HAPTIC ASSISTANCE STRATEGIES FOR ENHANCING THE LEARNING OF KINEMATICALLY REDUNDANT MOTOR TASKS

By

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ABSTRACT

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Advances in robotic technology and interfaces have led to the adoption of robot-mediated assistance for training motor skills in a wide array of fields ranging from neurorehabilitation to skill acquisition. The assistance from the robot to control movements during learning is 'haptic' – i.e., in the form of forces applied to the body. Even though numerous studies have explored haptic assistance strategies to enhance motor learning, this has been examined only in 'non-redundant' tasks where there is only a single movement solution available. Therefore, the purpose of this dissertation was to develop haptic assistance strategies for kinematically redundant motor tasks where multiple solutions are available.

We designed a kinematically redundant steering task and used it as a framework for this dissertation. The task was to manipulate a cursor placed at the mean position of the two hands along a 'W-shaped' path as fast as possible while maintaining the cursor inside the track. This made the task kinematically redundant because the same cursor position could be achieved with different hand positions. We then conducted three experiments to examine the role of haptic feedback when learning such tasks with redundant solutions.

In our first experiment, we explored the effects of task difficulty on learning and how kinematic redundancy is utilized during task learning, without any haptic feedback. We found that the participants exploited the redundancy in the task to enhance task performance and reduced variability that did not affect task performance with learning. Surprisingly, while task difficulty

had an effect on performance, we found no effect of task difficulty on the utilization of redundancy in the task.

In the second experiment, we enabled haptic assistance at the redundant effectors (hands) in two ways: (i) restricted the usage of redundant solutions, or (ii) allowed the usage of redundant solutions. We also compared the effect of training with progressively reducing assistance levels versus training at constant assistance levels. We found that restricting the usage of redundant solutions was detrimental to motor learning, indicating that using redundancy was critical to learning. Moreover, fading assistance linearly did not offer any learning benefits relative to constant assistance.

In the third experiment, we tested the effectiveness of a performance-adaptive assistance algorithm in comparison to linearly reducing assistance. We found that the adaptive assistance group showed enhanced learning over the linearly faded assistance group. Analysis of the task learning dynamics revealed how adaptive assistance was beneficial for different initially skilled participants. We have also presented a learning dynamic variable that correlated with the retention of task performance after training with haptic assistance.

Overall, this dissertation explored the application of haptic assistance strategies for kinematically redundant motor tasks with multiple effectors. The outcomes of this dissertation will motivate research for the exploration of novel haptic assistance strategies in neurorehabilitation, human-robot collaboration, athletic training, etc.

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Chapter 1

INTRODUCTION

Learning motor skills like reaching and walking is fundamental to human development. Even though humans are adept at acquiring many of these motor skills through trial and error without much external assistance, there are certain situations where external assistance is required because self-learning is slow and leads to sub-optimal motor performance. These situations include learning of complex skills where making errors have high consequences (like surgery), or in contexts of movement impairments, where assistance may be required to physically produce the desired movement. The focus of this work is to understand how one specific type of assistance - haptic assistance using a robot - can be used to facilitate the learning of motor skills.

1.1 Requirement for assistance in precision tasks

A large proportion of human motor skills involve the production of movements along spatial trajectories. Typically, predefined continuous trajectories are prescribed at the end-effector, and the learner practices to closely follow the prescribed trajectories. The end-effector could be a part of the body i.e., the hand or the position of a tool being directly moved by the user or an object at the output of the human-computer interface or the robot end position being teleoperated by the human user. For example, consider a motor learning context where a novice surgeon is learning to operate a surgical tool to conduct surgeries. Here, the surgeon is faced with the task of moving the tool along a prescribed spatiotemporal trajectory. There are two inherent features of the motor system that hinder the surgeon's ability to perform effectively. Firstly, the motor system is prone to internal and external disturbances leading to errors in produced trajectories. Such motor errors are magnified when trying to produce faster movements due to the Speed-Accuracy tradeoff i.e., the faster the movements the lesser the precision (Accot and Zhai, 1997; Fitts, 1954). Secondly, motor variability is an ubiquitous feature of the human motor control which reduces the ability of individuals in reproducing trajectories exactly (Harris and Wolpert, 1998; Jones et al., 2002; Newell and McDonald, 1992). Thus, the surgical task performance can be measured by how closely the end-effector follows the prescribed trajectory and how consistently the trajectories are reproduced. The former can be quantified by a 'spatial error' metric and the latter can be quantified by 'task variability'. Thus, the surgeon is required to maintain the spatial error and variability within admissible (depends on the task and implications) limits. Moreover, the end goal for the surgeon is to be able to perform the motor task in the absence of assistance. Thus, a central question in motor learning is therefore to understand how to setup practice conditions to assist learners in learning the task and improving task performance.

1.2 Haptic assistance for motor tasks

A common strategy to facilitate motor learning is by augmenting assistance during learning (Sigrist et al., 2013). Specifically, with respect to controlling variability, a method of aiding learners has been through the use of haptic assistance using robotic devices (Rosenberg, 1993). Unlike other forms of assistance that rely on the learners to change their movement, haptic assistance has an advantage in that it can be used to directly generate forces on the limbs to control movement variability and error. For the example of surgeon learning a spatiotemporal movement (with hand or teleoperated tools), software programmed force fields called 'virtual fixtures' can be overlaid on top of the reflected workspace to prevent deviations of controlled end-effectors into disallowed regions or to encourage movement along desired directions (Abbott et al., 2007; Moore et al., 2003; Park et al., 2001). In addition to directly altering movements, the haptic forces also convey perceptual information, reduce overloading of the visual modality, and reduce mental processing required to complete the task (Rosenberg, 1995). Going further, virtual fixtures in the form of force channels or tunnels were successfully applied in rehabilitation to maintain ‘spatial errors’ in movements and to control ‘task variability’ of the relevant joint (Banala et al., 2007; Duschau-Wicke et al., 2010). The use of virtual fixtures is a well-established method to assist learners in maintaining variability at the task level.

1.2.1 Assistance in the context of motor redundancy

But does minimizing ‘task variability’ mean that ‘motor variability’ also needs to be minimized? For example, the surgeon has constraints on the movement of the tool according to the requirements of the task, but not on the various joints in his/her arm that are responsible for the movement. This means that there may be multiple possible combinations of the joint angles in the arm that can lead to the same position of the tool. Such systems are called redundant systems where there are more elemental variables than required to generate the outcome or task variables (Bernstein, 1967; Turvey et al., 1982). The feature of redundancy means that motor variability essentially can be decomposed into two parts: a ‘task-space variability’ (or ‘bad’ variability), which influences the task variability, and a ‘null-space variability’ (or ‘good’ variability as it does not effect on task performance), which has no effect on the task (Latash et al., 2002; Scholz and Schöner, 1999). It is pivotal to understand the distinction between task variability that refers to outcome variability that is tied to task performance and ‘task space variability’ that refers to the component of the overall motor variability. If learners exploit the redundancy in the system, they could be performing with a higher overall motor variability while still maintaining a low task space variability (Latash, 2012).

This leads to the first question of this dissertation; how should haptic assistance be designed to control motor variability in redundant motor tasks? Prior studies using haptic assistance have relied almost exclusively on non-redundant tasks, where reducing task variability necessitates reducing motor variability. However, with a redundant system, there are now two possibilities: (i) provide haptic assistance to control all motor variability (i.e., both task space and null space variability), which restricts learners to use a stereotypical, repetitive solution (i.e., like a non-redundant system) or (ii) use haptic feedback to control only the task space variability, which allows learners to exploit redundancy in the system. The second possibility promotes flexibility in movements (Latash, 2010), whereas the first possibility promotes a use-dependent learning mechanism (Diedrichsen et al., 2010c). The possibilities can be applied to the context of the surgeon learning to manipulate the tool along a prescribed spatial trajectory. According to the first possibility, haptic assistance should be provided at the different joints responsible for the movement of the tool. Whereas, from the second possibility, haptic assistance should be provided only at the location of the tool. The first possibility restricts all variability whereas the second possibility restricts variability in the movement of the tool only. Which of the two possibilities, control all variability vs just task space variability enhances motor learning?

1.2.2 Enhancing performance versus learning

Haptic assistance undoubtedly enhances task performance when provided, but the performance drops significantly when assistance is subsequently removed (Crespo and Reinkensmeyer, 2008; Powell and O'Malley, 2012). Such observations are common with assistance strategies where the assistance is maintained at high levels throughout practice and provided very frequently during motor execution. Such strategies are not optimal for learning as this could make the learner over-dependent on assistance according to the 'Guidance hypothesis' (Salmoni et al., 1984), thereby leading to the significant deterioration in performance once the feedback is removed. Moreover, assisting movements physically alters the task dynamics and leads to the learning of an entirely different task. It is also posited that assistance might only be required in the initial stages of learning when the learner is facing the highest practice difficulty (Crespo and Reinkensmeyer, 2008). Thus, assistance should be reduced progressively to mitigate the overreliance effect and to gradually converge to the original task dynamics. However, it is not clear how effectively assistance should be reduced with learning given the myriad algorithms for reducing assistance.

Progressive assistance strategies can be divided into 'open-loop' and 'closed-loop' strategies. In open-loop strategies, the assistance levels are reduced progressively in training, independent of the performer. A simple way to implement open-loop strategy is to reduce the assistance levels in a linear fashion. Both the constant and progressive strategies mentioned earlier are 'open-loop' in that the change (or lack of change) in the assistance is unrelated to the learner's performance. Although implementing open-loop strategies is easier, a limitation is that they do not account for inter-individual variation in performance and rates of learning. Closed-loop strategies circumvent this limitation by adaptively setting practice conditions based on the individual learners' task difficulty. Thus, closed-loop strategies assign assistance levels by estimating assistance requirements for each learner independently and are consistent with the idea of a challenge point (Guadagnoli and Lee, 2004), which suggests that motor learning is optimal when the learner is challenged during task execution. The idea here is to continuously challenge the learner by manipulating the assistance level, which in turn changes the functional task-difficulty.

1.3 Dissertation aims and summary

With recent advancements in robotic technology, there has been an increased focus on haptic assistance strategies to aid in the learning/completion of physical tasks. The haptic assistance has almost exclusively been enabled for non-redundant tasks and at the final joint/effector whose movement determines task performance. However, for kinematically redundant motor tasks the movement at the joint/effector of interest is caused by multiple other joints or effectors. In this dissertation, we have tested the possibility of enhancing motor learning by enabling haptic assistance at the redundant joints. In summary, we conducted the dissertation with the following aims:

1. Determine how kinematic redundancy is utilized in the learning of the task under no haptic assistance
2. Determine whether restricting redundant solutions or allowing redundant solutions using haptic assistance is better for learning
3. Determine if performance adaptive manipulation of assistance (closed-loop) is better than fixed manipulation of assistance (open-loop).

We designed a kinematically redundant task to address the aims of the dissertation. The task was to manipulate a cursor placed at the mean position of the two hands along a ‘W-shaped’ path of definite width as fast as possible while maintaining the cursor inside the path. The task was kinematically redundant because a given position of the cursor could be reproduced with different spatial hand locations. We evaluated task performance using a score variable which was composed of the time taken to complete the movement and the time spent by the cursor outside the path. Since the task was redundant, the motor variability could be decomposed into null space variability that did not cause deviation of the cursor and task space variability that caused deviations in the position of the cursor. We derived task and null space variabilities throughout learning to determine how learners organized motor variability to learn the task.

1.3.1 Aim 1 – Determine how kinematic redundancy is utilized in the learning of the task under no haptic assistance

It has been observed that the structuring of motor variability or the exploitation of task redundancy changes with practice in systematically different ways depending on the nature of the task (Latash, 2010; Wu and Latash, 2014). We conducted Experiment 1 to characterize the utilization of redundancy in our task and to identify task parameters the task parameters that offered appropriate task difficulty and provided scope for the learning of the task. As expected, we found that the learners exploited the redundancy in the task to maintain task performance - they minimized task space variability by allowing higher null space variability. We also observed that irrespective of the task difficulty null space variability reduced monotonically with learning. Besides, participants traded-off task space variability to increase movement speeds with learning.

1.3.2 Aim 2 - Determine whether restricting redundant solutions or allowing redundant solutions using haptic assistance is better for learning

On one hand, the flexibility in movement solutions allows exploitation of redundancy to maintain task relevant variability (Latash, 2012). On the other hand, the repetition of similar movements across trials can promote a use-dependent learning mechanism (Diedrichsen et al., 2010c) and the formation of accurate inverse maps (Ranganathan et al., 2013). We conducted Experiment 2 to determine whether flexibility in adopting redundant solutions should be preserved while designing haptic assistance. We augmented haptic force channels that restricted the usage of redundant solutions during training for one group and allowed the usage of redundant solutions for another group. We found that restricting the usage of redundant solutions was detrimental to the learning of the task and increased learner's reliance on haptic assistance to complete the task. We believe that the inherent flexibility in hand movements promotes the stabilization of the cursor and exploration of the movement space, which could be critical especially in the initial phases of learning.

1.3.3 Aim 3 - Determine if performance adaptive manipulation of assistance (closed-loop) is better than fixed manipulation of assistance (open-loop).

Practicing at constant levels of assistance renders learners to rely on assistance to complete the task and incapable of performing in the absence of assistance (Heuer and Lüttgen, 2015; Powell and O'Malley, 2012). Therefore, in Experiment 2, we reduced the assistance levels by reducing the force gains linearly and progressively during training. Unexpectedly, we found that simply reducing assistance levels with learning did not provide any significant benefits overtraining at constant assistant levels. The failure of simple linear progressively reducing assistance, despite it being in accordance with the guidance hypothesis, directed our attention towards performance-based manipulation of assistance. The assistance level can be reduced based on the size of improvement in motor performance - assistance is reduced as the learner improves performance, and this continually challenges the learner to actively participate in the task (Guadagnoli and Lee, 2004). Since assistance is tailored to the requirements of the learner, we expect that adaptive or 'closed-loop' assistance will be more effective than 'open-loop' assistance strategies explored in the second aim. In Experiment 3, We implemented a performance adaptive algorithm to manipulate assistance during training for a new group of learners and found a subtle improvement in task performance over the group that practiced under linearly reducing assistance. Going further, we wanted to determine how the performance-based manipulation of assistance aided in the learning of the task. We proposed a method to analyze the learning dynamics by studying the dynamics between changes in assistance levels and task performance during training. We were able to show how learners of different initial skill levels and learning capabilities utilized the adaptive nature of assistance to improve task performance. We also identified a dynamic learning variable that correlated with the retention of performance in the absence of assistance. Even though several studies have demonstrated the benefits or shortcomings of assistance control strategies, we believe that this is the first attempt at evaluating the strategies by analyzing the effects of changes in assistance on learner's performance during training.

The outcomes of this dissertation have applications in domains where robotic technology can be used to augment assistance in the completion of motor activities. The results will motivate research in the exploration of novel haptic assistance strategies for motor tasks involving multiple effectors. Whether a surgeon is learning to perform a novel maneuver or a stroke survivor is relearning movements in a rehabilitation setting, adopting suitable haptic assistive strategies can lead to more effective learning. The presented evidence will also aid in designing and evaluating assistance paradigms that promote not just improvements in motor performance but the retention of performance in the absence of assistance.

Chapter 2

RELATED WORK AND BACKGROUND

2.1 Augmented assistance as feedback

Humans learn numerous motor skills throughout their lifetime through cooperative action of the sensory system and the motor system. The sensory system which provides feedback about the ongoing motor activity is integral to the closed-loop theory of motor learning (Adams, 1971). The feedback received by the motor system intrinsically in the form of sensory perceptual information is natural and mostly sufficient for several self-acquired motor skills. However, for increasingly complex motor tasks and shorter temporal learning requirements, it becomes necessary to augment feedback externally. For example, a novice surgeon, performing a complex surgical tool maneuver might be greatly difficult and might require extensive amounts of training to learn the skill. In such cases, external feedback can be augmented to provide greater information about motor performance. It has been established that making provisions for additional feedback during the movement known as the knowledge of performance (Wallace and Hagler, 1979) and after the movement in the form knowledge of results (Newell, 1976; Salmoni et al., 1984; Winstein, 1991) can assist learners in improving their motor performance. Such extrinsic feedback can be used to provide numerical feedback about task performance, direct attention towards certain aspects of the task, reiterate desired movements and task instructions, etc.

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feedback received by the motor system intrinsically in the form of sensory perceptual information is natural and mostly sufficient for several self-acquired motor skills. However, for increasingly complex motor tasks and shorter temporal learning requirements, it becomes necessary to augment feedback externally. For example, a novice surgeon, performing a complex surgical tool maneuver might be greatly difficult and might require extensive amounts of training to learn the skill. In such cases, external feedback can be augmented to provide greater information about motor performance. It has been established that making provisions for additional feedback during the movement known as the knowledge of performance (Wallace and Hagler, 1979) and after the movement in the form knowledge of results (Newell, 1976; Salmoni et al., 1984; Winstein, 1991) can assist learners in improving their motor performance. Such extrinsic feedback can be used to provide numerical feedback about task performance, direct attention towards certain aspects of the task, reiterate desired movements and task instructions, etc.

2.2 Haptic assistance strategies to control motor variability

Several motor tasks require the manipulation of the hand or foot or an external tool along a prescribed spatiotemporal trajectory. However, errors in the manipulation of the end-effector are inevitable and each repeated end-effector trajectory is kinematically different due to the effects of sensorimotor noise. Kinematic variability is unavoidable even for well-trained skills and it is almost impossible to completely nullify motor variability (Newell and Corcos, 1993). Such variability in motor execution is an outcome of the accumulation of noise in the motor pathways arising due to channel noise in neurons (White et al., 2000), synaptic noise (Calvin and Stevens, 1968) and also due to chaotic dynamics in neural networks (Van Vreeswijk and Sompolinsky, 1996). Moreover, such sensorimotor noise can be amplified with an increase in magnitudes of neural signals (Harris and Wolpert, 1998; Van Beers et al., 2004), the magnitude of impulsive forces, and amplitude of movements (Accot and Zhai, 1997; Fitts, 1954). Although it is evident that such variability can be decreased with practice, the initial variability and errors could be too large leading to safety concerns (Reinkensmeyer and Patton, 2009), for example, a patient who is retraining balance has a risk of falling in the absence of assistance. Moreover, with tasks that present high functional difficulty, unsatisfactorily large amounts of practice might be required, and the lack of performance (due to large errors) might curb motivation to practice the task (Sanger, 2004). A study on golf putting with robotically modulated task space variability found that assisting to lower task space variability improved skill and enhanced self-reported competence in comparison to practicing under no assistance for initially less skilled subjects (Duarte and Reinkensmeyer, 2015). Thus, the learning could be made more efficient by assisting in the control of such variability.

On the other hand, haptic assistive strategies can also be used to teach spatial characteristics of movement. The simultaneous visual and haptic exploration of trajectories might lead to an enhanced representation of shape memory. It is posited that the sensorimotor system optimally integrates multimodal visual and haptic information making it better than unimodal information (Helbig and Ernst, 2007). Significant learning benefits have been documented for handwriting learning due to visuo-haptic integration of feedback (Bara et al., 2004; Kalenine et al., 2011).

2.2.1 Position control strategies

Haptic assistance strategies that provide a varying degree of autonomy to learners have been employed. On one end, strict position control strategies have been adopted where the robot moves the learner's limbs along prescribed trajectories irrespective of the intentions of the learner. The idea behind such training is that the nervous system can derive topological information about the trajectory by processing the haptic force feedback (Liu et al., 2005). In a 3D tracing task, participants had to move their hand while gripping a robot end-effector along a desired trajectory on a 3-dimensional spherical surface under three different conditions: visual, haptic, and visuo-haptic (Feygin et al., 2002a). In the visual condition, participants watched the robot move along the desired trajectory, in the haptic condition the robot moved the participant's hands along the required trajectory but couldn't see their hand and in the visuo-haptic condition they could see their hand while being guided by the robot. The visual group could reproduce the shape better than the haptic only group and the visuo-haptic group performed as good as the visual only group in a short-term retention test. Another study adopted the same task but increased the number of practice trials and tested retention with a larger number of trials, but did not find any significant differences between the visual and visuo-haptic groups (Liu et al., 2005). Similarly, active robot training for reaching in stroke survivors provided no added benefit in comparison to training without any assistance (Kahn et al., 2006). Such position control strategies deter motor learning because it renders a passive role for the motor system (Powell and O'Malley, 2012) and curbs error-driven learning mechanisms (Emken and Reinkensmeyer, 2005). It has also been observed that limiting movement variability in simple reaching tasks can prolong the motor learning process (Scheidt et al., 2000). Moreover, providing assistance frequently deviates the dynamics of the task from the target task decreasing motor learning (Crespo and Reinkensmeyer, 2008), according to the "guidance hypothesis" (Salmoni et al., 1984; Schmidt and Bjork, 1992).

2.2.2 Bandwidth assistance strategy

Bandwidth based (Sherwood, 1988) assistance approaches have been employed to reduce the frequency of haptic assistance during motor execution, wherein the assistance is only enabled outside an error bandwidth. Thus, the learners only receive assistance when the end-effector deviates beyond a certain preset region around the target position. In a rowing task, the robot applied an elastic torque when the oar deviated outside an error threshold (Rauter et al., 2015). Similar elastic forces that pull the end-effector to the target position were adopted in training reaching during rehabilitation (Krebs et al., 1998) and for training automotive steering skills (Crespo and Reinkensmeyer, 2008). This method was first introduced in the form of ‘virtual fixtures’, wherein computer-generated force fields in the overlaid workspace were used to assist subjects in telemanipulating a robotic arm used to perform a peg insertion task (Rosenberg, 1993). Such virtual fixtures have been adopted extensively to prevent the deviation of the end-effector into forbidden regions and enhance task completion times in various telemanipulation applications (Abbott et al., 2007; Dewan et al., 2004; Li et al., 2007; Park et al., 2001). In the application of robotics in rehabilitation, such techniques are commonly referred to as ‘assist-as-needed’ (ANN) training methods (Emken et al., 2005). The assistance is typically implemented in the form of force tunnels or force channels that are created around the prescribed end-effector trajectories (Cai et al., 2006; Krebs et al., 2003). Haptic forces are applied to the end-effector when they deviate away from the boundaries of the force channels and usually, the forces are applied in proportion to the magnitude of the deviation. Such force channels have been used effectively in lower limb rehabilitation to control the deviation of the ankle from normative paths during gait (Banala et al., 2007; Duschau-Wicke et al., 2010). Such bandwidth-based assistance methods have also enabled the retention of novel motor skills significantly (Chen and Agrawal, 2013; Crespo and Reinkensmeyer, 2008; Marchal-Crespo and Reinkensmeyer, 2009; Williams and Carnahan, 2014a).

2.2.3 Fading assistance strategies to enhance learning

We have discussed the bandwidth strategy to reduce the frequency of haptic assistance provided within a given movement trial. A related question is how assistance should be manipulated/scheduled during practice over multiple trials to mitigate the overreliance effect. At the level of practice, training with constant assistance levels throughout the practice period can have detrimental effects on learning as discussed earlier. Specifically, practicing with constant assistant levels enhances performance when provided, but performance reduces significantly upon removal of assistance (Crespo and Reinkensmeyer, 2008; Heuer and Lüttgen, 2015; Powell and O'Malley, 2012; Williams and Carnahan, 2014a). Several studies that initially adopted haptic assistance for teaching motor skills reported significant drops in task performance upon removal of assistance and unsatisfactory retention of learned skills (Feygin et al., 2002a; Kahn et al., 2006; Li et al., 2009b; Liu et al., 2005; Teo et al., 2002). Thus, it would be beneficial to reduce the level of haptic assistance along with practice, such that the task dynamics can converge to the target task dynamics. In the context of using haptic forces to assist movements, the assistance level is determined by a force gain (also called stiffness coefficient when spring-like convergent forces are incorporated), and reducing assistance level is equivalent to reducing the force gain.

On a broad level, there are two fundamental strategies to fade assistance levels progressively with learning – open-loop and closed-loop. Open-loop strategies reduce the assistance levels in a predetermined manner for all learners. Very few studies have adopted open-loop strategies to reduce assistance and the results have shown mixed benefits towards learning (Chen and Agrawal, 2013; Heuer and Lüttgen, 2014a; Lee and Choi, 2010). However, learners possess different skill levels initially and some learners might benefit more from assistance than others (Marchal-Crespo et al., 2010a). Thus, the assistance could be tailored to the individual using simple performance adaptive approaches – a learner outputting high task performance might not require assistance as much as a learner having low task performance. Such manipulations of the assistance according to the requirement of the learner can be termed as closed-loop strategies. The closed-loop strategies for manipulation of assistance are also supported by the challenge point framework (Guadagnoli and Lee, 2004) - the learner is challenged to perform with a reduced assistance level after an increase in performance. Performance adaptive strategies were first adopted in rehabilitation studies with individuals affected by hemiparesis (Kahn et al., 2004; Krebs et al., 2003) where the assistance levels were manipulated according to either absolute performance measures or changes in performance measures. The assistance manipulation was also setup as an optimization problem with the quadratic costs on motor errors and assistive forces (Emken et al., 2005), which resulted in an effective algorithm to fade assistance to zero. Several studies that adopted performance adaptive assistance manipulation strategies reported favorable short term benefits for retention of motor skills especially with less skilled learners and benefits early on in learning (Banala et al., 2009; Crespo and Reinkensmeyer, 2008; Huegel and O'Malley, 2010; Li et al., 2009a; Marchal-Crespo et al., 2010a). However, some studies have reported null effects of reducing assistance in a performance adaptive manner (Lee and Choi, 2014).

Overall, according to the guidance hypothesis, open-loop strategies should benefit learning more than fixed assistance, and due to added learning benefits, closed-loop strategies should be more effective than open-loop strategies. However, there is a lack of research on effectively characterizing the learning benefits of closed-loop strategies in comparison to open-loop strategies. Moreover, prior studies have mostly looked at learning from a Pre-test to Post-test standpoint and ignoring the learning dynamics that occur while training with assistance. Analyzing the effects of manipulating assistance levels in an open-loop or closed-loop manner on the task performance throughout the training period might provide valuable insights about the learning process.

2.2.4 Error augmentation strategies

So far, we have only discussed haptic assistive strategies that resist any undesirable deviations of the end-effector from the prescribed trajectories. However, a number of studies have also tested the effects of strategies that increase errors in place of resisting them (Williams and Carnahan, 2014a). While the assistive strategies utilize convergent force fields, the error augmenting strategies adopt divergent force fields that force the end-effector away from the desired path. It is posited that such error augmenting strategies are effective because they enable error-driven learning (Emken and Reinkensmeyer, 2005; Patton et al., 2006; Shadmehr et al., 2010; van Beers, 2009). Moreover, such strategies are also supported by the challenge point theory (Guadagnoli and Lee, 2004) that suggests that learning is optimal when the learners are challenged sufficiently when executing motor activities. In agreement with the challenge point framework, error augmenting strategies have been found to be more effective than error resisting strategies for high skilled subjects and especially for adaptation paradigms (Cesqui et al., 2008; Lee and Choi, 2010; Patton et al., 2006; Tseng et al., 2007). However, such error augmenting strategies might be detrimental for less-skilled subjects and frequent large errors could lead to lower task performance resulting in lower motivation for training (Sanger, 2004). For complicated tasks and tasks posing safety concerns especially in the rehabilitation setting (Marchal-Crespo and Reinkensmeyer, 2009), error resisting strategies could be inevitable and favored more than error augmenting strategies.

