
<thead>
<tr>
<th>Block of Acquisition</th>
<th>Movement Time (s)</th>
<th>Tracing Error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean 95% CI</td>
<td>Mean 95% CI</td>
</tr>
<tr>
<td>1</td>
<td>18.3 [16.0, 20.7]</td>
<td>1.23 [0.94, 1.51]</td>
</tr>
<tr>
<td>2</td>
<td>17.8 [15.3, 20.3]</td>
<td>1.18 [0.94, 1.42]</td>
</tr>
<tr>
<td>3</td>
<td>16.2 [13.8, 18.6]</td>
<td>1.18 [0.92, 1.43]</td>
</tr>
<tr>
<td>4</td>
<td>16.1 [13.9, 18.3]</td>
<td>1.12 [0.86, 1.39]</td>
</tr>
<tr>
<td>5</td>
<td>14.8 [12.9, 16.6]</td>
<td>1.20 [1.00, 1.40]</td>
</tr>
<tr>
<td>6</td>
<td>14.7 [12.9, 16.5]</td>
<td>1.17 [0.96, 1.38]</td>
</tr>
<tr>
<td>7</td>
<td>14.4 [12.6, 16.1]</td>
<td>1.18 [0.87, 1.49]</td>
</tr>
<tr>
<td>8</td>
<td>14.4 [12.3, 16.5]</td>
<td>1.18 [0.98, 1.38]</td>
</tr>
<tr>
<td>9</td>
<td>12.8 [11.4, 14.2]</td>
<td>1.31 [0.99, 1.64]</td>
</tr>
<tr>
<td>10</td>
<td>13.0 [11.2, 14.8]</td>
<td>1.10 [0.92, 1.29]</td>
</tr>
<tr>
<td>11</td>
<td>13.2 [11.3, 15.1]</td>
<td>1.14 [0.90, 1.38]</td>
</tr>
<tr>
<td>12</td>
<td>12.7 [10.9, 14.4]</td>
<td>1.29 [0.94, 1.65]</td>
</tr>
<tr>
<td>13</td>
<td>12.3 [10.7, 14.0]</td>
<td>1.30 [0.95, 1.64]</td>
</tr>
<tr>
<td>14</td>
<td>12.4 [10.8, 13.9]</td>
<td>1.32 [0.98, 1.66]</td>
</tr>
<tr>
<td>15</td>
<td>12.4 [10.8, 14.0]</td>
<td>1.30 [1.07, 1.53]</td>
</tr>
<tr>
<td>16</td>
<td>12.5 [10.9, 14.0]</td>
<td>1.29 [1.01, 1.56]</td>
</tr>
<tr>
<td>17</td>
<td>12.3 [10.5, 14.1]</td>
<td>1.37 [1.02, 1.72]</td>
</tr>
<tr>
<td>18</td>
<td>11.8 [10.2, 13.4]</td>
<td>1.33 [1.06, 1.59]</td>
</tr>
<tr>
<td>19</td>
<td>11.6 [10.0, 13.1]</td>
<td>1.31 [1.05, 1.57]</td>
</tr>
<tr>
<td>20</td>
<td>12.0 [10.4, 13.6]</td>
<td>1.20 [0.99, 1.41]</td>
</tr>
</tbody>
</table>

2.3.3.1 Contributions of movement time and tracing error to overall performance on retention and transfer tests

Further analysis of movement time and tracing error indicated that the observed effects on cost function were due primarily to accuracy rather than speed. Movement time data yielded no main effects of group for any of the tests: immediate retention, $F(2, 24) = 0.6, p = .574, \eta^2_p = .05$; delayed retention, $F(2, 24) = 0.3, p = .743, \eta^2_p = .02$; transfer, $F(2, 24) = 0.5, p = .599, \eta^2_p = .04$. The mean movement times across all groups, were 13.6 s ($SD = 4.6$), 13.3 s ($SD = 4.9$), and 12.9 s ($SD = 4.3$) for the immediate retention, delayed retention and transfer tests, respectively. In contrast, analysis of the tracing error data revealed main effects of group for all retention and transfer tests: immediate retention, $F(2, 24) = 6.8, p = .005, \eta^2_p = .36$; delayed retention, $F(2, 24) = 4.9, p = .017, \eta^2_p = .29$; and transfer, $F(2, 24) = 5.9, p = .008, \eta^2_p = .33$ (Figure 2.7). Post hoc Tukey HSD comparisons indicated that for the immediate retention test, the error minimization group was less accurate than both the control ($p = .021$) and error augmentation ($p = .006$) groups; for the delayed retention test, the error minimization group was less accurate than the error augmentation group ($p = .016$); and for the transfer test, the error minimization group was less accurate than both the control ($p = .042$) and error augmentation ($p = .009$) groups.
Because there was some concern regarding equality of group variances for the transfer test, we also used Games-Howell post hoc comparisons, which called into question the significance of the difference between the error minimization and control groups \((p = .094)\).

Figure 2.7: Mean Tracing Error by practice group for each retention and transfer test. Error bars are 95% confidence intervals, \(* p < .05\).

2.4 Discussion

We asked participants to practice a curve-tracing task while being subjected to one of three conditions of haptic feedback regarding their tracing error: no augmented haptic feedback (control), error minimization or error augmentation. During skill acquisition and on retention and transfer tests, we instructed participants to trace the curve as quickly and as accurately as possible. We tested all participants, in the absence of any augmented feedback, at two time points—immediately after and one day after the acquisition phase. We measured movement time, tracing error and a composite performance variable—speed accuracy cost function—to determine which practice condition best facilitated learning of the task. While the immediate retention test showed immediate but transient effects of the practice conditions on post-
training performance, learning was specifically inferred from performance on the delayed retention and transfer tests.

For the speed accuracy cost function, we only observed group differences immediately after practice: the error minimization group showed worse performance than the error augmentation group. While there were no group differences in movement time on any of the tests, there were significant group differences in tracing error for all retention and transfer tests. We observed that the error minimization group was less accurate than both the control and error augmentation groups on both the immediate retention and transfer tests but less accurate than only the error augmentation group on the delayed retention test. It is important to note that the difference between the error minimization and control groups did not persist the day after training. This highlights the fact that conclusions drawn from tests immediately after practice are insufficient to infer learning. Overall, our results indicate that the error augmentation group learned more than the error minimization group. These results provide partial support for our hypotheses.

2.4.1 Type of task, training parameters & learning

One primary reason for the inconclusive results regarding the benefits of haptic training is that researchers have not clearly differentiated or discussed the features of the various motor tasks or training programs that might impact their results (Heuer & Lütgten 2015; Powell & O’Malley 2012). In addition to the basic difference between error minimizing and error augmenting types of haptic feedback, we have previously identified a subtle but important difference between implementations of haptic assistance, namely assistance as demonstration versus assistance as performance feedback (Williams & Carnahan 2014), which likely invoke different mechanisms of motor learning (Heuer & Lütgten 2015).

Researchers in (non-robotic) motor learning have long recognized the importance of these relationships among type of tasks, feedback parameters/practice conditions and motor learning. Singer (1977) noted that self-paced, closed skills that are performed in a stable environment, are generally targeted to automation. As such, reducing errors during practice, which encourages repetition of the correct performance, with minimal use of feedback, should be most beneficial for learning such tasks. In contrast, externally paced, open skills should be practiced for adaptability to a dynamic environment and should benefit more from the varied experience of errors during practice (Singer 1977). However, our results do not provide support for this assertion, as learning of our self-paced, closed skill did not benefit from error minimization during practice. One explanation could be that the task was not strictly self-paced because participants were instructed to move as quickly and as accurately as possible (Kreifeldt 1972).
Outside the laboratory, very few skills are strictly self-paced; that is, most functional self-paced skills (e.g., driving) do have some implicit or explicit guidelines for movement speed. Thus, the instructions utilized in the present study may be more ecologically valid for real-world, closed skills.

In a more recent review, Heuer and Lütten (2015) take a neuro-cognitive perspective to address these relationships, specifically in the context of robot assistance for motor learning. Using the presented classification scheme for the products of motor learning, our task can be described as requiring spatial trajectory learning (Heuer & Lütten, 2015). While other tracking or path-following tasks, such as drawing circles (Viviani & Terzuolo, 1982) and steering vehicles (Marchal-Crespo & Reinkensmeyer, 2008), may also include dynamic features of trajectory learning, we did not require participants to adhere to any particular velocity or timing-based profile. We measured movement time in order to observe and account for the speed-accuracy trade-off inherent in this type of self-paced task. Importantly, Heuer and Lütten (2015) indicate that when a trajectory is demonstrated (visually or haptically), the primary mechanism of motor learning is probably observational learning, while error-based or reward-based learning mechanisms are invoked when error feedback is available, as it was in our experiment. (This is along the same lines of the distinction we previously drew (Williams & Carnahan, 2014) between haptic demonstration and haptic feedback.) Based on the current literature, they go on to suggest that when error-based learning is the primary mechanism of motor learning, convergent (i.e., error minimizing) haptic training should inhibit learning while divergent (i.e., error augmenting) haptic training should facilitate learning. They also deduced that, based on current evidence, error augmentation may work best for tasks that involve simple paths and require precise hand movements. Our present results—the benefit of error augmentation for learning a simple path requiring precise hand movements—support both these conclusions.

2.4.2 The benefit of increased errors during skill acquisition

Our data clearly indicate that the error augmentation group experienced significantly more errors during skill acquisition than both the error minimization and control groups. Consistent with the predictions made by Heuer and Lütten (2015) as well as error-driven models of motor learning, the error augmentation group exhibited the best performance on retention and transfer tests. We propose that this group’s extensive experience with error-correction during skill acquisition strengthened the internal model for the task and led to greater learning (Thoroughman & Shadmehr, 2000; Wolpert & Ghahramani, 2000).

Our results are also consistent with previous studies of physical guidance, which reported that practice conditions that provide frequent on-target experience (such as our error minimization condition) were
detrimental for learning (Sidaway et al., 2008; Winstein et al., 1994). In the study by Winstein et al. (1994), participants who practiced an angular positioning task with a physical block reported that they moved quickly to the target without concentrating on stopping at the target location. The study authors proposed that this approach to practice disrupted information processing activities that are crucial for skill retention (Winstein et al., 1994). Similarly, it is possible that our error minimization participants simply traced the curve quickly without focusing much on accuracy because they knew that the device would keep them on target. This interpretation is compatible with theories suggesting that more effortful training conditions lead to better learning (Bjork, 1994; Linn & Bjork, 2006) as well as the notion of deliberate practice required to attain expertise in a given skill (Ericsson, Krampe, & Tesch-Römer, 1993). It is also interesting to note that the control group exhibited longer movement times than the error minimization group during skill acquisition. This suggests that, despite their errors being similar in magnitude to that of the error minimization group during skill acquisition, the control group may have exhibited more effort during practice. Indeed, the longer movement times can be attributed to increased effort devoted to ensuring that there were very few errors in their movement. In other words, although the control group did not experience large errors, they were actively engaged in error detection and error correction that were reflected in longer movement times. This effortful but largely errorless approach to skill acquisition may have led to the observed trends for the control group’s better accuracy in comparison to the error minimization group on retention and transfer tests. However, since we did not measure attention, motivation or effort, we cannot confirm these suppositions.

Another potential reason for the observed benefits of error augmentation is that divergent force fields and random perturbations are known to cause limb stiffness which can result in more precise movements due to co-contraction of muscles (Heuer & Lüttgen, 2015). This is also supported by the observation that random perturbations (and not just feedback related error augmenting forces) can facilitate performance improvement (Marchal-Crespo, Lopez-Oloriz, et al., 2014) and motor learning of spatial movement characteristics (J. Lee & Choi, 2010).

Comparing our results with other studies of haptic training is a little difficult given the differences between our experiment and others that targeted spatial features of trajectories and included evaluation of a haptic error augmenting training condition. Tasks in such studies included pursuit tracking around the outline of a figure (J. Lee & Choi, 2010; Powell & O’Malley, 2012), point-to-point movements (Burdet, Osu, Franklin, Milner, & Kawato, 2001; Su et al., 2011), as well as steering a simulated vehicle (H. Lee & Choi, 2014) and a wheelchair with a joystick (Chen & Agrawal, 2013).

Results for the studies utilizing pursuit tracking are mixed: Powell and O’Malley (2012) observed no group differences for performance immediately after practice while J. Lee and Choi (2010) observed that
noise-like haptic disturbance as well as repulsive (feedback-based) haptic disturbance both resulted in better learning (as observed on a delayed retention test) when compared to progressive haptic guidance. The primary difference between these tasks and ours is that our participants did not have to follow a fixed target speed, they were free to trade-off speed for spatial accuracy.

In contrast, both point-to-point movement tasks showed benefits of practising in error augmenting force fields for producing straight paths after the force fields were removed (Burdet et al. 2001, Su et al. 2011). However, it could be argued that this ballistic task does not provide the same online visual feedback information that characterizes our task and other path-following tasks.

With regards to steering tasks, results have not been entirely consistent with each other: H. Lee and Choi (2014) reported no differences in tracking errors between their control, progressive guidance, haptic disturbance and hybrid guidance/disturbance groups on a delayed retention test while Chen and Agrawal (2013) reported that their assistive and resistive force groups both outperformed their control group, but did not differ from each other, immediately after training. One likely reason for this inconsistency is the difference in dynamics between the two steering tasks. Nonetheless, it is interesting to note that Lee and Choi’s (2014) simulated vehicle was steered at a constant speed while Chen and Agrawal’s (2013) participants were instructed to travel at the maximum speed but, ultimately, could control the wheelchair’s speed. Even though both steering tasks were evaluated only on spatial accuracy, both sets of authors acknowledge that in addition to the spatial, error-cancelling aspect of performance, a dynamic feature of the task, specifically the timely initiation of turns, was essential to success. Similar dynamic features are likely involved in our task but we did not explicitly train or measure these features. Overall, our contribution to this body of literature is evidence that error augmentation provides benefits over error minimization for learning spatial accuracy, even when participants can trade speed for accuracy.

2.4.3 The detriment of increased error feedback during skill acquisition

It is known that feedback can provide motivation and information to guide future performance and, as such, more feedback can mean more information to enhance learning. However, studies have shown that learners can come to depend on increased amounts of feedback and ignore processing of other information (e.g., intrinsic feedback) that would contribute to learning and the development of error-detection capabilities (Salmoni et al. 1984, Schmidt 1991). These findings are summarized by the guidance hypothesis which predicts that too much guidance will lead to enhanced performance during skill acquisition but worse performance during retention tests. The error augmenting condition, could not, by definition and design, lead to improved performance during skill acquisition (i.e., provide guidance). We will there-
fore consider only the control and error minimization groups when discussing the relationship between learning and the amount of feedback received in skill acquisition.

