

TAKING INTO ACCOUNT SELF-MOTION IN DEPTH WHILE ASSESSING EXTERNAL
MOTION IN DEPTH

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Abstract

During sideways movement of an observer, optic flow parsing – in which an object’s speed is extracted from all the other movement present in the scene – has been shown to be incomplete, with an overestimation of self-motion and an underestimation of object speed, especially when target and observer move in opposite directions (Jörges & Harris, 2022). Here I assess the efficiency of optic flow parsing for an object moving in depth while the observer is also moving either towards or away from the object. Participants were asked to compare the speed of a sphere moving towards or away from them relative to a ball moving sideways either while they were stationary or during visually simulated self-motion. The data showed flow parsing in depth to be incomplete. Curiously, the underestimation of object speed was largely irrespective of whether the ball and the observer moved in the same or opposite directions. These findings may be accounted for by a Bayesian model that includes a “Regression to the Mean Speed” prior.

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1.0 Introduction

1.1 Flow Parsing

How accurately are we able to estimate the speed of moving objects when we ourselves are in motion? This process of gauging object motion during self-motion requires us to subtract or cancel out the motion created by our own self-motion from the motion of the moving object. The addition or subtraction of motion due to self-motion from the motion of the moving object in question is referred to as *flow parsing*. According to the Flow Parsing Hypothesis (Dupin & Wexler, 2013; Rushton & Warren, 2005; Warren & Rushton, 2008, 2009) upon receiving this input, the observer's task is to determine what amount of is due to their own motion. This amount then needs to be subtracted from the overall retinal input and the remaining speed can be attributed to object-motion. The Flow Parsing hypothesis has been demonstrated to accurately model the perception of object motion during self-motion – with some limitations - for upright observers and sideways translation (Dyde & Harris, 2008), rotating observers (Probst et al., 1995; Hogendoorn et al., 2017; Garzorz et al., 2018) and for motion-in-depth (Aguado & Lopez-Moliner, 2019; Dupin & Wexler, 2013; Gray et al., 2004).

During visually simulated self-motion in the laboratory, in the absence of actual physical motion, the self-motion component tends to be underestimated (Dokka et al., 2015). This may be due to a dissonance between the visual and vestibular systems since the participant does not actually move and their vestibular system is consequently quiet (Becker et al., 2002; Frissen et al., 2011; Jurgens & Becker, 2006). Any underestimation of self-motion when the observer's motion is visually simulated should then lead to a bias in the estimation of object-motion during self-motion because then, during flow parsing, the observer is likely to attribute less of their

overall retinal input to self-motion. As a result, when experiencing visually simulated self-motion, the observer would subtract less from their retinal input (since they are underestimating self-motion), thus leading to incomplete or less accurate flow parsing and an overall inaccuracy or bias in estimating the speed of object motion. For example, if an object is moving at a speed of 10m/s, and the observer is moving at 10m/s in the opposite direction, then the relative speed of the object would be 20m/s. In this case, if self-motion were underestimated (for example, at 8m/s), object-motion would be perceived as moving faster than its actual speed (i.e. $20 - 8 = 12$ m/s). However, if object-motion and observer-motion were in the same direction, resulting in a relative speed of 0m/s, object-motion would be underestimated ($0 - 8 = -8$ m/s).

When observer-motion is linear and parallel to object-motion and in the same direction, the observer tends to underestimate the speed of the object (lateral movement – Jörges et al., 2021; forward motion – Neihorster et al., 2017), compared to when the motion of the observer is orthogonal to the object motion (Butler et al., 2010). Similarly, when observer motion occurs in the opposite direction of an object's motion, the observer tends to overestimate the object's speed and perceive the object to be moving faster than it really is (Jörges et al., 2021).

1.2 Prior Knowledge

In addition to flow parsing, some studies suggest people may rely on a “prior” when making estimations concerning object motion in their external world while they themselves are in motion. While I will discuss priors and Bayesian modelling in greater depth later on in this thesis, a “prior” is essentially the tendency to rely on prior knowledge of what is expected when interpreting the sensory information being processed. Some studies that have looked at object

motion in depth have found evidence suggesting that when judging object speed, people rely not only on flow parsing, but also on priors, especially when the task at hand becomes increasingly difficult. For example, a study conducted by Aguado & Lopez-Moliner (2019) found that participants appeared to use a “slow motion prior” when assessing the speed of objects approaching them at varying velocities and angles. They found that the perceived speed of movement in depth was strongly underestimated. Aguado et al. (2019) attributed this finding to a Bayesian model that included a slow-motion prior. Essentially, when sensory estimates are combined with an expectation of nearly zero motion, this is likely to result in an underestimation of speed. The extent of the underestimation and the percentage of weighting on the prior would depend on the signal reliability. For example, if the reliability of the signal is low, the stimulus speed will be underestimated more strongly.

While Aguado & Lopez-Moliner, 2019 formulated a Bayesian model to test the predictions of a slow-motion prior, this prior was initially proposed by Welchman et al., (2008) and essentially suggests that if the reliability of the sensory input is low, people will be more likely to rely on this slow-motion prior and consequently underestimate the speed of the stimulus more strongly.

Welchman et al., (2008)’s slow-motion prior is just one example of how prior knowledge may play a role in the perception of object motion. Through Bayesian modelling, it is possible to test various types of priors and their possible roles in motion perception.

In a slightly different context, Willemsen et al., 2024’s study on distance reproduction applied a central tendency/regression to the mean prior in relation to vestibular path integration. They found that reproduced distances showed an overall positive central tendency effect, and that these results were largely compatible with predictions of a Bayesian Kalman filter model. This is a strong example of a cognitive process where a central tendency or “regression to the mean”

prior was effectively applied. The possible role of a Bayesian prior in the context of my experiment will be further elaborated later in this thesis.

1.3 Optic Flow and Self-Motion/Object-Motion Estimates

Optic flow is the pattern of motion of the images of objects and features in the outside world relative to an observer created by their own movement through the world. In other words, optic flow is caused by the relative motion between an observer and a scene. Optic flow is integral to the link between perception and action, and thus in perceiving self-motion. Gibson (Gibson 1950, 1966, 1977, 1979) was one of the first to discuss optic flow, how self-motion through an environment causes relative movement between the world and an observer and how this relative movement can provide useful information about the structure of the visual world and an observer's movement in it.

Previous studies involving extracting object motion from complex retinal motion have mostly looked at rotational movement (Garzorz et al., 2018; Hogendoorn et al., 2017; Probst et al., 1995) and lateral translation (Jörges et al., 2021) and very little work has yet been done on moving towards or away from objects that are also moving towards or away from the observer. While a study conducted by Gray et al. (2004) did involve both object and observer motion, Gray et al. (2004) focused their analysis on time-to-contact (TTC) or time to collision. Gray et al. (2004)'s study revealed that for objects moving towards or away from an observer that actually had the same speed relative to the observer, the speed of objects moving towards the observer were perceived to be higher than when observer-motion and object-motion were in opposite directions (i.e., for an object moving away from the observer). Gray et al. (2004) made their

speed estimates indirectly from assessing time-to-contact. In my study, I am interested in directly quantifying speed judgements. Unlike in Gray et al. (2004)'s study, the object-motion speed in my experiment remains constant within a trial and the object-motion will not give the impression of colliding with, or making contact with, the observer. A crucial difference between my study and Gray et al.'s is that the task judgements made in Gray et al.'s study were all egocentric (judgements relative to the observer) whereas the judgements made in my study are allocentric (relative to space). Furthermore, my study assesses perceived speed directly rather than inferring perceived object speed from time-to-contact or time-to-collision estimates. In this way, while Gray's study deals primarily with the relative speed of an object in motion, my study requires the participant to use flow parsing in order to estimate the speed of object motion relative to the world as recorded by comparing the motion of the target ball relative to a reference ball moving orthogonally to the movement of the target ball. This could only be done accurately if the motion of the target ball in space were accurately perceived. An experiment by Aguado & Lopez-Moliner (2019) also used the motion of a laterally moving probe ball to assess their target ball's perceived speed when moving at different angles relative to the observer. Aguado & Lopez-Moliner (2019)'s study did not involve self-motion or flow parsing but found a strong effect of a slow-motion prior in the perception of objects moving in depth.

Guo and Allison (2024) looked at whether binocular disparity could improve overall flow parsing as well as the ability to discriminate the motion direction of a target ball (approaching or receding, relative to the scene) while the observer was either stationary or moving forwards/backwards. They found that accuracy in discriminating the direction of target motion was exceptionally high during stationary observer conditions, less accurate during forward self-motion, and the least accurate during backward self-motion. Although the motion profiles and task itself was very similar to mine, the question focused on whether binocular disparity could

improve flow parsing. The analysis in my study focuses on whether target ball speed was over or underestimated in same and opposite ball-observer motion profiles. However, Guo and Allison's (2024) finding that binocular disparity was helpful in parsing, suggests optimal parsing in my task given that all my stimuli had appropriate binocular disparities.

Niehorster and Li (2017) investigated the accuracy of flow parsing during varying speeds of forward self-motion. Participants indicated the perceived motion direction of a probe that moved either vertically upwards, or laterally (left or right). Niehorster and Li (2017) found that flow parsing was incomplete and that the flow parsing gains remained constant, despite increasing self-motion and object speeds. Notably, my participants made speed judgements as opposed to directional judgments, and my experiment looked at both backward and forward self-motion, as opposed to just forward. With the observer moving forwards/backwards and the target ball also moving forward/backwards, my study allowed for a comparison of flow parsing accuracy when the ball and observer were moving in the same direction, and when the ball and observer were moving in the opposite direction. In this way, the investigation of object motion perception in depth is a key point where my study differs from Niehorster and Li (2017).

