**SPEED PERCEPTION DURING LATERAL SELF-MOTION**

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**Motivation**

When observing a moving target while an observer is moving, the same retinal speeds can correspond to vastly different physical velocities. When an observer moves in the same direction as the target, the retinal speed of the object is partially cancelled out, and vice-versa. Observers must thus obtain an accurate estimate of their own velocity, and subtract it from or add it to the retinal speed elicited by the target to obtain an accurate estimate of the object velocity. More specifically, the Flow Parsing Hypothesis (Dupin & Wexler, 2013; Warren & Rushton, 2008, 2009) posits that, to estimate object motion from ambiguous retinal input, observers first compute which components of retinal stimulation are caused by their own motion in the environment. Then, they subtract this self-motion information from the overall stimulation and attribute the remaining stimulation to object motion in the scene. When self-motion is experienced only visually while undergoing no physical motion, which entails a conflict between visual and vestibular input, self-motion is likely underestimated, leading to biases in judgments of object motion. This has been shown to some extent for vertical observer and object motion (Dyde & Harris, 2008), as well as for rotating observers (Probst, Loose, Niedeggen, & Wist, 1995) and motion in depth (Gray, MacUga, & Regan, 2004). Furthermore, it has been argued that self-motion information is noisier than retinal information concerning object motion (Dokka, MacNeilage, Deangelis, & Angelaki, 2015), especially when observers have only visual information about their own movement at their disposal (Fetsch, Deangelis, & Angelaki, 2010). Subtracting noisy self-motion information from retinal motion in order to obtain an estimate of target velocity should thus decrease precision. Interestingly, the literature presents a blind spot with regards to lateral motion; to our knowledge, no studies have investigated how lateral self-motion influences perceived lateral object speed. The aim of this project is thus to verify the impact of self-motion on accuracy and precision for object velocity judgments in a lateral motion paradigm, which will further our understanding of Flow Parsing. More specifically, our hypotheses are:

* When the observer is **static** during object motion observation, we expect the **highest accuracy** of velocity estimation.
* When the observer is **moving opposite to the object motion (e. g. observer moves to the right, object moves to the left)** during object motion observation, we expect them to **overestimate the observed velocity**.
* When the observer is **moving in the same direction as the target (e. g. both observer and target move to the right)** during object motion observation, we expect them to **underestimate the observed velocity**.
* Furthermore, we expect the **precision to be lower** when the subject experiences **self-motion during object motion observation** relative to when they are static.

**Participants**

We tested 16 participants from the population of PhD and undergrad students at York University with equal numbers of males and females. Due to the low-level nature of the phenomenon under study, we did not believe our results were likely to be relevantly skewed by WEIRD people effects (Henrich, Heine, & Norenzayan, 2010). Participants will have normal or corrected-to-normal vision and have to achieve a stereoacuity of 63 arc seconds or below on the Fly Stereo Acuity Test. The project has received ethics approval from the competent ethics board at York University.

**Apparatus**

All the experiments were performed in virtual reality with participants remaining physically static and seated. We programmed the stimuli in Unity (2019.2.11f1), while object motion, self-motion and the psychophysical staircases were controlled in C# via its integration with Unity. The Unity project is available on Open Science Foundation (<https://osf.io/u7yhb/>). Stimuli were presented in an Oculus Rift. Participants responded by means of a finger mouse.**Setup**

Our experiment consisted of a Two Interval Forced-Choice Task where participants were asked to indicate which of two intervals contained objects moving at the higher velocity. In one interval participants were presented a ball with a diameter of 0.33 m at a distance of 6 m in front of them, travelling to the right or to the left with 6.6 or 8.0 m/s (four target motion profiles). During this interval, participants were either static or experienced simulated body movement to the left or to the right with a Gaussian velocity profile (three self-motion profiles), accelerating until reaching peak velocity after 0.25 s and then slowing down until coming to a halt at 0.5 s. The position in time x(t) was given by a cumulative Gaussian distribution with a mean of 0.25 m/s and a standard deviation of 0.08 m/s, multiplied by -1 for trials with self-motion to the left. In the other interval, participants were shown a cloud of smaller moving balls each with a diameter of 0.1 m as comparison. The balls appeared 1.25 m to the left of the observer (if the big target in the same trial moved to right) or to the right of the observer (if It moved to the left), then moved in the same direction as the big target and disappeared after having travelled 2.5 m. They were spread out vertically over a distance of 1 m, and 10 to 15 were visible at any given moment. The speed of these smaller balls was controlled by a PEST staircase. We employed two staircases for each combination of self-motion (left, right or static) and object motion (-8, -6.6, 6.6 and 8 m/s), one of which started 33 % above the target’s speed, and the other one 33 % below target speed (two staircases for each combination of target motion and self-motion). Thus, there was a total of 4 target speeds x 3 motion conditions x 2 = 24 interleaved staircases. When participants answered that the ball cloud was faster, a lower velocity was displayed in the next trial of that PEST and vice-versa. The step sizes were governed by the following rules (Taylor & Creelman, 1967): the initial step size was 1.2 m/s. For the first five trials for each PEST, the step size was maintained. Starting from the eleventh trial, after a reversal (subjects answered “PEST is slower” in the second-to-last trial and “PEST is faster” in the last trial or vice-versa), the step size was halved. After the second same answer, the step size was maintained. After the third same answer, the step size was either maintained, when the step size had been doubled before the last reversal, or doubled when the step size had not been doubled before the last reversal. After four same answers, the step size was always doubled. Each PEST ended when it converged (five consecutive trials with step sizes lower than 0.1) AND participants had judged at least 20 trials of the staircase. If the staircase did not converge, the PEST was terminated after 35 trials. The experiment ended when all 24 PESTs had terminated. This took about an hour.