2.3 Haptic assistance at redundant effectors

2.3.1 Variability in redundant motor tasks

Most of the discussed studies employed haptic feedback to reinforce or notify errors caused at the end-effector. An important characteristic of the motor system is the feature of redundancy. The feature of redundancy means that a given motor task can be achieved using multiple movement solutions. Bernstein first documented this phenomenon when he observed a blacksmith adopt different movement paths of the tip of the hammer while still successfully hitting the target and termed it as ‘repetition without repetition’ (Bernstein, 1967). Almost all the motor activities that humans perform possess the feature of redundancy which manifests at different levels – kinematic, kinetic, temporal, muscle, and limb levels. In this dissertation, we particularly focus on kinematic redundancy observed at the limb level.

The feature of redundancy means that the end-effector can be manipulated along similar paths while adopting observably different kinematics at the redundant effectors. For example, we can maintain our fingertip at a given location in space while adopting different orientations of the wrist, forearm, and the upper arm. Therefore, it could be possible to have a high overall motor variability even while having low end-effector variability. The motor variability for kinematically redundant motor tasks can be decomposed into two components (i) task space variability – the component of variability that affects task variables (ii) null space variability – the component of variability that does not affect task variables (Domkin et al., 2002; Latash et al., 2001; Liu et al., 2010; Mosier et al., 2005; Scholz and Schöner, 1999). The notion of task variables is task dependent and for us, task space variability implies the component of the motor variability that leads to variability in the end-effector position and null space variability is the component of overall motor variability that does not contribute to the variability of the end-effector position.

2.3.2 Assistance to control variability

As discussed earlier, the task goal for end-effector control is to minimize errors from desired paths and variability between reproduced paths. Prior studies have only used haptic assistance to control the end-effector variability directly, even when multiple redundant effectors are contributing to the movement of the end-effector. However, for redundant tasks, the end-effector variability can be controlled by controlling the variability of the redundant effectors. A natural question is whether providing assistance at the redundant effectors is beneficial than providing haptic assistance only at the end-effector. Therefore, haptic assistance for redundant motor tasks presents the following two possibilities to control task space variability or the end-effector variability (i) provide assistance at the end-effector to control task space variability only (ii) provide assistance at the redundant effectors to control overall motor variability. The first possibility would mean that there is the flexibility to use redundant solutions over multiple trials, whereas the second possibility restricts the usage of redundant solutions. The question boils down to whether redundant solutions should be allowed or restricted while practicing kinematically redundant motor tasks.

On one end, we have theoretical and experimental evidence against restricting the adoption of redundant solutions. Optimal control models have proposed that it is optimal for the motor system to adopt multiple solutions to the same task as long as there are no deviations from the task goals which is also referred to as the minimum intervention principle for motor control (Diedrichsen et al., 2010a; Todorov and Jordan, 2002). Specifically, the minimum intervention principle states that the motor system has to correct movements of the redundant effectors only when there is a deviation of the end-effector from the required path. Experimental evidence that led to the uncontrolled manifold hypothesis (Scholz and Schöner, 1999) and the goal equivalent manifolds

(Cusumano and Cesari, 2006), and states that the motor system stabilizes task variables (low task space variability or goal equivalent variability) by allowing higher variability in the null space. Several other studies have reported results in agreement with the uncontrolled manifold hypothesis (Dingwell et al., 2013; Domkin et al., 2002; Latash et al., 2001; Müller and Sternad, 2004; Scholz et al., 2000; Wu et al., 2014). Besides, the usage of redundant solutions promotes exploration of the movement subspace (Sternad, 2018), reduces fatigue that could arise from repetitive movements, allows compensation for unexpected perturbations, and simultaneous solutions to secondary tasks (Latash, 2012).

On the other hand, repeating similar movements at the redundant effectors might offer learning benefits. Even though the minimum intervention principle states that variability that does not affect task performance need not be minimized, experimental evidence reveals a tendency of the motor system to reduce overall movement variability with learning (Domkin et al., 2002; Georgopoulos et al., 1981; Yang and Scholz, 2005). It was also found that the flexibility to use redundant solutions might be important only to learn task-relevant parameters and a flexible system uses redundant solutions only when there are constraints towards using a preferred set of solutions (Ranganathan and Newell, 2010). The repetition of similar movements might also promote a use-dependent learning mechanism which suggests that the motor system learns by repeating similar movements over successive trials (Diedrichsen et al., 2010c). The motor system naturally tends to reinforce successful movement solutions leading to a model-free learning mechanism and repeating successful solutions might benefit learning (Haith and Krakauer, 2013). Moreover, the repetition of similar movements can speed up the formation of inverse maps between the lower dimensional task space and higher dimensional joint space (Liu and Scheidt, 2008; Mosier et al., 2005; Ranganathan et al., 2013). Experimental evidence showing the benefits of using variable solutions have been mostly in adaptation paradigms where exploration is critical (Wu et al., 2014). Besides, practice conditions that enforced high null space variability were found to impair learning in a study requiring reduction of variability around a preferred solution (Cardis et al., 2017).

2.3.3 Bimanual tasks as a model for studying redundancy

We use our two hands to perform several motor tasks in our everyday life and most of the tasks involve interactions with external objects. The two hands coordinate in a multiple number of ways to cooperatively manipulate objects constituting a redundant system. Any given orientation of an object placed in between the hands can be obtained with different hand positions on the object. The minimum intervention principle and the uncontrolled manifold hypothesis were verified for the case of a bimanual redundant system, where two hands were used to control a cursor placed at the average position of the hands (Diedrichsen, 2007). Specifically, the variability in the position of the cursor was minimized by allowing variability in the position of the hands. Such a system is well suited to study the application of assistance to redundant systems because the assistive force channels can be independently integrated for the two hands.

The ubiquity of bimanual coordinated movements in our life and the dexterity afforded by our hands encourages the use of bimanual action for human-robot cooperation tasks (Talvas et al., 2014). Moreover, the past decade has seen a rapid advancement in the use of haptic enabled robotic systems for surgical interventions (Enayati et al., 2016). Alongside, virtual reality platforms have also made their way to train surgeons for certain surgical skills in training (Derossis et al., 1998). Encouraging transfer of skills from training to the operation room has been reported in surgical training studies (Escobar-Castillejos et al., 2016; Hyltander et al., 2002; Sturm et al., 2008; Vaughan et al., 2016). A fundamental question is how to effectively enable haptic feedback to the two hands to provide sufficient information during the surgical task and how to best organize surgical training to ensure the transfer of learned skills outside simulations. Lately, there has also been an increased use of the bimanual modality for telepresence and telemanipulation systems in applications for tasks in space (Artigas et al., 2016), disaster response activities (Katyal et al., 2014) and tasks in hazardous environments (Kron et al., 2004).

Two-handed training protocols have also been used extensively in rehabilitation due to the ubiquity of bimanual movements in the activities of daily living. A major goal for the rehabilitation of the upper limb is to restore the motor capabilities of bimanual coordination (Rose and Winstein, 2004). The coordination between the two hands can be retrained only using bilateral tasks and not by training each arm separately due to differing motor control processes (Waller and Whitall, 2008). Moreover, bilateral training can improve unilateral paretic limb functions partially due to neurophysiological mechanisms. Several clinical studies have adopted bilateral arm training using robot mediated assistance in acute and chronic stages post-stroke and have reported favorable results (Hesse et al., 2003; Lewis and Perreault, 2009; Stinear and Byblow, 2004; Whitall et al., 2000).

Simultaneous bimanual perception is also found to be superior to unimanual perception and visual perception of surfaces. Bimanual simultaneous exploration of haptic surfaces can provide more relevant information than unimanual exploration (Leganchuk et al., 1998). The integration of haptic feedback between the two hands increases the perception of curvature and allows better discrimination of surfaces (Panday et al., 2013). A kinematic chain is formed with the two hands and the object in between, and this leads to the transfer of learning between the hands. Moreover, a frame of reference is created between the two hands and that facilitates the reduction in task completion times without affecting task precision (Talvas et al., 2014).

Chapter 3

DIFFERENTIAL CONTROL OF TASK AND NULL SPACE VARIABILITY IN RESPONSE TO CHANGES IN TASK DIFFICULTY WHEN LEARNING A BIMANUAL STEERING TASK

The work presented in this chapter has been published (Lokesh and Ranganathan, 2019)

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3.1 Abstract

The presence of motor redundancy means that movement variability can be split into a 'task space' component that affects task performance, and a 'null space' component which has no effect on task performance. While the control of task space variability during learning is essential because it is directly linked to performance, how the nervous system controls null space variability during learning has not been well understood. One factor that has been hypothesized to govern the change in null space variability with learning is task difficulty, but this has not been directly tested. Here we examined how task difficulty influences the change in null space variability with learning. Healthy, college-aged participants (n = 36) performed a bimanual steering task where they steered a cursor through a smooth W-shaped track of a certain width as quickly as possible while

attempting to keep the cursor within the track. Task difficulty was altered by changing the track width and participants were assigned into one of three groups based on the track width that they practiced on - wide, narrow, or progressive (where the width of the track progressively changed from wide to narrow over practice). The redundancy in this task arose from the fact that the position of the cursor was defined as the average position of the two hands. Results showed that movement time depended on task difficulty, but all groups were able to decrease their movement time with practice. Learning was associated with a reduction in null space variability in all groups, but critically there was no effect of task difficulty. Further analyses showed that while the task space variability showed an expected speed-accuracy tradeoff with movement time, the null space variability showed a qualitatively different pattern. These results suggest differential control of task and null space variability in response to changes in task difficulty with learning and may reflect a strong preference to minimize overall movement variability during learning.

3.2 Introduction

The large number of degrees of freedom in the human body creates redundancy, which means that most motor tasks can be accomplished through multiple movement solutions (Bernstein, 1967). For example, when reaching to a location in 3D space, the human arm has at least 7 degrees of freedom at the joint level, which means that there are multiple arm postures that can be used to reach that location (Turvey et al., 1982). This example of mechanical redundancy allows movement variability to be decomposed into two components - (i) a 'task space' (or goal-relevant) component where the variability directly affects the task outcome, and (ii) a 'null space' (or goal-equivalent) component where variability has no effect on the task outcome (Cusumano and Cesari, 2006; Domkin et al., 2002; Mosier et al., 2005; Müller and Sternad, 2004; Scholz and Schöner, 1999). Understanding how the nervous system controls these two components of variability when learning a novel task is critical from both theoretical and applied viewpoints.

Although it is apparent that task space variability must be controlled with learning due to its direct link to task performance, the role of null space variability with learning remains rather unclear (Wu and Latash, 2014). On the one hand, there is evidence that overall movement variability (i.e., both task and null space variability) generally decreases with learning (Darling and Cooke, 1987; Ranganathan and Newell, 2010; Shmuelof et al., 2012), indicating that even in the presence of many solutions, there is a tendency to use certain 'preferred' solutions. However, on the other hand, reducing null space variability could also be considered 'wasted effort' since it has no impact on task performance (Todorov and Jordan, 2002). Moreover, reducing null space variability may also be counter-productive since the presence of null space variability may allow flexibility to accommodate perturbations or secondary tasks (Latash, 2012; Rosenblatt et al., 2014; Zhang et al., 2008). A recent review (Latash, 2010) revealed a mixed pattern of results – in some tasks, there was an increase in null space variability (relative to the task space variability) with learning, whereas in others there was a decrease. One potential hypothesis raised to explain this pattern of results was that of task difficulty - simple tasks with lower task difficulty generally showed greater reduction in null space variability, whereas complex tasks with higher task difficulty led to relative preservation of the null space variability. These results point to a need to clarify the role of task difficulty in the change of null space variability in learning.

However, a major limitation of inferring the role of task difficulty from prior work is the necessity to make comparisons between learning completely different tasks (e.g. pointing at a target vs. multi-finger force production). Although it seems intuitive that some tasks may be more difficult than others, there is no common metric of task difficulty across these different tasks, which is critical to quantitatively test this hypothesis. Here we overcome this limitation by using a single task that could be varied on a quantifiable metric of task difficulty. Specifically, we used a steering task where participants had to steer a cursor through a track while staying within a track. This paradigm allowed us to manipulate task difficulty by altering the width of the track, while holding all other experimental factors constant.

The goal of this study was to examine the effect of manipulating task difficulty on the change in null space variability with learning. Participants performed a bimanual steering task where the goal was to steer a screen cursor through a desired track of specified width as quickly as possible without crossing the boundaries of the track. Critically, the screen cursor position was determined as an average of the position of the two hands, which meant that the same cursor path could be achieved by different combination of hand paths. We manipulated the task difficulty by adjusting the track width; in two groups (wide and narrow), the track width was held constant throughout practice, and in a third group (progressive), we changed the track width during practice. We evaluated the change in null space variability with learning. Based on the task difficulty hypothesis (Latash et al., 2001), we hypothesized that there would be a reduction in variability with learning in both cases, but that the group with higher task difficulty (i.e., the narrow group) would show higher amounts of null space variability relative to the group with easier task difficulty. As a second exploratory aim, we also examined if progressive modification of task difficulty (gradually moving from lower to higher task difficulty) had a differential effect on the use of null space variability relative to the groups that practiced with the same level of task difficulty throughout.

3.3 Methods

3.3.1 Participants

Participants were 36 healthy college-aged adults (age range: 20-24 yrs., 20 females). Participants received extra course credit for participation. All participants provided informed consent and the procedures were approved by the Institutional Review Board at Michigan State University.

3.3.2 Apparatus

We used a bimanual manipulandum (KINARM Endpoint Lab, BKIN Technologies Ltd., ON), which consists of two separate robotic arms that allow motion in a 2-D horizontal plane. A handle located at the end of each arm could be grasped by participants. Participants were seated on a height-adjustable chair and looked into a screen at around 45-degree angle below eye level (Figure 3.1A). The visual information was presented in such a way that the objects on the screen appear to be located in the plane of the hands. Kinematic data from both handles were sampled at 1000 Hz.

3.3.3 Task Description

The participants controlled a cursor of diameter 4 mm and steered it from start position to end position along a smooth W-shaped track of length 738 mm (Figure 3.1B). The goal of the participants was to do this as quickly as possible, while maintaining the cursor within the track. The width of the track was always visible to the participant- both the track (i.e., the ‘allowed region’), and the surrounding region were highlighted in different colors. When the cursor deviated from the track, the surrounding region changed color serving as a visual cue to help maintain the cursor within the track. Regardless of the track width, the center of the track always remained in the same position in the workspace for all participants and conditions.

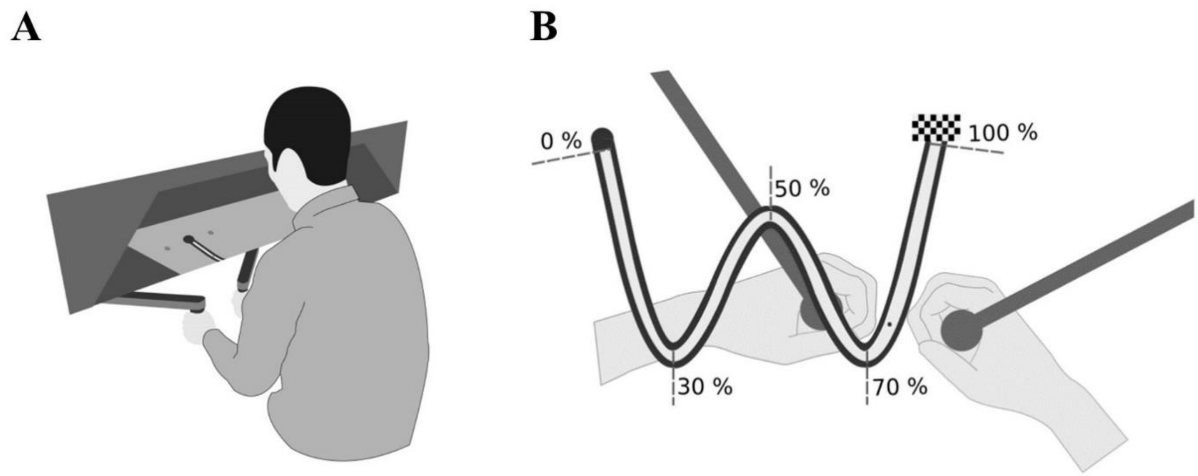

Figure 3.1 Experiment 1 setup and task schematic. (A) Schematic of experimental apparatus. Participants held the handles of a bimanual manipulandum and looked into a screen that displayed the image in the same plane as their hands. Participants could not see their hands directly. (B) Task Schematic. Participants were asked to steer a cursor though the W-shaped track as quickly as possible from start to finish while maintaining the cursor inside the track. The position of the cursor was displayed at the average position of the two hands (hands were not visible to the participant). Hands are drawn only for the sake of clarity and are not to scale.

3.3.4 Cursor mapping

The position of the cursor (XC, YC) was displayed at the average position of the two hand locations (X and Y coordinates of the left and right hands), making the task redundant (Diedrichsen, 2007). This 4-to-2-mapping can be represented as follows (Liu and Scheidt, 2008; Mosier et al., 2005)

$$C = \begin{bmatrix} X_C \\ Y_C \end{bmatrix} = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} X_L \\ X_R \\ Y_L \\ Y_R \end{bmatrix} = A\,H \tag{1}$$

Where C is the cursor position, A is the ‘mapping matrix’ and H is the vector of hand positions.

3.3.5 Procedures

At the start of each trial, participants saw two individual cursors (one for each hand), which allowed them to position each hand in its own start circle – this was done to ensure that the two hands always started at the same position for each trial. Once each hand reached its start position, the individual cursors disappeared and were replaced by a single cursor at the average position of the two hands. Participants then moved this cursor towards the finish position as fast as possible staying within the width of the track. Participants were asked to 'pass through' the finish box (i.e., they did not have to stop the cursor at the finish box).

To encourage participants to go faster while staying inside the track, participants were shown a 'Points Score' at the end of the trial that reflected their task performance - higher scores (max 100 points) were generated for faster times and for staying inside the track. Participants received a penalty in proportion to the time they took to complete the whole movement (tm) and the time that the cursor spent outside the track (to) (See equation below). If the cursor completely went outside even the surrounding region, they were awarded zero points on that trial.

$$\text{Points score} = 100 - 0.22 * (\mathrm{t_m})^2 - 6.66 * (\mathrm{t_o})^2 \tag{2}$$

3.3.6 Experimental Protocol

Participants were divided into three groups (n = 12/group) – Narrow, Progressive and Wide, based on the track width during practice. (Figure 3.2). All participants initially performed a familiarization block of 10 trials on the wide track, where they familiarized themselves with the task and the scoring system. Subsequently, each group practiced for 12 blocks (24 trials in each block) on a different track width over two days of practice. We decided the total number of trials based on pilot tests, mainly to allow sufficient practice for learning the task. And, given the large number of trials, we spread the practice trials over two days to avoid practice fatigue. The Narrow group had a 6 mm wide track, the Wide group had a 10 mm wide track, and the width for these two groups remained constant throughout all 12 blocks of the experiment (1 block = 24 trials). For the Progressive group, the track width started at 10 mm (i.e., same as the wide group) and was then gradually reduced by 2 mm after every two blocks until it reached 6 mm (same as the narrow group). After 10 blocks of practice, the Progressive group performed one block of trials on the narrow setting (6mm) on block 11, and one block of trials on the widest setting (10 mm) in block 12. Participants in the Progressive group were not explicitly informed about the changes in track width, although the width of the track was visible to them.

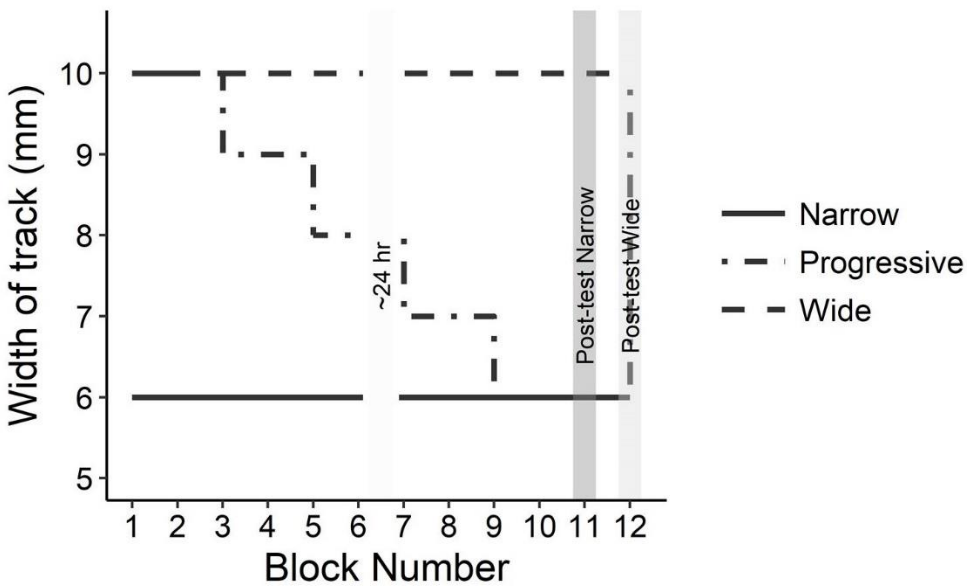

Figure 3.2 Experiment 1 protocol for the three groups. Each block of practice consisted of 24 trials with a ~24-h break between blocks 6 and 7. The Wide and Narrow groups practiced with track widths of 10 mm and 6 mm respectively throughout the experiment. For the Progressive group, the track width was reduced during practice (blocks 1 to 10) by 1 mm every 2 blocks, going from 10 mm in block 1 to 6 mm by block 9. After the last practice block (block 10), the progressive group faced a 6 mm track on block 11 (the same as the Narrow group) and faced a 10 mm on block 12 (the same as the Wide group). These two blocks essentially served as post-tests for comparisons with Narrow and Wide groups respectively.

3.4 Data analysis

3.4.1 Movement time

Based on our task instruction, the primary variable of interest was movement time. Movement time was measured as the time between the instant when the participant moved the cursor out of the start circle and the instant when the cursor moved into the finish box.

3.4.2 Error percentage

Because participants also had an accuracy requirement of staying inside the track, the error percentage was computed as the time duration that the cursor stayed outside the track in any given trial expressed as percentage of the movement time of that trial.

3.4.3 Task and null space variability

Because of the redundancy in the task, participants could maintain the same cursor position with differing positions of the individual hands. Therefore, the variability in hand positions could be further decomposed into task and null space variability (Liu and Scheidt, 2008; Mosier et al., 2005; Ranganathan et al., 2013).

The path from each trial was divided into 51 spatially equidistant points from the start to the end. At each point, the corresponding hand positions from all trials in that block were extracted into a matrix H (See Cursor mapping section) and the Moore-Penrose inverse matrix was used to decompose the hand positions into null space and task space components. Based on the mapping matrix A defined in the 'Cursor mapping' section, the null space (Hn) and task space (Ht) decomposition of hand positions were calculated as

$$\mathrm{H_t} = \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A} * \mathrm{H} \tag{3}$$

$$\mathrm{H_n} = (\mathrm{I_4} - \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A}) * \mathrm{H} \tag{4}$$

Where I4 is an identity matrix of size 4 x 4. The variances of these null and task components of the hand positions were computed and summed to obtain total null space and task space variability at each spatial point.

3.5 Statistical analysis

Based on the experimental design, we refer to blocks 1-10 as the ‘practice blocks’ and blocks 11-12 as the ‘post-test blocks’. Specifically, block 11, which was used to compare the Progressive and Narrow groups is referred to as Post-test Narrow; and block 12, which was used to compare the Progressive and Wide groups is referred to as Post-test Wide.

3.5.1 Analysis of practice blocks

The data from the first and last practice blocks (blocks 1 and 10) were analyzed to evaluate the effects of practice and task difficulty. For movement time and error percentage, we used a two-way repeated measures ANOVA (Practice x Group), with Practice being the repeated measure. For the task and null space variability, we used a three-way repeated measures ANOVA (Practice x Path Location x Group), with Practice and Path Location being repeated measures. Here, Path Location refers to five spatial points (0%, 30%, 50%, 70% and 100%) on the cursor path measured as a percentage of the total length of the path (these 5 Path Location points were identified from the 51 sampled points). The approximate locations of these path locations for any given block are shown in Figure 3.1B.

3.5.2 Analysis of post-tests

In order to evaluate the effect of progressive practice, we analyzed the post-tests focusing on the two groups which practiced on the same track width (thereby removing the effect of task difficulty). In the Post-test Narrow, we compared the narrow and progressive groups; and in the Post-test Wide, we compared the wide and progressive groups. For each post-test, we used a one-way ANOVA (Group) to analyze differences in movement time and error percentages and a two-way ANOVA (Path Location x Group) to analyze differences in task and null space variabilities.

The significance level was set at $\alpha = 0.05$. Post-hoc comparisons were adjusted using the Bonferroni correction and Greenhouse-Geisser corrections were applied to account for violations in sphericity.

3.6 Results

First, we examined null and task variabilities in each block and removed participants whose variability fell outside the Tukey's (Tukey, 1977) fences (Q3 + 1.5 *IQR and Q1 - 1.5 * IQR, Q1 = lower quartile, Q3 = upper quartile, IQR = Interquartile Range). There were 6 such outliers in total, which reduced the sample sizes to 10 in each group.

3.6.1 Movement Time

Practice. As expected, both task difficulty and practice influenced the movement time (Figure 3.3A). Participants in the Narrow and Wide groups were able to reduce movement time with practice, but the Progressive group did not show changes in movement time with practice (because the task difficulty was constantly increased in this group). The analysis of the practice blocks revealed a significant main effect of Group ($F(2,27) = 34.05$, $p < 0.001$), Practice ($F(1,27) = 59.05$, $p < 0.001$) and a significant Group x Practice interaction ($F(2,27) = 16.27$, $p < 0.001$). Pairwise Bonferroni adjusted comparisons for the Group x Practice interaction showed: block 1- that movement times were longer for the narrow group compared to the Wide and Progressive groups ($p < 0.001$), whereas there was no significant difference between the Progressive vs. Wide (p =

0.268), block 10-movement times for the wide group were significantly smaller than both Narrow and Progressive groups ($p < 0.001$), but there was no significant difference between the Narrow vs. Progressive ($p > 0.999$).

