

ANTICIPATORY CONTROL OF HUMAN LOCOMOTION REQUIRES
VISUO-SPATIAL ATTENTIONAL RESOURCES

BY

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- Ferris, J. S., **Owens, J. M.**, Berson, S. B., & Owens, D. A. (2002) How good are those headlights? A test of the Civil Twilight Criterion. Conference of the Eastern Psychological Association. Baltimore, March 2002.
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PREFACE

Writing this dissertation has been a rewarding, educational, and at times overwhelming experience. I couldn't have done it without the continued help and support of my advisor, William Warren, and the rest of the VENLab, including Jonathan Cohen, Elizabeth Chrastil, Hugo Bruggeman, Alexandra Chardenon, Michael Cinelli, Martin G  rin-Lajoie, Patrick Foo, Huiying Zhong, Jonathan Ericson, and all of the undergraduate research assistants who have been invaluable through my time here. I am also deeply indebted to my dissertation committee, Steven Sloman, Kathryn Spoe  r, and Michael Tarr, for their time, encouragement and critical viewpoints.

As my grandfather is fond of saying, we are the sum total of our experiences, and this is proven true in the strength that I have gained from the love and support of my family and friends over the years. Thank you to all, near and far, who have helped make me who I am, and most especially to my father and mother, Fred and Debbie Owens, my sisters Caitlyn and Abigail, and my brother-in-law Elijah.

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CHAPTER 1

INTRODUCTION

Background

One of the most universal and important behaviors in which humans and animals engage is the act of moving through the world. Whether on foot or by using a tool such as a bicycle or automobile, whether in pursuit of food, shelter, or the propagation of the species, the ability to traverse the environment is fundamental to survival.

On the surface, locomotion seems a simple activity – we merely move to avoid obstacles en route to whatever our goal happens to be. However, when we look a bit deeper, locomotion has the potential to be a tremendously complex act. We must sift through a vast amount of visual, spatial, and auditory information to navigate our way through the blooming, buzzing confusion that surrounds us, and yet we can do it from a very early age, as can nearly every animal. This is something that we share with babies, hawks, and rabbits alike. Evolution has outfitted every mobile animal on earth with some degree of (or the capacity to rapidly develop) interceptive and avoidance behavior.

A large body of research suggests that the majority of human and animal locomotion to visible targets and around visible obstacles is controlled online using only occurrent information; that is, requiring no higher-level prediction or planning (Gibson, 1979; Srinivasan et al, 1991; Fajen & Warren, 2007; Owens & Warren, Vision Sciences 2004, Psychonomics 2005). However, there are certainly cases in the world in which it is beneficial – and sometimes necessary – to anticipate the movement of objects before it occurs.

Consider the common case of driving an automobile. Not only must the driver

react to the actions of the road users around him, he must also be able to preemptively avoid potentially dangerous situations. These could be as varied as giving a wide berth to children on the side of the road, staying far behind a weaving driver, or veering to avoid a potential intrusion from a car entering the roadway. As Gibson & Crooks (1938) frame it, the driver must maintain a “field of safe travel”. They define this as the set of all possible paths that the vehicle can safely take at any moment in time. This is envisioned as an envelope (or “tongue,” as they phrase it) that extends in front of the car and is modified by the changing environmental circumstances as the driver moves through the world. The measure of a safe driver is whether he is able to perceive this field of safe travel and maintain his car’s path and stopping zone within it.

For example, when driving to work one morning in the middle lane of the highway, I noticed that the right lane was becoming clogged with traffic. Anticipating that an impatient driver might jump lanes to exit the clot, I switched to the left lane to avoid a potential lane intrusion. This was a simple movement, yet one I would not have undertaken had I not attended to and recognized a potentially hazardous situation. Indeed, this foresight is a large part of the learning process that all new drivers undergo on the way to becoming skilled.

As important as the ability to anticipate obstacle movement during locomotion is, not much work has been done to investigate the relation between this higher-order cognitive influence and online control. There is a growing body of literature that approaches this from several directions, but very little that combines these in a coherent

framework. I will first present an overview of the current state on online control models. Following this, I will introduce the idea of perceptual levels of control, and propose a framework for levels of locomotor control. I will then discuss the role that attention may play in mediating these levels of control, and present literature that examines the role of attention in the control of posture and gait. I will finally present a line of experiments that investigates the interaction of perception and cognition in the avoidance of predictable obstacles.

Online Control of Locomotion

Recent work on the online guidance of locomotion focuses on modeling human locomotor behavior using a dynamical systems framework. This is motivated by the theory of Ecological Perception put forth by Gibson (1979), which postulates that we should study perception at the level of the animal-environment interaction and avoid presuming internal representations where none are required. The research here is based specifically on the idea that human paths through the world can be modeled as trajectories through a state space of attractors (goals) and repellers (obstacles). Fajen & Warren (2007; 2003) present a line of research that uses a set of differential equations to model the behavioral dynamics of an agent moving through such a world.

In its initial formulation (Fajen & Warren, 2003), this model proposed that humans use a bearing-angle strategy to move through the world toward stationary goals and around stationary obstacles. Here, an agent's heading (direction of travel, ϕ) through

space over time for a given velocity can be described as being attached to the direction of a goal by a damped spring (β , Figure 1.1A), with this target heading angle closing to 0 as the agent turns toward the goal. For each time step, the solution to the series of differential equations specifies the position of the agent at the next time step. The fundamental equation specifies the agent's angular acceleration (Equation 1); the rest derive position from this using the agent's constant velocity.

$$(1) \ddot{\phi} = -b\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1 d_g} + c_2)$$

This is derived from a mass spring equation that describes a damped spring connecting the agent's heading to the direction of the goal (β). The equation states that angular acceleration is equal to a damping term that resists oscillation ($b\dot{\phi}$) combined with a stiffness term that pulls the agent's heading toward the direction of the goal ($-k_g(\phi - \psi_g)$). This stiffness term is modulated by the exponential distance term ($e^{-c_1 d_g} + c_2$), which reflects the finding that turning rate increases with proximity to the goal. These variables are depicted in Figure 1.1A. Parameter b (3.25 s^{-1}) represents the body's inertial resistance to turning; k_g (7.5 s^{-2}) represents the ratio of stiffness to the body's moment of inertia; c_1 (0.4 m^{-1}) represents a decay rate with distance, and c_2 (0.4) represents a minimum value to prevent the whole term from dropping to zero.

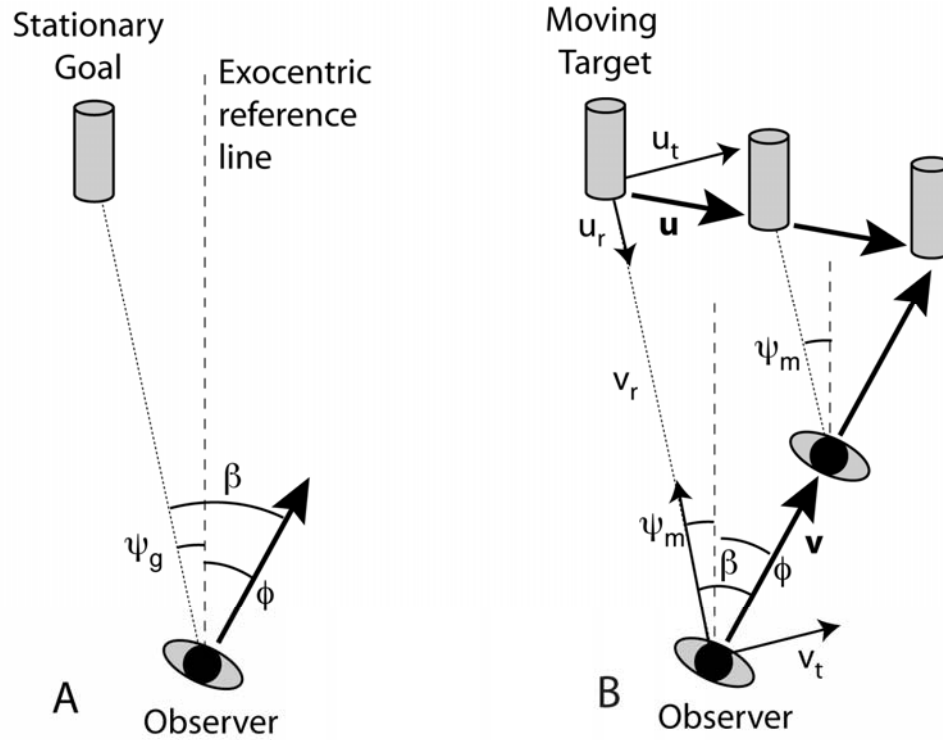


Figure 1.1 Perceptual variables used in the online guidance of human walking to (A) a stationary goal, and (B) a moving target.

This stationary goal model was then extended (Fajen & Warren, 2007) to predict human interception paths to moving targets. In this case, the agent nulls the change in ψ_m , the target's bearing angle (Figure 1.1B). This produces what is commonly known as the **constant-bearing** strategy, which is familiar to ship navigators as effective way to intercept targets on the open sea. In essence, this strategy entails keeping the target in the same visual direction in space at each time step while closing the z-distance between the agent and target ($v_{r,a} > v_{r,m}$). This model is instantiated in Equation 2:

$$(2) \quad \ddot{\phi} = -b\dot{\phi} - k_m(\dot{\psi}_m)(d_m + c_1)$$

Equivalently, in terms not requiring an extrinsic reference frame:

$$(2a) \quad \ddot{\phi} = -b\dot{\phi} - k_m(\dot{\beta} - \dot{\phi})(d_m + c_1)$$

This model does an excellent job describing human paths to targets moving at constant velocities in constant directions. Fajen & Warren (2007) immersed participants in a large virtual environment and asked them to intercept targets moving on a ground plane. They reported an r^2 of .87 between the time-series of model heading and that of human heading.

The model has also proven an excellent predictor of paths to targets moving on circular trajectories (Owens & Warren, 2004). In this case, interception paths followed the target and were curved as predicted; if participants were able to predict the target's trajectory, we might expect that they would be able to take shortcut paths directly to the targets. However, subjects appeared to rely only on current information in the environment, and did not anticipate target motion, but simply followed the target until they caught it.

Finally, Cohen, Bruggeman & Warren (in prep) present a model that combines a stationary goal with a moving obstacle, presented in Equation 3.

$$(3) \quad \ddot{\phi} = -b_g\dot{\phi} - k_g(\phi - \psi_g)(e^{-c_1 d_g} + c_2) + k_{mo}(-\dot{\psi}_{mo})(e^{-c_5|\dot{\psi}_{mo}|})(e^{-c_6 d_{mo}})$$

We can recognize the first half of the equation as being the stationary goal model presented in Equation 1. The second half of the equation references variables presented in Figure 1.2 below. Its form is similar to the moving target model presented in Equation 2, except that it is effectively the inverse ($+k_{mo}...$ instead of $-k_{mt}...$). This means that

instead of being attracted to a trajectory that nulls the change in the bearing angle (ψ_m), the agent is repelled from nulling change in obstacle bearing angle (ψ_{mo}). In other words, the agent follows a trajectory that keeps the obstacle at any position other than a constant bearing, which would result in a collision. If the agent does not maintain a constant bearing to the target, a collision will not occur. This model includes an additional term, $(e^{-c_s|\psi_{mo}|})$, which is a saddle-point function that allows the agent to pass ahead of or behind the obstacle.

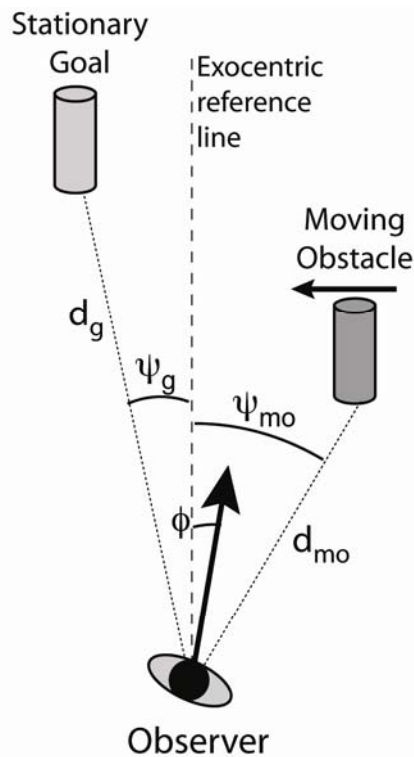


Figure 1.2 Perceptual variables used in the online guidance of human walking to a stationary goal while avoiding a moving obstacle.

Recent work (Owens & Warren, 2005; 2006), however, suggests that the constant-bearing model cannot account for interception paths in all situations, and some anticipation can occur. In previous experiments, target presentation order was randomized such that trials were unpredictable; participants had no way of knowing what path the target in the next trial was going to take. Although this may be a reasonable assumption in everyday life, we wanted to see if it was possible for subjects to modify their behavior if they could predict what target trajectory was likely to appear next. In this study, participants were presented with blocks of 15 trials, all with identical target trajectories. Two targets traveled in separate blocks on circular trajectories, and two accelerated on straight paths.

We predicted that if ideal path learning occurred, interception paths would shift from lagging behind the target (as seen in earlier studies) to being straight shortcuts directly toward the target. Participants did indeed modify their interception paths over the course of the blocks, and did so within three to seven trials in most cases. Their paths straightened significantly and shifted from being quite curved to being very nearly straight shortcuts (Figure 1.3 shows mean paths for the participants who exhibited a high amount of learning for this condition, $n = 10$ of 13). Further, most participants reported an awareness of the repetitive nature of the target paths, and an intention to try to “cut off the targets.” This implies that, at the very least, they had some sort of heuristic – or rough guess – about where the target would be moving over time.

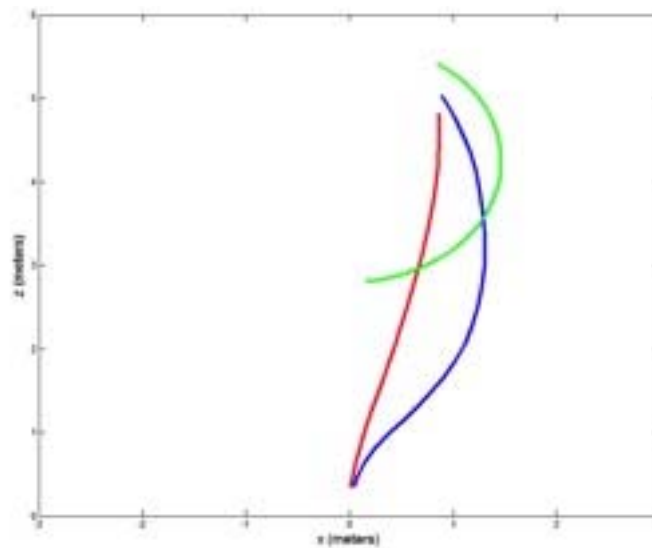


Figure 1.3 Mean human paths (initial trials = blue, later trials = red) to a circular target (green) for high-learning participants.

However, two factors lead us to believe that participants were not basing locomotion on a metric internal model of the target trajectory, even after many repeated exposures to the same target path. First, interception paths were not consistent, but varied trial-to-trial within subjects, and never reached perfect consistency across trials. Second, and perhaps more important, paths rarely perfectly predicted the target's position. There was generally a straight stretch to approximately where the target was to be caught, but there was nearly always a course correction just before interception. These two facts lead us to hypothesize that participants are not learning a metric target trajectory, but are developing heuristics of “about” how they should move to intercept the next target.

We can see, then, that while online control models do an excellent job explaining the informational basis for the majority of human locomotion, they do leave the door

open for higher-level anticipatory control. The methodology of the studies presented in this paper involves exploring under what circumstances obstacle avoidance paths deviate from and return to model predictions, and the effect of manipulating attentional resources.

Levels of Control

Levels of Behavioral Control

Rasmussen (1983) introduced the concept of a Skills-Rules-Knowledge (SRK) framework for control of human action. Working from an applied human factors perspective, Rasmussen was trying to develop a way of predicting how humans would act in a given situation. He rejected global “catch-all” theories of human perception and action as being too vague and imprecise for particular predictions in applied situations. Instead, he worked to develop a qualitative framework of action into which smaller quantitative models could be incorporated for prediction in individual situations. This framework comes in the form of three levels of control for human action. The most basic level, which encompasses fast motor movement, is termed the Skills level. The second level, which includes movements that are performed according to a learned script, is called the Rules level. The Knowledge level is the highest level of action control, and it includes actions which are cognitively planned. These are depicted in Figure 1.4.

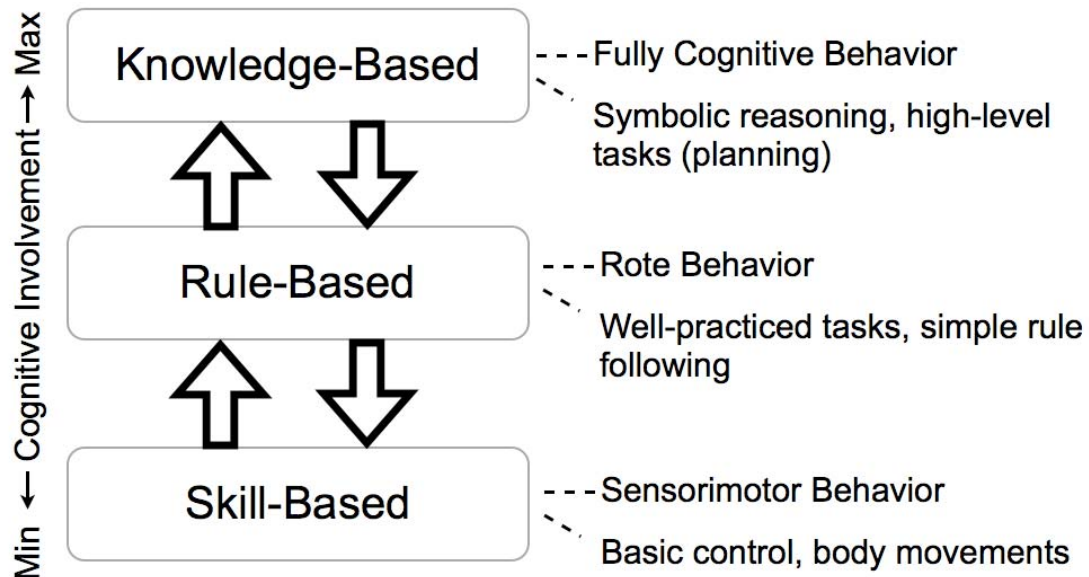


Figure 1.4 Rasmussen's Levels of Behavioral Control

The Skill-based level controls most fast, noncognitive movement. Taking information from the environment in the form of continuous signals, skill-based behavior is unconscious, fast, and based on information currently available. The signals on which skill-based control relies are conceptualized as “continuous quantitative indicators” of the surrounding world. They can be directly picked up and are always available. Examples of skill-based control include the primitive elements of walking, riding a bicycle, and performing a musical instrument (although higher levels of control can certainly mediate these actions by imposing higher-level constraints, such as “play quietly here”). Rasmussen’s initial foundation for skill-based control was that it was primarily

feedforward-based, with an internal model directing actions. While this original formulation is undoubtedly constructivist in nature, Rasmussen's idea of constant continuous interaction with the environment paved the way for future conceptions of this level to be ecologically based (Vicente & Rasmussen, 1992).

When Skill-based behavior requires higher-level input, behavior may become Rule-based. Rule-based behavior is cognitively controlled, but only in terms of following a set of procedures to complete a situation. Information is gained from "signs" from the environment, which serve to activate patterns of behavior. Unlike signals, signs do not provide continuous feedback about the environment; they simply serve to activate pre-existing behavior patterns. These signs can only serve as cues, and are not used for reasoning or symbolic processing. Examples of rule-based behavior involve following a recipe or changing your oil; these can be done by following someone else's instructions, and do not require problem solving. If the built-in simple behavior patterns fail, and problem solving becomes required, the person will likely shift to the highest level of behavioral control.

This highest level of control is Knowledge-based. This is the level devoted to problem solving; information from the environment is symbolic, and can be manipulated and used for problem solving. These symbols are formal operators that refer to internal concepts, which can be manipulated to form unique solutions. Rasmussen suggests that knowledge-based behavior occurs whenever we must explicitly formulate a way to reach a goal. Here we possess full-blown mental models of the situation, and we can work with

these to figure out a solution to the problem we face.

Levels of Locomotor Control

As the Rasmussen model describes control of behavior at only a general level, I propose a Levels of Locomotor Control framework to more specifically address the ways in which control guides movement through the world. These proposed levels, which mirror the ones proposed by Rasmussen, are shown in Figure 1.5.

At the most basic level of locomotor control, akin to the Skills level in Rasmussen's model, lies online control. As described in the section above, online control models do an excellent job predicting how people move through the world in the presence of visible, novel objects. I propose that this level is primarily responsible for the guidance of most everyday locomotion through the world. In cases where we do not need to make anticipatory judgments about the future, we can and do control our locomotion using only online information.

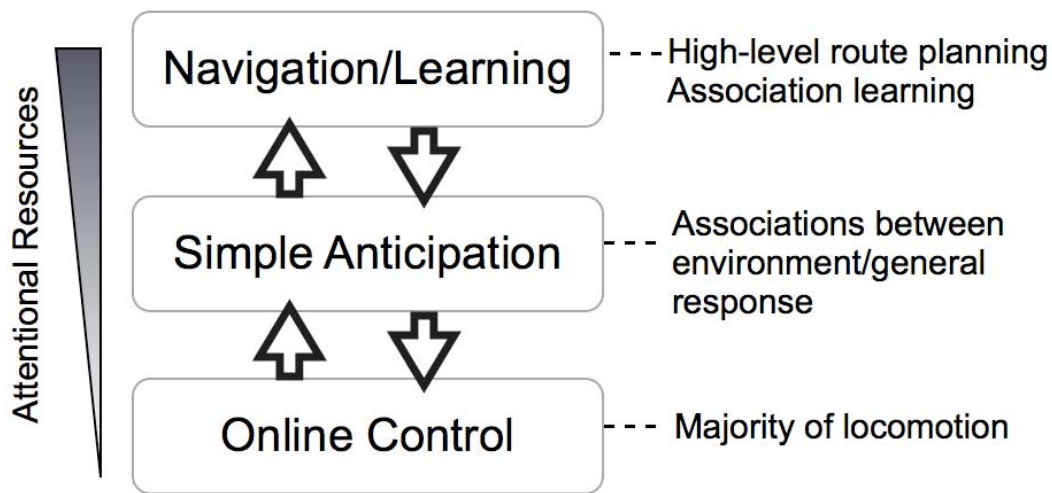


Figure 1.5 Proposed Levels of Locomotor Control

At the Rules level, I propose a level of Simple Anticipation (SA). Here, associations between environmental occurrences and actions can serve to guide locomotion in situations requiring some anticipation. For example, the pairing between “child” and “somewhat likely to run into road” could cause a driver to slow down or move toward the center of the street when he sees a child. This does not necessarily require explicitly cognitive planning or route plotting, but rather a simple association between an event and an action. As this association, however, requires inference from information not directly perceptible, it is distinct from the online control level.

On the highest level of locomotor control, Rasmussen’s Knowledge level, I propose the Navigation/Learning (N/L) level. Here are the specifically cognitive factors that drive locomotion, including navigation (plotting a route), learning associations (for

example, that children are more likely to run into roads than adults), and in some cases goal selection, among others.

Levels of Locomotor Control: Attentional Factors

Notice that an additional change from Rasmussen's levels of behavioral control to the proposed levels of locomotor control is the replacement of general "cognitive involvement" requirements with "attentional resources." Specifically, I propose that higher levels of control require more general (capacitive) attentional resources. Further, the type of attentional resources required will depend on the task being performed. As most locomotion requires visual input, it is proposed that most tasks contributing to the control of locomotion also require visuo-spatial attentional resources. As I will discuss below, the required resources are fairly low for basic online control of locomotion, but they should increase with the level at which behavior is being controlled. In other words, anticipatory control will require more overall attentional resources – and more visuo-spatial attention specifically – than online control. This will be discussed further in the following section.

Levels – Discrete or Continuous?

An additional consideration in this conceptualization of levels of control is whether these are discrete levels, where behavior can only exist in one at a time, or whether the levels are interrelated. I propose that they are hierarchical, that each level subsumes

those beneath it. Further, control at any level includes control in the underlying level(s). For example, anticipatory control also requires the use of online control to guide low-level movements while engaging in the anticipatory action.

In this conception, when humans “shift” levels of control, they are not engaged by one at the expense of the others, but their behavior is controlled by all levels up to and including the one what we consider currently in “control.” Here, all locomotion has an element of online control, but can be mediated by higher levels.

This brings us to the next phase of discussion, the idea that attention modulates our ability to switch among these levels. I will next present a general theory of attention and performance proposed by Wickens (2002), and follow that with a review of work that has been done on the role of attention in the control of basic posture and gait control. Finally, I will return to the concept of levels of locomotor control and discuss how Wickens’s theory of multiple resources makes predictions about how we move through the levels of control.

