Robotic Guidance: Velocity Profile Symmetry and Online Feedback Use During Manual Aiming

by

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A thesis submitted in conformity with the requirements for the degree of Master of Science
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Abstract

The current study evaluated whether robotic guidance can influence movement planning and/or the use of online proprioceptive feedback. Participants were divided into three groups wherein they practiced an aiming task unassisted or via a robotic device that led them through a trajectory with an asymmetric or symmetric velocity profile. Baseline performance was measured prior to training and a post-test included control and tendon vibration trials. Temporal, spatial, and kinematic variables were used to assess planning and online control mechanisms. Results indicated that tendon vibration altered the way individuals planned their movements and used online sensory feedback. Robotic-guided groups appeared to use online feedback to a lesser extent than the unassisted group during tendon vibration trials, based on kinematic data. Individuals may become less inclined to use erroneous proprioceptive feedback following robotic guidance, supporting the potential benefit of robotics in neuro-motor rehabilitation for those with proprioceptive deficits.
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Chapter 1. Review of Literature

1.1 Introduction

The ability to produce goal-directed actions, such as picking up a cup of coffee or pushing an elevator button, is a necessary component of autonomous living. The perceptual-motor mechanisms underlying such seemingly simple movements have been studied for over a century (Woodworth, 1899), but have yet to be fully understood. Moreover, researchers diverge in their views regarding how such movements are controlled, learned, and re-learned. This divergent thinking is not surprising considering the amount of neural processing involved in just a simple pointing movement. Further, understanding motor learning becomes even more complex when considering the use of robotic guidance during such processes. Indeed, there has been a growing use of robots in research and rehabilitation settings, although the impact of robotic guidance on the control and learning of goal-directed movements is not well understood. Perhaps one way to resolve this question is to start from the structures involved.

The central nervous system (CNS) must coordinate and integrate information from multiple sensory systems for movement planning and control to ensure maximal accuracy and efficiency. Vision provides information about the spatial configuration of the external world relative to the body, while proprioception provides the sense of the limb position and movement relative to the body. From a neurophysiological perspective, proprioceptive feedback encompasses information about muscle length and force production, based on afferent signals arising from muscle spindles, and Golgi tendon organs, respectively (Kandel, Schwartz, & Jessell, 2000). In this thesis, the visual and proprioceptive systems’ role in the control and acquisition of goal-directed actions will be the primary focus.

With respect to motor control research, the most notable contribution in the study of goal-directed movement is Woodworth’s two-component model (1899). Woodworth used reciprocal aiming movements to study the role of planning and sensory feedback during movement execution. The trajectories of these movements were recorded by having participants perform the task with a pencil over paper, which was attached to a rotating drum. The use of feedback obtained during the movement (i.e., online control) was assessed under conditions of eyes open and closed, while participants kept up with various metronome speeds. Woodworth observed a
significant impact of vision availability through visible trajectory amendments taking place late in the movement. These late amendments often lead to lengthened movement duration and more asymmetric movement profiles (i.e., more time spent after peak limb velocity).

Although there has been great deal of technological advancement since the publication of Woodworth’s monograph, discrete aiming movements continue to be used to provide insight into central mechanisms governing action. Technological breakthroughs, coupled with knowledge of motor control and learning principles provided an opportunity to establish novel training and therapeutic approaches. Specifically, robotic devices have emerged in recent years as a tool with the potential to improve rehabilitation practices, particularly for those whose impairments are neurological in nature. A primary concern with the current literature is the inability to explain results relative to movement control strategies. Specifically, does robotic guidance have a potential role in improving movement planning strategies, or online error correction mechanisms, or both? In addition, multiple sensory systems contribute to the control of action in various ways, depending on the information available, the context, and specific nature of the goals (i.e., spatial vs. temporal). Having this in mind, the current state of the literature has yet to (a) determine if robotic guidance can alter the weighting of sensory information, and (b) understand the effect of robotic guidance training on the comparative role of movement planning and online feedback in performing goal-directed actions. The purpose of the research presented in this thesis is to examine whether robot-guided training and the kinematic characteristics of the trajectory provided can influence movement control and multisensory integration strategies. The following review of literature provides a brief overview of motor control and learning principles relevant to the use of multisensory feedback and outlines the current state of knowledge about the use of robotic guidance systems in motor skill acquisition and rehabilitation.

1.2 Control of Goal-Directed Actions

As mentioned earlier, Woodworth (1899) provided a foundation on which a large proportion of the current motor control research lies. His results illustrated several characteristics of discrete aiming movements, including an initial, highly stereotyped segment, followed by discrete corrections closer to the target. Based on his results, Woodworth formulated a two-component model in which an initial impulse or ballistic phase is predominantly pre-planned and serves to bring the limb into the vicinity of the target, and a secondary current-control or homing phase,
during which feedback-based corrections are made (i.e., corrections made using feedback available after movement onset). Other scientists have built upon, and proposed alternative models explaining the visual regulations of movement (see Elliott et al., 2010 for a review). Yet, the premise of the two-component model (i.e., the ballistic and current control phases) has continued as a dominant explanation for the visual regulation of goal-directed movement. Interestingly, Woodworth’s results showed that discrete corrections were present even in the absence of vision. It is possible that these corrections were actually planned or based on a sensory modality other than vision (e.g., proprioception). Proponents of open-loop models of motor control (i.e., movements executed without any contribution of online feedback) have asserted that all features of the movement, including discrete corrections, perhaps based on previous movements, are planned prior to action initiation (Plamondon & Alimi, 1997). While such an explanation is difficult to formally refute, this thesis will build on the assumption that the discrete online trajectory corrections observed by Woodworth, in the presence and absence of online visual information, were based on feedback available during the trajectory (i.e., closed-loop control).

To infer the relative contribution of feedback on temporally constrained actions researchers have evaluated movement characteristics using spatial, temporal, and kinematic variables. Additionally, measures of discrete and non-discrete online trajectory corrections have been developed to understand how such feedback-based control strategies present during a movement. The developed methods of analyses (described in detail below) have proven useful when quantifying the effect of sensory manipulations relative to online control. Thus, researchers have determined stable attributes of movements performed under various conditions of sensory feedback availability. Moreover, based on these movement features, theories explaining the influence of practice on feedback-based control mechanisms have evolved (i.e., the role of adaptation and learning).

1.2.1 Visual regulation of movement and methods of inferring online control

The simplest sensory manipulation at the disposal of researchers involves altering the availability of vision. This technique has been employed using various methods, including, but not limited to: having participants close their eyes (e.g., Woodworth, 1899), extinguishing room lighting (e.g., Elliott, Garson, Goodman, & Chua, 1991), representing limb and target location using
LEDs or in virtual environments (e.g., Heath, 2005), and using liquid-crustal goggles (e.g., Elliott & Hansen, 2010). Without online visual feedback, any observed behaviour is deemed attributable to an alternative control strategy, such as pre-movement planning, or proprioceptive-based feedback. Therefore, the ease with which vision can be manipulated, relative to other sensory modalities, guided a large body of work revolving around such manipulations. It also became necessary to develop analyses to assess the influence of altering feedback, which have included various forms of trajectory assessments including measures of discrete path amendments, and more recently, indices of non-discrete adjustments. As such, the influence of visual manipulations on goal-directed behaviours is presented here in conjunction with a review of trajectory analysis methods.

Assessing movement outcomes using variables such as endpoint error values (e.g., constant error, variable error, etc.) and movement time provided information about the general features of actions performed with and without visual feedback. Not surprisingly, vision of the hand and environment leads to more optimal endpoint accuracy and slower movements compared to no-vision (Chua & Elliott, 1993; Khan, Franks, & Goodman, 1998). Investigations into the relationship between online control strategies and speed-accuracy trade-offs have manipulated target widths and instructions, resulting in changes in movement time and accuracy. For example, smaller target widths correspond to increased accuracy demands and result in longer movement times (Fitts, 1954; Fitts & Peterson, 1964). Instructions directing participants to focus on reaching the target as accurately as possible or as quickly as possible are also important to consider (e.g., Elliott et al., 1991). When participants are instructed to focus on speed, there is a significantly greater degree of error while a greater focus on accuracy elicits slower movement times to effectively reduce error when performing movements in full-vision (Elliott et al., 1991). While the consequences of manipulating visual feedback are evident, these consequences are not enough to infer the control strategies used by the CNS under different vision conditions. To understand the extent that feedback is used online, performance characteristics about the execution of the movement must be evaluated in conjunction with endpoint results.

Trajectory analyses exploring the persistence of online feedback use (visual and non-visual information) have examined the frequency and efficiency of discrete and non-discrete limb trajectory amendments (see Elliott & Hansen, 2010 for a comparison of analyses). For example, the relative proportion of movement time spent decelerating is deemed indicative of the
contribution of feedback-based corrective processes (see Elliott et al., 2010). One consistent outcome of greater online feedback processing is an increased asymmetry in the velocity profile, or more time spent after than before peak limb velocity (e.g., Chua & Elliott, 1993; Elliott et al., 1991; Elliott, Chua, Pollock, & Lyons, 1995). The operating assumption behind the observed velocity asymmetry is that individuals use the increased proportion of time spent decelerating to produce more efficient feedback-based corrections, thus yielding smaller endpoint error (see Elliott et al., 2010). Kinematic discontinuities in this secondary portion of aiming constitute the discrete trajectory corrections of Woodworth’s current control phase (1899; see Elliott et al., 2010). Such kinematic discontinuities are defined as zero-crossings in velocity and acceleration profiles as well as substantial deviations of acceleration (Meyer, Abrams, Kornblum, Wright, & Smith, 1988). Movement parsing techniques have yielded results showing that discrete adjustments occur in the absence of vision (i.e., proprioceptive-based; Woodworth, 1899) to the same extent as visually-based corrections, but are less helpful in reducing endpoint error (Elliott et al., 1991). Moreover, Elliott et al. (1991) calculated the correlation between the number of discrete corrections and radial error and time spent decelerating and radial error. The availability of vision and time spent decelerating better-predicted endpoint accuracy than the number of submovements leading to their suggestion of a potentially continuous or pseudo-continuous mode of control resulting in online corrections that are not apparent in the kinematic profiles.

The continuous/pseudo-continuous model argues that the absence of discontinuities, such as is typically observed in the ballistic phase, does not necessarily imply a lesser extent of online control (Elliott et al., 1991). Rather, Elliott and his colleagues (1991) contend that feedforward and feedback processes mediate comparisons of expected-to-actual sensory consequences, resulting in either gradual adjustments to muscular forces (i.e., continuous control) or small, discrete amendments that occur frequently and subsequently overlap (i.e., pseudo-continuous control). Consequently, methods to evaluate non-discrete corrections emerged using between-trajectory comparisons of positional variability to infer online and offline control mechanisms. The premise of this technique was that errors, due to movement planning limitations and/or inherent neuromotor noise, would persist or become amplified without the presence of online adjustments (i.e., variability early in the movement should be maintained or increased as the movement unfolds; Khan et al., 2006).
Khan et al. (2003) analyzed the control of aiming with and without visual feedback of the limb’s position in fast and slow movement time conditions. The standard deviation (SD) of the limb’s position at four kinematic markers (i.e., peak acceleration: PA; peak velocity: PV; peak deceleration: PD; and movement end: END) was calculated to obtain variability profiles. Additionally, a variability ratio was calculated for all markers comparing full-vision (FV) and no-vision (NV). Results showed few differences between FV and NV variability ratios during fast movements. However, during slow movements, the FV condition displayed a significant drop in variability between PD and END; an effect that was present but relatively smaller in the NV condition and further supporting the closed-loop contribution, particularly of vision, leading to late corrections (Khan et al., 2003). Moreover, these results support the idea that trajectory amendments do not necessarily take the form of discrete corrections and differences in movement control strategies can be identified using non-discrete trajectory evaluations.