Post-tests. Progressive practice did not facilitate reduction in movement time on the narrow track, and led to a small but significant increase in the movement time on the wide track. Comparisons in the Post-test Narrow revealed no significant differences between Progressive and Narrow groups ($F(1,18) = 0.79$, $p = 0.379$). In the Post-test Wide, movement times were higher for the Progressive group compared to the Wide group ($F(1,18) = 6.03$, $p = 0.024$).

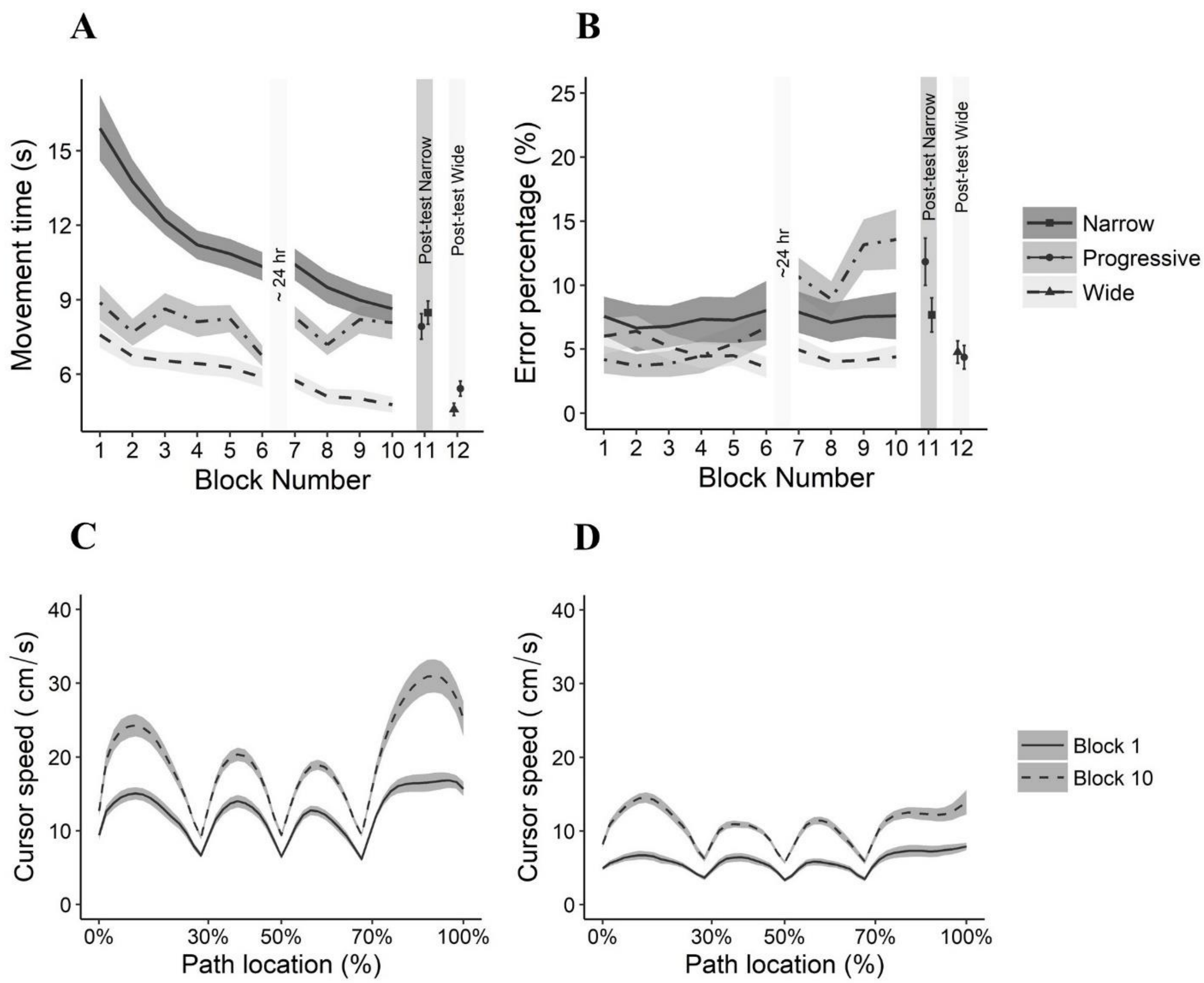

Figure 3.3 Experiment 1 task performance results. (A) Average movement time in each group as a function of practice. Movement times were affected by track width and practice. Blocks 1 to 10

Figure 3.3 (cont'd)…represent the practice phase and blocks 11 and 12 represent the post-tests. There was a ~24h break between blocks 6 and 7. (B) Average error percentage in each group as a function of practice. Error percentages were generally low, and remained constant throughout practice, except for the Progressive group. Error bars represent one standard error (between-participant). Average cursor speeds for (C) Wide Group and (D) Narrow Group in the first practice block (continuous line) and last practice block (dotted line). Improvements in speed were greater in the straighter portions of the track when compared to the curved portions of the track.

3.6.2 Error percentage

Practice. Overall, the error percentage was low for all groups (between 5-15%) (Figure 3.3B). Participants in the Narrow and Wide groups had nearly constant movement error percentages throughout practice whereas the Progressive group had an increasing movement error percentage (because of the gradual increase in task difficulty). The analysis of practice blocks revealed a significant main effect of Practice ($F(1,27) = 9.12$, $p = 0.005$) and a significant Group x Practice interaction ($F(2,27) = 15.76$, $p < 0.001$). Pairwise Bonferroni adjusted comparisons for the Group by Practice interaction showed: block 1- no significant differences between groups: Progressive vs, Narrow ($p = 0.130$), Progressive vs. Wide ($p = 0.88$) and Narrow vs. Wide ($p > 0.99$), block 10- error percentages were higher for Progressive in comparison to the Wide ($p = 0.013$) and there were no significant differences between Progressive vs. Narrow ($p = 0.170$) or Narrow vs. Wide ($p = 0.682$). The main effect of Group was also not significant ($F(2,27) = 1.78$, $p = 0.187$).

Post-tests. Progressive practice did not significantly affect the error percentage both on the narrow and wide tracks. Comparisons in the Post-test Narrow revealed no significant differences between Progressive vs. Narrow ($F(1,18) = 3.37$, $p = 0.082$) and comparisons in the Post-test Wide revealed no significant difference between Progressive vs. Wide ($F(1,18) = 0.10$, $p = 0.753$).

3.6.3 Task space variability

Cursor and hand trajectories of all trials in block 1 and block 10 of practice for a representative participant in each group are shown in Figure 3.4.

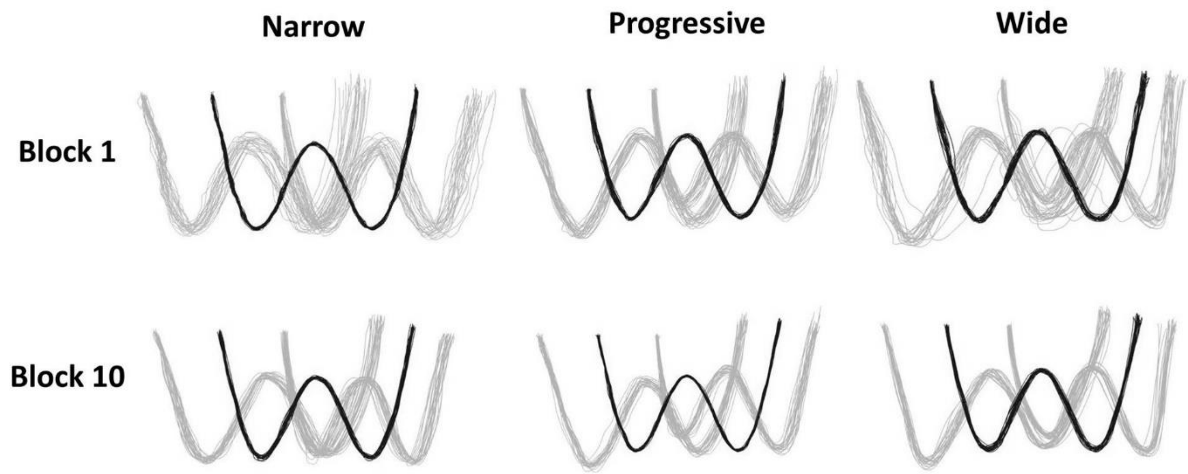

Figure 3.4 Participants empirical movement trajectories. Sample trajectories (cursor, left and right hand) from one participant in each group are shown for first block of practice (block 1) and last block of practice (block 10). The individual hand trajectories become less variable with practice even though cursor variability remains roughly the same.

Practice. Task space variabilities are shown as a function of path location for the first (block 1) and last block (block 10) of practice (Figure 3.5-A, B). Because the track width essentially constrains the task space variability, we expected to see group differences as a result of our experimental manipulation. In agreement, there was a significant effect of Group ($F(2,27) = 11.86$, $p < 0.001$), Path Location ($F(2.7,73.3) = 92.03$, $p < 0.001$), and a significant interaction effect Group x Path Location ($F(5.4,73.3) = 11.49$, $p < 0.001$).

Pairwise comparisons for the Group x Path Location interaction showed the following trends: while there were no significant differences between the groups at the 0% path location, the Narrow group had smaller variability than the Wide group throughout the rest of the path ($p < .001$). The Narrow group also had smaller variability than the Progressive group almost through the entire path (30% path location $p = 0.007$; 50% $p = 0.032$, 70% $p = 0.147$, 100% $p < 0.001$), whereas the Wide group had higher variability than the Progressive group throughout the path except at the end (30% $p = 0.077$, 50% $p = 0.033$, 70% $p = 0.035$, 100% $p > 0.99$). There were no other significant effects - Practice ($F(1,27) = 0.01$, $p = 0.911$), Practice x Group ($F(2,27) = 0.86$, p =

0.433), Practice x Path Location ($F(2.2,60.4) = 1.32$, $p = 0.273$) and Group x Practice x Path Location ($F(4.5,60.4) = 0.39$, $p = 0.834$).

Post-tests. Practicing with progressive widths did not affect task space variability on either of the post-tests (Figure 3.6-A, B). In Post-test Narrow, there was a significant effect of Path Location ($F(3.1,56.1) = 60.49$, $p < 0.001$) and a significant interaction effect Group x Path Location ($F(3.1,56.1) = 3.28$, $p = 0.025$). Paired comparisons at various path locations revealed a significant difference between the Progressive and Narrow groups generally in the latter half of the trajectory - 70 % path location ($p = 0.022$), but the 50% path location ($p = 0.109$) and 100 % path location ($p = 0.107$) were not significant. Group differences were not significant in the first half of the trajectory - 0% path location ($p = 0.928$), 30% path location ($p = 0.765$). There was no significant effect of Group ($F(1,18) = 2.80$, $p = 0.110$).

In Post-test Wide, there was a significant effect of Path Location ($F(2.4,43.9) = 44.05$, $p < 0.001$) which was similar to the effect seen in practice. There was no significant effect of Group ($F(1,18) = 0.55$, $p = 0.465$), or Group x Path Location ($F(2.4,43.9) = 0.43$, $p = 0.690$).

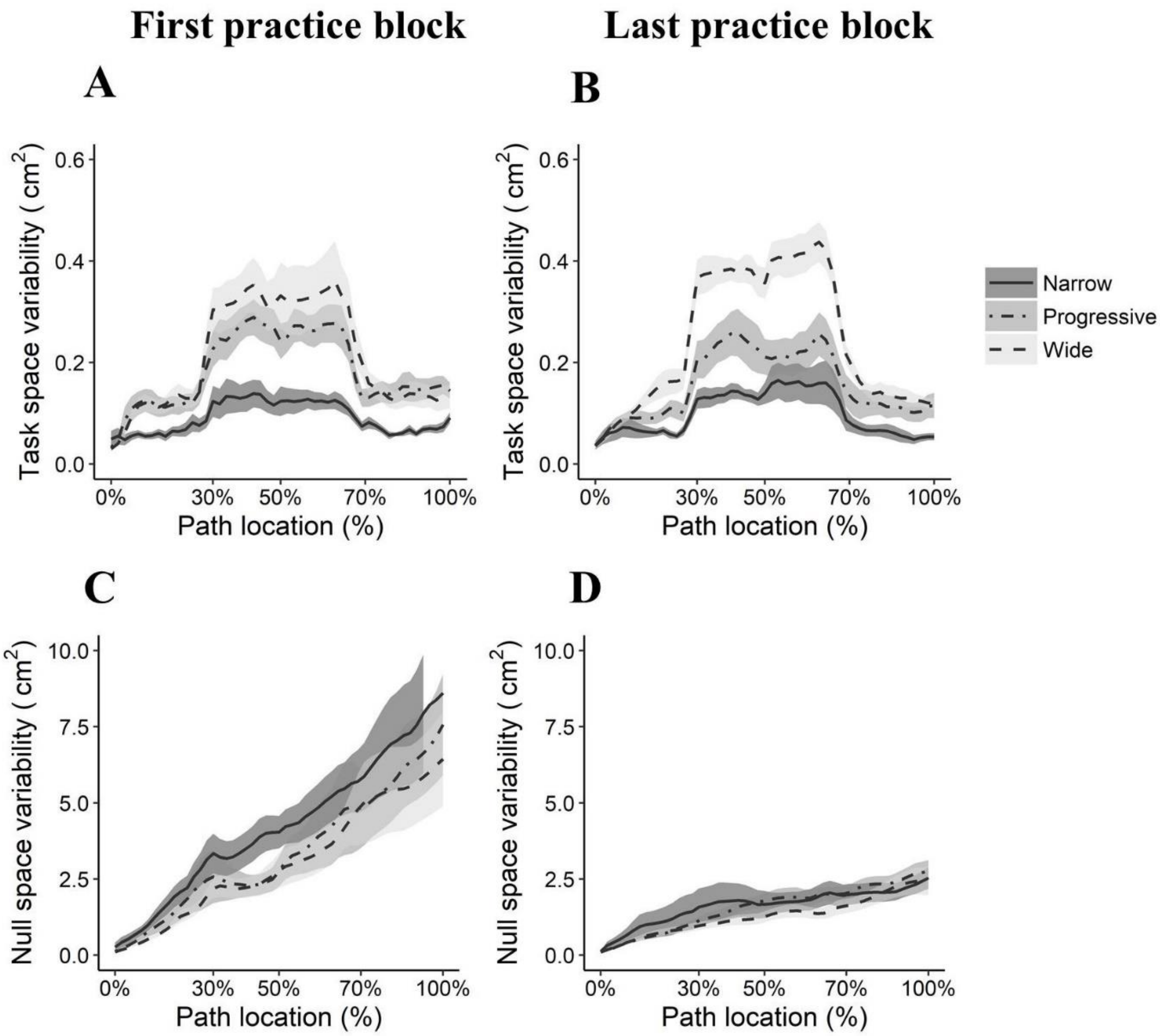

Figure 3.5 Task and Null space variabilities during practice. Average task space variability for each group in the (A) first practice block (block 1), and (B) last practice block (block 10). Task space variability differed between groups but did not change significantly with learning. Average null space variability for each group in the (A) first practice block and (D) last practice block. Null space variability was similar between the groups and showed reductions from the first to last block. Error bars indicate one standard error (between-participant).

3.6.4 Null space variability

Practice. Null space variabilities are shown as a function of path location for first (block 1) and last block (block 10) of practice (Figure 3.5-C, D). We observed that (i) null space variability showed an increasing trend along the path from start to finish, and (ii) there was a reduction in null space variability with practice for all groups and for all blocks. Comparisons of null space variability revealed a significant effect of Practice ($F(1,27) = 30.65$, $p < 0.001$), Path Location ($F(1.3,36.7) = 57.79$, $p < 0.001$), and Practice x Path Location ($F(1.3,34.5) = 15.71$, $p < 0.001$). Pairwise comparisons between blocks 1 and 10 at various path locations yielded an overall decrease in variability throughout the path at all path locations ($p < 0.001$) except at the 0% path location ($p = 0.296$). Importantly, there was no significant effect of Group ($F(2,27) = 1.518$, $p = 0.237$), or other interactions - Group x Practice ($F(2,27) = 1.27$, $p = 0.296$), Group x Path Location ($F(2.7,36.7) = 0.38$, $p = 0.924$), Practice x Group x Path Location ($F(2.5,34.5) = 0.47$, $p = 0.872$).

Post-tests. Progressive practice did not affect null space variability on either post-test (Figure 3.6-C, D). In Post-test Narrow, there was a significant effect of Path Location ($F(1.7,30.8) = 20.56$, $p < 0.001$) which showed a similar increasing trend from start to finish. There was no significant effect of Group ($F(1,18) = 0.93$, $p = 0.346$), or Group x Path Location ($F(1.7,30.8) = 1.21$, $p = 0.304$).

Similarly, in Post-test Wide, there was a significant effect of Path Location ($F(1.8,33.8) = 47.18$, $p < 0.001$), showing a similar increasing trend from start to finish. There was no significant effect of Group ($F(1,18) = 1.17$, $p = 0.292$), or Group x Path Location ($F(1.8,33.8) = 2.55$, $p = 0.095$).

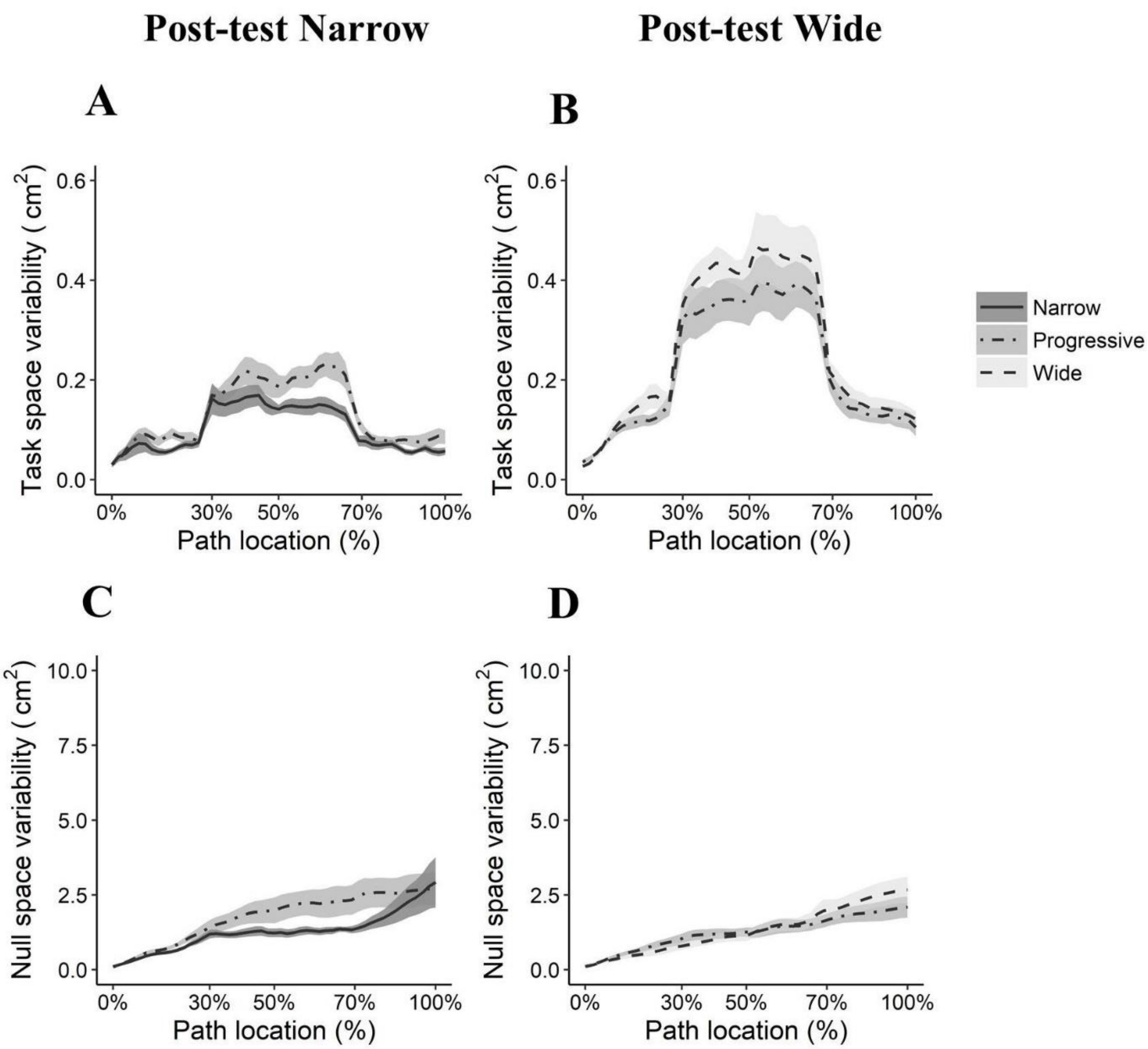

Figure 3.6 Task and Null space variabilities in post-test. Average task space variability for the relevant groups in the (A) Post-test Narrow (block 11), and (B) Post-test Wide (block 12). Average null space variability for the relevant groups in the (C) Post-test Narrow and (D) Post-test Wide blocks. There were no advantages to progressive practice either in task or null space variability in both post-tests. Error bars indicate one standard error (between-participant).

3.6.5 Variabilities as function of movement time

Finally, to examine speed-accuracy effects, we examined null and task space variabilities for all participants as a function of movement time in the first and last block of practice, block 1 and block 10 respectively (Figure 3.7-A,B). For this analysis, the task and null space variabilities were averaged across all path locations for each participant. Because the scatter plots indicated that relation was not linear, we used the Spearman's ranked correlation (ρ) to compute the correlation.

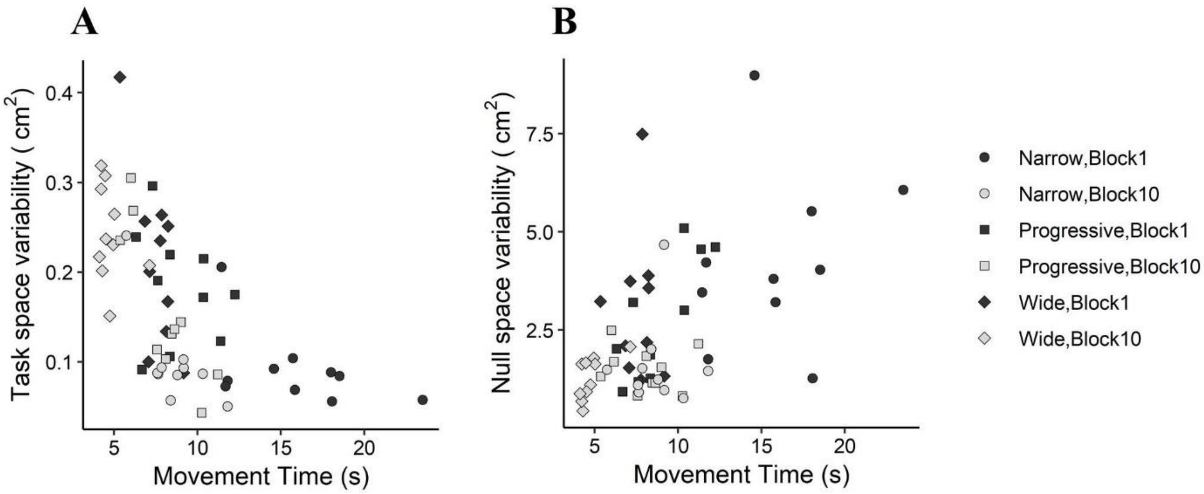

Figure 3.7 Variability as a function of movement time. (A) Average task space and (B) average null space variability plotted against movement time in the first practice block (black symbols) and the last practice block (grey symbols). Each symbol represents a participant, Task-space variability shows a negative correlation in both practice blocks, indicating a speed-accuracy tradeoff, whereas the null space variability shows a qualitatively different pattern, going from a slightly positive correlation in block 1 to a non-significant correlation in block 10.

Task space variability exhibited a speed-accuracy tradeoff both early and late in learning – i.e., shorter movement times were associated with higher task space variability. This was indicated by a significant negative correlation for both block 1 ($\rho = -0.69$, $p < 0.001$) and block 10 ($\rho = -0.81$, $p < 0.001$). However, null space variability showed a qualitatively different pattern of results. Rather than a speed-accuracy tradeoff (i.e., a negative correlation), the observed correlation was positive early in block 1 ($\rho = 0.455$, $p = 0.012$) and was not significant in block 10 ($\rho = 0.13$, $p = 0.479$).

3.7 Discussion

The goal of the study was to examine changes in null space variability when learning tasks of different difficulty. Participants performed a bimanual steering task through a W-shaped track and we modulated the task difficulty using the width of the track. Based on the task difficulty hypothesis (Latash, 2010), we hypothesized that the narrow group would show higher amounts of null space variability relative to the wide group. Our results did not support the hypothesis - although both task difficulty and practice had an effect on the movement time (indicating that the manipulation worked and there was learning), there was no effect of task difficulty on the null space variability. Instead, with practice, null space variability simply showed an overall reduction for all groups. With regard to our exploratory aim on progressive practice, we found that practicing with progressive difficulty did not have any beneficial effects (and in some measures resulted in slightly worse performance) relative to the groups that practiced with constant difficulty.

3.7.1 Effect of Task difficulty on Performance

Because error percentages were generally low for all groups and fairly constant, movement time was treated as the primary performance variable. Changing task difficulty had anticipated effects: movement times in the narrow track were longer relative to the wide track, indicating a speed-accuracy tradeoff (Fitts, 1954). Even though original version of the Fitts' law task was developed for discrete point-to-point movements, other versions for path-based control have been developed (Accot and Zhai, 1997). Such a tradeoff between movement time and accuracy (imposed by the track width) has been attributed to signal-dependent noise (Harris and Wolpert, 1998; Schmidt et al., 1979). However, with practice, participants were able to complete the task faster, which is consistent with the idea that learning results in reduced motor variability (Darling and Cooke, 1987; Georgopoulos et al., 1984; Gottlieb et al., 1988; Shmuelof et al., 2012). In particular, there was a greater improvement in speed in the straighter portions of the track when compared to the curved portions (Figure 3.3-C, D).

3.7.2 Effect of Task difficulty on Movement Variability

However, because this task was redundant, we could further examine how participants changed their performance with learning. First, we observed that the task space variability was constrained mainly by the track width and did not change with learning, which is consistent with the idea that participants did not reduce their task space variability any more than what was required to do the task. When we examined the null space variability however, there was no effect of task difficulty; instead the main change was simply an overall reduction with practice in all groups. In other words, as participants learned to move faster through the same track, their hand paths from trial-to-trial became more consistent, leading to a reduction in the amount of null space variability (even though the cursor variability was unaffected). These results are somewhat contradictory to the predictions of a two-stage learning model (Latash, 2010). In this model, the first stage of learning, which is more pronounced for tasks with higher task difficulty, should lead to strengthening of motor synergies (i.e., a relative preservation of the null space variability), followed by an optimization process (where null space variability may be decreased). Instead, we found that regardless of task difficulty, there was almost a steady reduction in null space variability during learning.

