

The Pennsylvania State University
The Graduate School
College of Health and Human Development

UTILIZING REDUNDANCY IN MOTOR LEARNING

A Dissertation in

Kinesiology

by

Rajiv Ranganathan

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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

December 2009

The dissertation of Rajiv Ranganathan was reviewed and approved* by the following:

Karl M. Newell
Professor of Kinesiology
Head of the Department of Kinesiology
Dissertation Adviser
Chair of Committee

Mark L. Latash
Distinguished Professor of Kinesiology

Dagmar Sternad
Professor of Kinesiology

Joseph P. Cusumano
Professor of Engineering Science and Mechanics

*Signatures are on file in the Graduate School

ABSTRACT

The issue of redundancy (Bernstein, 1967) is one of the central issues in motor control. In almost every motor task, there are infinite solutions to accomplish the task goal. We addressed the questions of how learning influences the utilization of redundancy and whether practice schedules that facilitate the use of redundant solutions enhance learning. We used a virtual interception task and examined the redundancy at the level of the movement path of the end effector.

In Experiment 1, we found that there was evidence for utilizing path redundancy even after extensive learning. Spatial variability in the middle of the path was greater than the variability near the target. With learning, there was a decrease in path variability throughout the movement path, but with extended learning there was a selective decrease in path variability only near the target. The structure of the movement variability also indicated that different paths were being used to hit the target.

In Experiment 2, we addressed the question of whether the ability to flexibly use redundant solutions was influenced by the degree to which redundancy was utilized during practice. Contrary to expectations, we found that the group with lowest utilization of redundancy during practice was better able to utilize multiple paths to hit the target, indicating that flexibility may be emergent from learning the target location. Additionally, these results also highlight the importance of the task context in drawing inferences based on analysis of movement variability.

In Experiment 3, we examined the influence of introducing variability at the task goal level and the execution redundancy level on retention and generalization. Variability at the task goal level was induced by changing the target location whereas variability at the execution redundancy level was induced by requiring participants to use different movement paths to achieve the same target location. The results showed that introducing variability at the task goal level led to better performance when the target was in different locations. However, the manipulation of movement variability at the execution redundancy level did not show any positive effects on retention or generalization.

Overall, the results support the view that skilled performance does not involve consistent repetition of a single movement pattern; instead, multiple solutions are always used to achieve the task goal. However, an important caveat is that the ability to utilize redundant solutions may be an emergent feature of learning a particular task-relevant parameter. As a result, practice schedules that explicitly constrain the participant to use different ways to achieve the task goal may not necessarily facilitate learning.

TABLE OF CONTENTS

LIST OF FIGURES.....	vii
LIST OF TABLES.....	viii
ACKNOWLEDGMENTS.....	ix
CHAPTER 1 INTRODUCTION.....	1
The Issue of Redundancy.....	1
Views on Redundancy.....	1
Focus of Dissertation.....	4
CHAPTER 2 LITERATURE REVIEW.....	6
Part 1: Variability in Motor Control.....	6
Variability as noise.....	7
Variability as functional.....	9
Structure of variability.....	11
Part 2: Movement Variability in Learning.....	13
Learning as the process of finding a unique solution.....	14
Learning as task-relevant optimization.....	16
Part 3: Introducing Variability in Practice.....	20
Creating interference.....	21
Facilitating generalization.....	22
Introducing variability at different levels of the task.....	25
CHAPTER 3 INFLUENCE OF MOTOR LEARNING ON UTILIZING PATH REDUNDANCY	28
Introduction.....	29
Methods.....	33
Participants.....	33
Equipment.....	33
Task.....	34
Procedures.....	36
Data Analysis.....	36
Performance.....	36
Spatial variability of the path.....	37
Correlation.....	37
Trial-dependent structure.....	38
Statistical Analysis.....	39
Results.....	40
Inclusion criteria.....	40
Performance.....	40
Spatial variability.....	43
Correlations.....	43
Trial-dependent structure.....	45

	Discussion.....	46
	Amount of variability.....	46
	Structure of variability.....	47
	Trial-dependence of paths.....	48
	Minimizing motor variability and exploring redundant solutions.....	49
CHAPTER 4	EMERGENT FLEXIBILITY IN MOTOR LEARNING.....	52
	Introduction.....	53
	Methods.....	56
	Participants.....	56
	Equipment.....	56
	Task.....	56
	Procedures.....	59
	Data Analysis.....	59
	Performance.....	59
	Spatial variability of the path.....	60
	Results.....	60
	Inclusion criteria.....	60
	Performance.....	61
	Spatial variability.....	64
	Discussion.....	68
	Enhancing flexibility.....	68
	Synergies and task context.....	70
CHAPTER 5	MOTOR LEARNING THROUGH INDUCED VARIABILITY AT THE TASK GOAL AND EXECUTION REDUNDANCY LEVELS.....	73
	Introduction.....	74
	Methods.....	77
	Participants.....	77
	Equipment.....	78
	Task.....	78
	Procedures.....	81
	Data Analysis.....	82
	Performance.....	82
	Spatial variability of the path.....	82
	Correlation.....	83
	Statistical Analysis.....	83
	Results.....	84
	Performance.....	84
	Spatial variability.....	86
	Correlation between target position and error.....	87
	Reach extent.....	89
	Correlations.....	89
	Discussion.....	92
	Variability of practice.....	92

	Manipulating path redundancy.....	93
	Generalization and the equilibrium-point hypothesis.....	95
	Redundancy and practice schedules.....	96
CHAPTER 6	GENERAL DISCUSSION.....	98
	Theme 1: Changes in Movement Variability and Redundancy with Learning.....	98
	Amount of variability.....	98
	Structure of variability.....	101
	Implications for models of motor learning.....	101
	Theme 2: Emergent Flexibility and Synergies.....	103
	Flexibility as an emergent phenomenon.....	103
	Synergies and task context.....	104
	Theme 3: Implications for Practice Schedules.....	106
	Limitations.....	108
	Conclusions.....	110
REFERENCES.....		111

LIST OF FIGURES

Figure 3.1	Schematic of the experimental setup.....	35
Figure 3.2	Schematic of the task.....	35
Figure 3.3	Computation of spatial variability and correlation between points on the movement path.....	39
Figure 3.4	Exemplar trials from a participant in (A) Block 1 of initial practice, (B) Block 8 of initial practice, and (C) Block 16 of extended practice.....	41
Figure 3.5	Performance in the initial and extended practice (A) Percentage of trials that were hits, (B) Absolute error measured from the edge of the target.....	42
Figure 3.6	Maximum spatial variability in the movement path and the spatial variability at the target in initial practice and extended practice.....	42
Figure 3.7	(A) Spatial variability at different percentages along the path during initial and extended practice. (B) Correlations between points at adjacent locations on the trajectories.....	44
Figure 4.1	Schematic of the experimental setup.....	58
Figure 4.2	Schematic of the task.....	58
Figure 4.3	Exemplar movement paths from a typical subject in the last block of practice in the: (A) Low-variability group, (B) Medium-variability group and (C) High-variability group.....	62
Figure 4.4	Percentage of hits in the pre-test, practice and during the retention and flexibility tests for the three groups.....	62
Figure 4.5	Absolute error during practice for the three groups.....	63
Figure 4.6	Absolute error on the retention and flexibility tests for the three groups....	63
Figure 4.7	Spatial variability during the first block and the last block of practice for the: (A) Low-variability, (B) Medium-variability and (C) High-variability groups.....	64
Figure 4.8	Spatial variability across the path during: (A) Immediate retention (B) 24-hr retention, (C) Immediate flexibility and (D) 24-hr flexibility tests.....	67
Figure 5.1	Schematic of the experimental setup.....	79
Figure 5.2	Exemplar trials from one subject in each of the four groups during the last block of practice.....	80
Figure 5.3	Absolute error during practice for all four groups.....	85
Figure 5.4	Absolute error of the four groups on: retention, and (B) generalization tests.....	85
Figure 5.5	Spatial variability of four groups during: (A) last block of practice, (B) Immediate retention test, (C) 24-hr retention test, (D) Immediate generalization test and (E) 24-hr generalization test.....	88
Figure 5.6	Slope of target position versus CE and (B) reach extent of the four groups in the immediate and 24-hr generalization tests.....	89
Figure 5.7	Pairwise correlations between adjacent spatial locations during: (A) last block of practice, (B) Immediate retention test, (C) 24-hr retention test, (D) Immediate generalization test and (E) 24-hr generalization test.....	90
Figure 5.8	Exemplar trials of two subjects in the immediate generalization test in: (A) Variable group and (B) Low-redundancy group.	91

LIST OF TABLES

Table 3.1	Average RMSE (in mm) for the actual and surrogate data sets during the last day of extended practice.....	45
Table 5.1	Summary of group comparisons of spatial variability at different locations on the movement path on the last block of practice, the retention tests and the generalization tests.....	86
Table 5.2	Summary of group comparisons of pairwise correlations at different locations on the movement path on the last block of practice, the retention tests and the generalization tests.....	91

ACKNOWLEDGMENTS

First, I would like to express my gratitude to my mentor, Dr. Karl Newell, for his guidance over the last 4 years. Karl has been both a tremendous source of inspiration and a constant driving force behind this effort and I consider it a great privilege to have had the opportunity to work with him. I also thank the members of my committee, Drs. Mark Latash, Dagmar Sternad, and Joseph Cusumano for their valuable comments and feedback. My interactions with them over the last few years have opened me up to different points of view and have been a significant influence in my academic development.

I would like to thank Tim Benner for his assistance with the software programming, without which this dissertation would have never been possible. I am also grateful to Mei-Hua Lee, Eric James, Adam King, Xiaogang Hu and all the members of the Motor Behavior Lab. I deeply value their friendship and will fondly remember the wonderful discussions on various topics ranging from the truly scientific to the absolutely bizarre. The fact that they have listened to me rant and ramble on many of those occasions is a testament to their patience!

A special thanks to Drs. Les and Mary Carlton, who started me off on this long journey and continue to be a source of knowledge and wisdom. Last, but not least, I am forever indebted to my parents and my brother. They have shielded me from the real world for what seems like an eternity, and their never-ending support has been the one constant factor on which I have always relied on in times of need. I dedicate this dissertation to them.

CHAPTER 1. INTRODUCTION

The Issue of Redundancy

Consider the seemingly simple motor task of tossing a piece of paper into the trash can. Though we are hardly aware of it, there are actually infinite ways of achieving the goal even in this mundane task. For example, there are many release velocity-angle combinations that will result in the piece of paper landing inside the trash can. Even if we select one particular release velocity-angle combination, the same problem exists at other levels – different hand trajectories, joint motions and muscle activations can be used to generate the same release velocity-angle combination. This issue in motor control is known as the degrees of freedom problem or the problem of redundancy (Bernstein, 1967; Greene, 1972; Turvey, Shaw, & Mace, 1978).

In other words, we encounter a many-to-one problem of having more than one solution for performing a motor task to achieve a specified goal. This is similar to the mathematical problem of solving a system of equations where there are fewer equations than unknowns. For example, at the kinematic level of the arm-hand effector unit, we have three joints that allow us to use a variety of shoulder, elbow, and wrist angle combinations to get the hand to a particular location. A fundamental question that naturally follows is – if there are infinite ways to perform a particular motor task, how are we able to learn and retain motor skills?

Views on Redundancy

Approaches in motor control have focused on two complementary aspects of the redundancy issue – the problem of control and the potential advantage of flexibility. From the control perspective, redundancy has been viewed as a problem to be eliminated

because a greater number of degrees of freedom implies that there is possibly a need for greater executive control from the central nervous system (although see Greene, 1982; Latash, 1996). Approaches that have been used to mitigate the redundancy problem fall into three broad categories (Rosenbaum, Meulenbroek, & Vaughan, 1996). First, the degree of redundancy can be reduced by potentially “freezing” certain degrees of freedom (Bernstein, 1967). For example, if the wrist angle is fixed at a particular value, then only the shoulder and elbow angle determine the position of the hand, which results in a reduction in the number of solutions possible. A second approach is to link degrees of freedom through equations of constraint (also see coordinative structures, Turvey, 1977) so that even though there are many degrees of freedom, the controller does not have to control all of them independently. Finally, there may also be constraints such as the minimization of cost functions that may provide additional constraints on reducing the number of choices available. Under such circumstances, there may be a single movement pattern that is optimal with respect to the criterion (for e.g., a movement that results in minimum energy expenditure).

In spite of the possible problems posed by redundancy in terms of control, the advantage of a redundant system is that it provides flexibility in achieving the task goal and may be critical for a functioning in an unpredictable environment (Edelman & Gally, 2001; Gelfand & Latash, 1998; Greene, 1982). If a solution is suddenly incapable of being executed because of a change in internal conditions (e.g., the shoulder is unable to move because of pain) or external conditions (e.g., there is a need to go around an obstacle), the redundancy in the system provides the opportunity to quickly switch to another solution to achieve the task goal. Consistent with this idea, several experiments

have found that experts in a motor task seem to utilize multiple solutions instead of repeating a single movement pattern (Arutyunyan, Gurfinkel, & Mirskii, 1969; Bootsma & van Wieringen, 1990). Given that there is always variability at multiple levels both in the organism as well as the environment, the ability to utilize different ways of performing the task goal may be critical to an organism's functional capacity.

Inferences about the utilization of redundancy are directly related to the analysis of movement variability. Using multiple solutions to achieve the task goal leads to increased variability in the movement pattern – however this variability is structured in a specific manner so that the task goal is always met. Different approaches have been used to examine the structure of movement variability at different levels (e.g. Scholz & Schöner, 1999; Müller & Sternad, 2004; Cusumano & Cesari, 2006). For example, the uncontrolled manifold (UCM) approach (Schöner, 1995; Scholz & Schöner, 1999) partitions movement variability into two components: (a) goal-equivalent variability (i.e., variability in the redundant dimension that does not affect the task performance), and (b) goal-relevant variability (i.e., variability that leads to changes or errors in task performance).

In view of the advantages and disadvantages of redundancy, one important question that arises is how motor learning influences the utilization of redundancy. As mentioned earlier, one hypothesis is that all movement variability is minimized with learning. This is consistent with finding a unique solution that may be optimal with respect to some criterion. An alternative hypothesis is that instead of minimizing all variability, only variability that leads to task error is minimized. Any movement variability that does not lead to task error (i.e., the variability in the redundant dimension)

need not be minimized. Instead this variability can be used to find flexible ways of achieving the task goal.

A second, but related issue from the perspective of the teacher or coach is whether practice schedules should accommodate the multiple redundant solutions that can be used to achieve the task goal. Even though experts have been shown to utilize redundancy, it is not clear if practice schedules have to incorporate the learning of redundant solutions or whether the use of redundant solutions emerges as a consequence of extensive practice. These issues form the core of the dissertation.

Focus of Dissertation

The problem of redundancy is one of the central issues in motor control (Bernstein, 1967). There is evidence that in many tasks, participants are capable of achieving a task outcome without repeating the same movement pattern, essentially using redundant solutions to solve the same problem. However, the interaction between learning and the utilization of redundancy, and how this relates to practice schedules is not well understood. In the dissertation, we addressed three primary questions: a) how does movement variability (specifically path variability) change with learning with respect to the utilization of redundancy? , (b) can the ability to flexibly use redundant solutions be enhanced through practice? , and (c) how does introducing variability at the task goal level or the execution redundancy level influence learning?

The task used was a virtual interception task where the participants had to move a pen on a graphics board from a start position and hit a stationary target while attempting to avoid an intermediate obstacle. In this task, the analysis of redundancy was at the level of the movement path. The path refers to only the spatial component of the trajectory

(i.e., the temporal component is not included) from the start to the end of the movement. There is redundancy at the level of the spatial path because there are infinitely many paths from the start position to the target.

In Experiment 1, we examined the influence of learning on changes in movement variability and the utilization of path redundancy. The specific aim was to determine whether the changes in path variability were consistent with finding a unique solution or whether there was evidence for the utilization of redundancy after learning. In addition to examining the amount of path variability, we also analyzed the structure of the variability to investigate if learning involved the use of single or multiple solutions.

In Experiment 2, we examined how the ability to flexibly use redundant solutions was influenced by the degree to which redundant solutions were utilized during practice. In particular, we were interested if practicing with low path variability (i.e., utilizing a limited range of solutions to perform the task) resulted in a loss of flexibility in using alternative solutions to achieve the task goal.

In Experiment 3, we investigated the issue of whether introducing variability in the movement path produced any facilitation in retention and generalization. We introduced variability at two levels – the task goal level and the execution redundancy level. Variability at the task goal level was introduced by changing the position of the target whereas variability at the execution redundancy level was introduced by constraining the participants to use different movement paths to hit the same target. Retention was tested by using a single target location and generalization was tested by using multiple target locations.

CHAPTER 2. LITERATURE REVIEW

The review of literature is split into three sections. Part 1 focuses on variability in motor control, with emphasis on how the role of variability has changed from being considered as noise to being a window into the functioning of the nervous system. Part 2 focuses on the changes in movement variability and redundancy with motor learning. Part 3 reviews the use of practice schedules that induce variability to facilitate motor learning.

Part 1: Variability in Motor Control

Variability is a ubiquitous feature of motor behavior. Whenever we perform a task multiple times, there is always variability that is observed at different levels of analysis – in end-point trajectories, joint angles, muscle activation patterns and so on. Despite years of practice performing thousands of trials, even very skilled performers in activities such as sports or music seem unable to eliminate motor variability. Indeed, even so-called “crystallized” behaviors like the adult birdsong (Tumer & Brainard, 2007) or phylogenetic activities such as locomotion are not exempt from variation. Variability also exists at different levels – between individuals (different individuals may perform the same task in different ways), between sessions (performing the task differently on different sessions), between trials (performing the task differently on different trials) and even within trials (performing the task differently during the trial). This review will focus on the trial-to-trial variability that exists within a single individual performing multiple repetitions of a discrete movement.

Variability as noise

Traditionally, variability was not a primary focus of interest in studies of motor control. In the field of neurophysiology, the focus was on patterns of movement governed by reflexes or central pattern generators (Brown, 1915; Sherrington, 1910). In the domain of experimental psychology, behavioral measures such as mean reaction time have been used as a primary index of the time needed to process information. Even in more recent computational approaches that involve optimization (e.g., Flash & Hogan, 1985), models have been used to predict the average behavior of the system (for e.g., end-point trajectory). A primary reason for the lack of focus on variability was the observation that in spite of the flexibility of the motor system, movements both between-trials and between-individuals show remarkable regularity under a large range of conditions. For example in reaching, movements are characterized by straight-line paths, bell-shaped velocity profiles and tri-phasic muscle activations under a large variety of situations. This led to the assumption that the goal of the motor system was to produce a particular unique behavior and any variations observed were a reflection of noise in the system (Newell & Corcos, 1993).

However, even under this assumption of variability as noise, several studies recognized that the nature of variability may in fact play an important role in influencing motor behavior. One of the earliest approaches was Fitts' law (1954), which was derived from information theory to explain the trade-off between speed and accuracy. Fitts proposed that there was a certain amount of noise associated with amplitude and rate of the response in the motor system. Therefore, if the channel capacity was fixed, whenever the amplitude of movements was increased (which led to more noise), there had to be a

reduction in the rate (increased movement time), to maintain the same end-point accuracy, thereby leading to the speed-accuracy tradeoff.

A related perspective that explicitly involved motor variability was the impulse variability theory of the speed-accuracy tradeoff (Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979). Schmidt et al. (1979) suggested that the variability of the force impulse (as measured by the standard deviation) was proportional to the magnitude of the impulse, and therefore bigger impulses (i.e., bigger amplitudes of movement or smaller movement times) resulted in a larger dispersion of end-points. While the linear relation between standard deviation of force and force variability has been challenged (Carlton & Newell, 1993; Newell & Carlton, 1988), the view that signal-dependent noise exists in the motor system (i.e., variability increases with magnitude of the signal) has provided a basis for making predictions about optimal behavior. More recently, Harris and Wolpert (1998) used this signal-dependent noise model to unify several different findings in motor control. They showed that attempting to maximize end-point precision (i.e., minimize end-point variability) in the presence of signal-dependent noise could account for not only the speed-accuracy tradeoff but also other features of motor behavior such as making smooth movements, symmetrical bell-shaped velocity profiles, the two-thirds power law and the trajectory of saccades.

In summary, considering motor variability as noise has provided significant advances in understanding the control of motor actions. Signal-dependent noise, in particular, seems to be an important factor in governing behavior in a number of different contexts. However, recent evidence has challenged the assumption of considering variability as only noise and this is discussed in detail in the following section.

Variability as functional

There are two lines of evidence that argue against considering variability as noise or an unintended consequence of motor actions: (a) the presence of variability is important in signal detection and exploratory behavior, and (b) the time-frequency analyses of variability reveal that there is structure to the variability that is distinguishable from a completely random white noise process.

While noise is generally considered to be detrimental to system performance, it can also be beneficial in certain situations. In stochastic resonance (Benzi, Sutera, & Vulpiani, 1981), adding a sub-threshold level of noise effectively increases the probability that a sub-threshold input signal can be detected. This phenomenon was used to improve the balance of patients with peripheral neuropathy by having them wear shoes with vibrating insoles (Priplata, Niemi, Harry, Lipsitz, & Collins, 2003). In essence, the vibrations in the insoles provided background noise which allowed the patients to better detect information coming from the sole of the foot that was previously below the threshold of detection. Additionally, neuronal noise can also contribute to robustness - artificial neural networks trained in the presence of neuronal noise show more robustness in the face of synaptic degradation when compared with networks trained in the absence of noise (Basalyga & Salinas, 2006).

Variability is also required to constantly explore different solutions and fine-tune performance according to task demands. Tumer and Brainard (2007) found that when they selectively disrupted birdsong by giving white-noise audio feedback depending on whether the frequency of a particular syllable was in a particular range, the birds were able to rapidly shift the frequency of that particular syllable to avoid disruption in their

performance. This trial-and-error learning requires motor variability and the association of variations to differential outcomes. This is similar to the process of natural selection in biological evolution, where variations in motor behavior that are beneficial to performance are preferred and selected. These continuous modifications to performance need to be made in the face of both short-term (e.g., immediate changes in the environment) and long-term changes (e.g., growth and aging). This implies that motor variability is critical to maintaining optimal performance in the face of constant changes in the organism, the task, and the environment.

The presence of variability is also essential for exploratory behaviors on a much larger scale. From a dynamical systems perspective, where behaviors are considered attractors, variability is important for creating transitions, i.e., for qualitative changes in the behavior of a system. In bimanual tasks, the transition of the fingers from an anti-phase pattern (abduction of one finger and the adduction of another) to an in-phase pattern (both fingers abducting and adducting together) with an increase in frequency is characterized by an increase in the amount of variability in the relative phase pattern before the transition (Kelso, 1984). The influence of variability on exploratory behaviors is also present over longer time scales. For example in infant development, Goldfield (1989, 1993) observed that infants with greater variability in locomotion behaviors prior to crawling showed a tendency to crawl earlier compared with infants who showed low variability. This suggests that variability may be a critical step in establishing new behaviors.