Heath (2005) also used a statistical approach comparing both within and between movements to determine the extent to which the limb’s position at PA, PV, and PD accounted for the variability in its final position, by calculating a correlation coefficient between the limb positions observed at each kinematic marker and limb positions at movement end. The coefficient was then squared for statistical analyses (i.e., $R^2$). The rationale for this analysis was that the more online control processes were responsible for movement endpoint, the less the limb position at a specific kinematic marker should be able to explain endpoint, resulting in smaller $R^2$ values (Heath, 2005). Therefore, stereotyped movements, resulting from a greater governance of pre-movement planning processes, should produce more robust $R^2$ values (Heath, 2005). In looking at the effect of limb vision versus target vision, Heath (2005) found that vision of the limb yielded the smallest endpoint error and least variability. The least endpoint error and variability were observed when both the limb and target were visible throughout the duration of the trial. Moreover, an interaction between limb vision and kinematic marker showed no significant difference at PA between limb visible and limb occluded trials, but $R^2$ values at PV and PD were significantly smaller when the limb was visible. Participants were most accurate when vision of both the limb and target was available, an effect attributable to online control processes based on the low $R^2$ evident in this condition (Heath, 2005). The trajectory analysis employed by Heath (2005), in conjunction with accuracy data, supports the importance of relevant visual cues for the
online control of movement and further evidences the CNS’s ability to make feedback based corrections, which do not necessarily emerge as discrete trajectory corrections.

Temporal and spatial variables are valuable tools in measuring the influence of different sensory conditions on aiming. However, it is important to note that the absence of marked differences among movement time and endpoint error values does not necessarily imply a common control strategy among different conditions. Rather, detailed assessments of trajectory characteristics (i.e., velocity profile symmetry and between-trajectory analyses) allow researchers to discern whether differences in endpoint accuracy (or lack thereof) were brought about by a change in movement control strategies. Moreover, closed-loop control strategies may not necessarily be reflected in discrete online trajectory amendments. Overall, a healthy and intact CNS is able to adapt and control movements to maintain or improve temporal and spatial movement characteristics. The described inferences about online control mechanisms are derived from visual manipulation studies and have predominantly been used to describe the visual control of movement. The proprioceptive contribution to movement control can be inferred, to some extent, from visual manipulations but alternative perturbations exist to allow for a more direct measurement of proprioceptive control.

1.2.2 Proprioceptive perturbations: The influence of tendon vibration

Visual manipulations have yielded insight into the mechanisms governing the visual regulation of movement and supported the existence of non-visual feedback based control strategies. As discussed in the previous section, by removing visual feedback, we can infer in the influence of proprioception and/or movement planning. Unlike visual manipulations, there is no simple method of removing and returning proprioceptive feedback. Currently, research aimed at measuring the effect of proprioceptive feedback withdrawal are limited to studying surgically deafferented monkeys (e.g., Polit & Bizzi, 1979) and individuals with sensory neuropathy (e.g., Sainburg, Ghilardi, Poizner, & Ghez, 1995; Sainburg, Poizner, & Ghez, 1993; Sarlegna, Gauthier, Bourdin, Vercher, & Blouin, 2006). Such studies have been instrumental in understanding the role of proprioception in motor control because they have illustrated the importance of proprioceptive feedback in multi-joint coordination (Sainburg et al., 1993) and in updating internal models (Sarlegna et al., 2006). Alternatively, non-invasive perturbations involving healthy participants have used tendon vibration to disrupt proprioceptive feedback.
Tendon vibration has provided an effective method to alter proprioceptive feedback in stationary (Goodwin, McCloskey, & Matthews, 1972) and moving limbs (Capaday & Cooke, 1981; Cody, Schwartz, & Smit, 1990; Inglis & Frank, 1990; Redon, Hay, & Velay, 1991). Vibrating the muscle (e.g., biceps tendon) of a static limb has shown an induced an illusory motion (i.e., muscle lengthening) when vision is unavailable (Goodwin et al., 1972), leading to the perception that the limb is extended further than it is in reality. “The distortion is most simply attributed to the vibration-induced discharges of muscle receptors being interpreted by the higher centres as if they were due to muscle stretch, the sensation being referred to the joint as if it were moving in the appropriate direction” (Goodwin et al., 1972, p. 709). When vibrating the biceps tendon of a stationary arm, and asking participants to match its position with the other arm, Goodwin and his colleagues (1972) found that participants would position their matching arm at an angle that was far more extended than the vibrated arm. Their argument for this effect was that vibration resulted in increased Ia muscle spindle activation, signalling muscle stretch (Goodwin et al., 1972). The perturbed perception of limb position has also been demonstrated when vibrating muscles during passive (Cordo, Gurfinkel, Bevan, & Kerr, 1995) and active motions (Capaday & Cooke, 1981; Inglis & Frank, 1990; Redon et al., 1991). Distorted endpoint accuracy results obtained when vibrating the lengthening muscle during a movement implies that proprioception contributes to the online control of movement (Redon et al., 1991), corroborating accounts based on visual manipulations (Elliott et al., 1991; Woodworth, 1899).

Redon et al. (1991) assessed the influence of vibrating the biceps brachii tendon during a goal-directed movement involving multiple joints (i.e., should and elbow) in a series of 3 experiments to quantify the proprioceptive contribution to online control. All 3 experiments required participants to aim to one of 4 targets without vision, as well as with and without vibration (blocked into 32 trials each). In the first experiment, vibration was applied throughout a 200, 500, and 800 ms movement resulting in a main effect of vibration on constant error in the x-axis (i.e., leftward bias). An interaction was present between vibration condition and movement time, with a significantly greater degree of leftward error in the 800 ms condition relative to the 500 ms condition. In their second experiment they used a single movement time of 800 ms, this time applying vibration for 200, 400, and 600 ms after movement initiation. While there was no significant difference in constant error in the primary direction as a function of the 3 vibration durations, movements were significantly more deviated to the left in the 800 ms condition (i.e.,
Experiment 1) relative to each of the 3 vibration conditions in Experiment 2. The final experiment in the set compared a 200 and 800 ms movement, with vibration applied for 200 ms, either encompassing the entire duration of the movement (i.e., MT: 200 ms), or the first or final 200 ms of the movement (i.e., MT: 800 ms). Vibration applied during the terminal 200 ms of movement resulted in a significantly greater effect on constant error (i.e., deviation to the left) than when vibration was applied during the first 200 ms of movement. Thus, Redon et al. (1991) demonstrated that the proprioceptive information could be used online to regulate movement.

### 1.2.3 Multisensory integration

Thus far, the contribution of individual sensory systems has been discussed, however withdrawing or perturbing a single sensory modality does not negate online feedback regarding the information transmitted by the modality in question. Rather, a greater contribution of other sources of information may be necessary (Welch, 1978). Even in the absence of any sensory manipulations, multimodal cues must be combined and integrated to provide an accurate and stable representation of the environment relative to the body (Ernst & Bülthoff, 2004). According to Ernst and Bülthoff (2004), the effective use of multisensory information requires *sensory combination* “to maximize information delivered from the different sensory modalities” (p. 162) and *sensory integration* “to reduce the variance in the sensory estimate to increase its reliability” (p. 162). When the CNS is unable to form a clear perceptual representation of a situation, based on one or more sources of information, it must continue to process, or combine, additional sensory cues until an accurate interpretation exists (Ernst & Bülthoff, 2004).

Redundant cues are processed using sensory integration strategies, which have been described using the *maximum-likelihood estimation* (MLE) model to explain how the CNS minimizes the inherent variance of the final perceptual estimate (Ernst & Banks, 2002). The MLE account posits that the CNS uses Bayesian rules to sum the contribution of individual modalities, each having an assigned weight proportional to its degree of reliability (Ernst & Banks, 2002). The modality having the greatest probability of delivering the least variable information (i.e., most reliable) is given the most weight (Ernst & Banks, 2002). While theories of sensory integration provide effective explanations of static perceptual processes relative to goals, we must also consider how such integration strategies change as a function of movement stage (i.e., planning and execution) and practice.
To understand multisensory coordination during movement planning processes, Rossetti, Desmurget, and Prablanc (1995) assessed the effect of visually displacing the limb’s starting position with a prism in comparison to presenting accurate visual feedback about limb’s initial position. Feedback about the target’s position was not altered and vision of the limb (in both true and displaced conditions) was removed at movement initiation. Movement endpoint in the displaced condition showed a bias of a third of the displacement in the direction opposite the displacement, indicating that visual and proprioceptive information about the initial limb position was “fused” to create a biased representation of starting limb position on which a motor plan was based (Rossetti et al., 1995). Specifically, the visual system was not solely responsible for encoding the movement plan. Proprioceptive feedback about the true starting limb position mitigated some of the effect of the prism displacement; otherwise the magnitude of endpoint error should have been proportionate to the displacement magnitude. Rather than “fusing” visual and proprioceptive feedback for a single purpose, as suggested by Rossetti and colleagues (1995), Sober and Sabes (2003) theorized that visual and proprioceptive information each play a dominant role in one of two distinct stages of movement planning. To test their theory Sober and Sabes used a virtual environment to displace visual feedback about starting limb position and ascertained the influence of such a manipulation by comparing initial reaching characteristics with computational models of movement planning. Results indicated that cues about start and end positions are used to identify distance parameters and the proprioceptive system specifies the muscular forces required to displace the limb by the appropriate distance (Sober & Sabes, 2003).

When coordinating information during movement execution, the CNS has a tendency to place more focus on visual feedback over other modalities (Hay, Pick, & Ikeda, 1965). This led Bernier, Chua, and Franks (2005) to predict that in the presence of a visuo-motor conflict, proprioception would not be calibrated if vision was available during adaptation. Bernier et al. (2005) asked participants to practice an aiming task in which the visual location of a cursor representing limb position was rotated 2.5 cm to the right of the limb’s veridical location. The task was performed with either full vision of the cursor throughout the movement or no-vision, in which the cursor extinguished at movement onset and a visual trace of the path appeared at the end of the trial. Pre- and post-tests were conducted with no-vision and no knowledge of results (KR; i.e., visual feedback about the movement path). Endpoint position was significantly more deviated at the end of acquisition and the initial half of the post-test in both groups, relative to
the pre-test. This effect faded towards the end of the post-test in the FV group but remained strong throughout the duration of the post-test in the NV group. When vision of the cursor was available, the CNS relied most predominantly on online visual feedback but when it was removed the CNS was forced to rely on proprioceptive feedback, which had not been attended to or calibrated to the induced bias (Bernier et al., 2005).

There is a clear distinction in the information visual and proprioceptive signals relay and their purpose in the planning and the execution of movement. The visual system provides a representation of the external environment relative to the body and limb positions and the proprioceptive system specifies an internal representation of limb position relative to body orientation. The availability of both sources of feedback does not imply that they are integrated equally; rather a clear emphasis is placed on visual information in the attainment of a spatial goal requiring accuracy (Bernier et al., 2005). The greater influence of vision is exhibited to the extent that visual feedback can mask the proprioceptive contribution to motor control (Bernier et al., 2005). Additional insight into multisensory integration processes has been derived from learning studies because individuals may adapt and change strategies as a function of experience with a given task. The influence of practice on such integration strategies is discussed in the following section.

1.2.4 Motor learning

While the effect of feedback on single trajectories has been discussed, we must now consider how feedback utilization changes as a function of practice. Models have been presented advocating that a shift toward open-loop control emerges with practice (e.g., Schmidt, 1975). However, alternative theories have claimed that an increasing reliance on feedback emerges as a function of practice (e.g., Proteau, Marteniuk, Girouard, & Dugas, 1987).