A simple explanation for these results is that our manipulation of task difficulty was simply not large enough – the wide and narrow groups did not differ sufficiently enough in task difficulty to create significant differences in the null space variability. However, we think that this explanation is unlikely because the effect of task difficulty is clearly seen in the movement time; the narrow group almost took twice as long as the wide group throughout the entire practice duration.

This raises the question – what is the purpose of reducing null space variability with learning if it has no effect on task performance? There are two possibilities – first previous literature on the learning of redundant tasks have argued that reductions in null space variability could be a reflection of learning the metric properties of the task space (Mosier et al., 2005) or the learning of an inverse map from cursor coordinates to hand coordinates (Liu et al., 2010; Ranganathan et al., 2013). Second, because the task here focused on reduction of variability, the reduction in individual hand variability (and therefore null space variability) could also be due to use-dependent or ‘model-free’ learning– in other words, repetition of successful movements (Diedrichsen et al., 2010c; Shmuelof et al., 2012). This is also consistent with evidence that high amounts of null space variability may impair this use-dependent learning mechanism and affect subsequent learning, even if it does not affect immediate performance (Cardis et al., 2017; Ranganathan and Newell, 2013). While the current study was not designed to address the mechanisms of how this variability was reduced with learning - i.e. reduction in motor noise vs. increased error correction gains (Hasson et al., 2016), the results show that null space variability, although having no effect on performance, is also tightly controlled with learning.

3.7.3 Control of task and null space variability

Interestingly, when considering performance at a single time point (i.e., ignoring the learning aspect), the task and null space variability showed patterns both within- and across-participants, that were consistent with an optimal feedback control framework (Todorov and Jordan, 2002). At the within-participant level, when we examined task variability along the track, task space variability was higher in the middle of the track compared to the start and end. However, when we examined the null space variability, we found an increasing trend throughout the path from start to finish, consistent with other evidence in static force production tasks (Shim et al., 2004). This is also consistent with the results based on optimal feedback control (Todorov and Jordan, 2002) because the system had nothing to gain by ‘correcting’ null space deviations (since they would be wasted effort), and therefore the variability simply accumulated throughout the path.

At the between-participant level, we also found that while the task space variability showed the typical speed-accuracy tradeoff (i.e., shorter movement times associated with higher task space variability), the null space variability showed a qualitatively different pattern, where faster movement times generally resulted in lower null space variability, particularly late in learning. These results are also consistent with optimal feedback control (Todorov and Jordan, 2002) - as participants went faster, there was less time for feedback-based compensation between the two hands, and therefore participants would have had to be more consistent with both hands (i.e., use less null space variability) to still be successful at the task.

3.7.4 Effect of Progressive practice

Finally, we examined the progressive group to investigate if changing task difficulty had any beneficial transfer effects (Day, 1956). We observed no benefits to gradually increasing task difficulty level relative to the groups that practiced with constant track width. In both post-tests, the progressive group did not outperform the group that had practiced on the constant track width (narrow or wide). In the Post-test Narrow condition, we in fact observed a higher null and task space variability in the progressive group, indicating that the progressive group had a carry-over effect of practicing with wider track widths, and therefore had slightly higher overall variability. In general, the results support a “specificity” account of learning (Bachman, 1961; Baker et al., 1950; Henry, 1958; Woodworth and Thorndike, 1901), where the best performance was obtained by direct practice on the to-be-learned condition.

There are a number of important caveats that need to be addressed. First, from a task paradigm perspective, in our task, participants were required to maintain task space variability, but were free to select movement time. There is some evidence that instructions have an effect on the use of redundancy – for example, in well-learned reaching movements, participants required to maintain the same movement time across task difficulty show changes in the use of null space variability (Tseng et al., 2003), however, this effect seems to disappear if participants self-select the movement time (Greve et al., 2015). Because our task was more novel, we expected to see if the non-significant differences found in Greve et al. were due to 'ceiling' effects of using a well-learned behavior, but surprisingly, this was not the case. Second, the mean position of the track was never changed during the experiment, which meant that participants really did not have to explore during learning, instead they only to reduce the movement time while maintaining the task variability. Although this argues against the use of null space variability as a buffer to avoid increased task space variability (Todorov & Jordan, 2002), this lack of exploration could have also resulted in decreased null space variability. While this is outside the scope of the current study, introducing task variations to enhance motor exploration (such as manipulating the position of the channel, or the contribution of the hands to the shared cursor) may be ways to examine if the null space variability is critical to exploration.

In summary, we found that task difficulty did not have any differential effects on the use of null space variability. Null space variability decreased with practice, even as movement times got faster. These results suggest that in tasks involving the reduction of variability, the nervous system may use null space variability early on in learning but rely on the strategy of reducing overall variability regardless of task difficulty.

Chapter 4

HAPTIC ASSISTANCE THAT RESTRICTS THE USE OF REDUNDANT SOLUTIONS IS DETRIMENTAL TO MOTOR LEARNING

The work presented in this chapter has been published - (Lokesh and Ranganathan, 2020)

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4.1 Abstract

Understanding the use of haptic assistance to facilitate motor learning is a critical issue, especially in the context of tasks requiring control of motor variability. However, the question of how haptic assistance should be designed in tasks with redundancy, where multiple solutions are available, is currently unknown. Here we examined the effect of haptic assistance that either allowed or restricted the use of redundant solutions on the learning of a bimanual steering task. 60 college-aged participants practiced steering a single cursor placed in between their hands along a smooth W-shaped track of a certain width as quickly as possible. Haptic assistance was either applied at (i) the 'task' level using a force channel that only constrained the cursor to the track, allowing for the use of different hand trajectories, or (ii) the 'individual effector' level using a force channel

that constrained each hand to a specific trajectory. In addition, we also examined the effect of simply ‘fading’ assistance in a linear fashion– i.e., decreasing force gains with practice to reduce dependence on haptic assistance. Results showed all groups improved with practice - however, groups with haptic assistance at the individual effector level performed worse than those at the task level. Besides, we did not find sufficient evidence for the benefits of linearly fading assistance in our task. Overall, the results suggest that haptic assistance is not effective for motor learning when it restricts the use of redundant solutions.

4.2 Introduction

Robotic training is widely adopted to assist in the learning of novel motor tasks, especially those requiring precision. For example, a stroke survivor attempting to place a cup of coffee on a narrow ledge is faced with a task of moving the cup in a specified trajectory while controlling task variability – i.e., variability that affects the movement of the cup. Although several different algorithms have been used to explore how haptic feedback can be used to influence motor learning in such contexts (Duarte and Reinkensmeyer, 2015; Lüttgen and Heuer, 2012; Marchal-Crespo and Reinkensmeyer, 2009; Reinkensmeyer and Patton, 2009; Sigrist et al., 2013), here we focus on ‘haptic assistance’ which is designed to minimize errors during training.

A critical issue in this regard is how to design haptic assistance to best control task variability. Prior studies have almost exclusively used non-redundant tasks where task variability can only be controlled directly by controlling the movement variability of the end-effector, i.e. enforcing the same movement from trial to trial (Feygin et al., 2002b; J. Liu et al., 2006; Teo et al., 2002; Teranishi et al., 2018). However, when tasks have multiple degrees of freedom, the redundancy associated with this arrangement leads to a situation where task variability can be controlled without necessarily repeating the same movements at all the individual effectors. This strategy of 'repetition without repetition' (i.e., achieving the same task goal without repeating the same movements) has been observed extensively in human motor control (Domkin et al., 2002; John et al., 2016; Scholz and Schöner, 1999; Sternad, 2018; Todorov and Jordan, 2002). However, the question of how haptic assistance has to be provided in such redundant tasks to enhance learning is not known.

Haptic assistance can be provided at two levels in redundant tasks - (i) the 'task' level where the assistance constrains deviations only when they interfere with the task, or (ii) the 'individual effector' level where the assistance constrains deviations of individual effector motions. The key distinction between these two levels is that haptic assistance at the task level allows the use of multiple redundant solutions and flexibility in movements from trial-to-trial (Latash, 2010). On the other hand, haptic assistance at the individual effector level limits such flexibility from trial-to-trial, but may still be able to facilitate learning through a 'use-dependent' learning mechanism (Diedrichsen et al., 2010c; Haith and Krakauer, 2013).

A second issue when providing haptic assistance is that of 'fading' assistance. Learners with constant haptic assistance throughout practice tend to become dependent on it (Winstein et al., 1994) leading to a significant deterioration in performance upon removal of assistance (Marchal-Crespo et al., 2013; Williams and Carnahan, 2014b). One strategy to counter this overreliance on haptic feedback is by fading assistance– i.e. gradually decreasing assistance with practice (Emken et al., 2007; Heuer and Lüttgen, 2014a; Huegel and O'Malley, 2009; Powell and O'Malley, 2012). Fading can also implicitly be built into the task by implementing 'assist-as-needed' protocols, wherein haptic assistance is provided only outside a bandwidth of errors and the forces are increased proportionally to errors (Wolbrecht et al., 2008). However, how the effect of fading interacts with the level of haptic assistance (i.e., task or individual effector) is not known.

Here, we examined the role of haptic assistance in learning redundant tasks. We developed a task where participants had to trace a complex trajectory using a cursor. Critically, the cursor was placed at the mean position of the two hands, which made the task kinematically redundant because the same cursor position could be achieved by different positions of the hands. We examined two specific questions in this context - (i) how does the level at which haptic assistance is provided – i.e. task or individual effector, influence motor learning, and (ii) how does the strength of haptic assistance – i.e. constant or faded, influence motor learning.

4.3 Methods

4.3.1 Participants

60 healthy college-aged adults (age range: 18-24 years, 20 men, 40 women) participated in the study and received extra course credit for participation. All participants provided informed consent and the procedures were approved by the Institutional Review Board at Michigan State University.

4.3.2 Apparatus

We used a bimanual manipulandum (KINARM Endpoint Lab, BKIN Technologies Ltd., ON), which consisted of two separate robotic arms that allowed motion in a 2-D horizontal plane. Each robotic arm had a handle located at the end which could be grasped by participants. Participants were seated on a height-adjustable chair and looked into a screen at around 45-degree angle below eye level as shown in Figure 4.1. The visual information was presented in such a way that the objects on the screen appear to be located in the plane of the hands. Kinematic data from both handles were sampled at 1000 Hz.

4.3.3 Task Description

The participants performed a bimanual steering task (Lokesh and Ranganathan, 2019). Participants controlled a cursor of diameter 4 mm and steered it from a start position to end position along a smooth W-shaped track of length 738 mm (Figure 4.1). The goal of the task was to complete the movement as fast as possible while maintaining the cursor within the grey track. The width of the track was always visible to the participant and consisted of two regions highlighted in different colors. The width of the inner grey track was 6 mm (the ‘allowed region’) and the width of the surrounding green track was 3mm. When the cursor deviated from the track, the surrounding track changed color to red serving as a visual cue to help maintain the cursor within the track.

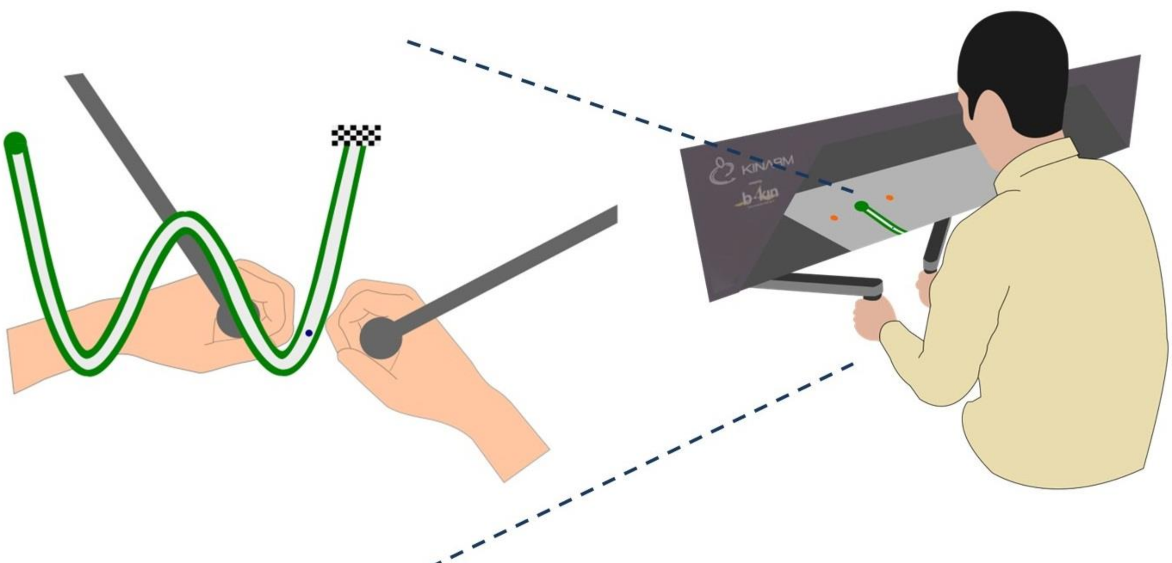

Figure 4.1 Experimental Setup. Participants held the handles of a bimanual manipulandum and looked at a screen that appeared to be in the plane of their hands. (left) They traced a ‘W’ shaped track using a blue cursor placed in between their hands, and the goal was to move as fast as possible while maintaining the cursor within the grey track.

4.3.4 Cursor Mapping

The position of the cursor (X_C, Y_C) was displayed at the average position of the two hand locations, making the task redundant. This 4-to-2-mapping can be represented as shown in (1):

$$C = \begin{pmatrix} X_C \\ Y_C \end{pmatrix} = A * [X_L \quad Y_L \quad X_R \quad Y_R]^T = A * h \tag{1}$$

Where C is the cursor position, A is the 'mapping matrix' and h is the vector of the left hand and right hand coordinates.

4.3.5 Procedures

At the start of each trial, participants saw two individual cursors (one for each hand), which allowed them to position each hand in its start circle – this was done to ensure that the two hands always started at the same position every trial. Once each hand reached its start position, the individual cursors disappeared and were replaced by a single cursor at the average position of the two hands. Participants then moved this cursor towards the finish position as fast as possible staying within the width of the track.

To encourage participants to go faster while staying inside the track, participants were shown a score at the end of the trial. Participants started with a maximum of 100 points at the beginning of a trial and received a penalty in proportion to the time they took to complete the whole movement (t_m) and the time that the cursor spent outside the track (t_o) according to (2). The equation was determined based on pilot studies and was consistent with our goal of getting the participants to move quickly (i.e., minimize movement time) while also staying in the channel (i.e., minimize out of time). If the cursor completely went outside the surrounding track, they were awarded zero points on that trial. In addition to the trial score, the sum of trial scores from the completed trials in the ongoing block was shown to the participants after each trial.

$$\text{Trial score} = 100 - 0.22 * (\mathrm{t_m})^2 - 6.66 * (\mathrm{t_o})^2 \quad (2)$$

4.3.6 Groups and Experimental Protocol

Participants were randomly assigned to 5 groups (n = 12/group) based on the mode of haptic assistance. Four groups received haptic assistance during training, and the fifth group received no haptic assistance. The four groups that received haptic assistance varied based on two factors – (i) the level at which haptic assistance was provided – at the task level (i.e., based on the motion of the cursor), or at the individual effector level (i.e., based on the motion of the individual hands), and (ii) the strength of the haptic assistance – constant or faded. Thus the four groups were (i) constant haptic assistance applied to the cursor (Cursor Constant – 'CursConst') (ii) faded haptic assistance applied to the cursor (Cursor Faded – 'CursFade') (iii) constant haptic assistance applied to each hand (Hands Constant – 'HandConst') (iv) faded haptic assistance applied to each hand (Hands Faded – 'HandFade'). The fifth group ('Unassisted') did not receive any haptic assistance during training. We used data for the 'Unassisted' group from an earlier experiment, where the task conditions were exactly the same (Lokesh and Ranganathan, 2019).

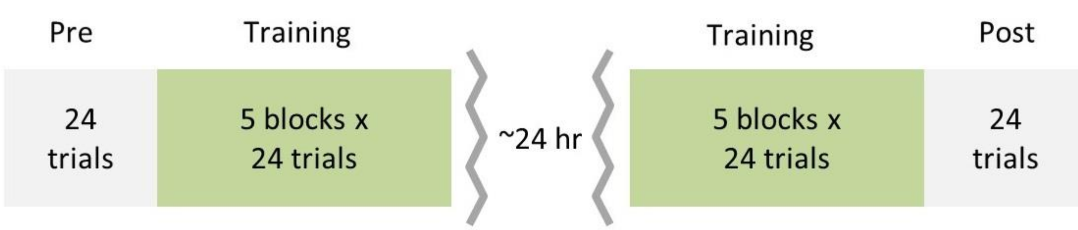

Figure 4.2 Experimental protocol for all 5 groups (Cursor Constant, Cursor Faded, Hand Constant, Hand Faded, Unassisted). Participants did a Pre-test followed by five blocks of training on the first day, and 5 blocks of training followed by a Post-test on the second day

The experimental protocol is shown in Figure 4.2. The track width and length of the track remained constant throughout the protocol and for all groups. All participants practiced initially for 10 trials without assistance, where they familiarized themselves with the task and the scoring system. After familiarization, they performed a Pre-test in which no haptic assistance was provided. This was followed by ten blocks of training where each participant received haptic assistance based on their group membership. Since the total number of trials in training was large enough to possibly induce fatigue in participants, we spread the training blocks over two days. At the end of the training on the second day, participants performed a Post-test in which no haptic assistance was provided. All blocks (Pre-test, training and Post-test) consisted of 24 trials each.

4.3.7 Haptic Assistance

Haptic assistance was provided either at the task level (i.e., based on the motion of the cursor) or the individual effector level (i.e., based on the motion of the individual hands). In both cases, a compliant force field channel modelled by a spring of stiffness (K = 1 N/mm) was programmed into the task in the form of a virtual fixture. The channel applied a force (F) proportional to the deviation of the cursor/hand (Δd) from the centerline of its track in a direction perpendicular to the track according to (3). The 'w' here represents the width of the track, and the force was 0 as long as the cursor/hand was within the track width.

$$F = f * K * \max\left(\Delta d - \frac{w}{2}, 0\right) \tag{3}$$

Depending on the level at which haptic assistance was introduced (task or individual effector), the channel was applied to the motion of the cursor or the two hands as shown in Figure 4.3. For the Cursor groups, the computed force according to (3) was applied to both the hands similarly. For the Hand groups, we first obtained reference channels for each hand using the average of the Post-test hand trajectories from the participants in the Unassisted group. Each hand then felt forces independent of the other hand, based on the deviation from its own channel.

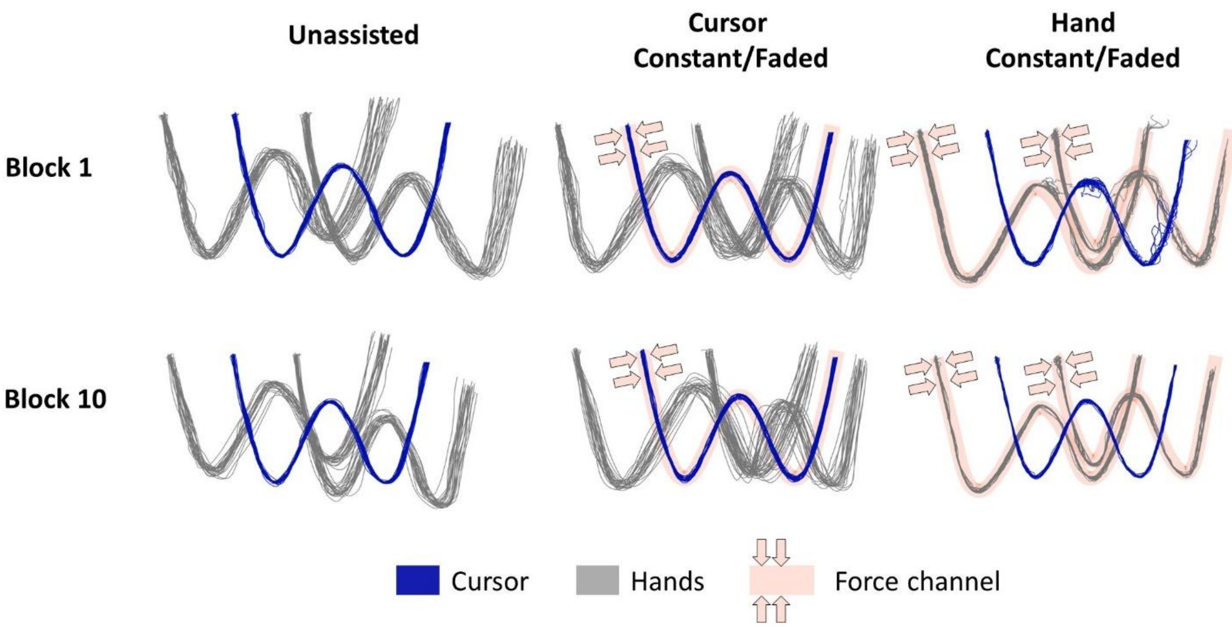

Figure 4.3 Haptic assistance design and empirical trajectories. Haptic assistance using spring-like forces were applied based on cursor motion for the Cursor groups and based on individual hand motion for the Hand groups. Cursor, left hand and right hand trajectories from a representative participant from each group are shown for Block 1 and 10 in training.

The strength of haptic assistance was either maintained constant or faded with practice in the training blocks according to Figure 4.4. We used a force factor (f) according to (3), to fade the level of haptic assistance, wherein a force factor of 2 represented the maximum haptic assistance (100%), and a force factor of 0 represented no haptic assistance (0%).

4.4 Data analysis

4.4.1 Block Score

The score provided to the participant on each trial was computed using (2). This score was averaged across all trials in a block for each participant.

4.4.2 Movement Time

Movement time was defined as the time between the instant when the participant moved the cursor out of the start circle and the instant when the cursor moved into the finish box. Movement times were averaged across all trials in a block for each participant.

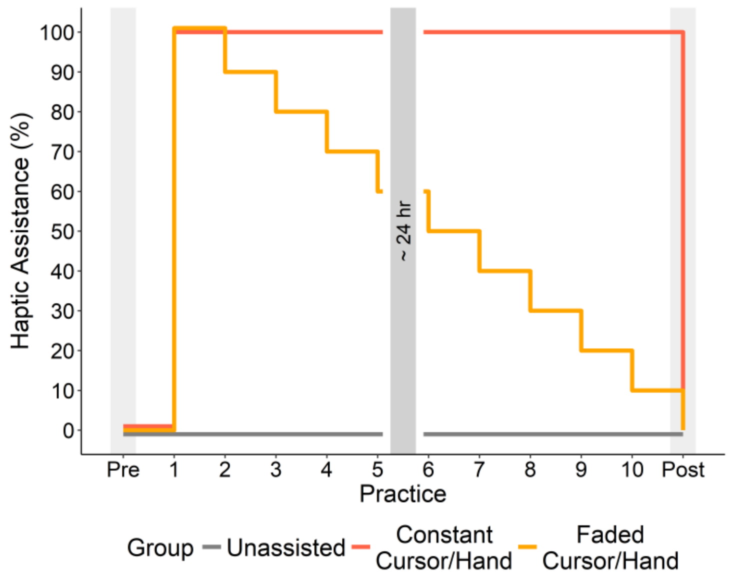

Figure 4.4 Assistance manipulation for linear assistance fading. During the training blocks, Constant groups received 100% assistance, whereas the Faded groups received a linear decrease in the assistance at the start of each block. The Unassisted group did not receive any haptic assistance during training. There was no haptic assistance during the Pre-test and Post-test blocks for all groups.

4.4.3 Out of Track Time

Out-of-track time was defined as the time that the cursor was outside the track from the start to the end of movement. The out of track time was then averaged across all trials in a block for each participant.

4.4.4 Task and Null Space Variability

Since the task was kinematically redundant, the variability in hand positions was decomposed into task and null space variabilities (Liu and Scheidt, 2008; Mosier et al., 2005; Ranganathan et al., 2013). The task space variability refers to the component of the movement variability that affects cursor motion whereas the null space variability refers to the component of the overall movement variability that has no effect on cursor motion. The path from each trial was divided into 51 spatially equidistant points from the start to the end. At each point, the corresponding hand vectors 'h' (as described in (1)) from all the 24 trials in the block were extracted into a matrix H as shown in (4) and the Moore-Penrose inverse was used to decompose the hand positions into null space (H_n) and task space (H_t) components(Liu and Scheidt, 2008; Lokesh and Ranganathan, 2019; Mosier et al., 2005) as shown in (5) and (6) respectively, where I_4 is an identity matrix of size 4.

$$\mathrm{H} = [\mathrm{h}_1\, \mathrm{h}_2\, \ldots \ldots \ldots \mathrm{h}_{23}\, \mathrm{h}_{24}] \tag{4}$$

$$\mathrm{H_t} = \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A} * \mathrm{H} \tag{5}$$

$$\mathrm{H_n} = (\mathrm{I}_4 - \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A}) * \mathrm{H} \tag{6}$$

The variances of the null and task components of the hand positions were computed and summed to obtain null space and task space variability at each sampled point. Then, the task and null space variabilities were averaged across the 51 sampled points to obtain null and task space variabilities for the block. These equations meant that if the cursor position was identical across multiple trials, then the task space variability would be zero. Additionally, if both hands were also at the same location in space across multiple trials, then the null space variability would also be zero.

4.4.5 Haptic Force Reliance

Because the haptic forces that participants experienced depended both on the error as well as the time they spent outside the track, the haptic reliance on each trial was calculated by computing the net force impulse – i.e. integrating the forces experienced by the participant from start to end of the movement. Note that the haptic reliance was zero for the Unassisted group during training, and in the Pre-test and Post-test block for all groups since there was no haptic assistance provided in these cases.

4.5 Statistical analysis

Our primary research questions were to determine the effect of the level of haptic assistance - HapticLevel (cursor/hand) and the strength of haptic assistance - HapticStrength (constant/faded) on the task outcome variables. Because the block score, movement time and the out-of-track time are mathematically related according to (2), we show all three variables on the graphs, but exclude the out-of-track time from the statistical analysis.

4.5.1 Training phase

To examine the effects of haptic assistance while it was provided, we used the last block of training (Block 10). Because our groups were based on a 2 x 2 design (HapticLevel x Haptic Strength), we used a 2 x 2 ANOVA on the Block 10 values with HapticLevel and HapticStrength as factors.

We compared the effects of haptic assistance relative to the Unassisted group by using a One-way ANOVA on Block 10 values with Group (5 groups) as a factor. For post-hoc comparisons, we used Dunnett tests to compare the four haptic groups with the Unassisted group.