The importance of variability for exploration and transition can also be seen in certain pathological conditions that are associated with an extreme lack of variability.

For example, disorders such as tardive dyskinesia and mental retardation are characterized by stereotypical movements that have very low variability even in the absence of an apparent specific goal (Newell, van Emmerik, & Sprague, 1993). Similarly, patients with Parkinson's disease who have deficits in balance control have been found to have less body sway than age-matched controls (Horak, Nutt, & Nashner, 1992) indicating a reduced tendency to explore their base of support. While a smaller body sway is often seen as an indicator of better balance, this counter-intuitive finding indicates that a certain amount of variability is essential and that exploratory behavior is reflective of a healthy and adaptive system (Van Emmerik & Van Wegen, 2002).

Structure of variability

The second argument against the variability as noise assumption is that variability in movement does not seem to be random, but instead has characteristic structure (Newell, Sosnoff, Deutsch, & Mayer-Kress, 2006). Variability is often quantified using the standard deviation, which assumes that the underlying distribution is Gaussian white noise. However, several studies have shown the existence of time-dependent and frequency-dependent structure in motor variability. In the time-domain, Pincus and Goldberger (1994) found that the heart rate became more regular (i.e., became more predictable) in patients with arrhythmia. This loss of complexity has also been found in other pathologies and is characteristic of aging although there is evidence that the direction of the change in complexity may also be dependent on other constraints on the system (Vaillancourt & Newell, 2002). Similarly, in analysis of the frequency structure of variability, there have been several studies that indicate the presence of $1/f$ scaling in different tasks such as tapping (Chen, Ding, & Kelso, 1997), gait (Hausdorff, Purdon,

Peng, Ladin, Wei, & Goldberger, 1996), postural sway (Riley, Wong, Mitra, & Turvey, 1997) and even reaction times (Gilden, Thornton, & Mallon, 1995; van Orden, Holden, & Turvey, 2003). These 1/f processes have been interpreted as a characteristic of systems with interaction-dominant dynamics (van Orden et al., 2003).

There is a second type of structure in variability observed in many tasks where variability seems to be organized in a task-specific manner. A classic example that is used to illustrate this phenomenon is from Bernstein (1967). When analyzing the kinematics of experienced blacksmiths hammering, Bernstein (1967) noted that the trajectories of the tip of the hammer varied from trial-to-trial although they always managed to finally hit the target. In effect, variability appears to be structured so that task performance is not affected. This ability to use motor variability to find multiple solutions to achieve a given task goal may provide flexibility in different contexts as well as reduce wear and tear on the system over many repetitions (Edelman & Gally, 2001).

In summary, there have been significant challenges to the standard assumption of studying the average behavior as the signal and considering variability as noise. In fact, several features observed in the average behavior may actually be influenced by the nature of variability. Also, it is evident that variability may have important consequences for adaptive and exploratory behaviors of the motor system. Finally, the structure of variability indicates that far from being a random process, the study of variability can provide insights into the organization and control of the motor system.

Part 2: Movement Variability in learning

Variability and skill are typically considered as the inverse of each other. Skilled performers in different domains exhibit not only a high level of performance, but extremely consistent performances often extending over long periods of time. Motor skills are no exception to this generalization. For example, from 2004 until 2009, Roger Federer reached at least the semi-final stage of 23 out of the 24 Grand Slam tournaments held in those years. If we consider variability at the level of motor performance, the ability to bring about a certain outcome consistently and with minimum variability is considered a hallmark of skilled performance. For example in the 2008 basketball season, José Calderón of the Toronto Raptors made 151 out of 154 free throws, a success rate of 98.1% (NBA.com). The notion of consistency is included in definitions of skill where skill is defined as being able to achieve a given outcome with maximum certainty and a minimum outlay of time and/or energy (Guthrie, 1935). Therefore, the role of variability in motor learning and how variability changes with learning is one of the most important issues in motor learning

It is important to recognize that the characteristics of the task have a significant influence on how the variability of the task outcome changes with learning. For example, in tasks in which the goal is to achieve maximal performance (e.g., a long jump), the variability of the task outcome may not show a monotonic decrease with increasing skill level. For instance, as the performer becomes more skilled, the variability of the outcome may even increase because there is a greater range of task outcomes that are theoretically achievable. Indeed, in these tasks, the performer's goal is to achieve maximal performance instead of reducing variability. Therefore, the focus of this review is on

motor tasks that involve achieving a prior defined desired outcome, and in which deviations from the desired outcome are considered detrimental to performance (e.g., dart throwing). These tasks essentially involve accuracy as the primary determinant to performance in the task where an increase in performance level has to be achieved by reducing the variability of the task outcome.

Learning as the process of finding a unique solution

Even in tasks where performance can be improved by reducing the variability of the task outcome, the changes in movement variability do not have to follow the same trend. This is because the redundancy present in the system precludes a direct relation between movement variability and outcome variability. However, coaches in sport often emphasize an ideal technique or movement pattern and use practice drills to facilitate consistently reproducing that movement pattern from trial to trial. Therefore, one view is that learning involves finding a unique, optimal movement pattern that would be reflected by a decrease in movement variability with practice.

The notion of a unique movement pattern is central to theories of motor programming such as schema theory (Schmidt, 1975) that postulated an increase in the strength of the motor program representation with practice. Other approaches that have emphasized this invariance in movement parameters have also suggested that invariants may be represented in the central nervous system (e.g., Atkeson & Hollerbach, 1985; Morasso, 1981). These assumptions formed the basis of optimization approaches that assumed that learning involved finding a unique optimal solution to minimizing cost functions such as jerk (Flash & Hogan, 1985), torque change (Uno, Kawato, & Suzuki, 1989) or end-point variance (Harris and Wolpert, 1998). In addition, the assumption that

an optimal pattern exists has been used as a basis for explaining related issues in motor control such as coincident timing. For example, in one particular approach to coincident timing, the assumption of a programmed swing effectively reduces the problem of trying to swing a bat to hit a moving ball to the problem of just deciding when to initiate the swing (e.g. Tyldesley & Whiting, 1975).

In terms of the variability of end-point trajectories, there has been support for the decrease in variability with learning. Georgopoulos, Kalaska and Massey (1981) found that when monkeys were trained to reach to targets in different directions, the spatial variability of the trajectory across trials decreased with practice. Georgopoulos et al. attributed this reduction in variability to both improved motor coordination and a better knowledge about the best aiming trajectory. Darling and Cooke (1987a) found a similar decrease in trajectory variability (considering variations in both space and time) in a single-degree of freedom task involving flexion of the elbow joint. A decrease in spatial variability were also reported by McDonald, Van Emmerik, and Newell (1989) who examined variability of the hand trajectory in external space during the learning of a dart throwing task. Similarly, Haggard, Leschziner, Miall, and Stein (1997) found that when participants were trained to reach for targets in different directions, the decrease in the spatial variability of the trajectory was not only in the direction that the participants trained, but also generalized to other directions.

Apart from the end-point trajectory, changes in the variability of joint kinematics and electromyographic responses with learning have also been investigated. Again, in studies that had a pre-defined external goal, joint angle variability typically decreases with practice (e.g., Jaric & Latash, 1999). Button, MacLeod, Sanders, and Coleman

(2004) demonstrated the variability in coordination as measured by angle-angle plots (e.g., shoulder vs. elbow angle) decreased with increasing skill level in the basketball free throw. Finally, in terms of variability of muscle activity, some studies have shown a decrease in the variability of EMG patterns with learning (e.g., Dugas & Marteniuk, 1989; Corcos, Jaric, Agarwal, & Gottlieb, 1993) though others have shown an increase in variability (Darling & Cooke, 1987b). These studies support the view that a process of optimization accompanies learning which results in a decrease of variability in the end-point trajectory.

Learning as task-relevant optimization

An alternative view to learning being a process of finding a unique optimal solution is to consider learning as task-relevant optimization, that is, only optimizing those aspects of movement that are critical to performance. Bernstein (1967) termed this phenomenon “repetition without repetition” (p. 134) referring to how the task goal was always achieved in spite of variability in movement execution. This phenomenon was also described by Bartlett (1932) - “...we may fancy that we are repeating a series of movements that we learned... (but) every time we make it (a movement), it has its own characteristics.” (p. 204). Several studies have proposed that instead of finding a unique solution to the degrees of freedom problem, degrees of freedom are covaried so that task performance remains unaffected. For example, studies on speech production (Hughes & Abbs, 1976) and reaching (Lacquaniti & Soechting, 1982) show that task goals are achieved using covariation among different motor elements. Similarly in learning, Darling and Cooke (1988) found that the variability of grasping kinematics did not

decrease with practice, and hypothesized that variations in grasping may be organized to maintain the distal contact sites of the finger and thumb.

As mentioned above, the necessary criterion for maintaining accurate task performance without decreasing movement variability is redundancy, that is, the presence of multiple solutions to achieve the goal of the task. This redundancy may be present at multiple levels both in the task and the organism. For example, consider the task of throwing a dart at the bull's eye of a dartboard (Müller & Loosch, 1999). First, the finite radius of the bull's eye allows a variety of different locations on the dart board that one could aim at and still achieve 50 points. If a particular location on the bull's eye is selected, one could throw the dart using different velocity-angle combinations to make the dart reach that particular location. Also, one could use different trajectories of the hand to achieve a particular velocity-angle combination, different joint angle combinations to achieve a given hand trajectory and so on. In essence, as long there is redundancy at any given level of analysis in the system, movement variability at that level *need not necessarily* affect task performance.

This implies that in a redundant task, there space of execution variables can be separated into two subspaces: (a) a goal-equivalent subspace, where variations in the execution variables do not affect task performance, and (b) a goal-relevant subspace where the variations affect task performance (Cusumano & Cesari, 2006; Scholz & Schöner, 1999). In most tasks, the goal of the performer is to essentially minimize errors or variations in the goal-relevant subspace. A prediction from a task-relevant optimization approach is that only variations in the goal-relevant subspace are minimized. Any variability in the goal-equivalent subspace, that does not lead to task error, is left

unaffected. This is because reducing any variability in the goal-equivalent subspace does not affect task performance and would be an unnecessary cost to the motor system. In other words, there is no need to reduce overall movement variability as long as the system is able to selectively channel the variance from the goal-relevant subspace into the goal-equivalent subspace. This is in contrast to the unique-solution approach where the overall variability (in both goal-equivalent and goal-relevant subspaces) is decreased with learning.

One model to explain this behavior is the optimal feedback control model proposed by Todorov and Jordan (2002). In contrast to other optimization approaches that predict one unique solution, the optimal feedback controller has a cost function that not only rewards accurate task performance but also penalizes corrections. This results in the controller adopting a minimal intervention principle of control, in which only deviations that affect task performance are corrected. Any deviations that do not lead to errors in task performance need not be minimized.

The results from learning studies, however, have been equivocal with respect to the prediction of a reduction only in goal-relevant variability. The majority of studies show a decrease of variance both in the goal-equivalent subspace and the goal-relevant subspace. Domkin, Laczko, Jaric, Johansson, and Latash (2002) showed that during the learning of a 2-D bimanual pointing task, the decrease in the variance in the goal-relevant subspace (i.e., an increase in pointing accuracy) was associated with a greater reduction of the variance in the goal-equivalent subspace. When the same task was repeated in 3-D, the variance in the goal-equivalent subspace decreased proportionally to the change in the variance in the goal-relevant subspace (Domkin, Laczko, Djupsjobacka, Jaric, &

Latash, 2005). However, the variance in the goal-equivalent subspace still showed a decrease with learning. Similarly, Mosier, Scheidt, Acosta, and Mussa-Ivaldi (2005) had participants wear a 19-DOF glove and learn a mapping between the motions of the hand and the motion of a two-dimensional cursor on the screen. Again, participants showed a tendency to decrease both goal-equivalent and goal-relevant variability with learning. Finally, Müller and Sternad (2004) showed that the contribution of the covariation component (that corresponded to utilizing multiple solutions) to improvement in a skittles task was rather modest, with the majority of the performance improvements coming from the noise reduction and tolerance components. In light of the evidence that the variance in the goal-equivalent subspace decreases with practice, there has been speculation that even within the goal-equivalent subspace, there may be smaller subspaces which may be preferred with practice. These smaller subspaces may have properties involving constraints such as smoothness or comfort (Latash, 2008) or properties specific to the task such as straightness of the trajectory (Mosier et al., 2005).

In summary, the changes in variability with learning can be separated into variability of task outcome and variability of the movement pattern. In cases where the primary determinant of performance is accuracy, there is a decrease in variability of the task outcome with learning. In terms of the movement variability, the evidence shows that even though there is an overall decrease of variability, multiple solutions to the task problem are often utilized. However, with further practice, even variability that has no effect on task performance tends to be reduced. This suggests the need for a model of motor learning that is able to account for both the decrease in variability as well as the utilization of multiple solutions.

Part 3: Introducing Variability in Practice

One of the important issues in motor learning is how learning can be facilitated through instructional strategies from an external agent (e.g. coach, teacher, or therapist). While the amount of practice is perhaps the most critical factor in determining skill level (Ericsson, Krampe, & Tesch-Romer, 1993), there has also been an interest in structuring practice to improve motor learning. This includes issues such as the type of augmented feedback (e.g. Annett, 1959), distribution of practice (e.g., Adams & Reynolds, 1954) and variability of practice (e.g., Schmidt, 1975). Here we focus on the issue of whether an external agent can facilitate motor learning by introducing variability into practice.

In considering the notion of whether introducing variability in practice is beneficial, it is important to consider the default hypothesis in motor learning that practice should be *specific* to the to-be-tested conditions (Henry, 1968), that is, practice should be undertaken in the same setting as the one requiring performance. The specificity of practice hypothesis implies that introducing variability in practice might be beneficial if the task itself requires variability in performance. This may be the case for many open skills such as playing tennis or soccer where the same movements are rarely repeated. However, if the task requires achieving a single goal (for e.g., a basketball free throw), the specificity of practice hypothesis proposes that constant practice, that is, practicing the single task goal without any variability would be optimal for learning. Proteau (1992) suggested that the specificity of practice may be due to the formation of specific sensorimotor representations that take into account the available information. Therefore, from this perspective, any changes that are introduced in practice that are different from the actual performance conditions would be detrimental to performance in

the new setting. In effect, the specificity of practice minimizes the role of any interventions that the external agent may introduce into learning.

However, different theoretical frameworks have proposed that introducing variability in practice might be beneficial for learning. The two common rationales for introducing variability in practice that are inter-related are: (a) creating interference during practice, and (b) facilitating generalization.

Creating interference

One of the early rationales behind introducing variability in practice was a way of introducing interference in learning. Studies in verbal learning have shown that tasks learned under intratask interference demonstrate better retention (Battig, 1972). In motor learning, interference is created by practicing two or more variations of the task in a random order (e.g., ABCBACBAC) instead of practicing them in blocked order (e.g., AAABBBCC). Shea and Morgan (1979) showed that the random practice resulted in better performance under both blocked and random test conditions. This effect, termed contextual interference, refers to the notion that random practice results in poor performance during practice, but enhances learning.

The hypothesis behind the contextual interference effect is that presenting conditions in a random order may have two effects: (a) random practice creates more contrast between the different conditions and, therefore, forces the participants into more cognitive processing that make the representations stronger (Shea & Zimny, 1983), or (b) random practice forces the participant to actively reconstruct the solution that may result in stronger retention rather than blocked practice which involves simply reusing the solution over and over again (Lee & Magill, 1983).

Contextual interference effects has been found in a number of tasks including the badminton serve (Goode & Magill, 1986), rifle shooting (Boyce & Del Rey, 1990) and baseball batting (Hall, Domingues & Cavazos, 1994). Hall et al. (1994) showed the contextual interference effect even in college-level baseball batters who practiced by facing different types of pitches in either a blocked or random order. There has also been some support for contextual in force field learning where participants learn to counteract the effects of an externally imposed force field during reaching. Participants who trained in the presence of catch trials (i.e., trials in which the force field is turned off) that were randomly interspersed within the force field trials (i.e., high contextual interference) were able to better retain their learning in the presence of an interfering force field (Overduin et al., 2006). On the other hand participants who trained with the force field on all trials showed susceptibility when presented with an interfering force field. However, Russell and Newell (2008) suggested that at least some of the effects in the literature could be explained by switching costs. The random practice group gains experience with task switching as compared to the blocked practice group and, therefore, may be at an advantage in the test where there is a need to switch between the two tasks.

Facilitating generalization

A second rationale for introducing variability in learning was based on the notion that learning should involve the ability to generalize, that is, learning should not only involve performing in the specific conditions practiced but also the ability to perform other novel variations of the task. One of the theories of generalization in motor learning was the schema theory of discrete motor skill learning (Schmidt, 1975). Schema theory postulated the formation of a rule or schema that associated parameters of the movement

with the particular outcome. The idea behind the variability of practice notion is that the schema or the rule governing the relation between movement parameters and the movement outcome, is better learned in the presence of variation in the movement parameters. In other words, as the participant experiences a greater range of parameter specifications, a more task-appropriate and stronger rule is generated, which in turn leads to improved retention and transfer to novel conditions both inside and outside the range conditions practiced. On the other hand, constant practice, where a single association between movement parameters and outcome is learned, does not lead to the strengthening of the rule and, therefore, does not facilitate generalization to novel conditions.

The evidence for the effects of variability of practice has been equivocal. Several studies have shown beneficial effects of variable practice (e.g., McCracken & Stelmach, 1977), especially in transferring to novel conditions that had not been practiced. It is important to note that the tasks used in these studies have been discrete movement scaling tasks (e.g., move 50 cm in 250 ms). In their review of experiments with variable practice, Shapiro and Schmidt (1982) concluded that the variable practice hypothesis had greater support in studies involving children, where the schema may not be well-established. More recently Braun, Aertsen, Wolpert, and Mehring (2009) also demonstrated that by introducing variation in the rotation angle in learning a visuomotor rotation task, participants were able to generalize to novel rotation angles that had not been practiced.

However, van Rossum (1990) performed a meta-analysis and concluded that there was little support for the variability of practice hypothesis. In particular, van Rossum noted that the benefits of variable practice in novel transfer conditions were sometimes

confounded by the lack of appropriate control groups and proximity effects. As an example of a proximity effect, consider a situation where the variable group practiced parameters of 1, 2, and 5 cm while the constant group practiced at 2 cm. If the transfer test was conducted at 3 cm, then the variable practice group would have an advantage because the mean of the variable group (2.66 cm) is closer to the task criterion than the constant group (2 cm).

Some studies have provided evidence in favor of constant practice. Seidler (2004) showed that increasing generalization by practicing multiple visuomotor rotations comes at a cost – that of decreased stability. That is, movements in participants who learned multiple visuomotor rotations were more susceptible to the effect of an external perturbation compared to participants who had a more limited range of experiences. A similar effect that highlights the importance of specific practice has also been found in studies of the basketball free throw. Keetch, Schmidt, Lee, and Young (2005) showed in skilled basketball players that shooting performance from the free-throw line was much greater than what would be predicted from the performance at nearby locations. Keetch et al. (2005) suggested that instead of learning a general rule, these *especial skills* could possibly result from learning specific parameter specifications that are optimal to performing that one particular instance of the task. This would also be consistent with the interpretation that specificity in practice leads to more robust representations of the task as compared to variable practice.

Introducing variability at different levels of the task

An important issue in the context of introducing variability in practice is that of redundancy. In a redundant task, variability can be introduced at different levels of the task. For example, consider a task that requires throwing a ball underhand to a horizontal target on the ground at a specified distance (Kudo, Tsutsui, Ishikura, Ito, & Yamamoto, 2000). Variability can be introduced by changing the distance that has to be thrown, or by throwing to the same target distance using different velocity-angle combinations. Therefore, there are at least two levels at which variability can be introduced: (a) the task goal level, and (b) the execution redundancy level.

Before introducing the different levels, it is important to define the level at which the redundancy is analyzed in the task. For example, the underhand throwing task can be defined as redundant with respect to two variables: (a) release velocity, and (b) release angle. Similarly, two fingers acting to produce a total force of 10 N can be defined as redundant with respect to the two individual finger forces. While the actual variables that can be used to describe the redundancy in a task are clearly not unique (for e.g., see Smeets & Louw, 2007), once a set of candidate variables are identified, variability can be introduced at two levels:

(a) Task goal level: At the task goal level, introducing variability requires the participant to find an *entirely new family of solutions* for successful performance. For example, in the underhand throwing task, changing the distance or height of the target creates a whole different family of velocity and angle combinations that satisfy the task. Essentially, changes in the task goal constrain the participant to use a different set of solutions at each variation.

(b) Execution redundancy level: At the level of execution redundancy, variability does not alter the family of solutions, but requires the participant to *relocate to a different section of the same family of solutions*. For example, a change in the mass of the ball may cause the participant to use velocity-angle combinations that have lower velocity even though the target is still at the same location. Alternatively, placing a barrier between the participant and the target may force the participant to utilize that part of the solution space where the ball can clear the height of the barrier. In these manipulations, the family of solutions to the task remains the same in all variations – however, different regions of the family of solutions may be emphasized by varying the task constraints.

Studies on variable practice based on schema theory have focused primarily at the task goal level. This is because schema theory did not deal with the problem of redundancy. Rather, the relation between the movement parameters and the movement outcome was assumed to be a one-to-one mapping under constant initial conditions. Therefore, in the absence of redundancy in the task, variability of practice in terms of schema theory was introduced at the task goal level.

However, there may be benefits to introducing variability in practice schedules at the execution redundancy level to enhance the exploration of redundant solutions. First, in dynamic environments, the ability to use redundant solutions is critical to performance because a single solution can rarely be repeated. Second, introducing variability may also facilitate the process of learning how to channel movement variability into redundant dimensions so that increased movement variability does not affect task performance. This may be especially important in rehabilitation where the intrinsic movement variability may be higher in patients with movement disorders. Finally, being forced to

explore redundant solutions may also involve search strategies for finding more optimal solutions than those that may be found under self-selected conditions.

With respect to variability being used to enhance search strategies, Schöllhorn and colleagues (Schöllhorn, 1999; Schöllhorn, Beckmann, Michelbrink, Trockel, Sechelmann, & Davids, 2006) introduced a differential learning approach that involves adding random variations to the task. The results from these studies show that adding fluctuations to movements during practice leads to better performance and retention. For example, Beckmann and Schöllhorn (2003) found that adding random movements to the shot put technique resulted in a greater increase in throwing distance both during practice and after practice compared to traditional training. This suggests that the induced movement variability aided participants in finding a solution that resulted in better performance compared to a condition in which there was no movement variability.

In summary, the impact of introducing variability in practice schedules is equivocal. Some studies of variable practice under schema theory have shown that variable practice may result in an increased ability to extrapolate to new conditions that have not been practiced before. Similarly, studies on contextual interference indicate that creating interference through variability may enhance cognitive processing and result in better learning. However, in the context of the redundancy present in most tasks, the role of introducing variability at the execution redundancy level to facilitate the utilization of redundant solutions has been relatively unexplored and awaits systematic investigation.