Attention and Multiple Resource Theory

A recent conception of attentional theory was proposed by Wickens (2002). Following from the ideas put forth by Kahneman (1973) that proposed distinct types of attentional interference modalities (and the structural interference that can arise when multiple tasks require one modality), Wickens describes a four-dimensional model of attentional and neural resources. Similar to Kahneman, he describes multiple channels of

resources that can be allocated to a task; if two tasks are being engaged in simultaneously, performance on one or both will degrade if they share resource channel, but will remain at a baseline level if they require independent channels. These four dimensions include processing stages, perceptual modalities, visual channels, and processing codes.

Briefly, processing stages refer to the finding that cognition and perception seem to occur at an “input” stage of processing, while responses occur as an “output.” For example, Wickens cites the case of an aircraft controller; his “input” functions of mentally monitoring the airspace would not be impaired by a sudden increased requirement to “output” responses about changes in aircraft states. If, however, he was given another perceptual or cognitive task, his performance on the monitoring task would decrease.

Perceptual modalities refer to separate attentional channels for each type of perception, e.g. vision and audition. Citing earlier research, Wickens suggests that cross-modal attention-sharing tasks are more easily done than intra-modal tasks. For example, it is more difficult to monitor two audio streams than one audio and one video stream.

Visual channels describe the two visual systems proposed by Leibowitz et al. (1982), which drew from Schneider’s (1969) discovery of two distinct visual pathways in the brain. The dorsal pathway is responsible what has come to be known as ambient vision, which is primarily responsible for determining locations in and guiding movement through the world (see also Norman, 2002); the ventral pathway is responsible for focal

vision that is used for the identification of objects in the world. Wickens uses the common example of walking while reading to illustrate that there is little overlap between these channels, and we can easily perform discrete tasks simultaneously.

Finally, processing codes refer to whether information is verbal or spatial in nature. This is distinct from the processing stages channel in that the information considered here can be on one end of the task alone. For example, he discusses that it is easier to provide a manual response (spatial) alongside a verbal response (verbal) than two manual or two verbal responses. This is, of course, confounded by the physical aspect of the situation (how would one produce two simultaneous verbal responses?); however, this is an important processing channel to which we will return later in the discussion of the line of experiments presented here.

Importantly, Wickens does note that this model does not necessarily mean that tasks can always be performed when there is no overlap. He cites Strayer & Johnston (2002), who found that drivers would become so preoccupied with a cellular phone task that they would completely neglect the concurrent (and non-structurally related) driving task. This is what Kahneman (1973) and others have termed capacitive interference, where the total attentional resources are consumed by a task, and other attention-demanding tasks, regardless of their underlying mechanisms, cannot be performed optimally.

In sum, Wickens proposes that a fundamental aspect of resource/attention allocation is the modality of the involved resources. If two tasks are distinct on all four

areas, he proposes that they can be performed with little or no performance decrement. However, if they overlap on one or more resource requirements, performance will drop accordingly. Further, it is possible to see performance decrements even in some cases where resources do not overlap, when one task consumes all the possible resources. This generally occurs when one focuses on one task to the complete exclusion of all others.

I will now turn to an overview of recent work on the role of attention in the control of gait and posture. This is an important literature to understand, as it will allow us to infer what types of attentional resources may be required for higher-level guidance of locomotion.

Attention & Gait/Postural Control

There has been quite a bit of recent research investigating the role of attention in the control of basic gait and posture. This work has not focused on path formation, but rather more on the kinematics of balance and walking. However, it provides an important baseline to understanding the fundamental role of attention in the control of locomotion.

Woolacott & Shumway-Cook (2002) provide a useful review of the current state of the field. They begin by defining attention as the total information processing capacity of an individual. Like the RAM in a computer, performance on an attentionally-demanding task decreases when multiple demands exceed the total capacity of the system. This is a simpler conception than presented by Wickens (2002), but it is repeated quite a bit throughout this literature. In the area of postural control, they describe several

studies that suggest that posture requires a small amount of attention. These studies were generally conducted by having participants do a balance task on a force plate while performing a secondary task. Importantly, across studies young adults show a small decrement in the ability to perform the secondary task, but their balance was not generally impaired by the secondary task.

A similar result was found when reviewing the literature on gait control; in general, gait control is unaffected by a secondary task. However, some tasks that require fine motor control or memory retention were found to have small effects on the control of gait in young adults. Woolacott and Shumway-Cook conclude that gait and posture are prioritized in young adults, and that secondary tasks are allowed to falter to maintain this control. As Woolacott and Shumway-Cook point out, and we will see shortly, this is not necessarily the case throughout a person's lifespan.

Yardley, Gardner, Leadbetter, & Lavine (1999) suggested a confound in earlier studies, which was that some of the postural effects that did occur could have been attributed to the vocalization involved in responding to the secondary task. They had participants complete several secondary tasks while maintaining balance, which attempted to tease apart the contributions of articulation and attention. They had a purely verbal task, a purely attentional task, a task that required both vocalization and attention, and one that required neither. They found a significant increase in postural sway associated with articulation, but not attention. Importantly to note, however, this was an extremely small effect; the biggest difference in sway between conditions when standing

on an unstable surface was only 2 cm, and this difference was only 1.5 cm when on a stable surface. Thus we may conclude that articulation may have a very minor effect on postural control, but not one that we need to consider when investigating path formation.

To further address this issue, Regnaud, Robertson, Smail, Daniel, & Bussel (2006) had young adult participants walk on a treadmill while performing a rather unusual secondary reaction time task, biting a pressure plate when an electrode was stimulated on their neck. The purpose behind this was to eliminate the potential confound raised by Yardley et al. (1999) of vocalization, and to minimize structural interference to the greatest extent possible. The task had two levels, a simple reaction task to stimulus, and a complex form where participants were instructed only to respond to weak shocks (and to ignore more powerful shocks). They found that neither level of dual task engagement impaired walking performance, while walking did cause a significant increase in reaction time to the shocks. This provides more evidence to suggest that while locomotion requires a small amount of attention to maintain, walking is generally prioritized over a secondary task.

Chen, Shultz, Ashton-Miller, Girdani, Alexander, & Guire (1996) found a somewhat different result when they asked young and old participants to walk and avoid a suddenly-appearing beam of light that crossed their path. Performance on this avoidance task decreased for both age groups when they were required to perform a secondary task that involved monitoring a set of lights and selectively responding when some lit up. Both age groups were significantly impaired; however, the performance of

the older group decreased twice as much as that of the younger group.

In a similar study, Weerdesteyn, Schillings, Duysens, & van Galen (2003) had young adults walk on a treadmill and avoid obstacles that dropped unpredictably in front of them from an occluded location. As a secondary task, participants performed a verbal Stroop test during some of the trials. In accordance with Chen et al. (1999), Weerdesteyn and colleagues found that participants had significantly more obstacle hits when performing this secondary task. They suggest that the decreased performance does not necessarily mean that participants were unable to prioritize walking; rather, as the objects were small and nonthreatening, and the participants were wearing a safety harness, it is possible that they were not motivated enough to maintain perfect walking. They further conclude that since even young adults showed an effect of capacity interference, older adults with a decreased overall capacity would be at greater risk.

An important contribution of this study was their explicit discussion of structural and capacitive interference. They distinguish between secondary tasks that interfere with the overall executive capacity of the attentional system, as discussed above, with secondary tasks that actually interfere with the psychological or physiological structures underlying the task. They were careful to choose the verbal Stroop, which did not require any resources that should have interfered with the visuo-spatial structures that guide locomotion.

The hypothesis of increased difficulty in divided attention and locomotion with advancing age is supported by a body of work on aging and attentional control of posture.

For example, Maylor & Wing (1996) found that older adults have a larger decrease in postural stability when faced with a spatial memory task than did young adults.

Importantly, they specifically targeted structural interference in this study, as the resources required for maintaining visual control of locomotion are presumably also tapped into when the visuo-spatial sketch pad (VSSP) is used for visual memory. Li, Lindenberger, Freund, & Baltes (2001) also found that older adults had decreased performance on a memory recall dual-task while walking, and preferred to use aids to maintain walking ability rather than aid the secondary task; young participants exhibited the opposite.

Further, Gérin-Lajoie, Richards, & McFadyen (2006) had young and old participants avoid stationary or moving obstacles while paying attention to auditory messages that included numerical, spatial, and object information. They asked the participants after each trial to repeat one of the three pieces of information provided to them during the course of the trial, to ensure that attention was paid at all times. They found that the older participants slowed down more than young participants during the trial, increased their personal space more, and made more mistakes answering the follow-up questions about what they had heard. In other words, even though they slowed their gait and became more cautious, it still was not sufficient to maintain performance on the attentional task. This result is consistent with an on-road driving study done by Owens, Wood, & Owens (2007), which found that older adults were slower and more cautious (tending to hug the edge of the road) than young adults when driving at night, especially

when tasked with reporting roadside objects; this was not enough to maintain daytime levels of street sign and obstacle recognition performance, however.

Siu, Catena, Chou, van Donkelaar, & Wollacott (2008) also used an auditory Stroop task to investigate the effects of capacity interference. They were interested in further examining the effects found by Chen et al. (1996) and Weerdesteyn et al. (2003), who both found impairments in obstacle avoidance with distraction. In this case, they proposed that the effect was not so much interference with walking ability, but with the fact that obstacle appearance was surprising (several hundred ms before contact in both cases). Here, they had participants walk down a corridor and step over obstacles that remained consistently in their path. The obstacles were two different heights, 2.5% and 10% of participant body height. In contrast to the previous studies, they found no effect of distraction on gait. They did, however, find impairment of performance on the Stroop task, which supports previous findings of prioritization of gait and posture control.

Similarly, Beauchet, Dubost, Herrmann, & Kressig (2005) had young adult participants perform backwards counting while walking. They found greater impairment of the counting task than of walking, although mean velocity decreased slightly. They concluded that the control of walking requires only minimal attention in young adults.

There have also been effects found of distraction on other physiological measures of locomotion. For example, Daniels & Newell (2003) asked participants to walk on a treadmill that varied in speed while performing mental arithmetic tasks. They found that participants exhibited a later walk-run transition (switched to running at a greater speed)

when performing the secondary task. They conclude that monitoring physiological signals of gait transition (leg muscle strain, for example) requires an allocation of attention, and that this can be impaired by a secondary task competing for these resources.

There are several take-home messages from this literature. First and foremost, it has been shown repeatedly that the control of basic posture and locomotion require a small amount of attentional resources. As the pool of available resources decreases with advancing age, it becomes more difficult to successfully maintain safe locomotor control while distracted. Further, it has been shown that structural interference with visuo-spatial distracters has a larger effect on dual-task performance than capacitive interference, although under extreme circumstances capacity interference can also impair performance. Small impairments can be found in either the primary or dual task, depending on the instructions and particular situation. In general, however, young adults are able to successfully maintain balance and gait while performing a secondary task.

Attention and Levels of Locomotor Control

These findings supports the idea that control of basic locomotion occurs at the Online level, where little attention is required. The question is, then, what role attention plays in the ability of humans to move through the levels of locomotor control. As shown in Figure 1.5, I propose that the higher the current level of control, the more general attentional resources are required. To paint this with a broad brush: Navigation

requires more attentional resources than Simple Anticipation, which requires more attentional resources than Online Control.

However, as Wickens describes, there is more to the concept of attentional resources than simply capacity (though, again, that can be overloaded). When considering what resources are required at each level, we must also consider what kinds of tasks are being done at each of these, and what types of resources they require.

To begin with, it is reasonable to assume that all locomotion requires both the input and output processing stages. As all locomotion requires receiving perceptual information and performing an action, we can consider this resource channel to always be somewhat in use. It is equally reasonable to assume that the Simple Anticipation and Navigation/Learning levels often utilize the cognitive input stage, in which case all three sub-stages would have activity. It is unlikely that the resources required completely overwhelm the processing system, however, as we quite often perform both input and output tasks while locomoting (listening to music, thinking, moving our arms, etc.)

For Wickens's second dimension, perceptual modalities, it is again safe to assume that all stages of locomotion rely on vision (with rare exceptions). Higher stages (SA and N/L) could well incorporate other modalities, depending on the situation. For example, the sound of a siren could be paired with the response of moving to the side of the road, as it indicates an approaching emergency vehicle.

The third dimension, visual channels, distinguishes between focal and ambient vision. There has been quite a bit of research on the relative contributions of these to

driving (Leibowitz & Owens, 1977), and in general it is accepted that both are required for safe locomotion. We require focal vision to recognize objects in the environment, and we require ambient vision to guide our movement through it. It is more likely that focal vision will be additionally required at higher levels of locomotor control, for example if one is looking at a map while driving.

The final dimension presented by Wickens is processing codes, or verbal and spatial processes in perception, memory, or response. All levels of locomotor control require spatial processing, as it is necessary to process the changing environmental information around during movement. It is predicted that higher levels of locomotor control will require verbal processes, as well, to form predictions and to inform higher level directions.

Using Attention to Explore Levels of Locomotor Control: Summary of Research

Now that we have a general layout of what types of attentional resources may be involved with different levels of control, we can explore ways to test this theory by manipulating attentional requirements. Ideally, we will be able to affect the level at which people control locomotion by occupying varying types of resources. The goal for the line of research I present here, then, is two-fold. First, it is necessary to show that people can learn to anticipate obstacle movement; that the Levels of Locomotor Control theory is supported by evidence. Second, I will attempt to shift the level of control at which people are operating by manipulating their attentional resources.

The first step in this process is to confirm empirically that people can in fact learn to anticipate obstacle movement. Experiment 1 was conducted as this initial baseline, to determine whether people will learn to anticipate predictable obstacle movement, and change their paths to take advantage of this knowledge. In this study, participants walked in virtual reality (described below) to a stationary goal while avoiding a moving obstacle that crossed their path. In each trial block, participants were faced with two types of obstacle, one that was designed to get in their way, and one that was not. I predicted that participants would take more efficient paths over time, discriminating “safe” from “dangerous” obstacles. This hypothesis was not supported, as participants did not exhibit consistent change over time; their paths were consistent with predictions of the constant-bearing model across trials.

Experiment 2 was a second attempt to determine if people can in fact learn to anticipate obstacle motion. The design was altered to force anticipation if participants were to avoid being hit; obstacles were designed to collide with participants if they did not preemptively veer. This proved successful, as participants diverged from model predicted paths after several trials.

Experiment 3 introduced a distractor task to see if participants would revert back to online control when their attentional resources were occupied. I used a Brooks visuo-spatial task for this, in order to maximally interfere with the processes underlying locomotion. In Wickens’s model, this task should interfere with the **processing stage**, as it introduces a cognitive load, as well as **processing code**, as it adds both a verbal

component (response) and an additional spatial load. Further, if the task is difficult enough, the total attentional resources required may exceed the total amount of resources available; thus, we may also see a capacity interference. The results showed mixed support for the hypothesis; people were less consistent in their avoidance than in Study 2, but were still able for the most part to anticipate obstacle motion.

Experiment 4 was conducted to see whether a more challenging version of the same task would decrease anticipatory performance; in other words, if increased attentional resource capture would cause a corresponding decrease in anticipation. This proved to be the case, as people rarely deviated from model-predicted paths, and there was little discrimination between different types of obstacles.

General Methods

The Virtual Environment Navigation Lab

All research presented here was conducted in the Virtual Environment Navigation Lab (VENLab) at Brown University. The basis of the lab is a large 12m x 12m room in which participants can walk freely while wearing a head-mounted display (HMD) that presents stereo virtual images through a pair of liquid crystal displays. For Experiment 1, this HMD was a Kaiser ProView 80 (Rockwell-Collins, Carlsbad, CA) with a 640x480 resolution and a field of view of 62(H) x 46(V). This HMD was replaced for Experiments 2-4 with a Cybermind Visette Pro with identical resolution and 60(H) x 40(V) field of view.

The environments for all experiments were nearly identical, with a featureless sky (black for the first experiment, blue for the remaining three) and a randomly-textured brown desert ground plane. The only objects in the environment were vertical poles that represented targets, obstacles, and starting positions.

The participant's head position was tracked using an Intersense IS-900 ultrasonic/inertial tracking system (Intersense, Bedford, MA). The receiver/inertia cube was securely mounted to the top of the HMD in all studies, and data were sent to the computer from an RF transmitter carried by the participant in a waistpack (Experiment 1) or a backpack (Experiments 2-4). The tracking system and rendering combined for an average display latency of roughly 70ms.

Tracking, graphical updating, and data collection were performed on an Alienware PC running Windows XP Professional, with a 3 GHz Intel Xeon processor, NVidia Quadro FX graphics card, and 2GB of RAM. The virtual environment in Experiment 1 was created using a proprietary program developed for our lab (eVEN), while Experiments 2-4 were conducted using Vizard, a commercial VR programming toolkit (Worldviz, Santa Barbara, CA). Virtual objects were created in 3D Studio Max and Adobe Photoshop and imported into the programming toolkits. Participant positional data in x, y, and z were collected at 30Hz for Experiment 1 and 60Hz for Experiments 2-4. Modeling was performed and data were analyzed using MATLAB, with SPSS, SAS, and Microsoft Excel used for additional analyses.

Participants

Participants were drawn from the Brown University undergraduate and graduate student populations, as well as the surrounding community. Participants all had normal or corrected-to-normal vision; for Experiments 2-4, participants had to have normal vision or be wearing contact lenses, as glasses would not fit under the HMD used for these. Participants were required to be over the age of 18, and were required to have no neurological impairments. The Brown University Institutional Review Board approved all research presented here, and all participants gave written and verbal informed consent. Participants were compensated \$8 for their participation regardless of whether or not they completed the study. An experimenter walked beside each participant at all times to gather the video cable to the HMD and to ensure the participant's safety.

Procedure

The general method was identical across all experiments; differences will be noted as they arise for each experiment. Prior to the arrival of each participant, the HMD and remote control were disinfected with rubbing alcohol. Upon arriving at the lab, participants were greeted and asked to sign a consent form. After completing the consent form, each participant was given a verbal introduction to the lab, including what he could expect virtual reality to be like. He was shown the HMD, the waistpack used for cable routing, and the remote control used to initiate trials. The experimenter also explained

that he would follow the participant throughout the duration of the study to gather the HMD cable and ensure the participant's safety.

Once the participant was familiar with the lab and equipment, the experimenter measured his inter-pupillary distance (IPD) using a metric ruler. He was then given a sanitary hairnet and fitted with the HMD. Once the HMD was adjusted comfortably, the experimenter adjusted the width of the eyepieces to match the measured IPD and the verbal report of the participant. This placement was then confirmed using a stereo computer display.

After initial fitting of the HMD, the experimenter turned off the room lights and allowed the participant to complete an initial "exploration" VR session that was designed to familiarize the participant with virtual reality. This took place in a virtual desert environment identical to the environment used in experimental trials. This environment contained a grey "home" pole (3m tall), a red "orientation" pole (3m tall), and seven blue "obstacle" poles (2m tall). Participants were instructed to walk to the home pole and turn to face the orientation pole (full instructions are reprinted in Appendix A-1 (Experiment 1), B-1 (Experiment 2), and C-1 (Experiments 3 & 4)). The orientation pole would then turn into a green target pole (3m tall), which participants were to walk to. This target would then disappear when walked into, and one of the blue obstacles would turn into a target. After this target was walked into, another obstacle would turn into a target, and so on until all the poles had disappeared. This exploration phase took roughly three minutes to complete, and all participants expressed comfort with virtual reality by its conclusion.

Had any participants either expressed or demonstrated any discomfort, they would have been thanked, compensated, and sent home.

After the exploration phase was finished, the experimenter handed the participant the remote control and initialized the main experimental code. The participant now received instructions for the practice section of the experiment. He then completed the practice trials (10-15 trials depending on experiment), and was asked if he had any questions. If he understood and was comfortable with the task (all participants were), the experimenter initiated the experimental trials. After the participant completed all the trials, the HMD and waistpack were removed, and he was asked to fill out a brief questionnaire. The participant was then debriefed, paid \$8, and thanked for his participation. All experiments took roughly an hour from participant arrival to departure.

CHAPTER 2

EXPERIMENT 1: WILL PEOPLE LEARN TO ANTICIPATE PREDICTABLE OBSTACLE MOTION?

Experiment 1 was conducted as a baseline to investigate whether people can anticipate obstacle movement and take advantage of this to develop more efficient avoidance paths. As previously found in Owens & Warren (VSS, 2005), people are able to learn to predict the movement of a single moving target and take more efficient interception paths. Here, the goal was to discover whether this ability carries over to the more everyday case of avoiding predictable obstacles. As discussed earlier, this is a common requirement in activities like driving where we are traveling at super-normal speeds; we must be able to predict which objects in the world are likely become obstacles if we are to react to them in time to avoid collision. A secondary goal was to investigate whether explicit previous knowledge of the relation between object appearance and movement would benefit this learning process.

The primary task in developing Experiment 1 was to develop obstacle movements that could be more efficiently avoided than they would be under online model-predicted behavior. In the previous moving-target learning studies, this was relatively simple to achieve by the use of curving target paths; straightening human interception paths were a direct measure of anticipation and efficiency. The solution, used through all four studies presented here, was to have two types of obstacle per trial block – one “dangerous,” that would pose a threat of collision, and one “safe”, that would never get in the participant’s way. Both obstacles in all cases were poles 0.5 m wide x 3 m tall, but they differed in color and the shape that was located at the top of each pole.

Each obstacle path consisted of two distinct movement phases. The initial phase of movement, which lasted 1.5 seconds, was consistent across trials. The second phase was where obstacle paths differed; here, one type of obstacle moved quickly to pose a threat to participants, while the other did not. Obstacle appearance was always a perfect predictor of its movement; for example, for a given block, a green pole with a cone-shape on top would always veer into the participant's path, while the other pole, a red pole with a sphere on top, would not. The hypothesis was that if participants are able to learn to discriminate "dangerous" from "safe" obstacles based on their appearance, they will exhibit anticipatory avoidance behavior before the obstacles change from the first to second phase of movement.

To address the second question presented above, whether prior knowledge of a relationship between obstacle appearance and movement would improve anticipatory learning, there were two groups of participants. In one group, participants were explicitly told that obstacle appearance was a cue to its movement; in the other, this line was omitted from the instructions (complete instructions are presented in Appendix A-1).

Participants' task in Study 1 was to walk in virtual reality from a starting position for each trial to a stationary target pole (0.5 m x 3 m) located 6m directly in front of the participant, while simultaneously avoiding a moving obstacle. When the participant successfully walked into the target, a tone would play, the target would disappear and the starting position for the next trial would appear. If the participant collided with an obstacle, a sound would occur to signal the impact.

Method

Participants

There were 22 participants in Study 1; however, three participants were excluded because of equipment failure, and one was excluded for failure to follow instructions. The remaining participants were evenly divided with nine males and nine females, with a mean age of 19.8 years (range 18-25 years).

Procedure

Participants first completed ten practice trials. There was one type of obstacle (a red brick pole 0.5 m wide x 3 m tall), which was always positioned 3 m ahead of the participant's starting position and 1.5 m to the left or right (randomized across trials). Immediately after the participant began walking toward the target, the obstacle began moving perpendicular to and toward the home-target axis at 0.65 m/s. These obstacles were not specifically designed to impede the participant's path, but to familiarize him with the task of avoiding them.

Participants then completed a baseline block of 12 trials with one obstacle (a stone textured pole) that again moved at a constant 0.65 m/s. This obstacle started slightly further away, from a starting position 3.5 m ahead of the participant and 1.5 m to the left. As all trials in this block featured identical obstacle movement, this was designed to act as a baseline of avoidance paths over time when no other factors were present. The obstacle path for the Baseline Block and the model-predicted human

avoidance path are presented in Figure 2.1. This plot, like the path plots to follow, presents a birds-eye view of human and obstacle paths over time. In this case, the obstacle path is plotted as a green line, and the modeled human path is a red line. A black marker on the obstacle path designates the predicted position of the obstacle at the point when the human passes it. It is important to note that this avoidance path was modeled using the mean speed for all participants.

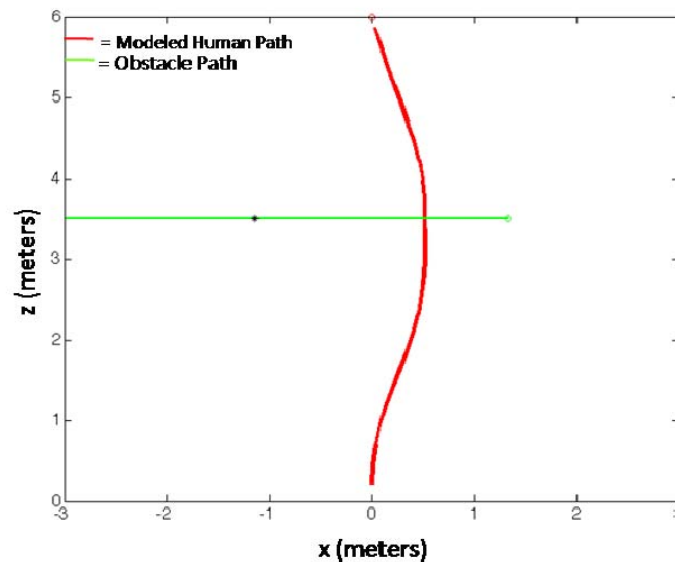


Figure 2.1 Obstacle and model-predicted human paths for baseline condition.