A study by Dupin & Wexler (2013) also looked at the perception of object motion in depth as seen by either stationary or moving observers. However, their task required participants to make judgments on the perceived direction of object rotation. A moving background was used to generate optic flow and simulate self-motion. The main conclusions of this study were that when the background moved in the same direction as the object, object motion was underestimated. When the background moved in the opposite direction, object motion was overestimated. While my study also has these conditions of the same and opposite self/object motion where self-motion is visually simulated, the task in my study asks participants to make speed judgments as opposed to directional judgments and looks at forward/backward movement

as opposed to rotational motion. Although many biologically relevant aspects of the perception of an object moving in depth such as whether and when it might collide with you may be extracted without knowledge of the object's actual speed, here I am specifically interested in the efficiency of flow parsing in depth. Will inaccurate flow parsing yield underestimations of object motion when the observer and object are moving in the same direction, and overestimation of object motion when the observer and object are moving in opposite directions?

In this thesis, I investigate the efficiency of flow parsing as it relates to object motion towards or away from an observer who is either stationary or experiencing simulated self-motion moving towards or away from the target object. This is important for understanding significant common behaviours such as driving a car or playing ball sports where correctly estimating the speed of objects in the world while you are moving can be critical.

2.0 Purpose and Hypotheses

In my master's thesis, I have investigated the accuracy with which an observer is able to estimate the speed of objects relative to the world when the object is moving in depth towards or away from them while they themselves are either stationary or simulated as being in motion: moving in the same or opposite direction to the target. All self-motion was visually simulated, and participants were immersed in a virtual reality environment. I conducted two experiments: Experiment 1 and Experiment 2. Experiment 1 and 2 differed in terms of self-motion speeds. In Experiment 1, the target ball's speed was either 3m/s or 10m/s, while the self-motion speed was – 6m/s. In Experiment 2, the ball's speed was the same as for exp 1(3m/s and 10m/s), while the self-motion speed was 10m/s. Each experiment had a separate self-motion speed to determine whether varying the self-motion speed would yield significantly different results as it created a different range of relative speeds between the target and observer in each experiment.

My hypotheses are:

1. Flow parsing will be incomplete. In the condition where the observer and target are moving in opposite directions, I expect the observer to assess the speed of the target to be greater than its actual speed.
2. In the condition where the observer and target are moving in the same direction, the observer will assess the speed of the target to be less than its actual speed.
3. Speed judgment biases will be roughly proportional to the self-motion speed and there will therefore be greater biases in Experiment 2 as compared to Experiment 1 due to the faster speed of self-motion.

4. Just Noticeable Difference (JND) will go up, signifying decreased precision in the presence of self-motion when participants are parsing.

3.0 Methods

3.1 Participants

I recruited 30 participants for each experiment through the Undergraduate Research Participant Pool (URPP) at York University. Participants received one university course credit as compensation. There were no exclusion criteria for participating in this experiment, and this study received ethics approval from the Human Participant Ethics Review Sub-Committee at York University. Informed consent was obtained from all the participants in writing and the experiment was conducted in accordance with the principles of the Declaration of Helsinki.

3.2 Apparatus

My experiment was performed in virtual reality with participants remaining physically static and seated. Stimuli were programmed in Unity (2019.2.11f1). The C# script built into Unity was used to program object motion, visually simulated observer motion, and the psychophysical staircases. Stimuli were presented in a VR (virtual reality) headset. I used an HTC Vive and required participants to respond using a computer keyboard.

My VR environment was a stereo display and included depth cues from the light, shadows, as well as range of textures on the floor and wall. My environment consisted of a brick wall and small potted plants across the tiled floor, as seen in figure 1.

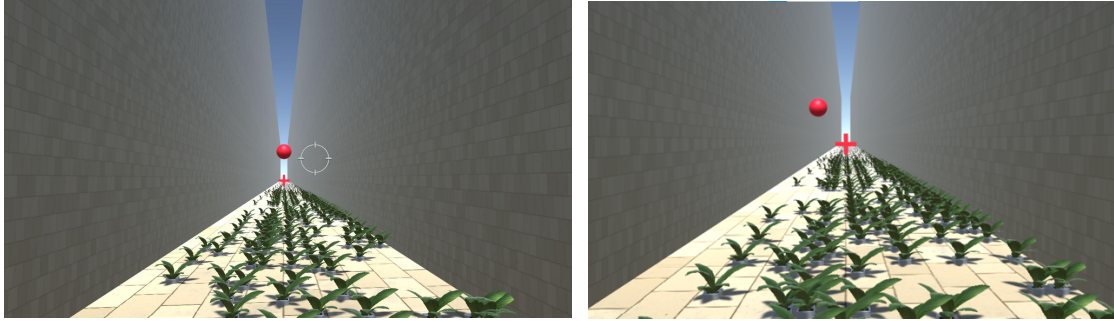


Figure 1. Screenshot of the experiment environment in virtual reality (VR) as seen through the HTC Vive headset. The environment includes depth cues from lighting, shadows, the textures of the floor and wall, as well as the green plants along the floor. The red fixation cross and a white target can be seen in the centre of the screen. (A) Shows the target sphere that moves either toward or away from the observer. (B) Shows the probe sphere that moves laterally across the screen.

3.3 Head Angle Control

Eye tracking was not included in this experiment but I ensured that the participant's head was still and facing in a consistent direction. Participants had to align a white target circle with the red fixation cross by adjusting the position of their head so that the white target aligned with the cross (see figure 1). Once aligned with the cross, the white target disappeared from the screen but reappeared in the participant's head drifted. The red sphere in Figure 1 is the target ball that moves towards or away from the observer in each trial. Shortly after the disappearance of the target ball, a second ball (the probe ball – not shown) moves laterally across the screen at a distance of 8m from the observer. The participants judge which of the two balls they perceived to be moving at a higher speed.

3.4 Experimental Design

Two experiments were conducted. Each experiment involved a separate set of participants and different self-motion/observer speeds. In experiment 1, the observer moved at 6m/s (in both directions) and in experiment 2, the observer's speed was set at 10m/s.

A red target sphere with a diameter of 40 cm appeared in front of the observer. For both observer-stationary and observer-moving conditions, the closest distance between ball and observer was set to 0.5m. Sometimes that was at the beginning of the trajectory (when the ball was moving away from the observer and sometimes at the end of the ball's travel, depending on self-motion speed and direction and the ball speed and direction (see table 1).

After the motion a second sphere (probe) appeared and moved across the display. Observers judged whether the speed of the probe was faster or slower than the target ball. The

probe's speed was controlled by two interleaved PEST staircases (see below for details) for each condition with starting values of 33% above and 33% below the actual speed of the target. To limit the overall experiment time, the PESTs each terminated when 15 trials were reached (30 trials/condition). The termination criterion was necessary due to the large number of conditions with 24 interleaved staircases running simultaneously.

The probe, like the target ball, was 40 cm in diameter and emerged from the side wall at a distance of 8 m in front of the observer. It always traveled all the way across the passageway (which had a width of 4 m). Both the target ball and the probe ball were simulated at 2 m above the floor and always moved parallel to the floor. Participants were seated and the camera was simulated 1.3 m above the ground (that is 70cm below the path of the target and probe balls).

While the motion of the probe ball was sideways and either went from left to right or right to left randomly, the target ball moved either forwards or backwards. In this way, the perceived speed of the target ball was assessed by comparing sideways and forwards/backwards moving balls.

There were three conditions of observer self-motion: The observer was 1) stationary 2) moving backwards 3) moving forwards at either 6m/s (experiment 1) or 10m/s (experiment 2) When the observer was not stationary, self-motion was either in the same direction as the target sphere, or in the opposite direction of the target sphere. All self-motion was passive and visually simulated.

To summarize, in experiment 1, the observer speed of 6 m/s (towards and away), was combined with a ball speed of 3 m/s and 10 m/s (towards and away) for the target. In experiment 2, the observer speeds were set at 10 m/s (towards and away) and combined with the same two ball speeds (towards and away). The conditions and resulting relative speeds are summarized in

table 2. The participant's task was always to extract the ball's speed relative to the world (i.e., either 3m/s or 10m/s).

	ball speed re scene	person speed re scene	ball speed re person	ball position		observer position	
				start	end	start	end
stationary	3	0	3	0.5	2	0	0
exp 1	3	6	-3	2	3.5	0	3
exp 2	3	10	-7	4	5.5	0	5
stationary	10	0	10	0.5	5.5	0	0
exp 1	10	6	4	0.5	5.5	0	3
exp 2	10	10	0	0.5	5.5	0	5
stationary	-3	0	-3	2	0.5	0	0
exp 1	-3	6	-9	5	3.5	0	3
exp 2	-3	10	-13	7	5.5	0	5
stationary	-10	0	-10	5.5	0.5	0	0
exp 1	-10	6	-16	8.5	3.5	0	3
exp 2	-10	10	-20	10.5	5.5	0	5
stationary	3	0	3	0.5	2	0	0
exp 1	3	-6	9	0.5	2	0	-3
exp 2	3	-10	13	0.5	2	0	-5
stationary	10	0	10	0.5	5.5	0	0
exp 1	10	-6	16	0.5	5.5	0	-3
exp 2	10	-10	20	0.5	5.5	0	-5
stationary	-3	0	-3	2	0.5	0	0
exp 1	-3	-6	3	0.5	-1	0	-3
exp 2	-3	-10	7	0.5	-1	0	-5
stationary	-10	0	-10	5.5	0.5	0	0
exp 1	-10	-6	-4	2.5	-2.5	0	-3
exp 2	-10	-10	0	0.5	-4.5	0	-5

Table 1. Table showing the start and stop positions of the target ball and observer relative to the world for all the experimental conditions as well as the speed of the ball relative to the world (col 1), and observer (col 3). The start/stop positions are shown for all combinations of ball and observer speeds for both Experiment 1 and Experiment 2.