CHAPTER 3: INFLUENCE OF MOTOR LEARNING ON UTILIZING PATH REDUNDANCY

Abstract

We examined how learning influences the utilization of path redundancy in an interception task. Participants used a pen on a digitizing tablet with the goal of moving to intercept a stationary target shown on a computer screen. Concurrent visual feedback of the cursor and knowledge of results were provided. Participants performed a total of 400 trials, and a subgroup of participants practiced for an additional 800 trials. Results showed that during initial practice, the increase in performance level with learning was associated with a decrease in spatial variability throughout the path. However, with extended practice, participants selectively reduced the spatial variability only near the target. The predictability of the movement paths at a spatial location from neighboring locations showed a decrease near the point of reversal during initial practice and near the target with extended practice. There was also a sequential relation from trial to trial with a tendency to use more similar movement paths on successive trials. These results show that even when movement variability is reduced through practice, there is still a tendency to use different solutions to achieve the task goal. Further, the analyses of trial-dependent relations suggest that this utilization of redundancy is reflective of a systematic search process.

Introduction

The problem of redundancy (Bernstein, 1967) arises from the fact that the human body has more degrees of freedom than required to perform most tasks. This redundancy leads to the existence of infinitely many solutions to accomplish a given motor task and is manifest at several different levels: end-point trajectory, joint angles, muscle activations etc. This then raises a question that is critical to motor learning: if there are infinite possible solutions to achieve a task goal, how are we able to perform and retain motor skills?

One approach to the redundancy problem is based on the observation that in spite of the seemingly infinite possible solutions, there are regularities or invariant features of movement that are present both within and across individuals. These invariant features include, for example, bell-shaped velocity profiles in reaching (Morasso, 1981), coupling between joint torques (Gottlieb, Song, Hong, & Corcos, 1996), and the speed-accuracy tradeoff (Fitts, 1954). Assuming that these invariant features are a reflection of the existence of a unique solution, one way to solve the redundancy problem is to impose a cost function and use an optimization approach to find a solution that exhibits the invariant features observed.

Although the optimization of cost functions does not necessarily imply that a single unique solution will be generated, the optimization models that have been typically used in motor control are open-loop where the role of sensory feedback is not included (Todorov & Jordan, 2004). A feature of these open-loop optimization approaches is that they predict a unique solution to perform a given motor task. For example, in reaching, Flash and Hogan (1985) proposed an optimization that minimized the mean squared jerk

of the end-point trajectory (for a review of optimization models, see Engelbrecht, 2001; Kawato, 1996). Therefore, from this perspective, motor learning can be considered as the process of finding the unique solution that is optimal with respect to some criterion to achieve the given task goal.

While this viewpoint is consistent with a general reduction in movement variability that is seen in many studies of motor learning (e.g., Darling & Cooke, 1987a; Georgopoulos, Kalaska, & Massey 1981), one of the assumptions behind this approach is that variability in the motor output is attributed to noise from multiple sources in the nervous system. In other words, the observed motor variability is predicted to be a consequence of random fluctuations that has no particular structure in either the time or frequency domains. However, it has been observed that variability in movements does not seem to be random but has structure that is directly related to the task. Bernstein (1967) noted that the tip of the hammer of an experienced blacksmith never followed the same trajectories even though they always managed to hit the target. Bernstein termed this phenomenon “repetition without repetition” (p. 134).

There have been several studies that support this observation that rather than trying to produce consistent movement patterns with low variability, movements are organized so that the task goal is always met in spite of variations in the movement pattern. For example, speech perturbation studies (Abbs & Graco, 1984; Kelso, Tuller, Bateson, & Fowler, 1984) have shown that when a particular perturbation is applied to the lower jaw, there are compensations in other parts of the speech production apparatus depending on the syllable to be uttered. Similarly, studies using the uncontrolled manifold technique have shown that the variance in the task-redundant dimension is

greater than the variance in the task-relevant dimension both in kinematics (e.g, Scholz & Schöner, 1999) and finger force production tasks (e.g., Latash, Scholz, Danion, & Schöner, 2001).

It has been proposed that the redundancy present in the task is utilized in order to produce a consistent task-relevant output, or in other words, stabilize a particular task variable (Latash, Scholz & Schöner, 2002). Todorov and Jordan (2002) modeled this phenomenon using an optimal feedback control model where the optimization not only involved maximizing performance, but also minimizing corrections. This controller produces “repetition without repetition” behavior (Bernstein, 1967) because it only corrects for deviations that affect task performance while allowing deviations that do not affect task performance. Therefore, instead of minimizing all movement variability to find a unique solution, this perspective predicts that only movement variability in the task-relevant dimension needs to be minimized.

A number of different methods have been developed to quantify the degree to which redundancy is utilized in a given task. These include the uncontrolled manifold (UCM) (Scholz & Schöner, 1999), the goal-equivalent manifold (Cusumano & Cesari, 2006) and the decomposition of variability into costs from tolerance, noise and covariation (TNC) (Cohen & Sternad, 2009; Müller & Sternad, 2004) (for reviews and comparisons of these different methods, refer Müller & Sternad, 2009; Schöner & Scholz, 2007). The UCM approach has been applied predominantly to the problem of mechanical redundancy (i.e., defined at the level of joint kinematics or finger forces) whereas the TNC approach has been applied in discrete tasks where there is redundancy

in task execution variables (e.g., velocity and angle in a throwing a projectile to a particular location).

In contrast, the phenomenon of trajectory and path redundancy in learning has not received much attention. In goal-directed movements, there are infinite trajectories for the end-point effector to move from point A to point B. Even if only the movement path is considered (i.e., the spatial component of the trajectory), there are still infinite paths to achieve a given task goal. Open-loop optimization models predict that a single unique path is learned and repeated with practice. For example, in reaching, the system may eventually settle on the path that involves the least mean squared jerk (Flash & Hogan, 1985), the least torque change (Uno, Kawato, & Suzuki, 1989), or minimum variance in the presence of signal-dependent noise (Harris & Wolpert, 1998).

However, Todorov and Jordan (2002) showed that the amount of path variability in between the start position and the target differed depending on whether there were intermediate targets present, and that the path variability was also dependent on the size of the intermediate targets. In particular, path variability was decreased in the presence of intermediate targets and adjusted according to the size of the intermediate target. These results support the notion that instead of generating a single optimal path with added noise, the path variability is only reduced in locations where it is relevant to the task goal.

The aim of the present investigation was to examine the changes in path variability and redundancy in the process of learning an interception task. In particular, we were interested in whether the path variability decreased with learning and if the variability was modulated at different points along the path depending on its relation to

task performance. In addition to analyzing the amount of path variability, we also examined the structure of the path variability to investigate changes in time-dependent and trial-dependent relations. Several studies have demonstrated that the analysis of these properties can reveal if the variability is indicative of a random, white-noise process or whether it has specific structure (Pincus, 1991; Newell, Deutsch, Sosnoff, & Mayer-Kress, 2006). Therefore, information about the structure of variability and the changes in the structure of the variability could provide insight into how redundancy is utilized with learning.

Methods

Participants

15 healthy volunteers (Mean Age = 24 ± 1 years; 4 females) volunteered for the study. All participants had normal or corrected-to-normal vision and were right-handed. Participants provided informed consent and the protocol was approved by the Institutional Review Board at Pennsylvania State University.

Equipment

A digitizing tablet and pen (WACOM Intuos A3, Saitama, Japan) were setup on a table in front of the participants. The height of the chair was set so that when the participants placed their forearm level on the table, the elbow was approximately 90° in flexion. The digitizing tablet sampled the pen position at 200 Hz. A 19 in. (48.2 cm) computer monitor was placed directly in front of the participant at a distance of 40 cm. The mapping between the tablet and the screen was set to 1:1 so that a movement of 1 cm of the pen on the tablet corresponded to a 1 cm movement of the cursor on the screen (Figure 3.1).

Task

The task of the participants was a virtual interception task. The screen that the participants saw consisted of a start circle, two obstacles and the target as shown in Figure 3.1. The target had a diameter of 15 mm. At the start of each trial, participants were asked to position the pen on the tablet so that the cursor was inside the start circle. Once the cursor was inside the start circle for 1 s, they heard a tone that indicated that they could initiate the movement. Participants then proceeded to make a movement with the goal of intercepting the target with the cursor (i.e., they had to pass through the target, not stop inside the target) without hitting the obstacles. During the trial participants could see the instantaneous position of the cursor which was indicated by a cross-hair. Each trial ended when the cursor passed 15 mm to the right of, and beyond the target. Movement time was computed as the duration between the instant at which the participant first moved out of the start circle to the instant at which the trial ended.

The goal of the participants was to get as many hits of the target as possible. To qualify as a hit, two criteria had to be satisfied: (a) the trajectory of the cursor had to pass through the target, and (b) the movement time had to be in between 550 ms and 650 ms. The movement time was selected in this range to allow the utilization of visual feedback from the cursor and also ensure that participants had a relatively low level of performance at the start. At the end of each trial, the trajectory of the cursor throughout the whole trial was shown (see Figure 3.2). If the trial was a hit, the target turned yellow in color and a counter at the bottom of the screen was incremented by 1. If the participant hit the obstacle, then the trajectory was only shown up to the point where the cursor hit the obstacle.

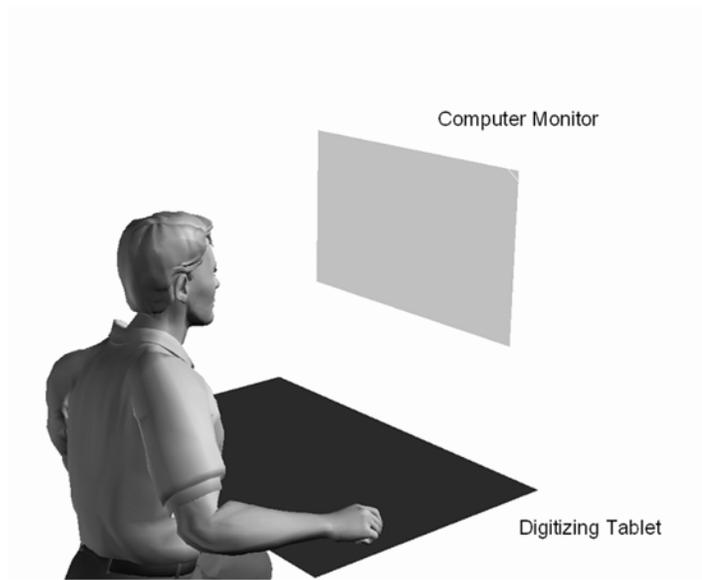


Figure 3.1. Schematic of the experimental setup.

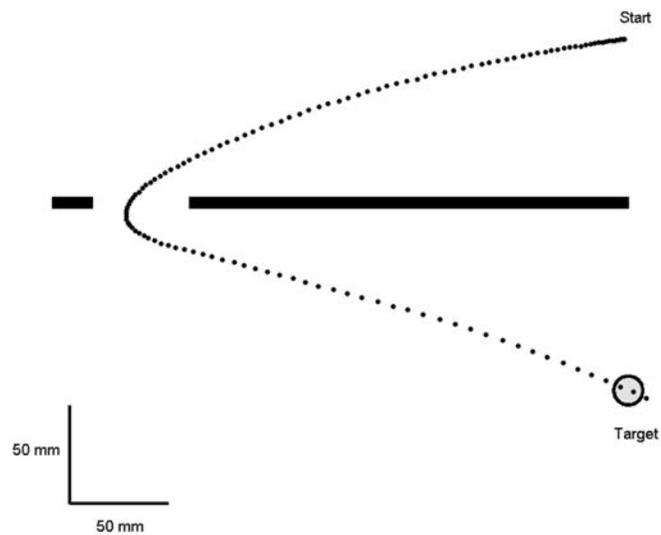


Figure 3.2. Schematic of the task. Participants started in the position on the top right and attempted to hit the target circle without hitting the obstacles in a time of 600 ± 50 ms. The dotted line indicates the trajectory feedback that the participants received at the end of every trial.

Bandwidth feedback was provided for the movement time. If the participants were too slow in completing the trial ($MT > 650$ ms), they heard a low-pitched beep (500 Hz tone). If participants were too fast ($MT < 550$ ms), they heard a high-pitched beep (4000 Hz tone). In addition, if they crossed the gap between the obstacles too early (<250 ms), the gap turned blue in color, and if they passed the gap too late (>350 ms), the gap turned red in color. The constraint on the gap crossing time was only used as a soft constraint to control the velocity profile and participants could achieve a hit even if they did not satisfy this constraint.

Procedures

Initial Practice. After a familiarization block of 50 trials, participants performed 8 practice blocks with each block consisting of 50 trials. Each trial lasted about 5 s and the whole session lasted for approximately 1 hr.

Extended practice. To measure changes that occur with more practice, a subgroup of 6 participants underwent extended practice. After the first 8 blocks of practice, they performed 16 additional blocks of 50 trials spread over 4 consecutive days (4 blocks per day). The time duration between performing the first 8 blocks of practice and the 16 subsequent blocks was more than 3 months for all participants.

Data Analysis

Performance

Performance was analyzed using the percentage of the trials the target was hit and the absolute error. The absolute error was computed as the shortest distance from the edge of the target to the movement path. This meant that if the target was hit, the absolute error on that trial was calculated as zero.

Spatial variability of the path

Spatial variability within each block was computed by first computing the mean spatial path. The path on each trial was split into equidistant increments of 10% from the start of the trial until the point it reached the closest to the center of the target. These were averaged to compute the mean spatial path. At each location along the path (in increments of 10%), the spatial variability was computed as follows: First, the line orthogonal to the instantaneous slope of the mean spatial path (i.e., the normal) was generated at each spatial location. Second, for every trial, the points at which the path intersected the normal at each spatial location were selected. Because we were interested only in the path variability and not in variations in movement time, we used a cubic spline to interpolate the path to find the closest point to the normal on each path. Essentially, this meant that almost all the variations were on the dimension along the normal (see Figure 3.3). Finally, the distribution of points at each spatial location was fitted with an ellipse using a principal component analysis. The square root of the first eigenvalue was taken as an index of the spatial path variability at that particular spatial location. If a path had points that were outside 3 standard deviations at any location on the spatial path, that trial was excluded from the analysis.

Correlation

To examine changes in the structure of variability, we computed the correlation between points on adjacent locations in the path (Figure 3.3). For example, points on the normal at 10% of the spatial path were correlated with points on the normal at 20% of the spatial path. Similar to the spatial variability, any path that was outside 3 standard deviations at any location was excluded from the analysis.

Trial-dependent structure

To examine if there was any dependence of the movement path on the sequence of trials, we computed the root-mean squared error (RMSE) between the movement paths of successive trials in a block (i.e., between trials 1 and 2, 2 and 3 and so on) in the extended practice period. The data from only the extended practice period was used because these consisted of longer sequences of practice trials without any invalid trials in the middle. We then compared the average RMSE in the actual data set to the average RMSE from a surrogate data set in which the order of the trials was shuffled in random order (similar to Müller & Sternad, 2003). We generated 50 surrogate data sets to compute a mean and standard error for the average RMSE for the surrogate data. A one-sample t-test was used to compare the average RMSE for the surrogate data set to the average RMSE of the actual data set. A significantly smaller average RMSE for the actual data set would indicate that movement paths in successive trials were more similar to each other compared to movement paths from randomly chosen trials.

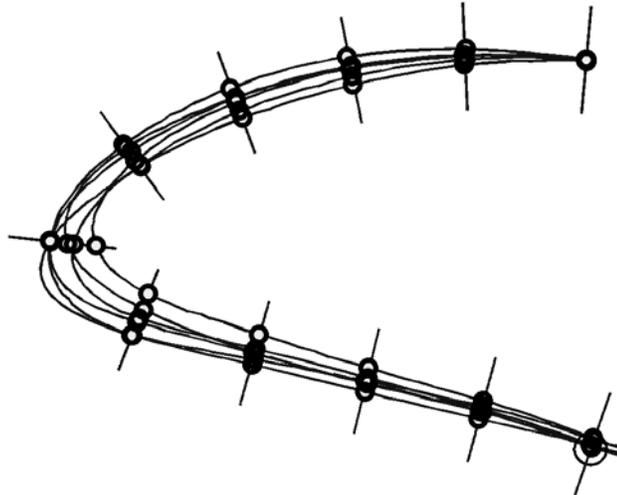


Figure 3.3. Computation of spatial variability and correlation between points on the movement path. The normal to the mean path was computed at equidistant intervals of 10 % from the start to the target. The circles describe the points where the individual movement paths intersect the normals to the mean spatial path. These points were used to compute the spatial variability and correlation between adjacent locations.

Statistical Analysis

All dependent variables were analyzed using a repeated measures analysis of variance (ANOVA). For initial practice, a one-way repeated measures ANOVA with practice block as the factor was used. Post hoc comparisons were performed using the Bonferroni correction. To limit the number of pairwise comparisons, we compared only Blocks 1, 4 and 8 in the post hoc tests. To analyze the extended practice, a 4 x 4 (Day x Block) repeated measures ANOVA was used. Violations of sphericity were corrected using the Greenhouse-Geisser correction. Post hoc comparisons were performed using the Bonferroni correction.

Results

Inclusion criteria

All trials where the trajectory did not hit the obstacle and the movement time was within 500 to 700 ms were included in the analysis. This resulted in an average inclusion rate of 86% of trials across all blocks. Examples of trajectories during the different stages of practice are shown in Figure 3.4.

Performance

Initial Practice. There was a significant main effect of block, $F(7, 98) = 15.19, p < .001$ on the percentage of hits. Post hoc comparisons showed that the percentage of hits was higher in Block 8 and Block 4 when compared with Block 1 ($ps < .05$) (Figure 3.5A). In terms of absolute error, there was a significant main effect of block, $F(7, 98) = 18.42, p < .001$. Post hoc comparisons showed that the absolute error was lower in Blocks 4 and 8 when compared with Block 1 ($ps < .05$). (Figure 3.5B)

Extended Practice. There was a significant main effect of day, $F(3,15) = 20.02, p < .001$, and block, $F(3,15) = 10.43, p = .001$ on the percentage of hits. The Day \times Block interaction was not significant. Post hoc comparisons revealed that Day 4 had a higher percentage of hits compared to all other days. Day 3 also had a higher percentage of hits compared to Day 1. Post hoc comparisons between blocks indicated that Block 1 had a lower percentage of hits compared to Blocks 2 and 4 (See Figure 3.5A). Similar trends were seen for the analysis of absolute error. There was a significant main effect of day, $F(3,15) = 5.99, p = .007$, and a significant main effect of Block, $F(3,15) = 12.18, p < .001$. The Day \times Block interaction was not significant. Post hoc comparisons showed

that Day 4 had lower absolute error than Day 1. Post hoc comparisons also showed that Blocks 2 and 4 had significantly lower absolute error than Block 1 (see Figure 3.5B).

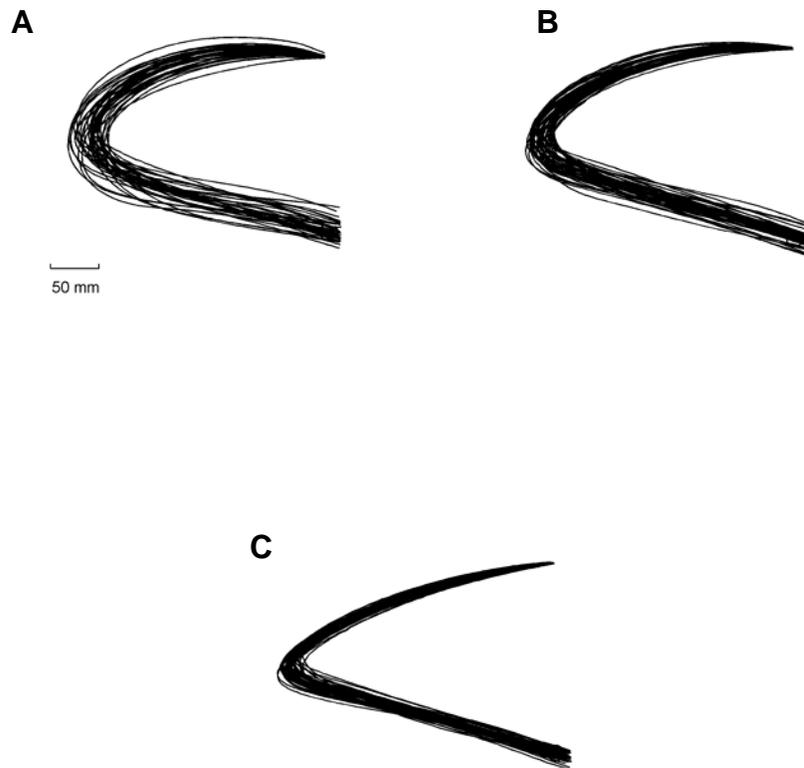


Figure 3.4. Exemplar trials from a participant in (A) Block 1 of initial practice, (B) Block 8 of initial practice, and (C) Block 16 of extended practice.

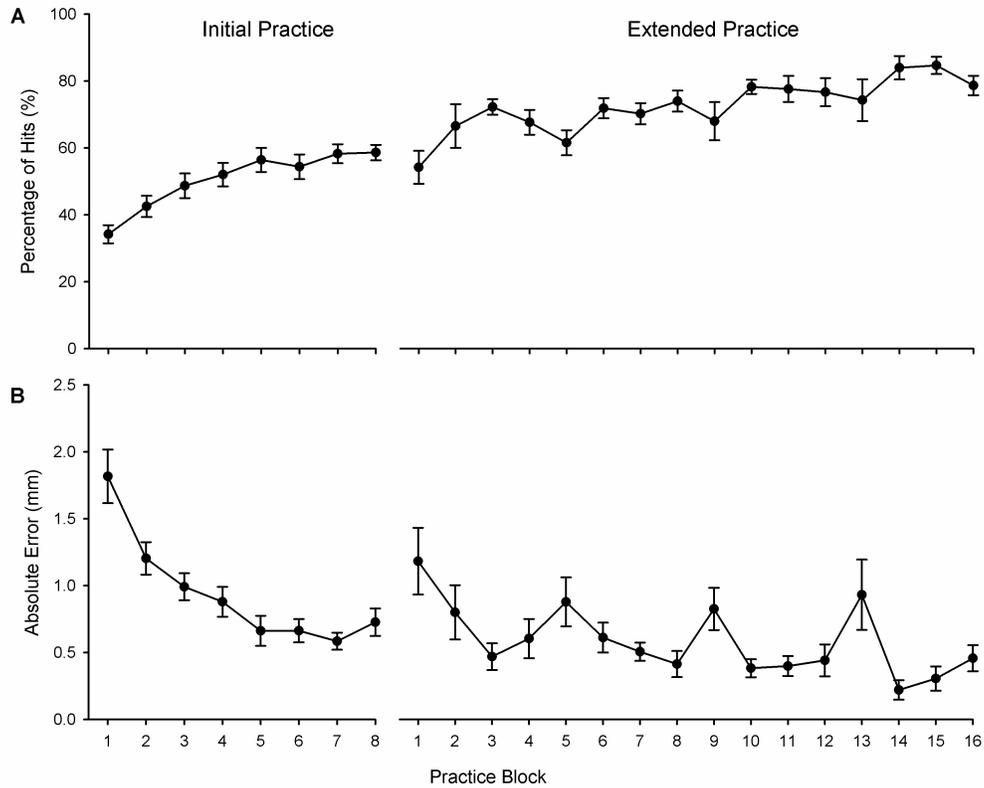


Figure 3.5. Performance in the initial and extended practice (A) Percentage of trials that were hits, (B) Absolute error measured from the edge of the target. Error bars represent one standard error.