After the baseline block, participants completed two experimental blocks, order-counterbalanced among participants. These blocks, as described above, each contained two types of obstacles, one that was designed to impede the participant's path, and one that was designed to never get in her way. There were 12 randomized trials of each type in each block.

In the Direction-Change Block (Figure 2.2), both obstacles began in the same position (3.5m ahead of the start, 1.5m to the right) with the same initial heading (perpendicular to the participant's initial position) and speed (0.65 m/s), but changed course $\pm 50^\circ$ after 1.5 seconds. One obstacle (Toward, Figure 2.2A) suddenly veered toward the participant (-50°), and the other (Away, Figure 2.2B) veered away ($+50^\circ$). The red lines on each plot represent the modeled human avoidance path, using the Cohen et al. (in prep) equation described above, using the mean participant velocity for each condition.

The Toward obstacle's path was designed such that participants traveling at 1.2 m/s (equal to the mean speed in Owens & Warren, VSS 2005) directly toward the target would be nearly hit by the obstacle. Conversely, the Away obstacle's path was designed to never pose a threat to the participant. The hypothesis for this block was that participants who learned to anticipate obstacle movement would turn earlier and more sharply in the first 1.5s when in trials with a Toward obstacle, and would straighten their path and veer less when encountering an Away obstacle.

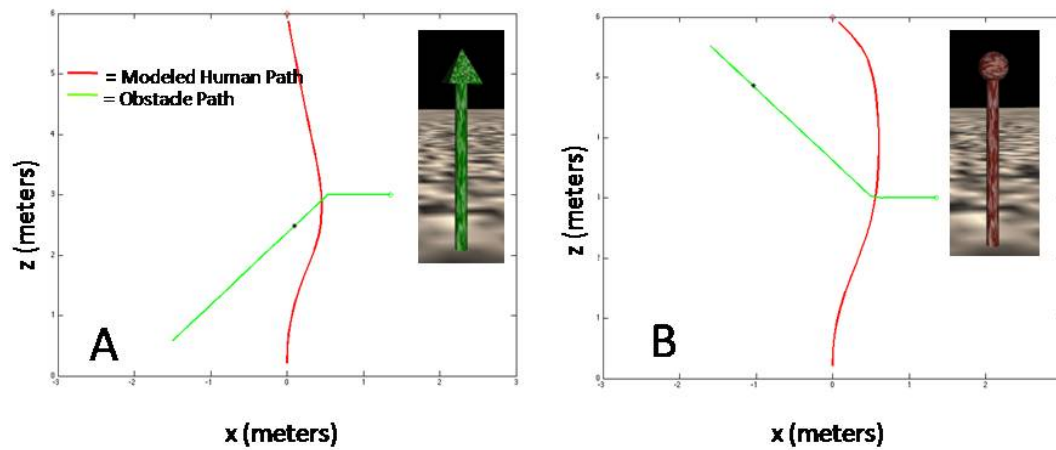


Figure 2.2 Model-predicted paths for (A) Direction-Change Toward and (B) Direction-Change Away trials.

The Speed-Change Block also consisted of 24 randomized trials (Figure 2.3). In this second block, instead of changing direction, the obstacles changed speed after 1.5s. The initial position, speed and direction were the same as in the previous block, except that they were mirrored to approach from the left. Here, one obstacle slowed to 0.2 m/s (Slower), while a different obstacle sped up to 1.0 m/s (Faster). These obstacle paths and corresponding model-predicted participant paths (again, based on actual mean first-trial speeds) are shown in Figure 2.3.

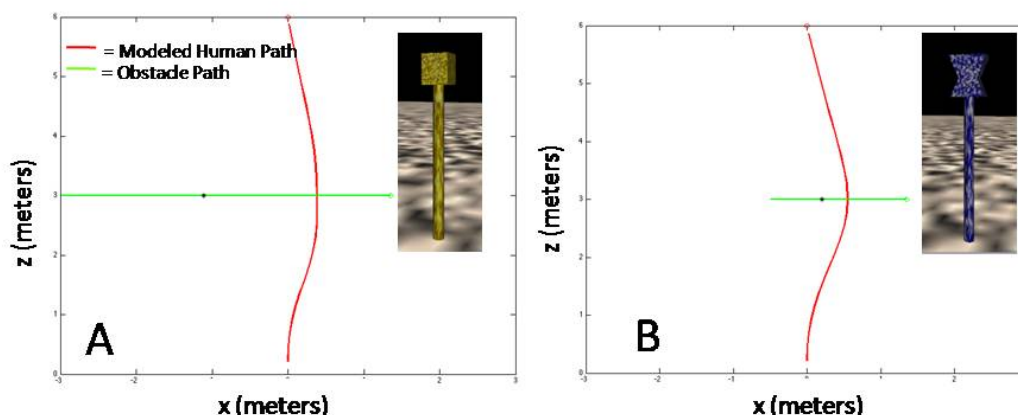


Figure 2.3 Obstacle and model-predicted human paths for (A) Speed-Change Faster and (B) Speed-Change Slower trials.

For this block, the Slower obstacle was designed to impede the path of participants traveling at roughly 1.2 m/s, while the Faster obstacle was designed to get out of the way before participants reached it. The hypothesis for this block was that people who were able to anticipate the movement of the obstacles would take a more consistent, smoother path around the Slower obstacle, and would take a straighter path for the Faster obstacle trials, as they would never pose a threat.

Results

Questionnaire Results

The post-study questionnaire (Appendix A-2) was administered as secondary measure of participants' ability to learn and predict obstacle movements. In theory, if cognition was used to modulate locomotion, participants should be aware of their learning of appearance/movement relations. Further, the questionnaire was an attempt to

discern whether participants' retrospective impressions of their performance matched the paths they took. There were two main questions: one that asked whether they noticed objects moving differently from one another, and one that asked whether the participant used any strategies to avoid the obstacles. These questions were intentionally vague, to avoid biasing responses.

All but one participant reported noticing that different obstacles moved differently (the one who did not report this was in the Explicit Cue group, interestingly enough). Further, even though the question was vaguely worded, five participants in the Explicit Cue and three participants in the No Cue group provided specific information that showed learning (generally pointing out at least one color/movement pair). For the second question, six of nine participants in each group reported developing strategies to avoid obstacles.

The questionnaire data seems to support the hypothesis that people are able to learn to predict obstacle movement and adapt their paths to take advantage of this knowledge. The next step is to turn to the quantitative path data to determine what participants actually did. In order to form a complete picture of potential learning effects, I will explore differences in mean participant headings across conditions, changes in correlation between human paths and model headings over time, changes in initial path angles over time, and changes in speed over time for each condition and participant group. These four aspects of performance provide a cohesive picture of whether participants learned to anticipate obstacle trajectories.

Mean Participant Paths

The first way to examine the data is to look at the average paths that people took around obstacles. Mean participant paths for the Baseline Block are presented in Figure 2.4. There was no significant difference in mean headings between the No Cue and Explicit Cue groups, $F(1,46) = 0.10$, $p = .76$. This was not surprising, since there was only one obstacle and one path in this block; there was no need to discriminate obstacle paths based on appearance.

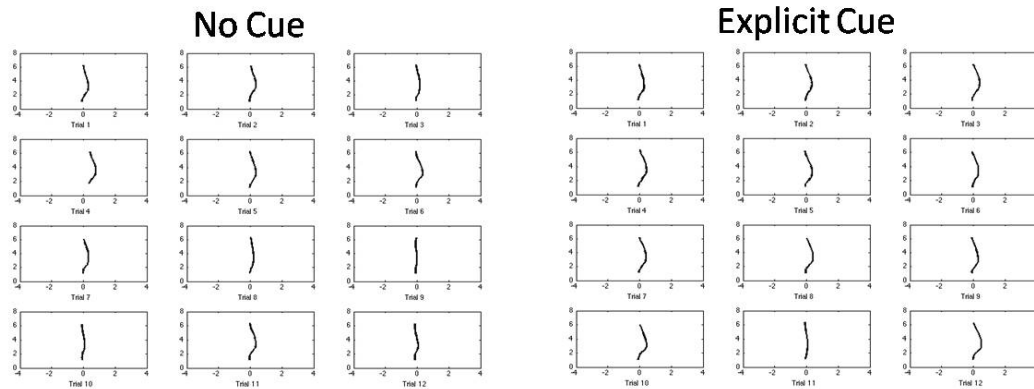


Figure 2.4 Mean Participant Paths for Baseline Block.

Mean paths for the Direction-Change Block are shown in Figure 2.5. Paths for Toward trials are shown in black, and paths for Away trials are shown in red. Somewhat surprisingly, there were no significant differences in mean heading between the No Cue and Explicit Cue groups in this block, either, $F(1,92) = 1.6$, $p = .20$. Further, there were no significant differences in mean participant heading between the Veer-Toward and

Veer-Away trials, $F(1,92) = 0.035$, $p = .85$. Finally, there was no significant interaction between Cue Group and Direction-Change Condition, $F(1,92) = 0.003$, $p = .96$.

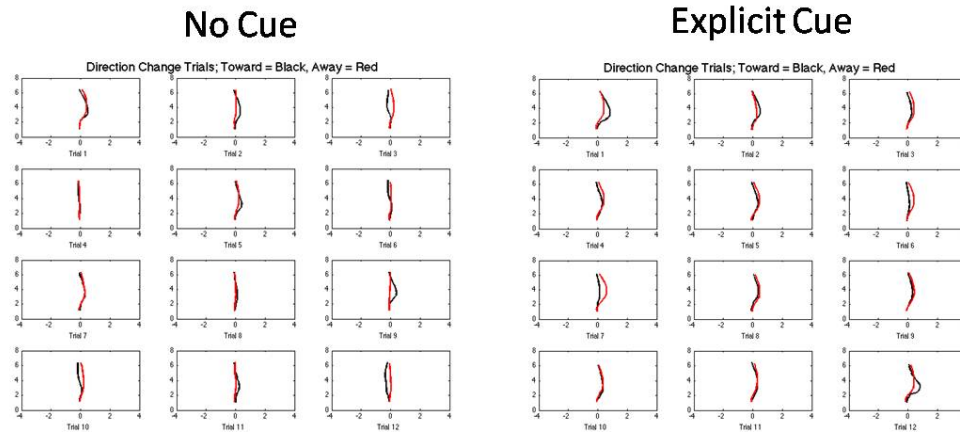


Figure 2.5 Mean Participant Paths for Direction Change Block.

Figure 2.6 presents the mean participant paths for the Speed-Change Block. Here, paths around obstacles that sped up from 0.65 m/s to 1 m/s (Faster) are presented in green, and paths around obstacles that slowed down to 0.2 m/s (Slower) are presented in blue. Again, in this condition there are no significant differences in heading between the No Cue and Explicit Cue groups, $F(1,92) = 0.179$, $p = .67$. There were also no significant differences between the Faster and Slower trials, $F(1,92) = 0.02$, $p = .90$, and no significant interaction, $F(1,92) = 0.07$, $p = .79$.

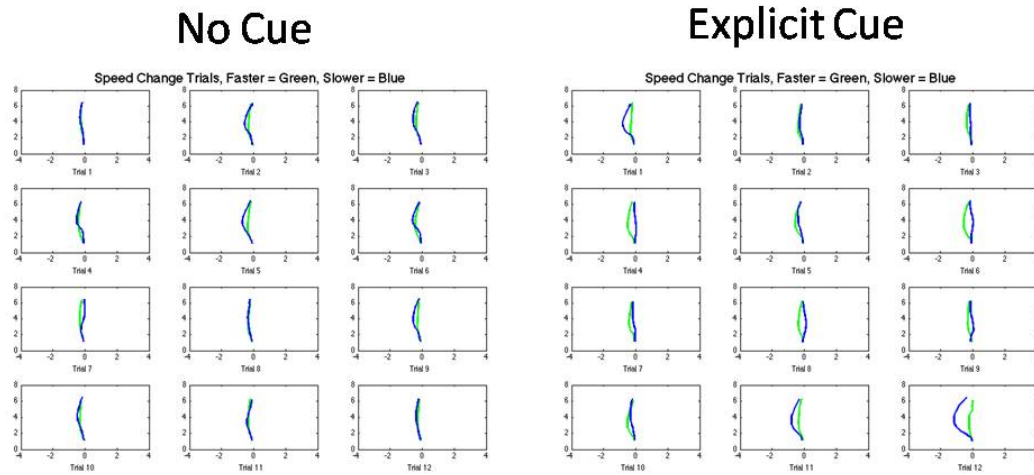


Figure 2.6 Mean Participant Paths for Speed Change Block.

In sum, there was no difference in mean headings between cue groups or “danger” level conditions. This was surprising, as discrimination and anticipation of obstacles was predicted to show up as differentiation of headings between conditions and groups.

Comparison Between Participant and Model Headings

In addition to looking at differences between mean participant headings, I examined the relationship between participant and model-predicted headings. Recall that the model predictions are based on a constant velocity equal to the mean participant velocity across trials for each obstacle type.

To enable comparison with model predictions, participant paths were standardized (downsampled) into 24 bins to account for differences in participant speed. This was accomplished by dividing the total number of samples of each trial (collected at 30 Hz) by 25, rounding down to an integer $\underline{n}$, and taking every $\underline{n}$ th sample. The model-predicted

path was also downsampled to 24 bins, which allowed a direct comparison between headings at corresponding locations in space.

Table 2.1

Coefficient of Determination (r^2) Between
Participant and Model Predicted Headings

	ExplicitCue	NoCue
Baseline	.91	.88
Veer-Toward	.85	.91
Veer-Away	.87	.76
SlowDown	.50	.86
SpeedUp	.94	.84

Table 2.1 presents the r^2 values for mean binned participant headings and binned model prediction headings. Overall, there was a strong relation between model predictions and human headings; the exception to this was the Slow-Down condition when participants were explicitly told of a relation between obstacle appearance and movement ($r^2 = .50$), which was due to two anomalous trials skewing the data. There was no significant difference between the Explicit Cue and No Cue groups, $t(8) = -0.4$, $p = .27$.

This tells us that there is an overall strong relationship between model-predicted headings and those of participants; a more specific question is whether this correlation changes over the trials within a block. If participants were learning to predict and take advantage of obstacle movements to create more efficient avoidance paths, we would expect to see consistent decreases in the relationship between their headings and those predicted by the model.

Table 2.2
 R^2 Between Participant and Model Predicted Headings
 Across Trials (Explicit Cue/No Cue)

	Trial 1	Trial 2	Trial 6	Trial 11	Trial 12
Baseline	.87/.91	.70/.68	.84/.81	.59/.84	.96/.71
VeerToward	.82/.66	.81/.75	.77/.52	.77/.88	.84/.33
VeerAway	.92/.21	.66/.81	.81/.68	.90/.18	.86/.63
SlowDown	.77/.11	.58/.28	.66/.78	.90/.75	.76/.48
SpeedUp	.82/.25	.92/.25	.91/.94	.92/.89	.29/.83

As we can see in Table 2.2, however, this does not seem to be the case. This table presents the r^2 in heading between participants and the model for trials 1, 2, 6, 11, and 12. The first value in each cell represents the Explicit-Cue group of participants, and the second value represents the No-Cue group. If participants were learning to anticipate, we would expect to see high path/model correlations in trials 1 and 2, while learning was taking place, with decreasing r^2 values across later trials. This is not the case, as the values in the final trials are similar to – and in several cases larger than – the

corresponding values in the first two trials. In sum, though there is certainly variation among trials and conditions, we see no consistent changes in correlation across trials, and no data to suggest that participants are learning to anticipate obstacle movement.

Initial Path Angles

We will next examine initial path angles over time. These represent mean participant path angles for the first 1.5 seconds of travel time, before the obstacles changed direction or speed. Recall that it was predicted that initial headings would change over trials; as people learn what individual obstacles would do, they would adapt their paths accordingly. For example, to avoid being hit by the Toward obstacle, participants would veer earlier in their path, before it changed direction.

However, here again there were no significant differences across trials for any of the conditions or groups. Table 2.3 presents ANOVA results for initial path angles over time for both participant groups (df values vary slightly because some data points were missing).

Table 2.3
Initial Path Angles Across Trials

	Explicit Cue	No Cue
Baseline	$F(11,77) < 1$	$F(11,75) = 1.54, p = .14$
Veer-Toward	$F(10,74) < 1$	$F(11,76) = 1.01, p = .44$
Veer-Away	$F(11,76) < 1$	$F(11,80) < 1$
Speed-Up	$F(11,77) < 1$	$F(11,73) = 1.40, p = .19$
Slow-Down	$F(11,79) < 1$	$F(11,74) < 1$

Mean Speeds

The final dependent measure is mean walking speeds across trials. It is possible that even if path headings did not change over time, learning (or task familiarity) led to changes in speed. As shown in Figures 1.7 - 1.8, mean speeds were somewhat lower than those found in previous studies (grand mean = .92 m/s). Further, there were significant differences in mean speed across trials for several conditions; for the Explicit Cue group (Figure 2.7), the Baseline, Veer Toward, and Slow Down trials all had a significant, though small, speed increase, and the Veer Away and Speed Up trials brought marginally significant speed increases. For the No Cue group (Figure 2.8), only the Baseline trials contained a significant speed increase.

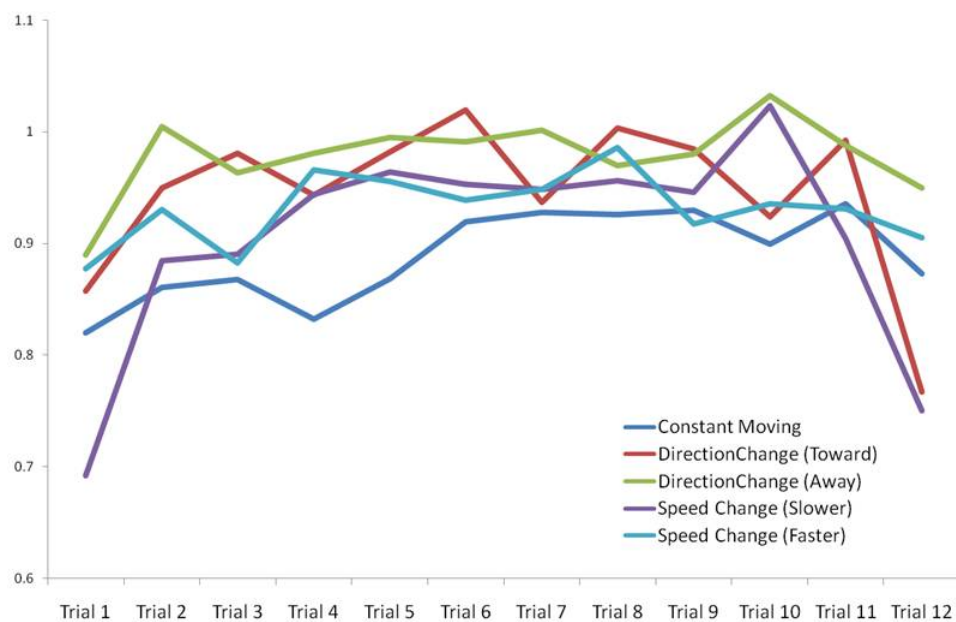


Figure 2.7 Mean speeds for participants in the Explicit Cue condition.

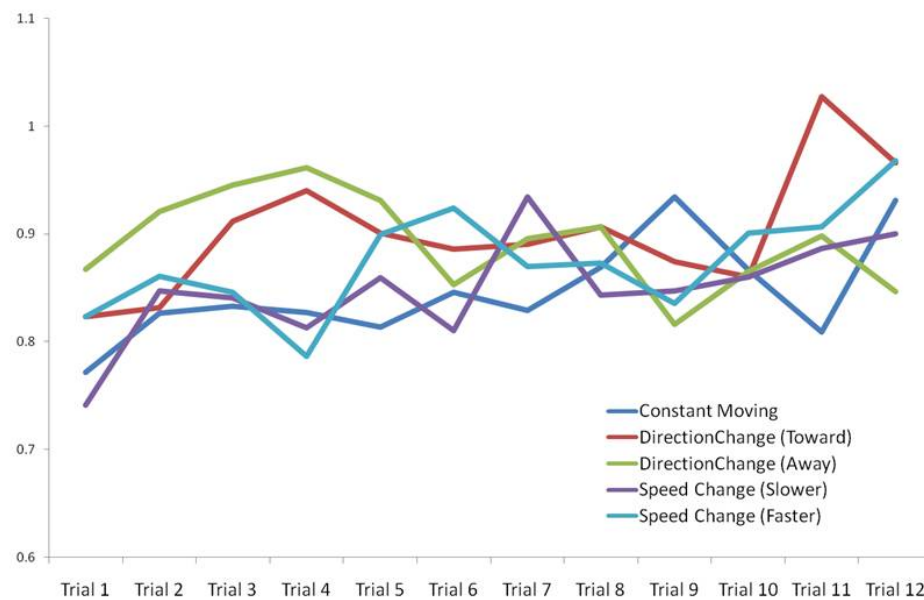


Figure 2.8 Mean speeds for participants in the No Cue condition.

Table 2.4

Tests For Speed Differences Across Trials

	Explicit Cue	No Cue
Baseline	F(11,77) = 2.19, p=.02	F(11,75) = 2.51, p<.01
Veer Toward	F(10,74) = 3.85, p<.001	F(11,76) = 1.5, p=.15
Veer Away	F(11,62) = 1.84, p=.07	F(11,81) < 1
Speed Up	F(11,70) = 1.89, p=.06	F(11,74) = 1.34, p=.23
Slow Down	F(11,69) = 5.41, p<.001	F(11,73) = 1.42, p=.18

Discussion

Counter to prediction, the only significant differences found in Experiment 1 were in mean walking speed, not in any measures of overall or initial heading across trials or in correlations with model-predicted heading. Further, while there was a significant increase in speed over trials for several conditions, the effect was fairly small. This is especially interesting in light of the fact that the majority of participants reported in the post-hoc questionnaire that they were aware of patterns of obstacle movement (several provided unrequested evidence of specific paired learning), and six of nine participants in each instruction group reported developing strategies to avoid obstacles.

The question, then, is why participants did not exhibit anticipatory avoidance behavior. One conclusion could be that the hypothesis was simply wrong; perhaps it is difficult or impossible for people to cognitively affect their locomotion. Perhaps locomotor guidance is solely based on online perceptual information, and is cognitively impenetrable. The consistently high correlations across trials between mean participant headings and model-predicted headings certainly support this theory. If this is the case, we could conclude that people are simply not able to anticipate obstacle movement and base walking paths on cognitive, top-down information.

An alternative explanation is that Experiment 1 failed to motivate people to anticipate obstacle movement. Recall that obstacles were designed to pose threats to people traveling at roughly 1.2 m/s; actual participant velocities in this study were slower than this (mean = .92 m/s). It is likely, therefore, that participants were not challenged by

veering and slowing obstacles to the extent that was intended. It is also possible that subtle speed changes allowed obstacles to pass harmlessly by the participant, without the need to change their heading from previous trials.

Further, even if they had been traveling at the predicted velocity, participants could have avoided the obstacles using online control. I predicted that people would prefer to make smoother, earlier turns to avoid having to jerk out of the way of obstacles; this may not have been the case, as there was no incentive aside from this to change avoidance strategies.

A final limitation is that obstacles only traveled for 1.5s before they changed their speed or direction. This was a function of the distance of the obstacles and the desire to start their movement within the field of view of the participant, but it may have been insufficient time for participants to recognize the obstacle, infer its future movement, and change their avoidance path.

Conclusion

Overall, participants exhibited very little change in path headings over time, and exhibited no significant anticipatory behavior. There are two reasonable explanations for these results: either participants were not able to anticipate obstacle motion, or they were not motivated to. Post-hoc questionnaire results suggest that people were aware of obstacles' predictable nature, which suggests the second explanation, unless locomotion

is truly cognitively impenetrable. Experiment 2 was designed to test these two hypotheses; to do so, it needed to address the limitations of Experiment 1.

CHAPTER 3

EXPERIMENT 2: CAN PEOPLE LEARN TO ANTICIPATE OBSTACLE MOTION WHEN NECESSARY TO AVOID COLLISION?

Experiment 2 was designed to further investigate why participants in Experiment 1 failed to show anticipatory behavior. It was specifically aimed at determining whether people are unable to learn to predict the movement of obstacles, or if they were simply not motivated to in the previous study. As noted in the last section, one of the limitations of Experiment 1 was that obstacle trajectories were predetermined and designed to get in the path of the average participant. However, participants traveled on average more slowly than expected, and variation in walking speeds meant that participants saw obstacles as varyingly threatening.