According to open-loop accounts of motor learning, in order to produce a movement, individuals must draw upon their previous experiences with similar movements to specify the muscular contractions necessary to achieve a desired goal. This set of experiences form what Schmidt (1975) coined a generalized motor program (GMP). At the heart of the GMP is the motor response schema that stores past responses to a set of conditions, or parameters, and their associated sensory and physical outcomes (Schmidt, 1975). It further stands to reason then that the more experiences individuals have with different parameters and their associated
consequences, the better they will be able to parameterize future movements to achieve a goal (Schmidt, 1975). According to this concept termed variability of practice, individuals should practice a task with several possible outcomes (e.g., movement distances) to improve their ability to parameterize future movements (see Shapiro & Schmidt, 1982). Schmidt’s (1975) schema theory argues that variable practice results in less reliance on afferent feedback online because individuals are becoming better at specifying parameters prior to movement start.

Proteau et al. (1987) assessed whether the utility of visual feedback was dependent on the type of information available (i.e., vision of the target vs. vision of the limb and target) by having participants acquire a 90 cm aiming skill of 550 ms in duration. Proteau and his colleagues (1987) also measured the efficacy of the described sources of visual feedback after moderate (i.e., 200 trials) or extensive (i.e., 2000 trials) practice, which included KR about endpoint accuracy after every trial. Participants were organized into 2 moderate and 2 extensive practice groups, each having a target only vision group and a target + limb vision group. All groups were evaluated in a no-KR transfer test of 20 trials while only having vision of the target. Vision of the limb and target resulted in less error (RMSE) during the final 20 acquisition trials in both the primary and secondary movement axes than with just the target alone in both moderate and extensive practice conditions. However, during transfer after moderate practice, the target + limb vision group was still significantly better (i.e., smaller RMSE) than the target only group, but the opposite was true after extensive practice. Proteau and his colleagues interpreted these results as evidence for a practice-specific sensorimotor representation (i.e., specificity of practice hypothesis: Proteau et al., 1987; Proteau, Marteniuk, & Lévesque, 1992). In other words, individuals come to increasingly rely on the sources of feedback available to them during practice, in this case vision of the limb. The specificity of practice hypothesis was later revised based on evidence that feedback utilization is not just specific to whatever modality is available during practice, but said reliance is attuned to the source of feedback which enables the best performance (Mackrous & Proteau, 2007; Tremblay & Proteau, 1998). This idea falls in line with the MLE account of multisensory integration (Ernst & Banks, 2002) as practice provides the CNS with more experience to base an estimate of the most reliable source of sensory information relative to the task.

Khan et al. (1998) used a similar approach to that of Proteau et al. (1987), in that participants were trained to acquire an aiming task across 2100 trials, in either FV or NV. However, NV and
no-KR transfer tests were conducted after 100, 1300, and 2100 trials, for all participants to assess changes in aiming behaviour using discrete correction and velocity profile analyses. All participants demonstrated improved accuracy and decreased movement times as a function of practice; however the FV group displayed better accuracy and longer movements than the NV group. Additionally, variability of the initial sub-movement was measured and found to be greater in NV than FV, however this difference became smaller with increased practice. The proportion of time spent in the deceleration phase was also greater in the FV group. Similar to the results of Proteau et al. (1987), there was a greater decrement to removing vision with increased practice (Khan et al., 1998). These combined results were taken to infer improved planning, as well as increased reliance on visual feedback to make more efficient corrections as a function of practice (Khan et al., 1998).

The availability of reliable feedback during practice improves individuals’ ability to pre-plan and control movements online. That being said, a well-established finding is that a lot of augmented feedback is beneficial to performance but is detrimental to motor learning (Schmidt, Young, Swinnen, & Shapiro, 1989). The suspected reason for the effect is that participants come to rely on that particular source of feedback and perform poorly once that feedback is removed (Salmoni, Schmidt, & Walter, 1984; Schmidt et al., 1989). For example, Salmoni et al. (1984) stated that “sufficient KR is needed so that performance is fairly accurate, but not so much KR that the subjects come to rely on it and neglect learning other aspects.” (p. 364). The detriment associated with a high degree of feedback extends to physical guidance because it does not promote individual learning of the necessary muscle activation patterns (i.e., agonist-antagonist) required to achieve a movement goal (Winstein, Pohl, & Lewthwaite, 1994).

Overall, the CNS is able shift movement control to optimize available sources of information, which promote the movement goals. Based on the dynamic nature of these optimization strategies (i.e., changes elicited with practice) the manipulation of feedback should be able to promote a desired mode of control. When highly reliable feedback is presented, its relative weight increases when processing sensory information to achieve a goal (Ernst & Banks, 2002), creating a practice-specific sensorimotor representation (Proteau et al., 1987; 1992; Tremblay & Proteau, 1998). Visual information has a tendency to dominate when it is available during practice, regardless of the value of information it provides (Proteau & Isabelle, 2002). The question remains as to whether there is a method to increase the value of movement planning
processes or online proprioceptive feedback to compensate when visual information cannot be used as optimally. Investigations into rehabilitation robotics have designed devices to test this idea with healthy and clinical populations to find novel ways of improving motor skill learning and rehabilitation practices.

1.3 Robotic Guidance

Technological advances witnessed over the past 20 years have revolutionized research and knowledge translation in basic and applied health sciences. More specifically, robotic devices have become a prominent tool to investigate human movement in healthy and clinical populations. Using robots has allowed for novel ways of studying motor learning, as well as for the assessment and treatment of neurological disorders. Robotic systems are becoming increasingly prevalent in research to develop innovative tools for skill acquisition and rehabilitation purposes.

Robotic guidance refers here to the physical guidance of a limb through a specific trajectory to a target by the end effector of a robotic device (see Johnson, 2006; Reinkensmeyer & Patton, 2009; Reinkensmeyer, Emken, & Cramer, 2004; Riener, Nef, & Colombo, 2005 for reviews). Others have used the term haptic guidance when referring to the physical guidance of a limb by a robot, due to the haptic interaction involved between the subject and the robot’s end-effector (Bluteau, Coquillart, Payan, & Gentaz, 2008; Feygin, Keehner, & Tendick, 2002; Liu, Cramer, & Reinkensmeyer, 2006). Therefore the scope of the present review includes previous work done in which any robotic guidance system is used to move a limb through a desired motion.

Before discussing the potential utility of robotic guidance systems, we must first establish the rationale for its inception and the physiological mechanisms by which it is believed to influence movement. Neuromotor rehabilitation techniques are based on the notion that the process of recovering a motor function and the mechanisms involved are similar to that of motor learning – in fact the rehabilitation of movement has been reasoned to be a relearning process (Carr & Shepherd, 1987). Motor Learning is defined as “a set of processes associated with practice or experience leading to relatively permanent changes in the capability for movement” (Schmidt & Lee, 2005, p. 302). In order to promote the practice required to facilitate motor recovery or relearning, rehabilitation therapists employ physical guidance techniques by guiding patients’ affected limbs through a specified movement pattern necessary to achieve a goal (Trombly,
Manual movement therapy provides patients with a proprioceptive reference of the correct movement pattern required to achieve a goal, while also delivering a safe environment such that no further injury occurs if a patient is unable to fully perform movements independently (Trombly, 1989). Robotic training tools can assist in the delivery of such aspects of treatment by providing highly repeatable trajectories and optimal intensities of training to maximize both recovery and the number of patients able to receive quality rehabilitation programs (Riener, Nef, & Colombo, 2005).

Arguments against the effective use of robotic guidance suggest that excessive feedback (Schmidt et al., 1989; Winstein et al., 1994) can be detrimental to motor learning. However, the potential of robotic guidance to provide highly accurate proprioceptive feedback about a movement indicates, based on MLE and the specificity of practice hypothesis, that it can effectively enhance the use of proprioceptive feedback for learning. What remains to be discussed below is whether the CNS optimizes such information, and how it is then integrated with vision. Preliminary studies using a clinical population provided some evidence of the effectiveness of robotic guidance on motor skill acquisition.

### 1.3.1 Investigations with clinical populations

Neurological injuries, such as those resulting from a cerebrovascular accident (CVA), or stroke, can lead to chronic and severe motor deficits and limits the quality of life (Lloyd-Jones et al., 2009; Public Health Agency of Canada, 2009). The diminished quality of life, heavy financial burden, and limited access to rehabilitation therapists has prompted robotic guidance researchers to emphasize stroke patients as their primary target population. The following section describes several studies that have investigated robot-guided rehabilitation in acute and chronic stroke patients.

Aisen, Krebs, Hogan, McDowell, and Volpe (1997) conducted initial investigations of robotic guidance using a custom-designed robot called the MIT-Manus (Hogan, Krebs, & Sharon, 1995) to determine whether robot-aided therapy of hemiplegic limbs could positively influence motor recovery in acute stroke patients (see also Krebs, Hogan, Aisen, & Volpe, 1998). Aisen and colleagues (1997) added robot-aided therapy sessions of hemiplegic limbs to the conventional treatment programs of acute stroke patients. Robot-aided therapy consisted of the repeated performance of goal-directed actions, shape drawing, with the guidance of the robot. Patients in
the experimental group with complete paralysis of the limb started off by being fully passive, relying entirely on the robot to perform the movement. As they progressed through the program and regained more functional use of their limb, active initiation was required on their part for the robot to perform the movement, a technique referred to as active-assisted robot-aided therapy. A control group received “sham” robot-aided therapy in which they actively moved the robot arm, therefore receiving no actual physical guidance to the desired endpoint by the robot. Patients in the control group who were unable to initiate movement solely with the affected arm could use the unaffected limb for addition support, or a clinician helped them. Both groups received visual and auditory feedback via a video monitor. Motor functioning improved in both groups, but the patients who received true robot-guided therapy showed larger improvements than those exposed to the sham robot therapy. Conventional assessment scales such as the Fugl-Meyer scale, (F-M), motor status scale (MSS), and motor power score (MP), were used, in addition to kinematic data acquired with the robot. Overall, the results of the preliminary work assessing robot-aided neurorehabilitation in acute stroke patients with the MIT-Manus provided evidence of positive consequences associated with its use and displayed its potential benefit for motor recovery (Aisen et al., 1997; Krebs et al., 1998). Moreover, a 3-year follow up showed that the observed improvements in motor functioning originally reported by Aisen et al. (1997) persisted in both groups, none of whom had received additional training (Volpe et al., 1999).

The influence of robot-guided rehabilitation on motor recovery was further examined in chronic stroke patients (Fasoli, Krebs, Stein, Frontera, & Hogan, 2003; Fasoli et al., 2004). The purpose of the study conducted by Fasoli et al. (2003) was to evaluate the ability of robotic guidance administered for 1 hour, 3 times per week, for 6 weeks to improve motor functioning of 20 patients with hemiparetic limbs, 1 to 5 years post-stroke. Conventional clinical assessment scales (i.e., the modified ashworth scale: MAS; Fugl-Meyer scale: F-M; MRC test of power; Motor Status Scale: MSS) were used to obtain baseline scores prior to treatment, and to evaluate recovery 3- and 6-weeks following training. Results indicated a significant improvement in clinical scores, suggesting a potential for robot-guided rehabilitation therapy in chronic stroke patients. Moreover, Fasoli et al. (2003) reasoned that the improvement in motor functioning after the expected spontaneous recovery time (i.e., 6-12 months post-stroke) was related to motor learning processes. A follow-up to the above study included a larger sample size and a 4-months post-treatment evaluation, which not only replicated the results of the earlier study, but also
showed the improvements remained statistically better at 4-months post-treatment than at admission to the program (Fasoli et al., 2004). The follow-up results of Fasoli et al. (2004) provided evidence that robotic guidance may be an effective motor learning and rehabilitation tool because its influence was persistent and stable.