		PERSON		
		Moving into scene	Moving out of scene	Stationary
BALL		Exp 1: 6 m/s Exp 2: 10 m/s	Exp 1: 6 m/s Exp 2: 10 m/s	
		Exp 1: +3-6 = -3 Exp 2: +3-10 = -7	Exp 1: +3+6 = 9 Exp 2: +3+10 = 13	3m/s
	Moving into scene +3m/s	Exp 1: +10-6 = +4 Exp 2: +10-10 = 0	Exp 1: +10+6 = 16 Exp 2: +10+10 = 20	10 m/s
	+10 m/s			
	Moving out of scene -3m/s	Exp 1: -3-6 = -9 Exp 2: -3-10 = -13	Exp 1: -3+6 = 3 Exp 2: -3+10 = 7	3m/s
		Exp 1: -10-6 = -16 Exp 2: -10-10 = -20	Exp 1: -10+6 = -4 Exp 2: -10+10 = 0	10 m/s
	-10 m/s			

Table 2. Table showing the ball speeds relative to the observer in all the experimental conditions.

The ball always has a speed of 3 or 10 m/s relative to the world. Positive values are into the scene and negative values are coming out of the scene (i.e., relative to the world). The resulting speeds relative to the observer are shown for all combinations of ball direction and self-motion direction. A negative sign indicates movement away from the observer, while a positive sign indicates movement towards the observer. The observer's task was to report the motion of the ball relative to the world (that was always 3 or 10m/s) irrespective of its speed relative to them.

3.5 Procedure

Participants were seated at a laptop in the lab setting. Participants were immersed in a VR environment (see figure 1) by wearing a VIVE headset. In each experiment they were shown one of a series of 12 randomly interleaved conditions (3 observer conditions: forwards/backwards/stationary, 2 ball directions: towards/away, 2 ball velocities: 3m/s or 10m/s with 2 staircases for each) followed by a probe ball moving laterally. They judged whether the laterally moving probe ball was moving faster or slower than the test ball (that moved in depth).

The two experiments differed only in the person's simulated speed and the corresponding start positions of the balls (see above) and were run with two different sets of participants.

3.6 Training

Each experiment began with pre-experiment practice trials during which participants received feedback indicating whether they had responded correctly or incorrectly. The practice trials maintained the same target ball and observer speeds as the actual experiment. If the participant perceived the probe ball to be moving faster than the target, they clicked the right arrow key on the desktop keyboard. If they perceived the target ball to be moving faster than the probe, they clicked the left arrow key on the keyboard. After the participant's response was recorded, a screen appeared, telling the participant their response was either "correct" or "wrong." These trials stopped after five minutes, and participants then completed the remaining experimental trials without any feedback. Whether their responses during the feedback trials were correct or not had no effect on the number of practice trials they were exposed to before proceeding which was determined exclusively by time. Participants' scores during the training trials were not recorded.

3.7 Experiment

Once training was complete, participants were presented with series of 24 interleaved PEST staircases x 15 trials each = 360 trials, taking a total of approximately 30-45min. In each trial they were presented with a red sphere (the test ball) moving either towards or away from them. Immediately after, a second red sphere (the probe ball) moved laterally across the screen

(see figure 1). Participants then responded by clicking the left mouse button if they believed the first sphere moving towards or away from them to be moving faster or clicking the right mouse button if they perceived the second sphere moving laterally across the screen to be moving faster just as in the practice trials.

While the target ball speeds remained the same (3m/s or 10m/s) in both Experiment 1 and Experiment 2, the self-motion speeds in Experiment 1 were set at -6m/s, 0m/s, and 6m/s, while in Experiment 2, self-motion speeds were set at -10m/s, 0m/s, and 10m/s where negative indicates away from the scene and positive indicates towards the scene.

4.0 Data Analysis

Data were collected using a Parameter Estimation by Sequential Testing (PEST) adaptive staircase method. The PEST staircase was invented by M. M. Taylor and C. Douglas Creelman in 1967. Essentially, the PEST staircase is a set of rules for adjusting task difficulty levels in order to reach a predefined performance level from the participant. The PEST presents trials at a certain level of the independent variable (IV) and according to the accuracy of the participant's response, the IV level was modified for the subsequent trial.

The PEST I implemented follows four general rules (Taylor & Creelman, 1967): (1) On every reversal of direction (i.e., from “too fast” to “too slow” or vice versa), halve the step size (2) The second step in a given direction, if called for, is the same size as the first (3) The fourth and subsequent steps in a given direction are each double their predecessor (4) Whether a third successive step in a given direction is the same as or double the second depends on the sequence of steps leading to the most recent reversal. If the step immediately preceding that reversal resulted from a doubling, then the third is not doubled, while if the step leading to the most recent

reversal was not the result of a doubling, then this third step is double the second. There are many possible stopping criteria for staircases, e.g., when the step size reaches a certain value, but here, from temporal constraints I terminated each staircase after 15 trials.

The data for each of the 24 data points from each pair of staircases were fitted with a cumulative logistic function (eq 1) using the ‘fit’ function in MATLAB to determine the Point of Subjective Equality (PSE) for each participant across conditions. I chose to determine PSEs through fitting a logistic curve because this not only identifies the PSE but also indicates how reliable the PSE is through the amount of variance which is depicted by the slope of the curve.

$$y = 1/(1+\exp(x-\text{PSE})/\text{slope})\dots\dots\dots\text{Eq 1}$$

where y is the probability of choosing “too fast”, x is the speed of the ball, PSE is the point at which the probability is 50% and the slope is related to the JND. A shallower slope is indicative of larger variance and low precision, and hence a larger JND. A steeper slope indicates lower variance, high precision, and a smaller JND.

As shown in figure 2, the PSE was measured as the 50% mark in each participant’s perceived speed estimates of the target ball in each condition across ball speeds.

PSEs were plotted for each participant across the three observer conditions (stationary, towards, away), and also across directions (towards/away) and ball speeds (3,10 m/s) to determine the accuracy of speed estimates across conditions making a total of 12 data points for each subject in each experiment.

Since my method does not allow me to determine the perceived direction of the ball (towards or away), all the perceived speeds are treated as positive in my analysis, independent of direction.

In order to test my hypotheses and assess whether estimates of the target ball speed were significantly different in each self-motion condition, I ran a total of four 2-Way Repeated Measures ANOVAs as a function of ball speeds and self-motion speeds using the PSEs collected from the output of the logistic fits. The ANOVAs were set up according to ball motion (towards or away) thus two ANOVAs were conducted for each experiment.

Specifically, the two ANOVAs for both Experiment 1 and Experiment 2 were set up in the following way:

ANOVA 1 compared the following three conditions: 1) Stationary (ball towards) 2) Same (ball towards) 3) Opposite (ball towards) for experiment 1.

ANOVA 2 compared the following three conditions: 1) Stationary (ball away) 2) Same (ball away) 3) Opposite (ball away) for experiment 2.

My Post Hoc tests included Tukey's test in order to correct for multiple comparisons.

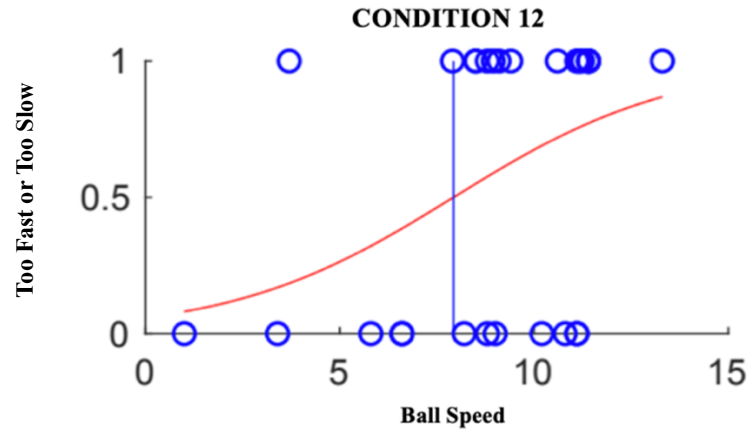


Figure 2. A logistic fit to a typical participant's data in condition 12. The x axis plots the ball speed (relative to the world) while the y axis shows whether the probe ball was perceived to be moving faster (1) or slower (0) than the probe ball. In this figure, the red line shows the best-fit cumulative logistic curve fitted through the data, while the blue line indicates the fitted PSE (50% point).

5.0 Results

5.1 Experiment 1

My main interest was the influence of the relative motion between ball and observer (i.e., when both were moving the same direction, when they were moving in opposite directions, or when the observer was stationary) on the perceived speed of the ball in space. To manage the complexity of the analysis, and because I had no hypothesis relating to the direction of ball motion, I conducted separate tests when the ball was moving into the scene (AWAY) and out of the scene (TOWARDS).

The fitted Points of Subjective Equality (PSEs) were taken as estimates of perceived speed and analyzed through 3 x 2 repeated measures ANOVAs as a function of ball speed (3,10 m/s) and self-motion conditions (stationary, same, opposite).

5.1.1 Motion of the ball towards the observer

For motion of the ball TOWARDS the observer (-ve ball speeds in this convention) the data are shown on the left sides of Fig 3a and b.

A main effect of self-motion was observed ($F(2, 42) = 35.14$, $MSe = 1.328$, $p = < 0.001$, $\eta_p^2 = 0.626$), showing that PSE's were different from and lower than when the participant was stationary than compared to when they were moving in the opposite direction to the ball (Fig 3b left) ($M_{diff} = 2.010$, $t(21) = 6.74$, $p = < 0.001$) and when moving in the same direction as the ball (Fig 3a left) ($M_{diff} = -0.616$, $t(21) = 2.89$, $p = 0.023$).