To address this issue, I created obstacle trajectories that were designed to always collide with participants if they walked directly from the home position to the target (Figure 3.1). These were triggered by the participant crossing an invisible trigger line that was positioned 2.5m in front of the starting position. When this trigger line was crossed (at any point along the x-axis), the obstacle veered at 5.5 m/s toward a position 0.1m in front of the trigger line, on the z-axis between the start and the target. As the obstacle moved at a constant 5.5 m/s, this meant that it traveled from the change point to the point of possible collision in 750 ms, making it nearly impossible to perceive and react to the obstacle in time to avoid it. This ensured that if participants did not change their path direction prior to reaching the trigger line, they would be hit by the obstacle, which would result in a siren sound. In other words, the only way to avoid being hit was to anticipate what the obstacle would do and preemptively veer out of the way.

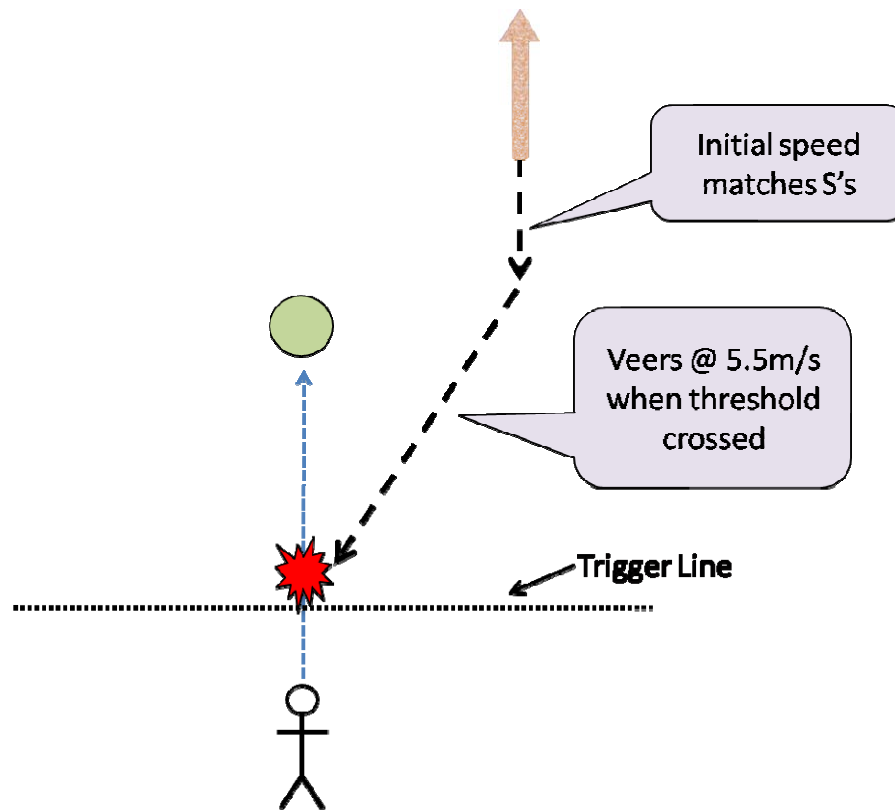


Figure 3.1 Example of a target designed to create a consistent danger.

A critical aspect of this design is that for obstacles that start out moving (as in Figure 3.1), the initial velocity of the obstacle was an exact (inverse) match to each participant's current velocity, updated at 60Hz. This allowed all obstacles to be at a consistent location when the participant crossed the trigger line, no matter the participant's initial velocity. This then allowed for a constant intercept angle and speed by "dangerous" obstacles.

Method

Participants

There were 16 participants in Study 2, 4 females and 12 males, with a mean age of 23.6 years (range 19-29 years).

Procedure

As there were no differences in Experiment 1 between participants who were given explicit information about obstacle predictability and those who were not, participants in Experiment 2 were not told of this contingency. The first block of trials for all participants consisted of 10 practice trials. In these, participants were instructed to walk to a target 6 m directly ahead of their starting position, while avoiding any obstacles that appeared. In all practice trials, a blue textured pole 2m tall moved from right to left at 0.65 m/s. Its starting position was always 3m in front of the participant and 1.5m to the right. This path was designed to present an obstacle to a participant traveling at roughly 1.3 m/s (slightly faster than the average walking speed, so as not to startle participants).

Participants then completed two main blocks of trials, counterbalanced among participants. Each block included one type of obstacle that would veer into the participant's path and one type that would move straight, never posing a threat. There were 20 instances of each obstacle type randomly presented per block, for a total of 40 trials per block (90 total trials including practice).

The first type of block, illustrated in Figure 3.2, contained obstacles that started out initially moving (Start-Move Block). These appeared 9 m in front of the participants' starting position (3 m behind the target), and 1 m to the right. Both types of obstacles in this block started in the same location, and both initially moved parallel to and in the direction of the participant. Key to the consistent danger described above is that the initial velocity of both obstacle types was an exact match to the each participant's velocity, updated at 60Hz. This allowed all obstacles to be at a consistent location when the participant crossed the trigger line. At this point, Move-Veer obstacles veered quickly toward a position directly in front of the trigger line, while Move-Straight obstacles continued on a trajectory parallel to the participant's initial trajectory. For this block, the Move-Veer obstacle was an orange pole with a cone shape on top, while the Move-Straight obstacle was a blue pole with an "X" shape on the top. As in the practice block, all obstacles in these blocks were roughly 2m tall.

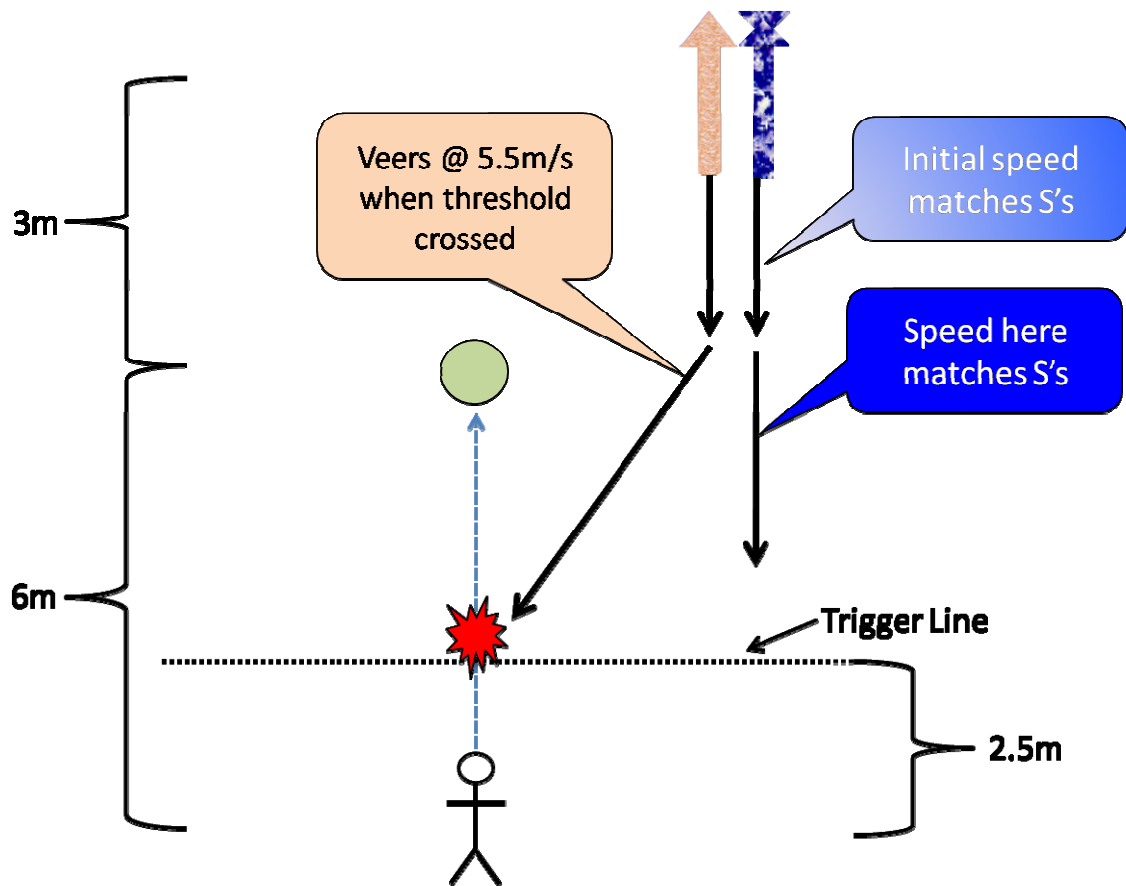


Figure 3.2 Start-Moving obstacle block.

The second type of block was similar to the first; however, obstacles started out stationary (Start-Stationary Block) at the point where the veering obstacle in the previous block changed direction (Figure 3.3). When the participant crossed the trigger line, the obstacles would then move in one of the two paths identical to the two paths presented above. The Stationary-Veer obstacle would veer toward the trigger line at 5.5 m/s, while the Stationary-Straight obstacle would move parallel to the participant's initial trajectory at a speed matching his. The purpose behind this block was to determine whether initial

movement differentially affects people's ability to predict what objects will do. As the Fajen & Warren (2003) model of stationary obstacle avoidance and the Cohen et al. (in prep) model of moving obstacle avoidance use slightly different perceptual variables (obstacle bearing angle and change in obstacle bearing angle, respectively), it is possible that moving and stationary obstacles differentially act upon initial avoidance behavior.

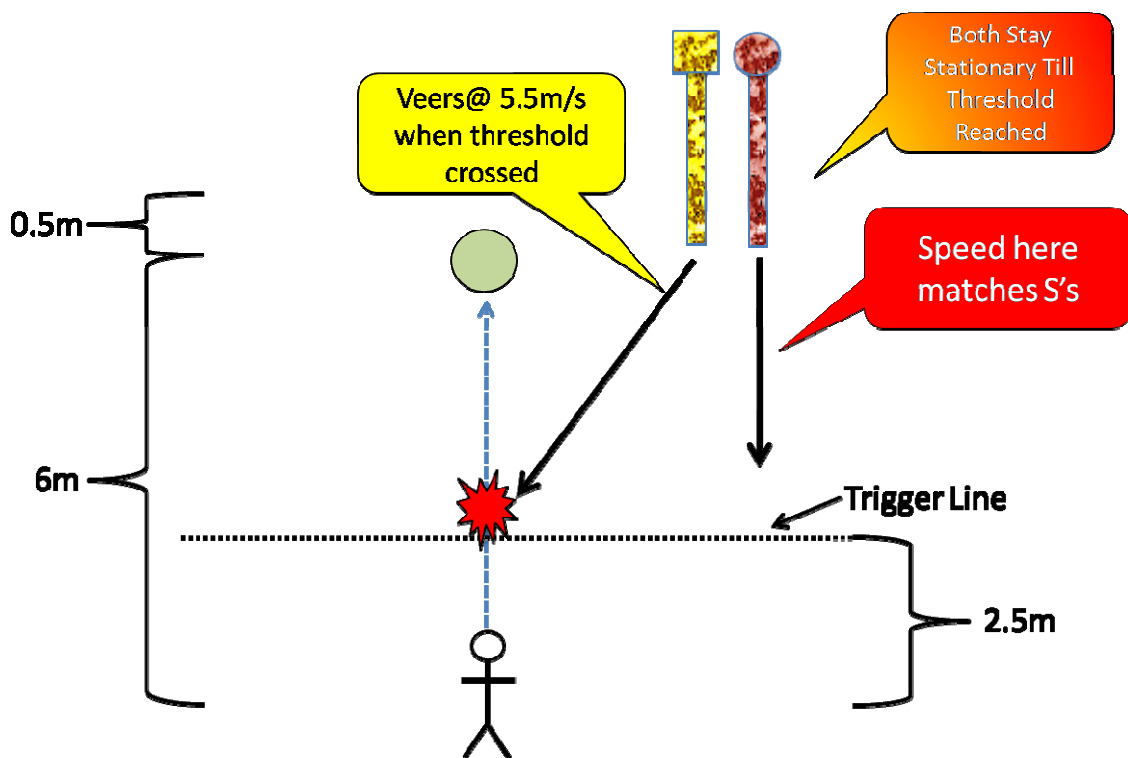


Figure 3.3 Start-Stationary obstacle block.

In sum, there were four total conditions: Move-Veer, Move-Straight, Stationary-Veer, and Stationary-Straight. These conditions were presented in two counterbalanced blocks of 40 trials each; half the participants saw the Move trials in Block 1 and the

Stationary trials in Block 2, and half saw the Stationary trials in Block 1 and the Move trials in Block 2.

Results

Questionnaire Responses

As described above, all participants completed a 2-page post-study questionnaire (Appendix B-2). All participants reported noticing obstacles moving differently from one another, and fifteen of sixteen provided specific trajectory information before being prompted. Fourteen of sixteen participants reported developing strategies for avoiding particular poles; all of these reported strategies involved curving away from the trajectories of dangerous obstacles. All but one participant were able to recall at least one trajectory they had seen; six perfectly recalled all color/trajectory combinations, with two more recalling three of four perfectly. The rest either misrepresented actual trajectories or mixed up pole/trajectory combinations. Finally, all participants reported that their avoidance behavior changed as they became more familiar with obstacles. Several participants indicated that they deviated from everything after getting hit, and later learned to discriminate safe from dangerous obstacles; several others reported getting faster to avoid dangerous obstacles (though this alone would not have resulted in avoidance).

Participant Paths

Figures 3.4 - 3.8 present example paths for Participant 1 from all four conditions. As there is a large amount of variability among participants, a set of example plots from a typical participant will provide a visual baseline from which we can interpret the following data analyses. Participant 1 experienced the Move-First block of trials in Block 1; Figures 3.4 and 3.5 show his paths for all trials in this block. Recall that the Move-Straight (Figure 3.4) and Move-Veer (Figure 3.5) trials were randomized within this block, although they are separated for these plots.

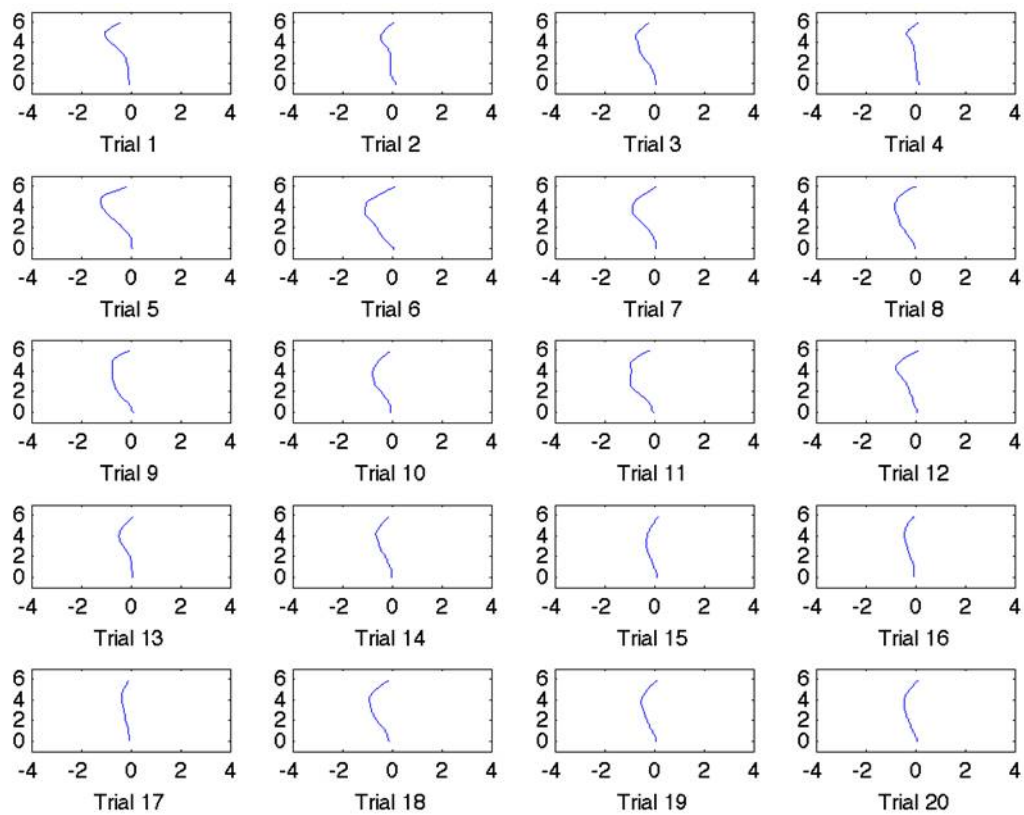


Figure 3.4 All Move-Straight Trials for Participant 1.

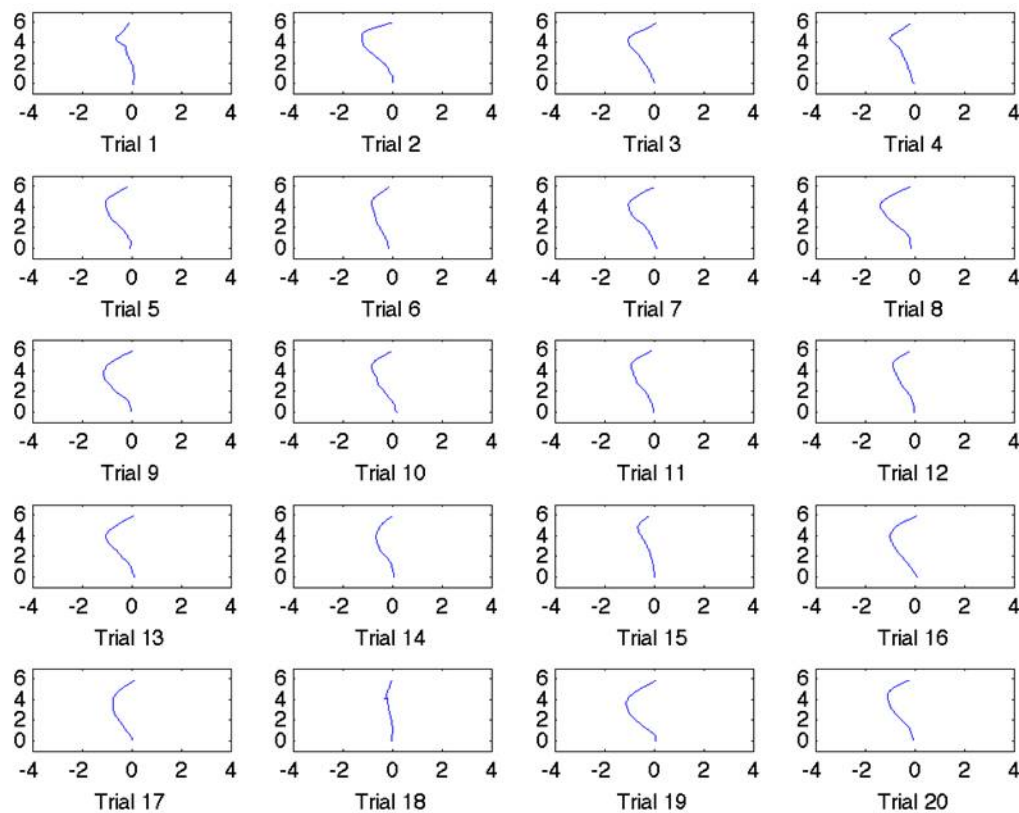


Figure 3.5 All Move-Veer Trials for Participant 1.

Though there is quite a bit of variability across trials, there are two main trends to note here. The first trial for both conditions has a relatively straight path until roughly 2.5m, when the trigger line is crossed, and the Move-Veer obstacle moves rapidly to the trigger line. This initial path segment is the important part of the trial; as before, anticipation of path movement should show up prior to the obstacle's change in movement. Second, in both cases the initial path segment swings left over the course of trials, and (with a few exceptions) this trend is stronger in the Move-Veer condition (Figure 2.5). This provides tentative support for the hypothesis that people's paths are

changing over time as they become more familiar with obstacle movements, and that they are discriminating between veering and straight-moving obstacles.

Figures 3.6 and 3.7 present the paths across trials for the Start-Stationary block, seen by Participant 1 in Block 2. Remember that the obstacles here were distinct in appearance from the ones in the previous block, and started out stationary; however, the post-trigger line movements were identical to the ones in the previous block. Notice here that the first trials for each have a noticeable initial deviation; as will be discussed later, there is a tendency for participants to deviate earlier for trials with unfamiliar obstacles when they have previous experience with veering obstacles.

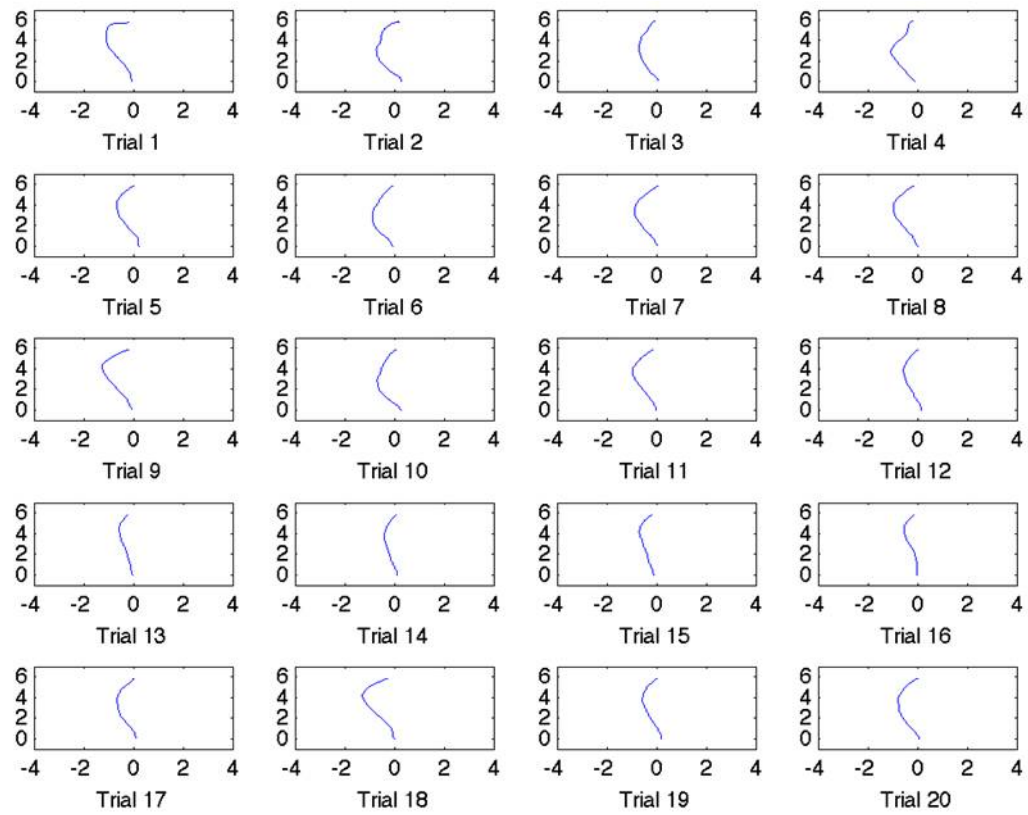


Figure 3.6 All Stationary-Straight Trials for Participant 1.

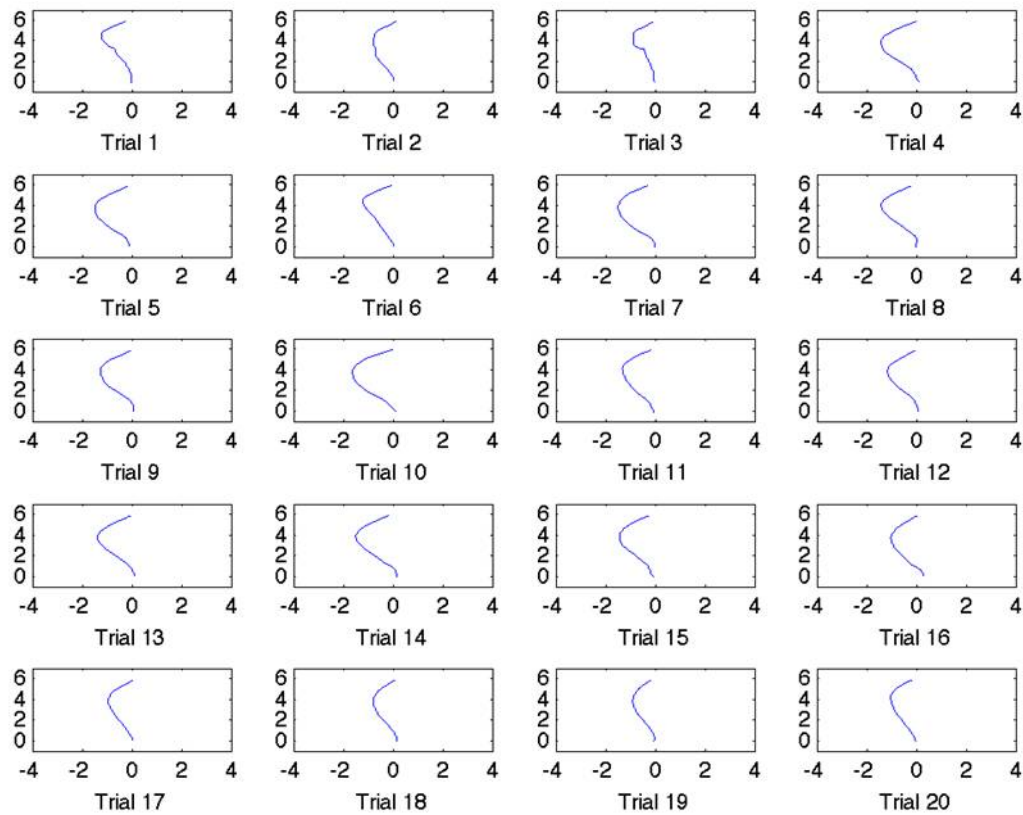


Figure 3.7 All Stationary-Veer Trials for Participant 1.