The amount of feedback experienced by participants in the error minimization group can be quantified via the proportion of samples per trial for which a participant received haptic feedback, i.e., the proportion of samples per trial that occurred outside the haptic feedback bandwidth. The amount of feedback that this group received was more or less constant throughout practice, averaging 45% of each trial in the first quarter of acquisition trials and 43% in the last quarter. Naturally, the amount of haptic feedback experienced by the control group was nil throughout skill acquisition. Other studies utilizing physical guidance have noted that the augmented information provided by physical guidance tends to be more guiding than feedback in the form of knowledge of results (as the control group received) because physical guidance has typically worked directly towards error reduction and successful task performance \cite{Winstein1994}. However, our results are inconclusive with respect to providing support for the guidance hypothesis: the control group was only significantly better than the error minimization group on the transfer test, and only for tracing error, not speed accuracy cost function. Superior performance on transfer indicates that the skills acquired during training have generalized to benefit performance on variations of the task. However, there was no difference between these groups on the delayed retention test and the Games-Howell post hoc procedure indicated that these groups were not different on the transfer test.

Another potential explanation for the error minimization group’s learning effects is that their practice formed an internal model of the task that included the dynamics of error minimization \cite{Armstrong1970, Schmidt1991}. As such, their internal model for the basic, unguided task was undeveloped and when they were asked to perform the task without any augmented feedback, minimal learning was observed. In contrast, the control group was tested under the same conditions as practice and so their internal model of the task was perfectly suited to the testing conditions. Furthermore, it would have been difficult for the error augmentation group to incorporate the dynamics of haptic feedback into their internal model of the task because the feedback they experienced was so disruptive.

\section*{2.4.4 The utility of error-altering haptic feedback}

We have demonstrated that there is benefit to using error augmenting haptic feedback over error minimizing haptic feedback for tracing a two-dimensional curve. Ultimately, however, our results indicated that the control (no haptic feedback) group’s learning was not significantly different from either of the experimental groups. Similar results have been observed in other studies \cite{J. Lee & Choi2010, Marchal-
This could indicate that error-altering haptic feedback is unnecessary for this task, perhaps due to its simplicity. However, it is possible that what error-altering feedback, and more specifically error augmenting feedback offers is greater efficiency in learning a task. Most studies of haptic training are designed with a view to future applications to fields such as robotic rehabilitation or surgical training where saving time and money are key factors when introducing new training programs. As such, researchers should not only seek to determine which error-altering haptic feedback strategies facilitate learning but also whether there are differences in the time required to achieve and maintain the desired level of performance.

2.4.5 Conclusions

Our study has contributed to the emerging body of literature that is exploring opposing forms of error-altering haptic feedback for learning a self-paced, trajectory-based skill. Our results showed that participants who experienced haptic error augmentation during skill acquisition learned more than those who experienced haptic error minimization. In particular, we have shown that haptic error augmentation is more beneficial than error minimization for learning spatial accuracy, even when learners have full control of the speed of performance. The error minimization group, which received more feedback than the control group during skill acquisition, tended to perform worse than the control group on retention tests but this difference was not significant on the delayed retention test (cf. Guidance hypothesis: Salmoni et al. 1984; Schmidt 1991). While the overall performance of the control group was not different from the error augmentation group on any tests, the error augmentation group was consistently more accurate than the error minimization group on retention as well as transfer tests. We believe that this was due to the nature of the error augmenting haptic feedback, which impeded successful task performance and provided a rich experience of error detection and correction processes during skill acquisition. Additionally, although the control group did not experience large errors during skill acquisition, this group also likely engaged in effortful practice (as inferred from the relationship between their movement time and tracing errors), which allowed them to achieve levels of accuracy comparable to the error augmentation group on tests of learning.

Taken together, our results suggest that the effortful detection and self-initiated correction of errors during practice can be more important than accurately-guided practice for the learning of curve-tracing. These findings should be extended to studies testing the design and long-term learning implications of physical guidance protocols in various practical settings, such as physical rehabilitation and sports.
Chapter 3

Learning effects of practice with error-altering haptic feedback depend on bandwidth: Are there implications for rehabilitation robots?

An earlier version of this manuscript has been accepted for publication:


3.1 Introduction

The most commonly studied form of haptic training is haptic guidance, which can refer to the use of haptic forces that provide feedback about movement by minimizing or reducing movement errors (Williams & Carnahan, 2014). Many researchers have begun to compare this form of training to haptic error augmentation or error amplification where movement errors are augmented. Both these feedback methods have been shown to have learning benefits for timing (Milot et al., 2010), target-hitting and pursuit-tracking tasks (Powell & O’Malley, 2012) among others. However, one aspect of feedback not usually discussed in these experimental studies of haptic training is that of feedback frequency. Studies from the field of motor learning have shown that excessive feedback often improves performance during practice but usually impairs post-practice performance, i.e., learning (Salmoni et al., 1984). This observation has been explained by the guidance hypothesis, which suggests that even though one of the functions of feedback is to guide performance, excessive feedback can facilitate dependence on augmented feedback to the detriment of attending to intrinsic feedback. Consequently, when augmented
feedback is removed during unguided performance of the task (e.g., a transfer test), performance suffers significantly (Schmidt, 1991). Alternatively, the consistency hypothesis proposes that frequent feedback during practice may encourage the learner to attempt corrections beyond the motor system’s level of precision (“maladaptive short-term corrections”), which prevents the development of stable behaviour required for learning (Schmidt, 1991).

To overcome the challenges of excessive feedback, researchers have found some success with strategies for reducing feedback frequency during practice (Winstein et al., 1994). One such strategy—bandwidth feedback—initially presented with knowledge of results (KR; terminal information about movement outcome), was first brought to the motor learning literature by Sherwood (1988). With this strategy of feedback provision, feedback about performance was provided only if it fell outside of a prescribed performance bandwidth. Bandwidth KR is an alternative to providing only qualitative or quantitative KR. In most studies of bandwidth KR, qualitative KR in the form of “correct” is provided either directly or indirectly when performance lies within boundaries of correctness. In contrast, quantitative KR that gives magnitude and direction error is provided when KR lies outside the bandwidth of correctness. Consequently, if learners improve their performance over the course of training and/or the bandwidth’s size is increased, then feedback frequency should also decrease. Studies have shown that bandwidth KR can facilitate the learning of a motor skill (Coca-Ugrinowitsch et al., 2014; T. D. Lee & Carnahan, 1990; Sherwood, 1988). However, it has been demonstrated that the information provided by bandwidth feedback improves learning more than just reduced frequency of information, suggesting that the meaning associated with bandwidth feedback (i.e., the interpretation of correct performance when feedback is withheld) rather than just the reduced feedback frequency, is important for learning (T. D. Lee & Carnahan, 1990).

It is important to note that most prior experiments comparing static or dynamic bandwidth sizes for feedback were done with sequential timing tasks (e.g., Ishikura, 2011; T. D. Lee & Carnahan, 1990) with a few others exploring more real-world, sport-related, target acquisition tasks such as golf putting (Smith, Taylor, & Withers, 1997) and dart throwing (Coca-Ugrinowitsch et al., 2014). To our knowledge, outside of applied settings such as driver training/lane keeping (e.g., Petermeijer, Abbink, & de Winter, 2015), researchers have not utilized a continuous task such as tracing. Consequently, the language used to discuss bandwidth size for spatial tasks like target acquisition or tracing is not always compatible with the rest of the literature—describing a bandwidth as a percentage of a movement time goal is not directly transferable to a bandwidth around a discrete target or a curve to be traced. Furthermore, while feedback frequency is usually viewed as the proportion of total trials for which feedback was provided, for continuous tasks, feedback frequency will likely be conceptualized in other ways such as the number.
of samples per trial that triggered or encountered feedback.

To our knowledge, the bandwidth approach to feedback has been used, though not formally explored, in haptic training (e.g., [Chen & Agrawal, 2013]). In a previous experiment, we explored the utility of haptic training for learning a self-paced, curve-tracing task ([Williams, Tremblay, & Carnahan, 2016]). Because this continuous task requires the use of feedback for online correction of movement errors, we experimented with concurrent, bandwidth haptic feedback to provide information about movement errors. Participants practised the task with either no haptic feedback, error minimizing haptic feedback or error augmenting haptic feedback. We observed that participants did not demonstrate any change in tracing error over the course of practice, suggesting that they may not have experienced a change in feedback frequency over the course of practice. Since this type of task has not been utilized in the bandwidth feedback literature, we wanted to explicitly explore the effect of feedback frequency via bandwidth on learning to perform this task.

Additionally, we have observed that some studies of rehabilitative haptic training have utilized a bandwidth or error tolerance without any justification for the size of the bandwidth. Therefore, it is unknown whether bandwidth could be affecting researchers' understanding of the efficacy of various haptics-based rehabilitation training paradigms.

The present experiment was designed to test whether a larger bandwidth would affect performance during acquisition or the learning effects that we previously observed for haptic feedback with a curve-tracing task. We compared four groups defined by a factorial combination of two types of haptic feedback (error minimization or error augmentation) with two levels of bandwidth (narrow or wide) to determine whether feedback frequency affects the utility of each type of haptic feedback for learning this task. We hypothesized that the bandwidth at which each type of feedback was provided would impact its effect on post-practice performance. Specifically, for haptic assistance we speculated that using a larger bandwidth might facilitate learning more than the narrow bandwidth, by striking a balance between providing information for learning and minimizing dependence on feedback. To determine the potential learning benefits of each practice condition, we used a transfer design, whereby skill acquisition under the assigned haptic feedback/bandwidth condition was followed by tests without any augmented feedback ([Salmoni et al., 1984]). This design allowed us to make a distinction between transient performance effects, attributable to the practice conditions, and learning effects that represent more stable and permanent changes in ability.
3.2 Methods

The University of Toronto Health Sciences Research Ethics Board approved the protocol. We recruited 52 community-living, university-affiliated adults with normal or corrected-to-normal vision, who reported no current neurological impairments: 41 women and 11 men with mean age 26.5 yr ($SD = 9.1$); 3 self-reported as being left-handed. All participants had no previous exposure to the apparatus, were naïve to the specific purposes of the experiments and gave written voluntary informed consent prior to participation, in accordance with the guidelines set out by the 1964 Declaration of Helsinki. Participants received gift cards valued at CAD$15 as compensation for their time.

3.2.1 Apparatus & task

The apparatus consisted of a SensAble Phantom Omni (currently Geomagic Touch; Rockhill, SC, USA) and standard computer monitor (Dell UltraSharp™ 2209WA) operated via a custom software program. The Phantom Omni is a desktop haptic device that can exert forces up to 3.3 N to the user through its end effector which has six degree-of-freedom positional sensing with resolution approximately 0.055 mm. The resolution of the computer monitor resulted in a visual gain of 1.47 between displacements on the monitor and movements of the haptic device in space. We programmed the Phantom Omni to allow users to trace a curve displayed on the monitor by controlling a cursor that represented the device’s end effector. Participants’ movements took place primarily in the vertical plane while seated at a desk and grasping the device’s stylus. The target curve (0.8 mm wide, 392.4 mm long) was defined by start and end points (155.6 mm apart along the Y-axis) near the bottom and top of the screen respectively, along with seven fixed control points, all of which were connected by sinusoidal curve fragments [Figure 2.1].

The behaviour of the device during operation was determined by the following programmed parameters: haptic feedback mode, haptic gain, magnitude, and channel bandwidth. The device was operated in one of two haptic feedback modes: spring assistance or spring disturbance. In the spring assistance mode, if the cursor deviated from the target curve beyond a specific limit (bandwidth), the device pushed the user back towards the target curve by producing a linearly increasing spring-like force. Conversely, in the spring disturbance mode, if the cursor deviated from the target curve beyond a specific limit (bandwidth), the device pushed the user farther from the target curve with a linearly increasing spring-like force. The rate of increase of these spring-like forces was determined by the haptic gain or $k$ in the spring-force equation, $f = k \times x$, where $x$ is the displacement between the cursor and its target position on the curve, and $f$ is the force exerted by the device. Magnitude indicates the maximum force to be exerted by the device while channel bandwidth indicates the radius of the force-free zone on either
side of the target curve within which no haptic feedback will be provided from the device. Gain and magnitude can be specified within the range [0, 1] which represents values of 0–0.5 N mm\(^{-1}\) for haptic gain, and 0–3 N for magnitude. Precise values of each of these parameters for each of our skill acquisition conditions were determined through pilot studies.

In a previous study which compared haptic error minimization and haptic error augmentation at a bandwidth of 0.8 mm (Williams et al., 2016), we found that the average tracing errors of the error augmentation group during skill acquisition varied between 1.6 mm and 2.4 mm. Additionally, we conducted a pilot study with different bandwidths to observe which ones resulted in different physical experiences of the bandwidths as well as the average numbers of samples/trial that were outside the bandwidth. Based on both sets of data, we chose 2.4 mm as the wide bandwidth for the present experiment.

### 3.2.2 Procedure

We chose two levels of each of the two practice factors of interest (feedback and bandwidth) to obtain four skill acquisition/practice conditions: error minimization with narrow bandwidth using spring assistive mode, gain = 0.4, magnitude = 1, channel bandwidth = 0.8 mm; (ii) error minimization with wide bandwidth using spring assistive mode, gain = 0.4, magnitude = 1, channel bandwidth = 2.4 mm; (iii) error augmentation with narrow bandwidth using spring disturbance mode, gain = 0.25, magnitude = 0.3, channel bandwidth = 0.8 mm; and (iv) error augmentation with wide bandwidth using spring disturbance mode, gain = 0.25, magnitude = 0.3, channel bandwidth = 2.4 mm.

Using the Research Randomizer website\(^1\), participants were randomized to one of these four conditions for practice of the task, with the constraints that each group was assigned the same number of participants (i.e., 13 participants in each group), and, as much as possible, the number of male participants were evenly distributed among the groups. This assignment procedure resulted in 2 males in the error minimization-narrow bandwidth group and 3 males in each of the other three groups. Additionally, there was one left-handed participant in each group except for error minimization-wide bandwidth.

Participants received an introductory explanation of the task and then performed three familiarization trials with a curve different from the target curve. With the target curve visible on the computer screen, participants started the trial by bringing the cursor to the start point. Participants were then allowed to trace the curve and the trial ended when the cursor was brought to the end point. Following each trial, participants’ movement time (in seconds to the nearest decisecond) and a red trace indicating their actual movement/tracing accuracy were presented on the screen. This familiarization phase was followed by skill acquisition (100 trials presented as 20 blocks) in which they were instructed to trace...
the curve as quickly as possible and informed to expect corrective/disruptive forces when they deviated too far from the target curve. Participants received visual feedback about their performance in the same manner as they did during the familiarization trials (red curve for tracing accuracy and numerical value of movement time).

After a brief retention interval (10 min), participants performed an immediate retention test in which they attempted two blocks (i.e., 10 trials) of the task without any augmented haptic or visual feedback (i.e., only the target curve and the cursor were visible). Then, after a longer retention interval ($M = 1.5$ day, $SD = 1.1$ day), participants returned to perform a delayed retention test which was identical to the immediate retention test.