When looking at the simple effect of self-motion for each ball speed, PSE's were lower in the stationary condition than during same ($M_{\text{diff}} = -1.31$, $t(21) = -5.67$, $p = <0.001$) and opposite direction ($M_{\text{diff}} = -2.31$, $t(21) = -7.88$, $p = <0.001$) self-motion for ball speed 3m/s, for ball speed 10m/s there was no difference in PSE's when the observer was stationary and both the ball and participant were moving TOWARDS ($M_{\text{diff}} = -0.08$, $t(21) = -0.29$, $p = 0.775$) (SAME condition in Fig 3b).

There was a main effect of ball speeds illustrating overall higher PSE's for ball speed 10m/s than for ball speed 3m/s ($F(1, 21) = 55.90$, $MSe = 1.347$, $p = < 0.001$ $\eta_p^2 = 0.727$) by 1.51m/s ($t(21) = -7.48$, $p = <0.001$). This confirms that participants were able to distinguish between ball speeds. Note, however that the mean perceived speed was numerically lower than the physical difference between speeds which would have been 7m/s.

There was also an interaction of self-motion and ball speeds ($F(2, 42) = 8.90$, $MSe = 0.598$, $p = <0.001$, $\eta_p^2 = 0.298$).

As depicted in figure 3, in the presence of same-direction self-motion, the mean difference between the PSE's for each ball speed was 0.7860 ($t(21) = 3.320$, $p = 0.033$) and in presence of opposite direction self-motion it was 1.5730 ($t(21) = -4.134$, $p = 0.005$) in comparison to a difference of 2.1733 ($t(21) = -12.452$, $p = <0.001$) when the observer was stationary.

5.1.2 Motion of the ball Away from the observer

For the motion of the ball AWAY from the observer (-ve) the data are shown on the right sides of Fig 3a and b.

The analysis revealed a main effect of self-motion ($F(2, 42) = 41.7$, $MSe = 1.319$, $p = < 0.001$, $\eta_p^2 = 0.665$) showing that PSE's were lower when participants were stationary than when they were moving in the opposite direction to the ball (Fig 3a right) ($M_{diff} = -2.191$, $t(21) = -7.59$, $p = < 0.001$), but no different when they were moving in the same direction (Fig 3b right) ($M_{diff} = 0.505$, $t(21) = 2.05$, $p = 0.125$).

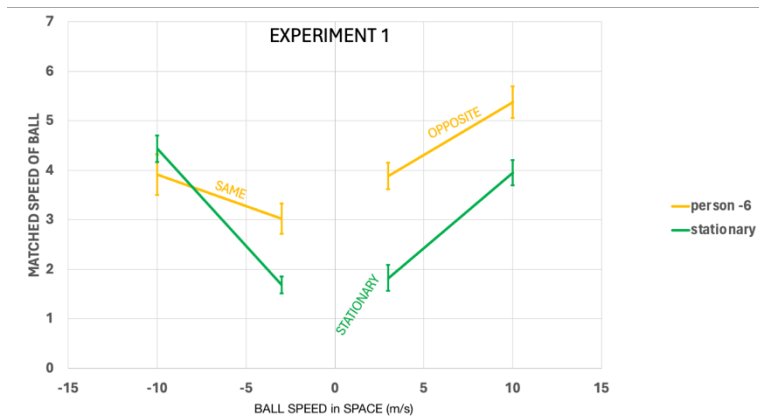
When looking at the simple effect of self-motion for each ball speed, while PSE's were lower in the stationary condition than during same ($M_{diff} = -4.45$, $t(21) = -5.41$, $p = < 0.001$) and opposite direction ($M_{diff} = -2.42$, $t(21) = -7.70$, $p = < 0.001$) self-motion for ball speed 3m/s, for ball speed 10m/s there was no difference in PSE's when the observer was stationary and both the ball and participant were moving AWAY ($M_{diff} = -0.44$, $t(21) = -1.58$, $p = 0.128$).

Again, there was an expected main effect of ball speeds ($F(1, 21) = 120.9$, $MSe = 1.042$, $p = < 0.001$, $\eta_p^2 = 0.852$) demonstrating overall higher PSE's for ball speed -10m/s than for ball speed -3m/s by 1.95m/s ($t(21) = -11.0$, $p = < 0.001$). As for TOWARDS, this confirms that participants were able to distinguish between ball speeds, but once again the mean perceived speed was numerically lower than the physical difference between speeds which would have been 7m/s.

There was also an interaction of self-motion and ball speeds ($F(2, 42) = 17.5$, $MSe = 0.607$, $p = < 0.001$, $\eta_p^2 = 0.455$).

As depicted in figure 3, in the presence of same direction self-motion, the mean difference between the PSE's for each ball speed was 0.850 ($t(21) = -3.373$, $p = 0.030$) and in the presence of opposite direction self-motion it was 2.274 ($t(21) = -7.037$, $p = < 0.001$), in comparison to a difference of 2.736 ($t(21) = -14.223$, $p = < 0.001$) when the observer was stationary.

A. Self-Motion Condition -6



B. Self-Motion Condition +6

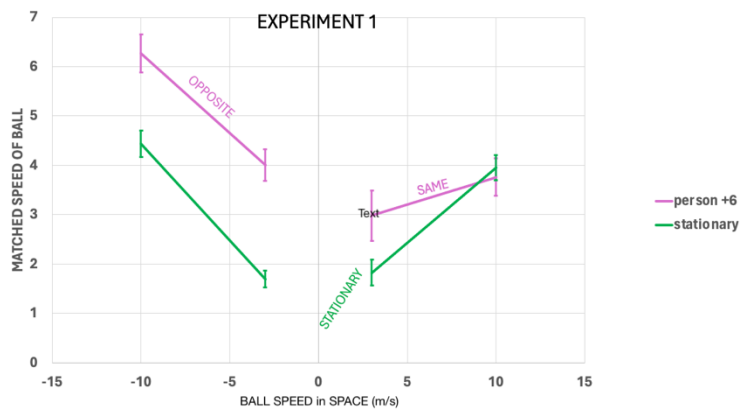


Figure 3. Matched, or perceived ball speed (y axis) was estimated as a function of the ball speed in space (x axis). Error bars represent one standard error of the mean. Plot (A) depicts perceived ball speed estimates in conditions where self-motion speeds were either -6m/s (yellow lines) or 0 (stationary) (green lines). Plot (B) depicts perceived ball speed estimates in conditions where self-motion speeds were either +6 (purple lines) or 0 (stationary) green lines. The right half of each graph represents the ball moving TOWARDS the observer (+ve velocities), the left half of the graph represents the ball moving AWAY from the observer (-ve velocities). All perceived ball speeds are plotted as positive (absolute values).

5.2 JND

5.2.1 Motion of the ball Towards the observer

For motion of the ball TOWARDS the observer, as seen in figure 4 (left panel), the analysis revealed a main effect of self-motion ($F(2, 42) = 5.7902$, $MSe = 1.0596$, $p = 0.006$, $\eta^2_p = 0.216$), showing that JND's were lower when participants were stationary (Fig 4 central panel) than when they were moving in the opposite direction ($M_{diff} = 0.740$, $t(21) = 3.37$, $p = 0.008$) or when moving in the same direction ($M_{diff} = -0.458$, $t(21) = -2.52$, $p = 0.051$). There was no main effect of ball speed ($F(1, 21) = 0.0335$, $MSe = 0.9469$, $p = 0.857$, $\eta^2_p = 0.002$). No interaction of self-motion and ball speed was observed ($F(2, 42) = 2.9781$, $MSe = 0.7428$, $p = 0.062$, $\eta^2_p = 0.124$).

When comparing JND's for each ball speed across the three motion profiles (same/opposite/stationary), no significant differences were found.

5.2.2 Motion of the ball Away from the observer

For movement of the participant AWAY from the screen (backwards), as shown in figure 4 (right panel), the analysis revealed a main effect of self-motion ($F(2, 42) = 4.00$, $MSe = 0.371$, $p = 0.026$, $\eta^2_p = 0.160$) but there was no significant difference in JND's when participants were stationary compared to when they were moving in the opposite direction to the ball ($M_{diff} = -0.362$, $t(21) = -2.36$, $p = 0.069$), nor when moving in the same direction ($M_{diff} = 0.126$, $t(21) = 1.07$, $p = 0.545$). There was a main effect of ball speed ($F(1, 21) = 4.93$, $MSe = 0.474$, $p = 0.037$, $\eta^2_p = 0.190$) demonstrating overall higher JND's for ball speed 10m/s than for ball speed 3m/s

by 0.266 ($t(21) = -2.22$, $p = 0.037$). There was an interaction of self-motion and ball speed ($F(2, 42) = 4.92$, $MSe = 0.538$, $p = 0.012$, $\eta_p^2 = 0.190$).

When comparing JND's for each ball speed across the three motion profiles (same/opposite/stationary), no significant differences were found.