4.5.2 Test phase

To examine the effect of learning in groups that received haptic assistance, we only used the test phases (i.e., pre- and post-test). Because our groups were based on a 2 x 2 design (HapticLevel x Haptic Strength), we used a 2 x 2 ANCOVA on the Post-test values with Pre-test values as covariate, and HapticLevel and HapticStrength as factors.

We compared the effects of haptic assistance relative to the Unassisted group by using ANCOVA on the Post-test values with Pre-test values as covariates and Group (5 groups) as a factor. For post-hoc comparisons, we used Dunnett tests on the adjusted means for comparing the four haptic groups with the Unassisted group. The significance level for all tests was set at $\alpha = 0.05$.

4.6 Results

To examine any outliers, we compared the overall change in the Block score from the pre- to post-test for all groups. Using Tukey's (Tukey, 1977) outlier criterion (i.e., above 1.5 IQR of the third quartile or below 1.5 IQR of the first quartile), we eliminated two participants from further statistical analysis (one from HandConst and one from HandFade).

4.6.1 Training Phase

Block Score

The Constant groups had higher scores relative to the Faded groups (Figure 4.5a). The ANOVA revealed a significant effect of HapticStrength ($F(1,42) = 60.86$, $p<0.001$), no significant effect of HapticLevel ($F(1,42) = 1.96$, $p = 0.16$) and no significant interaction effect ($F(1,42) = 2.22$, $p = 0.14$).

Comparison to Unassisted group. The haptic groups had higher scores relative to the Unassisted group (Figure 4.5a). The ANOVA revealed a main effect of Group ($F(4,53) = 19.31$, $p < 0.001$). Post-hoc Dunnett tests to compare the haptic groups with the Unassisted group indicated significantly higher scores for CursConst ($p < 0.001$), CursFade ($p = 0.0013$), HandConst ($p < 0.001$) and HandFade ($p = 0.0016$).

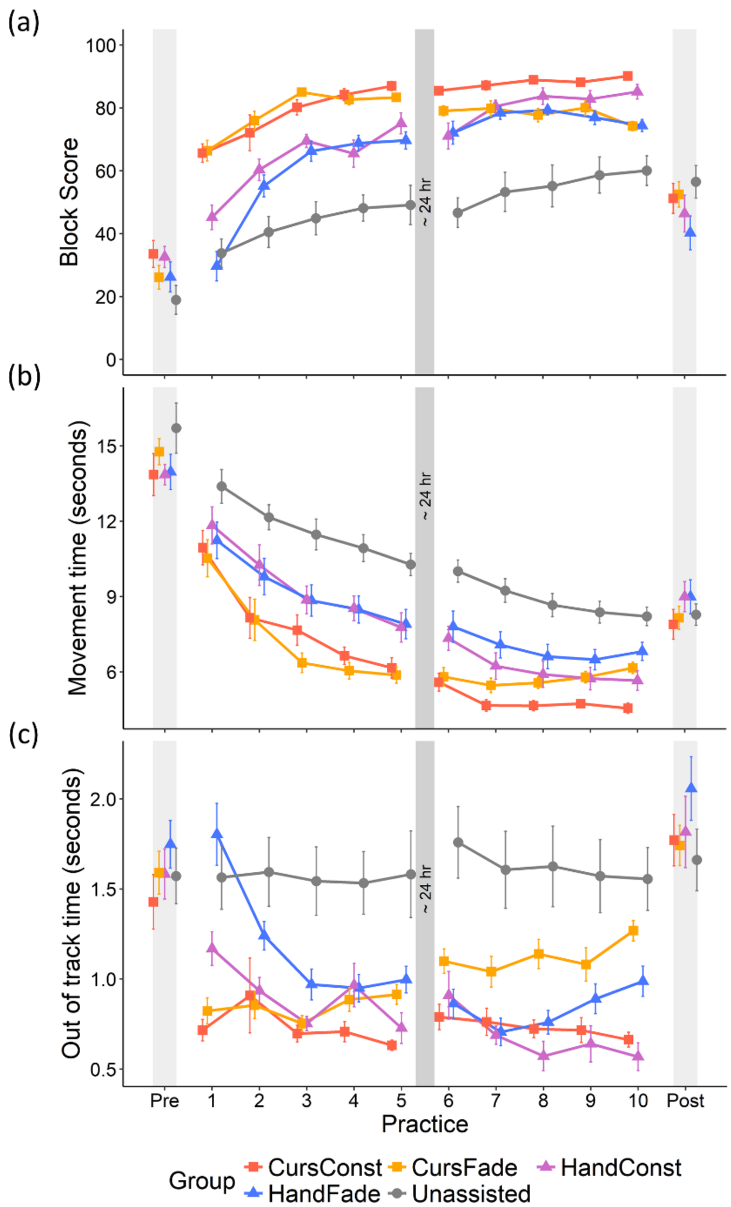

Figure 4.5 Plots of performance variables versus practice. (a) Block score- All groups improved scores with practice, but the Hand groups had relatively lower mean scores compared to the Cursor groups and the Null group (b) Movement time- All groups showed decreasing movement time with practice, and the Hand groups had relatively higher mean movement times in comparison to the Cursor and Null groups in the Post-test (c) Out of track time- Out of track times remained similar from Pre to Post, and the Hand groups showed relatively higher mean out of track times in comparison to the Cursor groups and the Null group in the Post-test.

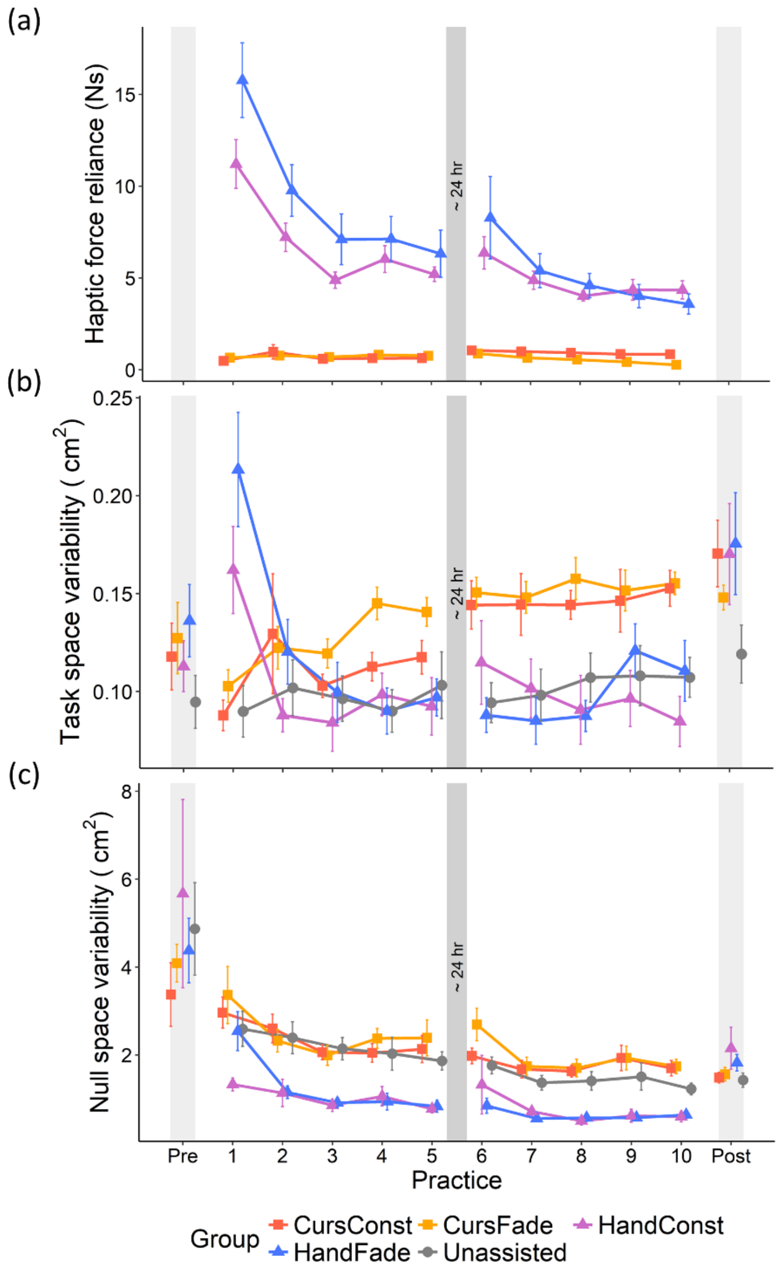

Figure 4.6 Plots of computed variables versus practice. (a) Haptic force reliance- The hand groups experienced greater but progressively reducing amounts of haptic force in training in comparison to the Cursor groups (b) Task space variability- The Cursor groups showed increasing task space variability whereas the other groups showed reducing or unchanging task space variability with practice (c) Null space variability- Null space variability reduced with practice for all groups, but due to our haptic manipulation the Hand groups had lower null space variability in comparison to the Cursor groups in training.

Movement Time

The Faded groups had higher movement times relative to the Constant groups and the Hand groups had higher movement times than Cursor groups (Figure 4.5b). The ANOVA revealed a significant effect of HapticStrength ($F(1,42) = 21.46$, $p < 0.001$), a significant effect of HapticLevel ($F(1,42) = 8.55$, $p = 0.005$) and no significant interaction effect ($F(1,42) = 0.55$, $p = 0.46$).

Comparison to Unassisted group. The haptic groups had lower movement times relative to the Unassisted group (Figure 4.5b). The ANOVA revealed a main effect of Group ($F(4,53) = 18.90$, $p < 0.001$). Post-hoc Dunnett tests to compare the haptic groups with the Unassisted group indicated significantly lower movement times for CursConst($p < 0.001$), CursFade ($p < 0.001$), HandConst ($p < 0.001$) and HandFade ($p = 0.011$).

Haptic Force Reliance

The Faded groups showed similar force reliance to that of the Constant groups within each HapticLevel factor, whereas the Hand groups experienced greater force reliance than the Cursor groups (Figure 4.6a). The ANOVA revealed no significant effect of HapticStrength ($F(1,42) = 3.57$, $p = 0.065$), a significant effect of HapticLevel ($F(1,42) = 92.16$, $p < 0.001$) and no significant interaction effect ($F(1,42) = 0.074$, $p = 0.78$).

Task Space Variability

The Cursor groups had higher task space variability in comparison to the Hand groups (Figure 4.6b), likely due to the fact that their movement times were lower. The ANOVA revealed no significant effect of HapticStrength ($F(1,42) = 1.51$, $p = 0.22$), a significant effect of HapticLevel ($F(1,42) = 25.5$, $p < 0.001$) and no significant interaction effect ($F(1,42) = 1.09$, $p = 0.30$).

Comparison to Unassisted group. The Cursor groups had higher task space variability relative to the Unassisted group (Figure 4.6b). The ANOVA revealed a main effect of Group ($F(4,53) = 7.88$, $p < 0.001$). Post-hoc Dunnett tests to compare the haptic groups with the Unassisted group indicated significantly higher task space variability for CursConst($p = 0.015$) and CursFade ($p = 0.0095$), and no significant differences for HandConst ($p = 0.41$) and HandFade ($p = 0.99$).

Null Space Variability

The Hand groups had lower null space variability in comparison to Cursor groups (Figure 4.6c), indicating that the manipulation was successful in restricting the use of redundant solutions. The ANOVA revealed no significant effect of HapticStrength ($F(1,42) = 0.081$, $p = 0.77$), a significant effect of HapticLevel ($F(1,42) = 60.89$, $p < 0.001$) and no significant interaction effect ($F(1,42) < 0.001$, $p = 0.99$).

Comparison to Unassisted group. The Hand groups had lower null space variability relative to the Unassisted group (Figure 4.6c). The ANOVA revealed a main effect of Group ($F(4,53) = 15.51$, $p < 0.001$). Post-hoc Dunnett tests to compare the haptic groups with the Unassisted group indicated no significant differences for CursConst($p = 0.061$), and significantly higher null space variability for CursFade ($p = 0.036$), and significantly lower null space variability for HandConst ($p = 0.0091$) and HandFade ($p = 0.015$).

4.6.2 Test Phase

Block Score

The Cursor groups had higher scores relative to the Hand groups in the Post-test relative to Pre-test scores (Figure 4.5a). The ANCOVA indicated a significant effect of HapticLevel ($F(1,41) = 4.31$, $p = 0.044$), no significant effect of HapticStrength ($F(1,41) = 0.57$, $p = 0.45$) and no significant interaction effect ($F(1,41) = 1.11$, $p = 0.29$).

Comparison to Unassisted group. The Hand groups and the CursConst group had lower scores in comparison to the Unassisted group (Figure 4.5a). The ANCOVA indicated a significant main effect of Group ($F(4,52) = 4.32$, $p = 0.004$). Post-hoc Dunnett tests to compare the haptic groups with the Unassisted group indicated significantly lower scores for HandFade group ($p = 0.0021$), HandConst group ($p = 0.0067$) and CursConst ($p = 0.037$), and no significant difference for CursFade group ($p = 0.32$).

Movement Time

The Hand groups had higher movement times in comparison to the Cursor groups in the Post-test with respect to the Pre-test times (Figure 4.5b). The ANCOVA indicated a significant effect of HapticLevel ($F(1,41) = 5.48$, $p = 0.024$), no significant effect of HapticStrength ($F(1,41) = 0.064$, $p = 0.80$) and no significant interaction effect ($F(1,41) = 0.017$, $p = 0.89$).

Comparison to Unassisted group. The haptic groups had movement times similar to the Unassisted group (Figure 4.5b). The ANCOVA indicated no significant main effect of Group ($F(4,52) = 1.79$, $p = 0.14$).

Task Space Variability

The Hand and Cursor groups had similar task space variabilities in the Post-test with respect to Pre-test variabilities (Figure 4.6b). The ANCOVA indicated no significant effect of HapticLevel ($F(1,41) = 0.46$, $p = 0.49$) or HapticStrength ($F(1,41) = 0.15$, $p = 0.69$) or their interaction ($F(1,41) = 0.51$, $p = 0.47$).

Comparison to Unassisted group. The haptic groups had task space variabilities similar to the Unassisted group (Figure 4.6b). The ANCOVA indicated no significant main effect of Group ($F(4,52) = 1.41$, $p = 0.24$).

Null Space Variability

The Hand and Cursor groups had similar null space variabilities in the Post-test with respect to the Pre-test variabilities (Figure 4.6c). There was no significant effect of HapticLevel ($F(1,41) = 2.4$, $p = 0.12$) or HapticStrength ($F(1,41) = 0.16$, $p = 0.68$) or their interaction ($F(1,41) = 0.40$, $p = 0.52$).

Comparison to Unassisted group. The haptic groups had null space variabilities similar to the Unassisted group (Figure 4.6c). The ANCOVA indicated no significant main effect of Group ($F(4,52) = 1.28$, $p = 0.29$).

4.7 Discussion

The goal of this study was to examine haptic assistance in the learning of tasks with redundancy. We specifically asked two questions - (i) how does the level at which haptic assistance is provided – i.e. task or individual effector, influence motor learning, and (ii) how does the strength of haptic assistance – i.e. constant or faded influence motor learning. We found that (i) haptic assistance at the individual effector level was detrimental to motor learning relative to the task level, and (ii) fading haptic assistance had no beneficial effect on learning relative to constant haptic assistance in our context.

When we examined the overall amount of learning based on the level of haptic assistance (task or individual effector), we found that all groups improved their performance substantially from pre- to post- test (movement times were cut by almost ~ 40% from pre- to post- test). However, the groups that received assistance at the level of individual effectors (i.e., the Hand groups) performed worse compared to the groups that received assistance at the task level (i.e., the Cursor groups). This was mainly driven by changes in movement time, with the Cursor groups going faster than the Hand groups. One potential reason for this effect is that the Hand groups had limited use of redundancy as evidenced by the lower null space variability during training. This meant that participants in these groups were not able to use the redundancy in the task to flexibly change their individual hand trajectories from trial to trial. Moreover, the use of redundant solutions also seemed to be a ‘natural’ tendency for the nervous system, which was impaired in the Hand groups.

This was reflected by the increased reliance on haptic forces in training and the sudden increase in null space variability during the post-test when the haptic forces were removed. We note here that the reference channels set for the Hand groups have might not been ideal for all participants. We chose the post-test of the unassisted group as the basis for the reference channels because Pre-test behavior was characterized by high variability. One important point is that because the reference channels for the Hand group were derived empirically, the midline of the reference channels was not perfectly aligned along the centerline of the track. However, we found that the final learned trajectories in all groups were similar to each other, and therefore, there was no evidence of a bias due to these reference channels. It would be of interest to see how the results would be impacted if reference channels were customized for participants based on their movement characteristics. Even though customization of reference trajectories for stereotypical movements like reaching and gait has been implemented (Marchal-Crespo and Reinkensmeyer, 2009; Vallery et al., 2008; Wu et al., 2018), similar methods for novel human-robot collaboration tasks are rarely adopted.

These results are consistent with theoretical perspectives (Sternad, 2018) such as the uncontrolled manifold (Latash, 2012; Scholz and Schöner, 1999) and optimal feedback control (Diedrichsen et al., 2010b; Todorov and Jordan, 2002) which suggest a critical role for the 'null space' in these redundant tasks. One particular idea is that the null space acts as a 'noise buffer' allowing task variability to be small; as a result, controlling the null space variability might have had a negative effect on learning the task. Although it is unclear if there is an optimal amount of flexibility which maximizes learning (since we had only 2 groups in this study), we show that limiting such flexibility can potentially have a detrimental effect on motor learning. Prior studies in multi-effector coordination tasks typically have shown that practicing with individual effectors sequentially is less effective than practicing simultaneously with the available redundancy (Wu et al., 2012). Here, we further strengthen this argument by showing that even when groups perform simultaneous bimanual movements, the group that is restricted in its use of redundant solutions shows poorer learning. Although this was not a primary aim of our study, our results in this bimanual task are also similar to observations in two-partner collaborated tasks (Che et al., 2016; Takagi et al., 2017), where sharing of haptic feedback between partners led to improvements in performance. Because the coordination between two limbs relies on very different mechanisms from the coordination between two partners, a more direct comparison of these strategies may be an interesting avenue to pursue in the future.

When comparing the groups that received haptic assistance with the Unassisted group, we found that in general, no group outperformed the Unassisted group. Even though the haptic groups had better performance over the unassisted group in the training blocks, they could not retain the same levels of performance in the post-test when the haptic assistance was removed. These results are consistent with prior work showing that haptic assistance has a stronger influence on performance but did not enhance learning (Williams and Carnahan, 2014b). While these results support the 'specificity of practice' principle (Henry, 1958; Shea and Kohl, 1990) (i.e., that learning is best when training conditions match testing conditions), it is also important to note that, in an absolute sense, the haptic assistance groups (esp. the Cursor groups) were relatively close to the performance of the unassisted group in the post-test. This indicates that haptic assistance may be especially useful in contexts where it may not be feasible to experience large errors even during training (for e.g., if there are safety issues involved with experiencing large errors) (Emken et al., 2007).

Finally, with respect to the effect of fading, surprisingly we found no significant effects of fading on learning. Even though a simple linear fading of assistance is in line with the guidance hypothesis (Powell and O'Malley, 2012; Salmoni et al., 1984; Schmidt, 1991), we did not find evidence for the benefits of fading assistance progressively. There are two possible reasons for this – first, because assistance was only applied when the cursor or hand exceeded the channel boundary, as participants performed better on the task, this naturally leads to a decrease in the reliance on haptic assistance, even though the strength of the haptic assistance was not changed. Second, the fading of the assistance was done in an open-loop fashion (i.e., all participants got the same strength regardless of performance) and may not have been optimal in our case because participants may not have had enough practice at a given haptic strength before moving to the next lower strength level. This is supported by the observation that even the Faded groups experienced a significant drop in performance going from the training block to the post-test. This suggests that performance of the faded groups was not completely stabilized towards the end of training and could have benefitted from an increased training time. Finally, we speculate that fading could be more effective if it is made 'closed-loop' and tied to task performance by using performance adaptive assistance algorithms (Colombo et al., 2012; Huegel and O'Malley, 2010; Krebs et al., 2003; Lee and Choi, 2014; Marchal-Crespo et al., 2013).

The current results potentially have important implications for the design of robots for rehabilitation. With the rise in the use of exoskeletons for learning and rehabilitation, a big unanswered question is how these devices need to be used to facilitate learning. Previous results have suggested that strategies that allow some degree of variability are important for motor learning (Lewek et al., 2009; Ziegler et al., 2010). Our results here further add to this evidence by showing that not only is variability important, but preserving the ability of the nervous system to use redundant solutions during learning is critical for learning. Therefore, rather than enforcing a ‘single’ movement pattern, it is likely that exoskeletons that allow for the use of these redundant solutions would be optimal for rehabilitation.

Chapter 5

PERFORMANCE-ADAPTIVE HAPTIC ASSISTANCE IN LEARNING A REDUNDANT TASK

5.1 Introduction

Robotic movement training has gained prominence over the last two decades due to advancements in robotic technology and assistive protocols. Such training has been particularly adopted for hemiparetic rehabilitation (Meng et al., 2015), surgical skills training (Bric et al., 2016), and bimanual haptic training (Talvas et al., 2014). The premise of robotic movement training lies in the employment of forces generated by a robot to assist in the execution and learning of motor skills. Typical advantages of such training are the high degree of repeatability of movements, greater control over kinematic/dynamic movement aspects, and precise and timely feedback about movements (Cao et al., 2014; Marchal-Crespo and Reinkensmeyer, 2009; Powell and O'Malley, 2012).

However, a fundamental shortcoming of current robotic training strategies is that they are successful in enhancing the performance of motor skills but not the retention of motor skills (Heuer and Lüttgen, 2015; Williams and Carnahan, 2014b). To be specific, the learners performed maximally as long as robotic assistance was enabled, but, the performance dropped significantly when assistance was withdrawn (Feygin et al., 2002b; Heuer and Lüttgen, 2015; Liu et al., 2006; Sigrist et al., 2013; Teo et al., 2002). It has been posited that providing robotic assistance physically alters the inherent task dynamics and practice with robotic assistance leads to the learning of a different task (Powell and O'Malley, 2012). Besides, from a motor control standpoint, assisting the learner concurrently renders a passive role for the motor system, decreases a participant's physical/mental effort, and leads to slacking in the preparation and production of movements (Marchal-Crespo and Reinkensmeyer, 2009). Moreover, from a learning standpoint, training at constant and high levels of assistance throughout the training period leads to overdependence on assistance for the completion of the motor task (Crespo and Reinkensmeyer, 2008; Heuer and Lüttgen, 2015; Salmoni et al., 1984; Schmidt, 1991). Therefore, one strategy that has been proposed to overcome the negative effects of concurrent and high assistance levels is to fade assistance levels progressively to enhance the retention of trained motor skills (Powell and O'Malley, 2012). The fading of the assistance level implies a gradual increase in motor requirements of the learner and lower control/forces exerted by the robot.

Progressive assistance reduction strategies can be broadly divided into open-loop and closed-loop strategies. Open-loop strategies reduce assistance levels in a predetermined fashion irrespective of learning outcomes (Huegel and O'Malley, 2010; Lee and Choi, 2010), whereas closed-loop strategies manipulate assistance levels based on the learner assistance requirements (Crespo and Reinkensmeyer, 2008; Emken et al., 2007; Huegel and O'Malley, 2010; Lee and Choi, 2014). Open-loop strategies are simple to design but do not account for differences in individual learning capabilities or the needs of the learner. A few studies have employed open-loop strategies and reported mixed benefits for motor learning (Chen and Agrawal, 2013; Heuer and Lüttgen, 2014b; Lee and Choi, 2010). On the other hand, closed-loop strategies provide assistance-as-needed, thus optimizing the assistance for each learner separately. Such closed-loop strategies are corroborated by the challenge point framework (Guadagnoli and Lee, 2004) because the learner is challenged to maintain task performance under reducing assistance levels. Thus, the manipulation of assistance is usually based on task performance metrics – assistance is reduced as performance improves and vice versa. Performance adaptive assistance manipulations were first proposed and implemented in neurorehabilitation of individuals affected by hemiparesis (Kahn et al., 2004; Krebs et al., 2003), and the algorithm for reducing assistance was explained using a mathematical model that optimizes movement error and robot effort (Emken et al., 2005).

Several studies have reported benefits of training with performance adaptive assistance strategies in rehabilitation (Banala et al., 2009, 2007; Kahn et al., 2006) and in the acquisition of novel skills (Crespo and Reinkensmeyer, 2008; Huegel and O'Malley, 2010; Marchal-Crespo et al., 2010b). A few of these studies also made comparisons between performance adaptive strategies (closed-loop strategy) and constant or fixed assistance strategy (open-loop strategy) (Crespo and Reinkensmeyer, 2008; Huegel and O'Malley, 2010), and found that the performance adaptive strategy was better than constant or fixed assistance strategy (Powell and O'Malley, 2012). However, these comparisons are confounded by the fact that the benefits could have due to closed loop manipulation of assistance rather than a systematic reduction of assistance (Schmidt, 1991). Therefore, the real advantage of closed-loop strategies can be more determined by comparing closed-loop strategies with open-loop faded assistance strategies under the same task and experimental settings.

The purpose of the study was to examine the differences in learning when the assistance level was manipulated in the following ways (i) open-loop – linearly reducing assistance (ii) closed-loop – performance adaptive assistance. Addressing this question allowed us to determine if there are any added benefits of 'performance-adaptive' assistance manipulations over open-loop assistance reductions. We also examined the learning dynamics of how changes in assistance influenced performance and learning using a novel analysis method.

5.2 Methods

Some portions of the methods (in sections 5.2.2, 5.2.3, 5.2.4 and 5.2.5) are identical to those used in our earlier study (Lokesh and Ranganathan, 2019), and are summarized here for completeness.

5.2.1 Participants

36 healthy college-aged adults (age range: 18-24 years, 20 men, 40 women) participated in the study and received extra course credit for participation. All participants provided informed consent and the procedures were approved by the Institutional Review Board at Michigan State University.

5.2.2 Apparatus

We used a bimanual manipulandum (KINARM Endpoint Lab, BKIN Technologies Ltd., ON), which consisted of two separate robotic arms that allowed motion in a 2-D horizontal plane. Each robotic arm had a handle located at the end which could be grasped by participants. Participants were seated on a height-adjustable chair and looked into a screen at around 45-degree angle below eye level as shown in Figure 5.1a. The visual information was presented in such a way that the objects on the screen appear to be located in the plane of the hands. Kinematic data from both handles were sampled at 1000 Hz.