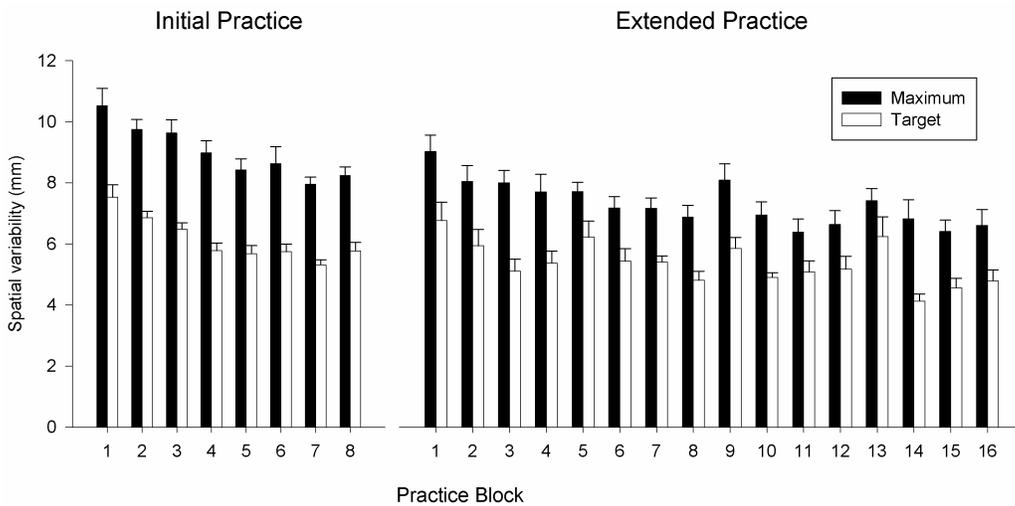


Figure 3.6. Maximum spatial variability in the movement path and the spatial variability at the target in initial practice and extended practice. Error bars represent one standard error.

Spatial variability

In all blocks, the maximum spatial variability of the movement path was always greater than the spatial variability at the target (Figure 3.6). When we examined the changes in spatial variability with learning, pairwise comparisons during initial practice revealed that the spatial variability in Block 1 was higher than the spatial variability in Block 8 at each spatial location throughout the path (Figure 3.7A). For extended practice, we compared the best performance block of Day 1 and the best performance block of Day 4 of each participant. The best performance block was selected to remove the effects of warm-up decrement that was present in the absolute error. The comparisons showed that the spatial variability in Day 4 was smaller than Day 1 only in the 90% and 100% portions of the path (Figure 3.6A).

Correlations

During initial practice, the correlation between 40% and 50% of the movement path, which approximately corresponds to the point of direction reversal, showed a decrease from Block 1 to Block 8 ($p = .002$) (Figure 3.7B). In extended practice, we compared the best block of Day 1 and the best block of Day 4. The comparisons showed that the correlations in between 90% and 100% of the movement path were significantly lower on Day 4 ($p = .009$), which corresponded to the location near the target (Figure 3.7B).

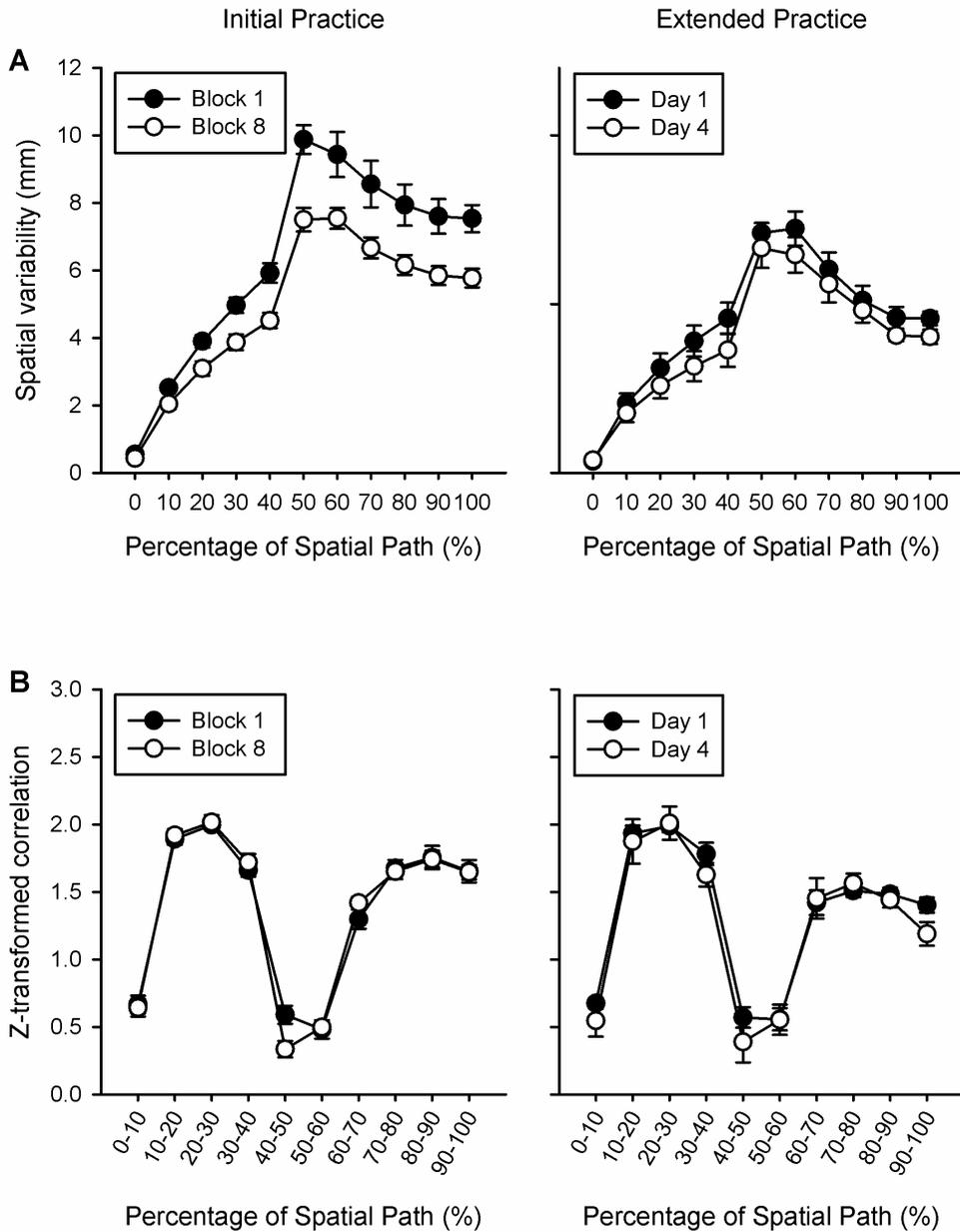


Figure 3.7. (A) Spatial variability at different percentages along the path during initial and extended practice. (B) Correlations between points at adjacent locations on the trajectories (i.e., between 0% and 10%, 10% and 20% etc.). Error bars represent one standard error. Correlations were Z-transformed to compute averages and standard deviations. A Z-transformed correlation of 2.0 corresponds to a correlation coefficient of 0.96.

Trial-dependent structure

There was also evidence for trial-dependent structure in the extended practice period. Out of the 16 blocks, 65% of the blocks showed that the average RMSE of the actual data set was significantly smaller compared to the average RMSE from surrogate data sets. 18% of the blocks showed no statistical difference and the remaining 17% showed higher RMSE for the actual data set compared to the surrogate data set. On the 4 blocks of practice on the last day, the number of blocks that showed smaller RMSE for the actual data set was approximately 80%. The average RMSE of the actual and surrogate data sets for the four blocks on the last day of practice for each subject is shown in Table 3.1.

Table 3.1.

Average RMSE (in mm) for the actual and surrogate data sets during the last day of extended practice. An asterisk (*) in the actual column indicates that the value is significantly smaller than the corresponding surrogate column (one-sample t-test, $p < .05$) and vice versa. Note that only one block (s05, Block1) has the average RMSE of the surrogate data set smaller than the actual data set.

	Block 1		Block 2		Block 3		Block 4	
	Actual	Surrogate	Actual	Surrogate	Actual	Surrogate	Actual	Surrogate
s01	8.99*	9.85	7.65*	7.90	7.21*	8.60	7.38*	8.44
s02	7.04*	7.43	8.16*	8.30	8.02*	8.33	7.95*	8.24
s03	10.14*	10.65	9.27	9.27	7.92*	8.77	8.39*	9.19
s04	9.05*	9.17	7.57	7.51	7.89	7.88	7.27*	7.70
s05	10.90	10.66*	9.61	9.52	8.31*	9.06	8.04*	9.04
s06	7.42*	7.61	6.19*	6.44	6.31*	6.76	5.93*	6.61

Discussion

The purpose of the study was to examine the influence of learning on the changes in the amount and structure of path variability in an interception task. In particular, we were interested if the changes in variability were consistent with exploiting the path redundancy in order to hit the target. It was anticipated that information about the changes in the structure of the variability may provide a greater insight into the utilization of redundancy in motor learning and Bernstein's (1967) general notion of repetition without repetition.

Amount of variability

In all blocks, the maximum spatial variability of the path was always greater than the spatial variability at the target. This is consistent with the prediction from Todorov and Jordan (2002) that as long as the movement is long enough to utilize sensory feedback, the path variability is not suppressed throughout the movement path, but only at the target, where it is relevant to task performance. The point of highest variability was near the obstacle, at the point where there was a reversal of movement direction.

The changes in path variability with learning showed two progressive phases. During initial practice, there was a decrease in the amount of spatial variability throughout the whole path even though only the variability near the target is directly relevant to task performance. This decrease in spatial variability throughout the movement path has been shown in earlier studies (e.g., Georgopoulos et al., 1981; Haggard, Leschziner, Miall, & Stein, 1997). However, in the extended practice period, there was evidence for a more selective decrease in spatial variability. The spatial variability near the target decreased from day 1 to day 4 whereas the variability in other

parts of the path did not show a significant reduction. These results support the hypothesis that there was a decrease in the variability that was task-relevant (i.e., the variability near the target), but not in the variability that was not directly relevant to the task. In other words, instead of finding a unique solution, there was a tendency to utilize multiple solutions by allowing variability at other locations while still keeping the variability near the target low. This selective decrease in variability near the target has been found in studies of hitting the ball in table tennis (Bootsma & van Wieringen, 1990) and is consistent with the predictions of optimal feedback control (Todorov & Jordan, 2002)

Structure of variability

The analysis of the structure of path variability also showed changes with learning that were consistent with utilizing multiple solutions. The correlations between adjacent locations on the path showed a change both during initial and extended practice. Initial practice resulted in a decrease in correlation near the location where the participants reversed direction. Extended practice on the other hand, led to a decrease in correlation between adjacent locations near the target. This decrease in the correlation between points on adjacent locations was due to the prevalence of increased crossover in movement paths between these locations that resulted in a lack of a one-to-one correspondence between adjacent spatial locations.

It is important to note that the decrease in correlation, especially between the 90% and 100% of the movement path in extended learning could not have been due to corrections based on online visual feedback because the average time taken between these locations was much shorter than the time required to process visual feedback

(Carlton, 1992). Rather, the findings support the proposal that different paths were being used to hit the target much earlier in the movement. This implies that while the decreased spatial variability is usually taken as evidence for an optimal path (e.g., Georgopoulos et al., 1981), the structure of variability reveals that there was not a single movement path with random fluctuations. This is also consistent with the findings of Carlton and Newell (1979), who showed that the inability to predict response outcome from the initial parts of the movement in discrete movements was indicative that variations were not simply due to random fluctuations. The general implication is that models of redundancy in motor control should not only account for changes in the amount of variability but also predict changes in the structure of variability with learning

Trial-dependence of paths

In addition to the time-dependent structure shown by the pattern of correlations, there was also evidence for sequential structure in the trial to trial relations. Movement paths from successive trials in a block were more similar (as measured by the RMSE) than two randomly chosen trials. This similarity indicates that instead of using completely different paths from trial to trial to achieve the task goal, there was a tendency to only slightly modify the movement path that was used on the previous trial.

The relation between previous and subsequent movements has been shown in other contexts. For example, Van der Wel, Fleckenstein, Jax, and Rosenbaum (2007) showed that there was a priming effect in hand movements in moving to a series of targets. When the hand had to move over an obstacle, subsequent movements were also higher compared to when there was no obstacle. In the present experiment, the dependence of the movement path on the previous trial indicates that that the exploration

of redundant solutions is not completely random, but instead may be reflective of a systematic search strategy (Gelfand & Tsetlin, 1971; Newell & McDonald, 1992). While previous research on trial-to-trial relations have focused on the analysis of a single score (e.g., Fine & Thoroughman, 2007; Spray & Newell, 1986), further research on trial-to-trial behavior of the movement pattern used may reveal characteristics of the particular search strategy used during the learning of redundant motor tasks.

Minimizing motor variability and exploring redundant solutions

Despite the evidence for utilizing redundant solutions, an important finding was that there was a decrease in spatial variability throughout the movement path, indicating that participants explored a smaller region of the potential solution space with learning. In other words, even though there was no requirement to reduce variability in the initial part of the movement (they only had to reduce variability enough to clear the obstacle), there was a tendency to decrease the overall spatial variability with practice. Several studies have reported a decrease in the goal-equivalent variability in redundant tasks even though reducing goal-equivalent variability has no effect on performance (Domkin, Laczko, Jaric, Johansson, & Latash, 2002; Mosier, Scheidt, Acosta, & Mussa-Ivaldi, 2005). One possible reason for these results is that there may be an optimization of other factors within the space of redundant solutions such as comfort or smoothness (Latash, 2008). There may also be other characteristics of the movement that are relevant to the task goal. For example, Mosier et al. (2005) showed that when the redundant motions of the fingers were mapped onto a two-dimensional cursor, participants started to produce rectilinear cursor trajectories with practice.

In the case of path redundancy, the reduction of overall spatial variability may also be relevant because of time-dependence. Unlike mechanical redundancy which can be defined at a particular time instant, path redundancy is defined by variability of spatial locations earlier in the movement to the variability at the end of the movement (more specifically, the location where variability matters to task performance). As a result, biomechanical factors may play an important role in influencing the amount of variability across the path. It has been shown that properties such as the inertia of the arm are taken into account when planning movements (Sabes, Jordan & Wolpert, 1998). Therefore, if there are large deviations from the average path during the early part of the movement, the inertia of the arm may cause any such deviations to persist and propagate further along the movement path, potentially leading to large errors or requiring large corrections.

In this context, the reduction in path variability during the initial part of the movement with learning may be an indication of the development of a ball park response (Greene, 1972). By using a ballistic phase in the initial part of the movement (Woodworth, 1899), the redundancy problem may be simplified as most of the trajectory/path is determined by the biomechanics of the system, obviating the need for explicit computation (Greene, 1982). Therefore, even if the motor system potentially has the ability to utilize redundant solutions, it may still be advantageous to minimize motor variability and not fully explore the range of redundant solutions.

In summary, we found that initial practice resulted in a decrease in the amount of spatial variability throughout the path. Extended practice resulted in a more task-relevant adjustment as indicated by a reduction in path variability only near the target. The

structure of variability also indicated that participants were actually using different solutions to achieve the task goal even after extended practice. These results are consistent with Bernstein's (1967) notion of repetition without repetition, and emphasize the need for examining the time-dependent and trial-dependent structure of variability in motor learning in understanding the redundancy problem.

CHAPTER 4: EMERGENT FLEXIBILITY IN MOTOR LEARNING

Abstract

We examined the effect of exploring redundant solutions during practice in enhancing the ability to flexibly use multiple solutions to achieve a task goal. Three groups used different degrees of path redundancy to perform a virtual interception task in which they attempted to hit a stationary target by moving around a stationary obstacle. The low-variability group always practiced with the same position of the obstacle on all trials; the medium-variability and high-variability groups practiced with the obstacle in different positions within a range of 1 cm and 2 cm respectively. After 8 blocks of practice, all participants were transferred to two tests: (a) a retention test where the condition was the same as that practiced by the low-variability group, and (b) a flexibility test where the condition was the same as that practiced by the high-variability group. Results showed that the low-variability group had the most accurate performance both in the retention and flexibility tests. The low-variability group showed the least path variability during the retention test but was also able to more effectively use different paths to hit the target during the flexibility test. It appears that flexibility in interceptive tasks is emergent from learning a particular task-relevant parameter related to the target location.

Introduction

In many task contexts where the objective is to achieve a desired task outcome, the ability to produce the specified outcome consistently and repeatedly is considered a hallmark of skilled performance. Conversely, performances with extremely variable outcomes are typically associated with low levels of skill. This inverse relationship between outcome variability and skill is consistent with the definition of skill as the ability to achieve a given outcome with maximum certainty and a minimum outlay of time or energy (Guthrie, 1935).

While definitions of skill place emphasis on reducing variability of the outcome, the role of movement variability in motor learning is less obvious. Several studies have shown that there is a decrease in movement variability with learning. In terms of the variability of the end-point trajectories in reaching, Georgopoulos, Kalaska, and Massey (1981) showed that there was a decrease in the spatial variability of trajectories with learning. Darling and Cooke (1987a) also showed in a single-degree of freedom task that the entire trajectory variability (considering both space and time) decreased with practice. Similar results have been reported in terms of the variability of joint kinematics (e.g., Jaric & Latash, 1999) and electromyographic patterns (e.g., Dugas & Marteniuk, 1989). This decrease in movement variability with learning has generally been taken as evidence for an optimization process.

However, there is also evidence that even highly skilled performers have variability in their movement pattern while achieving the same task goal (e.g., Arutyunyan, Gurfinkel, & Mirskii, 1969; Bootsma & van Wieringen, 1990). This pattern of findings has also been shown in well-learned movements such as speech, reaching and

grasping. For example, Darling and Cooke (1988) found that the variability of the kinematics of the finger and the thumb during grasping did not decrease with practice. However, these variations were not random; rather, the variations were organized so as to preserve the location of fingertip contact on the thumb. Similarly, in a postural task, Scholz and Schöner (1999) found that the variance in the joint angles that resulted in the center of mass being unchanged was much greater than the variance in the joint angles that led to changes in the center of mass.

The reason for the absence of a one-to-one relation between outcome variability and movement variability is the redundancy that is present in the human body due to the numerous degrees of freedom. Bernstein (1967) emphasized the notion of “repetition without repetition” (p.134), indicating how the task goal can be repeatedly achieved without repeating the details of the movement. For example, when two fingers act to produce a total force of 10 N, there can be variability at the level of the individual finger forces, but as long as there is negative covariation between the two finger forces, the goal of maintaining the total force at 10 N can still be achieved (Latash, Scholz, & Schöner, 2002). Thus, the redundancy in the system provides the system flexibility by allowing multiple options through which the task goal can be achieved.

An important issue in this regard is how flexibility is developed and whether flexibility can be enhanced through different practice schedules. From a specificity of practice notion (Henry, 1968; Proteau, 1992), constraining the participant to utilize multiple solutions during practice would facilitate flexibility. The contextual interference hypothesis (Battig, 1972; Shea & Morgan, 1979) also holds that the repeated use of the same solution may be detrimental to learning. From this hypothesis, practicing different

solutions from trial-to-trial may promote information processing and the active reconstruction of solutions that may enhance learning (Lee, 1991; Lee & Magill, 1983; Shea & Zimny, 1983). Similarly, the variability of practice hypothesis (Schmidt, 1975) holds that introducing variability into practice may facilitate the formation of a stronger rule (schema) between response parameters and outcome and lead to an enhanced ability to generate novel movement patterns.

However, flexibility might also be emergent, arising as a consequence of learning specific task parameters. For example, several studies of the equilibrium-point hypothesis show equifinality or the ability to return to the same final position even in the presence of transient perturbations (e.g., Kelso & Holt, 1980). This may be interpreted as flexibility in movement trajectory that arises from learning an equilibrium position. Studies on optimal feedback control have also found that flexible responses can be generated by setting up an optimal control policy where only deviations that are relevant to task performance are corrected (Todorov & Jordan, 2002). For example, Diedrichsen (2007) showed that the response to perturbations to a single arm in a bimanual task elicited corrections in both arms when the two hands shared a common cursor, but only in the perturbed hand when the two hands had separate cursors. Therefore, from a learning perspective, instead of directly working at the motor level and practicing different movement patterns, flexibility may be improved by using schedules that facilitate the learning of task-relevant parameters or control policies.

The aim of the present investigation was to examine whether flexibility could be enhanced by using different practice schedules that manipulated the degree to which redundant solutions were used during learning. In this case, we were interested in

redundancy at the level of the movement path when intercepting a virtual target on the screen. A secondary issue of interest was to examine if the performance in the flexibility test was related to changes in path variability during learning or the path variability in the retention test.

Methods

Participants

18 healthy volunteers (Mean age = 25 ± 2) years participated in the study. All participants had normal or corrected-to-normal vision. Participants provided informed consent and the procedures were approved by the Institutional Review Board at The Pennsylvania State University.

Equipment

A digitizing tablet and pen (WACOM Intuos A3, Saitama, Japan) were setup on a table in front of the participants. The sampling rate was set at 200 Hz. Visual feedback was provided using a 19 in. (48.2 cm) computer monitor was placed directly in front of the participant at a distance of 40 cm. The mapping between the tablet and the screen was set to 1:1 so that a movement of 1 cm of the pen on the tablet corresponded to a 1 cm movement of the cursor on the screen. (Figure 4.1).

Task

The task of the participants was a virtual interception task. The screen of the participants consisted of a start circle, two obstacles and the target as shown in Figure 4.2. The diameter of the target was 15 mm. Participants were seated on a chair so that when the participants placed their forearm level on the table, the elbow was approximately 90° in flexion. At the start of the trial, participants were asked to position

the cursor inside the start circle. Once the cursor was inside the start circle for 1 s, they heard a tone that indicated that they could initiate the movement. Participants then attempted to intercept the target circle with the cursor (i.e., they had to pass through the target, not stop inside the target) without hitting the obstacles. During the trial, participants could see the instantaneous position of the cursor that was indicated by a cross-hair. Each trial ended when the cursor passed 15 mm to the right of and beyond the target. Movement time was computed as the duration between the instant at which the participant first moved out of the start circle to the instant at which the trial ended.

The goal of the participants was to get as many hits of the target as possible. To qualify as a hit, two criteria had to be satisfied: (a) the trajectory of the cursor had to pass through the target, and (b) the movement time had to be in between 550 ms and 650 ms. At the end of each trial, if the trial was a hit, the target turned yellow in color and a counter at the bottom of the screen was incremented by 1. Also, visual feedback of the entire movement trajectory was shown (see Figure 4.2). In case participants hit the obstacle, then the path was only shown up to the point where the cursor hit the obstacle.