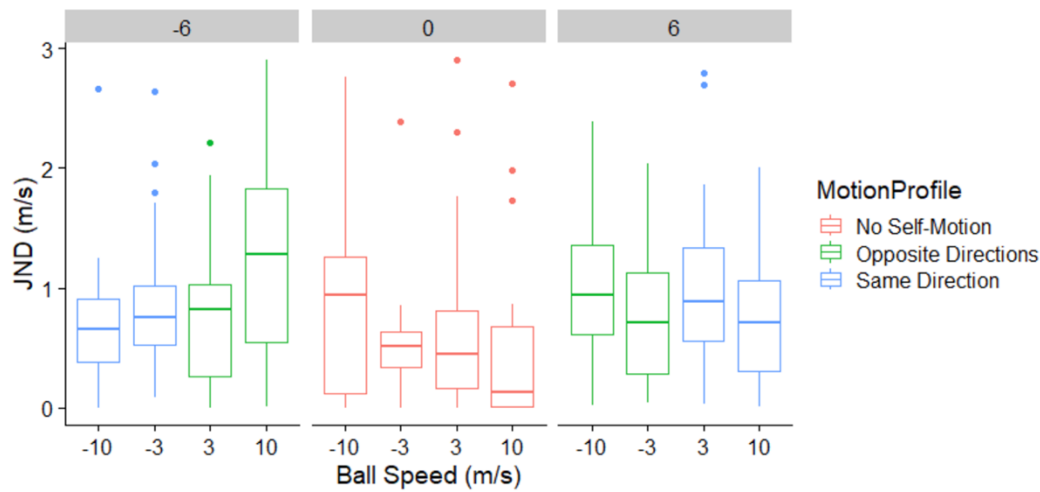


Figure 4. JND's (y axis) are plotted as a function of ball speed in space (x axis which was either 3 or 10m/s) for self-motion speeds of either -6m/s (towards the observer left panel), 0m/s (stationary, centre panel), or +6m/s (away from the observer right panel). The blue boxes represent the motion profile in which the observer and target were moving in the same direction. The green boxes depict the opposite direction motion profile, while the red boxes represent no self-motion. Each box represents the distribution of JND's at a given ball speed and self-motion condition, for one of the 3 motion profiles (1) No Self-Motion 2) Opposite Direction 3) Same Direction). The lines within the boxes represent the median, and the lines extending from the boxes represent the range of data extending from the minimum to maximum interquartile values. The dots represent the outliers.

5.3 Experiment 2

I followed the same analysis procedure for Experiment 2.

5.3.1 Motion of the ball Towards the observer

For the motion of the ball towards the observer (-ve) the data are shown on the left sides of Fig 5a and b.

A main effect of self-motion was observed ($F(2, 42) = 25.16$, $MSe = 5.61$, $p < 0.001$, $\eta_p^2 = 0.545$). The PSE's were lower when the observer was stationary than when they were moving in the direction opposite to the ball ($M_{diff} = 3.53$, $t(21) = 5.86$, $p < 0.001$) and when moving in the same direction ($M_{diff} = -2.29$, $t(21) = -4.99$, $p < 0.001$).

When looking at the simple effect of self-motion for each ball speed, PSE's were found to be lower in the stationary condition than during same ($M_{diff} = -2.95$, $t(21) = -5.68$, $p < 0.001$) and opposite direction ($M_{diff} = -4.01$, $t(21) = -7.64$, $p < 0.001$) self-motion for ball speed 3m/s. For ball speed 10m/s PSE's were also lower when the observer was stationary than when both the ball and participant were moving in the same ($M_{diff} = -1.63$, $t(21) = -3.22$, $p = 0.004$) and opposite direction ($M_{diff} = -3.05$, $t(21) = -3.86$, $p < 0.001$).

As expected, there was a main effect of ball speeds ($F(1, 21) = 11.05$, $MSe = 1.16$, $p = 0.003$, $\eta_p^2 = 0.345$) illustrating overall higher PSE's for ball speed 10m/s than for ball speed 3m/s by 0.62m/s ($t(21) = -3.32$, $p < 0.003$). This confirms that participants were able to distinguish between ball speeds. Note, however that the mean perceived speed was numerically lower than the physical difference between speeds which would have been 7m/s.

There was also an interaction of self-motion and ball speeds ($F(2, 42) = 3.24$, $MSe = 1.58$, $p = 0.049$, $\eta_p^2 = 0.134$).

As illustrated in figure 5, in the presence of same direction self-motion, the mean difference between the PSE's for each ball speeds was 0.0607 ($t(21) = -0.224$, $p = 1.000$) and in the presence of opposite direction self-motion it was 0.4250 ($t(21) = -0.931$, $p = 0.934$) in comparison to a difference of 1.3806 ($t(21) = -4.169$, $p = 0.005$) when the observer was stationary.

5.3.2 Motion of the ball Away from the observer

For the motion of the ball away from the observer (+ve) the data are shown on the right sides of Fig 5a and b.

The analysis revealed a main effect of self-motion ($F(2, 42) = 39.10$, $MSe = 2.101$, $p = < 0.001$, $\eta_p^2 = 0.651$). With the exception of the condition where the ball speed was 10m/s and both the ball and observer were moving forwards, the PSE's were lower when the observer was stationary than when they were moving in the opposite direction ($M_{diff} = -2.3367$, $t(21) = -8.295$, $p = < 0.001$) and when moving in the same direction ($M_{diff} = 2.3953$, $t(21) = -8.295$, $p = < 0.001$).

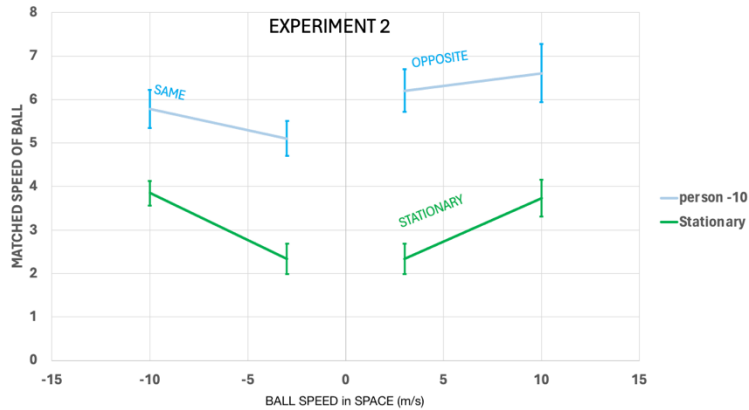
When looking at the simple effect of self-motion for each ball speed, while PSE's were lower in the stationary condition than during same ($M_{diff} = -2.84$, $t(21) = -7.74$, $p = < 0.001$) and opposite direction ($M_{diff} = -2.79$, $t(21) = -9.85$, $p = < 0.001$) self-motion for ball speed 3m/s, for ball speed 10m/s there was no difference in PSE's when the observer was stationary and both the ball and participant were moving in the same ($M_{diff} = -1.95$, $t(21) = -3.10$, $p = < 0.001$) and opposite direction ($M_{diff} = -1.89$, $t(21) = -5.10$, $p = < 0.001$).

Again, there was an expected main effect of ball speeds ($F(1, 21) = 43.40$, $MSe = 0.763$, $p = < 0.001$, $\eta_p^2 = 0.674$) demonstrating overall higher PSE's for ball speed -10m/s than ball speed -3m/s by 1.00m/s ($t(21) = -6.59$, $p = < 0.001$). As for TOWARDS, this confirms that participants were able to distinguish between ball speeds, but once again the mean perceived speed was numerically lower than the physical difference between speeds which would have been 7m/s.

There was also an interaction of self-motion and ball speeds ($F(2, 42) = 4.41$, $MSe = 0.672$, $p = 0.018$, $\eta_p^2 = 0.173$).

As shown in figure 5, in the presence of same direction self-motion, the mean difference between the PSE's for each ball speeds was 0.7045 ($t(21) = -2.319$, $p = 0.230$) and in the presence of opposite direction self-motion it was 0.6997 ($t(21) = -2.960$, $p = < 0.070$), in comparison to a difference of 1.6010 ($t(21) = -7.687$, $p = < 0.001$) when the observer was stationary. This indicates that participants had a harder time distinguishing ball speeds when self-motion was present in comparison to when no self-motion was present.

A. Self-Motion Condition -10



B. Self-Motion Condition +10

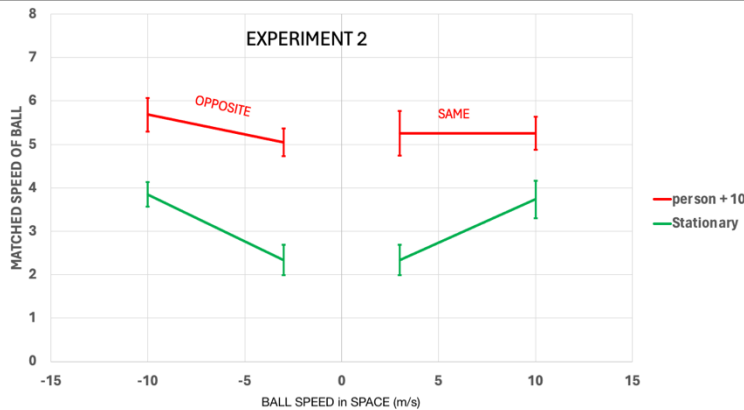


Figure 5. Matched, or perceived ball speed (y axis) was estimated as a function of ball speed in space (x axis). Error bars represent one standard error of the mean. Plot (A) depicts perceived ball speed estimates in conditions where self-motion speeds were either -10 or 0 (stationary). Plot (B) depicts perceived ball speed estimates in conditions where self-motion speeds were either +10 or 0 (stationary). While the right half of the graph represents the ball moving TOWARDS the observer, the left half of the graph represents the ball moving AWAY from the observer. All values have been plotted as positive (absolute values).

5.4 JND

5.4.1 Motion of the ball Towards the observer

For TOWARDS, as seen in figure 6, there was no observed main effect of self-motion ($F(2, 42) = 2.764$, $Mse = 2.345$, $p = < 0.075$, $\eta_p^2 = 0.116$) or ball speed ($F(1, 21) = 0.263$, $Mse = 2.469$, $p = 0.613$, $\eta_p^2 = 0.012$) on participants' JND's. An interaction of self-motion and ball speed was observed ($F(2, 42) = 4.122$, $Mse = 1.185$, $p = 0.023$, $\eta_p^2 = 0.164$).