5.2.3 Task Description

The participants performed a bimanual steering task (Lokesh and Ranganathan, 2019). Participants controlled a cursor of diameter 4 mm and steered it from a start position to end position along a smooth W-shaped track of length 738 mm (Figure 5.1a). The goal of the task was to complete the movement as fast as possible while maintaining the cursor within the grey track. The width of the track was always visible to the participant and consisted of two regions highlighted in different colors. The width of the inner grey track was 6 mm (the 'allowed region') and the width of the surrounding green track was 3mm. When the cursor deviated from the track, the surrounding track changed color to red serving as a visual cue to help maintain the cursor within the track.

5.2.4 Cursor Mapping

The position of the cursor (X_C, Y_C) was displayed at the average position of the two hand locations, making the task redundant. This 4-to-2-mapping can be represented as shown in (1):

$$C = \begin{pmatrix} X_C \\ Y_C \end{pmatrix} = A * [X_L \quad Y_L \quad X_R \quad Y_R]^T = A * h \tag{1}$$

Where C is the cursor position, A is the 'mapping matrix' and h is the vector of the left hand and right hand coordinates.

5.2.5 Procedures

At the start of each trial, participants saw two individual cursors (one for each hand), which allowed them to position each hand in its start circle – this was done to ensure that the two hands always started at the same position every trial. Once each hand reached its start position, the individual cursors disappeared and were replaced by a single cursor at the average position of the two hands. Participants then moved this cursor towards the finish position as fast as possible staying within the width of the track.

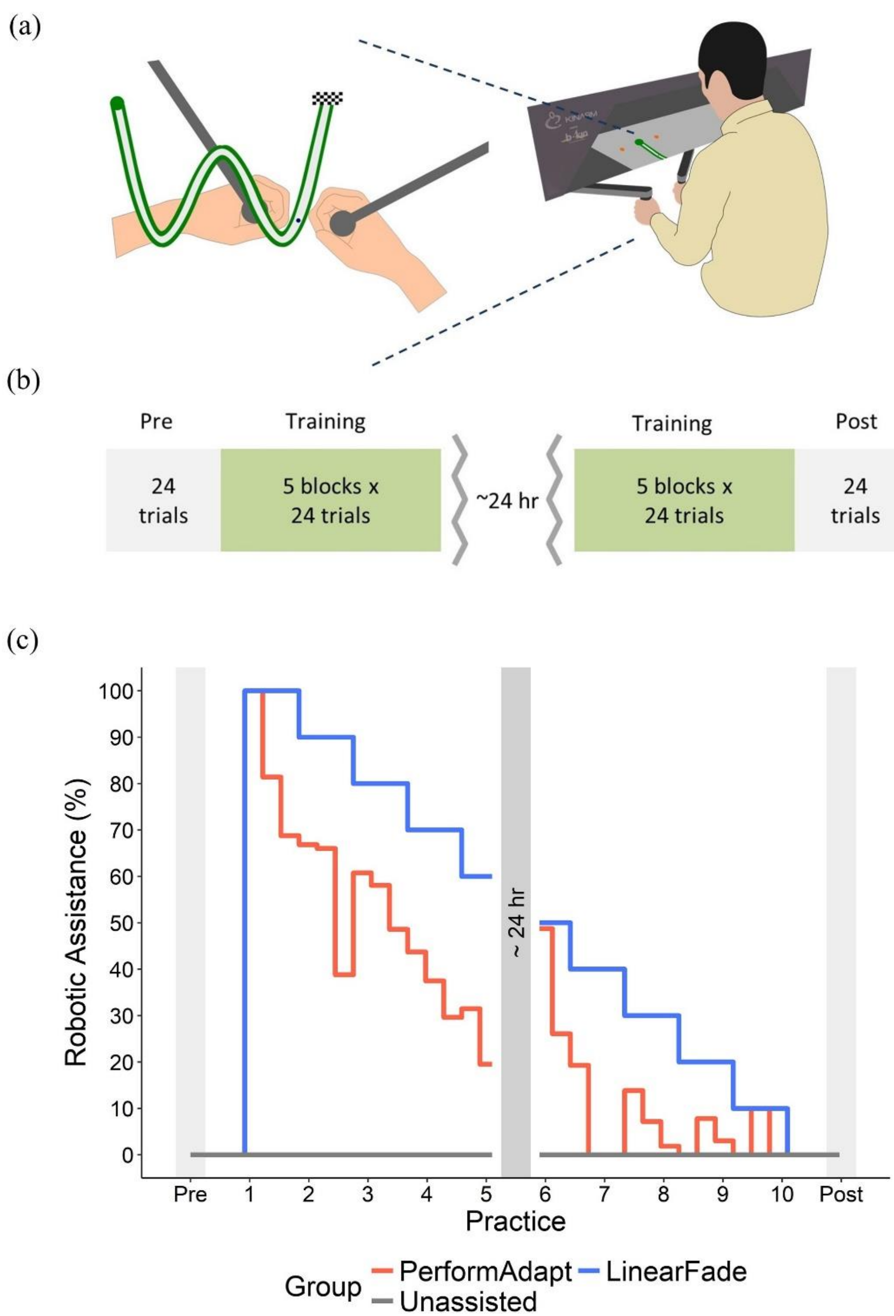

Figure 5.1 Experimental setup, protocol and adaptive assistance manipulation. (a) Experimental setup - Participants held the handles of a bimanual manipulandum and looked at a screen that appeared to be in the plane of their hands. (left) They traced a ‘W’ shaped track using a blue cursor placed in between their hands, and the goal was to move as fast as possible while maintaining the cursor within the grey track. (b) Experimental protocol for the 3 groups (PerformAdapt, LinearFade and Unassisted). Participants did a Pre-test followed by five blocks of training on the first day, and 5 blocks of training followed by a Post-test on the second day. (c) Robotic assistance manipulation. The assistance was reduced in a progressively linear manner during training for the LinearFade group, in a performance adaptive manner (one possible variation shown) for the PerformAdapt group, and maintained at zero for the Unassisted group.

To encourage participants to go faster while staying inside the track, participants were shown a score at the end of the trial. Participants started with a maximum of 100 points at the beginning of a trial and received a penalty in proportion to the time they took to complete the whole movement (t_m) and the time that the cursor spent outside the track (t_o) according to (2). The equation was determined based on pilot studies and was consistent with our goal of getting the participants to move quickly (i.e., minimize movement time) while also staying in the channel (i.e., minimize out of time). If the cursor completely went outside the surrounding track, they were awarded zero points on that trial. In addition to the trial score, the sum of trial scores from the completed trials in the ongoing block was shown to the participants after each trial.

$$\text{Trial score} = 100 - 0.22 * (\mathrm{t_m})^2 - 6.66 * (\mathrm{t_o})^2 \qquad (2)$$

5.2.6 Groups and Experimental Protocol

Participants were randomly assigned to 3 groups (n = 12/group) based on the manipulation of assistance levels with learning. Two groups received robotic assistance during training, and the third group received no assistance. The two groups that received assistance during training were as follows (i) 'LinearFade' – the assistance levels reduced in a linear fashion for all participants (ii) 'PerformAdapt' – the assistance levels were manipulated based on changes in the participant's performance.

The experimental protocol is shown in Figure 5.1b. The track width and length of the track remained constant throughout the protocol and for all groups. All participants practiced initially for 10 trials without assistance, where they familiarized themselves with the task and the scoring system. After familiarization, they performed a Pre-test consisting of 24 trials which were unassisted. This was followed by ten blocks of training with 24 trials in each block, where each participant received assistance based on their group membership, which we explain in subsection

5.2.8. Since the total number of trials in training was large enough to possibly induce fatigue in participants, we spread the training blocks over two days. At the end of the training on the second day, participants performed a Post-test consisting of 24 trials which were unassisted.

5.2.7 Haptic Assistance

The assistance was enabled in the form of a virtual force channel (Cai et al., 2006) centered around the W shaped track and having a width equal to the inner track as shown in Figure 5.1a. The force channel walls were modelled by a linear spring of stiffness (K = 1 N/mm). Thus, the channel applied a force (F) proportional to the deviation of the cursor (Δd) from the centerline of its track in a direction perpendicular to the track according to (3). The 'w' here represents the width of the inner track, and the force was zero as long as the cursor was within the track width.

$$\mathrm{F} = \mathrm{f} * \mathrm{K} * \max\left(\Delta \mathrm{d} - \frac{\mathrm{w}}{2}, 0\right) \tag{3}$$

Since the task was kinematically redundant, wherein the cursor was controlled by the two hands, we applied the force 'F' to both hands similarly in magnitude and direction.

5.2.8 Assistance manipulations

The assistance was manipulated by changing the spring stiffness factor 'f' (3). A force factor value equal to 2 represented 100% assistance and a force factor value of 0 represented 0% assistance. For the LinearFade group, the assistance was reduced in a stepwise manner from 100% to 0% in equal intervals after the end of each block from Block 1 to Block 10 in training as shown in Figure 5.1c. For the PerformAdapt group, each block was divided into three windows of 8 trials each, resulting in 30 windows in total from the 10 training blocks. The average movement time in each window was used as the performance measure. The assistance for the first window of Block 1 was set to 100% and the assistance for the subsequent windows was manipulated according to the update equation (4). The equation was based on the linear update method put forward by Kahn and Reinkensmeyer (Kahn et al., 2004), and the value for α was chosen by trial and error. Importantly, the assistance was manipulated linearly in proportion to the change in average movement time between the previous two windows. Thus, whenever average movement times reduced between two successive windows, the assistance was reduced for the following window and vice versa. The assistance was also bounded on the upper side by the linear faded assistance levels and bounded on the lower side by zero assistance. This ensured that the assistance levels reduced to zero by the end of the training.

$$\mathrm{w} = \text{window number } \in \{1, 2, 3 \ldots \ldots 28, 29, 30\}$$

$$\mathrm{A_w} = \text{assistance level of window w}$$

$$\mathrm{A_1} = \text{assistance level of first window} = 100\%$$

$$\mathrm{MT_w} = \text{average movement time of window w in seconds}$$

$$\mathrm{MT_0} = \text{average movement time of final 8 trials in Pre test}$$

$$\mathrm{A_{w+1}} = \mathrm{A_w} + \alpha * (\mathrm{MT_w} - \mathrm{MT_{w-1}}) \tag{4}$$

$$\alpha = 10$$

5.3 Data Analysis

5.3.1 Block Score

The score provided to the participant on each trial was computed using (2). This score was averaged across all trials in a block for each participant.

5.3.2 Movement Time

Movement time was defined as the time between the instant when the participant moved the cursor out of the start circle and the instant when the cursor moved into the finish box. The movement times were averaged across all trials in a block for each participant.

5.3.3 Out of Track Time

Out-of-track time was defined as the time that the cursor was outside the track from the start to the end of movement. The out of track time was then averaged across all trials in a block for each participant.

5.3.4 Task and Null Space Variability

Since the task was kinematically redundant, the variability in hand positions was decomposed into task and null space variabilities (Liu and Scheidt, 2008; Mosier et al., 2005; Ranganathan et al., 2013). The task space variability refers to the component of the movement variability that affects cursor motion whereas the null space variability refers to the component of the overall movement variability that has no effect on cursor motion. The path from each trial was divided into 51 spatially equidistant points from the start to the end. At each point, the corresponding hand vectors 'h' as described in (1) from all trials in that block were extracted into a matrix H as shown in (5) and the Moore-Penrose inverse was used to decompose the hand positions into null space (H_n) and task space (H_t) components (Liu and Scheidt, 2008; Lokesh and Ranganathan, 2019; Mosier et al., 2005) as shown in (6) and (7) respectively, where I4 is an identity matrix of size 4.

$$\mathrm{H} = [\mathrm{h}_1\, \mathrm{h}_2\ \ldots \ldots \ldots \mathrm{h}_{23}\, \mathrm{h}_{24}\,] \tag{5}$$

$$\mathrm{H}_\mathrm{t} = \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A} * \mathrm{H} \tag{6}$$

$$\mathrm{H}_\mathrm{n} = (\mathrm{I}_4 - \mathrm{A}' * (\mathrm{A} * \mathrm{A}')^{-1} * \mathrm{A}) * \mathrm{H} \tag{7}$$

The variances of the null and task components of the hand positions were computed and summed to obtain null space and task space variability in each block. These equations meant that if the cursor position was identical across multiple trials, then the task space variability would be zero. Additionally, if both hands were also at the same location in space across multiple trials, then the null space variability would also be zero.

5.3.5 Haptic Force Reliance

Because the haptic forces that participants experienced depended both on the error as well as the time they spent outside the track, the haptic reliance on each trial was calculated by computing the net force impulse – i.e. integrating the forces experienced by the participant from start to end of the movement. Note that the haptic reliance was set to zero for the Unassisted group during training, and in the Pre-test and Post-test block for all groups.

5.4 Statistical Analysis

Our primary research questions were to determine the effect of the haptic manipulations on the task outcome variables. Besides, we wanted to compare the two assisted groups with the Unassisted group. For the PerformAdapt group, we averaged the variables across the 3 windows in each block to obtain block variable values so as to allow comparisons with the other two groups.

5.4.1 Training Phase

Since the training phase consisted of 10 blocks, we compared the effects during training using the last block. We used a t-test to compare between the two assisted groups, PerformAdapt and LinearFade.

Comparison to Unassisted group. We used a one-way ANOVA on Block 10 values with the three groups as a factor. For post-hoc comparisons, we compared the two assisted groups with the Unassisted group using Dunnett's test.

5.4.2 Test Phase

To examine the effect of learning in groups that received assistance, we averaged the variables across the windows within the Pre-test and Post-test blocks. We used an ANCOVA on the Post-test values with Pre-test values as covariate and the Groups (PerformAdapt and LinearFade) as a factor.

Comparison to Unassisted group. We used an ANCOVA on the Post-test values with Pre-test values as covariate and the three groups as a factor. For post-hoc analysis, we compared the two assisted groups with the Unassisted group using Dunnett's test on the adjusted means.

5.4.3 Training to Test-phase

An important shortcoming of haptic assistance is the significant drop in performance upon removal of assistance. To analyze this effect, we compared the variables from the last block in training (where haptic assistance was enabled) to the Post-test (haptic assistance was removed). We used a 2x2 ANOVA with the Blocks (Block 10, Post-test) and Groups (LinearFade, PerformAdapt) as the two factors. For post-hoc analysis we used pairwise t-tests.

5.5 Results

5.5.1 Training Phase

Block Score

The LinearFade group had scores similar to the PerformAdapt group as shown in Figure 5.2a. The t-test indicated no significant effect of Group ($p = 0.23$).

Comparison to Unassisted group. The LinearFade group had higher block scores in comparison to the Unassisted group as shown in Figure 5.2a. The ANOVA indicated a significant effect of Group ($F(2,33) = 4.18$, $p = 0.024$). The Dunnett's test indicated no significant differences for PerformAdapt ($p = 0.12$) and significantly higher scores for LinearFade ($p = 0.014$).

Movement Time

The LinearFade group had movement times lower than the PerformAdapt group as shown in Figure 5.2b. The t-test indicated a significant effect of Group ($p = 0.014$).

Comparison to Unassisted group. The LinearFade group had movement times lower than the Unassisted group as shown in Figure 5.2b. The ANOVA indicated a significant effect of Group ($F(2,33) = 8.07$, $p = 0.0014$). The Dunnett's test indicated no significant differences for the PerformAdapt group ($p = 0.35$), and significantly lower movement time for the LinearFade group ($p < 0.001$).

Out of track time

The LinearFade group had out of track times similar to the PerformAdapt group as shown in Figure 5.2c. The t-test indicated no significant effect of Group ($p = 0.83$).

Comparison to Unassisted group. The assisted groups had out of track times similar to the Unassisted group as shown in Figure 5.2c. The ANOVA indicated no significant effect of Group ($F(2,33) = 1.68$, $p = 0.202$).

Haptic Force Reliance

The LinearFade group appeared to lower haptic force reliance in comparison to the PerformAdapt group as shown in Figure 5.3a. The t-test indicated no significant effect of Group ($p = 0.0507$).

Task Space Variability

The LinearFade group had task space variability similar to the PerformAdapt group as shown in Figure 5.3b. The t-test indicated no significant effect of Group ($p = 0.37$).

Comparison to Unassisted group. The LinearFade group had task space variability higher than the Unassisted group as shown in Figure 5.3b. The ANOVA indicated a significant effect of Group ($F(2,33) = 4.76$, $p = 0.015$). The Dunnett's test indicated no significant differences for the PerformAdapt group ($p = 0.089$), and significantly lower task space variability for the LinearFade group ($p = 0.009$).

Null Space Variability

The LinearFade group had null space variability similar to the PerformAdapt group as shown in Figure 5.3c. The t-test indicated no significant effect of Group ($p = 0.83$).

Comparison to Unassisted group. The assisted groups had null space variability similar to the Unassisted group as shown in Figure 5.3c. The ANOVA indicated no significant effect of Group ($F(2,33) = 2.11$, $p = 0.13$).

5.5.2 Test Phase

Block Score

The LinearFade group appears to have block scores lower than the PerformAdapt group as shown in Figure 5.2a. However, the ANCOVA indicated no significant effect of Group ($F(1,21) = 3.96$, $p = 0.059$).

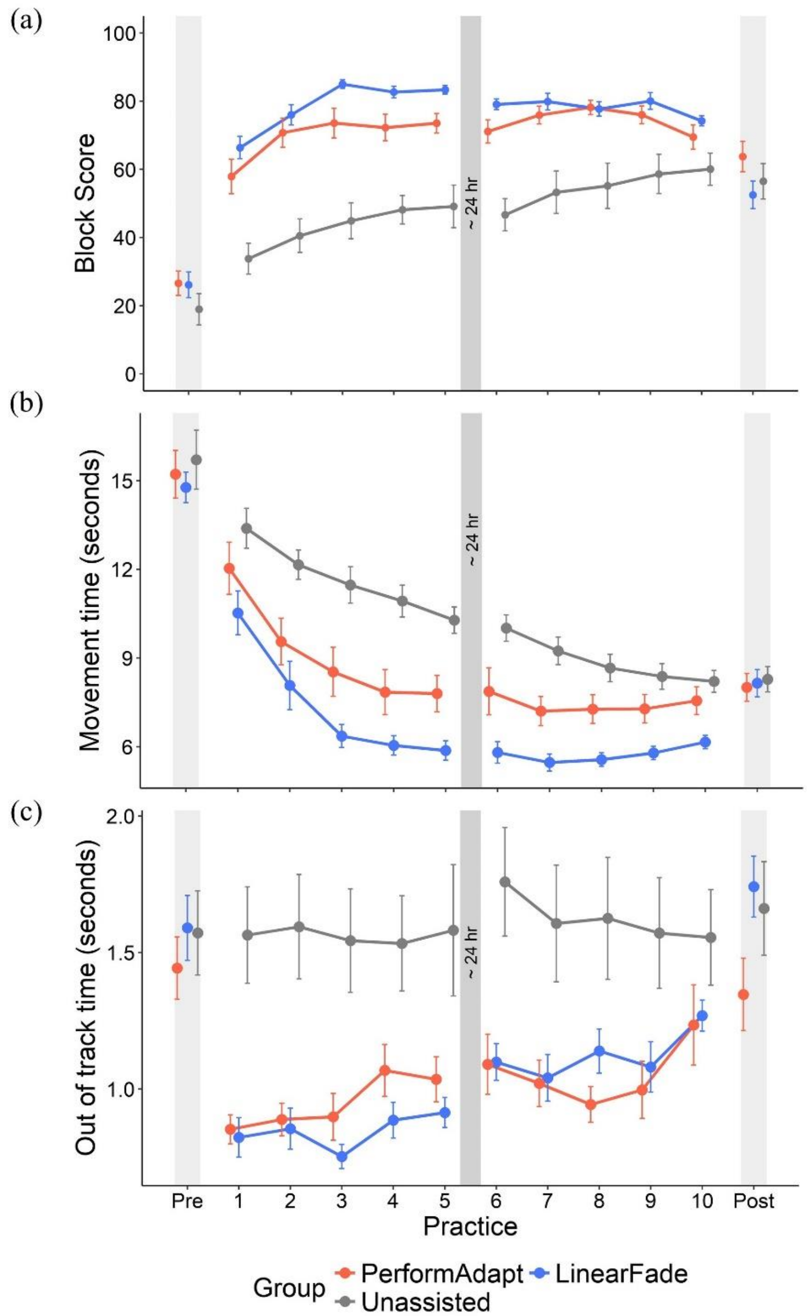

Figure 5.2 Plots of performance variables versus practice. (a) Block score- All groups improved scores with practice, and the assisted groups had higher scores in comparison to Unassisted group in training (b) Movement time- All groups reduced movement times from Pre-test to Post-test, and the LinearFade group had lower movement time in comparison to PerformAdapt group in training (c) Out of track time- Out of track times remained similar from Pre to Post, and the PerformAdapt group had relatively lower out of track time in comparison to the other two groups in the Post-test. (d) Haptic Force Reliance- The PerformAdapt group had lower haptic force reliance in comparison to the LinearFade group.

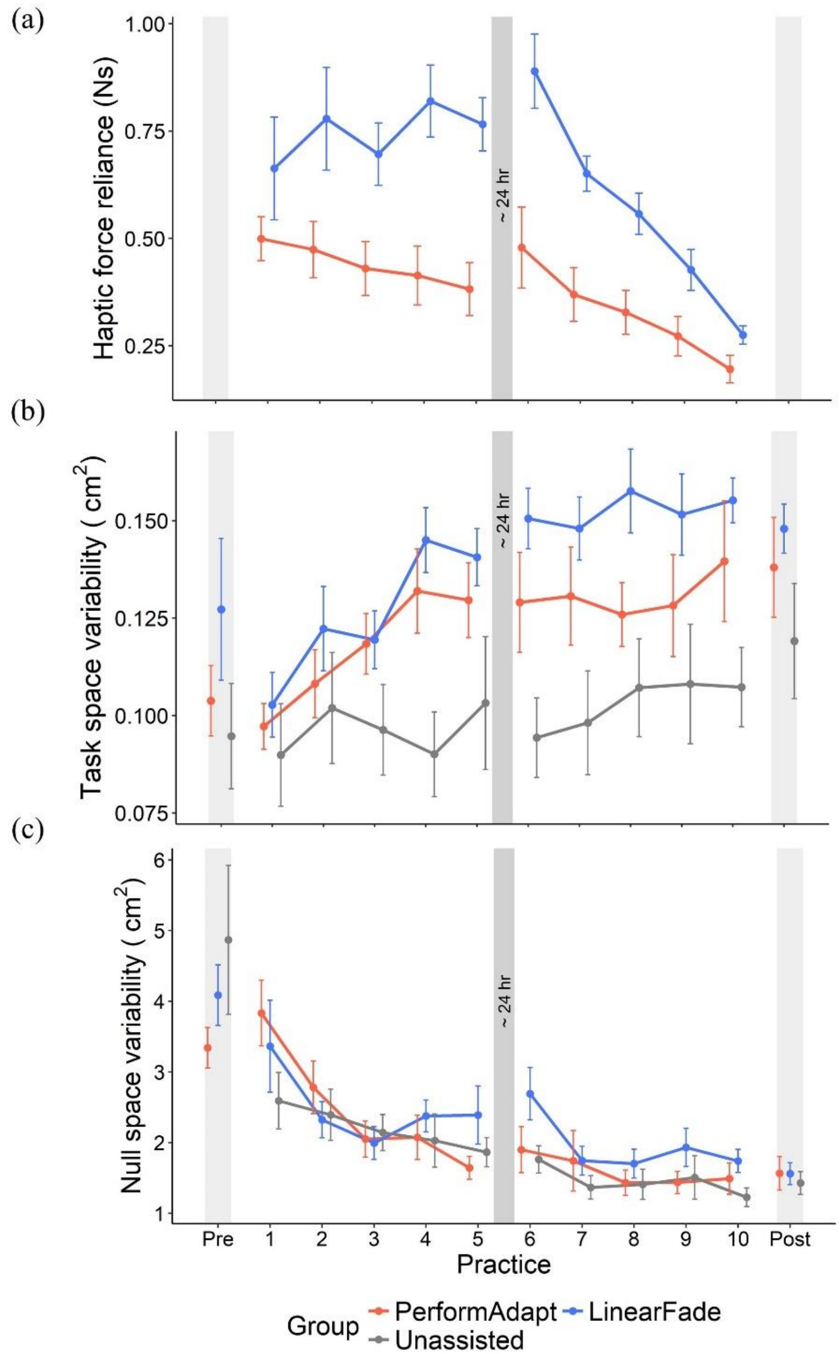

Figure 5.3 Plots of variability and haptic reliance versus practice. (a) Haptic force reliance- Both the assisted groups reduced reliance on haptic assistance with training and the PerformAdapt group had lower reliance in comparison to the LinearFade throughout training. (b) Task space variability- The assisted groups had higher task space variability in comparison to the Unassisted group in training, and they also showed increasing task space variability during training. (c) Null space variability – All groups practiced with similar null space variabilities throughout practice.

Comparison to Unassisted group. The assisted groups had scores similar to the Unassisted group as shown in Figure 5.2a. The ANCOVA indicated no significant effect of Group ($F(2,32) = 1.88$, $p = 0.16$).

Movement Time

The LinearFade group had movement times similar to the PerformAdapt group as shown in Figure 5.2b. The ANCOVA indicated no significant effect of Group ($F(1,21) = 0.48$, $p = 0.49$).

Comparison to Unassisted group. The assisted groups had movement times similar to the Unassisted group as shown in Figure 5.2b. The ANCOVA indicated no significant effect of Group ($F(2,32) = 0.14$, $p = 0.86$).

Out of track time

The LinearFade group had out of track time higher than the PerformAdapt group as shown in Figure 5.2c. The ANCOVA indicated a significant effect of Group ($F(1,21) = 4.67$, $p = 0.042$).

Comparison to Unassisted group. The assisted groups had out of track times similar to the Unassisted group as shown in Figure 5.2c. The ANCOVA indicated no significant effect of Group ($F(2,32) = 1.911$, $p = 0.16$).

Task Space Variability

The LinearFade group had task space variability similar to the PerformAdapt group as shown in Figure 5.3b. The ANCOVA indicated no significant effect of Group ($F(1,21) = 0.32$, $p = 0.57$).

Comparison to Unassisted group. The assisted groups had task space variability similar to the Unassisted group as shown in Figure 5.3b. The ANCOVA indicated no significant effect of Group ($F(2,32) = 0.78$, $p = 0.46$).

Null Space Variability

The LinearFade group had null space variability similar to the PerformAdapt group as shown in Figure 5.3c. The ANCOVA indicated no significant effect of Group ($F(1,21) = 0.038$, $p = 0.54$).

Comparison to Unassisted group. The assisted groups had null space variability similar to the Unassisted group as shown in Figure 5.3c. The ANCOVA indicated no significant effect of Group ($F(2,32) = 0.15$, $p = 0.86$).