Mean Absolute Deviation At Trigger Line

The main dependent measure for Experiment 2 is the mean absolute deviation (MAD) in X at the trigger line. This represents the participant's distance from the home-target axis at the point when the obstacle changes movement. This measurement is illustrated in Figures 3.8 and 3.9, which plot the online model-predicted path to the trigger line for the Start-Moving and Start-Stationary conditions. Note that these plots only represent model predictions until the agent reaches the trigger line, so the only information driving the path is what the participant would receive up to that point.

Further, they are based on mean participant velocity across trials for each initial movement condition. In other words, the plot for the Move-First condition is based solely on an obstacle moving parallel and toward the agent's starting position at a speed matching the agent's (.81 m/s), and the plot for the Start-Stationary is based on a stationary obstacle located at the change point (agent moving at .84 m/s). The MAD for the Move-First condition is 11 cm, and the MAD for the Stationary-First condition is 5.3cm.

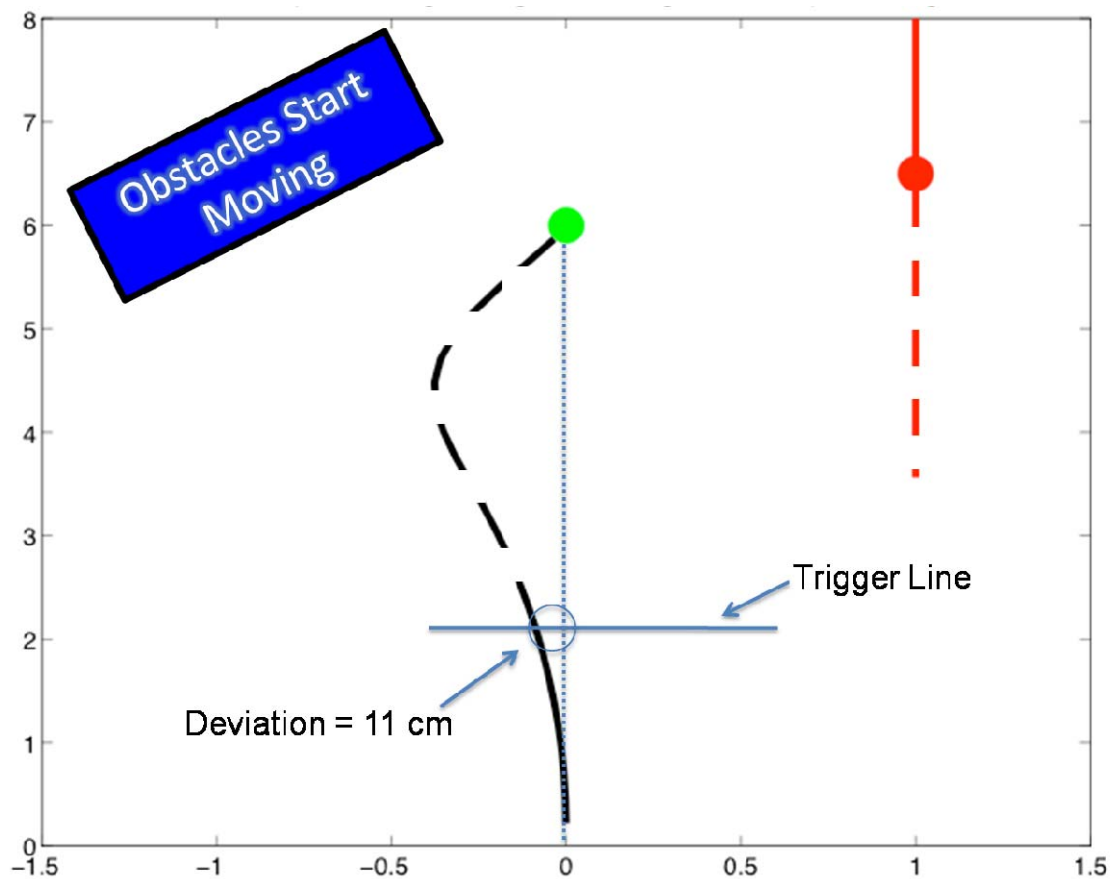


Figure 3.8 Model-predicted path (to trigger line) for Start-Moving condition.

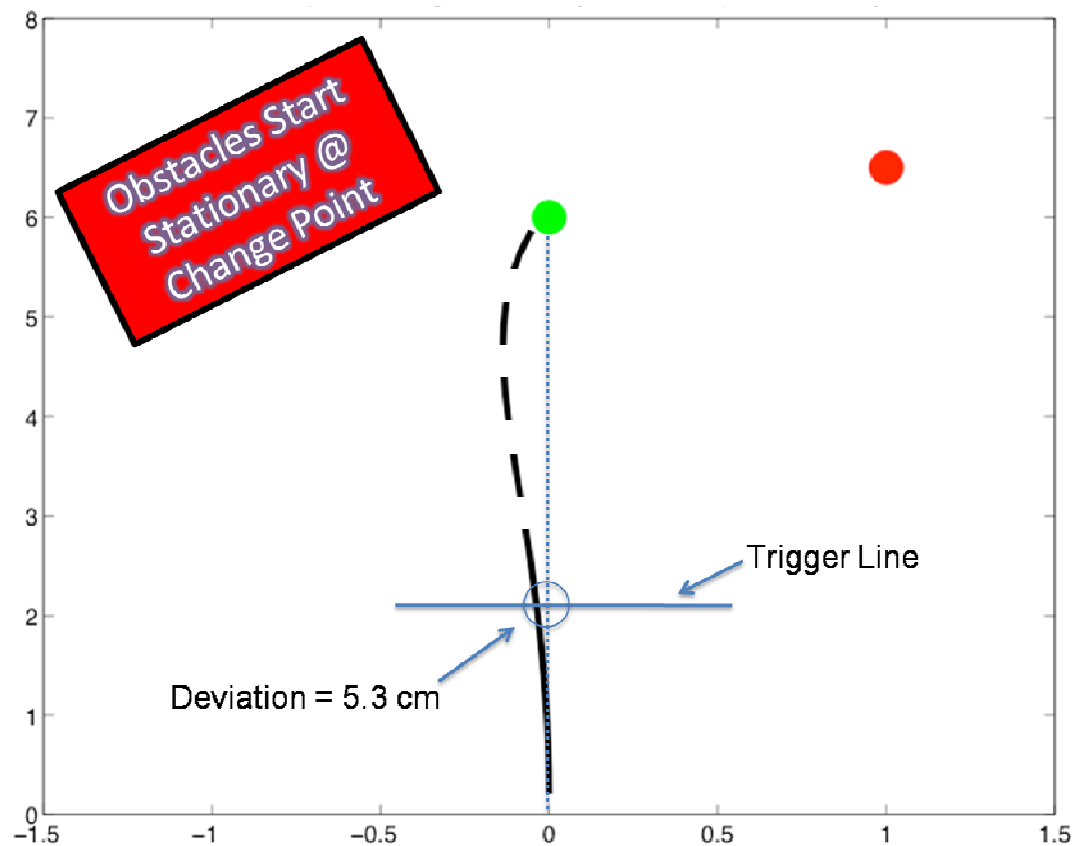


Figure 3.9 Model-predicted path (to trigger line) for Start-Stationary condition.

Mean Absolute Deviation Measures

I first present differences in MADs among conditions and across block orders. To analyze the overall effects, repeated-measures ANOVA was conducted on MADs over trials and across conditions. There was an overall main effect of obstacle type, $F(1,13) = 50.87$, $p < 0.01$, $\eta_p^2 = 0.80$; as this has a large effect size, it allows us to conclude that there was a sizable overall difference in MADs between Veering and Straight-moving objects. There was also a main effect of trial number, $F(19,247) = 3.16$, $p < 0.01$, $\eta_p^2 = .20$, which

suggests that participants changed deviation distance across trials. There was also a significant interaction between obstacle appearance and trial number, $F(19,247) = 3.07$, $p < .01$, $\eta_p^2 = .19$, which suggests that participants treated obstacles differently from one another as they experienced more trials. Finally, there was a significant three-way interaction between initial movement (Stationary vs. Moving), trial, and block order, $F(19, 247) = 3.10$, $p < .01$, $\eta_p^2 = .20$, which suggests that people's avoidance of obstacles with particular initial movements depended over time on what type of initial movement they had seen first. This should become clearer when we look at conditions individually below.

Second, we examine the participant block order groups separately, to better understand how anticipatory avoidance behavior depends on what obstacles were seen first. For each block, planned-comparison t-tests were conducted between initial movement conditions (Stationary vs. Moving) and between post-trigger line movement conditions (Veer vs. Straight). One-sample t-tests were also conducted for each condition at each trial with the model-predicted deviation, to determine at what points human paths deviated from model predictions. All t-tests were corrected using a Bonferroni adjustment ($\alpha/3$) since each set of means was being analyzed three times – twice with other trials, and once with the online model prediction. The hypothesis here was that increased anticipation will lead to increased deviation from model predictions.

Figures 3.10 and 3.11 plot the mean absolute deviations across trials for the Block 1 trials. Figure 3.10 shows the deviations for participants who saw Start-Stationary trials

in Block 1. Dashed lines represent obstacles that veered toward the participant after the trigger line was crossed, and solid lines represent obstacles that moved straight. The blue dotted line represents the model-predicted deviation for this condition (5.6 cm), while the green dotted line represents the minimum deviation an average participant would have to make to avoid being hit by the veering obstacle. This was based on the mean male/female half-shoulder width found in the NASA anthropometry table (<http://msis.jsc.nasa.gov/sections/section03.htm>) of 0.19 m plus 0.1 m for the radius of the pole. Thus, this is the mean estimated distance from the center of the pole (where the system measured the pole) to the center of the head (where the tracker was positioned) when the shoulder would contact the edge of the obstacle.

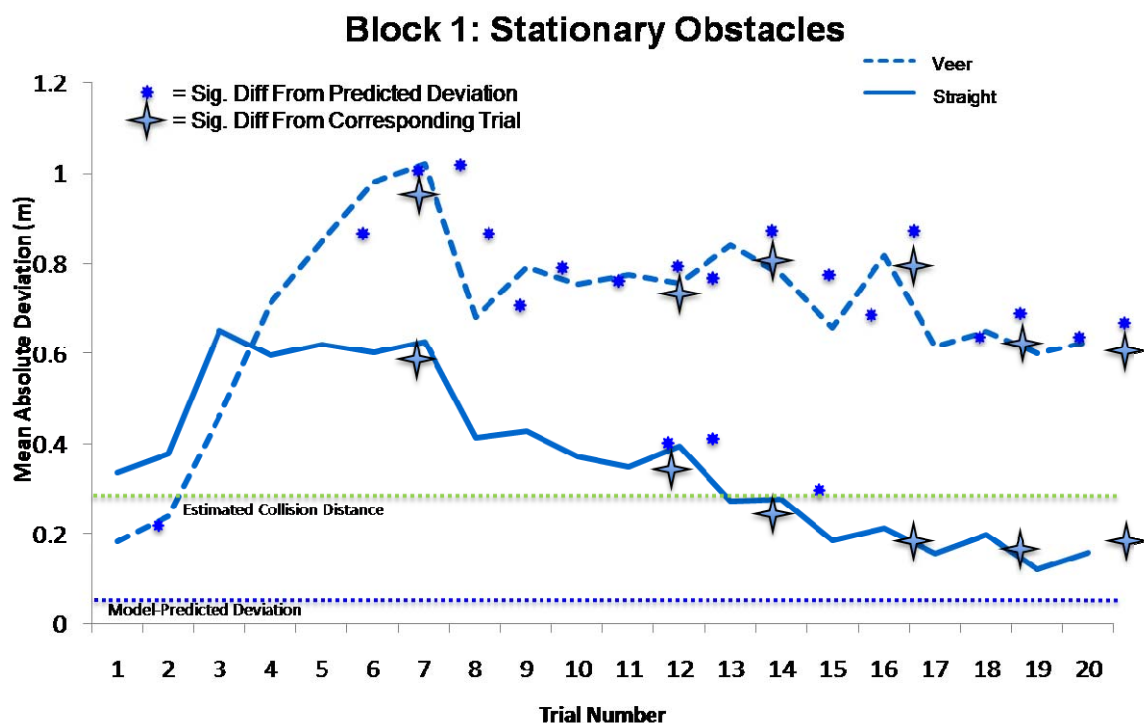


Figure 3.10 Mean absolute deviations for Stationary Obstacles, first block seen.

The overall mean absolute deviations for the Stationary Block 1 were .69 m for the Stationary-Veer trials and .37 m for the Stationary-Straight trials. Marker points at each trial for each line signify for what trials conditions were significantly different from each other (star-shaped markers), and for what trials conditions were significantly different from model-predicted deviations (asterisk markers).

There are several trends of note in this plot. First is that the first trial for both Veer and Straight conditions was relatively close to the model-predicted deviation. Deviations for both conditions in this block then increased for the first several trials, after which deviations began to decrease for the Straight condition, down to nearly the model-predicted deviation and closer to midline than the estimated collision distance for Veer trials. On the other hand, deviations for the Veer condition continued to climb for several more trials, followed by a brief decrease and a stabilization at roughly 0.75m, or about 0.55m farther out than the final deviation of the Stationary-Straight condition. This difference could reflect discrimination between obstacles based only on obstacle appearance (remember that these deviations are at the exact moment the obstacle changes path).

These trends are supported by the t-tests, as there was no significant difference ($p < .017$, Bonferroni correction) between conditions until trial seven, and the difference was not consistently significant until trial twelve. Hence, it took roughly twelve trials for participants to reliably discriminate veering from straight obstacles based on their

appearance. However, deviations on trials with Veer obstacles were significantly greater than the model-predicted deviation from trial six onward.

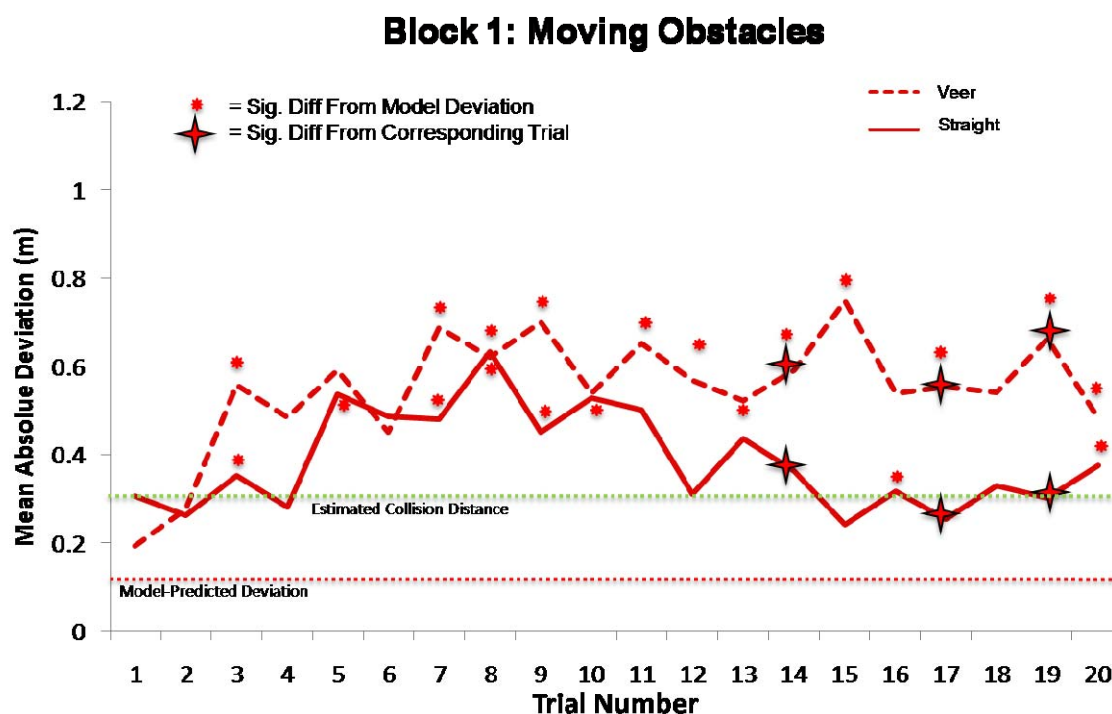


Figure 3.11 Mean absolute deviations for Moving Obstacles, first block seen.

Figure 3.11 shows the deviations for participants who saw Start-Moving obstacles in Block 1. The first thing that is worth noting is that the mean absolute deviations appear to be lower and more tightly clustered than those of the participants who saw the Start-Stationary block first. Mean deviations for this block were .55 m for the Veer trials, and .39 m for the Move-Straight trials. This difference with the other group's Block 1 did not rise to the level of statistical significance in the omnibus ANOVA, but it is worth noting.

When looking at the shape of the deviation plots, a similar trend emerges to what we saw in the previous group. There was a similar initial increase in both the Straight and Veer trials, though this time the participants' ability to discriminate between them does not arrive until approximately trial 12. Discrimination between obstacle types was less consistent here, but it appeared sporadically from trial 12 through the last trials. Again, however, participants consistently deviated from model predictions in the Veer condition, as well as staying beyond the collision distance.

To conclude, examination of Block 1 for both groups of participants showed two interesting trends. First, people are anticipating the movement of dangerous obstacles, and are veering farther and more consistently in the Veer conditions than the Straight conditions. Second, discrimination between veering and straight-moving obstacles did not occur immediately for either group; it took roughly 12 trials for both to see consistently different discrimination.

Figure 3.12 plots the deviations across trials for participants who saw Start-Stationary obstacles in Block 2. The overall mean absolute deviations for the Start-Stationary block were 0.58 m for the Veer trials and 0.37 m for the Straight trials.

Block 2: Stationary Obstacles

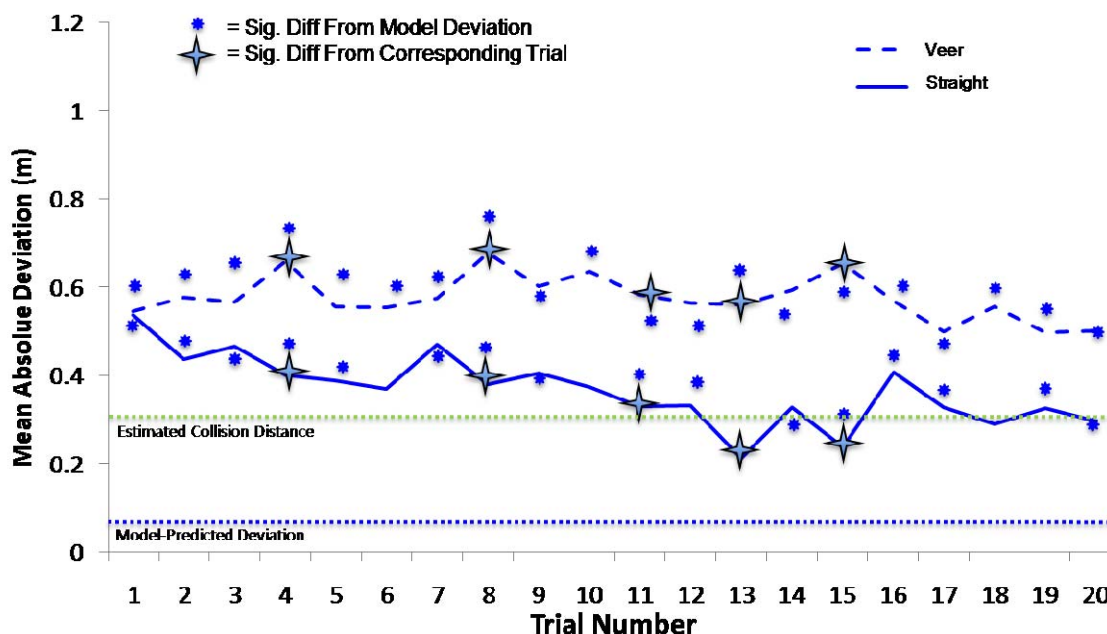


Figure 3.12 Mean absolute deviations for Stationary Obstacles, second block seen.

Again, the asterisks on this plot mark trials where the deviation for that condition differs significantly from the model prediction, and the stars designate trials where the conditions differed significantly from each other. The first trend to notice is that discrimination between veering and straight-moving obstacles happened much earlier for the Stationary trials in Block 2 than in Block 1. The deviations began to separate from trial 2, they were first significantly different at trial 4, and were relatively consistently different after that. Further, every trial for the Veer condition, and most trials for the Straight condition, were significantly different from the model predicted deviation.

Figure 3.13 plots the deviations across trials for the group who saw the Start-Moving obstacles in Block 2. Mean deviations were 0.53 m for the Veer trials and 0.22

m for the Move-Straight trials.

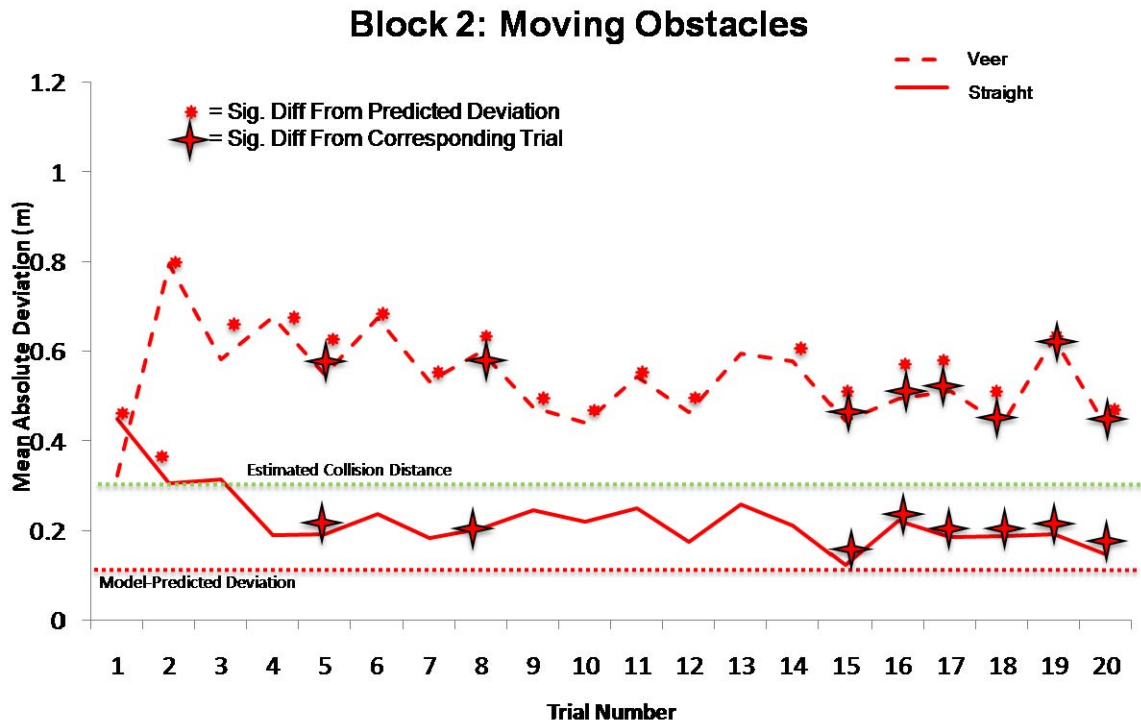


Figure 3.13 Mean absolute deviations for Stationary Obstacles, first block seen.

We can see that the same trend occurred here – discrimination between the obstacle types showed up much earlier than when the same condition was seen in Block 1, starting at trial 5, and deviations during Veer trials were consistently significantly different from model predictions.

Speed Plots

Figures 3.14 and 3.15 present the mean speeds over trials for both Stationary-First and Move-First groups. Interestingly, the first few trials for the first block encountered were the slowest. Participants in both groups reached a consistent velocity for each

condition within 3 trials, which was consistent across all conditions for the Stationary-First group. For the Move-First group, the mean speeds for the second (Start-Stationary) block were slightly faster on average (0.89 m/s) than the mean speeds for the first block or for any of the conditions in the Stationary-First group. It is unclear whether this represents a true difference in block order, or simply individual variability between groups.