### 3.2.3 Outcome measures & data analysis

Efficacy of our practice condition manipulations was checked by noting the percent of samples outside the bandwidth per trial. This value was then averaged over each block to provide 20 data points for each participant. This data was subjected to a mixed ANOVA (2 feedback x 2 bandwidth x 20 block) with repeated measures on the block factor. To determine if, and when, any change in this variable plateaued during skill acquisition, we conducted planned simple contrasts on the block factor with the last block (block 20) as the reference category.

Performance during skill acquisition and retention tests was evaluated through tracing error, movement time and a composite performance variable—speed accuracy cost function. The tracing error (in mm) was calculated for each trial in a similar fashion as the mean modulus error (Poulton, 1974) and described previously in Equation 2.1. Meanwhile, the time elapsed in seconds (to the nearest millisecond), from the start of the trial to the end of the trial, constituted the movement time. The product of these two measures was used to calculate a measure of overall performance efficiency: \( \text{CostFunction} = \text{TracingError} \times \text{MovementTime} \) (Culmer et al., 2009). Because this task necessarily involves a speed accuracy trade-off, this measure of overall performance allowed us to take this into account and meaningfully compare performances. A large value of the cost function, which results from a slower movement, a movement with larger errors, or both, indicates less efficient, poorer performance of the task. Additionally, to obtain a measure of trial-to-trial performance consistency, we calculated the standard deviation of the speed accuracy cost function for each block of acquisition and both retention tests.

The speed accuracy cost function was our primary dependent measure and we conducted mixed ANOVAs (2 feedback x 2 bandwidth x 20 block in acquisition; 2 feedback x 2 bandwidth x 2 block x
2 test in retention) with repeated measures on the block and test factors. As with analysis of samples outside the bandwidth in acquisition, we also performed planned simple contrasts on the block variable in acquisition, with the last block as the reference category. To clarify the mechanisms leading to any statistically significant effects in the cost function variable, we conducted similar analyses on movement time, tracing error and standard deviation of the speed accuracy cost function. If Mauchly’s test indicated any violations of the assumption of sphericity for repeated measures factors, Greenhouse-Geisser (for $\epsilon < .75$) or Huynh-Feldt (for $\epsilon > .75$) corrections were applied and adjusted degrees of freedom were reported with one decimal place. Effects of all analyses were considered statistically significant at $p < .05$ and effect sizes associated with F-tests were estimated using values of partial eta squared ($\eta^2_p$).

3.3 Results

The immediate effects of our haptic feedback manipulations (via feedback type and bandwidth) were determined from the results of the skill acquisition data analysis, while we inferred learning effects from the analysis of the retention test data. One participant in the error augmentation-narrow bandwidth group completed only 55% of the skill acquisition blocks, thus, this participant’s data were excluded from all analyses.

3.3.1 Manipulation checks

Figure 3.1 shows the percent of samples outside the bandwidth for each practice condition on each block of skill acquisition. Analysis of the percent of samples outside the bandwidth was used as a proxy for the proportion of the movement for which haptic feedback was received and should be dictated primarily by the nature of the haptic feedback (error minimization or error augmentation) and the allowed error tolerance (bandwidth). For this analysis, Mauchly’s test of sphericity was significant, $\chi^2(189) = 591.7, p < .001, \epsilon < .75$, so degrees of freedom were corrected using Greenhouse-Geisser estimates. There were main effects of feedback, $F(1,41) = 17.3, p < .001, \eta^2_p = .30$, bandwidth, $F(1,41) = 137.4, p < .001, \eta^2_p = .77$, and block, $F(3.7,153.1) = 2.7, p = .034, \eta^2_p = .06$. As expected, error minimizing haptic feedback resulted in a lower percentage of samples outside the bandwidth, $M = 25.2\%, SE = 2.6\%, 95\%CI [20.0,30.4]$ than error augmenting haptic feedback, $M = 41.1\%, SE = 2.9\%, 95\%CI [35.4,46.9]$, and the narrow bandwidth resulted in a greater proportion of samples outside the bandwidth, $M = 55.6\%, SE = 2.7\%, 95\%CI [50.2,61.0]$ than the wide bandwidth, $M = 10.7\%, SE = 2.7\%, 95\%CI [5.2,16.2]$. Interestingly, planned contrasts on the block factor showed that percent of samples outside the bandwidth on block 20 was significantly greater than for blocks 1 to 2, blocks 10
to 12 and block 14 (Table 3.1).

3.3.2 Performance during skill acquisition

3.3.2.1 Performance efficiency

The analysis of speed accuracy cost function showed that Mauchly’s test of sphericity was significant, $\chi^2(189) = 944.6$, $p < .001$, $\epsilon < .75$, so degrees of freedom were corrected using Greenhouse-Geisser estimates. There was a significant interaction between block and feedback, $F(5.1, 207.6) = 5.0$, $p < .001$, $\eta^2_p = .11$ (Figure 3.2). We conducted a simple main effects analysis to compare performance across blocks for each type of feedback. For brevity and consistency with the planned contrasts, we report here differences between block 20 of acquisition and previous blocks. Our results showed that for those who experienced error minimizing haptic feedback, performance on block 20 was significantly better (i.e., lower speed accuracy cost function) than performance on blocks 2 ($p = .028$) and 3 ($p = .017$). However, for those who experienced error augmenting haptic feedback, performance on block 20 was significantly
better than performance on blocks 1 to 7 (all \( p < .001 \)), block 8 (\( p = .038 \)), block 11 (\( p = .009 \)), and block 18 (\( p = .034 \)). The bandwidth factor had no statistically significant effect on performance efficiency, \( F(1, 41) = 0.2, p = .698, \eta^2_p < .01 \).

### Table 3.1: Mean values of Proportion of Samples Outside the Bandwidth, across all practice groups, for each block of skill acquisition

<table>
<thead>
<tr>
<th>Block of Acquisition</th>
<th>Samples Outside the Bandwidth (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>1*</td>
<td>29.5</td>
</tr>
<tr>
<td>2*</td>
<td>31.0</td>
</tr>
<tr>
<td>3</td>
<td>32.7</td>
</tr>
<tr>
<td>4</td>
<td>33.0</td>
</tr>
<tr>
<td>5</td>
<td>33.0</td>
</tr>
<tr>
<td>6</td>
<td>33.4</td>
</tr>
<tr>
<td>7</td>
<td>32.8</td>
</tr>
<tr>
<td>8</td>
<td>33.3</td>
</tr>
<tr>
<td>9</td>
<td>33.2</td>
</tr>
<tr>
<td>10*</td>
<td>32.4</td>
</tr>
<tr>
<td>11*</td>
<td>32.9</td>
</tr>
<tr>
<td>12*</td>
<td>32.7</td>
</tr>
<tr>
<td>13</td>
<td>33.8</td>
</tr>
<tr>
<td>14*</td>
<td>33.2</td>
</tr>
<tr>
<td>15</td>
<td>34.1</td>
</tr>
<tr>
<td>16</td>
<td>33.5</td>
</tr>
<tr>
<td>17</td>
<td>34.7</td>
</tr>
<tr>
<td>18</td>
<td>35.1</td>
</tr>
<tr>
<td>19</td>
<td>34.4</td>
</tr>
<tr>
<td>20</td>
<td>34.6</td>
</tr>
</tbody>
</table>

*Significantly different from block 20, \( p < .05 \)

#### 3.3.2.2 Contributions of movement time and tracing error to performance efficiency

To better understand the interaction effect described above for overall performance efficiency, we conducted separate mixed ANOVAs on both movement time and tracing error. Unlike the results of the cost function analysis, there were no interactions between block and feedback for either movement time or tracing error. However, there were main effects of feedback for both movement time, \( F(1, 41) = 5.2, p = .028, \eta^2_p = .11 \), and tracing error, \( F(1, 41) = 20.9, p < .001, \eta^2_p = .34 \), where the error minimization feedback groups displayed shorter movement time (\( M = 10.2 \) s, \( SE = 0.9 \) s) and lesser tracing error (\( M = 1.04 \) mm, \( SE = 0.16 \) mm) than the error augmentation groups (movement time: \( M = 13.2 \) s, \( SE = 1.0 \) s; tracing error: \( M = 2.14 \) mm, \( SE = 0.18 \) mm). There was also a main effect of block for movement time, \( F(21, 855) = 43.7, p < .001, \eta^2_p = .52 \). Planned contrasts for block showed that movement time for block 20 was significantly shorter than that for all blocks (all \( p < .05 \) except
blocks 15 and 17–19.

Figure 3.2: Mean Speed Accuracy Cost Function by feedback type for each block in acquisition. Error bars are 95% confidence intervals. Symbols highlight blocks significantly different from block 20 for the respective feedback types: *$p < .05$, †$p < .01$, ‡$p < .001$.

### 3.3.2.3 Performance consistency

The analysis of standard deviation of speed accuracy cost function showed that Mauchly’s test of sphericity was significant, $\chi^2(189) = 902.4$, $p < .001$, $\epsilon < .75$, so degrees of freedom were corrected using Greenhouse-Geisser estimates. As with performance efficiency, there was a significant interaction between block and feedback, $F(5.7, 216.6) = 2.4$, $p = .029$, $\eta^2_p = .06$ (Table 3.2). The simple main effects analysis revealed that, unsurprisingly, performance consistency for the error augmented group was worse (i.e., higher standard deviation) than that of the error minimizing group on every block of acquisition (all $p < .01$). Additionally, reporting on differences between block 20 of acquisition and previous blocks, the analysis showed that for those who experienced error augmenting haptic feedback, performance on block 20 was significantly more consistent than performance on blocks 1–8 (all $p < .05$ except for blocks 1 and 8 with $p < .01$, and block 5 with $p < .001$). For those who experienced error minimizing haptic feedback, performance consistency on block 20 was not significantly different than any other blocks. The bandwidth factor had no statistically significant effect on performance consistency, $F(1, 38) = 0.4,$
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$p = .557, \eta_p^2 < .01$.

Table 3.2: Means of standard deviation (SD) of the Speed Accuracy Cost Function by feedback type, for each block of acquisition

<table>
<thead>
<tr>
<th>Block of Acquisition</th>
<th>Error Minimization</th>
<th>Error Augmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SD (mm/s)</td>
<td>95% CI</td>
</tr>
<tr>
<td>1</td>
<td>1.8 [-0.9, 4.6]</td>
<td>12.6† [9.3, 15.9]</td>
</tr>
<tr>
<td>2</td>
<td>2.0 [-1.1, 5.1]</td>
<td>11.1* [7.3, 14.9]</td>
</tr>
<tr>
<td>3</td>
<td>1.8 [-1.0, 4.6]</td>
<td>10.2* [6.8, 13.6]</td>
</tr>
<tr>
<td>4</td>
<td>1.9 [-0.7, 4.5]</td>
<td>11.8* [8.7, 14.9]</td>
</tr>
<tr>
<td>5</td>
<td>2.2 [-1.6, 5.9]</td>
<td>14.0‡ [9.4, 18.6]</td>
</tr>
<tr>
<td>6</td>
<td>1.6 [-0.4, 3.6]</td>
<td>10.8* [8.3, 13.2]</td>
</tr>
<tr>
<td>7</td>
<td>1.6 [-1.1, 4.4]</td>
<td>9.0* [5.7, 12.4]</td>
</tr>
<tr>
<td>8</td>
<td>1.5 [-2.5, 5.5]</td>
<td>10.6‡ [5.7, 15.5]</td>
</tr>
<tr>
<td>9</td>
<td>1.7 [-0.7, 4.1]</td>
<td>9.7 [5.8, 12.6]</td>
</tr>
<tr>
<td>10</td>
<td>1.5 [0, 3.0]</td>
<td>7.7 [5.9, 9.6]</td>
</tr>
<tr>
<td>11</td>
<td>1.3 [-0.1, 2.7]</td>
<td>8.6 [6.9, 10.2]</td>
</tr>
<tr>
<td>12</td>
<td>1.5 [-1.1, 4.1]</td>
<td>8.3 [5.2, 11.5]</td>
</tr>
<tr>
<td>13</td>
<td>1.3 [-1.0, 3.5]</td>
<td>7.2 [4.4, 9.9]</td>
</tr>
<tr>
<td>14</td>
<td>1.5 [0, 3.0]</td>
<td>6.4 [4.5, 8.2]</td>
</tr>
<tr>
<td>15</td>
<td>1.3 [-0.7, 3.4]</td>
<td>8.6 [6.1, 11.1]</td>
</tr>
<tr>
<td>16</td>
<td>1.2 [-0.1, 2.6]</td>
<td>7.0 [5.4, 8.7]</td>
</tr>
<tr>
<td>17</td>
<td>1.4 [-0.1, 2.9]</td>
<td>6.1 [4.3, 7.9]</td>
</tr>
<tr>
<td>18</td>
<td>1.6 [-0.6, 3.8]</td>
<td>8.9 [6.3, 11.6]</td>
</tr>
<tr>
<td>19</td>
<td>1.3 [-0.4, 2.9]</td>
<td>6.2 [4.2, 8.2]</td>
</tr>
<tr>
<td>20</td>
<td>1.3 [-1.5, 4.0]</td>
<td>7.4 [4.0, 10.7]</td>
</tr>
</tbody>
</table>

Significantly different from block 20: *$p < .05$, †$p < .01$, ‡$p < .001$

3.3.3 Performance on retention tests

3.3.3.1 Performance efficiency

The analysis of speed accuracy cost function on retention tests revealed a significant interaction between feedback and bandwidth, $F(1,47) = 4.2$, $p = .046$, $\eta_p^2 = .08$ (Figure 3.3). Simple main effects analysis showed that the feedback factor was significant at the level of the narrow bandwidth ($p = .002$) but not the wide bandwidth ($p = .600$). There were also main effects of test, $F(1,47) = 6.0$, $p = .018$, $\eta_p^2 = .11$ and block, $F(1,47) = 24.6$, $p < .001$, $\eta_p^2 = .34$ whereby performance on the immediate retention test ($M = 12.3$ mm s, $SE = 0.4$ mm s) was better than performance on the delayed retention test ($M = 13.2$ mm s, $SE = 0.5$ mm s) and performance on the second block of the tests ($M = 12.0$ mm s, $SE = 0.4$ mm s) was better than performance on the first block ($M = 13.4$ mm s, $SE = 0.5$ mm s).
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3.3.3.2 Contributions of movement time and tracing error to retention performance efficiency

Both sets of analyses revealed that only the block factor had any statistically significant effect. For movement time: $F(1, 47) = 30.1, p < .001, \eta^2_p = .39$, where block 1 was performed with a shorter movement time ($M = 11.9$ s, $SE = 0.7$ s) than block 2 ($M = 11.0$ s, $SE = 0.6$ s). For tracing error: $F(1, 47) = 4.7, p = .035, \eta^2_p = .09$ where block 1 was performed with less tracing error ($M = 1.25$ mm, $SE = 0.07$ mm) than block 2 ($M = 1.27$ mm, $SE = 0.07$ mm).