These results arising from clinical research provide evidence that robotic guidance can facilitate motor skill acquisition. However, it is important to determine the CNS mechanisms governing the influence associated with robotic guidance to fully optimize its effects and employ specialized treatment strategies for different clinical populations. Recruiting neurologically intact participants may allow for a better understanding the CNS mechanisms influenced by robot-guided acquisition and augmented research efforts. However, studies that do not involve clinical patients are not as conclusive in their findings as those described above.

1.3.2 Investigations with healthy populations

Research paradigms from the motor control and learning literature have been applied in studying the efficacy of robotic guidance in a healthy population and the sensory-motor mechanisms responsible. For example, visual manipulations provide a simple and effective way of gaining insight into goal-directed behaviour and as such have been employed to study the influence of robot-guided practice on said behaviour. More specifically, visual manipulations provide an avenue to understand how robotic guidance technologies can influence sensory combination and integration of redundant cues (e.g., Ernst & Banks, 2002). To understand the role of robotic guidance on sensory integration strategies, the studies described below compared robotic guidance with visual demonstration, and the effect of removing vision during, and after robot-guided acquisition.

Feygin et al. (2002) trained healthy participants to perform 3-dimensional movements lasting 10 s. Their training conditions included (a) guidance without vision, (b) guidance with full vision, and (c) visual demonstration alone of the desired trajectory. After performing two movements under the same training condition, participants performed a “recall” movement in which they reproduced the trained movement either in full or no vision. This process was repeated 15 times for each combination of the training and recall conditions. When analyzing recall trials, Feygin et al. (2002) found that guidance without vision improved the temporal matching accuracy of movements relative to visual demonstration, but the opposite effect was found for shape and
position matching accuracy. Interestingly, guidance training with vision had comparable results to visual training alone with respect to shape and position matching. This final result appears counter to expectations, as physical practice combined with vision provides the nervous system with increased information about the trajectory by way of two sensory modalities. Additionally, this finding goes against the principle that the active performance of a movement is necessary in order to alter the way sensory information is used to perform a motor task (e.g., Held & Hein, 1963).

Liu et al. (2006) expanded on the findings of by Feygin et al. (2002), by comparing the effect of visual demonstration alone versus robotic guidance coupled with vision. However, Liu et al. (2006) adjusted the task by having subjects learn a less complex 3-dimensional movement and with a shorter duration than that of Feygin et al. (2002). Liu and colleagues reasoned that these changes would allow for a more effective evaluation of robotic guidance when learning a new trajectory, one that more closely resembles natural movements performed daily. Additionally, Liu et al. (2006) lengthened the training and recall phases to include 7 trials in each, repeated in 9 blocks. The recall phase required participants to reproduce the trained trajectory with the end effector of the passive robot in full-vision. The results of Feygin et al. (2002) were replicated, in that the two training modes were comparable when tracing the shape of the trained trajectory in the recall phase. Both groups showed increasingly accurate ability to trace the path with the presentation of each subsequent recall phase. Moreover, while tracing error decreased as a function of training, tracing error always increased over the course of trials once robotic guidance was no longer present (Liu et al., 2006). Liu et al. concluded that while there is a potential motor learning benefit associated with robotic guidance, the effect is transient in nature and visual feedback is an essential component of robot-guided rehabilitation.

Training with just visual demonstration alone produces similar results as training with robotic guidance and vision together when learning of a novel trajectory (Feygin et al., 2002; Liu et al., 2006). These counterintuitive results can be explained by the specificity of practice hypothesis (Proteau et al., 1987; 1992), which, as stated earlier, asserts that participants show an increasing reliance on the sources of feedback available to them throughout practice, in particular vision. Due to the complex movement pattern used by Feygin et al. (2002) and Liu et al. (2006), the visual system provided more reliable information about the correct movement pattern than did the proprioceptive system. Therefore, visual feedback about the trajectory dominated whether
participants were physically guided through the task or not. Based on the specificity of practice hypothesis and the MLE account of sensory integration we can speculate that when learning a complex trajectory, guidance did not facilitate improved spatial accuracy due to the lack of benefit additional proprioceptive feedback had relative to the task. In addition, the specificity of practice hypothesis explains why there was such a decrement in performance in recall with vision after robotic guidance training without vision (Feygin et al., 2002). According to the specificity of practice hypothesis, not only is there a detrimental effect of removing feedback that was available during practice, but also the addition of sensory information that was not present during practice can have adverse effects on performance (Proteau et al., 1992). Therefore, after training without vision, the addition of vision in the recall phase could have had a negative effect on performance.

Alternatively, the lack of benefit robotic guidance exhibited, relative to visual demonstration, can be explained by the robot’s excessive presentation of augmented feedback about the correct movement pattern. The extent of feedback availability during training may have led to a dependence on it by participants, damaging performance once the feedback was removed in the recall phase, a principle discussed earlier and known as the guidance hypothesis (Schmidt et al., 1989; Winstein et al., 1994). The detriment of physical guidance also exists in what Reinkensmeyer and Patton (2009) describe as the dynamic adaptation component of learning or “the process of learning the muscular forces that achieve the target motion trajectory given the dynamics of the task” (p. 43). In essence, the dissimilarities between the exerted limb dynamics of guided versus self-initiated movements may lead to the formation of separate internal models (Reinkensmeyer & Patton, 2009; Winstein et al., 1994). However, the different representation of force requirements of the limb in guided and manual aiming motions may be attributable to the artificial nature of the task participants are asked to learn. Many robotic guidance studies have assessed shape matching of complex trajectories (e.g., Bluteau et al., 2008; Feygin et al., 2002; Liu et al., 2006), and serial movements (Casadio, Morasso, Sanguineti, & Giannoni, 2009) lasting several seconds in duration. Few, to our knowledge, have assessed goal-directed movements having a spatio-temporal profile comparable to that of a discrete action (i.e., less than 1 s duration). Furthermore, many commonly used systems (i.e., MIT-Manus, Phantom) are restricted to only two or three Degrees of Freedom (DOF), also limiting the ability to guide a limb using a natural movement pattern.
In studies described above, individuals were able to decrease their shape matching error comparably as practice progressed, whether they were guided by visual or physical feedback. Based on these results we can speculate that neurologically intact individuals can extract comparable benefits from visual demonstration and robotic guidance. However, these studies primarily focused on the spatial aspects of limb trajectories, which do not fully reflect the planning and online control processes.

As described earlier, the augmented proprioceptive feedback associated with mechanical physical guidance does not diminish the visual dominance associated with complex spatial task (Feygin et al., 2002; Liu et al., 2006). Members of our laboratory recently sought to determine whether this finding extends to discrete, goal-directed upper limb movements by comparing the effects of training with manual aiming and robotic guidance (Alekhina, Manson, Williams, Srubiski, & Tremblay, 2011; Srubiski, Manson, Alekhina, & Tremblay, 2011). We assessed changes in manual aiming behaviour pre- and post-training, in full-vision and no-vision, to better understand the influence of robot-guided practice on both vision and proprioception. A key difference between our work and research from other labs is the use of an industrial, high-torque, selective compliant assembly robot arm (SCARA) able to move in 4DOF. The SCARA robot’s end-effector is able to replicate the spatial-temporal characteristics of a natural aiming movement, thus potentially providing a better indication of the influence of robot-guided training on the use of sensory feedback. Alekhina et al., 2011) found comparable endpoint accuracy across training conditions, replicating the results of Feygin et al. (2002) and Liu et al. (2006). However, further trajectory analyses revealed that robot-guided acquisition led to an increase in the amount of time participants spent after peak limb velocity and to the emergence of more stereotyped movements in the post-test (based on correlational trajectory analyses). These results suggest that either a greater reliance on pre-movement planning strategies emerged or that an increased reliance on proprioceptive feedback evolved with robotic guidance.

To elaborate on these results we conducted a study similar to that of Alekhina et al. (2011) but had participants train with the robot or unassisted, either in full or no vision (Srubiski et al., 2011). Once again the effect was assessed using a pre- and post-test conducted in full- and no-vision. Again, we found no difference in between groups’ endpoint accuracy. However, the proportion of time spent after peak limb velocity significantly decreased from the pre- to the post-test in the no-vision condition only after robot-guided acquisition. The observed effect of
robotic guidance occurred whether individuals trained in full or no vision. When vision was available, robotic guidance did not influence normal reaching behaviour; however when vision was removed, it altered the movement control strategies used to accomplish endpoint results similar those achieved with normal unassisted reaching. As compared to physical practice, these data suggest that robotic guidance may yield comparable endpoint performance through different online control processes (i.e., less online control with robotic guidance). Moreover, visual manipulations have demonstrated that different control strategies present after robot-guided acquisition but are insufficient to fully understand the mechanisms responsible for the change in control strategies. A key principle guiding robot-aided rehabilitation is its potential to improve proprioceptive functioning; perhaps implementing a proprioceptive perturbation will allow for a better understanding of the CNS mechanisms involved after robot-guided acquisition.

1.4 Rationale and Hypotheses

Various studies have illustrated the effectiveness of robot-guided therapy (e.g., Krebs et al., 1998), however its benefits over other sources of training (i.e., visual demonstration) have not yet been realized (Feygin et al., 2002; Liu et al., 2006). To fully capitalize on robot-guided therapy, we must first discover effective protocols to exploit the influence of physical guidance on CNS control strategies (e.g., planning vs. online control). While motor learning can lead to increased reliance on specific sources of sensory feedback (Proteau et al., 1987; 1992), motor acquisition protocols designed to increase the CNS reliance on movement planning or other modalities (i.e., proprioception) could provide a hopeful strategy for those with neurological injuries which have impaired online control mechanisms. Robotic guidance has demonstrated little benefit in improving spatial accuracy in healthy populations (Feygin et al., 2002; Liu et al., 2006), but displays some ability to alter temporal and trajectory characteristics (Alekhina et al., 2011; Feygin et al., 2002; Srubiski et al., 2011). More specifically, movement appears to become more stereotyped. Changes to kinematic profiles occur after robot-guided acquisition, without a decrement in performance, suggesting that while visual feedback regulation is not necessarily decreased, pre-movement planning strategies and/or proprioceptive based corrections may become more efficient. Robotic guidance appears to have limited benefits in healthy populations with respect to improving endpoint accuracy but shows some ability to influence trajectories. The present experiment aimed to determine whether robot-guided acquisition could alter movement control strategies (i.e., facilitate planning vs. online control processes). Based on the
findings of Ernst and Banks (2002), one can expect that training with highly reliable and repeatable proprioceptive feedback about the trajectory would result in a greater reliance on online proprioceptive feedback, at least immediately after the robot is removed.

However, should the robot provide participants experience with a trajectory having a symmetric velocity profile, thus limiting the time after peak velocity and, in turn, the opportunity for online corrections one would expect that the CNS would adapt to minimize its use of online feedback. As such, guidance through a symmetric velocity profile could be expected to result in less reliance on online proprioceptive feedback, at least immediately after training.

This thesis aimed to answer the following two questions. First, can robotic guidance influence pre-planning and online proprioceptive feedback use mechanisms? If so, can symmetric robot-guided trajectories decrease the reliance on online proprioceptive feedback compared to asymmetric (i.e., natural) trajectories?