Bandwidth feedback was provided for the movement time. If the participants were too slow in completing the trial ($MT > 650$ ms), they heard a low-pitched beep and if participants were too fast ($MT < 550$ ms), a high-pitched beep was heard. In addition, if they crossed the gap between the obstacles too early (< 250 ms), the gap turned blue in color, and if they passed the gap too late (> 350 ms), the gap turned red in color. The constraint on the gap crossing time was only a soft constraint to control the velocity profile and participants could achieve a hit even if they did not satisfy this constraint.

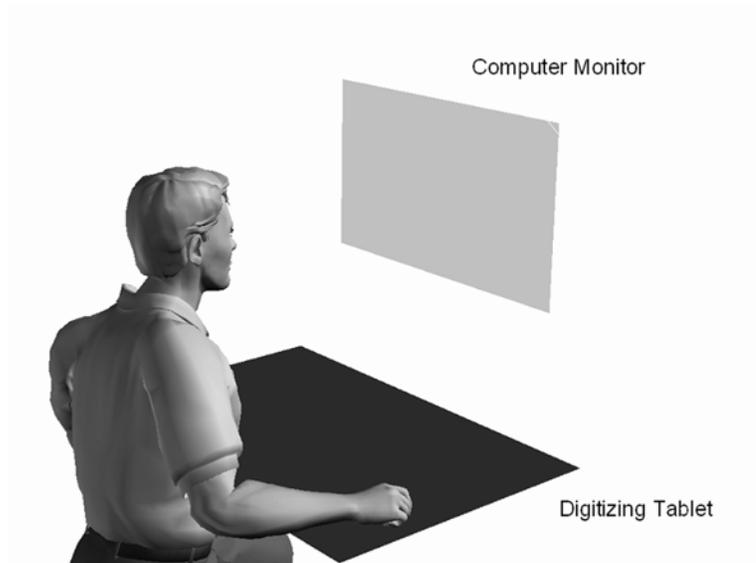


Figure 4.1. Schematic of the experimental setup.

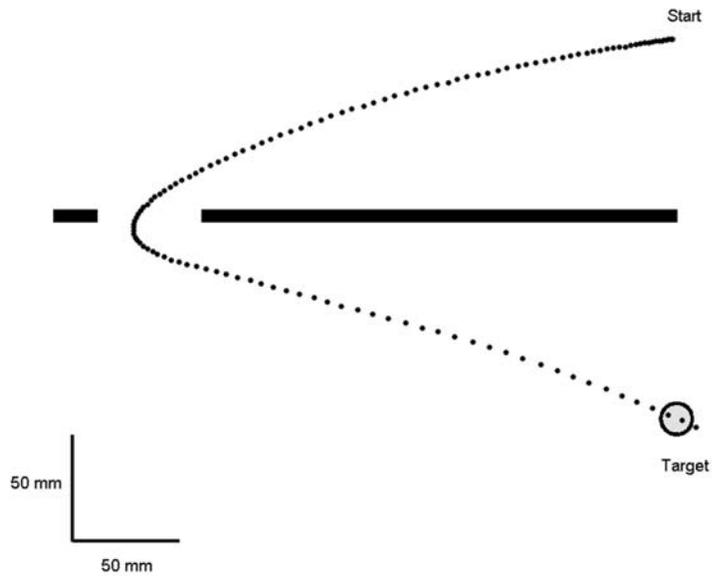


Figure 4.2. Schematic of the task. Participants started in the start circle at the top right and attempted to hit the target circle without hitting the obstacles in a time of 600 ± 50 ms. The dotted line indicates the feedback of the trajectory that the participants received at the end of every trial.

Procedures

Participants were split into three groups ($n = 6$) which differed in the amount of path variability required to perform the task. Initially we had a pre-test with the target and the obstacle and the different groups were matched for the number of hits they had on the pre-test (Figure 4.4). For the low-variability group, the obstacles always stayed in the same position for all trials. For the medium-variability group, the obstacles were in different positions from trial-to-trial. The horizontal and vertical position of the obstacles was selected randomly from a uniform distribution in the range of ± 1 cm. For the high-variability group, the horizontal and vertical positions were selected randomly from a uniform distribution in the range of ± 2 cm. After 8 blocks of 50 trials in the practice period, participants were transferred to two tests: (a) a retention test where the test condition was the same as that practiced by the low-variability group, and (b) a flexibility test where the test condition was the same as that practiced by the high-variability group. These tests were also repeated after 24-hr to assess if the effects were present on a longer time scale. The order of tests was counterbalanced with the constraint that two similar tests were not taken consecutively.

Data Analysis

Performance

The absolute error was used to quantify the performance in the task. The absolute error was calculated as the shortest distance from the edge of the target to the movement path. This meant that if the target was hit on a certain trial, the absolute error on that trial was zero.

Spatial variability of the path

Spatial variability within each block was determined by first computing the mean spatial path. The path on each trial was split into equidistant increments of 10% from the start of the trial until the point it reached the closest to the center of the target. These trials were averaged to compute the mean spatial path. At each spatial location along the path (in increments of 10%), the spatial variability was computed as follows: First, the normal to the path (i.e., the line orthogonal to the instantaneous slope) was generated at each spatial location. Second, the points on each path that were closest to the normals at each spatial location were selected. Because we were interested only in the path variability and not in temporal variations, we used a cubic spline to interpolate the path to find the closest point to the normal on each path. Essentially, this meant that almost all the variations were on the dimension along the normal. Finally, the distribution of points was fitted with an ellipse using a principal component analysis. The square root of the first eigenvalue was taken as an index of the spatial path variability at that particular spatial location. If a path had points that were outside 3 standard deviations at any location on the spatial path, that trial was excluded from the analysis.

Results

Inclusion criteria

All trials that did not hit the obstacle and had a movement time between 500-700 ms were included in the analysis. This resulted in an average inclusion rate of 84% during practice and 90% during the transfer tests. There were no significant differences between groups on the number of accepted trials. Examples of the movement paths of a typical participant in each of the different groups are shown in Figure 4.3. The

percentage of hits in each block is shown in Figure 4.4. The movement time between the groups was not significantly different.

Performance

Practice. There was a significant main effect of block, $F(7,105) = 18.74, p < .001$ during practice. Post hoc comparisons revealed that the absolute error in Block 8 was lower compared with Block 4 and Block 1. Block 4 also had a lower absolute error compared with Block 1 (Figure 4.5). There was also a significant main effect of group, $F(2,15) = 9.48, p = .002$. Post hoc comparisons showed that the high-variability group had greater absolute error than both the low-variability and the medium-variability groups.

Retention. There was a significant main effect of group, $F(2,15) = 5.71, p = .014$ on the retention tests. The effects of day and the Day \times Group interaction were not significant. Post hoc comparisons indicated that the high variability group had greater absolute error compared to the low variability group (Figure 4.6).

Flexibility. There was a significant main effect of group, $F(2,15) = 7.93, p = .004$ on the flexibility test. The effect of the day and the Day \times Group interaction were not significant. Post hoc comparisons again indicated that the high variability group had greater absolute error compared to the low variability group (Figure 4.6)

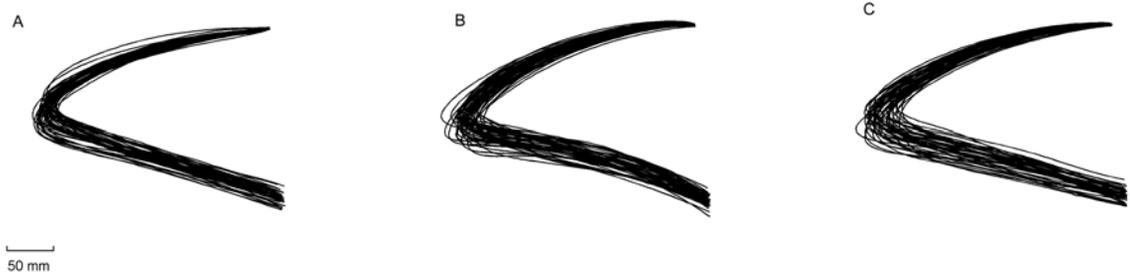


Figure 4.3. Exemplar movement paths from a typical subject in the last block of practice in the: (A) Low-variability group, (B) Medium-variability group and (C) High-variability group.

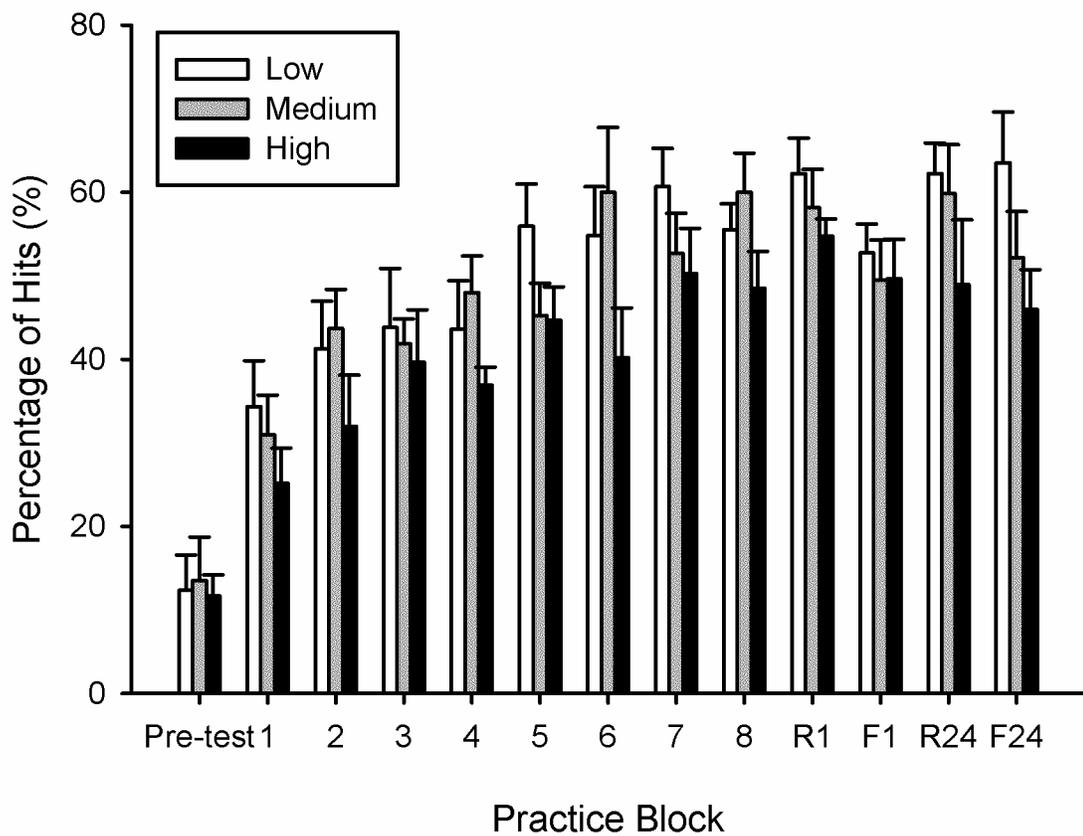


Figure 4.4. Percentage of hits in the pre-test, practice and during the retention and flexibility tests for the three groups. R1 = Immediate retention test, F1 = Immediate flexibility test, R24 = 24-hr retention test, F24 = 24-hr flexibility test. Error bars represent one standard error.

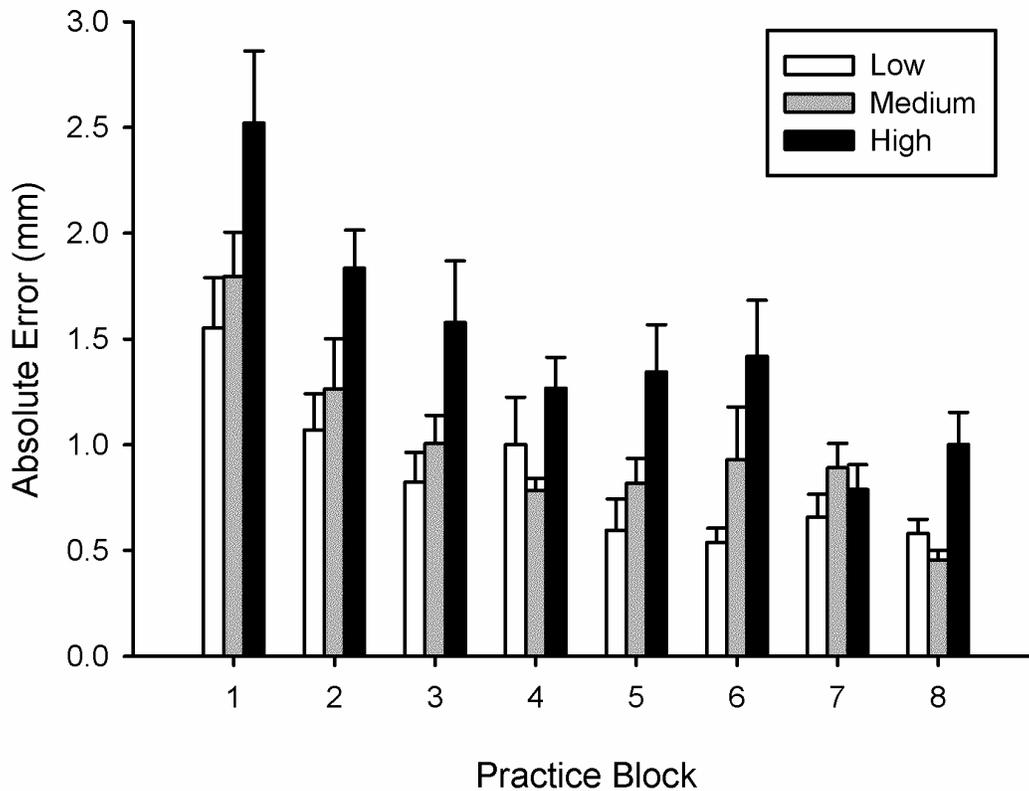


Figure 4.5. Absolute error during practice for the three groups. Error bars represent one standard error.

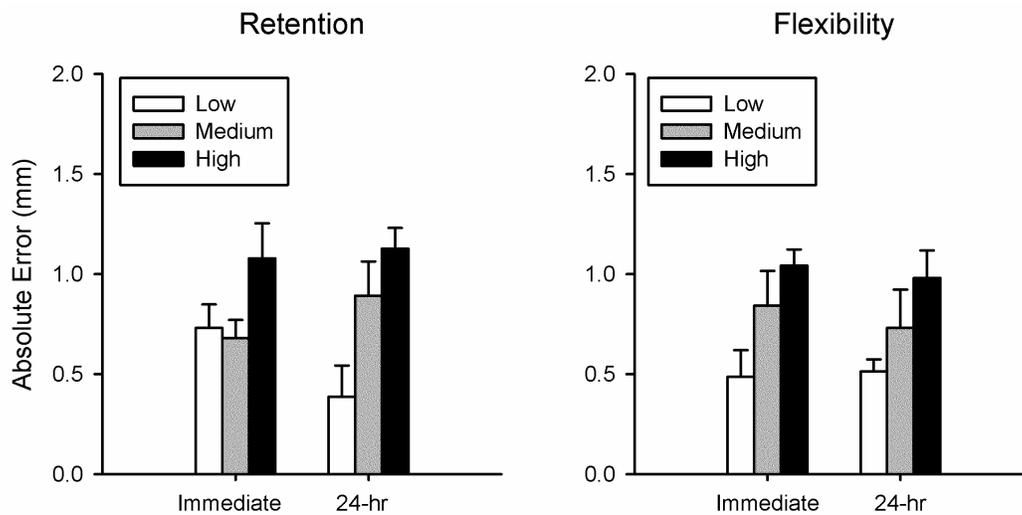


Figure 4.6. Absolute error on the retention and flexibility tests for the three groups. Error bars represent one standard error.

Spatial variability

Practice. The three groups were analyzed separately on how they changed from block 1 to block 8 at three different locations in the movement path – the start, the mid-point and near the target (at 0%, 50% and 100%). The low-variability group showed a significant decrease in spatial variability at the start and the mid-point of the path ($ps < .05$) and the change in variability near the target was marginally significant ($p = .08$). The medium-variability group showed a significant decrease in variability at the start and near the target ($ps < .05$) but no change at the mid-point. The high-variability group showed a significant decrease only near the target (see Figure 4.7)

An 11 x 3 (Spatial location x Group) mixed-model ANOVA was used to compare the groups at the last block of practice. The within-subject factor was spatial location (from 0% to 100% in increments of 10%) and the between-subject factor was group. There was a significant main effect of spatial location, $F(2.7, 40.4) = 139.31, p < .001$, and group, $F(2,15) = 21.2, p < .001$, that was mediated by a significant Group \times Spatial location interaction, $F(5.4,40.4) = 4.94, p < .001$. Post hoc comparisons showed that the spatial variability of the high-variability group was higher than both the low-variability and the medium-variability groups from the start of the path until 80% into the path. Additionally, the variability of the medium-variability group was lower than the high-variability group at 40% into the path. At 50% into the path, all three groups were significantly different from each other with the low-variability group having the lowest spatial variability and the high-variability group having the highest spatial variability. These effects essentially confirmed that the manipulation of the obstacle position had the desired change in the spatial variability of the movement paths.

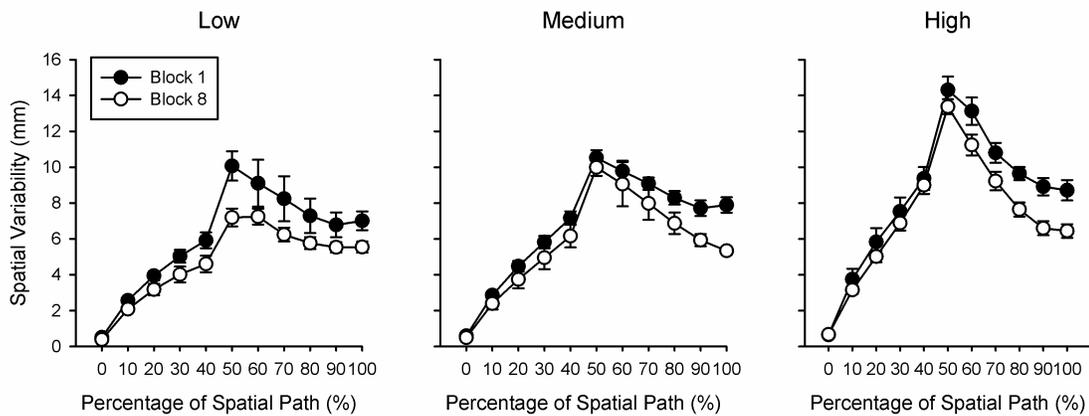


Figure 4.7. Spatial variability during the first block and the last block of practice for the: (A) Low-variability, (B) Medium-variability and (C) High-variability groups. Error bars represent one standard error.

Retention. In the immediate retention test there was a significant main effect of spatial location, $F(2.4, 36.4) = 102.47, p < .001$ and group, $F(2,15) = 5.20, p = .019$.

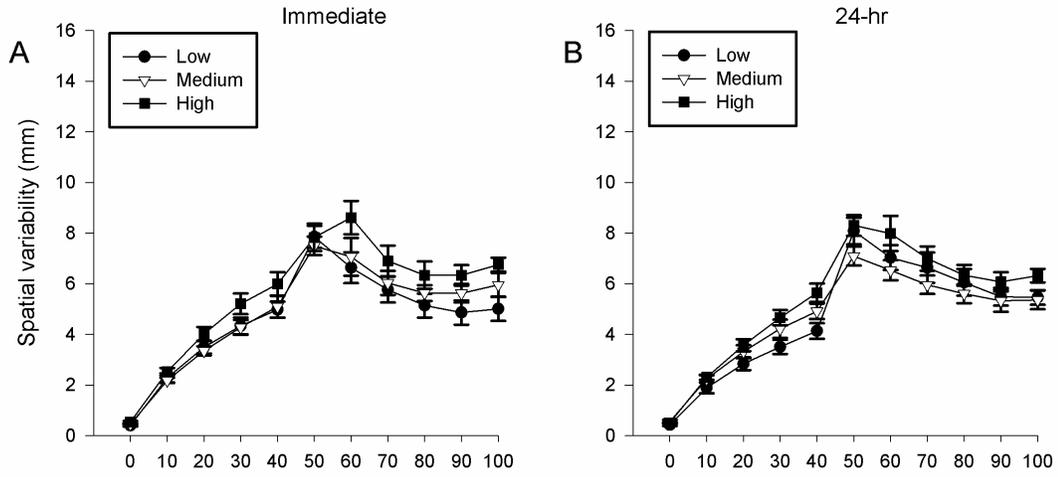
Post hoc comparisons showed that the spatial variability of the high-variability group was higher than both the low- and medium-variability groups (Figure 4.8A). The results were similar in the retention test after 24-hr. There was a significant main effect of spatial location, $F(3.5, 52.6) = 163.75, p < .001$, and group that was close to significance, $F(2,15) = 2.88, p = .089$. Post hoc comparisons indicated that the high-variability group tended to have higher spatial variability than the other two groups (Figure 4.8B).

Flexibility. In the immediate flexibility test there was a significant main effect of spatial location $F(3.18, 47.7) = 174.67, p < .001$, and group, $F(2,15) = 7.71, p = .005$.

Post hoc comparisons indicated that the high-variability group had higher spatial variability than the low-variability group. However, when the groups were compared at

the point of maximum spatial variability, there was no significant difference ($p = .813$) (Figure 4.8C). After 24-hr, the results were similar. There was a main effect of spatial location, $F(2.95, 44.17) = 258.43, p < .001$, and group, $F(2, 15) = 4.82, p = .024$. Post hoc comparisons again showed that the high-variability group had higher spatial variability than the low-variability group. Once again the comparison of groups at the point of maximum spatial variability was not significant ($p = .908$) (Figure 4.8D)

Retention



Flexibility

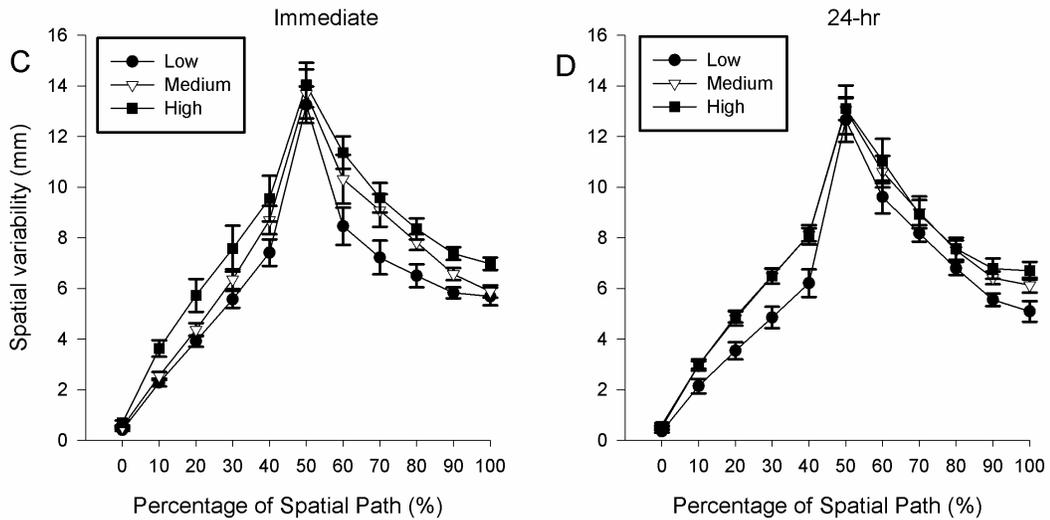


Figure 4.8. Spatial variability across the path during: (A) Immediate retention (B) 24-hr retention, (C) Immediate flexibility and (D) 24-hr flexibility tests. Error bars represent one standard error.