When comparing JND's for each ball speed across the three motion profiles (same/opposite/stationary), no significant differences were found.

5.4.2 Motion of the ball Away from the observer

For AWAY, as shown in figure 6, the analysis revealed a main effect of self-motion ($F(2, 42) = 6.603$, $MSe = 1.392$, $p = 0.003$, $\eta_p^2 = 0.239$) showing no significant difference in JND's when participants were stationary than when they were moving in the opposite direction ($M_{diff} = -0.446$, $t(21) = -2.28$, $p = 0.081$), and lower JND's when participants were stationary than when moving in the same direction ($M_{diff} = 0.914$, $t(21) = 3.26$, $p = 0.010$). There was no observed main effect of ball speed ($F(1, 21) = 0.003$, $MSe = 1.190$, $p = 0.954$, $\eta_p^2 = 0.000$). No interaction of self-motion and ball speed was observed ($F(2, 42) = 0.307$, $MSe = 1.369$, $p = 0.738$, $\eta_p^2 = 0.014$).

When comparing JND's for each ball speed across the three motion profiles (same/opposite/stationary), no significant differences were found.

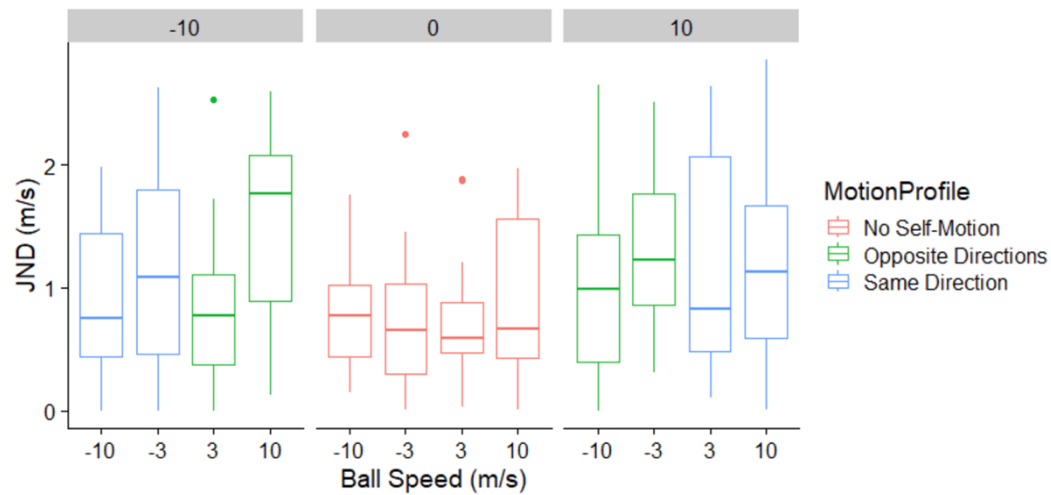


Figure 6. JND's (y axis) were estimated as a function of ball speed in space (x axis) which was either 3 or 10m/s. This box plot depicts JND's in conditions where self-motion speeds were either -10m/s, 0m/s, or +10m/s. The blue boxes represent the motion profile in which the observer and target were moving in the same direction. The green boxes depict the opposite direction motion profile, while the red boxes represent no self-motion. Each box represents the distribution of JND's at a given ball speed and self-motion condition, for one of the 3 motion profiles (1) No Self-Motion 2) Opposite Direction 3) Same Direction). The lines within the boxes represent the median, and the lines extending from the boxes represent the range of data extending from the minimum to maximum interquartile values. The dots represent the outliers.

6.0 Discussion

There are three main takeaways so far from my study. Firstly, participants' PSEs were generally higher (ball judged as moving faster) when the participant and ball were in the either the same or opposite directions during self-motion compared to the stationary condition. This shows that parsing was not complete and does not support my hypothesis, as I had predicted lower PSEs for when ball and participant were moving in same direction, and higher PSEs when they were moving in opposite directions. Secondly, there was an interaction between self-motion and ball speeds which revealed the mean difference between the PSEs across the two ball speeds was smaller when self-motion was present than when the observer was stationary. Thirdly, while there were some exceptions as noted in the results, participants' JNDs were usually higher (less precise) when the participant moved. This last finding suggests that the task became more difficult in the presence of self-motion.

The first finding, that participants' PSEs were higher both when participant and ball motion were in the same as well as opposite directions, is not only contradictory to my hypotheses, but is also not supported in the admittedly sparse literature reviewed. The literature offers two separate findings in terms of object speed judgments during self-motion, but in each case, speed estimates were found to go in opposite directions in same and opposite self-motion conditions. Specifically, object speed judgements tend to be underestimated when observer and object motion are in the same direction and overestimated when observer and object motion are in opposite directions.

For example, in the study conducted by Gray et al. (2004), object speed judgments were found to be higher when object-motion and self-motion were in the same direction, and lower when object-motion and self-motion were in opposite directions (Gray et al., 2004).

Similarly to Gray et al. (2004), Jörges et al. (2021) found an underestimation of object speed when object-motion and self-motion were in the same direction and an overestimation of object speed when object-motion and self-motion were in opposite directions (Jörges et al., 2021). Hence, our finding of participants' PSEs going in the same direction for both same and opposite direction self-motion is not supported by previous literature.

My second finding showed an interaction between self-motion and ball speeds and revealed that the mean difference between the PSEs for each ball speed was smaller when self-motion was present. This may indicate that the accuracy of ball speed estimates was compromised in the presence of self-motion.

Thirdly, an analysis of participants' JNDs revealed higher values in the presence of self-motion. These findings suggest that the task became more difficult in the presence of self-motion.

Looking at the data in Figs 3 and 5 confirms that the perceived speed of the ball in space when the ball was moving in the same direction as the person was much faster than would have been expected. Under these conditions the simple flow parsing model (perceived speed = ball speed $\times$ gain1 – self-motion speed $\times$ gain 2) (see eq 1 below) with a gain1 of about 0.4 (from the stationary data) predicts a much slower perceived speed of the ball when the ball and person are moving in the same direction and the relative speed is therefore quite slow (see figure 7).

However, the perceived speeds in most cases were much higher than predicted such that it hardly varied with ball speed in space at all and appeared for a given self-motion speed and direction to be remarkably constant.

7.0 Regression to the mean

Overall, particularly the fact that self-motion biases PSEs in unpredicted ways is an initially perplexing aspect of this data set. However, as we will detail in this following section, we believe that a regression to the mean could account for the more surprising patterns found in our data and mask the expected effects of self-motion. First of all, even in the stationary condition, the PSE difference between ball speeds is lower than their physical difference, i.e., perceived speed appears to be compressed. This constitutes initial evidence that participants partially rely on a regression to the mean-like mechanism to solve the task. Further, we found that this regression to the mean became stronger in the presence of self-motion, which participants also found harder to execute (as evidenced by the higher JNDs). While there are different ways to model a regression to the mean, this latter observation motivated us to model it as a *Bayesian prior*.

Bayesian models of perception posit that in order to obtain the most likely estimate of the state of the world (“posterior” in Bayesian terms), humans integrate sensory information (“likelihood”) with prior knowledge about the world (“prior”) according to Bayes rule: the posterior probability of a state of the world $p(W/I)$ is proportional to the product of the likelihood function $p(I/W)$ and prior probability distribution $p(W)$: $p(W/I) \propto p(I/W) \times p(W)$. This is a probability expression in which $p(W/I)$ typically represents the conditional probability of event W occurring, given that event I has occurred. That is, the more reliable sensory information becomes the less observers rely on prior information, and the less reliable sensory information becomes (such as in the presence of self-motion in our experiment), the more observers rely on prior information.