The effect of robot-guided acquisition was examined by dividing participants into three groups. Two groups practiced with the robotic device either using a natural asymmetric velocity profile, or a symmetric velocity profile that is uncharacteristic of human aiming movements performed in full vision. A third group practiced the task unassisted by the robotic device (i.e., manual aiming). In order to discern the influence of practice condition on movement planning and online control, the experiment was conducted in three phases. Baseline measures were taken during a familiarization phase, which involved manual aiming movements to a target. The familiarization phase was followed by an acquisition phase where individuals practiced the task in their respective groups. Finally, a post-test was conducted that included two conditions. During a vibration condition, tendon vibration was applied to the right bicep brachii distal tendon during the movement to assess reaching trajectories in the presence of a proprioceptive perturbation. The motivation behind this manipulation was to determine whether individuals would alter the way they processed and integrated visual and proprioceptive feedback as a function of training group. Second, a control condition (i.e., no-vibration) was included that was identical to the baseline trials to measure the influence of training group on typical aiming movements compared to when vibration was applied; and to provide a measure of how behaviour changed from baseline trials.
It was hypothesized that if robotic guidance prompted a change in pre-planning and/or the use of online proprioceptive feedback, there would be differences in endpoint error during tendon vibration trials as a function of training condition, accompanied by changes in velocity profile symmetry. Specifically, if robotic guidance promoted the use of proprioceptive feedback, as is predicted based on the MLE account of sensory integration (Ernst & Banks, 2002), a greater undershoot bias and longer times after peak limb velocity would have been exhibited by the robot groups compared to the unassisted group. If robotic guidance promoted pre-planning mechanisms rather than influencing online feedback utilization, a smaller undershoot bias, longer times to peak velocity, and shorter reaction times would have been observed in the robot groups compared to the unassisted group with the symmetric group showing the least error and greatest velocity profile symmetry.
Chapter 2. Methods

2.1 Participants

Thirty members of the University of Toronto Community (16 males and 14 females), between the ages of 19 and 33 (M = 23.7, SD = 3.28) participated in this study. All participants were right-handed and had a visual acuity score of at least 0.6, assessed using the Freiburg Visual Acuity test (Bach, 1996). Informed consent was obtained prior to any involvement in the experiment, which was carried out in accordance with the 1964 Declaration of Helsinki and approved by the University of Toronto’s Office of Research Ethics.

2.2 Experimental Setup

Participants were fitted with an orthotic wrist guard and seated in an ergo pro massage chair (StrongLite), outside a security cage (2 m x 2 m x 2 m), facing the experimental setup housed within the cage. A high-intensity cylindrical vibrator (Dynatronic VB100, excursion 0.5 mm, 38 mm diameter, 75 mm long, 125 g, 80 Hz) was secured to participants’ distal biceps brachii tendon. An infrared emitting diode (IRED) was affixed to the participants’ right index finger and monitored by an Optotrak Certus motion tracking system (Northern Digital, Inc.) sampling at 200 Hz. Additionally, participants wore liquid crystal goggles (PLATO, Translucent Technologies, Inc.), which could alternate between a transparent and translucent state. The primary experimental task involved an orthogonal aiming movement carried out on a custom-built aiming console (51 cm x 29 cm x 9 cm) composed of a metal case and a translucent Plexiglas surface. A 1 cm x 1 cm piece of Velcro was fixed to the console’s surface to represent the home position and 3 targets, signified by light emitting diode (LEDs), were installed beneath the Plexiglas surface. The aiming console rested on a table (60 cm in height) within the cage, such that T2 was positioned along the body’s midline. Three targets were located at a resultant distance of 27 cm (T1), 30 cm (T2), and 33 cm (T3) to the right and at an angle of ~45° from the home position (see Figure 1). A piezoelectric buzzer delivered auditory signals to initiate movement (Go signal: single 50 ms tone) and return to the home position once movement was complete (Return signal: two 50 ms tones, 50 ms apart). The state of the LEDs, piezoelectric buzzer, and goggles were controlled by a custom MATLAB program (Mathworks, Inc.) via a parallel port interface (i.e., break-out box).
A selective compliant assembly robot arm (SCARA; E2L853S-UL, Seiko Epson Corp.) stood on a table, also within the security cage, directly behind the aiming table. The SCARA robot is able to move in 4DOF and uses high-torque motors. In addition, the robot was fitted with a custom handle on its end effector and a 6-axis force/torque sensor (Mini-45 F/T Transducer, ATI Industrial Automation) mounted between its end effector and the handle. Force data was acquired using a PCI-6034E analog-to-digital board (National Instruments). Security switches were installed on the handle and cage doors and were monitored using a PCI-6009 USB interface (National Instruments), whereby the robot would stop moving when any of the switches were released. The robot’s position, average velocity, and acceleration were controlled by a custom Spel+ program (Seiko Epson Corp.). The trajectory of the robot was pre-defined by a point-to-point movement curve (see section 2.3.2.1).

2.3 Procedure

The experimental protocol required approximately 2-hours to complete and consisted of the following three experimental phases: familiarization, acquisition, and post-test. Participants were assigned to one of three groups, which determined the protocol used in their acquisition session (see section 2.3.2), while the familiarization and post-test phases were the same for all groups.

2.3.1 Familiarization phase

The familiarization phase allowed participants to become accustomed to the task as well as for a baseline measurement of individuals’ performance prior to training. During this phase participants reached from the home position to T2 within a 400-600 ms movement time bandwidth. Each typical trial (see Figure 2A) began with the participant seated and their right index finger positioned comfortably on the home position, while the goggles occluded vision of their limb and environment (i.e., translucent). The goggles then became transparent at the same time the target illuminated, giving participants a 1 s preview of the target. The “Go” signal sounded, cueing participants to reach to the target as accurately as possible within the required movement time bandwidth. Vision was occluded when participants reached a velocity criterion of 400 mm/s during the deceleration phase to prevent terminal visual feedback. Once the movement was complete the “Return” stimulus was presented. Vision remained occluded between trials and participants were forced to rely on tactile feedback to return to the home position. The familiarization phase consisted of 10 trials.
2.3.2 Acquisition phase

Participants completed the acquisition phase in one of three groups. An unassisted group performed an aiming task similar to the one presented in the familiarization phase, with the exception that vision was available from movement start until movement end (i.e., allowed terminal visual feedback). The remaining groups performed this phase with the assistance of a robotic device. The difference between the robot-guided groups was the velocity profile symmetry of the trajectories used to guide the limb. One group received trajectories with an asymmetric, human-like, velocity profile (asymmetric group) and the other group received trajectories with a symmetric velocity profile (symmetric group).

Robot-guided trials began with the participant seated with their right hand holding the robot’s handle and the goggles in a translucent state. The goggles became transparent when the target appeared, providing a 1 s preview of the target before the go signal. After the go signal, there was a 250 ms delay before the robot initiated its movement to the target. Vision remained available until movement end, at which point the goggles became translucent. To ensure active participation in the task, summary feedback was presented every 5 trials in the form of a graph displaying the averaged sum of forces applied in the primary and secondary axes of movement. In addition, a reference curve was plotted on the graph that displayed what the force curve would look like if there were no external forces applied to the robot (i.e., the participant’s hand) during the course of the movement. Participants were instructed to actively follow the robot in order to replicate the reference curve as closely as possible. Observed differences between the two curves provided participants with feedback about how well they were following along with the robot’s movement (i.e., lagging or pushing). The purpose of the described feedback was to ensure participants were actively engaging in the task and not just allowing the robot to move their limb without having involved any movement planning or control mechanisms.

The acquisition phase consisted of 210 trials, divided into 7 blocks of 30 trials. All three targets were used during acquisition to promote variable practice. Each target was presented 10 times per block in a pseudorandom order, where no target was presented more than twice consecutively. Participants were required to take a 2-minute break in between blocks and a 5-minute break between the final acquisition block and the post-test.
2.3.2.1 Robot trajectory generation

The trajectory used in the asymmetric condition mimicked the spatial, temporal, and kinematic characteristics of a natural aiming movement, which included an asymmetric velocity profile (i.e., peak velocity occurred at 40% of movement time). The symmetric group was presented with a trajectory having the temporal characteristics of a natural aiming movement, but used a smooth and symmetric velocity profile (i.e., peak velocity occurred at 51% of movement time), which is atypical of discrete human movements. A custom MatLab program was used to create both sets of robot curves from 10 trajectories of 5 individuals who were well practiced in the pointing task. The X, Y, and Z coordinates of finger position were taken every 5% of the movement and then averaged within and across participants to obtain a 21-point movement curve. The averaged curves were passed through a 2nd order, low-pass Butterworth filter. An adjustment factor was then applied to the X curve (primary movement axis) to get 3 trajectories of 27, 30, and 33 cm in amplitude. These curves were interpolated to obtain the three 101-point movement curves used in the asymmetric group. To produce the symmetric trajectory, the smoothed 21-point X-curve was differentiated to obtain the velocity profile. The acceleration and deceleration portion of the curve were then multiplied by the appropriate adjustment ratio, resulting in a symmetric velocity profile. The velocity profile was transformed back into a displacement curve and multiplied by an adjustment factor to get 3 trajectories with amplitudes of 27, 30, and 33 cm. The adjusted symmetric X-curves, along with the original Y and Z curves were interpolated to produce the three 101-point trajectories used in the symmetric group.

2.3.3 Post-test phase

The post-test comprised of vibration trials, in which vibration was applied to the right biceps brachii tendon for the entire duration of the movement (i.e., onset to offset; see Figure 2B); and no-vibration trials, which were identical to the familiarization trials. All trials included visual feedback (i.e., goggles open) until the participant’s limb reached a velocity criterion of 400 mm/s during deceleration. Each condition was blocked into 10 trials for a total of 20 trials in the post-test, all using T2. The order of block presentation was counter-balanced across participants.

2.4 Data Analysis

Dependent variables included measures of temporal, spatial, and kinematic movement characteristics. Temporal variables included reaction time (RT) and movement time (MT).
Spatial accuracy was assessed using constant error (CE) and variable error (VE) in the primary and secondary axes of movement. The displacement profile was differentiated to attain peak limb velocity (PV), time to reach PV from movement start (TtPV), time between PV and movement end (TaPV), and the relative proportion of time spent after PV (PTaPV). A description of how each variable was calculated is detailed in the following chapter.

To test for the influence of practice and tendon vibration, all variables were submitted to a 3 group (unassisted, symmetric, asymmetric) by 3 test (baseline, vibration, no-vibration) mixed ANOVA (i.e., main ANOVA). To determine whether adaptations were present across the tendon vibration trials, a 3 group (unassisted, symmetric, asymmetric) by 2 test (vibration, no-vibration) by 2 block (Block 1: Trials 1-5; Block 2: Trials 6-10) mixed ANOVA was also conducted (i.e., blocked ANOVA) to determine whether individuals adapted to the tendon vibration manipulation in the post-test. In all cases where the assumption of sphericity was violated, a correction factor was applied to the degrees of freedom using the Huynh-Feldt method. All main effects and interactions involving more than two means were examined using Tukey’s HSD post-hoc procedure.
Chapter 3. Results

A small proportion of trials were discarded (3.2%) due to technical errors during data collection (e.g., movement onset occurring before data collection onset). Endpoint error in the X (i.e., primary or amplitude), Y (i.e., secondary or direction), and Z (i.e., tertiary or elevation) axes was also examined using an outlier procedure. Trials that had an error in any of the three axes of 2.5 or more standard deviations away from their respective mean were also discarded (2.9%). A total of 6.1% of trials were eliminated due to technical errors or outliers.

3.1 Temporal Variables

Movement start was determined to be the first of three consecutive samples exceeding the velocity threshold of 30 mm/s. Movement end was identified as the first of 3 consecutive samples to fall below 30 mm/s with the condition that the elevation (i.e., Z position) was less than 5 mm above the start elevation position, to ensure that the full movement was captured. The reaction time was then calculated as the time between stimulus presentation and movement start and movement time was calculated as the time between movement start and end.