Discussion

The purpose of the current study was to examine if the ability to use redundant paths to hit the same target was influenced by the degree to which path redundancy was used during practice. A secondary issue that we examined was if the movement variability during learning and the retention tests was predictive of performance in the flexibility test. These questions are important to understanding the adaptive use of redundancy (Bernstein, 1967) in motor learning.

Enhancing flexibility

We compared three groups that differed in the extent to which path redundancy was used (as measured by the spatial variability in the middle of the path) during practice to examine the effectiveness of practicing multiple solutions in learning. In all the analyses, the medium-variability group tended to lie in between the low- and high-variability groups. Therefore, for the sake of brevity, the following discussion will focus only on the comparison between the low-variability and high-variability groups.

The analysis of absolute error during practice blocks showed that all three groups were able to decrease the error at the target, though the high-variability group tended to have more error compared to the other two groups. In the retention tests, the low-variability group had the best performance in terms of the accuracy of hitting the target. The analysis of the spatial variability in the retention test showed that the low-variability group had lower spatial variability throughout the movement path compared to the high-variability group. These findings are consistent with the predictions from the specificity of practice hypothesis (Proteau, 1992).

Surprisingly, in the flexibility tests, the low-variability group outperformed the high-variability group. This finding is counter-intuitive because the high-variability group had practiced this condition for 400 trials whereas the low-variability group did not practice this condition even once prior to the test. In terms of spatial variability, the low-variability group showed lower spatial variability than the high-variability group except at the point near crossing the obstacle, indicating that it was able to increase spatial variability to adapt to the different positions of the obstacle while still being able to hit the target.

The high repeatability in intercepting the target location in spite of variation in the intermediate positions of the movement path is consistent with the equilibrium-point (EP) hypothesis of motor control (Asatryan & Feldman, 1965; Feldman, 1966). In the EP hypothesis, learning to intercept a target at a particular location requires only learning a single equilibrium position. In fact, these results from the flexibility tests are consistent with an earlier study on spinal frog reflexes (Berkinblit, Feldman, & Fukson, 1986; Fukson, Berkinblit, & Feldman, 1980) that showed that spinal frogs were able to wipe off nociceptive stimuli using their hind limbs in different body configurations even though the movement trajectories and paths taken by the hind limb were completely different.

The inference is that the ability to utilize redundant solutions may be emergent, arising as a consequence of learning a particular task-parameter related to the target position. The evidence that the target position was better learned in the low-variability group is seen from the lower absolute error both during practice and the retention tests. In other words, the variation in obstacle position in the high-variability group contributed to an inability to learn the target position. Therefore, an important finding is that while

experts are able to utilize redundant solutions (Bernstein, 1967), directly forcing the utilization of redundant solutions during practice is not effective practice strategy as it may interrupt the learning of task-relevant parameters. Instead, practice that facilitates learning of critical task-parameters may result in greater ability to effectively use redundant solutions.

Synergies and task context

The results are also relevant to the notion of synergies based on the amount of covariation between different motor elements in producing a common task output. Once movement variability is partitioned into goal-equivalent and goal-relevant variability (Schöner, 1995; Scholz & Schöner, 1999; Latash et al., 2002), the strength of the synergy is quantified using a variable that measures the goal-equivalent variance relative to the goal-relevant variance (usually computed as a ratio or a difference). The assumption is that a comparatively higher goal-equivalent variance is reflective of the stabilization of a particular task variable.

In the present study, the low-variability group showed a decrease in the spatial variability throughout the movement path even though only spatial variability near the target is relevant to task performance. This is consistent with studies that have shown a decrease in overall spatial variability in the movement path with learning (Georgopoulos et al., 1981) and that learning causes decreases in both goal-relevant and goal-equivalent variability even though decreasing goal-equivalent variability has no effect on task performance (e.g., Domkin, Laczko, Jaric, Johansson, & Latash, 2002; Yang & Scholz, 2005). Similarly, in the retention tests, the low-variability group had the lowest path variability. However, when the task-context was changed in the flexibility tests where

there was a requirement to utilize multiple movement paths for successful performance, the low-variability group was able to adapt to the change in obstacle position and hit the target with high accuracy.

These results emphasize that the observed movement variability cannot be used to directly make inferences about the system without considering the task context. If the task context does not explicitly require the utilization of particular redundant solutions for successful performance, even a flexible system that is capable of utilizing redundant solutions may choose a strategy of low movement variability, leading to a decrease in both goal-equivalent and goal-relevant variability. However, as the results of the present study show, the reduction in movement variability may only be indicative of the preferred solution space of the system, not the solution space it is potentially capable of exploiting. Therefore, a decrease in the synergy strength with practice (e.g., Domkin et al., 2002) need not necessarily imply that certain task variables are being destabilized or that the system loses the ability to utilize redundant solutions. Rather these findings may indicate the existence of preferred solution spaces within the entire solution space.

The importance of task context in influencing the amount and structure of movement variability has been shown in the study of other motor control issues. For example in the investigation of center-of-pressure (COP) in standing posture, Van Wegen et al. (2002) found that young and old adults did not differ significantly in the amount of COP variability when standing normally. However, when the participants were asked to lean close to the edge of the base of support, young adults were able to reduce COP variability whereas older adults increased COP variability. Similarly, in terms of the time-dependent structure of variability, where more unpredictability is considered

reflective of a healthy system, Vaillancourt and Newell (2003) showed that young adults had higher unpredictability than older adults when producing a constant force waveform, but had lower unpredictability than older adults when producing a sinusoidal waveform (also see Sosnoff & Voudrie, 2009). These results indicate that movement variability is adapted according to the task requirements, and consequently the degree to which redundancy is exploited is dependent on the task context. A flexible system may utilize a greater range of redundant solutions only when the task constraints limit the ability to repeatedly use a preferred set of solutions.

In summary, we found evidence that flexibility to use redundant solutions to accomplish a task goal is an emergent property of learning a particular task-relevant parameter. Using practice schedules that directly require the utilization of redundant solutions may not be effective in improving flexibility as the induced variability could interfere with the learning of the task-relevant parameter. Finally, inferences about stabilization of task variables or the flexibility of the system that are based on analyzing movement variability need to be made in an appropriate task context because the preferred behavior of the system may not reflect the potential capability of the system.

CHAPTER 5: MOTOR LEARNING THROUGH INDUCED VARIABILITY AT THE TASK GOAL AND EXECUTION REDUNDANCY LEVELS

Abstract

We examined the influence of introducing variability at different levels of the task in the learning of an interception task. Variability at the task goal level was introduced by changing target location whereas variability at the execution redundancy level was introduced by using an intermediate target that constrained participants to use different paths from trial to trial to intercept the same target. After practice, participants were transferred to two test conditions: (a) a retention test, where the position of the target was unchanged, and (b) a generalization test, where the position of the target was varied from trial to trial. The results from the manipulation at the task goal level were consistent with predictions from the specificity of practice hypothesis. In both the retention and generalization tests, the group that practiced in the test condition had the best performance. At the execution redundancy level, practicing multiple solutions to achieve the task goal did not improve performance in either the retention or generalization tests. These results show that introducing variability at the task goal and execution redundancy levels has different effects on retention and generalization and practice schedules that constrain the participant to use redundant solutions may not facilitate learning.

Introduction

The design of practice schedules to facilitate learning is an important issue in motor learning. There are several dimensions along which this problem has been studied, including distribution of practice (e.g., Adams & Reynolds, 1954), feedback information (e.g., Annett, 1959), and variability in practice (e.g., Schmidt, 1975). In particular, the issue of introducing variability in practice is critical because it directly relates to the notion of generalization, or how we adapt the movement pattern to perform in a wide variety of situations and contexts that may or may not have been experienced before. With regard to introducing variability in practice, there are two general and contrasting hypotheses that are applicable to motor learning: (a) the specificity of practice hypothesis (Proteau, 1992) and (b) the variability of practice hypothesis (Schmidt, 1975).

The specificity of practice hypothesis (Henry, 1968; Proteau, 1992) holds that practice should be specific to the conditions in which performance is required. For example, in an open skill such as playing tennis or soccer that inherently requires the ability to produce variable outcomes, the specificity of practice hypothesis predicts that using a practice schedule that incorporates these variations would facilitate learning. On the other hand, in a closed skill such as basketball free throw shooting or dart throwing that requires no variation in motor output for successful task performance, the prediction would be that learning is facilitated by a practice schedule with no externally induced variability.

In contrast, the variability of practice hypothesis based on the schema theory of motor learning (Schmidt, 1975) proposes that variability is not only important for learning of open skills, but may even facilitate the learning of closed skills (such as

basketball free throw shooting). The rationale behind the variability of practice hypothesis was that introducing task goal variations creates a stronger rule (schema) between response parameters and task outcome and this leads to enhanced learning and facilitates the ability to generalize to conditions that have not been previously experienced. Several studies have supported the claims of the variability of practice hypothesis (for reviews, see Shapiro & Schmidt, 1982, Wulf & Schmidt, 1997; although see van Rossum, 1990).

A related idea about introducing task-variation in learning is that of contextual interference (Battig, 1972; Shea & Morgan, 1979). The contextual interference hypothesis holds that in addition to task variation, the order in which task variation is introduced is influential in facilitating learning. In particular, creating variation from trial to trial (random practice) may be more beneficial than having a block of trials on one task followed by a block of trials on another task. The hypothesis behind the contextual interference effect has been that changing the task from trial to trial may enhance active reconstruction of solutions (Lee & Magill, 1983) or allow the participant to compare and contrast different solutions that may enhance memory representation (Shea & Zimny, 1983) (for reviews of the contextual interference effect, see Magill & Hall, 1990, Wulf & Shea, 2002).

One of the critical features is that the aforementioned studies on variable practice have primarily focused on the task outcome or discrete measures such as the relative timing and relative force. The consequence is that there has been very little systematic examination of how variable practice influences the learning of the movement pattern. In the context of the redundancy problem (Bernstein, 1967), skilled performance can either

result from a decrease in movement variability or by exploiting the redundancy available in the task. An open question, however, is whether variable practice creates a more optimized movement pattern with low variability, or whether it leads to exploiting more of the redundancy that is available in the task.

It is important to recognize that variability can be introduced at different levels of the task. Typically, variable practice derived from schema theory has introduced variability in the outcome or the level of the task goal. This is because schema theory assumes a one-to-one relation between response parameters and response outcome. However, given that the human body is highly redundant and has more degrees of freedom than required to perform most tasks (Bernstein, 1967), there exist multiple ways to achieve the same outcome. Therefore, variability can also be introduced at the level of execution redundancy, where there is no change in the intended outcome or task goal, but variation is introduced in how the task goal is achieved from trial-to-trial.

For example, consider the redundant task of using two fingers to produce a discrete pulse of force so that the peak total force is 10 N (Latash, Scholz, & Schöner, 2002). At the task goal level, variability could be introduced by changing the total force level from 8 N through 12 N. This would be similar to a variable practice schedule derived from schema theory. At the execution redundancy level, variability could be introduced so that participants use different combinations of finger forces on each trial to reach 10 N. So, if the finger forces are represented as (F_1, F_2) , then introducing variability at the execution redundancy level would involve practicing combinations like $(5, 5)$, $(6, 4)$, $(4, 6)$, $(7, 3)$ and so on.

In view of this distinction between levels of task goal and execution redundancy, the question arises as to whether a practice schedule that involves utilizing redundant solutions facilitates learning. A number of studies indicate experts are able to utilize the redundancy available in the task (Arutyunyan, Gurfinkel, & Mirskii, 1969; Bernstein, 1967; Bootsma & Van Wieringen, 1990). However, there has been little investigation into whether practicing redundant solutions benefits learning. In this context, Schöllhorn and colleagues (Schöllhorn, 1999; Schöllhorn, Beckmann, Michelbrink, Trockel, Sechelmann, & Davids, 2006) proposed a practice schedule termed differential learning in which variability is added to the movement during training to facilitate individuals to find their own optimal performance. However, similar to studies on variable practice, the effectiveness of differential learning has been measured through only the outcome score and there is little information on the variability of the movement pattern with respect to exploiting redundancy in the task.

In this study, we addressed the following two questions in the learning of an interception task: (a) how does induced variability at the task goal level influence variability of the movement, and (b) does induced variability at the execution redundancy level (i.e., utilizing redundant solutions) during practice facilitate learning? In addition to the outcome scores, we analyzed the variability of the movement path to examine the degree to which different spatial paths were being used to intercept the target.

Methods

Participants

32 healthy volunteers (M age = 26 ± 4 years) participated in the study. All participants were right-hand dominant and had normal or corrected-to-normal vision.

Participants provided informed consent and the procedures were approved by the Institutional Review Board at The Pennsylvania State University.

Equipment

A digitizing tablet and pen (WACOM Intuos A3, Saitama, Japan) were setup on a table in front of the participants. The height of the chair was set so that when the participants placed their forearm level on the table, the elbow was approximately 90° in flexion. The digitizing tablet sampled the pen positions at 200 Hz. A 19 in. (48.2 cm) computer monitor was placed directly in front of the participant at a distance of 40 cm. The mapping between the tablet and the screen was set to 1:1 so that a movement of 1 cm of the pen on the tablet corresponded to a 1 cm movement of the cursor on the screen. (Figure 5.1).

Task

The task of the participants was a virtual interception task. The screen of the participants consisted of a start circle, two obstacles and the target as shown in Figure 5.2A. The target circle had a diameter of 15 mm. At the beginning of each trial, participants were asked to position the pen on the tablet so that the cursor was inside the start circle. Once inside the start circle for 1 s, they heard a start tone. Participants then proceeded to make a movement with the goal of intercepting the target with the cursor without hitting the obstacles. During the trial, participants could see the instantaneous position of the cursor which was indicated by a cross-hair. Each trial ended when the cursor passed 15 mm to the right of the target. Movement time was computed as the duration between the instant at which the participant first moved out of the start circle to the instant at which the trial ended.

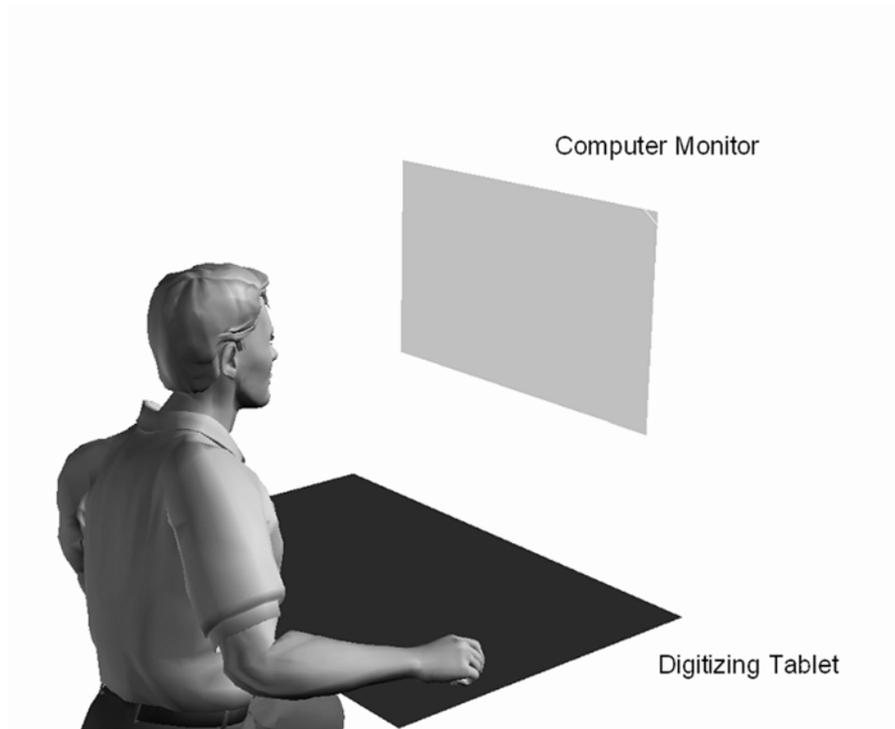


Figure 5.1. Schematic of the experimental setup. Participants held a pen in their hand to draw on the digitizing tablet.

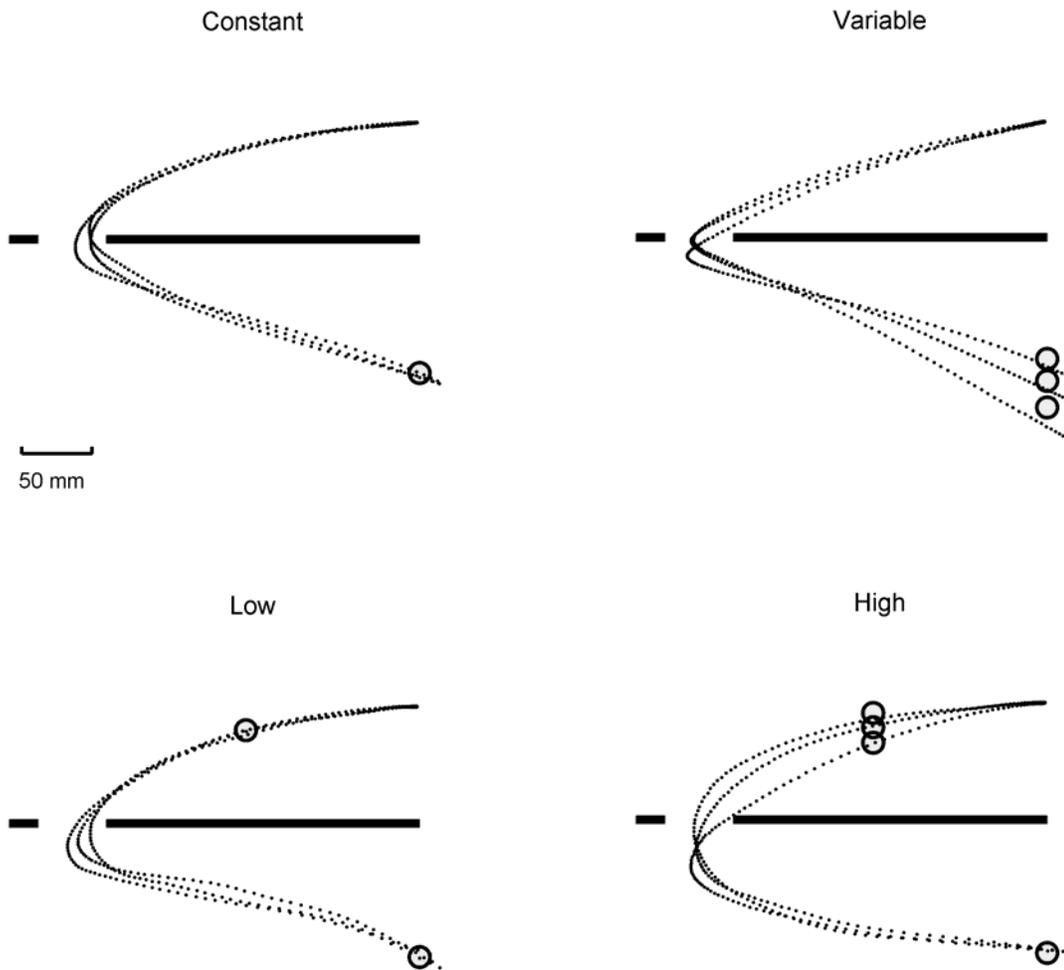


Figure 5.2. Exemplar trials from one participant in each of the four groups during the last block of practice. The constant group practiced with the same position of the target on all trials. The variable group had the target in different positions from trial to trial in the vertical direction. The low-redundancy group had an intermediate target that was always in the same position. The high-redundancy group had the intermediate target in different positions from trial to trial in the vertical direction.

The goal of the participants was to get as many hits of the target as possible. To qualify as a hit, two criteria had to be satisfied: (a) the trajectory of the cursor had to pass through the target, and (b) the movement time had to be between 550 ms and 650 ms. At the end of each trial, if the trial was a hit, the target turned yellow in color and a counter at the bottom of the screen was incremented by 1. Also, at the end of each trial, the movement trajectory of the pen during the whole trial was shown (see Figure 5.2). However, if the participants hit the obstacle, then the trajectory was only shown up to the point where the cursor hit the obstacle.

Movement time was controlled using bandwidth feedback. Participants heard a low-pitched beep if they were too slow ($MT > 650$ ms) and heard a high-pitched beep if they were too fast ($MT < 550$ ms). In addition, if they crossed the gap between the obstacles too early (< 250 ms), the gap turned blue in color, and if they passed the gap too late (> 350 ms), the gap turned red in color. The constraint on the gap crossing time was only a soft constraint to control the velocity profile and participants could achieve a hit even if they did not satisfy this constraint.

Procedures

Participants were split into four groups ($n = 8$) after an initial pre-test so that the pre-test scores of the four groups were approximately equal. The constant group practiced the task with no variation in the position of the target. For the variable group, the y-position of the target was different on each trial and was picked randomly from a uniform distribution in the range of ± 4 cm. For the low-redundancy group, there was an intermediate target of diameter 15 mm. The x-position of the intermediate target was at the midpoint between the start circle and the middle of the gap. The y-position of the

intermediate target was adjusted so that it matched the average path of the constant group. Finally, for the high-redundancy group, the mean y-position of the intermediate target was the same as the low-redundancy group but the y-position was varied randomly from trial to trial in the range of ± 2 cm. Exemplar trials from all four groups are shown in Figure 5.2.

After 8 blocks of 50 trials in the acquisition period, participants in all four groups were transferred to two test conditions: (a) a retention test where the test condition was the same as that practiced by the constant group, and (b) a generalization test where the test condition was the same as that practiced by the variable group. These tests were also repeated after 24-hr to assess more long-term effects. The order of tests was counterbalanced with the constraint that two similar tests were not taken consecutively.

Data Analysis

Performance

Performance was analyzed using the absolute error. The absolute error was computed as the shortest distance from the edge of the target to the movement path. This meant that the absolute error for trials where the target was hit was zero.