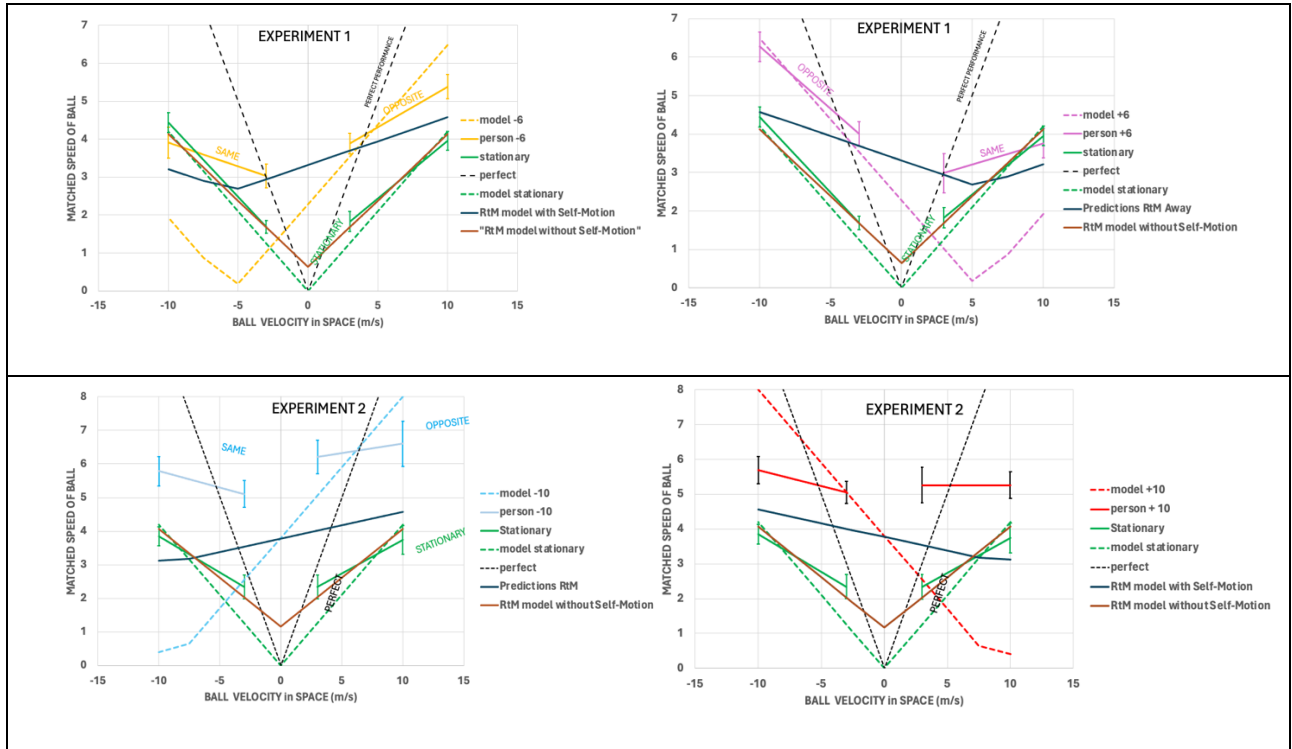


Figure 7. Same plots as figure 3 and figure 5, plotting matched or perceived ball speed (y axis) as a function a ball speed in space (x axis), but with additional black lines representing the “perfect” answer (i.e., where the ball speeds are accurately perceived to be either 3m/s or 10m/s, independent of any concurrent self-motion), as well as lines depicting the Regression to the Mean Model predictions (with and without self-motion). The flow parsing model fails to be a good fit for the data, particularly in the “same direction” motion profile.

In order to investigate whether some of the more surprising results of this study could be explained by a (Bayesian) regression to the mean, I compared the results of two separate models: the simple Flow Parsing model and the more complex Regression to the Mean model, which on top of flow parsing, *also* models a regression to the mean. The complexity of the models is determined by the number of free parameters within them. The Flow Parsing model uses two parameters: 1) flow parsing gain and 2) a relative speed gain

$$v_{subj} = (v_{object} - v_{self}) * k_{relative\ speed} + v_{self} * k_{flow-parsing}$$

where v_{subj} depicts the perceived speed, $v_{object} - v_{self}$ denotes object speed minus observer speed, resulting in relative speed, $k_{relative\ speed}$ depicts relative speed gain, v_{self} is the self-motion speed, and $k_{flow-parsing}$ represents the flow parsing gain.

My Regression to the Mean model uses three parameters: 1) flow parsing gain, 2) speed gain, 3) regression to the mean.

$$v_{subj} = \left((v_{object} - v_{self}) * k_{relative\ speed} + v_{self} * k_{flow-parsing} \right) * (1 - w_{prior}) + w_{prior} * prior$$

where v_{subj} represents perceived speed, $v_{object} - v_{self}$ depicts the weighting of the prior, $k_{relative\ speed}$ is the speed gain, v_{self} represents self-motion speed, $k_{flow-parsing}$ is the flow parsing gain, w_{prior} is the weighting of the prior, and $prior$ is the prior itself.

In my Regression to the Mean model (Eq2) the parameter “Flow Parsing” captures the percentage of self-motion the observer adds onto the perceived ball speed (rather than successfully parsing it out). The parameter “Speed Gain” refers to the percentage of object speed that is interpreted as speed relative to the world. It might be related to the underestimation of depth in VR (Petukhov et al., 2024). Such compression of space is one of the factors that explains why the ANOVA analyses revealed that the ball speed was still underestimated even when the observer was stationary. Such a compression of space skews the relative distance between objects in the VR environment and hence confuses an observer’s sense of motion and distance travelled, leading to an underestimation of object speed.

Thirdly, “regression to mean” (the additional parameter in the Regression to the Mean model) captures the participants’ tendency to perceive the ball to be moving at a mean average of the ball speeds of previous trials in trials where self-motion speeds are higher. This third and additional parameter is the prior I predict participants are using to judge the speed of the target ball. It captures to what extent participants rely on the prior versus to what extent they rely on the immediate sensory information, i.e., the likelihood in a Bayesian framework.

Since more complex models with more parameters will naturally provide a better fit for the data, I used a Likelihood Ratio Test (Wilks, 1938) to penalize the Regression to the Mean model and ensure that the better fit was not solely due to increased number of parameters in the model. The Likelihood Ratio Test takes observed and predicted values from both models and demonstrates how likely it is to observe the actual values under one model in comparison to the other.

8.0 Results: Regression to the Mean Model

When using the Likelihood Ratio Test to compare the Flow Parsing model with the Regression to the Mean model and assess which model provided a better fit for the data, I found that the Regression to the Mean model was significantly better than the Flow Parsing model ($p < 0.001$). This indicates that the “Regression to the Mean” prior had a significant effect, as this was the only additional parameter that was not included in the Flow Parsing model. Plots (A) and (B) in figure 9 provide a clear visualization of the model fits: unequivocally, the points in the scatterplot fit more closely around the regression line in the Regression to the Mean model (Plot A) and compared to the Flow Parsing model (Plot B) in which the spread of the data is a lot noisier.

Notably, the R^2 value obtained for the Regression to the Mean model was 0.80, while the R^2 value obtained for the Flow Parsing model was 0.65. As the R^2 value is a measure of the goodness of fit, this is a clear indication that the Regression to the Mean model was a better fit for the data than the simpler Flow Parsing model.

A. Model without Regression to the Mean

B. Model with Regression to the Mean

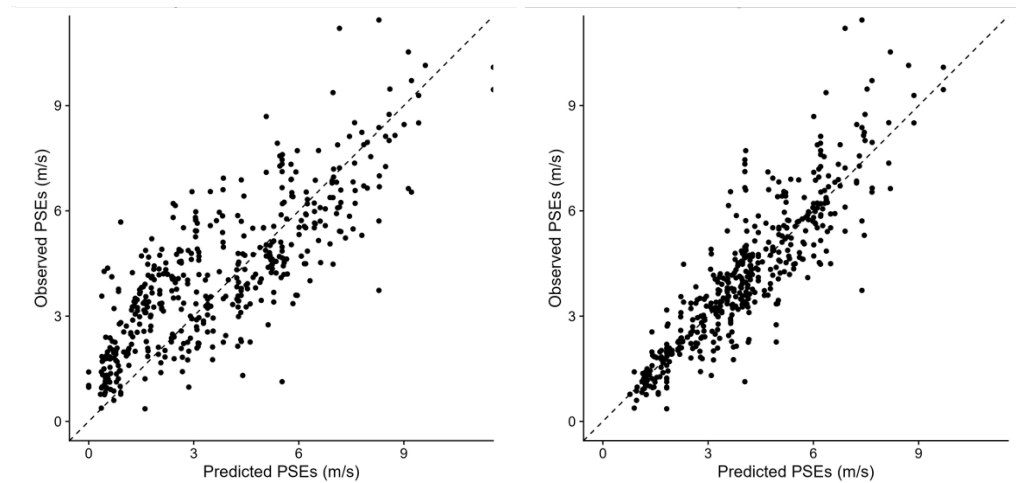


Figure 8. Fitted observed PSEs (y axis) as a function of predicted PSEs (x axis). (A) Data in this plot has been fit using the simpler Flow Parsing model which did not include the “regression to the mean” parameter. The equation for this simpler model is: Perceived Speed = Ball Speed * Speed Gain + Flow Parsing Gain * Self-Motion Speed (Eq 1). (B) Data in this plot has been fit using the more complex Regression to the Mean model which included the “regression to the mean” parameter. The equation for the Regression to the Mean model is:

$$\text{Perceived Speed} = (1 - \text{Weighting of Prior}) * (\text{Ball Speed} * \text{Speed gain} + \text{Flow Parsing Gain} * \text{Self-Motion Speed}) + \text{Weighting of Prior} * \text{Prior (Eq 2)}.$$

A. Model without Regression to the Mean

B. Model with Regression to the Mean

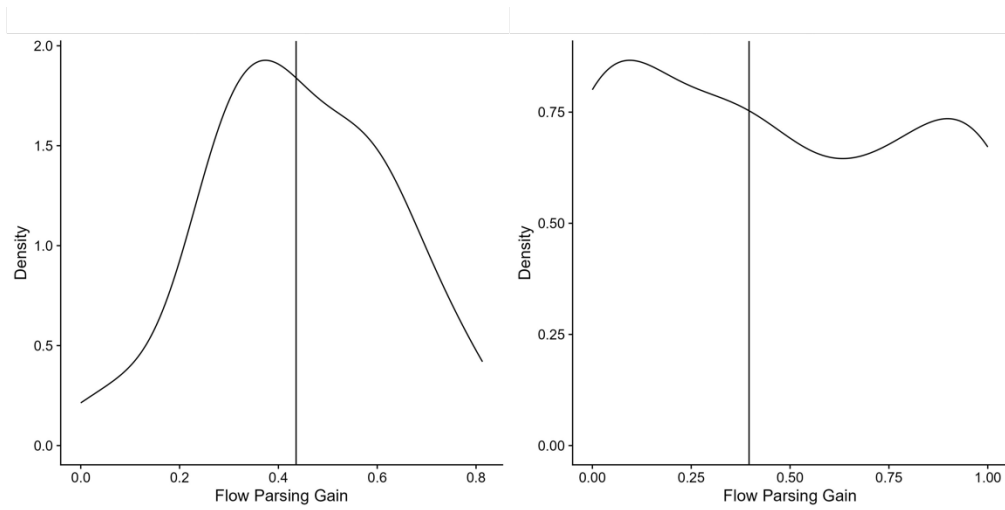


Figure 9. Distribution of flow parsing gains in (A) the simpler Flow Parsing model and in (B) the more complex Regression to the Mean model.