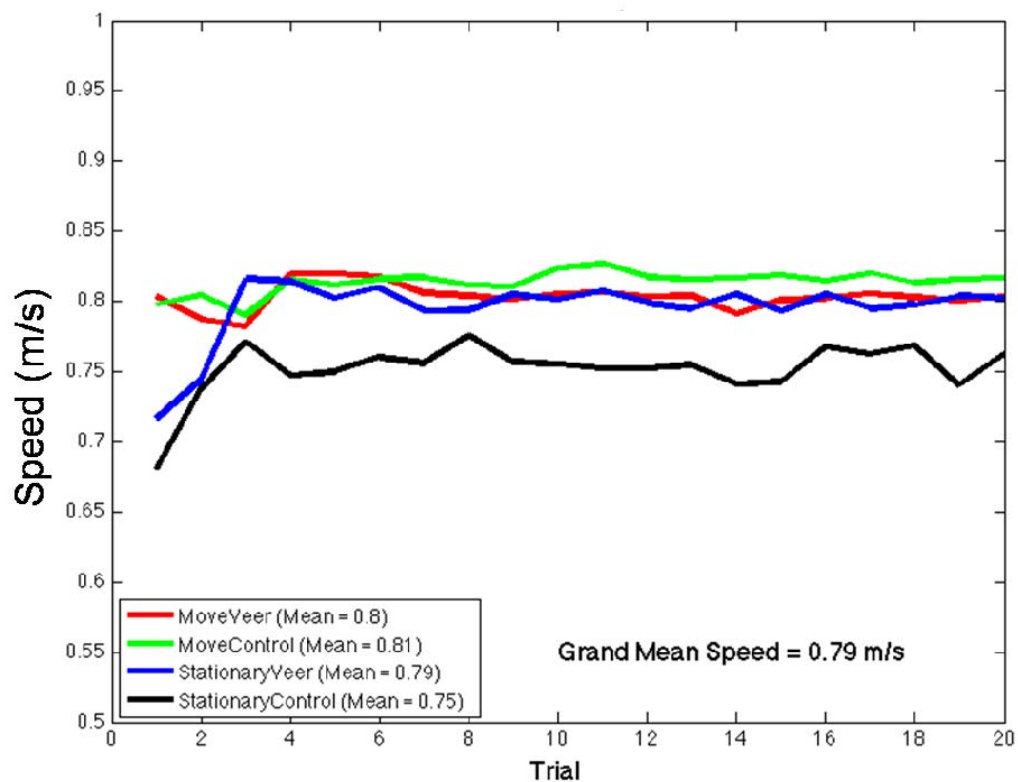


Figure 3.14 Mean speeds for Stationary-First group.

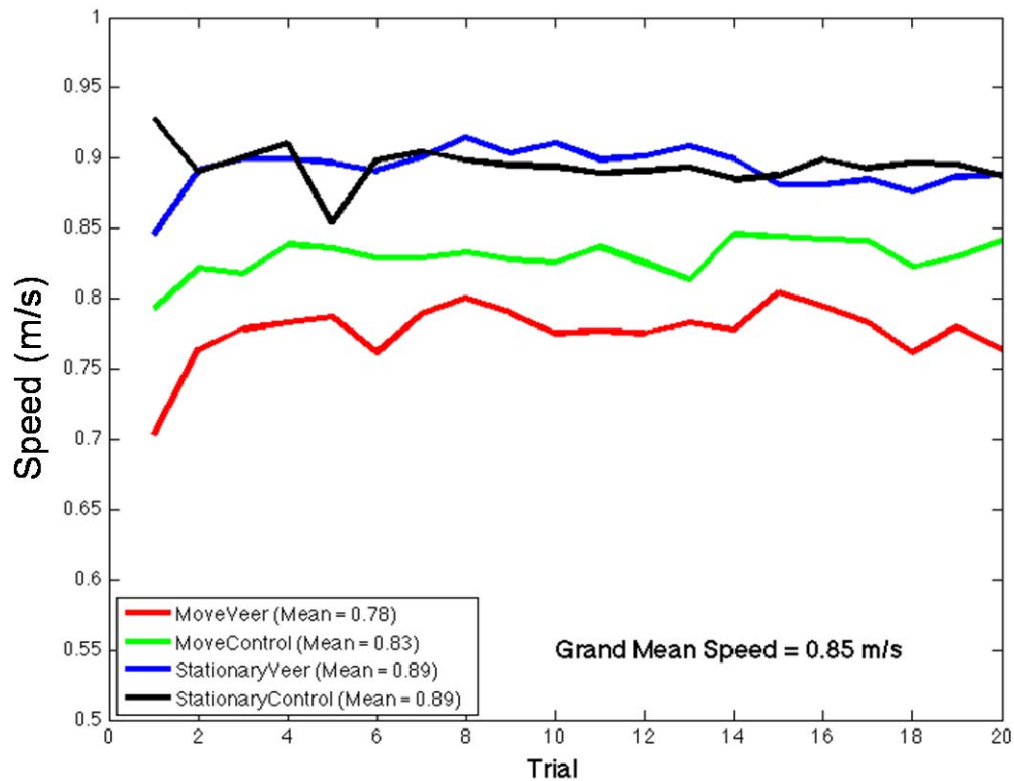


Figure 3.15 Mean speeds for Move-First group.

Discussion

Experiment 2 provided firm evidence that participants can and will learn to anticipate obstacle motion when this is necessary to avoid collision. In all trial blocks, participants learned to deviate significantly beyond model-predicted values, as well as beyond the estimated collision distance, for obstacles that were going to veer toward them. This suggests that they were moving to a higher level of control, as they were using information not currently in the environment – that obstacles would change direction in the future – to guide their current movement.

Further, there seemed to be a very interesting dual-stage learning process occurring. In Block 1 for both groups, it took a number of trials for participants to consistently discriminate veering from straight-moving obstacles; prior to this discrimination, participants avoided all objects equally. This suggests that the deviations for the first few trials were not based on the appearances of the obstacles per se, but on a simple “obstacles = veer” pairing. This is likely to occur at the Simple Anticipation level of control, as it did not take advantage of higher-level contextual relationships.

After discrimination did occur, however, it was maintained relatively consistently for the remainder of the trials; once people learned they only needed to deviate when veering obstacles appeared, they did not deviate beyond the collision zone for straight-moving obstacles. This implies a second, higher-level learning process took place, where participants created a specific mapping between obstacle appearance and future movement. This likely occurred at the highest Navigation/Learning level of control.

For Block 2 in both participant groups, this discrimination occurred much earlier and more consistently. This suggests that when participants have had experience discriminating two different types of moving obstacles, they are primed to more quickly make this distinction in the future. This block order effect further supports the idea that locomotion is cognitively penetrable, as previous experience with similar – though distinct – obstacle types helps participants more rapidly categorize future obstacle movements.

Conclusion

As Experiment 2 provided strong support for the existence of multiple levels of locomotor control, Experiment 3 was designed to probe the boundaries among these using a visuo-spatial distractor task. It was hypothesized that the addition of such a task would impair both the Simple Anticipation control and the higher level Navigation/Learning control. If this was the case, we would expect to see increases in the amount of trials taken to learn to veer from all obstacles and to discriminate between obstacle types, respectively, or to see one or both of these learning behaviors completely disappear.

CHAPTER 4

EXPERIMENT 3: TO WHAT EXTENT DOES A BASIC VISUO- SPATIAL DISTRACTOR AFFECT PEOPLE'S ABILITY TO ANTICIPATE OBSTACLE MOVEMENT?

As Experiment 2 showed that people do in fact have the ability to anticipate and preemptively avoid obstacles if they will pose a threat, we now turn to the question of what resources are involved in this process. To determine whether this is truly a “cognitive” process that requires attentional resources above and beyond those required by basic locomotion, participants were required to perform a distractor task while performing the goal interception/obstacle avoidance task.

The goal for this experiment was to use a distractor that should maximally interfere with people’s ability to perform at higher levels of locomotor control. If the distractor interfered with the resources required for performance, it was predicted that behavior would revert to online control; people would be less able to both learn a general avoidance response and to learn the specific mappings between objects and movements.

It was decided that a purely visuo-spatial distractor would be used, as it would likely interfere with people’s ability to visually recognize and associate objects with movements; in addition, as discussed earlier, previous research has found that postural control requires a minimal amount of visuo-spatial resources. As described earlier, this task was specifically predicted to interfere with the processing stage, as it introduces a cognitive load, as well as processing code, as it adds both a verbal component (response) and an additional spatial load. Again, if the task was sufficiently difficult, the total attentional resources required might be great enough to show overall attentional capacity interference.

The task was a variant of the classic Brooks letter task (Brooks, 1968), which

requires the participant to visualize herself traveling clockwise around the perimeter of a capital block letter (essentially, a mental rotation task). There are many versions of the task in the literature; here, the participants were instructed to report the direction they would turn to continue on around the letter. Importantly, participants were required to respond in time with a metronome ticking at 1 Hz, to ensure that they were constantly attending to the secondary task. This was verbally enforced throughout the study.

The task was explained to participants using Figures 4.1 and 4.2 below, which will assist in explaining it here. Each participant was first shown a sheet of 8 ½" x 11" paper with Figure 4.1 printed on it. The experimenter explained that for each trial the participant would be asked to visualize one of the capital block letters pictured on that sheet. These letters were selected because they had minimum of 4 “corners” or junction points. After ensuring that the participant was comfortable visualizing each of these letters in the standard form printed there, the experimenter showed her a second sheet of paper with Figure 4.2 printed on it, and explained the task:

“You should picture yourself starting at the bottom left corner of the letter you’re given for that trial. Imagine yourself then traveling around that letter in a clockwise direction, as shown on the “F”. Whenever you get to a corner or junction, I want you to tell me out loud which direction you will turn to stay on that letter. For example, the first responses on an “F” would be Right, Right, Right, Left, and Left [tracing out corners with a pointer]. Can you finish out the rest of the corners on the “F” for me?”

A E F H K L
M N P R T
V W X Y Z

Figure 4.1 Page given to participants listing all letters used in Brooks distractor task.

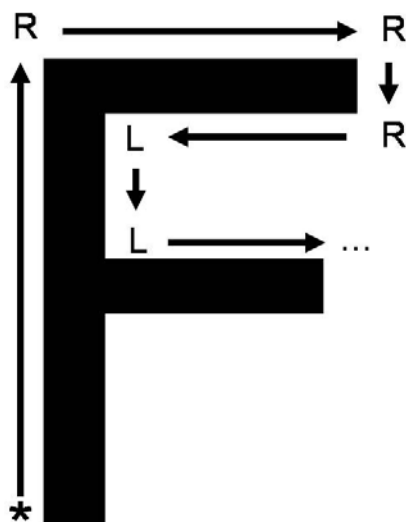


Figure 4.2 Visual demonstration of the letter task.

After the participant correctly completed the practice “F”, the experimenter presented her several more trials with different letters to ensure that she was comfortable with the task. Each participant received at least 4 more practice trials, or until she was visibly and reportedly comfortable with the task. The participant was then told that the letter task itself would be performed while walking in virtual reality, and that there would be a metronome ticking once per second that she would be asked to respond in time with.

Method

Participants

There were 15 participants in Study 3, 6 females and 9 males, with a mean age of 21.6 years (range 18-37 years).

Procedure

The design of Experiment 3 was a combination of conditions from the previous two studies. As before, participants completed a series of 10 practice trials that were identical to the practice trials in Experiment 2. However, this time the practice trials were split into two sections. The first four trials, as before, allowed participants to practice the basic task of walking to a target while avoiding a moving obstacle. Assuming they performed this task acceptably (all did), six additional trials allowed participants to practice the letter task along with the avoidance task (full instructions are located in Appendix C-1).

After the practice trials, participants completed two main blocks of trials. Again, two groups of participants completed these blocks in opposite orders. In both blocks, the target was a stationary green pole 6 m ahead of the participant's starting position.

The Random block consisted of 20 trials of randomly presented identical obstacles that had varying starting positions and movements. The purpose of this block was to determine the effects of the distractor task on basic locomotion, when no anticipation was possible. This was critical to understanding the attentional mechanisms behind anticipation, as it was important to segment out the basic effects of the attentional task on locomotion. Previous research (Siu et al. 2008) had found no effect of a secondary auditory distractor on locomotion, but a visuo-spatial task was found to have an effect on basic postural control in younger and older adults (Maylor & Wing 1996). Hence, if performance was significantly degraded in the anticipation task, it would be important to ensure that it was not similarly degraded in a locomotion task not requiring anticipation.

The obstacle paths for the Random block were the Toward, Away, Faster, and Slower paths used in Experiment 1; however, in this block these obstacles all appeared as identical blue poles. Recall that the initial movement was identical in each case, so here it was impossible to predict what an obstacle would do on any given trial based on appearance or initial movement. Each appeared randomly 5 times, three times approaching from the right and twice approaching from the left. As Experiment 1 showed that paths around these obstacles - even when prediction was possible - were highly correlated in heading with model predictions, degradation in ability to circumvent

these obstacles would result in a lower correlation with model predicted headings.

The Predictable block was identical to the Start-Moving Block from Experiment 2. The initially moving trials were chosen to match the initial circumstances (stationary goal, moving obstacle) in the Random block. The hypothesis here was that if the distractor task impaired resources necessary for higher levels of locomotor control, these trials would show less consistent deviations from model-predicted veer distances at the trigger line. As in Experiment 2, there were 40 trials in this block, for a total of 60 trials including practice. Since there was an additional training session at the beginning for the distractor task, total experiment time stayed constant at about an hour.

Results

Questionnaire Results

Participants in Experiment 3 completed a slightly expanded version of the questionnaire (Appendix C-2) from Experiment 2. All participants noticed obstacles moving differently from one another, and all but one described specific strategies they used for avoiding obstacles. Twelve of these mentioned learning to veer out of the way of certain obstacles, six mentioned changing speed, particularly with the Random trials, and one person noted that she had to pay more attention during the Random trials. Nine participants claimed that the distractor task impaired their ability to avoid obstacles, while others said that it was a simple enough task to allow multitasking.

Random Block: Participant Paths

Figures 4.3 and 4.4 show the mean participant paths for the Direction-Change and Speed-Change trials in the Random block, separated by trial order. Prior to averaging, paths with obstacles approaching from the left were reflected across the z-axis so that all means were conducted on paths avoiding obstacles from the same direction.

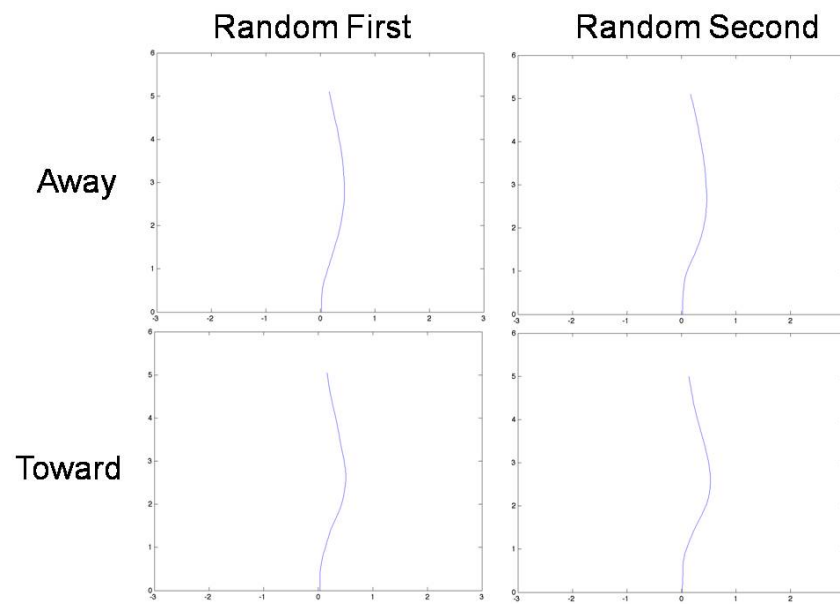


Figure 4.3 Mean participant paths for Random Block, separated by block order.

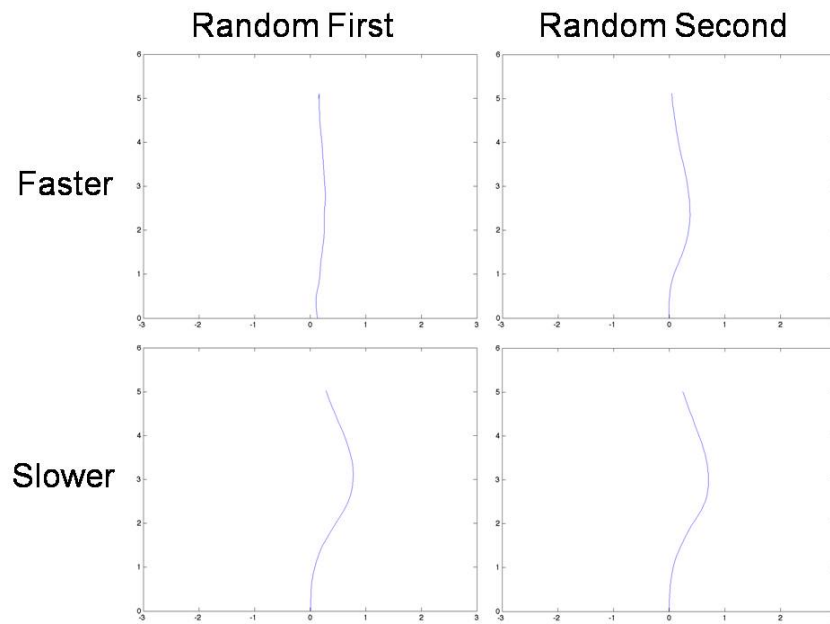


Figure 4.4 Mean participant paths for Random Block, separated by block order.

There does not appear to be a difference in mean heading between the Random First and Random Second groups; paired t-tests support this, as no pair has a p value less than $p = .91$.

These data were also binned, as in Experiment 1; however, since the data sampling rate had doubled to 60Hz with this study, the binning doubled as well, for a total of 48 bins. Table 4.1 presents the r^2 values between the headings in the Random block and the model predictions for each. Model predictions were based on the mean velocity for each condition for each participant group. These correlations are somewhat lower than those found in Experiment 1, but there was still a strong relation between model predicted

headings and the headings found in this block. There was no significant difference between the two order blocks, $t(6) < 1$. There was, however, a marginally significant difference between the values found here and the ones from Experiment 1, $t(14) = 2.15$, $p = .05$.

Table 4.1
Coefficient of Determination (r^2) Between
Participant and Model Predicted Headings

	RandomFirst	RandomSecond
Toward	.58	.60
Away	.81	.76
Slower	.52	.60
Faster	.82	.74

We can conclude, therefore, that there is only a small decrement of a basic visual-spatial secondary task on participants' ability to avoid unpredictable, random obstacles. This is consistent with the literature, and strengthens the case that any impairments we find in the avoidance of predictable obstacles are related to cognitive aspects of task performance.

Predictable Block: Participant Paths

Figures 4.5 and 4.6 show sample paths over time from an average participant in the Predict-First group for Move-Veer trials and Move-Straight trials, respectively. For this

participant, there appears to be a trend for deviating from the midline over trials in both cases, although this looks to be stronger in the Veer trials. For this one participant, at least, anticipation was not impaired by a distractor task.

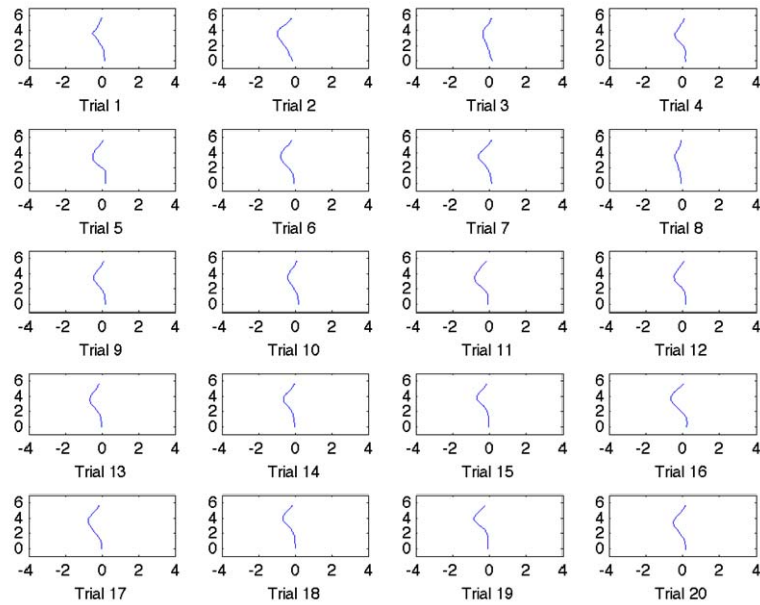


Figure 4.5 Sample Move-Veer paths over trials for participant in Predictable Block First group.

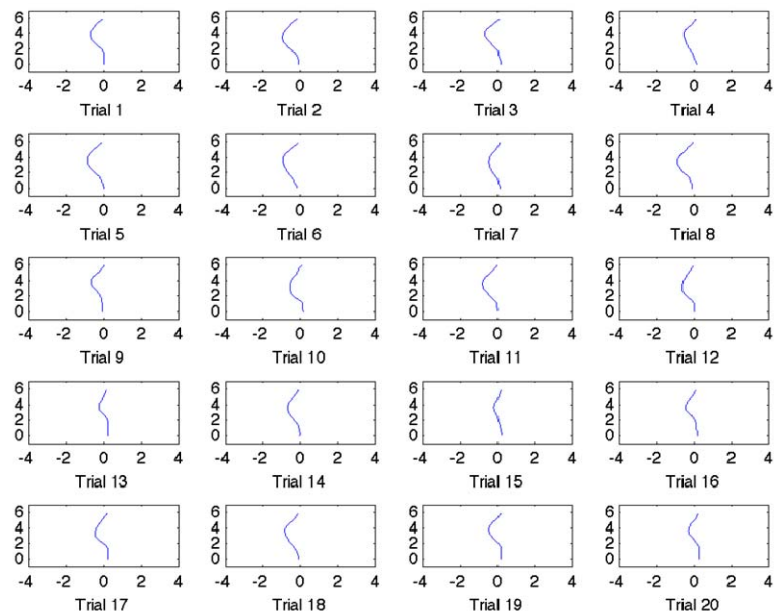


Figure 4.6 Sample Move-Straight paths over trials for participant in Predictable Block First group.

Predictable Block: Mean Absolute Deviations

As in Experiment 2, the primary dependent measure for the Predictable Block is mean absolute deviations. Figure 4.7 plots the deviations over trials for the group of participants who saw the Predictable block first. The model predicted deviation was also 11cm for Experiment 3, based on mean participant velocity across trials. Again, asterisks designate trials where each condition significantly differs from the model predicted deviation, and stars represent trials where the conditions differ significantly from each other and discrimination occurred. As before, one-sample and paired t-tests were performed, respectively, using a Bonferroni correction of $(.05/2)$.

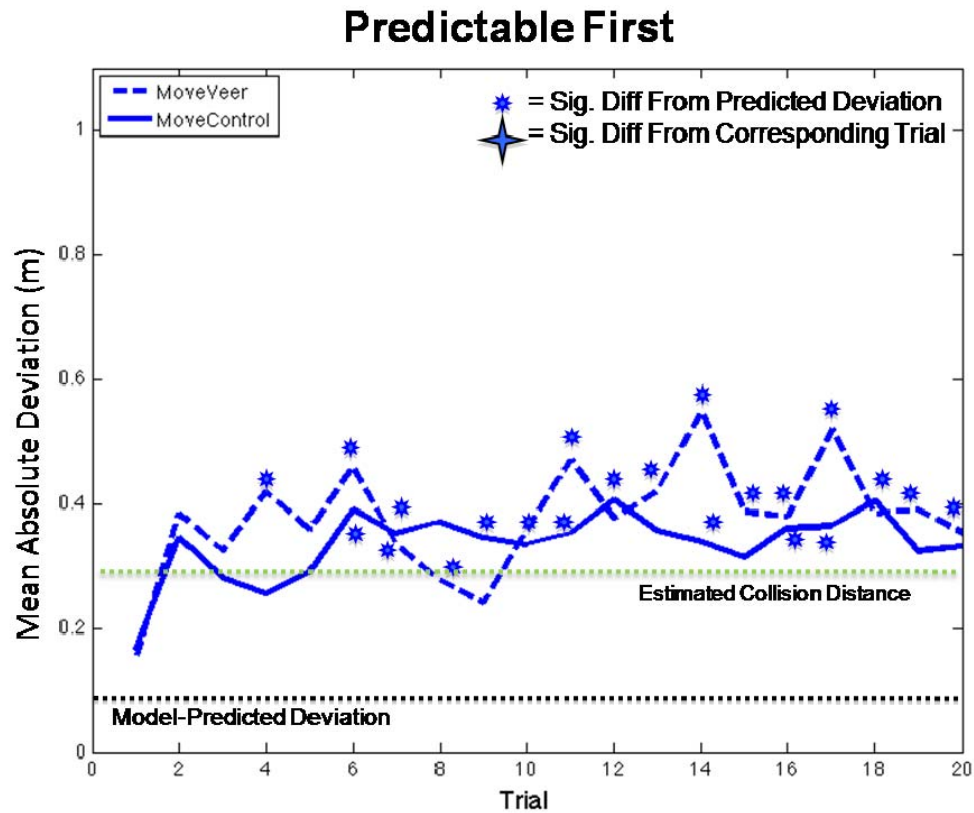


Figure 4.7 Mean absolute deviations in the Predictable condition for group who saw the Predictable block first.