Spatial variability of the path

Spatial variability within each block was computed by first computing the average spatial path. Each trial was split into increments of 10% from the start of the trial until the point it reached the closest to the center of the target. These trials were averaged to compute the mean spatial path. At each location along the path (in increments of 10%), the spatial variability was computed as follows: First, the line orthogonal to the instantaneous slope of the mean spatial path (i.e., the normal) was generated at each

spatial location. Second, the points on each movement path that were closest to the normals were selected. Because we were interested only in the path variability and not in temporal variations, we used a cubic spline to interpolate the path to find the closest point to the normal on each path. Essentially, this meant that almost all the variation was on the dimension along the normal. Finally, the distribution of points was fitted with an ellipse using a principal component analysis. The square root of the first eigenvalue was taken as an index of the spatial path variability at that particular spatial location. If a path had points that were outside 3 standard deviations at any location on the spatial path, that trial was excluded from the analysis.

Correlation

To examine changes in the structure of variability, we computed the correlation between points on adjacent locations in the path. For example, points on the normal at 10% of the spatial path were correlated with points on the normal at 20% of the spatial path. Similar to the spatial variability, any path that was outside 3 standard deviations at any location was excluded from the analysis.

Statistical Analysis

All performance variables during practice were analyzed using an 8 x 4 (Block x Group) ANOVA. Performance measures for the retention and generalization tests were analyzed using a 2 x 4 (Delay x Group) mixed-model design. The within-participant factor was delay (Immediate, 24-hr) and the between-participant factor was practice group.

Results

Performance

Practice. During the practice blocks, there was a significant main effect of block, $F(2.05, 57.39) = 18.68, p < .001$, and group, $F(3, 28) = 5.72, p = .004$. Post hoc comparisons showed that Block 8 had lower absolute error than Block 4 which in turn had lower absolute error than Block 1. The variable group had higher absolute error than the constant and the low-redundancy groups (Figure 5.3).

Retention. There was a significant Delay \times Group interaction, $F(3, 28) = 3.16, p = .042$. Post hoc comparisons showed that there was a significant difference between constant and variable groups on the immediate retention test, whereas there were no significant differences on the 24-hr retention tests (Figure 5.4A)

Generalization. There were significant main effects of delay, $F(1, 28) = 18.13, p < .001$, and group, $F(3, 28) = 6.20, p = .002$, that were mediated by a significant Delay \times Group interaction, $F(3, 28) = 3.61, p = .025$. Post hoc comparisons showed that the variable group had the best performance on both days. The low and high-redundancy groups were not significantly different from the constant group on the immediate generalization test, but were significantly different on the 24-hr generalization test. (Figure 5.4B)

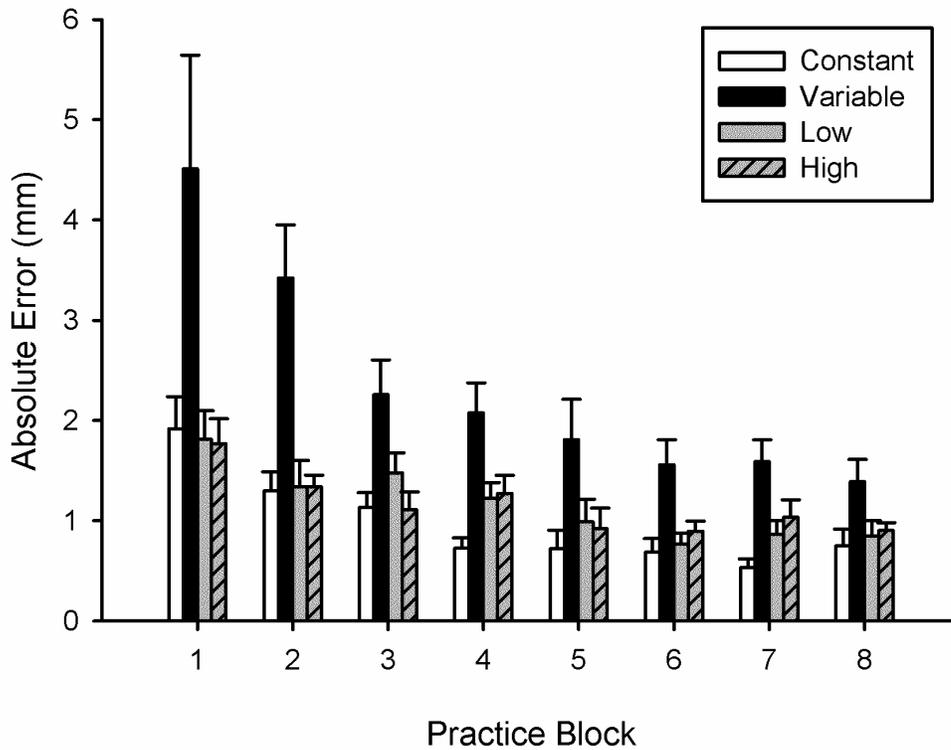


Figure 5.3. Absolute error during practice for all four groups. Error bars represent one standard error.

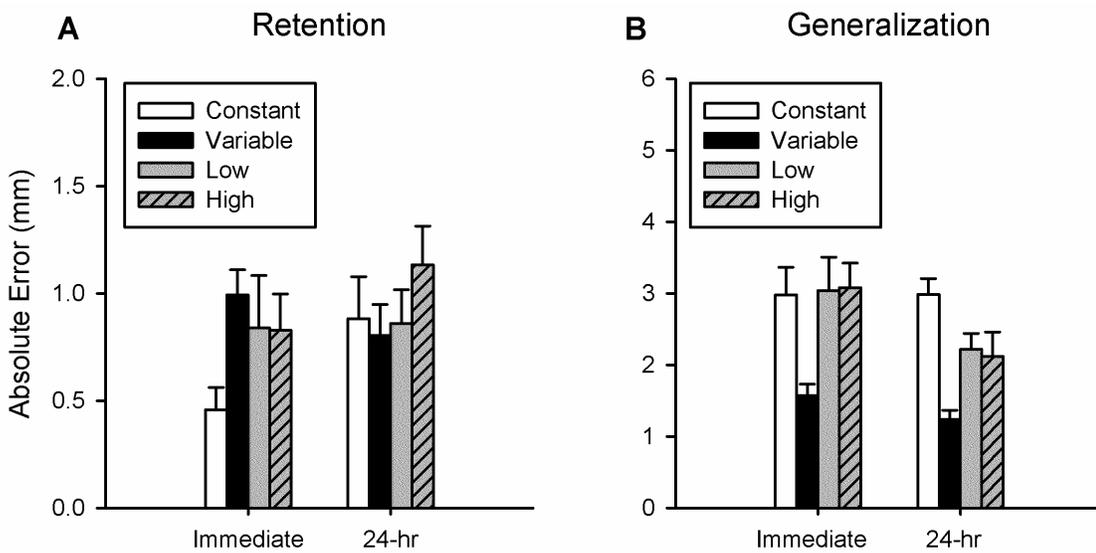


Figure 5.4. Absolute error of the four groups on: retention, and (B) generalization tests. Error bars represent one standard error.

Spatial variability

The spatial variability of the four groups in practice, retention and generalization tests is shown in Figure 5.5. In order to compare the spatial variability, we ran separate ANOVAs at each spatial location from 0% to 100%. Each of these ANOVAs was set at a level of .05 and the between-group comparisons were done using the Tukey test. The results of the post hoc comparisons are summarized in Table 5.1.

Table 5.1.

Summary of group comparisons of spatial variability at different locations on the movement path on the last block of practice, the retention tests and the generalization tests. C = Constant, V = Variable, L = Low-redundancy, H = High-redundancy. n.s. = non-significant

% of spatial path	Practice	Retention		Generalization	
		Immediate	24-hr	Immediate	24-hr
0%	n.s.	n.s.	n.s.	n.s.	n.s.
10%	H > C, L, V	n.s.	H > C	n.s.	n.s.
20%	H > C, L, V	n.s.	H > C	n.s.	n.s.
30%	H > C, L, V	n.s.	n.s.	n.s.	n.s.
40%	H > C, L, V	n.s.	n.s.	n.s.	n.s.
50%	n.s.	n.s.	L > C	n.s.	n.s.
60%	n.s.	n.s.	n.s.	n.s.	n.s.
70%	n.s.	n.s.	n.s.	n.s.	n.s.
80%	V > C, L, H	n.s.	n.s.	n.s.	V > L
90%	V > C, L, H	n.s.	n.s.	V > C, L	V > C, L; H > L
100%	V > C, L, H	V > C	n.s.	V > C, L, H	V > C, L, H

Correlation between target position and error

In the generalization tests, we computed a regression between the constant error on each trial against the y-position of the target. The constant error was computed only along the vertical dimension from the center of the target. A negative slope indicates that high targets were missed low and low targets were missed high. The results showed a main effect of block, $F(1, 28) = 12.34, p = .002$. The slope on the 24-hr generalization test was less negative than the slopes on the immediate generalization test. There was also a significant main effect of group, $F(3, 28) = 8.13, p < .001$, with the slopes in the variable group being significantly less negative than the other three groups (Figure 5.6A). The average R^2 values in the regression for the constant, variable, low-redundancy and high-redundancy groups were 0.44, 0.13, 0.41 and 0.35, respectively.

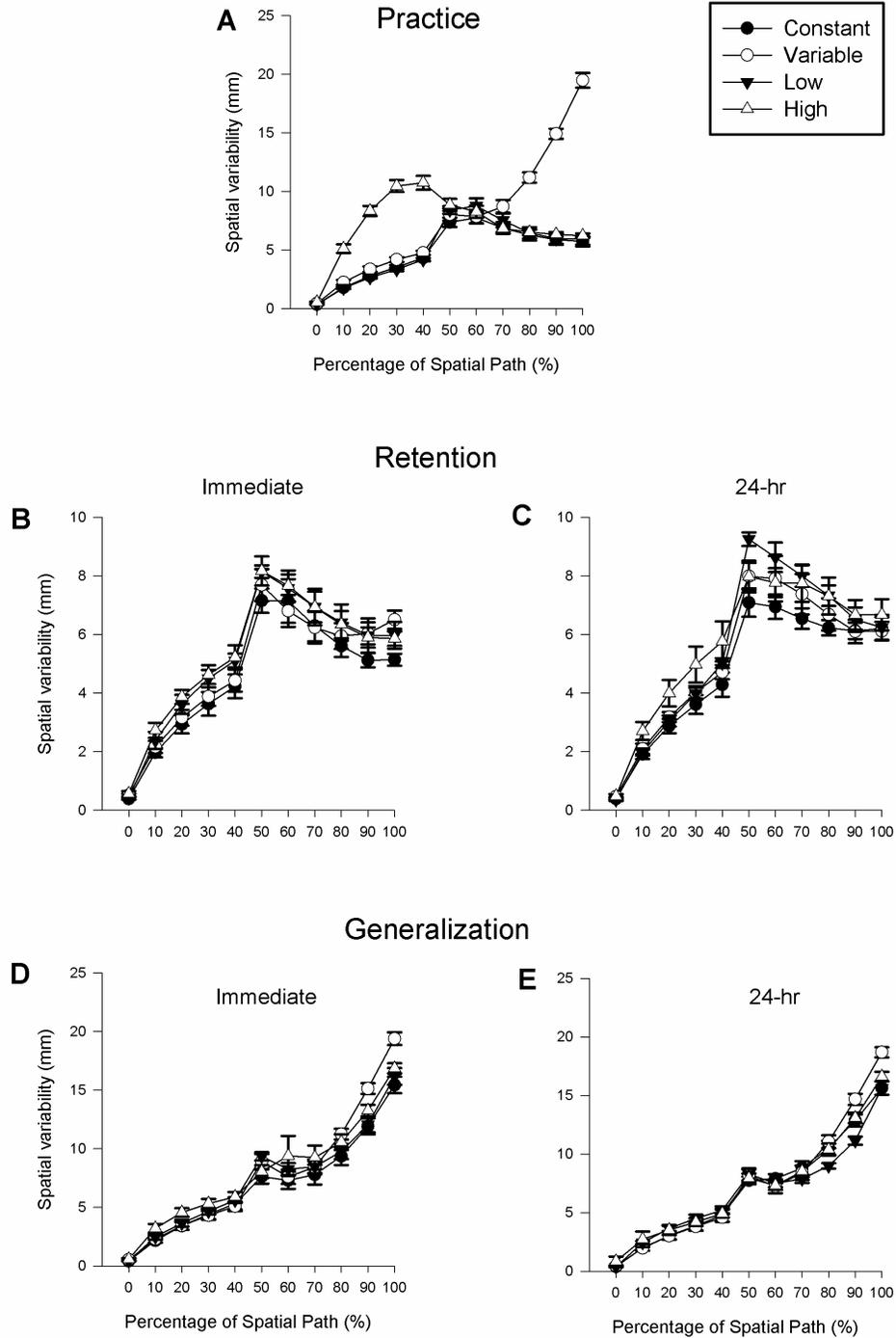


Figure 5.5. Spatial variability of four groups during: (A) last block of practice, (B) Immediate retention test, (C) 24-hr retention test, (D) Immediate generalization test and (E) 24-hr generalization test. Error bars represent one standard error.

Reach extent

We also computed the reach extent in the generalization tests as the standard deviation of the y-positions of each trial at the point the path crossed the target along the x-axis. This effectively measured the range (along the y-axis) that the participants were able to use in the generalization test in trying to hit the different targets. There was a main effect of group, $F(3, 28) = 14.30, p < .001$. Post hoc comparisons showed that the reach extent of the variable group was higher compared to all other groups (Figure 5.6B).

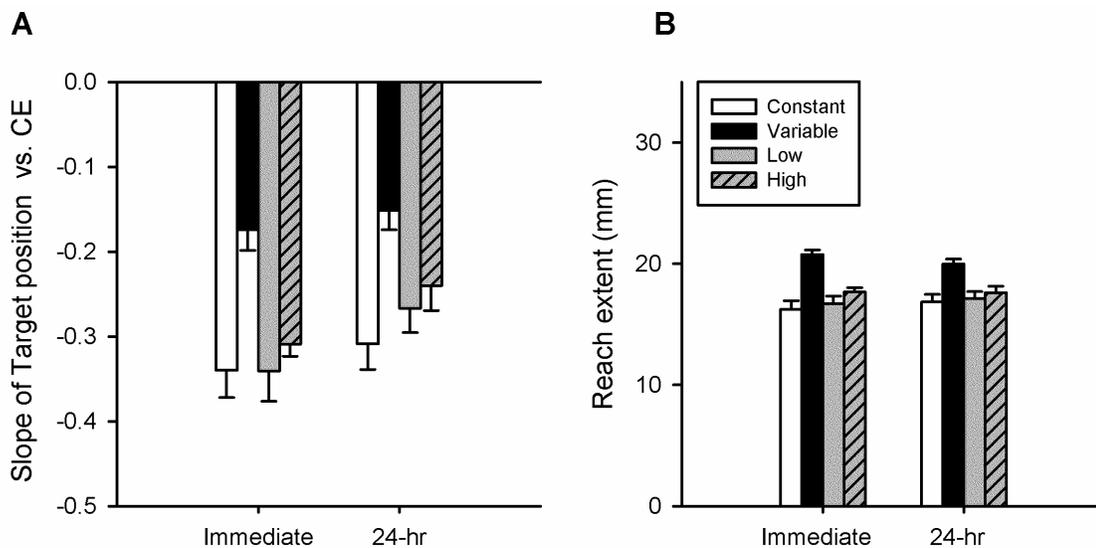


Figure 5.6. (A) Slope of target position versus CE and (B) reach extent of the four groups in the immediate and 24-hr generalization tests. Error bars represent one standard error.

Correlations

We examined the structure of variability using a pairwise correlation technique between adjacent spatial locations on the trajectory. Similar to the spatial variability, we compared the groups at each pairwise correlation. The correlations are shown in Figure 5.7 and the list of significant comparisons is shown in Table 5.2.

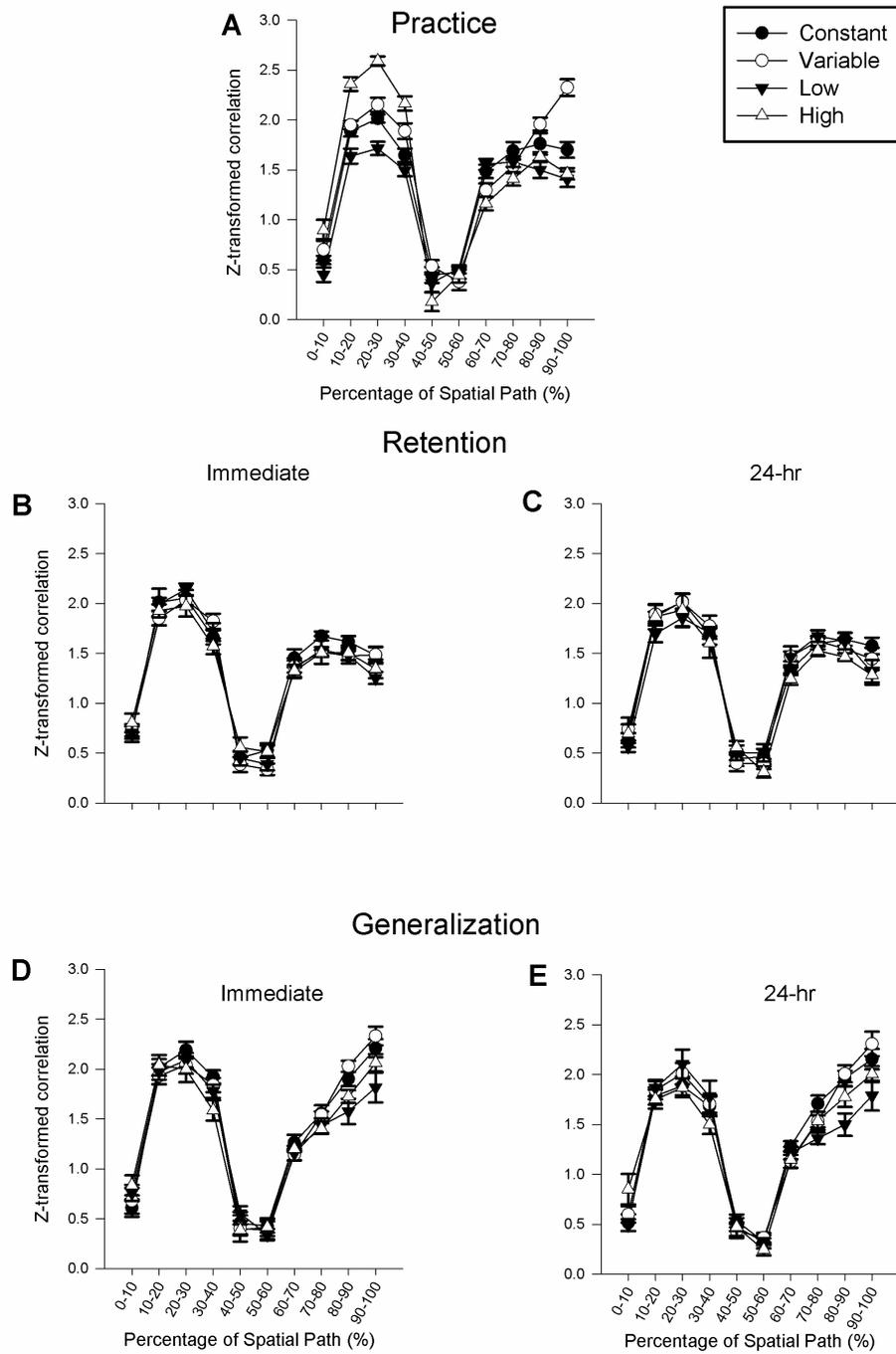


Figure 5.7. Pairwise correlations between adjacent spatial locations during: (A) last block of practice, (B) Immediate retention test, (C) 24-hr retention test, (D) Immediate generalization test and (E) 24-hr generalization test. Error bars represent one standard error.

Table 5.2.

Summary of group comparisons of pairwise correlations at different locations on the movement path on the last block of practice, the retention tests and the generalization tests. C = Constant, V = Variable, L = Low-redundancy, H = High-redundancy. n.s. = non-significant

% of spatial path	Practice	Retention		Generalization	
		Immediate	24-hr	Immediate	24-hr
0%-10%	L<H	n.s.	n.s.	n.s.	n.s.
10%-20%	L<C,V,H; C,V<H	n.s.	n.s.	n.s.	n.s.
20%-30%	L<C,V,H; C,V<H	n.s.	n.s.	n.s.	n.s.
30%-40%	C,V,L <H; L<V	n.s.	n.s.	H<C	n.s.
40%-50%	H<V	n.s.	n.s.	n.s.	n.s.
50%-60%	n.s.	n.s.	n.s.	n.s.	n.s.
60%-70%	V<L,H; C<H	n.s.	n.s.	n.s.	n.s.
70%-80%	n.s.	n.s.	n.s.	n.s.	L<C
80%-90%	L,H<V	n.s.	n.s.	L<V	L<C,V
90%-100%	C,L,H<V;L<C	n.s.	n.s.	L<V	L<C

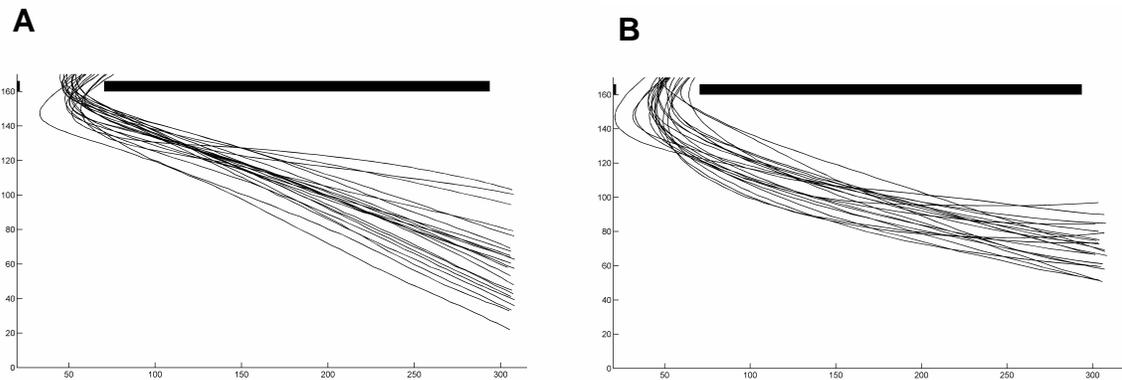


Figure 5.8. Exemplar trials of two subjects in the immediate generalization test in: (A) Variable group and (B) Low-redundancy group. Axes have been adjusted to show the movement path below the obstacle. Note that the movement paths in the variable group have minimal cross-over whereas the low-redundancy group not only has smaller end-point variance but also a greater degree of cross-over in the movement paths near the end.

Discussion

The purpose of the study was to investigate two questions – (a) how does variability of the task goal influence spatial variability of the movement path and (b) does induced variability at the execution redundancy level (i.e., utilizing different redundant movement paths) during learning facilitate retention and/or generalization? These questions are central to understanding the role of redundancy in learning (Bernstein, 1967) and the effect of inducing variability in practice in order to facilitate motor learning.