In the context of my study, a “flow parsing gain” refers to the efficiency with which an observer is able to subtract their own speed from the object speed. If the observer is able to subtract their entire speed and flow parsing is complete/perfect, the gain would be 1 or 100%. The average flow parsing gain found was similar between both models. The gain for the simpler Flow Parsing model was found to be 0.2, while the gain for the Regression to the Mean model was 0.35. Both of these gains are fairly low and appear to indicate that participants were not often relying on flow parsing to estimate the speed of the target ball while they themselves were in motion.

9.0 Discussion: Regression to the Mean Model

The main takeaway from the results of the Bayesian modelling analyses is that the Regression to the Mean model provided a better fit for the data as compared to the Flow Parsing model. This finding lends support to my hypothesis that participants were making object speed judgments by relying on a prior when the task became increasingly difficult due to the increasing speed of self-motion.

As hypothesized, the prior being activated appears to be a “regression to the mean.” To reiterate, the simpler Flow Parsing model had only two parameters: (1) Flow Parsing Gain and (2) Speed Gain. The Regression to the Mean model was more complex as it included one third, and additional parameter: regression to the mean. Since the Regression to the Mean model was a significantly better fit than the Flow Parsing model, and the Likelihood Ratio Test technique controlled for the Regression to the Mean model being a better fit simply because it was more complex, this tells us that the “regression to the mean” was indeed the parameter responsible for an enhanced goodness of fit.

As my initial analyses focused on flow parsing, the Bayesian modelling supports the notion that the ANOVAs are likely not the best way to explain the data obtained from this study. The ANOVA analyses left me with some puzzling results that, as discussed above, did not support our predictions, nor were those results supported by the literature. The Bayesian modelling offers an explanation as to why the study yielded the seemingly counter-intuitive results that it did, and why object motion was underestimated regardless of whether object and observer motion was in the same or opposite direction.

According to my findings, as self-motion speeds increased, the task became more difficult, and participants – likely unconsciously – assessed the ball speed to be the mean of the ball speeds from all the previous trials by relying on “prior knowledge.”

10.0 Limitations and Future Directions

This study has potential limitations. The experimental design did not assess which direction the participants were perceiving the target ball to be moving in, and thus all PSE values were plotted as positive absolute values. In the future, a second part can be added to the task requiring participants to make directional judgements and respond whether the target ball was moving TOWARDS or AWAY. This would allow values to be plotted as both positive (TOWARDS) and negative (AWAY) and may reveal a different pattern to be noted in the PSE plots.

If this experiment was to be run again in virtual reality, I would consider adding a shadow of the target ball to the environment floor in attempt to enhance the richness of visual cues and make it closer to a real world setting.

Visually simulated self-motion creates a dissonance between the vestibular and visual system, as the visual system is active and the vestibular system is quiet. I would anticipate more successful flow parsing if self-motion was physical as opposed to visually simulated. In the future, placing participants on a moving platform may be a way to introduce physical self-motion in the experimental design.

In addition, I would like to increase the number of self-motion speeds in the next iteration of this experiment since this study only had 3 observer speed conditions per experiment (i.e. - 6m/s, 0m/s, +6m/s).

As discussed, a virtual reality environment also leads to a general underestimation of self-motion due to factors such as compression of space. If given the opportunity to expand on this study, I would consider taking the task out of VR and using physical self-motion in a real-world environment with a wider range of self-motion speeds, and an added task for target ball directional judgements.

10.1 Conclusions

To reiterate my central question: How do individuals perceive the speed of objects moving around them when they themselves are in motion? Overall, two central conclusions may be drawn from my study. Firstly, the low flow parsing gains indicate that parsing was incomplete, and participants do not seem to be relying on flow parsing to estimate object speed during self-motion. If not flow parsing, what method might participants be using to perceive object speed? That leads to the second conclusion that participants appear to rely on a “Regression to the Mean” prior based in Bayesian modelling.

I did not find evidence that participants were relying on flow parsing when perceiving object speed. The flow parsing gains found were relatively low, coming to 20% for the flow parsing model and 35% for the Regression to the Mean model. These low gains suggest incomplete and inefficient flow parsing and are in line with the findings of Dokka et al. (2013). Dokka et al. (2013) also found low gains of 47% when participants were required to judge whether a horizontally moving object was moving left or right in the presence of lateral self-motion using solely visual cues.

A similar observation was made by Dyde and Harris 2008, who also found incomplete flow parsing during visually simulated self-motion. Niehorster and Li (2017) found flow parsing gains to be less than unity (<75%) and incomplete as well. Greater task difficulty may be a reason why, although still incomplete, Niehorster and Li (2017)'s gains of <75% were comparatively higher than the very low gains of 20% found in my study. Notable factors that likely increased my task difficulty were the presence of the laterally moving probe ball in addition to the target ball, the addition of backward self-motion as well as forward, the target ball moving forwards/backwards in depth as opposed to laterally, and also the requirement from participants to make speed judgments (faster/slower) versus directional judgments (left/right). Making judgments regarding target ball speed in depth, especially in the presence of the laterally moving probe ball while the participant themselves was moving either forwards or backwards, complicates our task overall in comparison to previous studies, and can partially explain our very low gains.

In contrast, Jörges et al. (2021) found parsing to be near complete, with gains as high as 103% when self-motion was visually simulated in the same direction as the target object. Jörges et al. (2021) found slightly lower gains for the “opposite direction” motion profile, but gains were still quite high, averaging at 80%. Notably, Jörges et al. (2021) used lateral self-motion.

According to Noel et al. (2023), due to the misattribution of flow-vectors, flow parsing is typically easier and more complete during lateral self-motion as opposed to forward/backward self-motion as used in my experiment.

Jörges et al. (2021) also attributed their higher gains to increased richness of visual cues to self-motion in their experimental environment, as well as a more ecological display. Given that my VR environment was extremely similar to Jörges et al. (2021) how might one account for the low gains found in this study?

In my study, this has been explained by a prior based in Bayesian modelling. My data suggests that participants are relying less on flow parsing to estimate object speed and are depending more heavily on a "Regression to the Mean" prior when self-motion speeds are higher. While flow parsing does play a role in the perception of object speed in the presence of self-motion, when the task becomes too difficult, people seem to rely on prior knowledge when making these speed estimates. Specifically, when self-motion made the task noisier, flow parsing failed and participants were found to use the prior to judge object speed.

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Appendices

Appendix A: Informed Consent Form

Informed Consent Form Template

Date: Summer 2022

Study Name: Seeing while moving

Researchers: Laurence Harris 1022 SHSRC harris@yorku.ca; Björn Jörges 1018 SHSRC bjoerges@yorku.ca

Purpose of the Research:

What You Will Be Asked to Do in the Research: You will be asked to wear a virtual reality helmet in which will be presented moving targets while you are either static, in a simulated moving environment, or physically moved on a motion platform. Some experiments will be performed using the York University Tumbling Room to tilt you relative to gravity. During any physical motion, you will be secured by means of a fivepoint harness. Motion profiles will be slower than those experienced in normal walking. You may also sit facing the York University Large Field Display rather than use virtual reality in which case there will be no physical motion or tilt. You will be asked to make judgements about the target's movements. All experiments will take less than one hour. Tilts to unusual positions will be for less than 5 mins.

Risks and Discomforts: It is possible that you may feel nausea or disorientation as a result of wearing the virtual reality headset, or by seeing the visual world tilted or moving. An experimenter will be with you at all times. If you report feeling nauseous or disoriented you will be asked to take off the headset and sit quietly until you are able to resume or decide to terminate the experiment.

Benefits of the Research and Benefits to You: If eligible you will receive course credit at the rate of 1 credit / hour or an amazon gift card valued at 45 CAD.

Voluntary Participation and Withdrawal: Your participation in the study is completely voluntary and you may choose to stop participating at any time. Your decision not to volunteer, to stop participating, or to refuse to answer particular questions will not influence the nature of the ongoing relationship you may have with the researchers or the nature of your relationship with York University either now, or in the future. If you stop participating, you will still be eligible to receive the promised course credit for agreeing to be in the project. In the event you withdraw from the study, all associated data collected will be immediately destroyed wherever possible.

Confidentiality: All information will be held in confidence and unless you specifically indicate your consent, your name will not appear in any report or publication of the research or in any data depository. Data will be collected through the experimental computer program and by the researcher. Your personal information and data will be safely stored in a locked facility on a password-protected computer and destroyed on completion of the study. Only research staff will have access to this information. Confidentiality will be provided to the fullest extent possible by the law.

Questions About the Research? If you have questions about the research in general or about your role in the study, please feel free to contact Dr. Harris either by telephone at (416) 736-2100, extension 66108 or by e-mail (harris@yorku.ca). This research has received ethics review and approval by the Human Participants Review Sub-Committee, York University's Ethics Review Board and conforms to the standards of the Canadian Tri-Council Research Ethics guidelines. If you have any questions about this process, or about your rights as a participant in the study, please contact the Sr. Manager & Policy Advisor for the Office of Research Ethics, 5th Floor, Kaneff Tower, York University (telephone 416-736-5914 or e-mail ore@yorku.ca).

Legal Rights and Signatures:

I _____ consent to participate in Predicting while Moving conducted by Drs Harris and Jörges. I have understood the nature of this project and wish to participate. I am not waiving any of my legal rights by signing this form. My signature below indicates my consent.

Signature _____
Participant

Date _____

Signature _____
Principal Investigator

Date _____