3.3.3.3 Performance consistency

Similar to the analyses of movement time and tracing error, the only significant effect on performance consistency was from the block factor, $F(1, 47) = 4.5, p = .039, \eta^2_p = .09$. Performance on block 2 was more consistent ($M = 2.3$ mm s, $SE = 0.3$ mm s) than performance on block 1 ($M = 3.3$ mm s, $SE = 0.6$ mm s).

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Figure 3.3: Mean Speed Accuracy Cost Function by feedback type and bandwidth size in retention. Error bars are 95% confidence intervals, *$p < .05$. 

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3.4 Discussion

We asked participants to practice a self-paced tracing task using a tabletop haptic device providing one of four practice conditions determined by crossing two types of haptic feedback (error minimization and error augmentation) with two levels of error tolerance (narrow bandwidth and wide bandwidth). Participants were instructed to trace the curve as quickly and as accurately as possible. Following skill acquisition, participants were asked to perform the task immediately and one day later, given the same instructions but in the absence of any augmented feedback. We assessed performance using tracing error, movement time and speed accuracy cost function (an indicator of overall performance efficiency) as well as the standard deviation of speed accuracy cost function to indicate performance consistency. Learning was inferred by comparing the groups’ performances on the retention tests.

As we noted previously [section 3.1, paragraph 3], most of the prior work on bandwidth feedback has utilized timing or target acquisition tasks. As such, the descriptions and sizes of the bandwidths are not directly comparable to the task and bandwidth descriptions we have used here. Nonetheless, we believe it is useful to review and understand general trends in findings from previous research. Furthermore, it is reasonable to draw parallels between wider versus narrower bandwidths or bandwidth versus 100% KR, but not compare specific bandwidth percentages/sizes between any previous study and the present one.

In motor learning studies exploring the use of bandwidth feedback, little attention has been paid to exploring the optimal bandwidth for maximizing learning (Coca-Ugrinowitsch et al., 2014). When previous studies have compared multiple bandwidth conditions, the results have generally shown a benefit for a wider bandwidth which provides a higher tolerance for error (Sherwood, 1988; Smith et al., 1997; Ugrinowitsch, Coca-Ugrinowitsch, Novellino Benda, & Tertuliano, 2010). However, at least one study has shown some benefit of a narrow bandwidth (Coca-Ugrinowitsch et al., 2014). The benefit to learning is most often in the form of improved movement consistency for the bandwidth versus 100% KR group (Ishikura, 2011) or the wide bandwidth versus narrow bandwidth group (T. D. Lee & Carnahan, 1990; Sherwood, 1988; Smith et al., 1997). Studies have also found that skill acquisition with a bandwidth (narrow, wide or dynamic) can positively impact both consistency and accuracy after skill acquisition (Coca-Ugrinowitsch et al., 2014; Ugrinowitsch et al., 2010).

During skill acquisition, we observed that there was no effect of bandwidth on either performance efficiency or consistency: for each type of feedback, participants in the narrow and wide bandwidth groups performed similarly. This is consistent with Ishikura (2011) who found no impact of bandwidth size on either accuracy or consistency during acquisition of a timing task, and partially consistent with Ugrinowitsch et al. (2010).
itsch et al. (2010) who found no impact of bandwidth size on accuracy but that a narrower bandwidth produced less variability during acquisition of a force production task. One possibility is that the impact of our feedback types, which directly and significantly impacted both accuracy and consistency, simply overshadowed any immediate effects that bandwidth may have had on acquisition performance. It is also possible that the wide bandwidth in the present study was too liberal and participants essentially experienced too little feedback (typically 0 to 20% of a trial) to impact their accuracy or consistency, making their experience of skill acquisition comparable to that of a group that experienced no haptic feedback. In a previous study (Williams et al., 2016), we showed that performance efficiency of a control group was significantly different from that of a narrow bandwidth-error augmentation group during skill acquisition. However, because there were no main effects of, or interactions with, bandwidth in the present study, it is unlikely that our wide bandwidth groups were in fact equivalent to a no haptic feedback condition during skill acquisition.

Despite the absence of bandwidth effects in acquisition, our retention results showed that bandwidth did play a role in learning with respect to performance efficiency but not consistency: an interaction between feedback and bandwidth indicated that differing learning effects of the feedback types were only evident at the narrow bandwidth. These results provide only partial support for our hypotheses because the wider bandwidth did not modulate the effect of feedback types in the way that the narrow bandwidth did. Specifically, our results did not indicate that error minimization was more beneficial for learning when provided at a larger bandwidth. Smith et al. (1997) also observed an interaction between feedback type and bandwidth when they compared two types of feedback (transitional information or knowledge of results) provided at three different bandwidths (0, 5 and 10%) for learning a golf chipping task. They showed that the two types of feedback produced significantly different movement consistency only at the widest bandwidth (transitional information led to more consistent movements).

In contrast to most of the literature which suggests that a wide bandwidth would confer benefits to learning, our results showed that learning was maximized when error augmenting haptic feedback was provided at a narrow bandwidth. It is possible that we may have found differential effects of bandwidth if we had chosen a mid-sized bandwidth, between the sizes of our narrow and wide bandwidths. It is impossible to know for certain how this bandwidth would have impacted learning. Nonetheless, we can reasonably conclude that for this task, the type of feedback provided is a more salient learning variable than bandwidth size. This is consistent with previous observations that type, not amount of information provided, is key for learning (Reeve, Dornier, & Weeks, 1990). Results from skill acquisition show that the wide bandwidth groups were experiencing very different amounts of feedback in comparison to their narrow counterparts, but at the same time producing similar values of tracing error and moving at
similar speeds. Furthermore, because there was no significant difference in learning between the error
minimizing haptic feedback groups, our results do not provide support for the guidance hypothesis.

With respect to the consistency hypothesis: although we expected a wider bandwidth to benefit
movement consistency by preventing maladaptive short-term corrections, there was no such effect. It is
known that bandwidth KR explicitly encourages participants to repeat the previous action, providing
movement stability [T. D. Lee & Carnahan 1990]. However, response stability is also promoted by
blocked/constant practice where the task goal remains the same throughout [Lai & Shea 1998]. Therefore,
it is possible that our training conditions already provided a measure of response stability and the
added stability of bandwidth feedback was redundant.

The primacy of feedback type that we have observed for learning this task also supports the idea that
participants need to experience error-detection and error-correction during skill acquisition to learn effec-
tively. This was readily provided by error augmenting haptic feedback with the narrow bandwidth group
having more error-detection experience than the wide bandwidth group. In fact, the nature of this task
suggests that error-based learning is the dominant learning mechanism and therefore error augmented
feedback should be best for learning [Heuer & Lüttgen 2015]. Interestingly, during acquisition, the error
augmented haptic feedback groups, irrespective of bandwidth, showed improved performance consistency
across practice blocks. This, along with these groups’ significant improvements in performance efficiency
over the course of practice, quite likely led to their superior performance at retention.

3.4.1 Implications for rehabilitation robots

Much of the work in the haptic training field sits between the basic motor learning and applied robotic
rehabilitation fields. It is not surprising then that some studies of haptic training have incorporated a
bandwidth or error tolerance in training systems being tested with tasks such as steering/line-following
in a wheelchair [Chen & Agrawal 2013] and a tennis forehand stroke [Marchal-Crespo, Rauter, & Wyss
2012]. Similarly, some rehabilitation studies mention use of a zone or band with no haptic forces or dif-
ferring haptic forces that accommodate motor noise so as to ignore insignificant errors in performance
[Chen & Agrawal 2013; Patton et al. 2006] or encourage active participation by learners [Kahn, Zygm-
man, Rymer, & Reinkensmeyer 2006]. However, this description of the “dead band” or error tolerance is
not routinely accompanied by a discussion or explanation of how that band was determined or optimized
for the task of interest.

The motor learning research thus far shows that bandwidth can impact learning but the rules sur-
rounding those effects are still unclear, particularly with respect to the nature of the task. As such,
it is unknown whether the bandwidths being chosen by researchers may be affecting the results and conclusions being drawn about the efficacy of various rehabilitation training and feedback paradigms being tested. One benefit of haptic training systems is the ease with which procedural settings such as bandwidth can be adjusted for repeated testing. If researchers in this domain included bandwidth as a variable in their published studies, it could provide clues to both the motor learning and robotic rehabilitation communities about how this factor interacts with task type and other components of task training. In particular, studies of robotic rehabilitation are increasingly comparing error minimizing and error augmenting training modes (Alexoulis-Chrisovergis, Weightman, Hodson-Tole, & Deconinck, 2013). As we have shown in the present study, the bandwidth at which these feedback paradigms are presented can affect whether they are deemed differentially beneficial for learning. This is particularly relevant for studies where no differences were found between these training modes (see Alexoulis-Chrisovergis et al., 2013 for a review). Importantly, we acknowledge that significant findings in kinematic measures may not translate to significant findings in clinical measures (Rozario, Housman, Kovic, Kenyon, & Patton, 2009), however, kinematic data can provide explanatory support for clinical findings which can further contribute to the improved design of rehabilitation robots and their training paradigms. We encourage researchers in all domains—motor learning, haptic training and rehabilitation robotics—to expand their exploration of bandwidth as a learning variable in a variety of laboratory and real-world tasks.
Chapter 4

Enhancing haptic assistance training through self-controlled feedback: Influences of feedback frequency and opinions of haptic assistance

A later/revised version of this manuscript has been accepted for publication and is in press\(^1\) (© 2017 Williams, Tseung and Carnahan). It is reproduced here under the terms of the Creative Commons Attribution License CC BY 4.0\(^2\):


4.1 Introduction

One criticism of studies in motor learning is the overemphasis on the role of the teacher to direct the learning experience while the role of the learner has been minimized (Janelle, Kim, & Singer\(^3\), 1995). Recently, more researchers have begun to explore this notion by distributing the responsibilities for learning between experimenter/instructor and participant/learner. Results have consistently shown that there are learning benefits when learners are given the opportunity to control aspects of the practice environment such as feedback schedule (Aiken, Fairbrother, & Post\(^4\), 2012; Chiviacowsky & Wul\(^5\), 2002; Fairbrother, Laughlin, & Nguyen\(^6\), 2012; Janelle, Barba, Frehlich, Tennant, & Cauraugh\(^7\), 1997; Janelle et al., 1995), use of assistive devices (Hartman\(^8\), 2007; Wul\(^9\) & Toole\(^10\), 1999), amount of practice (Lessa & Chiviacowsky\(^11\), 2015), and task difficulty (Andrieux, Boutin, & Thon\(^12\), 2015; Andrieux, Danna, &

\(^1\)https://www.frontiersin.org/articles/10.3389/fpsyg.2017.02082/abstract
\(^2\)https://creativecommons.org/licenses/by/4.0/
Although numerous studies have demonstrated the advantage of self-controlled practice for learning, there is little empirical evidence to clearly support the reasons for this advantage (Sanli, Patterson, Bray, & Lee, 2013). Most authors have cited either motivational or cognitive (i.e., related to information processing) processes for the observed benefits but an antagonistic relationship between the two has also been suggested (Bund & Wiemeyer, 2004).

Proponents of the perspective that motivational processes are behind the benefits of self-controlled practice propose that self-control, in and of itself, can provide benefits to motor learning by satisfying the fundamental need for autonomy (Lewthwaite, Chiviacowsky, Drews, & Wulf, 2015). Furthermore, self-control contributes to greater perceived competence (Chiviacowsky, 2014) because participants tend to request feedback after perceived good trials (Chiviacowsky & Wulf, 2002, 2007; Fairbrother et al., 2012).

However, proponents of the perspective that cognitive influences are the root cause of self-controlled learning benefits, point to findings that task-relevant (versus task-irrelevant) choices (Carter & Ste-Marie, 2017) and choosing feedback after (versus before) trials (Carter, Carlsen, & Ste-Marie, 2014; Chiviacowsky & Wulf, 2005) are critical for producing the self-controlled learning benefits. Furthermore, several studies have failed to find differences between groups with and without self-control of the practice context for measures of perceived autonomy or competence (Carter & Ste-Marie, 2017) and intrinsic motivation (Ste-Marie, Carter, Law, Vertes, & Smith, 2015). Instead of having an impact on these motivational factors, these researchers believe that participants with self-control engage in greater information processing during skill acquisition than those without self-control (Sanli et al., 2013; Wulf, 2007). There is, in fact, some evidence that self-control of feedback leads to improved error estimation abilities (Carter et al., 2014; Chiviacowsky & Wulf, 2005) and enhanced feedback processing (Grand et al., 2015). The reason for enhanced information processing may be that these participants are able to request feedback when they think it will be useful or they are inherently more engaged in the learning process; however, these ideas remain to be empirically supported (Grand et al., 2015; Sanli et al., 2013).

Despite the well-documented benefits of self-controlled learning, researchers have yet to explore whether self-control could be beneficial for motor learning in the haptic training domain. The most well-studied form of haptic training is assistive haptic feedback, also known as haptic assistance, haptic guidance or robot assistance (Williams & Carnahan, 2014), which concurrently provides feedback about performance while minimizing errors to assist in task performance (see Heuer & Lüttgen, 2015 for a review). Importantly, there is one major difference between the paradigms of haptic training and self-controlled learning that might modulate the effects of self-controlled haptic feedback on motor learning. Specifically, studies of self-controlled practice typically employ terminal feedback as opposed to the
concurrent feedback provided by haptic guidance. This is particularly relevant because researchers have consistently found that self-controlled learners tend to prefer receiving feedback after perceived good or bad trials (Carter & Patterson, 2012; Chiviacowsky & Wulf, 2007; Laughlin et al., 2015) and previous research using terminal feedback suggests that self-controlled feedback is effective when it is based on the learner’s performance, i.e., the decision to receive feedback is made after the trial (Carter et al., 2014; Chiviacowsky & Wulf, 2005). However, with concurrent feedback, the learner is unable to choose feedback after a trial; participants must decide whether to have feedback either before or during a trial.

To date, there have been only a few studies utilizing self-controlled concurrent feedback. A pair of studies led by the same author and both published in 2009, investigated self-controlled concurrent feedback in two very different practice contexts. In the first study, the task was a complex perceptual-motor door crossing task whereby participants had to adjust their walking speed on a treadmill such that they would cross a virtual door threshold when the opening between doors was the widest (Huet, Camachon, Fernandez, Jacobs, & Montagne, 2009). The concurrent feedback available represented the error that would result if participants maintained current walking speed. In the second study, the task was landing a virtual aircraft in a fixed-base flight simulator with available feedback representing augmented information about the aircraft’s current glide slope, that is, the angle of approach to the runway (Huet, Jacobs, Camachon, Goulon, & Montagne, 2009). Participants in both studies could choose to display visual concurrent feedback about performance at multiple time-points during a trial. Results from both studies showed that the self-controlled feedback participants outperformed their yoked counterparts (each “yoked” participant is matched to and receives the same feedback schedule as that chosen by a self-controlled participant). Interestingly, participants in the door crossing study opted for a faded feedback schedule (i.e., they reduced their requests for feedback over the course of skill acquisition) (Huet, Camachon, et al., 2009), while participants in the virtual aircraft landing study did not fade their feedback but adapted the functional role of feedback requests from discovery to confirmation of the relationship between relevant sources of information (Huet, Jacobs, et al., 2009).