3.1.1 Reaction time

For the main ANOVA, there was a main effect for test ($F_{1.8, 47.4} = 6.86, p < .01; HSD = 22$ ms). The post-hoc analysis revealed that vibration resulted in a significantly longer reaction time ($M = 288$ ms, $SD = 47$) than in baseline ($M = 263$ ms, $SD = 40$) and no-vibration trials ($M = 259$ ms, $SD = 40$) (see Figure 5). The blocked ANOVA also yielded a main effect for test ($F_{2.27} = 21.13, p < .001; HSD = 13$ ms), which replicated the difference in RTs between vibration and no-vibration trials (see Figure 6).

3.1.2 Movement time

For the main ANOVA, a main effect for test ($F_{2.54} = 7.13, p < .01; HSD = 20$ ms) was found. The post-hoc analysis indicated that individuals took more time to complete their movements in the vibration condition ($M = 485$ ms, $SD = 54$) than in their baseline trials ($M = 454$ ms, $SD = 41$) (see Figure 7). The no-vibration trials ($M = 467$ ms, $SD = 37$) did not yield different movement times compared to the baseline and vibration trials.
In the blocked ANOVA, there was a main effect for test \((F_{1,27} = 4.75, p < .05; \text{HSD} = 18 \text{ ms})\) and a test by block interaction \((F_{1,27} = 6.89, p < .05; \text{HSD} = 20 \text{ ms})\). In contrast with the main ANOVA, post-hoc analysis of the main effect for test yielded longer MTs in the vibration compared to the no-vibration trials. Further, the test by block interaction revealed that it was only in block 1 that vibration trials \((M = 492 \text{ ms}; \text{SD} = 71)\) yielded longer MTs than no-vibration trials \((M = 459 \text{ ms}; \text{SD} = 47)\) (see Figure 8). In Block 2, vibration trials \((M = 480 \text{ ms}; \text{SD} = 51)\) yielded comparable movement times than no-vibration trials \((M = 475 \text{ ms}; \text{SD} = 35)\).

### 3.2 Spatial Variables

Constant error was calculated in the primary (X or amplitude) and secondary (Y or direction) movement axes to determine the effect of training and vibration on movement endpoint. Negative values in the primary axis indicate that individuals’ movement amplitude fell short of the target while a positive value indicates an overshoot bias. Also, negative values in the secondary axis indicate an upper-left directional bias while positive values represent a downward-right bias; further referred to left and right, respectively. Precision of movements was based on variable error, or the standard deviation of endpoint error values, in both the primary and secondary movement axes.

#### 3.2.1 Constant error

In the primary movement axis CE analysis, the main ANOVA yielded a main effect for test \((F_{1,7, 44.4} = 59.02, p < .001; \text{HSD} = 2.6 \text{ mm})\). Post-hoc analysis revealed participants undershot the target significantly more when vibration was applied \((M = -2.2 \text{ mm}, \text{SD} = 6.9)\) than during the baseline trials \((M = 4.2 \text{ mm}, \text{SD} = 4.4)\), which in turn also yielded shorter endpoint amplitudes compared to the post-test no-vibration trials \((M = 8.4 \text{ mm}, \text{SD} = 5.1)\) (see Figure 9).

The blocked ANOVA for the primary axis CE revealed a main effect for test \((F_{1,27} = 127.07, p < .001; \text{HSD} = 2.0 \text{ mm})\) and block \((F_{1,27} = 18.59, p < .001; \text{HSD} = 1.5 \text{ mm})\), as well as a test by block interaction \((F_{1,27} = 22.86, p < .001; \text{HSD} = 2.9 \text{ mm})\). Again the test effect showed that individuals undershot the target more when vibration was applied than during the no-vibration condition. While participants exhibited greater movement amplitudes in Block 2 \((M = 4.6 \text{ mm}, \text{SD} = 7.3)\) compared to Block 1 \((M = 1.6 \text{ mm}; \text{SD} = 10.1)\), post-hoc analysis of the test by block interaction revealed a significant reduction of undershooting between Block 1 and 2 for the
vibration trials (see Figure 10). Specifically, vibration trials yielded a larger undershooting bias compared to no-vibration trials in Block 1 (vibration: $M = -5.6$ mm, $SD = 7.9$; no-vibration: $M = 8.8$ mm, $SD = 6.0$) and this difference was smaller albeit significant in Block 2 (vibration: $M = 1.0$ mm, $SD = 7.3$; no-vibration: $M = 8.2$ mm, $SD = 5.4$).

In the secondary movement axis CE analysis, the main ANOVA revealed a main effect for test ($F_{2, 54} = 15.98$, $p < .001$; HSD = 1.9 mm). Post-hoc analysis revealed a significant leftward bias when vibration was applied ($M = -4.6$ mm, $SD = 6.8$) compared to baseline ($M = -0.2$ mm, $SD = 4.4$) and no-vibration trials ($M = -1.5$, $SD = 5.7$) (see Figure 11).

There was a main effect for test ($F_{1, 27} = 16.07$, $p < .001$; HSD = 1.6 mm) and a test by block ($F_{1, 27} = 9.98$, $p < .01$; HSD = 1.8 mm) interaction observed when conducting the blocked ANOVA on the secondary axis CE. Once again, vibration resulted in a leftward bias compared to no-vibration trials. Post-hoc analysis of the test by block interaction revealed that the larger leftward bias observed in the vibration trials was only significant in Block 2 (see Figure 12). Specifically, vibration trials did yield comparable leftward biases compared to no-vibration trials in Block 1 (vibration: $M = -3.5$ mm, $SD = 7.0$; no-vibration: $-1.8$ mm, $SD = 5.7$). The leftward bias for the vibration trials in Block 2 was significantly larger relative to no-vibration trials in Block 2 (vibration: $M = -5.7$ mm, $SD = 7.0$; no-vibration: $-1.1$ mm, $SD = 6.1$) and vibration trials in Block 1 (see above).

3.2.2 Variable error

In the main ANOVA for the primary axis VE, there was a main effect for test ($F_{2, 54} = 9.70$, $p < .001$; HSD = 1.5 mm) in which vibration resulted in significantly more variable movement endpoints ($M = 7.9$ mm, $SD = 3.2$) than during baseline ($M = 5.9$ mm, $SD = 2.0$) and no-vibration trials ($M = 5.4$ mm, $SD = 2.3$) (see Figure 13).

The blocked ANOVA for the primary axis VE revealed a main effect for test ($F_{1, 27} = 11.01$, $p < .01$; HSD = 1.1 mm) and for block ($F_{1, 27} = 16.97$, $p < .001$; HSD = 0.8 mm). As expected, the average VE for the two blocks of trials was greater when vibration was applied than when it was not (vibration: $M = 6.8$ mm, $SD = 3.4$; no-vibration: $M = 4.9$ mm, $SD = 2.7$). Also, variability decreased from the first to the second block (Block 1: $M = 6.7$ mm, $SD = 3.6$; Block 2: $M = 5.0$ mm, $SD = 2.5$) (see Figure 14).
The main ANOVA for the secondary axis VE did not yield any significant differences or interactions (F’s < 1.40, p’s > .2) (see Figure 15).

The blocked ANOVA on the secondary axis VE yielded a main effect for block (F_{1,27} = 8.23, p < .01; HSD = 0.7 mm), and a group by block interaction (F_{2,27} = 3.68, p < .05; HSD = 1.9 mm). As for the main ANOVA, individuals became less variable from Block 1 (M = 5.0 mm, SD = 2.5) to Block 2 (M = 4.0 mm, SD = 1.8). The post-hoc analysis of the group by block interaction was explained by a drop in variability from block 1 to 2 for the robot-symmetric group only (see Figure 16).

### 3.3 Kinematic Variables

Movement displacement profiles for each trial were differentiated to obtain a velocity profile. From that the peak limb velocity (PV), the maximal limb velocity attained, was found. The time to reach peak limb velocity (TtPV) from movement start was then determined as well as the time after peak limb velocity (TaPV) or the time between PV and movement end. In addition, the relative proportion of movement time spent after peak velocity (PTaPV) was also calculated to attain a measure of profile symmetry.

#### 3.3.1 Peak Limb Velocity

For the main ANOVA, there was a main effect for test (F_{1,54} = 8.04, p < .001; HSD = 0.06 m/s). Participants exhibited a significantly smaller peak velocity during the no-vibration trials (M = 1.21 m/s, SD = 0.11) than in the vibration trials (M = 1.31 m/s, SD = 0.16) and the baseline trials (M = 1.28 m/s, SD = 0.13) (see Figure 17).

For the blocked ANOVA, there was also a main effect for test (F_{1,27} = 20.58, p < .001; HSD = 0.04 m/s) wherein vibration trials yielded larger peak limb velocities compared to no-vibration trials (see Figure 18).

#### 3.3.2 Time to Peak Limb Velocity

For the main ANOVA, a main effect for test was found (F_{1,5,41} = 10.99, p < .001; HSD = 12 ms) where vibration resulted in a significantly shorter time to reach peak velocity (M = 189 ms, SD = 20) than during the baseline (M = 206 ms, SD = 27) and no-vibration (M = 206 ms, SD = 19) trials (see Figure 19).
The blocked ANOVA also yielded a main effect for test (F_{1,27} = 46.42, p < .001; HSD = 5 ms), replicating the shorter times taken to reach peak velocity in the vibration compared to the no-vibration trials (see Figure 20).

3.3.3 Time after peak limb velocity

The main ANOVA yielded a main effect for test (F_{1.8, 49.1} = 24.02, p < .001; HSD = 18 ms) where vibration trials resulted in significantly longer times between peak velocity and movement end (M = 296 ms, SD = 54) than during baseline (M = 248 ms, SD = 33) and no-vibration (M = 262 ms, SD = 28) trial (see Figure 21).

The blocked ANOVA yielded a main effect for test (F_{1,27} = 17.93, p < .001; HSD = 17 ms), as well as a test by block (F_{1,27} = 15.32, p < .001; HSD = 17 ms) and a test by block by group (F_{2,27} = 3.32, p = .05; HSD = 40 ms) interaction. As in the main ANOVA, the time taken after peak limb velocity was longer in the vibration compared to the no-vibrations trials. The test by block by group interaction revealed that, in the Block 1 of vibration trials, the unassisted group exhibited longer times after peak velocity (M = 337 ms, SD = 84) as compared to the robot-asymmetric group (M = 276 ms, SD = 46). The contrast between the unassisted group and the robot-symmetric group (M = 299 ms, SD = 63) just fell short of the HSD (i.e., 38 ms difference vs. HSD = 40 ms) (see Figure 22).

3.3.4 Proportion of time after peak limb velocity

For the main ANOVA there was a main effect for test (F_{2,54} = 34.50, p < .001; HSD = 1.8%) where a significantly greater proportion of movement times were devoted to the period following peak velocity during vibration trials (M = 60.2 %, SD = 5.4) than during baseline (M = 54.3 %, SD = 4.7) and no-vibration trials (M = 55.6 %, SD = 3.1) (see Figure 23).