5.5.3 Training to Test-phase

Block Score

The LinearFade group had significant reduction in block scores and the PerformAdapt group had similar block scores, going from the last block in training to the Post-test as shown Figure 5.2a. The ANOVA indicated no significant effect of Group ($F(1,44) = 0.82$, $p = 0.37$), a significant effect of Block ($F(1,44) = 14.7$, $p < 0.001$), and a significant interaction effect ($F(1,44) = 4.99$, $p = 0.03$). Pairwise t-test between the two blocks revealed a significant lower Post-test scores for LinearFade ($p < 0.001$), and no significant difference in block scores for PerformAdapt ($p = 0.33$).

Movement Time

Both assisted groups had relatively higher movement time going from the last block in training to the Post-test as shown Figure 5.2b. The ANOVA indicated no significant effect of Group ($F(1,44) = 2.23$, $p = 0.14$), a significant effect of Block ($F(1,44) = 8.45$, $p = 0.0056$), and no significant interaction effect ($F(1,44) = 3.36$, $p = 0.073$).

Out of track time

Both assisted groups had higher out of track times going from the last block in training to the Post-test as shown Figure 5.2c. The ANOVA indicated no significant effect of Group ($F(1,44) = 3.35$, $p = 0.073$), a significant effect of Block ($F(1,44) = 6.23$, $p = 0.016$), and no significant interaction effect ($F(1,44) = 2.37$, $p = 0.13$).

Task Space Variability

Both assisted groups had similar task space variabilities going from the last block in training to the Post-test as shown Figure 5.3b. The ANOVA indicated no significant effect of Group (F(1,44)

= 1.36, p = 0.24), no significant effect of Block (F(1,44) = 0.16, p = 0.68), and no significant interaction effect (F(1,44) = 0.068, p = 0.79).

Null Space Variability

Both assisted groups had similar null space variabilities going from the last block in training to the Post-test as shown Figure 5.3c. The ANOVA indicated no significant effect of Group (F(1,44) = 0.38, p = 0.53), no significant effect of Block (F(1,44) = 0.072, p = 0.79), and no significant interaction effect (F(1,44) = 0.41, p = 0.52).

5.6 Learning analysis

An important aim of this study was to analyze the differences between open-loop and closed-loop manipulation of assistance levels with learning. For the closed-loop condition, the assistance was manipulated according to (4) after each window in training based on changes in the average movement times between successive windows. Since the change in assistance depended on how participants changed their movement times, each participant received assistance based on his/her requirements. We analyzed the dynamics between changes in assistance and changes in movement time for each participant to understand the effects of the closed-loop manipulation.

5.6.1 Assistance levels in training

Firstly, the assistance levels for the 12 participants from the PerformAdapt group are plotted for the 30 windows in training as shown in Figure 5.4. The assistance levels used for the LinearFade group have been plotted in grey for reference. Each participant in the PerformAdapt group utilized different magnitudes of assistance levels throughout the training. Besides, the participants trained under assistance levels lower than the LinearFade group early on in training. However, some participants trained with assistance levels equal to the LinearFade assistance levels towards the end of the training.

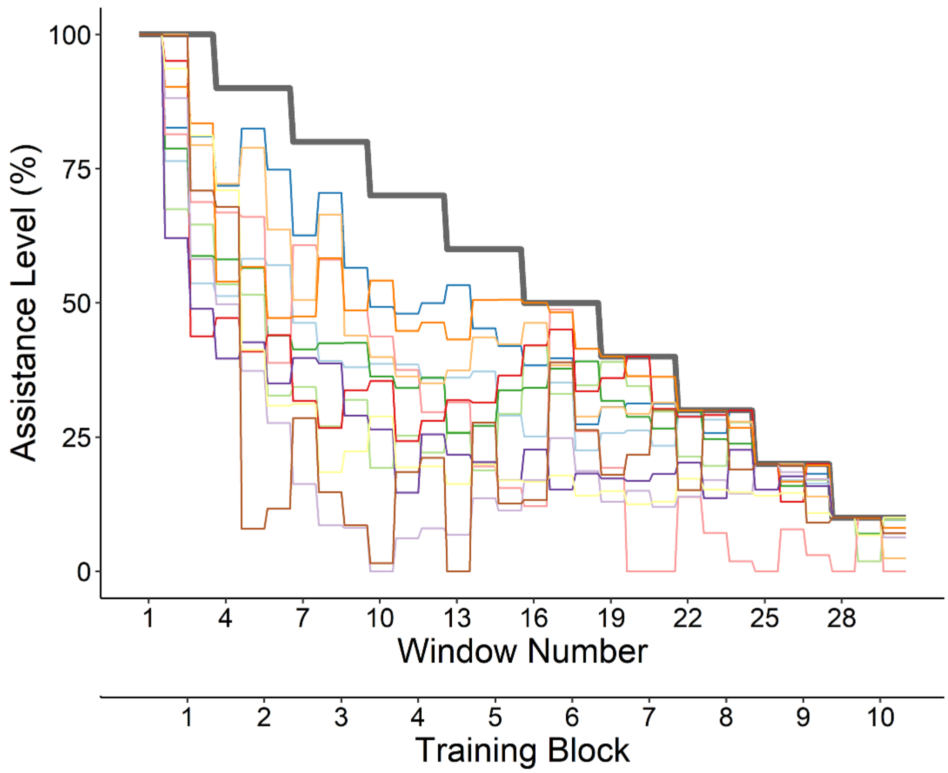

Figure 5.4 Plot of assistance levels for PerformAdapt group in training. Plot of assistance levels for the 12 participants from the PerformAdapt group for the 30 windows in training shown in different colors. The assistance level for the LinearFade group is shown in grey for reference. All participants practiced under assistance levels lower than the LinearFade reference early on in training.

5.6.2 Response to changes in assistance

The following four performance (movement times) response conditions were identified for any changes in assistance levels between two successive windows in training - (i) 'Performance Improvement'- assistance increases and participants expectedly decrease movement time. (ii) 'Performance Decrement'- assistance decreases and participants expectedly increase movement times. (iii) 'Learning' - assistance decreases, and if the participants are learning they reduce movement times. (iv) 'Forgetting'- assistance increases, and if the participants are forgetting, they increase movement times. The four response strategies are assigned to the four quadrants created by setting the change in assistance levels as the x-axis and the change in movement times as the y-axis as shown in Figure 5.5.

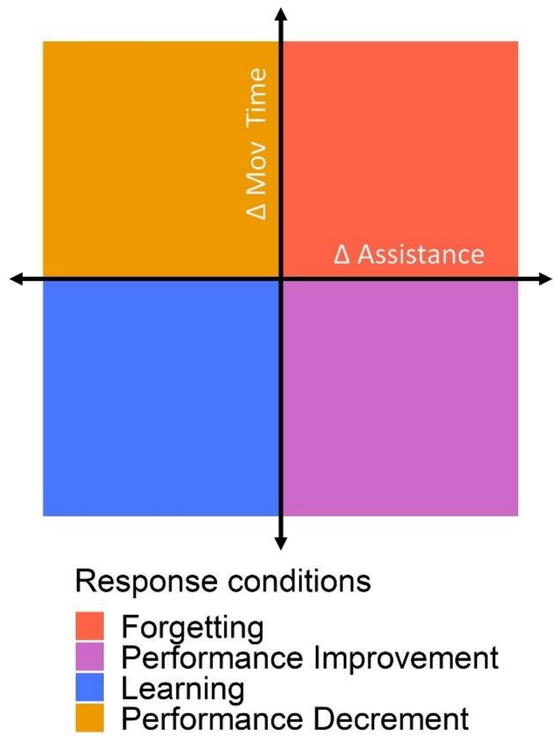

Figure 5.5 Responses (changes in movement time) to changes in assistance shown in the cartesian space. The four quadrants showing the four different response conditions. Quadrant I – Forgetting, assistance increased and movement time increased. Quadrant II – Performance Decrement, assistance decreased and movement times increased. Quadrant III –Learning, assistance decreased and movement times decreased. Quadrant IV – Performance Improvement, assistance increased and movement times decreased.

5.6.3 Evolution of response conditions in training

The changes in response conditions for the 30 windows in training was used to model the learning dynamics. For example, the evolution of Learning responses can be used to understand how if participants are learning the task. The cumulative frequency of each response condition was plotted as a function of the training window for each participant. An example plot from a participant in the PerformAdapt group is shown in Figure 5.6 along with the average scores in the Pre-test and Post-test blocks.

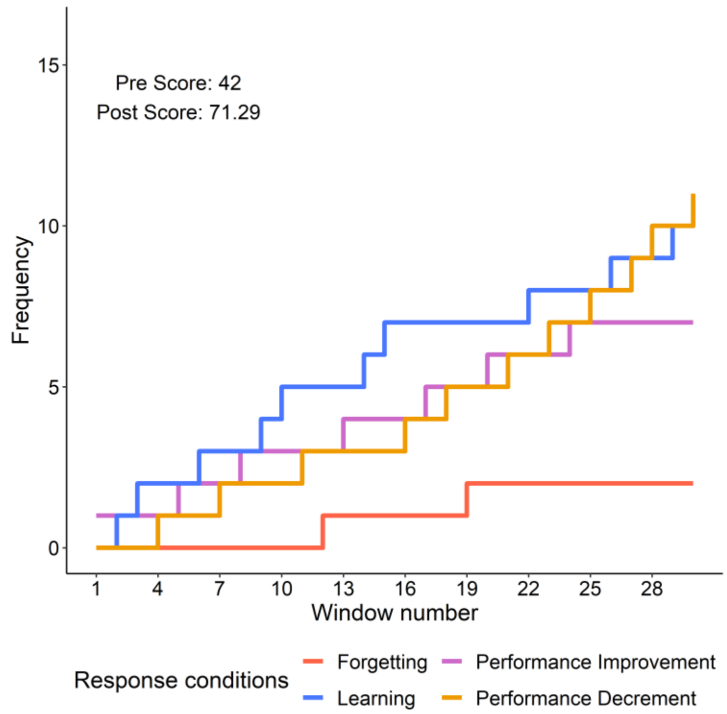

Figure 5.6 Dynamics of response conditions across training. The frequency of response conditions plotted as a function of window number in training for a participant from the PerformAdapt group. A higher frequency of Learning response conditions shows that the participant was able to improve on movement times even upon decreasing assistance.

5.6.4 Response condition transition proportions

An interesting observation from Figure 5.6 is that the Performance Improvement and Performance Decrement responses alternate between the windows 17 and 24. Thus, identifying the transition between response conditions can provide an insight into how participants learnt the task from the standpoint of our model. To this end, for each response condition, we identified the response condition for the following window and calculated the proportion for each transitioned response condition. The transition proportions are plotted for the same participant from Figure 5.6, in Figure 5.7. We have also plotted the overall proportion for the observed response conditions from all the windows as larger bars. The participant had higher proportions of the Learning and Performance Decrement responses, wherein, most of the Learning responses were followed by a Performance Decrement response.

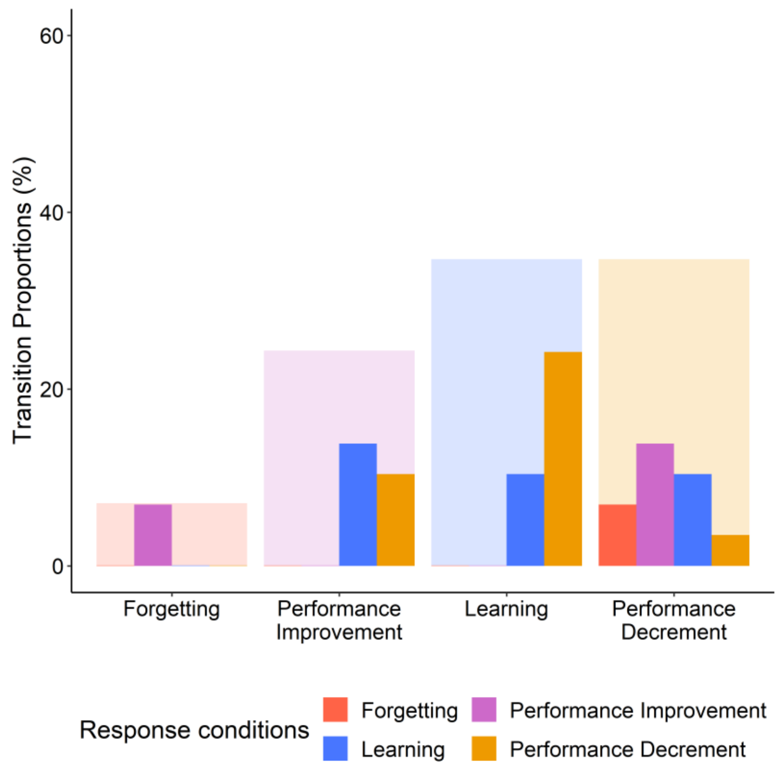

Figure 5.7 Response condition transition proportions. For each response condition, the proportion of succeeding response condition is shown as smaller bar plots. The overall proportions of each response condition in training are shown as larger bars. This participant had higher proportions of the Learning and Performance Decrement responses, with each Learning response followed mostly by a Performance Decrement response.

5.6.5 Individual differences in response to changes in assistance

As shown in Figure 5.4, each participant experienced unique changes in assistance levels after each window in training. Moreover, they displayed different levels of Pre-test and Post-test performance. The distinct characteristics of the evolution of response conditions are shown for two participants from the PerformAdapt group as shown in Figure 5.8; (i) Participant A had the lowest

Pre-test score and a very high Post-test score (ii) Participant B had the highest Pre-test score and the highest Post-test score. The plots of transition proportions are also shown in Figure 5.9.

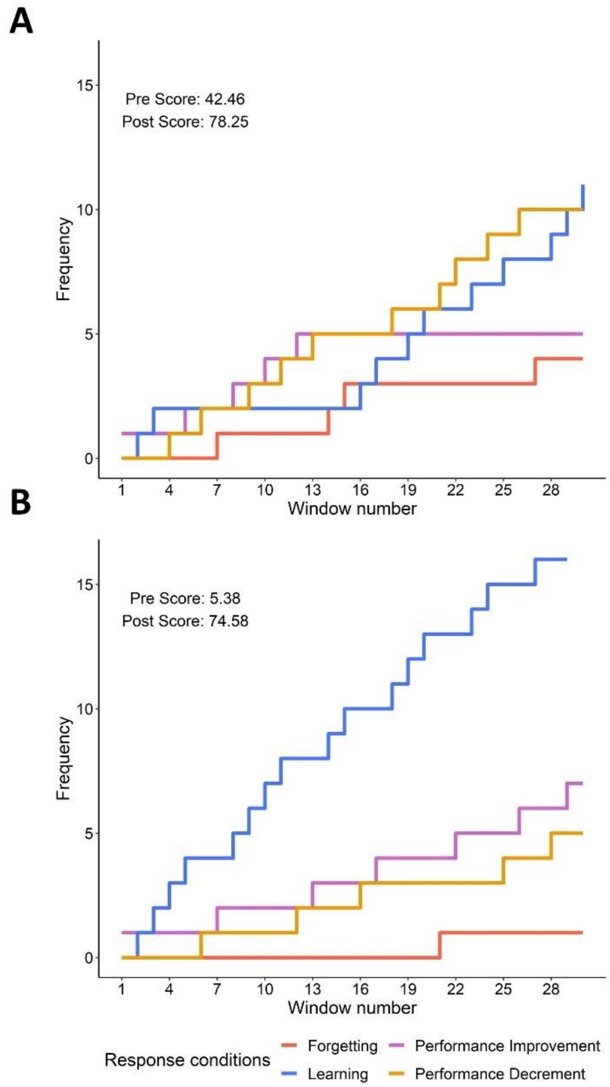

Figure 5.8 Learning dynamics for participants with different initial performance. The evolution of response conditions with window numbers for two participants A and B from the PerformAdapt group, with pre-test and post-test scores inset the plot. Participant A had low initial performance and participant B had high initial performance, but both participants improved scores significantly.

Both the participants benefitted from the assistance as evident from their post-test scores, but each of them displayed seemingly different learning dynamics. Participant A had a larger number of Learning responses which were spread throughout training, whereas Participant B alternated between Performance Improvement and Performance Decrement responses early on in training, before eventually showing Learning responses later on in training. Thus, the performance adaptive strategy seems to be helpful for differently initially skilled participants and was adaptive to their learning requirements.

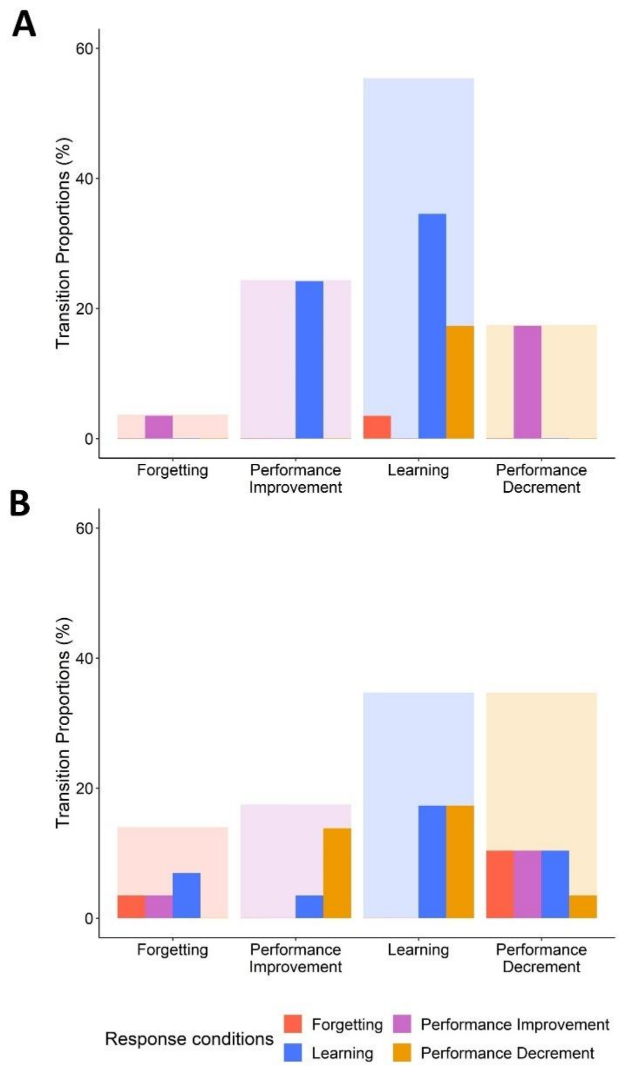

Figure 5.9 Response transition proportions for participants with different initial performance. Transition proportions for the two participants A and B, who had the lowest and highest performance in the Pre-test. Participant A had a higher proportion of Learning responses in training and a higher proportion of transitions from the Learning response were into the Learning response which indicated task learning. Whereas, participant B had similar proportions of Learning and Performance Decrement responses, with equal transitions into Learning and Performance Decrement responses from the Learning response.

Going further, we hypothesized that the Learning responses should be responsible for the learning of the task i.e. the number of Learning responses should correlate to the change in participant's scores from the Pre-test to the Post-test. We correlated the difference between the Post-test score and the Pre-test score against the total count of Learning responses in training for all the participants (n = 12) as shown in Figure 5.10. The Pearson correlation test indicated a significant positive correlation for the regression ($r(10) = 0.76$, $p = 0.0039$).

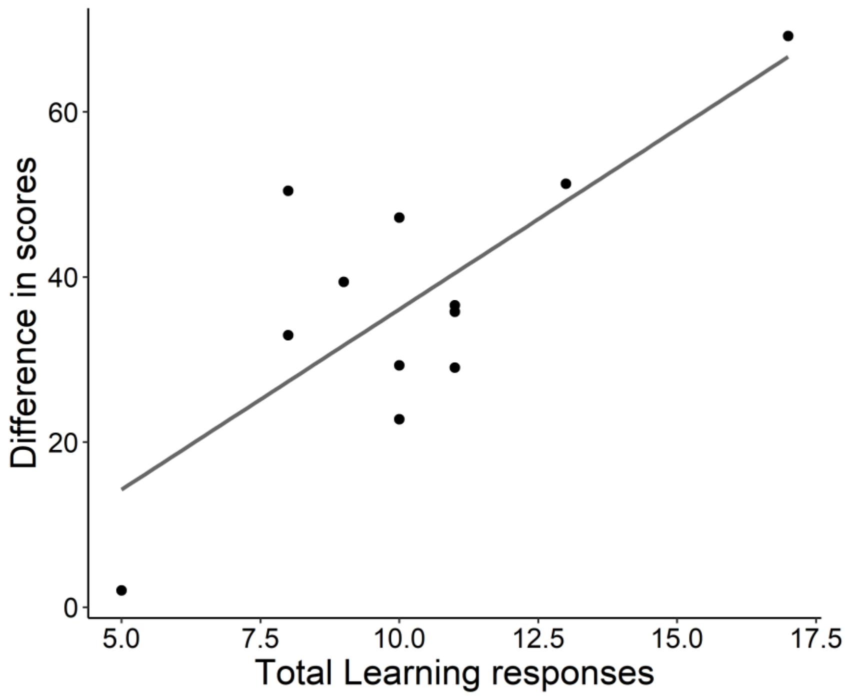

Figure 5.10 Correlation between Learning responses and the difference between Post-test and Pre-test scores. The scatter plot of the difference between Post-test and Pre-test scores against the total Learning responses for the 12 participants in the PerformAdapt group. The correlation was significant indicating that the Learning responses could predict improvements in performance for the participants.

5.7 Discussion

The goal of this study was to determine the efficacy of performance adaptive control strategies from two standpoints (i) Pre to Post-test analysis and comparison with a simpler linearly reducing assistance strategy (ii) Training analysis of the interplay between assistance and task performance during the learning process. We found subtle but non-significant advantages for the group that trained under the performance adaptive assistance algorithm in comparison to the group that trained under linearly reducing assistance for short-term retention of performance. However, there was no evidence for significant benefits of either mode of assistance in comparison to training under no assistance. From the learning standpoint, we have put forward a model to understand the dynamics between assistance manipulations and performance changes, and to evaluate any given assistance manipulation strategy.

The analysis of the effects of assistance in the training phase revealed significant improvements in the movement time for the assisted groups even as the assistance decreased. However, as the participants went faster, the out of track times increased possibly due to the speed-accuracy tradeoff (Accot and Zhai, 1997; Fitts, 1954), and is also consistent with results for bimanual movements where the errors were larger when the two hands travelled faster in a near symmetrical fashion (Sherwood and Enebo, 2005). From the viewpoint of the Uncontrolled Manifold Hypothesis (Latash et al., 2002), the variability in the null space can be used as a noise buffer to stabilize the movement of the cursor leading to lower movement errors. Our observation is in line with this hypothesis, wherein the null space variability is significantly larger than the task space variability. Besides, the null space variability reduced, and the task space variability increased systematically with practice for both assisted groups which possibly explains the increase in the out of track times, i.e. a lower null space variability implied a lower stabilization of the cursor.

From analyzing the reliance on haptic assistance, we observed that the magnitude of haptic forces experienced by the participants reduced with practice, and according to the guidance hypothesis (Powell and O'Malley, 2012; Schmidt, 1991), this should be beneficial to learning. Besides, the group with adaptive assistance had lower reliance on haptic assistance in comparison to the group that practiced with linearly reducing assistance. This observation was true for all the participants in the performance adaptive group, showing that none of the participants required assistance levels as high as that of the linear assistance especially in the early stages of training. Even though this seems to indicate that the closed-loop manipulation was better than open-loop manipulation, an open-loop strategy that reduced assistance non-linearly and quickly early on in training could also be equally effective. However, it is unclear if the open-loop manipulation can be tailored to each participant's requirements.

While examining the effect of the different assistance manipulations on the short-term retention of performance, we found that the performance adaptive group had relatively higher scores in comparison to the linearly fading group. This was mainly driven by the out of track time variable, whereas there was no significant difference in movement times. Here, we have shown that performance adaptive assistance strategies could be beneficial towards teaching learners to control movement errors. Besides, unlike the linearly fading group, the performance adaptive group did not show decrements in performance from the last block in training to the post-test. This could be due to the following two results; Firstly, the performance adaptive group had lower haptic force reliance and assistance levels on average in the last block of training in comparison to the linear faded group resulting in a smaller assistance change going into the unassisted post-test block. Secondly, the participants in the performance adaptive group experienced different magnitudes of changes in the assistance levels in training leading to possibly stronger schematic learning (Moxley, 1979; Shea and Wulf, 2005), in comparison to the linear faded group which faced reductions of assistance in equal steps.

Overall, the assisted groups did not exhibit enhanced learning over the unassisted group. Although the performance adaptive group seems to show better performance in the post-test, the benefits diminish when the Pre-test performance is considered. These results show that robotic assistance might not be detrimental to the retention of spatial movement skills contrary to the reports of some studies (Heuer and Lüttgen, 2015) if the assistance is reduced appropriately with practice. Moreover, the assisted groups maintained performance levels significantly above the unassisted groups which might be advantageous in training situations posing safety concerns like balance training in rehabilitation, surgical operations, etc. (Marchal-Crespo and Reinkensmeyer, 2009), and to maintain practice motivation for tasks that could otherwise impose high levels of functional difficulty.

Finally, we examined the interplay between assistance and performance during training. The idea behind using a performance adaptive algorithm was to account for the skill level differences at baseline and for the different learning capabilities. Even though it was expected that learners would make use of the adaptive nature of the strategy according to their needs, none of the studies had attempted to understand the dynamics between learning and augmented assistance. By adopting an assistance-response model derived by pairing changes in assistance to the corresponding changes in task performance, we were able to show the different learning dynamics. The assistance was helpful for both initially high skilled and low skilled participants in as shown in Figures 5.7 and 5.8. This result adds to the observations from studies that reported benefits of haptic assistance particularly for initially lesser skilled participants (Duarte and Reinkensmeyer, 2015; Marchal-Crespo et al., 2015, 2010b). Most importantly, we were also able to show that the retention of performance in the post-test correlated directly to the number of Learning responses seen during training. Overall, we believe that such an analysis of dynamics in training can provide valuable insights for the evaluation and design of assistance control strategies for robotic training.

The results of this manuscript show that performance-based assistance manipulation strategies could possibly be better than simpler open-loop strategies like linear fading of assistance for robotic movement training. However, more experiments with other open-loop strategies that non-linearly reduce assistance are required to make definitive comparisons. The evaluation of assistive manipulation strategies can be carried out using the training data as demonstrated by the model in addition to a pre to post-test analysis. Further refinement is necessary to ensure the appropriate application of such a model towards characterizing the dynamics between augmented assistance and learner's performance.