It is also useful to consider that in addition to providing concurrent feedback, haptic guidance also provides physical assistance to complete the task, in part by altering the task difficulty. Study of the latter function (assistive/difficulty-reducing) is likely necessary to fully understand how these two practice features (haptic guidance and self-control) interact; especially because, in contrast to choosing feedback, choices about assistive devices and task difficulty are made before a trial. Studies exploring learning benefits of self-controlled physically assistive devices offered their self-controlled participants the use of poles for learning to use a ski simulator (Wulf, Clauss, Shea, & Whitacre, 2001; Wulf & Toole, 1999) or stabilometer (Chiviacowsky, Wulf, Lewthwaite, & Campos, 2012; Hartman, 2007). These studies
found that the self-controlled assistance participants adopted a fading schedule for using the poles and performed better and/or more efficiently in retention when compared to their yoked counterparts. Additionally, Hartman (2007) reported that the self-controlled assistance group asked for the pole when trying new movement strategies. However, studies have shown that while provision of assistive devices can facilitate exploration of movement strategies, it can also prevent this exploration by keeping participants “on-target” (Wulf & Shea, 2002). Studies of task difficulty have also shown that participants who could control task difficulty in skill acquisition showed learning benefits in relation to those who experienced externally-imposed task difficulty (Andrieux et al., 2015, 2012; Williges & Williges, 1977) and these benefits were enhanced when choice was only available in the first half of practice (Andrieux et al., 2015). The strategy of these self-controlled task difficulty participants was to continually challenge themselves throughout practice, moving towards the level of difficulty of the retention test.

In sum, it is unknown whether self-control of haptic guidance, which serves both feedback and assistive functions, will be beneficial for learning a self-paced curve-tracing task, how participants will choose to schedule it or for what functional role(s) participants will use it. As such, the present study had three aims: (i) to explore how self-controlled participants choose to schedule haptic guidance; (ii) to determine whether self-control of haptic guidance during skill acquisition is beneficial for learning; and (iii) to explore the rationales and opinions held by both self-controlled and yoked participants with respect to their chosen or externally-imposed guidance schedules and whether these are related to motor learning. Phase One addressed the first two aims while the third aim was addressed in Phase Two.

Motor learning was assessed using a transfer design. Specifically, skill acquisition, under various conditions defined by presence and choice of augmented haptic feedback, was followed by retention tests without any augmented feedback (Salmoni et al., 1984). This design allows for a distinction between the immediate and transient performance effects seen during and immediately after practice, and learning effects that represent more stable and permanent changes in ability.

We hypothesized that, in accordance with studies of self-control of perceived assistive devices (e.g., Hartman, 2007), and concurrent feedback (e.g., Huet, Jacobs, et al., 2009), self-controlled participants selecting assistive haptic feedback before skill acquisition trials, would display a learning advantage. Additionally, we anticipated that differences in rationales, opinions or strategies related to the use of assistive haptic feedback would also have some bearing on motor learning (Carter, Rathwell, & Ste-Marie, 2016).
4.2 Phase One

4.2.1 Methods

The University of Toronto Health Sciences Research Ethics Board approved the protocol. We recruited 45 community-living, university-affiliated adults with normal or corrected-to-normal vision, who reported no current neurological impairments: 35 women and 10 men (M = 26.3 yr, SD = 7.2 yr); 5 were classified as left-hand dominant based on the online version of the Edinburgh Handedness Inventory\(^3\) (Oldfield, 1971). All participants were naïve to the specific purposes of the experiment and gave written voluntary informed consent prior to participation, in accordance with the guidelines set out by the 1964 Declaration of Helsinki. Participants received gift cards valued at CAD$15 as compensation for their time.

4.2.1.1 Apparatus & task

The apparatus consisted of a tabletop haptic device (SensAble Phantom Omni, currently Geomagic Touch; Rockhill, SC, USA) and standard computer monitor operated via a custom software program as previously reported in Chapter 2 (Williams et al., 2016), with a few noted exceptions, and we refer interested readers to that article for details omitted here. The computer monitor used in the present study was a Dell UltraSharp\(^\text{TM}\) 1703FP and the resolution resulted in a visual gain of 1.38 between displacements on the monitor and movements of the haptic device in space. The device was programmed such that it was possible to deliver assistive feedback forces as users, seated at a desk, attempted to trace a curve (Figure 2.1) by manipulating the device’s stylus with their non-dominant arm. The position of the stylus was represented onscreen by a circular cursor.

4.2.1.2 Procedure

There were three skill acquisition conditions: (i) a control (CN) condition with no manipulation of tracing errors using the “none” haptic feedback mode; (ii) a self-controlled (SC) error minimization condition using the “spring assistance” mode of haptic feedback; and (iii) a yoked (YK) error minimization condition using the “spring assistance” mode. Using the Research Randomizer website\(^4\), participants were randomized to one of these three conditions for practice of the task, with the constraints that group assignments were equal in number (i.e., 15 participants in each group) and a self-controlled participant must precede its yoked counterpart.

After introductory explanation of the task, participants were allowed three familiarization trials with

\(^3\)http://www.brainmapping.org/shared/Edinburgh.php
\(^4\)http://www.randomizer.org/
a curve different than the one to be learned. Once participants were comfortable with the device and the task, they did a pretest consisting of 5 trials of the task: once the target curve appeared on the computer screen, participants started the trial by moving the cursor to the start-point near the bottom of the screen and ended the trial by moving the cursor to the end-point near the top of the screen. The target curve and the cursor were visible for the entire trial and participants were instructed to trace the curve as quickly and as accurately as possible. Solely the cursor and the target curve were visible throughout these pretest trials and participants did not receive any augmented haptic feedback or other feedback about performance.

Following this was the skill acquisition/practice phase: 60 trials organized as 12 blocks (5 trials/block). Before beginning, all participants were informed that, like the pretest, all tests following practice would not contain any haptic or visual feedback about performance. The experimenter then explained, per their group assignment, what they should expect with respect to feedback (haptic and otherwise) during the practice phase. For participants in the CN group, the trial would proceed in the same way as the pretest trials. However, after each trial, feedback regarding the tracing accuracy (a red trace of their movement superimposed over the target curve) and movement time (a numerical value displayed in seconds to the nearest decisecond) were provided on-screen. For SC participants, the experimenter asked whether they wanted to have haptic feedback (termed “guidance”) prior to each block of trials. If they opted to have haptic feedback, then each trial in the block was accompanied by assistive haptic feedback in accordance with their performance. They were informed that they could choose to have as many or as few guided blocks of practice as they liked. Each YK participant was matched to a participant in the SC group and was simply informed whether each upcoming block of trials would have haptic feedback available. SC and YK participants also received the other forms of visual feedback regarding tracing accuracy and movement time that were available to participants in the CN group.

Ten minutes after the end of practice (after completing a pen-and-paper questionnaire—see Phase Two below), participants completed an immediate retention test which was identical to the pretest. After approximately one day ($M = 1.2$, $SD = 0.4$), participants returned for a delayed retention test (identical to the immediate retention test).

### 4.2.1.3 Outcome measures & data analysis

For each SC participant, we noted the blocks for which haptic guidance was requested and employed a paired samples t-test to compare the number of guided blocks in the first and second halves of practice. Tracing error for each trial, measured in mm, was calculated as described in Equation 2.1. Movement time for each trial was measured as the time (in seconds to the nearest millisecond) from when the
cursor was moved to the start-point, to when the cursor was moved to the end-point. From the previous two measures, we calculated the Speed Accuracy Cost Function (with units mm/s) as a measure of performance efficiency: \( \text{CostFunction} = \text{TracingError} \times \text{MovementTime} \) (Culmer et al., 2009; Raw et al., 2012; Williams et al., 2016). A large cost function indicated less efficient and overall, poorer, task performance.

Cost function values were averaged over each block of 5 trials to provide 12 data points for skill acquisition and three data points for tests of skill (pretest, immediate and delayed retention). We first conducted a one-way between-subject ANOVA, to compare the effect of practice group on pretest cost function values. There were no significant differences between groups (\( M = 26.23 \text{ mm/s}, SD = 7.11 \text{ mm/s}; F(2, 40) = 1.74, p = .189, \eta^2_p = 0.08 \)) so we proceeded with the analyses described below and data from the pretest will not be discussed further. We conducted two mixed ANOVAs (3 group x 12 block in acquisition; 3 group x 2 test in retention) with repeated measures on each of the respective last factors.

Because we expected that performance would improve over the course of acquisition (i.e., cost function would decrease), main effects or interactions involving block in acquisition were explored using contrasts with the first block as the reference category. When Mauchly’s test indicated that the assumption of sphericity had been violated for repeated measures factors, Greenhouse-Geisser corrections were applied (all \( \epsilon < .75 \)) and adjusted degrees of freedom were reported to the nearest decimal. When simple main effects analyses were used to explore significant interactions, Bonferroni corrected p-values were reported. Effects for all analyses were considered statistically significant at \( p < .05 \) and effect sizes associated with F-tests were estimated using partial eta squared values (\( \eta^2_p \)). Analyses of data from acquisition and immediate retention demonstrate the immediate effects of our practice conditions, both during and shortly following practice. However, learning effects were inferred based on analyses of delayed retention data.

4.2.2 Results

Data from two participants (one from each of the SC and CN groups) were excluded from quantitative analyses of performance in acquisition and retention data because these participants struggled with correct use of the device. Their observed difficulties were also evident as elevated means and standard deviations of speed accuracy cost function throughout practice and retention.
4.2.2.1 Requests for haptic guidance

The range for requests for haptic guidance was large with a minimum of 0 guided blocks and maximum of 11 guided blocks (1 participant requested each of the minimum and maximum values, respectively). On average, SC participants requested haptic guidance for 36.3% of skill acquisition blocks. Guidance was requested for $M = 2.0$ blocks ($SD = 1.5$) in the first half of practice and $M = 2.4$ blocks ($SD = 2.3$) in the second half of practice. A comparison of requests in each half indicated no significant difference, $t(13) = -.717, p = .486$.

4.2.2.2 Performance during skill acquisition

For skill acquisition data, Mauchly’s test of sphericity was significant, $\chi^2(65) = 168.2, p < .001$, so degrees of freedom were corrected using Greenhouse-Geisser estimates. There was a main effect of block, $F(6.3, 246.2) = 9.2, p < .001, \eta^2_p = 0.19$ (Figure 4.1 line graph, left side) and contrasts revealed that cost function on acquisition block 1 was significantly higher than cost function on blocks 5 to 7 (all $p < .05$) and blocks 8 to 12 (all $p < .001$). However, there was no effect of practice group, $F(2, 39) = 1.4, p = .248$, $\eta^2_p = 0.07$.

![Figure 4.1: Overall performance efficiency (as measured by the speed accuracy cost function; line graph with SE bars) and percentage of all participants performing with haptic guidance (bar graph) for each phase of the experiment. Blocks of acquisition are numbered A1 through A12 and retention tests are IR (immediate retention) and DR (delayed retention). Bracketed acquisition blocks represent those significantly different from block 1 with respect to performance efficiency. Performance on IR and DR were also significantly different. *$p < .05$, **$p < .001$.](image-url)
4.2.2.3 Performance on retention tests

There was a main effect of test, $F(1, 40) = 4.2$, $p = .048$, $\eta_p^2 = 0.09$, whereby performance on the immediate retention test was significantly better than performance on the delayed retention test, $M_{diff} = -0.93 \text{mm/s}$, $95\% CI [-1.85, -0.01]$ (Figure 4.1 line graph, right side). Meanwhile, the effect of practice group was not statistically significant, $F(2, 40) = 2.8$, $p = .074$, $\eta_p^2 = 0.12$.

Because it is known that frequent feedback during skill acquisition can negatively impact learning (Park, Shea, & Wright, 2000; Salmoni et al., 1984), we conducted an additional analysis of retention performance for the experimental groups (SC and YK) to determine if this was the case here. The distribution of requests for haptic guidance was such that 64% of SC participants requested 4 or fewer guided blocks—these participants were classified as Low Frequency; the remaining 36% of participants requested 6 or more guided blocks and were classified as High Frequency. We conducted a 2 guidance frequency x 2 practice group x 2 test ANOVA with repeated measures on the last factor. This analysis revealed a significant interaction between guidance frequency and practice group, $F(1, 25) = 4.3$, $p = .050$, $\eta_p^2 = 0.15$ (Figure 4.2). No other effects were statistically significant (all $Fs < 2.3$). Simple main effects analysis of this interaction indicated that SC participants who practised with a low frequency of guidance had better learning outcomes than those who practised with a high frequency of guidance, $M_{diff} = 6.26 \text{mm/s}$, $95\% CI [0.99, 11.54]$, $p = .022$. Additionally, for low frequency participants, there was a difference approaching significance based on practice group whereby SC participants appeared to outperform the YK participants, $M_{diff} = 4.31 \text{mm/s}$, $95\% CI [-0.15, 8.76]$, $p = .058$.

4.3 Phase Two

4.3.1 Methods

4.3.1.1 Procedures

Participants were those from the self-controlled and yoked groups in Phase One described above. At the end of practice (before the immediate retention test), participants were asked to complete a pen and paper questionnaire regarding their practice experience. The questions (Table 4.1) were based on questionnaires employed in previous studies (Carter et al., 2016; Laughlin et al., 2015).

Participants were allowed up to 10 min to complete the questionnaire and the experimenter answered any clarifying questions. Upon completion of the questionnaire, the experimenter asked for clarification on responses deemed illegible or the likely result of a misunderstanding by the participant. For example, in response to the question “Did you receive it [haptic guidance] at the right times for you?” addressed
Figure 4.2: Performance efficiency (as measured by the speed accuracy cost function) across retention tests by experimental group and frequency of haptic guidance during skill acquisition. Error bars are 95% CI. Dashed line indicates a difference approaching significance ($p = 0.058$). *$p < .05$.

Table 4.1: Open-ended questions asked of participants at the end of practice

<table>
<thead>
<tr>
<th>Thinking about the first/last six blocks of trials:</th>
<th>Self-controlled Group</th>
<th>Yoked Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>When did you ask for haptic guidance?</td>
<td></td>
<td>Did you receive haptic guidance at the right times for you?</td>
</tr>
<tr>
<td>Why did you ask for haptic guidance at these times?</td>
<td></td>
<td>If so, why were these times right? If not, when would you have preferred to receive haptic guidance? Why would these times have been better?</td>
</tr>
</tbody>
</table>

Reflecting on the entire session: What changes, if any, did you notice in your approach, thinking or process over the course of practice? Is there anything else you want us to know about your experience?
to YK participants, some interpreted the question as a query regarding whether guidance within a trial was appropriately applied. In such cases, the experimenter explained that the question instead referred to the placement of guided blocks within the practice period.