The blocked ANOVA revealed a main effect for test (F_{1,27} = 40.64, p < .001; HSD = 1.5 %), as well as a test by block interaction (F_{1,27} = 17.44, p < .001; HSD = 1.8 %). Just as in the main ANOVA, the relative time spent after peak limb velocity was greater in the vibration than in the no-vibration trials. The test by block interaction revealed that during the no vibration trials there was a significant increase in the relative time spent after peak velocity from Block 1 (M = 54.3 %, SD = 3.4) to Block 2 (M = 56.9 %, SD = 3.9). Despite the relative increase across blocks in the no-vibration trials, there was still a significantly greater proportion of time spent after peak
velocity in the vibration trials (Block 1: $M = 60.9\%$, $SD = 6.1$; Block 2: $M = 59.6\%$, $SD = 5.4$) (see Figure 24).
Chapter 4. Discussion

The purpose of the present study was to determine if practice of goal-directed movements with highly reliable and repeatable robotic guidance can influence the use of online proprioceptive feedback. While typical visual manipulations have been used to study the influence of single sensory modalities during goal-directed movements (Elliott et al., 1991; Elliott & Hansen, 2010; Heath, 2005; e.g., Woodworth, 1899), this study used a proprioceptive perturbation to understand if and how multisensory integration strategies differed after being exposed to different training methods. Moreover, the symmetry of velocity profiles can be an indicator of pre-movement planning and online control strategies (see Elliott et al., 2010). For this reason the velocity profiles of robot trajectories were manipulated such that one group received a typical and human-like asymmetric velocity profile while the other robot group was trained with a symmetric velocity profile. Both groups were compared with an unassisted aiming group prior to and post-training.

4.1 Movement Planning and Online Control Mechanisms

It was evident that the most salient influence observed was that of tendon vibration during the post-test phase. The effect was most prominent across endpoint accuracy and also influenced endpoint precision as well as temporal and kinematic variables. As for the effects of training type, post-test no-vibration trials exhibited minor differences from baseline trials in constant error amplitude and peak velocity. There was also some evidence that training type influences movement execution, although such effects were limited to endpoint precision in the secondary movement axis and time after peak limb velocity. Overall, these results suggest that tendon vibration altered movement planning strategies, making it difficult to compare across training conditions. However, a transient effect of training condition on limb kinematics indicates that robotic guidance can briefly influence the control of voluntary movements in neurologically-intact individuals. The following sections summarize the results and outlines the possible CNS mechanisms responsible relative to the processes underlying visual and proprioceptive control of goal-directed movements; integration of said sources of feedback; principles of motor learning; and previous work utilizing robotic guidance technologies.
4.1.1 Tendon vibration influences planning and online control strategies

Longer reaction times are typically tied to more intricate movement planning processes (see Klapp, 1996 for a review). Aside from tendon vibration, the nature of the current task did not differ among the test conditions (i.e., target amplitude and movement time bandwidth). As such, differences among reaction times were most likely guided by movement programming or response parameterization rather than stimulus identification and/or response selection processes. Pre-planning mechanisms were likely influenced by several cues, which became available to participants via conscious and unconscious means. Firstly, participants were told when they would receive tendon vibration (i.e., Trials 1-10 or Trials 11-20) at the start of the post-test, although they were never informed about the sensory consequences associated with vibration. Second, visual feedback during movement allowed the CNS to compare visual and proprioceptive signals about limb position, leading the CNS to deduce that proprioceptive feedback was not reliable leading individuals to spend more time specifying movement parameters prior to action initiation. During the planning stage, the visual system specifies the necessary movement distance while the proprioceptive system is responsible for designating the correct muscle patterns to produce the desired force necessary to cover said distance (Sober & Sabes, 2003). During vibration trials, force specification prior to movement initiation would differ with the internal representation of limb position during the latter portion of movement, thus relying on such a plan would not be the most effective strategy in trying to move as accurately as possible. As a result, participants may have engaged in different movement planning strategies to minimize the influence of tendon vibration during the trajectory. In other words, participants may have engaged in some anticipatory control strategy to reduce the use of online proprioceptive feedback, which could also explain trial-to-trial adaptations (see below). Lastly, it is crucial to emphasize that all further comparisons between vibration and no-vibration trials are made from movements that were most likely planned differently.

In addition to longer reaction times, participants displayed longer movement times when vibration was applied, compared to baseline trials. Also, the first block of vibration trials yielded longer movement times than the first block of no-vibration trials. These differences in movement times were observed although the different conditions yielded movements that remained within the required bandwidth (i.e., 400-600 ms). More importantly, these results indicate that participants not only planned the vibration trials differently than no-vibration trials, but also
increased their opportunities to implement online trajectory corrections through longer movement times. Specifically, they spent more time during the vibration trajectories, perhaps in an attempt to correct the trajectory biases arising from tendon vibration.

The most prominent and anticipated effect of tendon vibration was the undershoot bias in movement amplitude. A well-established effect of muscle tendon vibration is that when it is applied to a lengthening muscle (i.e., biceps brachii), it increases firing rate of the primary muscle spindle afferents, which is interpreted by the CNS as greater limb extension (Capaday & Cooke, 1981; Goodwin et al., 1972). As a result, individuals have a tendency to undershoot the target when vibration is applied to the lengthening muscle (Redon et al., 1991). As expected, vibration trials exhibited a greater undershoot compared to both baseline and no-vibration trials. While this effect is not surprising, previous research indicates that the effect of tendon vibration is attenuated (Lackner & Taublieb, 1984) or absent (Capaday & Cooke, 1981; Goodwin et al., 1972; Redon et al., 1991, Exp. 1) in the presence of vision. Even though visual information was available throughout the majority of the movement, participants were unable to fully adjust their trajectories online and could not compensate for the disparity between visual and proprioceptive feedback about limb position. More interestingly, the decrease in endpoint error across vibration blocks was observed in the absence of changes to movement times between vibration blocks. It thus becomes of interest to contrast the phases of the trajectory that were most influenced by tendon vibration (re: planning vs. online control variables). Indeed, this effect of block for constant error, but not for movement time, suggests that participants were able to make adjustments based on visual information acquired during the movement. The inability to fully compensate for the proprioceptive perturbation further implies that proprioceptive information was also used online and maintained its influence, even in the presence of visual feedback. It is also possible that the removal of vision prior to movement end prevented individuals from making final adjustments to their endpoint position. As discussed earlier, Redon et al. (1991) found that the tendon vibration was just as effective in producing an undershoot bias when applied towards the end of the movement as when it was applied throughout the entire movement. What is clear is that despite some evidence of more involved movement preparation (re: reaction time data), participants did not attempt to minimize the impact of tendon vibration through faster movements but perhaps tried to use online feedback (e.g., vision) to correct for the proprioceptive bias.
The constant error in movement direction (i.e., secondary axis) also revealed a bias in movement endpoint as a result of tendon vibration; endpoints were more leftward with vibration than during baseline and no-vibration trials. Interestingly, the blocked analysis associated with this effect was opposite to the one observed in the amplitude. Individuals showed more leftward bias in the second than in the first block of vibration trials. Also, this leftward bias was larger with vibration compared to no vibration for the second block of trials. It is possible that as individuals were correcting for errors in movement amplitude, fewer and/or later online corrections took place in the movement direction axis across blocks of trials. Such a proposal can be supported by a qualitative assessment of the typical trajectory profile during vibration. The trajectory profiles illustrated in Figure 4 depict the averaged amplitude and direction values of a typical participant during Block 1 and Block 2 of vibration and no-vibration trials. Following a close inspection of the vibration blocks, we can observe the larger target undershoot in the first block than the second block of vibration trials. In addition, it can be surmised that there was a leftward bias early in the trajectory for the first block of vibration trials that emerged later in the trajectory in the second block of vibration trials. Because this leftward bias emerged later, it could not be corrected by movement end. Overall, the endpoint accuracy results suggest that individuals attempted to mitigate the tendon vibration across blocks of post-test trials. While they succeeded in improving endpoint amplitude bias, this could have induced errors by movement end in the secondary axis.

Not surprisingly, tendon vibration generated increased variability in movement amplitude endpoint compared to baseline and no-vibration trials. The greater variability could be a by-product of the increased proprioceptive noise in the CNS. The blocked analysis demonstrated the ability of individuals to stabilize their performance across post-test blocks, with and without tendon vibration. In contrast, the direction variability displayed no differences across conditions. Based on the principle of MLE (Ernst & Banks, 2002), it can be argued that the increased variability associated with tendon vibration elicited a shift in which proprioceptive information was given a lower weight. Such a claim would help explain the smaller effect of vibration on constant error in amplitude across blocks. It is apparent that influence of proprioceptive feedback was not completely diminished as endpoint error never fully recovered to an optimal level during vibration. Even in the presence of a highly conscious proprioceptive perturbation, which introduced a large amount of noise, the CNS did not completely disregard proprioceptive
feedback. Such an effect supports the concept that the CNS processes sensory feedback based on a weighted average (i.e., Ernst & Banks, 2002), rather than allowing one modality to fully dominate the sensory representation of a neurologically-intact individual, even when one source of feedback is so obviously unreliable.

With respect to kinematics, vibration trials exhibited higher peak limb velocities than no-vibration trials. In addition, vibration trials yielded shorter times to reach peak limb velocity and longer absolute and relative times after peak limb velocity, compared to no-vibration trials. The effect of vibration on time to and time after peak limb velocity in conjunction with the higher peak velocities may reflect a strategy individuals used to deal with the proprioception perturbations. Specifically, they were likely covering as much distance as possible with their initial ballistic movement, perhaps allowing them to be closer to the target for the movement deceleration phase. Because longer times after peak velocity enable the use of online feedback (see Elliott et al., 2010), individuals may have tried to use visual feedback to mitigate the erroneous proprioceptive feedback resulting from vibration.

Overall, individuals planned their movements differently when tendon vibration was applied, making it difficult from the outset to infer differences in control strategies between vibration and no-vibration trials, let alone making comparisons as a function of training condition. It is still interesting to see that comparing vibration to no-vibration trials led to (a) longer movement times, at least for Block 1; (b) greater endpoint undershoot, especially in Block 1; (c) more leftward endpoint bias; (d) greater endpoint variability; (e) higher peak velocities; and (f) less time before, but more time after peak limb velocity. These results are all consistent with the proposal that participants engaged in anticipatory parameter control (Johansson & Cole, 1992) by getting to the target earlier in the movement in an attempt to use visual feedback to correct for the proprioceptive bias. As tendon vibration is known to influence limb control, especially late in the trajectory (i.e., when the tendon of the vibrated muscle is active), it is surprising to see that individuals spend more time in that phase and yet strategically manage to counteract the vibration (e.g., less undershoot in Block 2 vs. Block 1). According to the results of Redon et al. (1991), longer movement times yield greater effects of tendon vibration on movement endpoint (i.e., undershoot) and tendon vibration likely produces its strongest effects in the latest portions of the trajectory. Thus, an optimal strategy would have been to decrease movement time and
time after peak velocity in order to lessen any effect induced by vibration; however movement times remained relatively stable across vibration trials.

4.1.2 Efficiency of aiming improves with practice

When contrasting no-vibration trials before and after training, one can infer some effects of practice. Although neurologically-intact individuals exhibit signs of very flexible CNS processing, there was some evidence that the training phase had an effect on the control of discrete goal-directed movements.

Peak velocities decreased from baseline trials to the post-test no vibration trials with no evident changes to the absolute or relative times to and after peak velocity. If practice promoted the use of planning and/or online sensory feedback, we would have expected to see higher peak velocities, bringing the limb closer to the target earlier in the movement, to promote feedback-based corrections late in the trajectory (i.e., longer times after peak velocity; e.g., Elliott et al., 1995). In contrast, higher peak velocities without longer time after peak velocity should be more associated with better planning processes. As such, the lack of changes to velocity symmetry implies that the practice schedule did not promote the use of online feedback. Alone, this result is difficult to interpret.

In addition, participants travelled a greater distance in movement amplitude (i.e., more overshoot) in the no-vibration trials than the baseline trials. It is seldom that humans do not engage in significant and economical endpoint undershoot (e.g., Elliott, Hansen, Mendoza, & Tremblay, 2004), especially as a function of practice. Based on the increased overshoot, one might reason that participants became more errorful after practice although alternative explanations could also be forwarded. Such a significant target overshoot has been previously observed when a temporal constrain was employed (re: MT bandwidth; see Elliott et al., 1991 Exp. 2). Alternatively, it is possible that there was a discrepancy between location of the finger and the marker. Perhaps participants tried to bring the pad of the index finger to the target although the marker was at the tip of the index (i.e., a few mm further). The fact that the measured target undershoots in the vibration condition was only -2.2 mm support this latter proposal.
We can conclude that practice did not promote the online use of feedback, but resulted in lower peak velocities and a greater distance travelled despite the absence of changes in movement time. Individuals were able to travel further after training without taking more time to do so, perhaps expending less energy in the process.