Interestingly, there are no trials in this block where the obstacle types differ significantly from one another. This is a significant difference from Experiment 2, as both conditions in that study had several trials that differed, no matter whether seen first or second. This suggests that, for this group at least, discrimination was more difficult when a secondary task was present. Second, although both conditions exhibit regular differences from model predictions, these are much less consistent than in Experiment 2. For the Veer condition, only 9 trials significantly differed in deviation from the model, as opposed to 12 trials in the equivalent (Move-First Veer) condition in Experiment 2.

Finally, notice that the overall mean for the Straight condition is similar to Experiment 2, at .33m; however, the overall mean deviation for the Move-Veer condition is quite a bit lower than in Experiment 2, at 0.38m. Thus the compression we see seems to result from participants not veering as far in the Veer-Toward condition as seen previously with no secondary task.

Figure 4.8 presents the mean absolute deviations for the group that saw the Predictable block second. These results are noticeably different from the results of the group that saw the Predictable trials first.

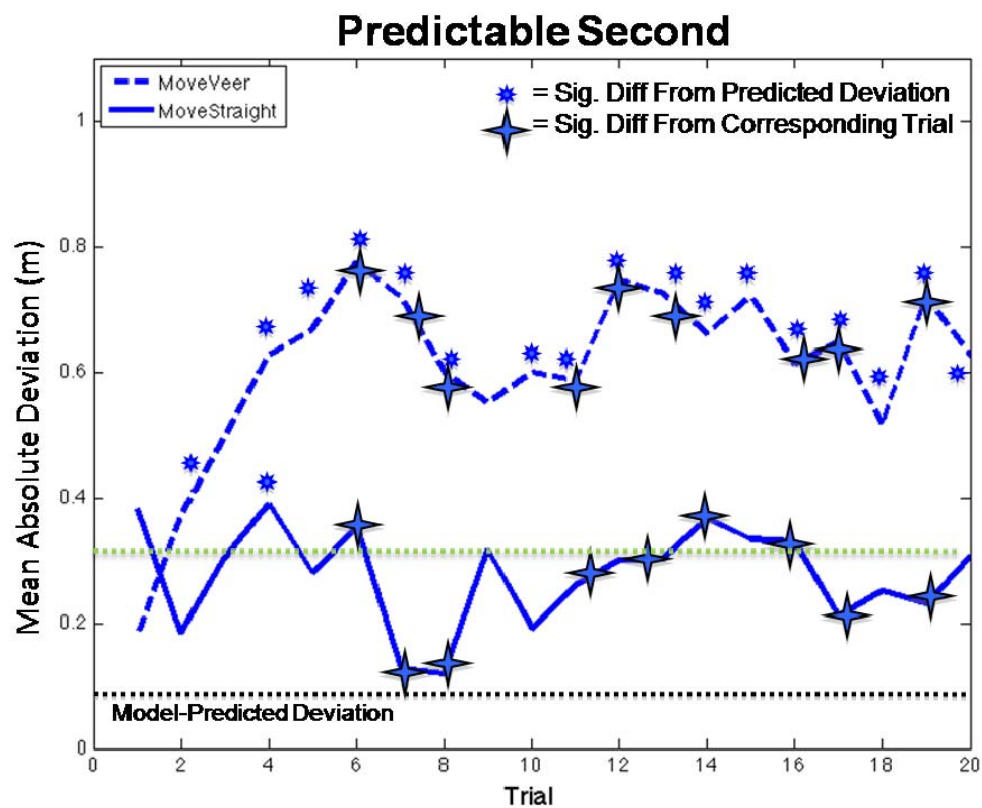


Figure 4.8 Mean absolute deviations in the Predictable condition for group that saw the Random block first.

To begin with, participants were able to discriminate conditions as well as they did in Experiment 2; starting at trial 6, deviations for each trial regularly differ between conditions. Second, by trial 4 participants were regularly deviating beyond model predictions for the Move-Veer condition. Finally, the absolute deviations for this group are more consistent with those seen in Study 2, with Move-Veer having a mean of .61m, and Stationary-Veer having a mean of .28m.

Predictable Block: Speed Plots

Figures 4.9 and 4.10 present the speed plots averaged across participants for the Predictable-First and Random-First groups, respectively. The speeds here are significantly slower than what was found in Experiment 2, $t(158) = 8.9$, $p < .001$, particularly for the Veer trials in the Predictable-First group. There was a significant difference between the Veer and Straight speeds for this group, $t(19) = -50.9$, $p < .001$, as well as between this condition and the Move-First Move-Veer condition from Study 2, $t(38) = 37.7$, $p < .001$. There was also a significant difference in speed between the conditions in the Random-First group, $t(19) = 2.7$, $p = .016$.

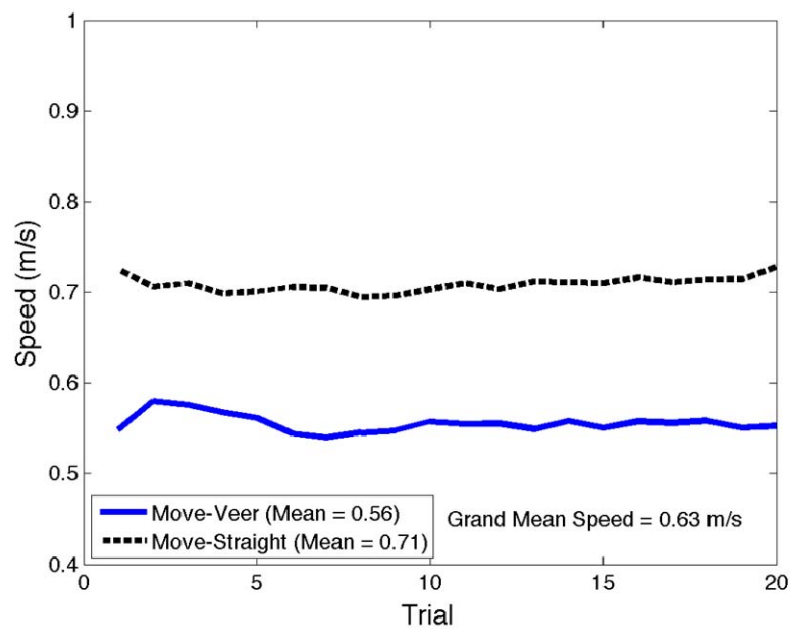


Figure 4.9 Speed profile for group who saw Predictable block first.

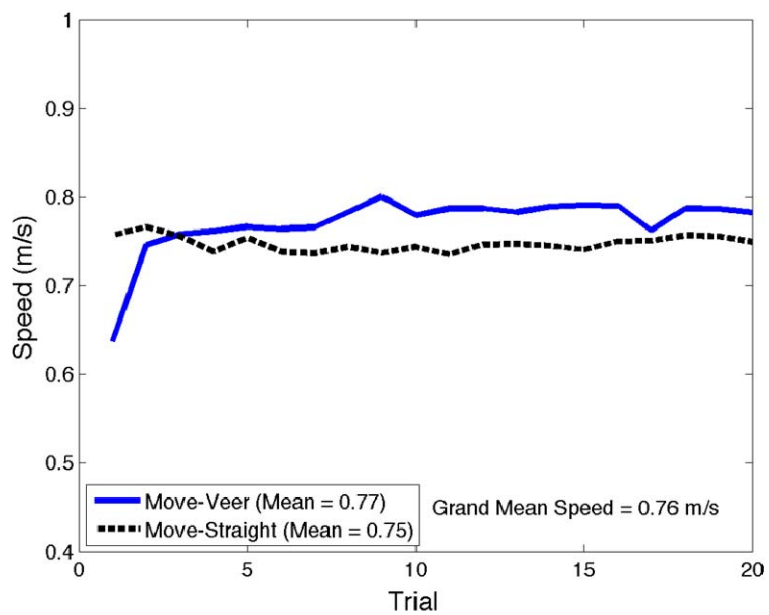


Figure 4.10 Speed profile for group who saw Random block first.

Discussion

The results of Experiment 3 did not quite confirm the hypothesis that a visuo-spatial distractor would decrease performance on a task requiring anticipation. Participants in both order groups significantly deviated from the online model's predicted absolute deviation, indicating that the simple-pairing aspect of learning showed little degradation. However, there was a very strong block order effect. For participants who saw the Predictable block first, no trials were significantly different from one another; the higher level object-discrimination learning disappeared. For participants who experienced the Predictable block second, however, performance was equal to that of Experiment 2 in both avoidance and discrimination. In all cases, participants deviated outside the collision zone.

This disparity in discrimination implies that there was a strong learning effect of the secondary task. Unlike Experiment 2, the benefit of having a prior block of trials cannot be attributed to learning that there is a relation between obstacle appearance and movement, as this was not the case in the Random block. Hence, we can conclude that the beneficial effect of having a prior block of trials was, in this case, due to familiarity with the secondary task. In fact, a number of participants reported feeling more comfortable with the task over time, and many described parsing strategies that they used once they were familiar with the task.

In sum, when participants were faced with a novel visuo-spatial task, their discriminatory performance was impaired. This suggests that the secondary task, when

novel, occupied the attentional (and processing) resources required to operate at the highest Learning level of locomotor control. However, as deviations were still significantly different from those predicted by the online control model, it does not appear that this distractor adversely affected the middle, Simple-Anticipation level of control. Further, experience with the task seems to have allowed automatization, as performance for experienced participants was no different from that seen previously with no distraction.

Conclusion

To conclude, the distractor used for Experiment 3 did not produce the expected decrement in both phases of learning. Upon first exposure to the task, participants were unable to learn higher-level pairings between objects and actions, but this disappeared with twenty trials of practice. The goal for Experiment 4, then, was to develop a task that would similarly impact high-level learning, but would both require more resources and be harder to automatize. If this proved to be the case, we would expect to see a consistent decrement in performance on both types of learning: people would fail to both discriminate objects and to deviate from the predictions of the online-control model.

CHAPTER 5

EXPERIMENT 4: WILL A MORE DIFFICULT AND COMPLEX
SECONDARY TASK FURTHER IMPAIR BOTH ASPECTS OF
ANTICIPATORY PERFORMANCE?

Experiment 3 found a varied set of results, where participants' ability to discriminate predictable obstacles would be substantially degraded when they were faced with a novel visuo-spatial secondary task; however, if they were practiced with the task, their performance was similar to what had been seen previously by non-distracted participants. This led to the conclusion that the task used in Experiment 3 was perhaps too simple and easily learned.

For Experiment 4, the goal was to determine if a more difficult variant of the same basic distractor would produce more consistent impairment of anticipation and discrimination. If anticipation degraded linearly with task difficulty across similar tasks, this would show that there is a range of distraction and impairment, and that similar tasks can differentially impair separate levels of locomotor control.

Experiment 4 again used the Brooks Letter Task. However, the version used here had two important differences. First, as several participants in Experiment 3 commented on the use of "parsing up" strategies for familiar letters, I now included eight backwards letters in addition to the 16 standard letters (Figure 5.1). These were the eight non-symmetrical letters used in Experiment 3, and they were randomly presented in addition to the original letters during the experiment. The purpose of their inclusion was two-fold: first, to have additional letters that met the minimum complexity criteria, and second, to make the overall task more challenging, as they should be harder to visualize.



Figure 5.1 Modified letter set for Brooks Letter Task, including backwards letters.

The second major change for Experiment 4 was the introduction of an additional aspect of the task that had to be performed along with the original, in time with the same 1Hz metronome beat. This doubled the output requirements, putting an additional load on this stage of the system (and further loading the verbal processes). This second task was that in addition to reporting what direction they would turn at each corner, participants were required to report whether each corner they reached was at the very top or bottom of the letter, in which case they would respond “yes”, or was an intermediate point, in which case they would answer “no”. The final version of the task they had to

perform was a joint response, where the first word was the direction they had to turn to stay on the letter, and the second was the top/bottom task; for example, “Right/Yes, Left/No...”

This task is illustrated in Figure 5.2, which shows the final example given to participants. As in Experiment 3, the task was explained one step at a time (e.g. first the visualizing, then the direction task, then the top/bottom task, then the combination), giving participants practice with each step until they were comfortable. Finally, as before, each participant was permitted to practice the final task with a minimum of five different letters (including backwards ones), until they were reportedly and demonstrably comfortable with the task.

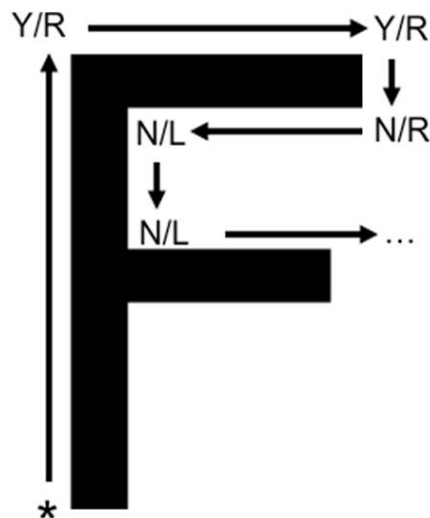


Figure 5.2 Final example letter explaining the task.

Method

Participants

Fifteen total participants were tested in Experiment 4; two of these were excluded from analysis for failure to follow instructions. One additional participant was not able to learn the secondary task, and she was excused from participation. Of the remaining 13 participants, there were four females and nine males, with a mean age of 22.7 years.

Procedure

The design of Experiment 4 was identical to Experiment 3, with a block of Random trials and a block of Predictable trials. These were identical to the blocks in Study 3, except that four trials were removed from the Random block. This was to allow participants an additional four practice trials, to help compensate for the increased difficulty of the secondary task. There were now of four practice trials with no secondary task, and ten trials with the secondary task. Other than this, and the increased instruction time, there was no difference in the design of Study 3 and Study 4.

Results

Questionnaire Results

Participants in Experiment 4 completed a questionnaire identical to the one in Experiment 3 (Appendix C-2). All participants noticed that some obstacles moved differently from others, and all but two reported using strategies to avoid some obstacles.

Notably, these were less explicit than previously; most of the strategies reported were along the lines of “tried to dodge” or “tried to step out of the way;” only five participants explicitly stated that they were anticipating where obstacles would be and changing their paths. Ten of thirteen participants reported that the secondary task impaired their ability to avoid obstacles. However, five of these explicitly stated that they felt the inverse was true as well, that the avoidance task impaired their ability to do the secondary task. No participants reported one block of trials feeling more impaired by distraction than the other.

Random Block: Participant Paths

Figures 5.3 and 5.4 present the mean paths for the Random block, separated by block order group. As in Experiment 3, trials where obstacles approached from the left were reflected over the z-axis prior to averaging. Table 5.1 presents the r^2 values between the binned mean paths and the model prediction for each condition, based again upon mean participant speed for that condition. These values are somewhat lower than those in Study 3; however, there was no significant difference between correlations for Study 3 & 4; $t(14) < 1$. There was, however a significant difference in correlations between Study 4 and Study 2, $t(14) = 2.72$, $p = .02$. There was also a nearly-significant difference between the block orders, $t(3) = -5.2$, $p = .06$.

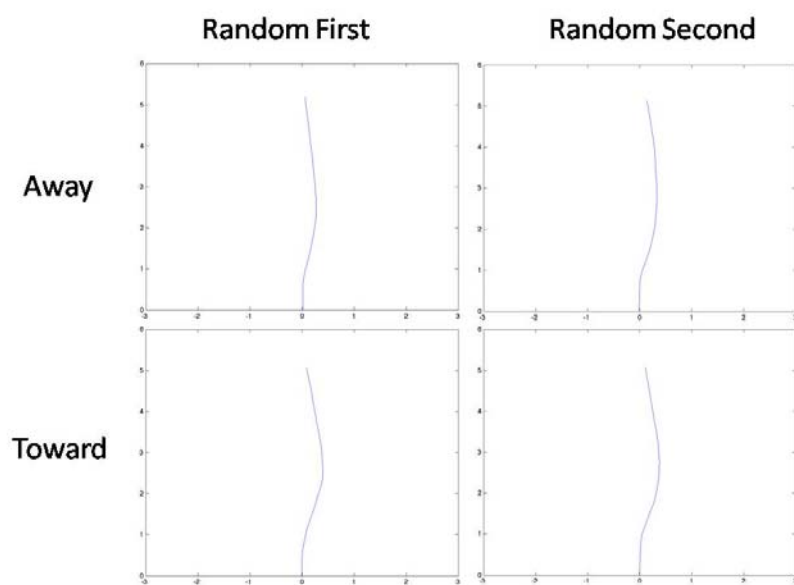


Figure 5.3 Mean participant paths for Random Block, Direction-Change trials separated by block order.

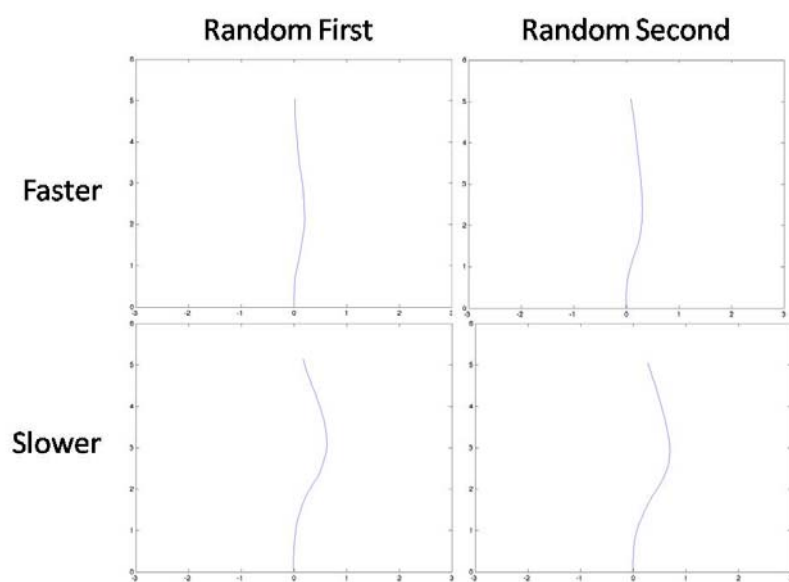


Figure 5.4 Mean participant paths for Random Block, Speed-Change separated by block order.

Table 5.1
Coefficient of Determination (r^2) Between
Participant and Model Predicted Headings

	RandomFirst	PredictFirst
Veer-Toward	.47	.61
Veer-Away	.61	.81
SlowDown	.67	.74
SpeedUp	.56	.71

We again see a significant – though small – decrease in correlation with model-predicted heading, particularly in the group who saw the Random block first. It appears that this more complex task also had an effect on overall locomotion, though it was fairly small; correlations with model predictions are still quite high.

Predictable Block: Participant Paths

Figures 5.5 and 5.6 show example paths over time from a typical participant in the Predict-First group for Straight trials and Veer trials, respectively. This participant still exhibits some degree of anticipatory behavior, though it seems less than found in Experiment 3.

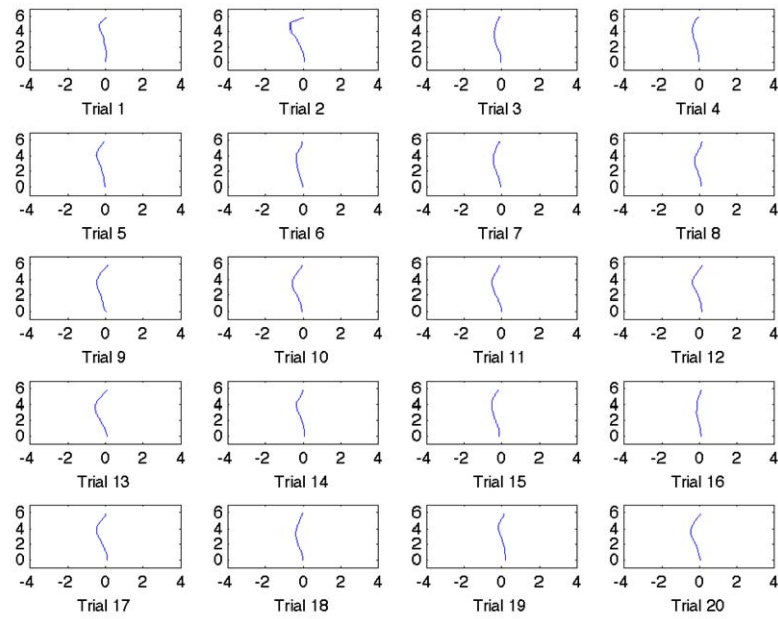


Figure 5.5 Sample Move-Straight participant path from the Predictable-First block.

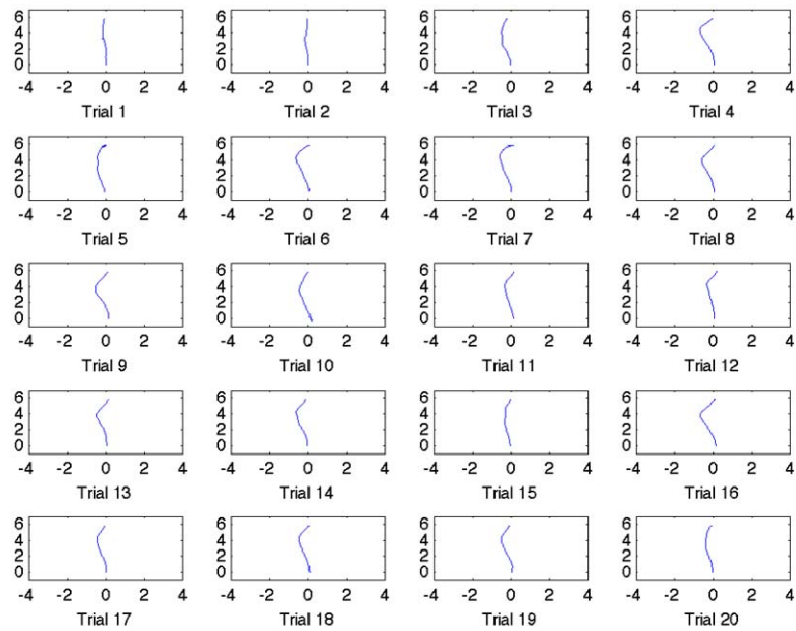


Figure 5.6 Sample Move-Veer participant path from the Predictable-First block.

Predictable Block: Mean Absolute Deviations

Figure 5.7 plots the mean absolute deviations over time for the group who saw the Predictable block first. The model predicted deviation was 12cm, again based on mean participant velocity across trials. As in the previous experiments, asterisks mark trials where each condition significantly differs from the model predicted deviation, and stars represent trials where the conditions differ significantly from each other. As before, I conducted one-sample and paired t-tests respectively, again with a Bonferroni correction of $.05/2$. The mean overall deviation for the Veer condition was 0.38m, and the mean deviation for the Straight condition was 0.26m.

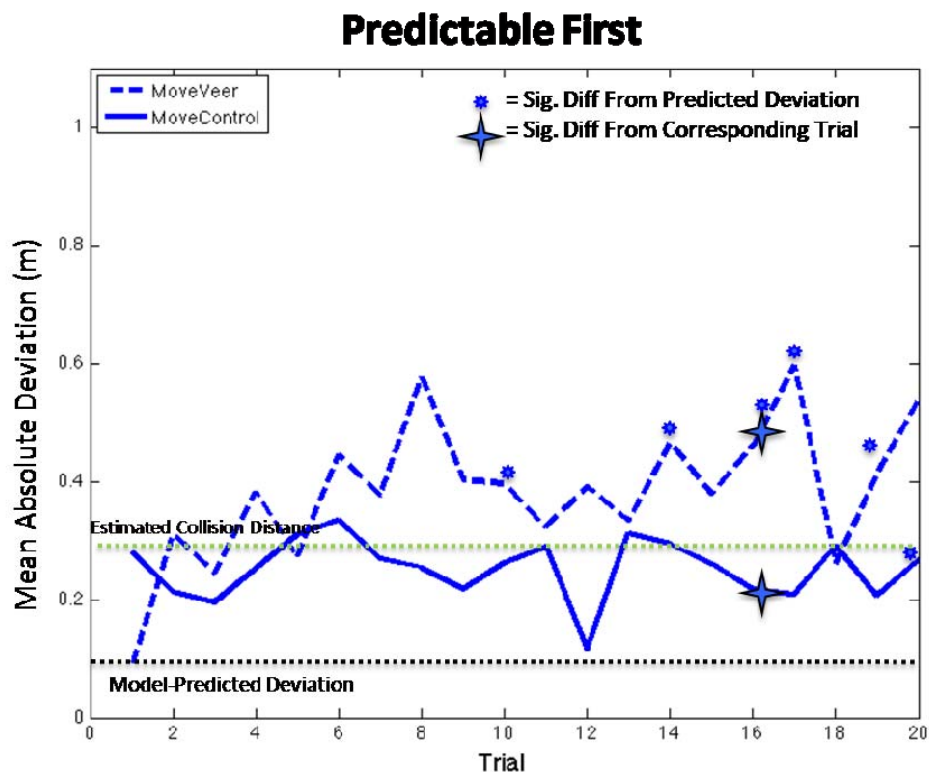


Figure 5.7 Mean absolute deviations for participants who experienced the Predictable block first.