### 4.3.1.2 Qualitative data analysis

Data consisting of text responses to the open-ended questions were analyzed using an inductive thematic analysis (Braun & Clarke, 2006). The primary analyst (CKW) transcribed each response then reviewed all responses repeatedly to get a sense of the whole. Subsequently, considering the response to each question for each participant separately, the analyst tagged each individual idea represented in the text with a code. For example, in response to the question “When did you ask for haptic guidance?”, a SC participant replied “When frustrated w/ doing task w/o guidance—difficult to do w/left hand; When performance w/o guidance was not too great.” This entire excerpt was tagged with the codes “Chose guidance to improve performance” and “Chose guidance to make the task easier.” Each excerpt/response was tagged with as many codes as required to capture all the ideas present. Codes were kept organized according to the questions on the questionnaire to keep track of whether they applied to a SC or YK participant and whether they applied to the first or second half of practice.

Once the analyst was satisfied that all ideas in the data had been captured by codes, the codes were examined for similarities within and across questions. Similar codes within questions were consolidated and similar codes across questions were renamed to be represented by the same code. Subsequently, all codes were reviewed multiple times, paying attention to any potential differences between choice-related practice groups (SC and YK). However, when considering the data for the SC and YK groups separately, themes emerging from each data set were very similar. As such, data from these groups were combined. Finally, in an iterative process, related codes were grouped into themes that applied across both groups of participants. Representative excerpts for each theme were noted.

We employed analyst triangulation whereby a second analyst (VT) independently reviewed the codes and themes developed by the primary analyst. At the time of analysis, VT was a doctoral candidate who employed qualitative methods in a research area unrelated to motor learning. The purpose of analyst triangulation is to produce multiple ways of seeing the data and facilitate discussions to ensure that a rich, robust and comprehensive description of the data was represented in the final set of themes (Yardley, 2015).
4.3.1.3 Quantitative data analysis

Once the themes were finalized, the primary analyst used the codes supporting each theme to assign each participant’s responses regarding the first and second halves of practice to one of the emergent themes. For example, if an excerpt from a participant regarding the first half of practice was tagged with code A, and code A supported Theme 1, then the participant’s comments about the first half of practice were assigned to Theme 1. Following this, each participant’s questionnaire was reviewed in full to confirm the themes assigned to responses given for the first and second halves of practice, respectively. Where a participant’s responses were ambiguous or multiple codes relating to multiple themes were present, responses to the last two general questions (i.e., questions not referring to a practice half) were used to help inform theme assignment. These procedures were employed to ensure that contextual information was accounted for when assigning themes.

Based on these thematic groupings, we first conducted Fisher’s Exact chi-square tests to determine whether participants’ choice group (SC or YK) was associated with the thematic groups identified in each half of skill acquisition. Effect sizes for these analyses are represented by Cramer’s $V$, whose value increases from 0 to 1 with the strength of association between two variables. Next, following the analyses employed by Carter et al. (2016), we conducted a 2 Thematic Group (Dominant, All Others) x 2 Test (Immediate, Delayed) ANOVA with repeated measures on the last factor, for each half of practice.

4.3.2 Results

4.3.2.1 Emergent themes

Analysis revealed four themes related to how SC and YK participants viewed the utility of haptic guidance during skill acquisition: (i) positively for performance; (ii) positively for learning; (iii) neutrally or heterogeneously with respect to performance and/or learning; and (iv) negatively with respect to performance and/or learning. These themes are defined below, the distribution of these views across participants and the two halves of practice are shown in Figure 4.3 and selected quotes are presented in Table 4.2.

Guidance viewed positively for performance: Participants expressing this view of haptic guidance referred to the use of guidance to facilitate immediate and short-lived changes in the practice experience such as help/assistance, enhanced performance or reduction of effort. Participants expressing this view also spoke of becoming dependent on haptic guidance to maintain their desired level of performance (both accuracy and speed) as well as using haptic guidance to make the task easier, alleviate fatigue
Figure 4.3: Frequency of each view of haptic guidance (resulting from emergent themes) among Self-controlled and Yoked participants in each half of skill acquisition.
Table 4.2: Selected quotes from Self-controlled (SC) and Yoked (YK) participants which support each of the four emergent themes

<table>
<thead>
<tr>
<th>Guidance viewed positively for performance</th>
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</tr>
</thead>
<tbody>
<tr>
<td>SC “In B1, I observed there were too many deviations especially towards the end and was taking more time than accounted; so decided to take guidance to improve performance”</td>
<td>P36, 1st half</td>
</tr>
<tr>
<td>YK “It helped decrease time of completion”</td>
<td>P21, 2nd half</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Guidance viewed positively for learning</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SC “I wanted to see how much I would improve after using the guidance - in particular how accurate/fast I trace in the trials without guidance after getting the help”</td>
<td>P1, 1st half</td>
</tr>
<tr>
<td>YK “It helped decrease time of completion”</td>
<td>P21, 2nd half</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Guidance viewed neutrally or heterogeneously with respect to performance and/or learning</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SC “Only to try it out &amp; see if I could practice after that one experience”</td>
<td>P29, 1st half</td>
</tr>
<tr>
<td>YK “It didn’t matter”</td>
<td>P5, 1st half</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Guidance viewed negatively with respect to performance and/or learning</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>SC “I wanted the practice to replicate the test conditions so I didn’t use guidance”</td>
<td>P23, 2nd half</td>
</tr>
<tr>
<td>YK None</td>
<td></td>
</tr>
</tbody>
</table>

and boredom, or reduce the need for concentration or effort. This view was prevalent in the YK group, in both halves of skill acquisition.

**Guidance viewed positively for learning:** Participants expressing this view of haptic guidance referred to the use of haptic guidance to facilitate learning or improve performance on later trials without haptic guidance (e.g., the tests), or otherwise indicated consideration of or aspiration towards ongoing and/or lasting improvement of performance in concert with the use of haptic guidance. This view was primarily observed in the SC group; in fact, it was the dominant view within this group in the first half of practice. Interestingly, whereas the prevalence of this view decreased in the SC group from the first to second half of practice, it increased in the YK group over time.

**Guidance viewed neutrally or heterogeneously with respect to performance and/or learning:** Participants expressing this view of haptic guidance made mention of it without any clear indication or whether it could or should be used to facilitate performance or learning or indicated multiple views regarding the utility of haptic guidance without a clear dominant view. The comments supporting this theme included descriptions of the chosen haptic guidance schedule, the use of haptic guidance to “test it out” or “try it out” as well as observations that the use of haptic guidance appeared to be unrelated to performance. This theme was more prevalent among the YK group and, interestingly,
disappeared from the SC group in the second half of practice.

**Guidance viewed negatively with respect to performance and/or learning:** Participants expressing this view described their refusal of or doubts about the utility of haptic guidance to facilitate performance or learning, or otherwise indicated that haptic guidance would not be beneficial for performance or learning. This theme was notably absent from the YK group and, in the SC group, increased in prevalence from the first to the second half of practice.

**4.3.2.2 Relationship between themes and choice groups**

For view of guidance in the first half of skill acquisition (refer to Figure 4.3 for cell counts), there was a significant association between choice group and first half view, $\chi^2(3) = 10.9, p = .008$, Cramer’s $V = .63$. This seems to represent the fact that, while 50.0% of SC participants expressed a learning view of haptic guidance, only 6.7% of YK expressed this view; additionally, while 60.0% of YK participants held a performance view, only 14.3% of SC participants did. There was also a significant association between choice group and second half view, $\chi^2(3) = 11.9, p = .005$, Cramer’s $V = .64$. This relationship seems to represent the fact that while no YK participants expressed negative views of haptic guidance, 42.9% of SC participants did; additionally, while no SC participants expressed neutral or mixed views of guidance, 33.3% of YK participants did.

To have sufficiently large cell sizes for the statistical analysis described below, we selected the dominant view of guidance across all participants (performance view) as a comparator for all other views of guidance. To maintain consistency with that analysis, we repeated the Fisher’s Exact chi-square analyses described above with these two thematic groups (performance, all other views). These analyses revealed that the association between thematic group and choice group remained significant for the first half of skill acquisition only: first half, $\chi^2(1) = 6.4, p = .021$, Cramer’s $V = .47$; second half, $\chi^2(1) = 1.0, p = .450$, Cramer’s $V = .19$.

**4.3.2.3 Impact of views of guidance on learning**

With respect to views of guidance in the first half of practice [Figure 4.4], there was a main effect of first half view, $F(1, 27) = 6.5, p = .017, \eta^2_p = 0.20$, such that participants with a performance view had worse learning outcomes than those with one of the other views of guidance, $M_{diff} = 4.40 \text{mm s}$, 95%CI [0.87, 7.92]. The effect of test was not statistically significant, $F(1, 27) = 0.3, p = .580, \eta^2_p = 0.01$.

For views of guidance in the second half of practice, neither second half view, $F(1, 27) = 0.6, p = .442$, $\eta^2_p = 0.02$, nor test, $F(1, 27) = 0.2, p = .647, \eta^2_p = 0.01$, were statistically significant for retention
performance.

Figure 4.4: Performance efficiency on the retention tests for Self-controlled and Yoked participants based on their view of haptic guidance in the first half of skill acquisition. Error bars are 95% CI of the mean.

4.4 Discussion

Participants attempted to learn a self-paced tracing task using a tabletop haptic device under one of three practice conditions: control (no augmented haptic feedback), self-controlled assistive haptic feedback (guidance), or yoked assistive haptic feedback. We instructed participants to trace the curve as quickly and as accurately as possible, and measured overall performance efficiency by the speed accuracy cost function where a lower value of the cost function indicates better, overall more efficient task performance. During skill acquisition, the average rate of request for assistive haptic feedback by self-controlled participants (36.3%) was very similar to the 38% and 41% use frequency of assistive devices reported by Hartman (2007) and Chiviacowsky et al. (2012), respectively. Although there was no difference in the number of haptic feedback requests in the first and second halves of practice, participants improved their performance over the course of skill acquisition. Also, there were no performance differences between groups throughout skill acquisition. Our first hypothesis was that there would be a learning advantage for participants who were able to self-control their use of assistive haptic feedback.
during skill acquisition. We found only partial support for this hypothesis as we discovered that the frequency of guidance, as determined by the SC group, interacted with choice group such that there was a trend for SC participants who choose a low frequency of haptic guidance to outperform their YK counterparts. Interestingly, we did find strong support for our second hypothesis that participants’ goals and strategies as determined through qualitative analysis of open-ended questions directly impacted motor learning.

4.4.1 Self-control interacted with guidance frequency to impact motor learning

While the effect of self-controlled learning has been robust in the motor learning literature, there are a few possible explanations for our failure to find a direct impact of self-control of concurrent haptic feedback for enhancing learning of our tracing task. Firstly, from the perspective of haptic guidance as feedback, Chiviacowsky and Wulf (2005) showed that the benefit of self-control for motor learning was demonstrated when participants were able to make a decision about receiving feedback after a trial as opposed to before a trial. However, because assistive haptic feedback is provided concurrently, it must be selected before or during a trial. Due to our experimental paradigm, participants chose whether to receive haptic guidance before each block of trials. As such, decisions regarding the use of haptic feedback were not based on participants’ performance and this may have limited the extent to which participants engaged with or processed the information as useful feedback.

Secondly, from the perspective of haptic guidance as an assistive device, our task had no appreciable physical risk, e.g., the risk of falling as with previous studies using poles for a ski simulator and stabilometer. Chiviacowsky et al. (2012) reported that for participants with Parkinson’s disease learning a balance task, self-controlled participants were less nervous than yoked participants before a trial, possibly because having self-controlled access to the physical assistance device relieved anxiety about ability and task performance, which is known to negatively affect motor learning. Although we did not measure anxiety, it is very unlikely that the ability to select haptic feedback had any bearing on our participants’ anxiety levels since the minimal physical risks involved in the task were not differentially affected by the presence of haptic guidance. Furthermore, other studies of self-control of an assistive device have used relatively complex tasks which encouraged participants to use the assistive device to facilitate experimentation with various strategies for performance (Chiviacowsky et al., 2012) Hartman (2007) or perform at levels that would not have been possible without more practice (Wulf et al., 2001; Wulf & Toole, 1999). That is, the device facilitated exploring the “perceptual-motor workspace” (Newell,
However, our tracing task was relatively simple and as such, our participants likely did not or could not effectively use the assistance for this type of performance support (Wulf & Shea, 2002).

Lastly, our results were impacted by varying levels of guidance frequency during skill acquisition. Although the effects of the guidance hypothesis—the idea that excessive feedback during practice is beneficial for performance but has detrimental effects on learning (Salmoni et al., 1984; Schmidt, 1991)—are well known, we opted to allow participants full control over the feedback schedule. We observed that, similar to a subset of previous findings (Hansen, Pfeiffer, & Patterson, 2011; Patterson & Carter, 2010), participants did not opt for a faded schedule. Instead, participants could be differentiated by whether they choose/experienced a high (> 4 of 12 blocks) or low (≤ 4 of 12 blocks) frequency of guidance. In previous studies of concurrent feedback where researchers tried to mitigate the detrimental effects of high feedback frequency, results showed that while reduced-frequency concurrent feedback can be beneficial for performance during skill acquisition, these benefits often disappear on no-feedback retention tests (Camachon, Jacobs, Huet, Buekers, & Montagne, 2007; Park et al., 2000). One study of haptic guidance using a reduced frequency of haptic guidance was shown to produce learning benefits in comparison to a control group (Marchal-Crespo, McHughen, et al., 2010) but other studies have failed to demonstrate learning benefits in relation to a group that received haptic guidance on all acquisition trials (Marchal-Crespo & Reinkensmeyer, 2008). In contrast, our results show that reduced frequency feedback has beneficial learning effects on no-feedback retention tests in relation to a high feedback frequency group, but only for self-controlled learners.

Hence, our findings that low guidance frequency was beneficial for SC participants provide some support for the guidance hypothesis (Salmoni et al., 1984; Schmidt, 1991) as well as the idea that differential information processing (versus motivational processes) is key for realizing the benefits of self-controlled practice. In this case, strategic decisions made by the SC group led to either a high or low frequency of guidance. Unfortunately, a high frequency of guidance is unhelpful at best, if not detrimental, for learning this task (Marchal-Crespo, McHughen, et al., 2010; Williams et al., 2016). Essentially, self-control allowed for strategic (mis)use of haptic guidance and SC participants had the freedom to optimize or sabotage their learning experiences. While we could have avoided the negative impacts of a high guidance frequency on learning, we were interested to know how participants would choose to use this type of assistive haptic feedback without explicit instructions about its benefits or drawbacks. Knowing that some participants are likely to misuse it in this way opens the door for additional questions about how use frequency might change if participants receive some introductory training or suggestions about “best-practices” for learning. This sort of investigation would mimic the type of control that learners would have under more ecologically valid learning situations such as at-home.
rehabilitation training or unsupervised simulation-based training for health professions education.