4.1.3 Training type influences online control strategies

The unassisted group spent more time after peak velocity than the asymmetric robot group and the symmetric robot group (though it was narrowly short of being significant) during the first vibration block. This finding in conjunction with previous work from our laboratory (Alekhina et al., 2011; Srubiski et al., 2011), supports the idea that robot-guided acquisition favours a diminished opportunity for late online trajectory amendments. When subjected to tendon vibration, participants in the unassisted group likely prepared comparable initial impulses to robot groups as time to peak velocity and peak velocity analyses did not yield any effects or interactions involving the group factor. As the movement unfolded, the unassisted group likely attempted to use online visual feedback to correct for the proprioceptive biases induced by tendon vibration, which can explain the longer times after peak velocity. As stated earlier, presenting tendon vibration in the deceleration phase is known to maximize endpoint biases (see Redon et al., 1991). In contrast, it could be proposed that robot-training groups made fewer attempts to employ online feedback, resulting in less time spent in the deceleration phase. Thus, it is possible that comparable endpoint accuracy and precision were obtained for all groups through different online control mechanisms. Specifically, the unassisted group may have emphasized the promotion of a more reliable source of feedback (i.e., vision), at least initially, while robot groups exposed themselves less to the deleterious influences of tendon vibration by spending less time in the deceleration phase. The ability to obtain the same goal (i.e., endpoint accuracy) through different control or muscle activation mechanisms is a well-documented phenomenon and has been termed motor equivalence (see Abbs & Cole, 1987). The results observed here illustrate the potential of robotic guidance to induce a different pattern of limb control for a short time.

One reason why robot training may not enhance or favour the use of proprioception (re: guidance studies) is that contact with an external object at the extremity of the effector provides highly contrasting proprioceptive feedback compared to when reaching normally. Moreover, the
augmented feedback regarding the correct movement pattern may impede learning the correction muscle activation patterns (i.e., guidance hypothesis).

As for the decreased endpoint variability in movement direction observed in the symmetric group between Blocks 1 and 2, it could merely be explained by a quick recovery from being exposed to such an atypical trajectory profile. Participants in the unassisted group were not more variable than the other groups in Block 1, nor were they less variable in Block 2. As such, the observed improvements may reflect slightly better planning and/or online control when returning to voluntary control. The fact that participants did not exhibit different symmetries in their limb velocity profiles suggests that symmetric robotic guidance could be not used to avoid being influenced by tendon vibration. It could also be the case that reducing the opportunity for individuals to see and feel their movement in the late phases of the movement (i.e., less time after peak velocity) yielded some transient effects on limb control. Perhaps the challenge to control endpoint amplitude was large enough in the symmetric group to at least induce some temporary effects on the control of endpoint direction.

4.2 Implications

Overall, the effects of robot-guided training were minimal as compared to unassisted training and reproduced previous findings that individuals can achieve comparable endpoint accuracy regardless of training group (i.e., Feygin et al., 2002; Liu et al., 2006) and illustrated that this same effect is present when a proprioceptive perturbation is applied. Limb trajectories exhibited shorter durations of time spent after peak limb velocity after robot-guided training versus unassisted training. A shorter deceleration phase could indicate a greater involvement of pre-planning processes. However, the influence on robot training on pre-planning processes should have also been reflected in the reaction time and time to peak velocity results, which was not the case. The alternative explanation is that participants in the robot training groups were less likely than the participants in the unassisted group to use late online sensory feedback. Therefore, robotic guidance may not be a beneficial rehabilitation tool for individuals diagnosed with a condition affecting movement planning. Robotic guidance shows some influence on online control but the result is counterintuitive to expectations. As discussed earlier, robot-guided therapy can provide highly reliable and repeatable proprioceptive feedback, which based on MLE (Ernst & Banks, 2002), would indicate that the relative weight of proprioceptive feedback...
should be greater after exposure to robotic guidance. It appears that individuals actually gave
themselves a lesser opportunity to use proprioceptive feedback when they were exposed to robot-
guided acquisition as compared to participants who practiced unassisted. It is possible that with
extensive exposure to robotic guidance, individuals would continue to disregard proprioceptive
feedback, particularly when their proprioceptive system has become less reliable due to an
injury, such as after a stroke. Perhaps the focus that robot-guided rehabilitation research has
placed on training or improving proprioceptive deficits may need to shift to promote individuals
to disregard the erroneous feedback provided by the proprioceptive system.

4.3 Limitations

It is important to note some inherent limitations within the present study’s design. Firstly, to
reduce the extent of potential adaptations to tendon vibration, the number of trials per condition
was kept at a minimal number (10 trials) and the presentation of tendon vibration was limited to
only the post-test phase. As a result, the absolute and relative times spent prior to and after peak
limb velocity were the primary dependent variables used to infer planning and online control
mechanisms. An additional method would have been to conduct a between-trajectory analysis
such as those used by Khan et al. (2003) or Heath (2005). Unfortunately, the relatively low
number of trials per condition was insufficient to enable a reliable estimate of online control
strategies from such measures. Moreover, a pre- and a post-test comparison of tendon vibration
trials may have allowed for a more thorough investigation into the influence of robot-guided
versus unassisted training on online proprioceptive feedback use during aiming. However, we
have already discussed the potential for individuals to change movement planning and control
strategies in response to tendon vibration; thus it is reasonable to hypothesize that exposure to
tendon vibration could influence motor acquisition processes as well. Despite the employed
precautions, it is clear that individuals were able to adapt control mechanisms to minimize the
effect of tendon vibration within a small number of trials.

Second, for safety purposes the robot’s handle was positioned above the aiming board’s surface
and never actually touched the board’s home and target positions. The elevated position of the
robot’s handle yielded a different limb configurations during robot-guided trials compared to
baseline, post-test, and unassisted training trials, and could have resulted in different muscle
activation patterns and proprioceptive feedback. Moreover, during baseline, post-test, and
unassisted training trials individuals touched the board at the start and end of movement. This initial and terminal tactile feedback was not possible during robot-guided trials, which required participants’ hands to be in constant contact with the robot’s handle. Overall, the different somatosensory feedback elicited when the robot was present versus when it was not may have lead to different sensorimotor representations of the task.

4.4 Conclusions

One possible interpretation of the results from this study is that robotic guidance does not influence movement planning, but can alter online control mechanisms, including how online vision and proprioception contribute to endpoint control. It is important to note that the only effect of robotic guidance on endpoint position was the ability of the symmetric robot group to decrease variability as a function of block in the secondary axis. There were no differences among groups with respect to endpoint accuracy observed as a function of vibration condition. Therefore, any changes to control strategies resulting from the different training types were insufficient in mitigating the influence of vibration on endpoint error. One thing is clear, robot-guided acquisition did not involve the same online control strategies as unassisted training.

Overall, the rapid changes in endpoint performance during suggest that quick adaptation mechanisms are taking place in neurologically-intact individuals. When contrasting the results from other studies with neurologically-intact individuals (section 1.3.2) and studies with patients (section 1.3.1), one could suggest that a patient population exposed to such training protocols will be more influenced by the robot guidance than the participants included in the present study. Therefore, non-clinical populations may not be the most appropriate participant group when assessing the potential of robot-guided rehabilitation. As such, robotic guidance in conjunction with motor control and learning paradigms, such as those employed within this study, may be better applied within a clinical population to better understand the overall influences on movement planning and online control strategies.

The present study contributed to the study of robotic guidance by helping to better understand its role in motor skill acquisition; particularly its influence in the planning and execution stages of goal-directed actions. The results also suggest that the benefit of robotic guidance may be in its ability to reduce the use of erroneous proprioceptive feedback rather than to enhance and improve its functionality. Finally, previous studies involving robotic guidance have relied
predominantly on visual manipulations to infer its effect on proprioception. This study used a novel approach, by directly manipulating proprioceptive feedback via tendon vibration, to evaluate differences between training conditions. In addition, the robot’s trajectory characteristics were manipulated (i.e., velocity profile) to assess whether movement planning strategies could be promoted over online feedback utilization. Moreover, the ability to produce movements with the same degree of accuracy does not necessarily imply that comparable control strategies are implemented in achieving the goal. Overall, this thesis has applied paradigms from the motor control and learning literature to uncover the CNS mechanisms that may benefit from robotic guidance. While we have been able to expose some transient effects of robotic guidance on goal-directed actions, future studies should look at applying similar paradigms to clinical populations.
References


Srubiski, S. L., Manson, G., Alekhina, M. I., & Tremblay, L. (2011, October). The effect of robotic guidance on the use of visual information during a pointing task. Presented at the meeting of the Canadian Society for Psychomotor Learning and Sport Psychology (SCAPPS). Winnipeg, MB.


Figure 1. Overhead view of the experimental setup.
Figure 2. Depiction of the timeline of a single trial as a function of limb velocity during baseline and no-vibration trials (A) and vibration trials (B).
Figure 3. Averaged displacement profiles of a typical participant in the baseline, vibration, and no-vibration trials.

Figure 4. Averaged displacement profiles of a typical participant for Blocks 1 and 2 of vibration and no-vibration trials.
Figure 5. Box and whisker plots of Reaction Time (RT) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 6. Box and whisker plots of Reaction Time (RT) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean).
Figure 7. Box and whisker plots of Movement Time (MT) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 8. Box and whisker plots of Movement Time (MT) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean).
Figure 9. Box and whisker plots of Constant Error Amplitude (CEamp) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 10. Box and whisker plots of Constant Error Amplitude (CEamp) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean).
Figure 11. Box and whisker plots of Constant Error Direction (CEdir) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25<sup>th</sup> to 75<sup>th</sup> percentile), solid line (median), and “+” (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 12. Box and whisker plots of Constant Error Direction (CEdir) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25<sup>th</sup> to 75<sup>th</sup> percentile), solid line (median), and “+” (mean).
Figure 13. Box and whisker plots of Variable Error Amplitude (VEamp) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 14. Box and whisker plots of Variable Error Amplitude (VEamp) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean).
Figure 15. Box and whisker plots of Variable Error Direction (VEdir) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 16. Box and whisker plots of Variable Error Direction (VEdir) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean).
Figure 17. Box and whisker plots of Peak Limb Velocity (PV) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean). Significant differences ($p < .05$) are denoted by asterisks (*).

Figure 18. Box and whisker plots of Peak Limb Velocity (PV) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and "+" (mean).
Figure 19. Box and whisker plots of Time to Peak Limb Velocity (TtPV) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean). Significant differences ($p < .05$) are denoted by asterisks (*).

Figure 20. Box and whisker plots of Time to Peak Limb Velocity (TtPV) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean).
Figure 21. Box and whisker plots of Time after Peak Limb Velocity (TaPV) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 22. Box and whisker plots of Time after Peak Limb Velocity (TaPV) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean).
Figure 23. Box and whisker plots of Proportion of Time after Peak Limb Velocity (PTaPV) as a function of test for each group. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+” (mean). Significant differences (p < .05) are denoted by asterisks (*).

Figure 24. Box and whisker plots of Proportion of Time after Peak Limb Velocity (PTaPV) as a function of group for Blocks 1 and 2 of vibration and no-vibration trials. Each box plot includes: whiskers (minimum to maximum values), box (25th to 75th percentile), solid line (median), and “+”