Variability of practice

To examine the variability of practice hypothesis (Schmidt, 1975), we compared only the constant and variable groups. The constant group showed better performance on the immediate retention test, but not on the 24-hr retention test. This was due to a decrement in performance of the constant group on the 24-hr test. The analysis of the spatial variability during the immediate retention test revealed that even though the constant group had better performance, the constant group did not have lower spatial variability throughout the movement path. Instead, there was a significant difference in spatial variability only at the end of the movement path, near the target. This is consistent with results from table tennis (Bootsma & Van Wieringen, 1990) that have shown that variability is channeled so that it is only reduced at the point where it becomes relevant to task performance (Todorov & Jordan, 2002). This ability to channel the path variability near the end of the movement path was disrupted by variable practice, resulting in worse performance. The fact that there was no significant difference in

absolute error at 24-hr indicates that this ability to reduce variability near the target may be disrupted by warm-up effects.

However, in the generalization tests, the variable group had significantly better performance than the constant group. The constant group was unable to increase its spatial variability to match the new locations of the target. The regression between the y-position of the target and the constant error also indicated a significantly higher negative slope in the constant group compared to the variable group that was also associated with a smaller effective reach range. These results reveal that the constant group showed a tendency to go near the originally practiced target, indicating that the target location may have been learned. These effects were also seen in the low-redundancy and high-redundancy groups that practiced the same target, and this issue is discussed further under the *Generalization and the equilibrium-point hypothesis* section.

Manipulating path redundancy

The second question of the study examined whether utilizing more or less path redundancy influenced retention or generalization. During learning, the high-redundancy group had more variability in the initial part of the trajectory, but was reduced quickly to match the variability of the low-redundancy group. In other words, the variability introduced by the intermediate target was suppressed after crossing the obstacle, well before reaching the final target (see Figure 5.3D). This behavior may be reflective of a simplifying strategy that makes the second part of the movement independent of the perturbations in the path caused by the intermediate target and is consistent with studies on frog wiping reflexes (Fukson, Berkinblit, & Feldman, 1980) that showed during the

wiping reflex that the limb adopts a particular intermediate posture before proceeding to wipe the stimulus.

We also observed changes in the structure of the path variability. The correlations between adjacent locations on the spatial path were significantly higher in the high-redundancy group. More importantly, the low-redundancy group also had significantly lower correlation than the constant group that was reflective of a greater degree of cross-over in the movement paths near the intermediate target. This indicates that the presence of the intermediate target in the low-redundancy group changed the structure of the path variability even though it had the same amount of path variability as the constant group.

However, in spite of these changes during practice, there were no significant differences in the performance from the constant group during the retention tests. Interestingly, the spatial variability of the high-redundancy group was not significantly different from either the low-redundancy or the constant groups, indicating that even though participants in this group had the ability to exploit more variations, they did not utilize a greater degree of redundant paths to hit the target. This suggests that that of the two strategies of coping with high movement variability, the strategy of reducing overall variability may be preferred over the strategy of channeling variability into task-redundant dimensions. This is consistent with studies showing that the degree to which redundancy is utilized does not correspond to the level of performance (Gorniak, Duarte, & Latash, 2008; Zhang, Scholz, Zatsiorsky, & Latash, 2007)

Similar to the retention tests, there was again no difference in performance between the two redundancy groups in the generalization tests. In terms of spatial variability near the target, both had significantly smaller spatial variability than the

variable group. The high-redundancy group tended to have slightly higher spatial variability near the end of the movement compared to the low-variability group but this did not reflect in any changes in performance. Similar to the constant group, the analysis of the slope between the target position and CE and the reach extent indicated that the two groups showed a tendency to approach the target location that was practiced. The structure of variability also revealed that the low-redundancy group in particular had lower correlations towards the end of the movement, indicating that there was a greater degree of cross-over in the movement paths (Figure 5.8).

Generalization and the equilibrium-point hypothesis

The generalization results showed that regardless of the movement path variability, groups that aimed at a single target during practice (i.e., the constant, low-redundancy and the high-redundancy groups) suffered a decrement in performance when subsequently aiming to targets at different positions. These data are consistent with the equilibrium-point hypothesis (Asatryan & Feldman, 1965; Feldman, 1966). According to the equilibrium-point hypothesis, intercepting the target in the same location requires the learning of only a single parameter. Several studies have shown that the reproduction of final position is more accurate than other parameters such as distance (e.g., Jaric, Corcos, Gottlieb, Ilic, & Latash, 1994; Posner, 1967). Similarly, studies in force-field adaptation have shown that there is a limited ability to generalize to different parts of the workspace after training at a single location (Malfait, Gribble, & Ostry, 2005). Therefore, the ability to generalize to different parts of the workspace may only be enhanced by practicing targets at different locations.

Redundancy and practice schedules

Several studies have emphasized the advantage of utilizing redundancy in motor performance (e.g., Latash et al., 2002; Müller & Sternad, 2004; Todorov & Jordan, 2002). However, it is important to consider whether such utilization of redundancy needs to be incorporated directly into practice schedules. The results from the present study show that learning multiple ways of solving the motor task did not produce any benefits in retention or generalization. This indicates that the ability to achieve the task goal using multiple solutions may be a consequence of learning to produce consistent values of certain task relevant parameters instead of explicitly practicing multiple ways of solving the task. That the exploitation of redundancy might be emergent is seen from studies of speech perturbation (Abbs & Graco, 1984; Kelso, Tuller, Bateson, & Fowler, 1984) or grasping (Cole & Abbs, 1986) where compensations to perturbations are immediate and occur in degrees of freedom that are remote to the site of perturbation, even though there is presumably no explicit training to practice different ways of performing the goal.

Additionally, while the term “variability of practice” has been used to refer to a wide variety of parameter manipulations (e.g., force, time, distance, orientation), it is important to consider the level at which variations are introduced. In the present study, variations in the task goal created improvements in generalization whereas creating variations in the ways of solving the same task did not seem to facilitate retention or generalization. This shows that at least part of the advantage of variable practice is not due to cognitive processing or problem-solving during practice (Lee, Swanson, & Hall, 1991), but rather from a wider exploration of the perceptual-motor workspace. Further, the distinction between the two levels at which motor variability can be introduced may

provide a basis for understanding the effect of different parameter variations that is critical to understanding the role of variability in practice.

In summary, we found that variable practice using different target locations interfered with the reduction of spatial variability near the target on the retention test. Constant practice, on the other hand, resulted in an inability to increase spatial variability to hit different targets. Further, practicing the use of different paths to hit the same target did not show any facilitation of learning over constant practice. Thus, introducing variability at the task goal and execution redundancy levels has different effects on learning. In particular, practice schedules that directly constrain the participant to use multiple solutions may not be effective for learning. Further research is needed to examine if the skill level of the learner plays an important role in determining the effectiveness of practice schedules that utilize redundant solutions.

GENERAL DISCUSSION

The dissertation examined the issue of variability and redundancy in motor learning. The focus of the experimental studies was at the level of the movement path in the context of learning to perform a virtual interception task. There were three general questions that were addressed by the dissertation: (a) how does learning influence the change in movement variability (specifically path variability) and the utilization of redundancy?, (b) can the flexibility to use redundant solutions be enhanced through practice?, and (c) how does introducing variability at the task goal level and the execution redundancy level facilitate learning? These questions are discussed below under three general themes.

Theme 1: Changes in Movement Variability and Redundancy with Learning

Amount of variability

With respect to the change in the amount of movement variability, we found that there was evidence against finding an optimal path with learning. In particular, the path variability during the middle of the movement path was much higher than the variability near the end. This suggests that instead of an optimal path with the same amount of variability (or increasing variability) throughout the path, there was preferential reduction of movement variability near the target. This is consistent with the prediction of Todorov and Jordan (2002), that the system operates on a minimum-intervention principle, only reducing variability where it is relevant to task performance.

Though we did not manipulate visual feedback in the current set of experiments, it is evident that participants could have used visual feedback given that instantaneous visual feedback of the cursor position was provided and the total movement time was 600

ms (Carlton, 1992). We also tested two subjects without visual feedback of the cursor after they had learned the task with vision and found that there was a significant decrement in performance. This indicates that the selective reduction in variability near the target was regulated by visual feedback.

However, with initial learning, there was a reduction in the spatial variability throughout the movement path even though task performance is primarily determined only by the variability near the target. While the reduction in variability in the middle could have been partially due to the presence of the obstacles, the path variability observed was much smaller than what would be required to successfully navigate the obstacle. Therefore, participants were either adopting a bigger safety margin to clear the obstacles or reducing the path variability in the middle along with reducing the path variability near the target. This overall reduction in path variability is consistent with a number of studies that indicate that the overall movement variability (i.e., both goal-equivalent variability and goal-relevant variability) is reduced with learning (Domkin, Laczko, Jaric, Johansson, & Latash, 2002; Yang & Scholz, 2005). With extended practice, we found evidence for a more selective decrease in spatial variability near the target.

This raises the question as to why the system reduces variability throughout the movement path when it is only the variability near the target that is relevant to performance. There has been speculation that this may be a result of optimization of cost functions apart from performance such as comfort or smoothness of the movement (Latash, Scholz, & Schöner, 2007). Mosier, Scheidt, Acosta, and Mussa-Ivaldi (2005)

also hypothesized that in novel conditions, there may be a tendency to represent certain properties of task space (for e.g., moving in straight lines between two points).

In addition to these factors, we also found that there are history effects that may also contribute to this reduction in variability. The model proposed by Todorov and Jordan (2002) assumes a memory-free controller where each trial is independent of the previous trial. However, there have been many studies in motor control that have shown time-dependent relation between successive movements or trials (Spray & Newell, 1986; Van der Wel, Fleckenstein, Jax, & Rosenbaum, 2007). When we analyzed the sequence of the paths taken, paths that were from successive trials were more similar than paths that were arbitrarily chosen from the block.

This indicates that there might be a cost to using a completely different solution on each trial irrespective of the solution used on the previous trial. As a result, there may be a tendency to only slightly modify the movement on the previous trial and reuse the same “ball park” solution (Greene, 1972). This effect is also seen in Experiment 3 where the high-redundancy group that practiced different movement paths to hit the target reduced its overall path variability in the retention test. Given this reliance on the previous trial, once participants achieve good performance on the task, they may be less likely to explore the whole space of solutions, leading to a reduction even in variability that does not affect task performance. In view of these findings, the analysis of the trial-to-trial dynamics (e.g., Dingwell, John, & Cusumano, 2009) may provide an important window into how the redundancy is explored.

Structure of variability

The analysis of the structure of path variability also indicated that even though the spatial variability decreased with learning, it was not consistent with the production of an optimal movement path corrupted with noise. Learning caused a decrease in correlations between adjacent locations near the target, due to a significant cross-over of movement paths near the target, which indicated that different paths were being used to hit the target. This effect also challenges the common assumption that a reduction in spatial variability is consistent with the use of a single, optimal path (for e.g., see Georgopoulos, Kalaska, & Massey, 1981). Even when the path variability was decreased, the structure of variability revealed the utilization of redundant solutions. This highlights that examining time-dependent properties of the variability may reveal important properties that are not extracted in the amount of variability.

Implications for models of motor learning

The results suggest that models of motor learning have to be modified to incorporate both the reduction of variability as well as the utilization of redundant solutions. For models that have emphasized motor learning as the process of obtaining a single optimal movement pattern (e.g., Georgopoulos et al., 1981), the results show that there is not one single solution that is used with learning. The reduction in motor variability with learning is consistent with these models. However, even when the variability is reduced, the system exploits the redundancy in the task and channels variability into task-redundant dimensions (Todorov & Jordan, 2002). This results in multiple solutions being used to achieve the task goal even after extended practice.

On the other hand, for models that focus on learning as exploiting redundancy (Todorov & Jordan, 2002), the results show that not all possible redundant solutions are used with learning. Optimal feedback control models have emphasized only the role of task performance in the cost function which is based on the assumption that all solutions that lead to the task goal are equally effective. However, the reduction in motor variability with practice (even when it has no effect on task performance) indicates that not all solutions are used with practice. These set of solutions may be advantageous in terms of other factors such as the sensitivity to error (Cusumano & Cesari, 2006; Hu & Sternad, 2007).

In addition to the task, factors related to the organism such as comfort (e.g., Rosenbaum, van Heugten, & Caldwell, 1996) and the stability of different coordination patterns (e.g. Kelso, 1984) may also play a pivotal role in determining which solutions are used with extended practice. For example, Ranganathan and Newell (2009) showed that the stability of the in-phase pattern in a bimanual finger force production task resulted in better performance on a retention test even though it was not the optimal strategy when considered only from a performance perspective. Finally, the similarity of the solutions between consecutive trials indicates that there may also be higher costs associated with switching between widely different solutions from trial to trial. Incorporating these various factors into models of motor learning may provide a more comprehensive account of the changes in the amount and structure of variability with learning.

Theme 2: Emergent Flexibility and Synergies

The second question we addressed was the relation between flexibility and the degree to which path redundancy was utilized during practice. Experiment 2 showed that practicing with low path variability did not affect the ability of the system to utilize redundant solutions. In this experiment, the low-variability group which practiced with the obstacle in the same position used a small range of movement paths during practice and showed a further reduction in path variability with learning. However, when transferred to a condition where the obstacle was in different positions from trial to trial, requiring the use of different movement paths, the participants in this group were able to adapt almost immediately and in fact showed even better performance than the group that practiced with the obstacles in different positions.

Flexibility as an emergent phenomenon

These findings are consistent with the hypothesis that flexibility is emergent from learning a task-relevant parameter (Berkinblit, Feldman, & Fukson, 1986). In the present case, this parameter was related to the target location. The low-variability group was able to learn the target location during practice as evidenced by the low absolute errors at the end of practice. As a result, even when the obstacles were in different positions, it was able to flexibly adapt its movement path to reach the same target location. The evidence that the target location was learned is also seen from Experiment 3, where the groups that practiced the same target location have difficulty adapting to shifts in target location.

This stabilization of task performance in the presence of perturbations has been shown in other contexts. For example, studies in speech have shown that in the presence of a perturbation, multiple degrees of freedom in the speech apparatus act flexibly in

order to preserve the sound of a particular syllable (Abbs & Graco, 1984; Kelso, Tuller, Bateson, & Fowler, 1984). While we did not perturb the limb mechanically in our experiments, the change in obstacle position effectively acted as a perturbation in changing the movement path. From these results, we speculate that flexibility may be developed through learning the appropriate task parameter(s) instead of explicitly practicing different movement patterns to achieve the task goal.

Synergies and task context

Another important finding is that the flexibility of the system does not have a “universal signature” and cannot be inferred from observing the movement variability without reference to the task context. While the low-variability group was able to adapt its variability in the flexibility tests, it had the lowest path variability throughout the movement path in the retention test, where there was no need to utilize different movement paths. This suggests that the ability of the participant to utilize redundancy has to be inferred in a specific task context. In particular, measuring the *naturally* occurring movement variability may not be indicative of the potential capability of the system. For example, several studies in learning have found that decrease of goal-equivalent variability and the strength of the synergy with learning (Domkin et al., 2002; Yang & Scholz, 2005). This has been considered a counterintuitive finding because: (a) decreasing goal-equivalent variability does not improve performance, and (b) a decrease in the synergy strength implies that there is a lesser amount of covariation that corresponds to reduced stability of the performance variable.

However, these counter-intuitive findings might be resolved if a distinction is made between the *observed* strength of the synergy and the *potential* strength of the

synergy. The observed strength of the synergy is based on the observation of the preferred behavior of the system in a particular task condition, that is, on the naturally occurring movement variability. On the other hand, the potential strength of the synergy is not concerned with the preferred behavior of the system, but rather it is based on the potential capability of the system. In other words, it is based on using a task condition where the task constraints actually require the utilization of redundancy for successful performance.

For example consider a redundant force production task of two fingers trying to produce a total of 10 N. The observed strength of the synergy can be measured when participants perform the preferred pattern. However, in order to measure the potential strength of the synergy, it is necessary to introduce constraints so that one finger varies its force (for e.g., from 1 N until 9 N) and then observe if the system is still able to compensate using the force on the other finger to produce a total force of 10 N. Therefore, while the observed synergy strength may increase, decrease or stay the same with learning (Latash et al., 2007), we speculate that the potential synergy strength will show an increase with learning, reflecting the increased ability to utilize multiple solutions to achieve the task goal.

A similar analogy between observed variability and variability in a task-context exists in the gait literature with respect to distinguishing between local stability and global stability of walking. There have been studies that have used the naturally occurring variability to quantify the local stability of walking using Lyapunov exponents (e.g., Dingwell & Cusumano, 2000). However, these local stability measures do not correlate very well with global stability or the ability to maintain balance. For example,

Dingwell and Cusumano (2000) found that patients with peripheral neuropathy (who are known to have balance problems) had higher local stability than control participants. They suggested that experimental protocols that induce large perturbations may be required to measure global stability. Similarly, in the context of the redundancy-flexibility issue, while the study of naturally occurring movement variability and redundancy provides an insight into the control of the system, using task conditions that use perturbations or constraints to force the utilization of redundancy may provide a more functionally relevant assessment of the flexibility of the system and the task variables that are being stabilized.

Theme 3: Implications for practice schedules

Finally, in Experiment 3, we examined if changing the self-selected strategy by introducing variability in the practice schedule had any effect on learning in terms of retention or generalization. In previous studies that have investigated the change in the utilization of redundancy with learning, there has not been explicit manipulation of the redundancy to examine how it affected learning. We introduced variability at two levels – (a) the task goal level, in which the position of the target was varied from trial to trial, and (b) the execution redundancy level, in which the final target was in the same position but different paths were used to intercept the target.

In general, we found a specificity of practice effect – practicing in the to-be-tested condition results in optimal performance on that task. With respect to the retention tests, where the obstacle and the target always were in the same position on all trials, introducing variability at either the task goal level or the execution redundancy level created detrimental effects on performance in the retention test. This suggests that the

condition where there was no externally induced variability may result in better learning of a task-relevant parameter (for e.g., the target location). However, with respect to the generalization tests that required the ability to intercept targets at different locations, the group that practiced variable targets showed a greater ability to intercept different targets. This has been found in force field adaptation where adaptation to reaching in a particular location in the workspace does not generalize to other parts of the workspace (Malfait, Gribble, & Ostry, 2005).

In the framework of the variability of practice hypothesis proposed by Schmidt (1975), we found that practicing with variable target locations resulted in better generalization than practicing a constant target location as predicted by schema theory. However, in the retention tests, the variable group showed poorer performance compared to a constant group. In particular, we found increased spatial variability near the target that was not indicative of a stronger schema with learning. Furthermore, from the contextual interference perspective (Shea & Morgan, 1979), making practice more cognitively effortful or creating interference by forcing the participant to utilize redundant solutions did not facilitate learning or generalization. This may be partly due to the nature of tasks that are typically examined. Contextual interference effects have been shown in tasks such as the learning of sequences that involve a memory or cognitive component to the task. However, in the current experiments, the task was an accuracy task that required a reasonably quick movement while attempting to decrease variability near the target. In these cases, introducing variability may not facilitate the reduction in variability. Similarly, we found that exploring the workspace by practicing redundant solutions did not facilitate retention or generalization, which is counter to the predictions

of the differential learning perspective (Schöllhorn, Beckmann, Michelbrink, Trockel, Sechelmann, & Davids, 2006),.

Finally, with regard to introducing variability, there has been evidence of stochastic resonance effects in motor control (Priplata, Niemi, Harry, Lipsitz, & Collins, 2003). With respect to motor learning, Hu and Sternad (2007) showed that adding an optimal amount of noise may enhance the learning of a virtual throwing task. An important difference is that the study by Hu and Sternad (2007) did not introduce noise directly in the motor output. Instead, the authors used noisy feedback that actually resulted in a decrease in the amount of motor variability. Therefore, while there is the possibility that an optimal amount of variability in terms of feedback may enhance the learning of task-relevant parameters, the current experiments support the idea that introducing fluctuations that increase motor variability does not seem to facilitate learning in novices.

Limitations

There were a number of limitations in the current experiments. First, the visual feedback was presented on the screen in front of the participants whereas the hand movements were made horizontally on the table. This effectively meant that participants had to do a mapping from forward and backward in the tablet space to up and down in the screen space. Though this may have made the task more artificial compared to more natural interceptive behaviors like hitting a ball, there are several scenarios like playing video games or performing laparoscopic surgery that involve a similar mapping between the workspace and the screen where visual feedback is presented.

Second, we did not consider the effects of contact forces (both normal and frictional forces) between the pen and the table or between the hand and the table. Therefore, some of the changes in the path variability could have been due to changes in the forces applied. We made the assumption that even if there were individual differences in these variables, they would be randomly distributed so that the between-group comparisons would not be affected. Also measurements of joint kinematics and EMG could provide insight into how other levels of redundancy are related to the changes in the movement path.

Finally, we did not analyze eye movements to examine if there were changes in eye movement strategies with learning. Several studies in the interception of ball sports have shown that experts tend to foveate at different locations in the environment compared to novices (e.g., Land & McLeod, 2000). Therefore, we were not able to assess if changes in motor variability that were seen with learning or between-group differences were associated with changes in where the participants foveated during the task. An important difference is that the studies that have shown differences in eye movements between experts and novices are usually in contexts that require the extraction of information from dynamic stimuli (for e.g., intercepting moving objects or anticipating outcome from movement kinematics). In our experiments, all objects were stationary in a given trial. Therefore, we assumed that the effects of changing eye movement strategies on the results are minimal.

Conclusions

In summary, the dissertation showed the following key results:

- (1) Redundant solutions are exploited even after extended learning. Though there was a decrease in path variability with initial learning, this was not consistent with producing an optimal path with noise. Extended learning produced a decrease only in task-relevant variability (i.e., variability near the target) and the structure of movement variability also showed that different paths were used to hit the target.
- (2) Flexibility is emergent from learning particular task-parameters. Though there was a reduction in path variability with learning, there was an ability to utilize redundant paths to hit the target if necessary. This highlights the importance of considering the task context in inferring the flexibility of the system. A flexible system may not exhibit its flexibility unless the task constraints require it to.
- (3) Practice strategies are in general specific to the task required. Practicing with a single target location improved performance in the retention tests whereas the ability to generalize to different targets was facilitated by practicing variable targets. Introducing variability at the execution redundancy level and using redundant solutions during practice to hit the target did not facilitate either retention or generalization. This suggests that introducing motor variability at the execution redundancy level may not be a useful practice schedule at least early in learning.

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VITAE

Rajiv Ranganathan

Education

- 2009 Ph.D. Kinesiology
 The Pennsylvania State University
- 2005 M.S. Kinesiology
 University of Illinois at Urbana-Champaign
- 2003 B.E. Electronics and Communication Engineering
 University of Madras, India

Honors

- 2009 Alumni Association Dissertation Award
 The Pennsylvania State University
- 2008 Kligman Graduate Fellowship
 The Pennsylvania State University
- 2005 University Graduate Fellowship
 The Pennsylvania State University
- 2003,2004 Carol Chittenden Fellowship
 University of Illinois at Urbana-Champaign

Peer-Reviewed Publications

- Ranganathan, R.** & Newell, K. M. (2009). Influence of augmented feedback on coordination strategies. *Journal of Motor Behavior*, *41*, 317-330.
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