4.4.2 Motor learning was influenced by views about haptic guidance

There is evidence that self-control, in and of itself, is not sufficient to produce a motor learning advantage. For example, Brydges, Carnahan, Safir, and Dubrowski (2009) and Zimmerman and Kitsantas (1996) both found that self-controlled learners who set process goals outperformed those who set product or outcome goals for practicing a wound closure skill using video-based instructions and a dart-throwing task, respectively. In fact, it is widely accepted in the cognitive and academic skills domains that personal factors such as beliefs and knowledge of learning strategies, as well as contextual factors such as the nature of the task and learning environment, can impact the effectiveness of self-controlled learning (Boekaerts & Niemivirta, 2000; Garcia & Pintrich, 1994; Randi & Corno, 2000). Our emergent themes indicated that participants held beliefs or views centred around the utility of haptic guidance for performance and learning. In the first half of practice, SC participants were more likely to have a learning view of guidance while YK participants were more likely to have a performance view. This distinction seems to parallel the process versus outcome goals distinction that can also affect learning outcomes (Brydges et al., 2009). Furthermore, the negative view of guidance was absent from the YK group and we suggest that this offers some evidence of psychological differences between the SC and YK groups. It is possible that less autonomy support for YK participants led them to minimally engage in the learning process and therefore limited how critically they thought about the practice context. In short, the YK participants’ lack of control likely led them to more readily accept all aspects of the training program as good and useful for learning, or led them to focus on immediate performance instead of strategizing about how to optimize learning (performance on the tests).

Ultimately, we believe that SC participants’ views of guidance contributed to their strategic decisions regarding guidance frequency. To test this hypothesis, we ranked the views of guidance, as listed in Table 4.2, from 4 to 1 and conducted Spearman rank correlations between views of guidance in each half of practice and number of guided blocks, for SC and YK groups respectively. This analysis revealed that for the SC group, the number of guided blocks was significantly correlated with the view of guidance in both halves of practice (First half: $r_s(12) = .53$, $p = .050$; Second half: $r_s(12) = .81$, $p < .001$) but there were no significant correlations for the YK group (both $r_s(13) \leq .2$, $p > .4$). This means that SC participants more likely to view guidance positively were more likely to choose a higher frequency of guidance and suggests that SC participants chose a guidance frequency in accordance with their beliefs about the utility of haptic guidance. This finding, in concert with the observed trend for low frequency
SC participants to outperform low frequency YK participants on retention tests, lends credence to the idea that while self-control may foster specific ways of seeing and interacting with the practice context, and these beliefs have powerful impacts on learning, it is the strategic decisions borne from these beliefs that modulate learning effects. In sum, our findings add to the body of research in the motor domain demonstrating that it matters what the learner believes when engaged in self-controlled learning practices.

The very fact that we could glean such themes from our data is a testament to the utility of open-ended questioning. Earlier studies of self-controlled motor learning employed multiple choice questionnaires and focused exclusively on when and why participants chose to receive feedback (Chiviacowsky & Wulf, 2002; Hartman, 2007). More recent studies have begun to use open-ended questionnaires (e.g., Carter et al., 2016) and interview formats (e.g., Laughlin et al., 2015) to allow participants more freedom in their responses. While the findings discussed by Carter et al. (2016) were focused on strategies related to when and why feedback was chosen, Laughlin et al. (2015) discussed more global goals and strategies for performance. Like our findings, these types of global goals and beliefs about the training environment provide key insights into participants’ motivations and foci of attention during training. Additionally, we have gained information about the participants’ experience of the training system that could be used to inform future studies. For example, some participants mentioned that they would have liked to receive guidance only on the more difficult portions of the curve: “I’d have preferred to receive haptic guidance when I was in the ‘edges’ (corners)”—YK group, P24. This is certainly something that trainers using haptic-based methods could explore. In short, there are substantial benefits to qualitative approaches (in contrast to multiple choice surveys) in motor learning studies when the study goals include gaining in-depth insights into participants’ rationales and experiences of the practice context.

4.5 Conclusions

In accordance with our first aim, we observed that self-controlled participants chose guidance for about one third of practice blocks but did not employ a faded schedule. Findings with respect to aims 2 and 3 (determining whether self-control or opinions about the haptic feedback schedule impacted motor learning) were closely linked. We have provided additional support for the idea that choice alone is not sufficient to impact motor learning but in fact, that choice facilitates or affords access to certain learning strategies or informational benefits that can confer a learning advantage. In the present case, the learning outcomes were impacted by learners’ beliefs about the utility of guidance for performance or learning, by way of the guidance frequency chosen/experienced during skill acquisition. Self-controlled
learners who chose a practice schedule characterized by low guidance frequency (which was associated with more neutral, mixed or negative views about guidance) had a significant learning advantage over self-controlled learners who chose a high guidance frequency (associated with more positive views of guidance for learning and performance) and a marginally significant advantage over yoked learners who received a low guidance frequency (not significantly associated with any view of guidance).

These findings add some support to the notion that informational processes are the root of self-controlled learning benefits. Additionally, our results highlight that instructors should not make assumptions about how participants will view or use elements of the learning environment. In fact, participants' views or beliefs about various training elements will likely be informed by their knowledge of learning strategies and past experiences, and change over the course of practice. If, as movement scientists, the ultimate goal is the implementation of effective real-world training programs, it is important to investigate these assumptions and, if necessary, provide participants with some introductory training or rationale for use of practice elements [Brydges et al., 2009; Bund & Wiemeyer, 2004; Sanli et al., 2013; Zimmerman & Kitsantas, 1996]. We encourage researchers to continue employing rigorous qualitative methods in addition to quantitative evaluations of frequencies and moments of feedback requests (e.g., Huet, Jacobs, et al., 2009) to further explore how learners enact their views and beliefs about the practice context for the purpose of learning.
Chapter 5

General Discussion

The overall goal of this dissertation was to explore parameters that would be expected to optimize the use of haptic feedback for learning a simple laboratory task, in a healthy population. Each of the three experiments described in the previous chapters chronicles attempts to provide useful information for learning while preventing or mitigating the learners’ dependence on haptic feedback. This goal was in accordance with the guidance hypothesis, as described above in Chapter 1.

In all experiments, motor skill learning was operationalized as a relatively permanent change in skill and thus I utilized transfer designs to infer learning. With a transfer design, skill acquisition under experimental conditions is followed by retention and/or transfer tests for all participants under the same no-feedback conditions (Salmoni et al., 1984). All experiments utilized a 10-minute immediate retention test and a 1 day delayed retention test (experiment one also include a 1 day transfer test). This design allowed for distinction between the transient performance effects caused by our practice conditions and more permanent changes in ability (Schmidt & Bjork, 1992).

In this chapter, I begin by summarizing the findings and main conclusions from each experiment. Following this, I will review the results from multiple theoretical perspectives and outline some limitations of the present studies. Finally, I will suggest some future directions for research and practical implications for applied fields utilizing haptic training.

5.1 Review of Findings

5.1.1 Experiment one

In the first experiment, I sought to determine whether no haptic feedback, assistive haptic feedback or error-augmenting haptic feedback during skill acquisition, would be best for learning the self-paced,
curve-tracing task. Performance was assessed by movement time and tracing error, which were then used to calculate a measure of overall performance efficiency—the speed accuracy cost function (Culmer et al., 2009; Raw et al., 2012). The results showed that during skill acquisition, the error augmentation group had the worst performance efficiency. However, on the immediate retention test, this group had significantly better performance efficiency than the assistive haptic feedback group, and the control (no haptic feedback) group displayed better accuracy than the assistance group. Additionally, on the delayed retention and transfer tests, the error augmentation group had significantly better accuracy than the assistance group.

5.1.2 Experiment two

In the second experiment, I investigated whether the error tolerance or bandwidth at which haptic feedback was provided would have an impact on learning outcomes. Assistive and error-augmenting modes of haptic feedback were each presented at two bandwidths (narrow and wide). The narrow bandwidth was the same as that used in experiment 1. I assessed movement time, tracing error, performance efficiency via the speed accuracy cost function, and performance consistency via standard deviation of the speed accuracy cost function. The results indicated that, throughout skill acquisition, the error augmentation groups had slower, less accurate and less consistent movements but improved in performance efficiency over the course of practice. In contrast, the assistance groups had faster, more accurate and more consistent movements but plateaued in performance efficiency relatively early in practice. Additionally, while there were no effects of bandwidth on performance during skill acquisition, performance efficiency in retention indicated that bandwidth interacted with haptic feedback type. Specifically, there were no learning differences between the types of haptic feedback when presented at the wider bandwidth but the results of the narrow bandwidth groups replicated the results seen in experiment 1: error augmentation enhanced learning relative to assistance.

5.1.3 Experiment three

While in experiment two I attempted to assess whether a reduction of intra-trial haptic feedback frequency might enhance learning, one motivation for the third experiment was to determine whether a reduction of global assistive haptic feedback frequency might enhance learning. However, instead of an experimenter-imposed reduced feedback frequency, I opted to allow one group of learners to choose their own feedback frequency. In Phase One of this study, I investigated the effect of self-control of the haptic feedback schedule on motor performance and learning of the task using a yoking procedure. A control
group (no haptic feedback) was also included in the initial analysis and performance efficiency for all groups was assessed by the speed-accuracy cost function. Phase Two was a qualitative assessment of the views and opinions of both self-control and yoked participants regarding their respective self-selected or externally-imposed haptic feedback schedule and an additional investigation of whether these views and opinions had any impact on motor learning.

The results of Phase One indicated that self-control participants, on average, requested assistance on approximately one third of the skill acquisition blocks but did not adopt a faded feedback schedule. While participants improved their performance over the course of practice, there were no differences in performance among the control, self-controlled or yoked groups. Furthermore, there were no differences between groups on retention tests. However, when the experimental groups were sorted based on the global frequency of assistance experienced during skill acquisition (high: greater than 4 of 12 blocks of acquisition; low: 4 or fewer blocks), there was an interaction between frequency and group such that low frequency self-controlled participants exhibited better retention performance than their high frequency counterparts and the difference between low frequency self-controlled and low frequency yoked participants approached significance.

Data analysis from Phase Two resulted in themes regarding participants’ views of the utility of haptic assistance for performance and learning of the task: positive for performance, positive for learning, neutral or mixed views, and negative for learning and/or performance. Interestingly, these views were differentially distributed across the experimental groups suggesting that group assignment did in fact influence participants’ mindset during the training experience. Notably, in the first half of practice, while half of the self-controlled participants viewed haptic assistance positively for learning, the majority of yoked participants viewed it primarily as an aid for performance. In the second half of practice, a great proportion of self-controlled participants viewed haptic assistance negatively for learning and performance while no yoked participants expressed negative views. Importantly, when these views of haptic assistance were assessed in relation to motor learning, it was found that participants who held a positive performance view in the first half of practice had worse learning outcomes than those holding any other view of haptic assistance.

5.1.4 Summary

Altogether, these studies have demonstrated the following with regards to learning a curve-tracing task with augmented haptic feedback:

1. Error-augmenting haptic feedback is more beneficial for learning than assistive haptic feedback.
2. Lower intra-trial haptic feedback frequencies provided by wider bandwidths do not necessarily enhance learning.

3. When self-selected, lower global frequencies of assistive haptic feedback tend to enhance learning.

4. Experience of a self-selected or externally-imposed haptic feedback schedule is related to learners' beliefs about the utility of assistive haptic feedback.

5. Learners' beliefs about the utility of assistive haptic feedback are associated with their self-selected global frequency of assistive haptic feedback.

6. Performance-oriented beliefs about the utility of assistive haptic feedback are associated with degraded motor learning.

The results of these experiments have emphasized the primacy of an error-based learning mechanism for this task. That is, the experience of error-detection and error-correction, in contrast to multiple, guided, on-target repetitions of the correct movement, were deemed essential for motor learning. The results showed that while error-augmenting haptic feedback was ideal for providing a rich experience of error-detection and error-correction, the control condition (no haptic feedback) could also provide this experience (as in study 1). However, when the control condition was compared to groups that practised with variable combinations of blocks with no haptic feedback and assistive haptic feedback (study 3), there was no significant difference in learning outcomes. Taken together, these findings suggest that while there may not be a benefit to reducing intra-trial feedback feedback (study 2), reducing global feedback frequency may be beneficial, particularly when the frequency is self-selected (study 3). Overall, the key concepts for learning in this context appear to be error-based learning, global feedback frequency, learner autonomy and learner beliefs about the training environment.

5.2 Theoretical Interpretations

5.2.1 Theories of motor learning

In discussing the theoretical interpretations of the present body of work, I will discuss predictions from previously introduced theories of motor learning specifically in relation to the key concepts that have emerged from a summary of the findings (section 5.1.4). It is important to note that, in contrast to OPTIMAL theory, both Adams’ closed-loop theory and Schmidt’s schema theory were developed based on or for a specific class of movements. In the case of Adams’ theory, it was self-paced, positioning tasks and for schema theory, it was discrete movements, particularly those that are rapid, ballistic,
goal-directed movements or slower, linear-positioning movements. However, the task studied in this dissertation fits within none of these categories. Instead, the task would likely fall somewhere on the continuum between serial and continuous movements as it is more comparable to continuous tasks such as tracking and steering than the discrete skills addressed by schema theory. Since there have been no further developments or expansions to these theories to account for such tasks, some of the predictions of these theories may be inappropriate or inapplicable for this specific task.

Overall, findings from all three studies appear to challenge the predictions of both Adams’ theory and schema theory, with respect to feedback frequency: none of the studies showed enhanced learning with higher intra-trial or global feedback frequency. However, it is important to note that these findings are hard to interpret due to the confound between the guiding and informational roles of feedback (cf. guidance hypothesis, [Salmoni et al., 1984]), which is made even more important because haptic feedback is more guiding than verbally or visually presented KR. While the prediction of schema theory regarding feedback frequency was not supported, its predictions regarding the importance of experiencing errors for learning were supported by the present findings. Studies 1 and 2 both showed that error-augmenting haptic feedback was beneficial for learning, which strongly suggests that error-based learning is the primary learning mechanism at play for this task.

Interestingly, neither Adams’ theory nor schema theory address the key concepts of autonomy and learner beliefs that were highlighted by study 3. While OPTIMAL theory does account for these concepts, unfortunately, many of the predictions of this theory cannot be verified by the present findings because they would require analysis of variables which were not measured. Nonetheless, I can speculate about relevant ideas based on the collective results from all three studies.

I suggested in [section 1.3.4] that haptic demonstration may direct learners’ attention internally, in contrast to visual demonstration which likely directs learners’ attention externally. Although the present studies did not utilize haptic demonstration, I propose that haptic assistance may produce a similar effect—directing learners’ attention internally. Consequently, based on OPTIMAL theory, any presentation of haptic assistance may already be poised for sub-optimal motor performance and learning. One may argue that the performance of the control groups in studies 1 and 3, provide evidence against this because these groups did not outperform the experimental groups; however, the authors’ of OPTIMAL theory note specifically that most learners default to an internal focus of attention without specific instructions to do otherwise ([Wulf & Lewthwaite, 2016]).