We can see a major difference here between this plot and deviation plots from Experiments 2 and 3. To begin with, there is only one trial where the conditions differ significantly from one another. Secondly, there are only five trials in the Veer condition where the participants deviated significantly from model predictions, these only occur toward the very end of the block, and only intermittently then. It appears from these results that the more difficult secondary task significantly impaired people's ability to anticipate obstacle movement for participants who had no experience with the task. In addition, as there was only one trial with a significant difference between conditions, we conclude that the higher level object-pairing learning was also significantly impaired.

To see whether, as in Experiment 3, this was readily overcome with experience, we now turn to the group of participants who experienced the Predictable block second. The mean absolute deviations for these are plotted in Figure 5.8.

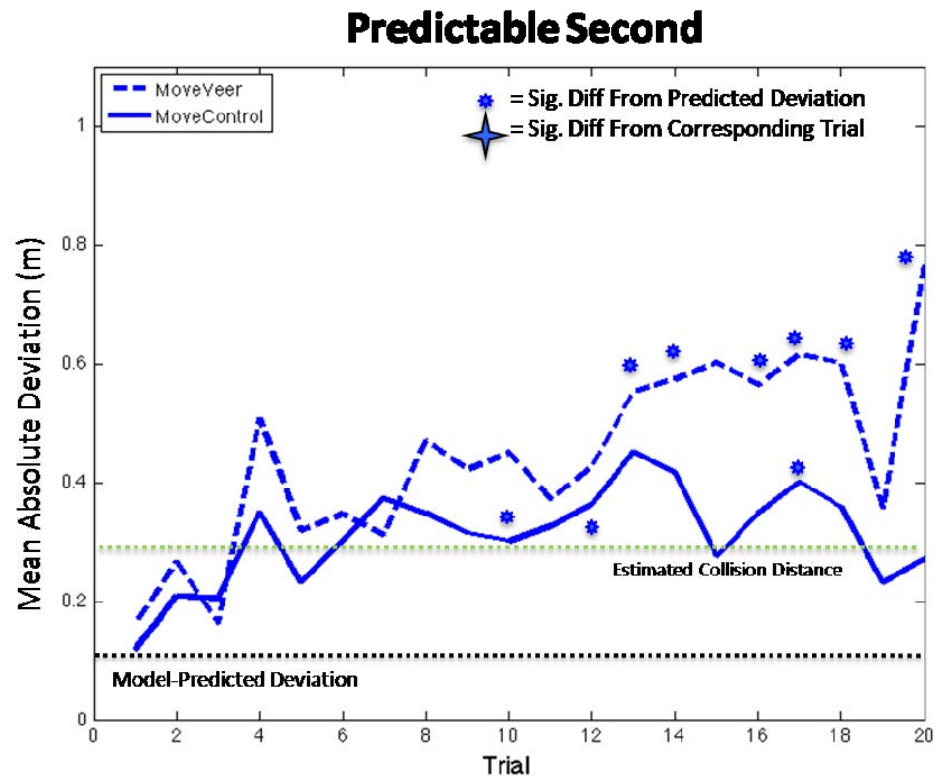


Figure 5.8 Mean absolute deviations for participants who saw the Predictable block second.

Here, the mean deviation for the Veer condition was 0.44m, and the mean deviation for the Straight condition was 0.31m, both very similar to the previous group. Consistent with the hypothesis, we see significant degradation in this group as well. There were no significant discriminations between conditions for any trial, and there were only six trials in the Veer condition where participants deviated significantly from the model prediction. It appears, then, that the more difficult distractor eliminated the effects of practice: both Simple-Anticipation and Navigation/Learning levels of control were significantly impaired in this experiment.

Predictable Block: Speed Plots

Figures 5.9 and 5.10 present the speed profiles averaged across participants for the Random-First and Predictable-First groups, respectively. Overall, these speeds were significantly slower than those in Experiment 3, $t(158) = 3.9$, $p < .001$, and were also significantly slower than those in Study 2, $t(158) = 21.6$, $p < .001$.

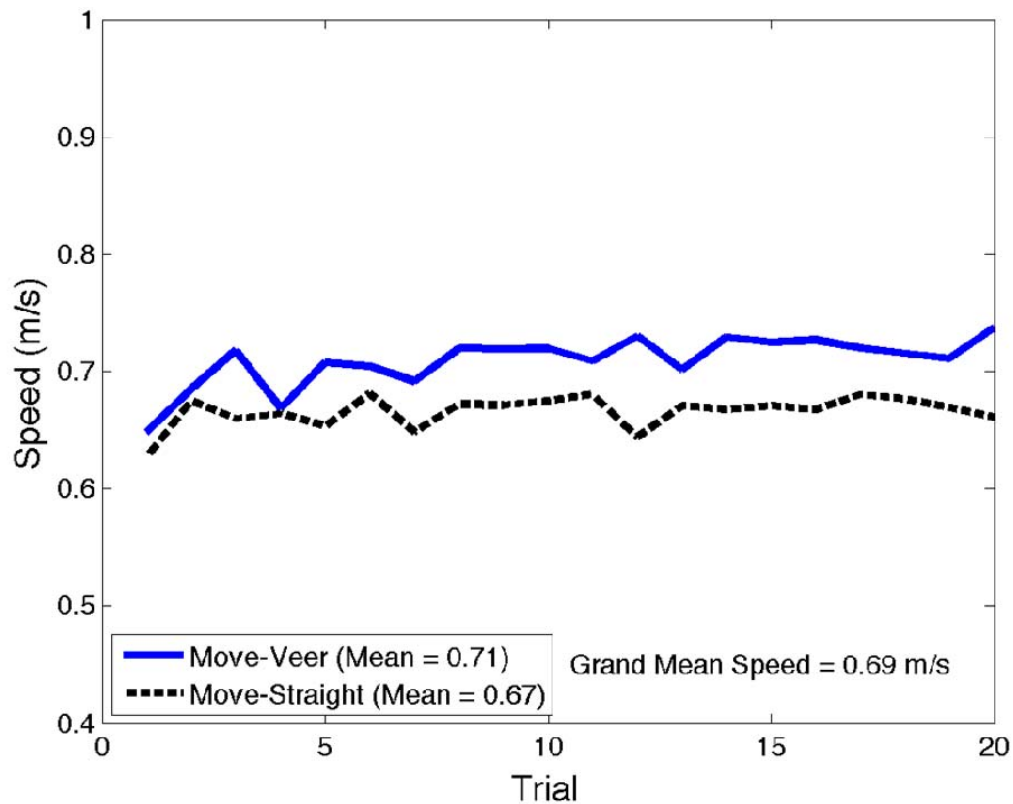


Figure 5.9 Speed profile for the Random-First group.

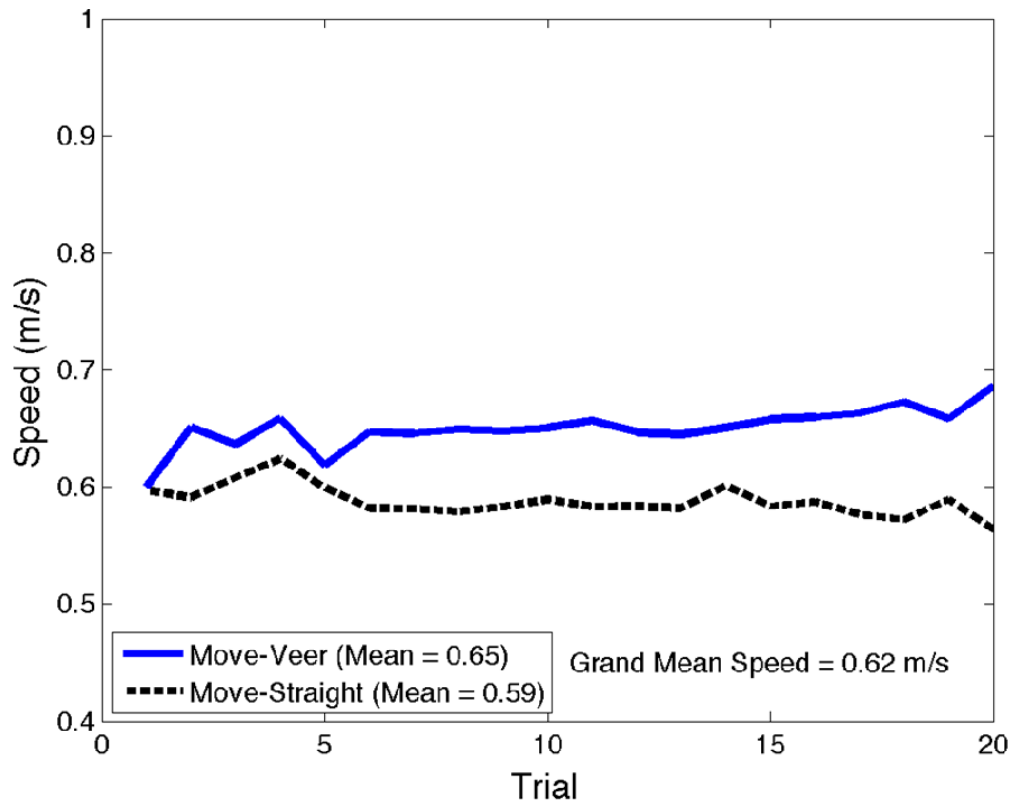


Figure 5.10 Speed profile for the Predictable-First group.

Discussion

To conclude, there were decrements in all dependent measures in Experiment 4. Trials in the Random block exhibited a small, though significant, decrease in correlation with model-predicted headings. In the Predictable blocks, participants did not deviate significantly from model predictions for more than a few trials, no matter whether they had practice with the task or not. Further, participants did not exhibit the ability to discriminate obstacle movements based on appearance in either order block. Finally, participants traveled significantly slower than in previous studies.

This suggests that the difficult visuo-spatial secondary task chosen for this study had the predicted effect; it deprived participants of the use of the higher two levels of locomotor control, caused them to walk more slowly, and to behave more similarly to the predictions of the online control model. Though there was a decrease in heading correlation between random trials and model predictions, this decrease is small, and these correlations still remained high. Thus, it is unlikely that this can entirely explain the sizable results we saw in the Predictable block. In sum, Experiment 4 showed that a complex visuo-spatial distractor can occupy enough processing and coding resources to preclude people from controlling their behavior using cognition or simple anticipation.

CHAPTER 6

GENERAL DISCUSSION

This series of experiments was designed to explore the possibility that humans have several levels at which they can control their locomotion. The lowest of these is proposed to be Online Control, which requires little attentional resources. Above this, Simple Anticipation takes advantage of basic mappings between objects in the world and likely actions. Finally, the top level of control, Navigation/Learning, contains true “high-level” cognition. It is proposed that these two higher levels of control require more overall attentional resources, as well as requiring specific processing code and stage resources (Wickens, 2002). Further, these levels are not distinct from one another, but are hierarchical; control at higher levels incorporates and “directs” control at lower levels.

The four experiments presented here investigated the idea of levels of online control from two angles. The first, which was explored in Experiments 1 and 2, was whether people have the ability to anticipate obstacle movement and change their trajectories to take advantage of this anticipation. Successful anticipation would provide evidence that people are able to shift control of their locomotion when the situation requires. The second question, examined in Experiments 3 and 4, was whether attentional resources are required to move among the levels of control, and whether by manipulating the attentional resources available we can preclude the use of higher levels of control.

The first two experiments showed that people do in fact have the ability to anticipate obstacle movement when necessary. Interestingly, this did not show up when

the benefit to anticipation was greater path efficiency alone; instead, people only exhibited anticipatory behavior when necessary to avoid collision. This finding supports the hypothesis put forth by Fajen & Warren (2007) that the majority of human locomotion is controlled online by current perceptual information. Only in extreme circumstances such as imminent, predictable risk do people shift from online control to anticipation.

The second two experiments demonstrated that higher levels of control require progressively more attentional and processing resources. Further, by selectively degrading these resources, they successfully parsed apart performance at the second (Simple Anticipation) and highest (Navigation/Learning) levels of locomotor control. In Experiment 3, participants were asked to avoid predictable obstacles while performing a relatively simple visuo-spatial distractor task. Only participants who were unpracticed with the secondary task were significantly impaired; those participants who had previous experience with the same distraction were unaffected by it, and their performance matched that of participants who were not distracted.

Further, this impairment in the unfamiliar block was limited to participants' ability to discriminate veering from straight-moving obstacles, as participants in all cases were able to learn relatively quickly to deviate to avoid being hit. In other words, people unpracticed with the secondary task were still able to avoid veering obstacles, but they did not deviate significantly less when facing straight-moving obstacles. Thus, it appears that a simple visuo-spatial task occupies resources needed to execute locomotor behavior

from the highest level of control (learning to discriminate), but does not interfere with the Simple-Anticipation level of control (veer away from everything).

Study 4 was conducted as an attempt to impair both higher levels of control. It included a more difficult version of the distractor task that was designed to occupy enough resources in general, and enough spatial resources in particular, to preclude participants from using anticipatory control. This proved to be the case, as performance of all participants was significantly impaired, no matter whether they were practiced at the secondary task or not. This performance decrement was seen in both high-level discriminatory learning, as found in Experiment 3, and in general avoidance learning, which was not seen in Experiment 3. A more complex version of the same visuo-spatial task, then, proved to require enough resources to effectively block participants from moving to higher levels of control.

An important consideration to these findings is that there were significant declines in the relationship between headings in the Random blocks and model-predicted headings for both Studies 3 and 4. This implies that even basic locomotor processes were somewhat impaired by a secondary task, and more so with increased difficulty. If the decrease in the magnitude of correlations was on the same scale as the decrease in anticipatory behavior, we would be unable to conclude that the anticipatory processes themselves relied upon attentional resources. In other words, if the entire effect across conditions could have been explained by a decrease in basic locomotor ability, there would have been no reason to attribute attentional requirements to anticipation.

This did not seem to be the case, however, as the magnitude of difference in Random-Model heading correlations across studies was rather small, and the decreases in anticipatory behavior were rather large. Thus, we can conclude that at least a sizable part of the decrement in anticipatory behavior with distraction was due to the fact that anticipatory locomotion does require visuo-spatial attentional resources. The question of specific allocation of resources remains open, however, and is worthy of future research.

Limitations

There are several limitations with these studies that should be kept in mind when interpreting results. First, it is important to remember that these studies were conducted in virtual reality. While our system is highly immersive and allows for free walking, a simulation can never entirely replicate reality. The resolution of the display was relatively low at 640x480, the field of view was narrow compared to real life (though fairly wide compared to other head-mounted displays), and participants were required to wear both the HMD and a light backpack, both of which could theoretically impact their kinematics of movement.

Second, the type of distractor used here was limited to the visuo-spatial domain, one that had previously been shown to be directly involved with the maintenance of human locomotion. It remains to be seen, first, whether other types of secondary tasks will have similar effects; and second, whether the types of distraction that occur in the real world correspond well with the ones I have used here.

Third, although participants were forced by the experimenter to respond in-time with a metronome ticking once per second, a number of participants reported that they still treated this as a secondary task. This is an important issue to consider, and a fruitful area for future research: under what conditions are tasks considered primary and secondary?

Fourth, and related to this, secondary task performance was not analyzed here. A full accounting of shifting levels of control will require a complete understanding of changing task priorities over time.

Fifth, compared to the real world, occurrences here were scripted and predictable. This was necessary for the design of the experiment, but it is likely that the real-world tradeoff between predictability and real danger was not quite matched. Related to the question posed above, future research would do well to investigate what effect predictability of occurrences has on attentional resources and requirements.

Future Directions

Now that the groundwork has been laid for a feasible theory of levels of locomotor control, there are a number of important questions that can and should be addressed. I will present several here, but there are no doubt many more.

First, what exactly are people learning to anticipate? As Experiment 3 showed, there are likely at least two processes occurring when people learn to avoid obstacles. There is an initial, general avoidance behavior that causes people to simply avoid

everything, and a higher level learning that pairs specific types of objects with specific movements. It would be worthwhile to investigate what, exactly, people are learning in the second case. Are they learning the metric routes that objects will take, are they behaving as though those objects are somewhere close to their future position, or doing something different entirely? Preliminary analysis of the results presented here suggests the second option, that people are behaving as if predictable obstacles are already at the predicted location of impact. However, a full answer to this question will require direct experimental manipulation of the circumstances of obstacle movement and the information that participants receive.

Second, as mentioned above, it is an open question what specific aspects of basic locomotor control rely on resources shared with higher levels of control, and what requirements are unique to these higher levels. Future research would do well to try to parse these further apart.

Third, how does task prioritization factor into the shifting of levels of control? In the experiments presented here, every effort was made to maintain a constant level of distraction. This may or not be the case in more naturalistic scenarios, and deserves study.

Fourth, as discussed in the limitations section, this series of experiments used only a visuo-spatial distractor. There are many other attentional resources and processes that may be involved with shifting levels of control, and they should be examined as well.

Finally, the original motivation of this research was the question of how drivers are able to maintain a Field of Safe Travel when maneuvering their cars at high speeds. Though these studies were conducted at an entirely different level of locomotor complexity, it is quite possible that the findings here underpin the control of vehicular locomotion as well. There are a great many studies that can be conducted both in driving simulators and on the road that can illuminate the similarities and differences between the control of walking and driving, and the practical road safety implications that follow.

Conclusion

In conclusion, this research found that people are able to learn to predict obstacle movement and preemptively avoid dangerous obstacles; however, this ability decreases when visuo-spatial attentional resources are occupied by a secondary task. These four studies represent an initial foray into a series of useful and interesting questions that have both practical and fundamental implications. There are a number of questions remaining to be answered about the role of attentional resources in the safe guidance of locomotion. Under what circumstances does locomotion require anticipation? How do we decide how to allocate it? What competing requirements exist in a given situation, and how do we decide among them? How does expertise affect a person's ability to perform multiple tasks simultaneously; are parents in fact more able to drive and talk? These questions, and many more, remain to be answered; however, this line of studies has helped form a foundation upon which they may be addressed.

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APPENDICES

APPENDIX A-1

INSTRUCTIONS FOR EXPERIMENT 1 (COMPRESSED FOR SPACE)

Explore Session (all studies):

“This section of the experiment will help get you familiar with virtual reality. You will see several blue poles, a red pole, and a grey pole. The grey pole marks your starting position. Walk to it, stand right inside it, then turn to face the red pole. When you’re correctly positioned inside the grey pole, the red pole will turn green. When it turns green, you should walk into it, then turn to find the next green pole. Continue doing this until all the poles have disappeared.”

Practice Session:

“Good! You’re now ready to start the practice section. For each trial, your starting location will be a green pole. You should walk to the green pole, stand inside it, and turn to face the yellow pole that’s a few feet away. When you’re inside the green pole facing the yellow pole, click the trigger button on the remote control. This will cause the yellow pole to disappear and be replaced by a red pole. If the yellow pole doesn’t disappear, make sure you’re right inside the green pole and try again. When the red pole appears, your task is to simply to walk to it. However, there may be an obstacle that gets in your way while you’re walking. You should avoid touching this obstacle while walking to the red pole. If you hit an obstacle, it will make an annoying sound like this: [sound inserted] If you have any questions, please ask the experimenter.”

Post-Practice:

“Great, you’ve now completed the practice trials. You’re about to start the real experiment. Remember that the your target is always the red pole, and anything else that gets in your path is an obstacle you should avoid. Please feel free to ask the experimenter if you have any questions, and remember you can stop at any time if you feel uncomfortable. Good luck!”

- OR (second 10 subjects) –

“Great, you’ve now completed the practice trials. You’re about to start the real experiment. Before you do, there’s one important piece of information you should know. You can tell how an obstacle will move by what it looks like; in other words, objects with the same appearance will always move the same way. Please feel free to ask the experimenter if you have any questions, and remember you can stop at any time if you feel uncomfortable. Good luck!

APPENDIX B-1

INSTRUCTIONS PRESENTED TO PARTICIPANTS FOR EXPERIMENT 2

Experiment 2 Main Instructions:

“Now that you’ve finished the exploration phase, you’re now ready to start the practice section. For each trial, your starting location will again be a grey pole. You should walk to the grey pole, stand inside it, and turn to face the red pole that’s a few feet away. When you’re inside the grey pole facing the red pole, click the trigger button on the remote control. This will cause the red pole to disappear and be replaced by a green pole. If the red pole doesn’t disappear, make sure you’re right inside the grey pole and try again.

When the green pole appears, your task is simply to walk to it. However, there may be an obstacle that gets in your way while you’re walking. You should avoid touching this obstacle while walking to the green pole. If you hit an obstacle, it will make a siren sound like this: [sound inserted] Finally, after you walk into the target pole, a voice will tell you which direction to turn to find the next grey pole. If you have any questions, please ask the experimenter.”

Study 2 Post-Practice Instructions:

“Great, you’ve now completed the practice trials. You’re about to start the real experiment. Remember that the your target is always the green pole, and anything else that gets in your path is an obstacle you should avoid. Please feel free to ask the experimenter if you have any questions, and remember you can stop at any time if you feel uncomfortable. Good luck!”

APPENDIX B-2
QUESTIONNAIRE FOR EXPERIMENT 2 (COMPRESSED FOR SPACE)

- 1) What is your gender? M F
- 2) How old are you? _____
- 3) Do you play any sports? Please list:
- 4) Did you notice some obstacles moving differently than others? Did you use any strategies when avoiding obstacles? Please explain.

[Please don't look ahead...complete this page first!]

- 5) Can you recall any specific obstacle trajectories? If so, please sketch them below:
- 6) Do you feel that your avoidance behavior changed as you became more familiar with the obstacles? Please explain.
- 7) Do you have any general comments about this study?

Thank you for your time!

APPENDIX C-1

INSTRUCTIONS FOR EXPERIMENTS 3 & 4

For the first 4 practice trials:

“Now that you’ve finished the exploration phase, you’re now ready to start the practice section. For each trial, your starting location will again be a grey pole. You should walk to the grey pole, stand inside it, and turn to face the red pole that’s a few feet away. When you’re inside the grey pole facing the red pole, click the trigger button on the remote control. This will cause the red pole to disappear and be replaced by a green pole. If the red pole doesn’t disappear, make sure you’re right inside the grey pole and try again.

As you are walking toward the green pole,, there may be an obstacle that gets in your way. You should avoid touching this obstacle while walking to the green pole. If you hit an obstacle, it will make a siren sound like this: [sound inserted] Finally, after you walk into the target pole, a voice will tell you which direction to turn to find the next grey pole. If you have any questions, please ask the experimenter.”

For the next 6 practice trials (10 trials in Experiment 4):

When the green pole appears, your task is to walk to it. Before you do, however, a voice will instruct you which letter you should imagine to do your visualization task. Remember to visualize this letter as a capital block letter that you are traversing starting at the bottom left. Whenever you reach a vertex point, state out loud whether you are turning left or right to continue on the letter. When you take a few steps toward the green pole, a metronome sound will start. This is your cue to start the visualization task. If you get the whole way around the letter before you catch the green pole, just keep going around that letter.

Post-Practice

“Great, you’ve now completed the practice trials. You’re about to start the real experiment. Remember that the your target is always the green pole, and anything else that gets in your path is an obstacle you should avoid. Also remember to perform the visualization task in time to the metronome to the best of your ability. Please feel free to ask the experimenter if you have any questions, and remember you can stop at any time if you feel uncomfortable. Good luck!”

APPENDIX C-2
QUESTIONNAIRE FOR EXPERIMENTS 3 & 4 (COMPRESSED FOR SPACE)

- 1) What is your gender? M F
- 2) How old are you? _____
- 3) Are you right or left handed?
- 4) Do you play any sports? Please list:
- 5) Did you notice some obstacles moving differently than others? Did you use any strategies when avoiding obstacles? Please explain.
- 6) Did you feel that your ability to avoid obstacles was impaired by the visualization task? Did it seem to affect one block of obstacles more than the other? Please explain.
- 7) Do you have any other comments about this study?

Thank you for your time!