Chapter 6

GENERAL DISCUSSION

There has been an increase in the use of robots to assist in the training of motor skills and to collaboratively execute specialized physical tasks. The presence of kinematic redundancy in our motor system means that the assistance from robots and feedback about task execution can be enabled at multiple redundant effectors/joints. However, very few studies have researched the effects of providing assistance/feedback at multiple redundant effectors. We have addressed this gap in previous research through the following three central pieces of work in the dissertation; (i) we developed a bimanual redundant task and characterized learning in terms of task performance and changes to the structure of motor variability (ii) we augmented haptic assistance that either restricted or allowed the use of redundant solutions and reported the effects on learning (iii) we compared learning benefits from an open-loop strategy to a performance-based closed-loop strategy for manipulation of assistance with practice, and we showed that studying the interplay between changes in assistance and task performance can provide valuable insights about the process of learning. We believe that our work will influence the development of novel haptic assistance strategies and motivate new directions for research. In this chapter, we have holistically summarized our findings, discussed avenues for future work, and addressed the limitations of the dissertation.

6.1 Haptic assistance for redundant tasks

6.1.1 Limiting motor variability

In experiment 1, when the ability to self-organize variability was preserved, we made an interesting observation that learners from all the groups employed similar amounts of null space variability at any given point in training. The magnitudes of null space variability were similar even under different levels of task difficulty and when the observed task space variabilities were different. Besides, the null space variability reduced monotonously with practice for all the groups which is not supported by the minimum intervention principle (Todorov and Jordan, 2003) or the UCM hypothesis (Latash et al., 2002). This seems to indicate that the observed high null space variability was required in the earlier stages of learning to maintain task space variability within the admissible limits. But with greater practice, the motor system could develop greater control over task space variability and thus a stabilization mechanism using large null space variability was unnecessary. Moreover, once an optimal solution (Todorov and Jordan, 2002) or a use dependent solution (Diedrichsen et al., 2010c) is developed, using that solution repeatedly could be preferred unless the task conditions change or unpredictable perturbations arise. We also observed that the task space variability increased concurrently during training for the assisted groups that had the flexibility to use redundant solutions, and the higher task space variability was retained in the post-test. A reason could be that since the groups went faster their variability increased due to the speed-accuracy tradeoff (Accot and Zhai, 1997; Fitts, 1954) and due to the effects of signal dependent noise (Harris and Wolpert, 1998).

When the assistance was enabled to control variabilities systematically, there were significant performance differences. Importantly, assistance that constrained the use of redundant solutions was detrimental to performance and the learners had to adapt to such constraints before they could increase their performance. Here, by restricting the usage of redundant solutions we reduced the magnitude of null space variability available for the motor system. Under a natural learning setting, the null space variability is generally exploited by the motor system to minimize task space variability (Latash, 2012; Scholz and Schöner, 1999), and disrupting such a mechanism could have hindered motor learning. Besides, learners who were allowed to freely use null space variability performed significantly better than the learners whose null space variability was restricted. The unrestricted learners used null space variability magnitudes similar to the learners who trained under no assistance indicating that the assistance did not interfere with the natural organization of variability. Although we show that practicing with constrained null space variability is detrimental to motor performance, it is unclear if there is an optimum amount of null space variability that should be enabled or if complete autonomy in organizing variability should be enabled to facilitate the best motor performance.

Even in the immediate retention test, the assisted groups that were constrained in the use of redundant solutions performed worse in comparison to the assisted groups that had flexibility in using redundant solutions. Since the constrained group had lower performance in training, the low performance was mostly carried forward into the immediate retention test. This was predicted from the point of view of the ‘guidance hypothesis (Salmoni et al., 1984; Schmidt, 1991) because the constrained groups relied on the assistance greater than the flexible groups in training. Besides, the abrupt increase in null space variability for the constrained groups in the short-term retention test seemed to indicate that the task conditions in the retention test could be largely different and novel in comparison to the task conditions in training. A large difference in task dynamics between the constrained task condition and the unassisted task conditions can also lead to such learning decrements (Powell and O’Malley, 2012). Thus, even when the assistance is enabled at the redundant effectors it should be designed in such a way that the inherent task dynamics is preserved to a maximum extent (Powell and O'Malley, 2012).

Recommendation 1*: We note here that the retention test was administered immediately after the last block in training with assistance, and any effects of training observed in the retention test might be short-lived and a result of the washout effect of adaptation (Huang and Krakauer, 2009). Thus, delayed retention might be more suitable to confirm the learning effects and extend the implications of assistance for real-life tasks.*

6.1.2 Integration of haptic and visual feedback

From a feedback point of view, we observe fundamental differences between the restricted and the unrestricted assistance conditions. The unrestricted assistance conditions received haptic feedback only when the cursor deviated from the track, and importantly the force channel was visible to the learners. However, for the constrained assistance condition, the learners received haptic feedback even when the cursor did not deviate from the track, and the force channels nor the hands were shown visually. Thus, the agreement between the haptic and visual feedback in the flexible assistance condition could have led to the optimal integration of cues and enhanced learning of the shape of the trajectory (Ernst and Banks, 2002; Helbig and Ernst, 2007). On the other hand, the disagreement between the haptic and visual feedback for the constrained groups could have disrupted the integration of feedback. Therefore, we propose that the haptic assistance should be designed in such a way that the visual information goes hand-in-hand with the haptic information wherever possible.

6.2 Manipulating haptic assistance with learning

6.2.1 Assistance enhances performance

Even though assistance was manipulated using different strategies, the task performance when with assistance was significantly higher than the performance without assistance. This result was expected because the assistance is by definition supposed to help learners complete the task successfully. This is especially useful in a rehabilitation setting where practicing without assistance raises safety concerns to the impaired, for example, the rehabilitation of lower limbs without assistance could present the risk of imbalance and falls (Emken et al., 2007). Moreover, practicing under low motor errors and higher task performance motivates the learners to practice continually and dedicate efforts towards acquiring motor skills (Duarte and Reinkensmeyer, 2015; Marchal-Crespo and Reinkensmeyer, 2009; Sanger, 2004). However, higher task performance with assistance does not necessarily guarantee the same levels of performance when demanded in the absence of assistance (Heuer and Lüttgen, 2015).

6.2.2 Fading assistance with learning

In the framework of the guidance hypothesis (Salmoni et al., 1984; Schmidt and Bjork, 1992) and the assist-as-needed recommendations (Cai et al., 2006), reducing the amount of assistance with learning can benefit the retention of trained motor skills. Firstly, we adopted a bandwidth assistance strategy to provide assistance only when the deviations were unsatisfactorily large to reduce the amount of feedback within a movement trial. Secondly, in experiments 2 and 3, we ensured the reduction of assistance levels with practice using open-loop (Lee and Choi, 2010) and closed-loop strategies (Crespo and Reinkensmeyer, 2008; Kahn et al., 2004) respectively. The simple open-loop strategy did not provide significant learning benefits in comparison to fixed guidance, and there were significant drops in performance for both conditions when assistance was removed in the retention test. This observation indicated that there was probably not enough duration of training enabled at the lower assistance levels. Moreover, assistance might only be required in the early stages of learning and can be reduced faster in a non-linear fashion (Powell and O'Malley, 2012).

Recommendation 2: *An open-loop strategy that reduces assistance at faster rates early in training in a non-linear fashion might be more suitable and should be tested in the future. The training duration could also be increased with more training at each assistance level to observe the stabilization of performance by the end of the training phase.*

The challenge point theory (Guadagnoli and Lee, 2004) adds to the argument of the guidance hypothesis from the point of view of challenging the learners optimally even while assisting them. Accordingly, in experiment 3, we reduced the assistance level whenever the learners improved their performance and vice versa. In addition to challenging the learners continually, the nature of reduction is typically faster in the early stages of learning as observed in our experiment and previous studies (Crespo and Reinkensmeyer, 2008; Huegel and O'Malley, 2010). Thus, closed-loop strategies simultaneously adhere to the recommendations of the challenge point theory and the guidance hypothesis. We observed a subtle advantage for the closed-loop strategy over the simple open-loop strategy in terms of learning to control motor errors. Moreover, the abrupt drop in performance upon removal of assistance was completely absent with the closed-loop strategy.

Recommendation 3: *A more meaningful comparison between closed-loop and open-loop strategies would require training at similar assistance levels for both conditions. To that end, given the assistance levels from the closed-loop condition, an open-loop strategy with assistance levels yoked from the closed-loop group of learners could be tested in the future.*

6.2.3 Modelling learning dynamics with haptic assistance

Previous studies have mostly inferred the effects of assistance in a black-box fashion, where performance before training (baseline) and performance after training (retention) are analyzed. However, with the use of more complex assistance manipulation strategies, it could be important to look at the effects of such manipulations on the learner motor behavior. Thus, we studied the effect of each instance of change in assistance on the subsequent change in the learner performance for the duration of application of assistance. We proposed a simple method to conduct such analysis by classifying the assistance responses into the four quadrants formed by setting changes in assistance level on the abscissa and the changes in performance on the ordinate. The plots of these assistance responses with the progression of training and their proportions revealed the different learning dynamics exhibited by the different learners and how the closed-loop manipulation aided in the process of learning. Going further, we particularly focused on the 'learning' response which promoted learning, which was an observation of improvements in performance even when assistance was reduced. We observed a significant positive correlation between the number of such responses observed in training and the learner's performance in the retention test. We believe that this method can be used to compare the assistance effects under different manipulation strategies.

Recommendation 4: *We were not able to make comparisons between the open-loop and closed-loop strategies with the above model because the assistance was not manipulated in the same intervals for the two strategies. Moreover, further research would be needed to refine and develop new methods to evaluate the assistance manipulation strategies by utilizing the wealth of information available from the learning process.*

6.3 Summary of results

In summary, we have reported the following key results in this dissertation.

1) Functional task difficulty does not influence the exploitation of motor variability. The functional task difficulty influenced task performance and task space variability but did not have any differential effects on null space variability. Moreover, irrespective of the changes in performance with learning, there was a monotonous reduction of null space variability.
2) Constraining the use of redundant solutions undermined task performance and learning. Constraining redundant solutions meant that the null space variability was also minimized which could have disrupted the early stages of learning. Moreover, the differing feedback from the haptic and visual modes might have prevented the optimal integration of multimodal feedback.
3) Closed-loop performance adaptive manipulation of assistance presented significant learning advantages over open-loop linear fading manipulation. The adaptive manipulation prevents abrupt degradation of task performance going from training to retention tests and was helpful for initially differently skilled learners. The proposed learning response metric derived by analyzing the effects of manipulation of assistance on task performance correlated positively with task performance in retention.

APPENDICES

APPENDIX A – IRB APPROVAL LETTER

MICHIGAN STATE
UNIVERSITY

Modification APPROVAL
Pre-2018 Common Rule

January 23, 2020

To: Rajiv Ranganathan

Re: **MSU Study ID:** LEGACY14-933
IRB: Biomedical and Health Institutional Review Board
Principal Investigator: Rajiv Ranganathan
Category: Expedited 4, 7
Submission: Modification MOD00002488
Submission Approval Date: 1/23/2020
Effective Date: 1/23/2020
Study Expiration Date: 8/4/2020

Title: Assessing Arm Motor Function using a Bimanual Robot

This submission has been approved by the Michigan State University (MSU) Biomedical and Health Institutional Review Board . The submission was reviewed by the Institutional Review Board (IRB) through the Non-Committee Review procedure. The IRB has found that this study protects the rights and welfare of human subjects and meets the requirements of MSU's Federal Wide Assurance (FWA00004556) and the federal regulations for the protection of human subjects in research (e.g., pre-2018 45 CFR 46, 28 CFR 46, 21 CFR 50, 56, other applicable regulations).

Office of Regulatory Affairs
Human Research Protection Program

4000 Collins Road
Suite 136
Lansing, MI 48910

517-355-2180
Fax: 517-432-4503
Email: irb@msu.edu
www.hrpp.msu.edu

Approved modification for a change in Personnel: Addition of new research assistants and deletion of old research assistants

How to Access Final Documents
To access the study's final materials, including those approved by the IRB such as consent forms, recruitment materials, and the approved protocol, if applicable, please log into the Click™ Research Compliance System, open the study's workspace, and view the "Documents" tab. To obtain consent form(s) stamped with the IRB watermark, select the "Final" PDF version of your consent form(s) as applicable in the "Documents" tab. Please note that the consent form(s) stamped with the IRB watermark must typically be used.

Continuing Review: IRB approval is valid until the expiration date listed above. If the research continues to involve human subjects, you must submit a Continuing Review request at least one month before expiration.

Modifications: Any proposed change or modification with certain limited exceptions discussed below must be reviewed and approved by the IRB prior to implementation of the change. Please submit a Modification request to have the changes reviewed. If changes are made at the time of continuing review, please submit a Modification and Continuing Review request.

New Funding: If new external funding is obtained to support this study, a Modification request must be submitted for IRB review and approval before new funds can be spent on human research activities, as the new funding source may have additional or different requirements.

Immediate Change to Eliminate a Hazard: When an immediate change in a research protocol is necessary to eliminate a hazard to subjects, the proposed change need not be reviewed by the IRB prior to its implementation. In such situations, however, investigators must report the change in protocol to the IRB immediately thereafter.

Reportable Events: Certain events require reporting to the IRB. These include:

- Potential unanticipated problems that may involve risks to subjects or others
- Potential noncompliance
- Subject complaints
- Protocol deviations or violations
- Unapproved change in protocol to eliminate a hazard to subjects
- Premature suspension or termination of research
- Audit or inspection by a federal or state agency
- New potential conflict of interest of a study team member
- Written reports of study monitors
- Emergency use of investigational drugs or devices
- Any activities or circumstances that affect the rights and welfare of research subjects
- Any information that could increase the risk to subjects

Please report new information through the study's workspace and contact the IRB office with any urgent events. Please visit the Human Research Protection Program (HRPP) website to obtain more information, including reporting timelines.

Personnel Changes: Key study personnel must be listed on the MSU IRB application for expedited and full board studies and any changes to key study personnel must to be submitted as modifications. Although only key study personnel need to be listed on a non-exempt application, all other individuals engaged in human subject research activities must receive and maintain current human subject training, must disclose conflict of interest, and are subject to MSU HRPP requirements. It is the responsibility of the Principal Investigator (PI) to maintain oversight over all study personnel and to assure and to maintain appropriate tracking that these requirements are met (e.g. documentation of training completion, conflict of interest). When non-MSU personnel are engaged in human research, there are additional requirements. See HRPP Manual Section 4-10, Designation as Key Project Personnel on Non-Exempt IRB Projects for more information.

Prisoner Research: If a human subject involved in ongoing research becomes a prisoner during the course of the study and the relevant research proposal was not reviewed and approved by the IRB in accordance with the requirements for research involving prisoners under subpart C of 45 CFR part 46, the investigator must promptly notify the IRB.

Site Visits: The MSU HRPP Compliance office conducts post approval site visits for certain IRB approved studies. If the study is selected for a site visit, you will be contacted by the HRPP Compliance office to schedule the site visit.

For Studies that Involve Consent, Parental Permission, or Assent Form(s):

Use of IRB Approved Form: Investigators must use the form(s) approved by the IRB and must typically use the form with the IRB watermark.

Copy Provided to Subjects: A copy of the form(s) must be provided to the individual signing the form. In some instances, that individual must be provided with a copy of the signed form (e.g. studies following ICH-GCP E6 requirements). Assent forms should be provided as required by the IRB.

Record Retention: All records relating to the research must be appropriately managed and retained. This includes records under the investigator's control, such as the informed consent document. Investigators must retain copies of signed forms or oral consent records (e.g., logs). Investigators must retain all pages of the form, not just the signature page. Investigators may not attempt to de-identify the form; it must be retained with all original information. The PI must maintain these records for a minimum of three years after the IRB has closed the research and a longer retention period may be required by law, contract, funding agency, university requirement or other requirements for certain studies, such as those that are sponsored or FDA regulated research. See HRPP Manual Section 4-7-A, Recordkeeping for Investigators, for more information.

Closure: If the research activities no longer involve human subjects, please submit a Continuing Review request, through which study closure may be requested. Human subject research activities are complete if there is no further interactions or interventions with human subjects and/or no further analysis of identifiable private information.

For More Information: See the HRPP Manual (available at hrpp.msu.edu).

Contact Information: If we can be of further assistance or if you have questions, please contact us at 517-355-2180 or via email at IRB@msu.edu. Please visit hrpp.msu.edu to access the HRPP Manual, templates, etc.

Expedited Category. Please see the appropriate research category below for the full regulatory text.

Expedited 1. Clinical studies of drugs and medical devices only when condition (a) or (b) is met.

(a) Research on drugs for which an investigational new drug application (21 CFR Part 312) is not required. (Note: Research on marketed drugs that significantly increases the risks or decreases the acceptability of the risks associated with the use of the product is not eligible for expedited review.)
(b) Research on medical devices for which (i) an investigational device exemption application (21 CFR Part 812) is not required; or (ii) the medical device is cleared/approved for marketing and the medical device is being used in accordance with its cleared/approved labeling.

Expedited 2. Collection of blood samples by finger stick, heel stick, ear stick, or venipuncture as follows:
(a) from healthy, nonpregnant adults who weigh at least 110 pounds. For these subjects, the amounts drawn may not exceed 550 ml in an 8 week period and collection may not occur more frequently than 2 times per week; or
(b) from other adults and children, considering the age, weight, and health of the subjects, the collection procedure, the amount of blood to be collected, and the frequency with which it will be collected. For these subjects, the amount drawn may not exceed the lesser of 50 ml or 3 ml per kg in an 8 week period and collection may not occur more frequently than 2 times per week.

Expedited 3. Prospective collection of biological specimens for research purposes by noninvasive means.
Examples: (a) hair and nail clippings in a nondisfiguring manner; (b) deciduous teeth at time of exfoliation or if routine patient care indicates a need for extraction; (c) permanent teeth if routine patient care indicates a need for extraction; (d) excreta and external secretions (including sweat); (e) uncannulated saliva collected either in an unstimulated fashion or stimulated by chewing gumbase or wax or by applying a dilute citric solution to the tongue; (f) placenta removed at delivery; (g) amniotic fluid obtained at the time of rupture of the membrane prior to or during labor; (h) supra- and subgingival dental plaque and calculus, provided the collection procedure is not more invasive than routine prophylactic scaling of the teeth and the process is accomplished in accordance with accepted prophylactic techniques; (i) mucosal and skin cells collected by buccal scraping or swab, skin swab, or mouth washings; (j) sputum collected after saline mist nebulization.

Expedited 4. Collection of data through noninvasive procedures (not involving general anesthesia or sedation) routinely employed in clinical practice, excluding procedures involving x-rays or microwaves. Where medical devices are employed, they must be cleared/approved for marketing. (Studies intended to evaluate the safety and effectiveness of the medical device are not generally eligible for expedited review, including studies of cleared medical devices for new indications.)
Examples: (a) physical sensors that are applied either to the surface of the body or at a distance and do not involve input of significant amounts of energy into the subject or an invasion of the subject’s privacy; (b) weighing or testing sensory acuity; (c) magnetic resonance imaging; (d) electrocardiography, electroencephalography, thermography, detection of naturally occurring radioactivity, electroretinography, ultrasound, diagnostic infrared imaging, doppler blood flow, and echocardiography; (e) moderate exercise, muscular strength

testing, body composition assessment, and flexibility testing where appropriate given the age, weight, and health of the individual.

Expedited 5. Research involving materials (data, documents, records, or specimens) that have been collected, or will be collected solely for nonresearch purposes (such as medical treatment or diagnosis). (NOTE: Some research in this category may be exempt from the HHS regulations for the protection of human subjects. 45 CFR 46.101(b)(4). This listing refers only to research that is not exempt.)

Expedited 6. Collection of data from voice, video, digital, or image recordings made for research purposes.

Expedited 7. Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies. (NOTE: Some research in this category may be exempt from the HHS regulations for the protection of human subjects. 45 CFR 46.101(b)(2) and (b)(3). This listing refers only to research that is not exempt.)

Expedited 8. Continuing review of research previously approved by the convened IRB as follows:
(a) where (i) the research is permanently closed to the enrollment of new subjects; (ii) all subjects have completed all research-related interventions; and (iii) the research remains active only for long-term follow-up of subjects; or
(b) where no subjects have been enrolled and no additional risks have been identified; or
(c) where the remaining research activities are limited to data analysis.

Expedited 9. Continuing review of research, not conducted under an investigational new drug application or investigational device exemption where categories two (2) through eight (8) do not apply but the IRB has determined and documented at a convened meeting that the research involves no greater than minimal risk and no additional risks have been identified.

APPENDIX B – IRB CONSENT FORMS FOR ALL EXPERIMENTS

Research Participant Information and Consent Form

You are being asked to participate in a research study. Researchers are required to provide a consent form to inform you about the research study, to convey that participation is voluntary, to explain risks and benefits of participation, and to empower you to make an informed decision. You should feel free to ask the researchers any questions you may have.

Study Title: Assessing Arm Motor Function using a Bimanual Robot
Researcher and Title: Rajiv Ranganathan, PhD
Department and Institution: Kinesiology, MSU
Address and Contact Information: 308 W Circle Dr Rm 203
Sponsor:

1. PURPOSE OF RESEARCH

- You are being asked to participate in a research study of how participants adapt arm movements to changes in mechanical and visual environments.
- You have been selected as a possible participant in this study because you are a healthy adult participant (between the ages of 18 and 80) with no history of neurological or orthopedic impairment that affects your ability to move
- From this study, the researchers hope to learn more about the process of motor learning and how to design interfaces such as prosthetic devices
- Your participation in this study will take about 90 minutes/visit. You may be asked to come to the lab for multiple visits (up to a maximum of 15 visits).
- In the entire study, 500 people are being asked to participate.

2. WHAT YOU WILL DO

- You will be asked to fill out a questionnaire about your demographic details, and prior experience with physical activity

- You may be asked to fill out a questionnaire to determine your handedness

- You will be seated comfortably in front of a robot and a computer screen. In some cases, a Velcro strap will be used to secure you to the chair (like a seatbelt) in order to minimize trunk motion.

- Depending on the experimental condition, you will be asked to either hold one (unimanual) or both of the robot's handles (bimanual). The position of the handles will be displayed on the screen.

- You will then be asked to perform various tasks that require movement of one or both handles. These tasks are typically reaching tasks (i.e. moving the cursor to a target), striking tasks (i.e. virtually hitting a target) or tracking tasks (following a target on a screen). These will be similar to playing simple video games.

- During the experiment, the robot may sometimes apply mechanical loads on your arms (e.g. either assisting or resisting your movement, or moving your arm to a given position). In addition, visual feedback may also be altered to examine how well you can perform the task. These changes may be introduced without your knowledge – in any case, just try to complete the task specified by the experimenter.

3. POTENTIAL BENEFITS

- You will not directly benefit from your participation in this study. However, your participation in this study may contribute to the understanding of humans learn motor skills. This may be useful in developing movement rehabilitation paradigms (for conditions such as stroke) and designing prosthetic devices.

4. POTENTIAL RISKS

- You might experience some mild fatigue/muscle soreness. You can take short breaks during the experiment in between trials to minimize this fatigue.
- There is also potential for injury due to the robot. However, this is unlikely as the robot has several features designed to minimize risk of injury. If at any point during the experiment, you feel uncomfortable with the force exerted by the robot, just let go of the robot handles and the brakes will engage. Alternatively, you can let the experimenter know and he/she will disable the robot using an emergency stop button. The reach of the robot is also designed so that when you are in a normal seated position, it cannot come into contact with your body other than your arms. The robot also is programmed only for a peak force of 60 N (equivalent to the force exerted by a 13lb weight)

5. PRIVACY AND CONFIDENTIALITY

- All information collected in the study is strictly confidential, and your name will not be identified at any time. Your data will be grouped with data that others provide for reporting and presentation. Consent forms will be stored in a locked file cabinet and on a password protected computer. Only the principal investigator, his collaborators, as well as the MSU Human Research Protection Program (HRPP) will have access to the project data. Your confidentiality will be protected to the maximum extent allowable by law. The consent form, your participant code, or videos made will be retained securely for at least three years after the close of the study. The results of this study may be published or presented at professional meetings, but the identities of all research participants will remain anonymous (unless you explicitly give us permission to use these videos/images).

- Open Data: The data and samples from this study might be used for other, future research projects in addition to the study you are currently participating in. Those future projects can focus on any topic that might be unrelated to the goals of this study. We will give access to the data we are collecting to the general public via the Internet and a fully open database.
  The data we share with the general public will not have your name on it, only a code number, so people will not know your name or which data are yours. In addition, we will not share any other information that we think might help people who know you guess which data are yours.
  If you change your mind and withdraw your consent to participate in this study you can contact the Principal Investigator, Rajiv Ranganathan (rrangana@msu.edu), we will not collect any additional data about you. We will delete your data if you withdraw before it was deposited in the database. **However, any data and research results already shared with other investigators or the general public cannot be destroyed, withdrawn or recalled.**

6. YOUR RIGHTS TO PARTICIPATE, SAY NO, OR WITHDRAW

- Participation is voluntary. Refusal to participate will involve no penalty or loss of benefits to which you are otherwise entitled. You may discontinue participation at any time without penalty or loss of benefits to which you are otherwise entitled.

7. COSTS AND COMPENSATION FOR BEING IN THE STUDY

- You will not receive any money for your participation in the study. If you are a Kinesiology student enrolled in KIN 251, KIN360, KIN330 or KIN365, you may be eligible to earn extra credit for participation (1% of the total grade for the course for each visit, up to a maximum of 3%). This will depend on the class policy specified in the instructor's syllabus. However, if extra credit is offered but you do not wish to participate in this research, other ways to earn extra credit for these classes will be provided by the instructor.

8. THE RIGHT TO GET HELP IF INJURED

- If you are injured as a result of your participation in this research project, Michigan State University will assist you in obtaining emergency care, if necessary, for your research related injuries. If you have insurance for medical care, your insurance carrier will be billed in the ordinary manner. As with any medical insurance, any costs that are not covered or in excess of what are paid by your insurance, including deductibles, will be your responsibility. The University's policy is not to provide financial compensation for lost wages, disability, pain or discomfort, unless required by law to do so. This does not mean that you are giving up any legal rights you may have. You may contact Rajiv Ranganathan at 517-353-6491 with any questions or to report an injury.

9. CONTACT INFORMATION

- If you have concerns or questions about this study, such as scientific issues, how to do any part of it, or to report an injury, please contact the researcher (Rajiv Ranganathan, 308 W Circle Dr. Rm 203, East Lansing MI 48824, rrangana@msu.edu, 517-353-6491).

- If you have questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this study, you may contact, anonymously if you wish, the Michigan State University's Human Research Protection Program at 517-355-2180, Fax 517-432-4503, or e-mail irb@msu.edu or regular mail at 4000 Collins Rd., Suite 136, Lansing, MI 48910.

10. DOCUMENTATION OF INFORMED CONSENT

Your signature below means that you voluntarily agree to participate in this research study.

_______________________________________ _____________________________

Signature Date

You will be given a copy of this form to keep.

I agree to allow to be videotaped and/or photographed while performing the experiment.

☐ Yes ☐ No Initials____________

I agree to allow the video and/or photos to be used later in publications or presentations.

☐ Yes ☐ No Initials____________

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