One prediction of OPTIMAL theory states that challenge accompanied by success produces a dopaminergic response that contributes to learning beyond that which could be achieved by challenge or success alone ([Wulf & Lewthwaite, 2016]). In studies 1 and 2, haptic error-augmentation presented a chal-
lenge for performance but also likely facilitated a sense of success as participants’ performance improved over the course of practice. This experience of success may have also served to enhance expectancies for future performance (one key contributor to motivation in the theory) and contributed positively to learning. This interpretation could also help to explain why the wide bandwidth haptic error-augmentation group did not facilitate learning in relation to its haptic assistance counterpart—this group did not get the same experience of challenge provided to the narrow bandwidth group. In study 3, the experience of a low frequency of guided blocks may have also provided a balance of challenge and success that enhanced learning in relation to higher frequencies of guided blocks. Importantly, this learning benefit was observed only for the self-control group which may also speak to the importance of autonomy (the second key contributor to motivation) for motor learning.

Related to the idea of challenge culminating in success, is the prediction that training conditions which optimize performance also facilitate learning. At first glance, this may appear to be at odds with the literature on contextual interference (T. D. Lee & Simon, 2004; Magill & Hall, 1990) and the guidance hypothesis (e.g., Park et al., 2000; Schmidt, Young, Swinnen, & Shapiro, 1989; Winstein et al., 1994). Certainly, the level of performance attained at the end of skill acquisition, for each of the three studies, did not predict the learning trends that were observed based on retention performance. However, this prediction of OPTIMAL theory is more complicated that mere optimization of performance during skill acquisition. As noted by T. D. Lee and Simon (2004), metacognition is a key component during skill acquisition. Do learners perceive that their performance is improving? Are learners equating performance improvements with learning? How learners perceive their experience is essential to their experience of, engagement with and approach to the learning environment. As such, the optimization of motor performance during training also includes optimization of observable improvements in motor performance. This interpretation of the theory would be supported by the findings of study 2 whereby, in contrast to assistive haptic feedback, error-augmenting haptic feedback produced improvements in performance efficiency and performance consistency over the course of skill acquisition.

Although none of the predictions of OPTIMAL theory specifically mention feedback, based on the prediction that temporally associated conditions that enhance expectancies should benefit motor performance, an additional consideration may be the extent to which our feedback presentations may have acted as one such temporally associated condition. Given that participants knew that the retention tests would be conducted in the absence of any haptic feedback, even if participants judged that their performance was improving over the course of practice, the fact that they continued to receive haptic feedback throughout skill acquisition (in studies 1 and 2) may have degraded their expectancies for success and negatively affected learning. Some participants’ responses to the open-ended questionnaire in study 3
indicated that they were in fact using guided blocks to judge whether or not their performance had improved. If learners’ perceptions of the amount of haptic feedback received on such blocks did not signal performance improvement, this may have fed into the “vicious cycle” described by Wulf and Lewthwaite (2016, p. 1405): low self-efficacy, decreased expectancies, increased self-focus with decreased focus on the task goal, degraded motor performance and therefore sub-optimal learning.

5.2.2 Error-based learning & internal models

As evident from the discussion above, the degree to which I can provide an adequate interpretation of findings though the lens of any one theory is limited. Error-based learning is a key concept not adequately described by any of the above theories but which, I believe, is important for understanding this body of work. I briefly described error-based learning and internal models in Study 1: Discussion (section 2.4) but provide a fuller discussion of these concepts here.

Learning from errors or error-based learning is a well-known, though contested (e.g., Sanli & Lee, 2014), concept in motor learning (Seidler, Kwak, Fling, & Bernard, 2013) and our current understanding of an error-based learning mechanism has grown out of the development of forward model control theories (Diedrichsen, White, Newman, & Lally, 2010). “Internal models” are models within the brain that predict or map the sensory consequences of an action as opposed to literal representations of transformations governed by physics in the world (i.e., our bodies and the environment) (Wolpert, Ghahramani, & Flanagan, 2001).

Inverse models represent the transformation of desired goals into a plan for achieving them while forward models simulate or predict the outcomes of a given movement plan (Kawato, 1999). When sensory systems detect movement errors, this information is used to update motor commands for subsequent actions. However, because there is a time delay between sending an initial motor command and receiving the resultant sensory information, the central nervous system (CNS) would be disadvantaged by relying solely on sensory feedback. Additionally, ongoing movements lead to continuously changing state variables, such as limb position and limb velocity, which make it even more difficult to make precise adjustments in response to movement errors. As such, forward models exist to predict the sensory outcomes of planned movements and facilitate more accurate adjustments to movements (Lalazar & Vaadia, 2008; Seidler et al., 2013; Wolpert et al., 1995). Moreover, the forward model is useful for facilitating the following functions: (i) predicted sensory outcomes compensate for limitations and noise of the sensory system (Wolpert et al., 1995); (ii) predicted sensory outcomes are used to anticipate and remove the actual sensory effects of self-initiated movements from all incoming stimuli (Lalazar & Vaadia, 2008).
Wolpert et al. (1995); and (iii) the difference between actual and predicted sensory outcomes is interpreted by the CNS as a feedback error signal which updates any subsequent motor commands and guides learning of the internal models or can be used for mental practice (Lalazar & Vaadia, 2008; Wolpert et al., 2001, 1995).

Motor learning, therefore, is a process of updating motor commands or acquiring “forward and inverse internal models appropriate for different tasks and environments” (Wolpert et al., 2001). For new skills, the CNS will not have much experience updating the forward model and so prediction errors will be large. As such, learning proceeds through repeated exposure to motor errors (typically through physical practice; cf. Adams’ (1971) closed-loop theory of motor learning) which serve to refine the forward model (Donchin, Francis, & Shadmehr, 2003; Vercher, Sarès, Blouin, Bourdin, & Gauthier, 2003).

This conceptualization of learning supports the observed benefits of error-augmenting haptic feedback for learning, the failure to obtain better learning outcomes with a wider bandwidth/greater tolerance for error, as well as the benefits of reduced global feedback frequency for learning. In each case, the rich and varied experience of detecting and correcting errors (whether augmented or naturally occurring) likely strengthened the internal model for the task and enhanced learning. In contrast, the experience of assistive haptic feedback throughout all or most skill acquisition trials (studies 1 and 2, and high feedback frequency learners in study 3) likely strengthened the internal model for a slightly different task (one that included the dynamics of assistance/error minimization) or interfered with the development and strengthening of the internal model required to perform the task in the absence of augmented (haptic or visual) feedback.

It is important to make a distinction here between the products of motor learning (i.e., an internal representation of the desired trajectory or transformation) and the processes or mechanisms of motor learning of which there are a few, each with their own related neural mechanisms (Heuer & Lüttgen, 2015). Error-based learning is only one such learning mechanism that can lead to the development of appropriate internal representations. In theory, different learning mechanisms will operate together to create an appropriate internal representation for the desired movement goal. However, based on the details of the task and environmental conditions, one or more specific learning mechanisms may be dominant (Heuer & Lüttgen, 2015) and in this dissertation, I have proposed that the findings indicated the primacy of an error-based learning mechanism for the investigated task. While this interpretation of findings does not fit with Adams’ theory of motor learning, it does resonate with some predictions of schema theory and may be part of the goal-action coupling mechanism identified in OPTIMAL theory.
5.3 Limitations

Although the findings of the dissertation are fairly consistent across all three studies, there are some important caveats that should be considered. First, the results obtained herein relate to only one task, presented under very specific conditions. It is impossible to say how generalizable the findings will be for other tasks or for different parameters of haptic feedback presentation, for example, gain or magnitude (see Study 1: Methods, section 2.2), and to some extent, bandwidth (see Study 2/Chapter 3).

Second, we attempted to measure intra-trial feedback frequency via percentage of samples within the bandwidth but a more useful measure may have been the number of bandwidth crossings per trial. This measure would have provided information about the number of corrections that participants made—another way of considering performance consistency in relation to the bandwidth. It is unknown how such a measure may have altered our interpretation of findings for any of the presented studies.

Third, as mentioned in Study 1, section 2.4.2, a possible reason for the benefit of error-augmentation is that random perturbations cause co-contraction of muscles which can increase movement precision (Heuer & Lütten, 2015). While I did not attempt to separate the contribution of this phenomenon from the proposed error-based learning mechanism, future studies could attempt to do so by monitoring limb stiffness with both forms of haptic feedback and exploring the impact of varying the predictability of perturbations.

Fourth, although we obtained some important insights into participants’ thought processes via the open-ended questionnaire (Study 3: Phase 2, section 4.3), the questionnaire was retrospective; that is, participants answered questions about each half of practice at the end of practice. One possible consequence of this approach is that participants were unable to accurately recall their thoughts regarding each half of practice and/or that they were unable to make distinctions between thoughts pertaining to each half of practice. This, of course, is a threat to the validity of the findings. One alternative was to present a separate questionnaire regarding each half of practice immediately following each half of practice. However, this procedure could introduce bias by changing how participants assessed their task performance and formulated strategies for the second, upcoming half of practice. As such, the decision to present the entire questionnaire at the end of practice was a trade-off and the fact that we obtained differential results for each of half practice suggests that, at the very least, participants were able to differentiate thoughts related to each practice half.

Fifth, due to time constraints, in study 3 we did not include measures of any constructs related to motivation or other states of mind, such as anxiety. As such, any conclusions regarding participants’ motivation as it related to whether or not they had autonomy regarding haptic feedback schedule, are
merely speculative. Measurement of motivation (Sanli et al., 2013) and related constructs such as self-efficacy and affect would have been useful for supporting and informing interpretation of the themes that emerged from qualitative data analysis.

5.4 Future Directions & Practical Implications

Extending the line of research outlined in this dissertation could include explorations of how participants choose to schedule both types of haptic feedback after receiving some introductory training on the use of feedback and learning strategies as they relate to the task. An additional line of research could assess the impact of allowing learners to select haptic feedback intermittently during performance of the task. These investigations would help clarify whether a performance-based, self-directed feedback schedule would produce the benefits of autonomy observed in so many other motor learning studies and whether the nature of feedback (assistive versus error-augmenting) remains important under autonomy-supportive experimental conditions. As discussed previously, measurement of motivation-related concepts such as self-efficacy, affect and confidence, would also help to determine the importance of motivational versus cognitive processes on any observed learning effects. Finally, it would be interesting to explore whether my hypothesis regarding focus of attention as a function of assistive versus error-augmenting haptic feedback is empirically supported.

For researchers in applied fields that utilize or are beginning to explore haptic training, the findings outlined in this dissertation also offer a number of suggestions for enhancing current training practices as well as avenues for further exploration of this training modality. The present results highlight the importance of assessing the tasks of interest to determine the most relevant mechanism(s) of learning (Heuer & Lüttgen, 2015). One learning mechanism (error-based) was particularly relevant for the task employed in this dissertation. As such, efforts to utilize other learning mechanisms to facilitate learning of this task would likely be futile. Similarly, if trainers/rehabilitation care providers/experimenters are tapping into inappropriate learning mechanisms or utilizing training approaches that do not capitalize on the most relevant learning mechanism(s), then training outcomes will likely be sub-optimal. A recent systematic review of error-augmentation approaches for motor recovery of the upper extremities after stroke found moderate evidence in support of using error-augmentation post-stroke but noted that there is not enough high quality evidence to make a conclusion regarding its utility (Israely & Carmeli, 2016). While Heuer and Lüttgen (2015) suggested that error-augmentation should be beneficial primarily for dynamic and kinematic transformation learning, inspection of the eight studies included by Israely and Carmeli revealed that the trained tasks included transformation as well as trajectory-based tasks (such
as reaching). As such, one reason for the equivocal results may be sub-optimal matching of tasks to training procedures.

The findings of study 2 demonstrated that a technical feature of haptic training paradigms can impact observations regarding its relative utility for training. The highlighted feature was bandwidth or tolerance for error. While most researchers do not specifically state what bandwidth was used or if it was optimized for the task, the findings of study 2 indicated that bandwidth influenced the relative benefits of assistive and error-augmenting haptic feedback. As such, I encourage researchers to be explicit about this technical feature of haptic training and explore how it impacts the effectiveness of their training paradigms.

Data from study 3 strongly suggest a link between learner beliefs, the enactment of learning strategies, and motor learning. I suspect that these relationships will be even more important and their effects more evident in applied environments, such as sports training and rehabilitation, where the practice context is laden with meaning beyond “research participation.” Recently, Dobkin (2016) outlined arguments for the inclusion of behavioural training in self-management techniques in rehabilitation services. Behavioural training could include information regarding the use of feedback about performance, the consequences of (in)action in relation to health, and instruction for goal-setting. He argued that such training could enhance self-efficacy and increase the amount of time spent exercising as part of formal rehabilitation sessions and during home programs. Fuller investigations of these factors (beliefs, self-efficacy, etc.) will require additional methodologies and expertise but are poised to enrich our understanding of the mechanisms underlying motor learning and motor recovery.

Finally, it is imperative that researchers in applied fields clearly define the framework for the term “learning.” I have advocated for adoption of the definition most often used in the motor learning literature and encourage applied researchers to design studies that can adequately make conclusions, not just about performance under or immediately following experimental conditions, but about learning—long-term, relatively permanent changes in the ability to perform a task. Such protocols will utilize the principles of a transfer design and employ retention and/or transfer tests (as opposed to test-retest or cross-over experimental paradigms) and ideally, between-group comparisons.

5.5 Conclusions

In this dissertation, I explored multiple ways of optimizing the presentation of haptic feedback when learning a self-paced, curve-tracing task. The results have shown that error-augmenting haptic feedback is better than assistive haptic feedback for facilitating learning and that self-selected reduction of global
feedback frequency (but not experimenter-imposed reduction of intra-trial feedback frequency via wider bandwidth) also facilitated learning. These findings are significant because:

1. They add to the body literature demonstrating the benefit of error-augmentation for particular tasks.

2. They call into question various haptic training studies that purport to report learning effects but have not utilized a transfer design.

3. They indicate that, in contrast to the majority of the motor learning literature, narrower bandwidths can be more beneficial for learning.

4. Importantly, they demonstrated relationships among learners’ beliefs about the training environment, their strategic decisions regarding training, and motor learning.

These findings have implications for continued experimental research in haptic training, especially in light of the recently proposed OPTIMAL theory of motor learning, as well as applications of these concepts in applied fields such as rehabilitation and sports training. In sum, it is recommended that researchers interested in developing haptic training programs, for similar tasks, focus on error-augmented delivery of haptic feedback at relatively narrow bandwidths but also explore autonomy-supporting training features and the impact of learners’ beliefs about the training environment and procedures.
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Declaration of Previous Publication

This dissertation includes four original papers that have been published or accepted for publication in peer reviewed journals. Details regarding each paper (full citation and publication status) are provided in their respective chapters or sections of the dissertation: Section 1.3, Chapter 2, Chapter 3, Chapter 4. Permissions have been obtained from the various copyright owners to include these materials in my dissertation.

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