Before starting the actual data collection, participants perform a training session with one PEST where the big target moves at 4 m/s. Subjects are asked to repeat the training if the step size in any of the last five trials is above 0.3 m/s. If they still fail to meet the criterion after a second repetition they are excluded from the experiment.

**Analysis**

To assess the **Just Noticeable Difference (JND)** as a measure of precision, we employ General Linear Mixed Modelling, implemented in the R package lme4, according to the recommendations in (Moscatelli & Lacquaniti, 2012). We first establish a Test Model, in which responses are fitted to a cumulative Gaussian, with subject ID (“Subject”) and horizontal velocity (, with values -8, -6.6, 6.6 and 8 m/s) as random effects with random intercepts, and self-motion (binary variable “” with the values “Yes” and “No”) and difference in velocity between target and ball cloud (“”) and their interaction as fixed effects. In lme4 syntax, this corresponds to:

We furthermore establish a Null Model with subject and horizontal velocity as random effects with random intercepts, and subject motion profile and difference in velocity between target and ball cloud as fixed effects, but not their interaction:

We then use an ANOVA to test whether the test model is significantly better than the null model. If the interaction term improves the model significantly, the subject motion profile has a relevant influence on the slope of the fitted cumulative Gaussian. We expect the interaction parameter to be lower for Motion = “Congruent” and Motion = “Incongruent”, thus putting into evidence that self-motion decreases precision in object velocity judgments during self-motion.

To assess the **Point of Subjective Equivalence (PSE)**, our Test Model contains the same random effects as above and the self-motion profile (ternary variable “” with the values “Congruent”, “No Motion” and “Incongruent”) and the velocity difference between target and ball cloud (“”) as fixed effects (Moscatelli & Lacquaniti, 2012). The lme4 syntax is:

The Null Model contains the same random effects, and only the difference in speed between target and ball cloud as fixed effect.

We compare both models with an ANOVA and expect the Test Model to be significantly better than the Null Model, indicating that self-motion has an impact on the PSE. Self-motion in the same direction as the target should decrease perceived target velocity, and self-motion in the opposite direction of the target should increase perceived target velocity.

**Power Analysis**

Based on the analysis plan above, we proceeded to a power analysis via simulation. We first created datasets that would roughly resemble the data we are expecting to collect. At the core of the simulation of these datasets is the assumptions that responses could be described by a cumulative Gaussian function (which approximates what is commonly known as “Psychometric Function”). The mean of the cumulative Gaussian corresponds to the PSE, and its standard deviation is proportional to the JND. We varied the means of the Gaussian according to the self-motion profile. Pilot data (see below) show consistently a bias to interpret the dot cloud as faster; when the observer is static, we thus assume a PSE of 2/3 of the presented velocity. When the observer moved opposite to the target, we expected the PSE to be higher than in the static condition, and when the observer moved with the target, we expect the PSE to be lower. We conducted the power analysis assuming a difference of 1/8 of the mean presented self-motion velocity; (Dokka et al., 2015) found biases up to 50 % of self-motion. Their task, directionality judgments about downward motion with a lateral left- or righrward component, bears some similarities to ours, but is different enough to warrant a more conservative estimate for the sake of the power analysis. For the standard deviation, we parted from a Weber fraction of 7 % for the static condition (McKee, 1981), which corresponds roughly to a standard deviation of 10 % of the PSE. Where the observer is moving, we expected increased JNDs and therefore an increased standard deviation. For the sake of this power analysis, we assume that the standard deviation in this case might be 1/4 higher than the standard deviation for a static observer. (Dokka et al., 2015) found increases of up to 200 % in thresholds from no self-motion to visually simulated self-motion. We choose a much more conservative value to account for task differences. Additionally, we varied the PSE and SD per subject by multiplying them with random values drawn from a normal distribution with a mean of 1 and a standard deviation of 0.1. To account for the fact that our staircase leads to a concentration of responses around the PSE, we drww the stimulus strengths from a Cauchy distribution with a location of 1 and a scale of 0.02. We drew 55 stimulus strengths for this distribution (per combination of target velocity and self-motion, we use two PESTs with about 27 trials each; see above) and fed them into the cumulative Gaussian we established per condition and subject. This yielded the answer probability per trial. We then used these probabilities to draw binary answers (PEST faster yes/no) from a Bernoulli distribution for each trial.

We simulated 100 of these data sets, conducted the analyses described above over each and reported the percentage where the Test Model was significantly better than the Null Model.

**With the above values, we achieved a power of 0.925 for the differences in JNDs, and a power of nearly 1 for the differences in PSEs.**

The R code used for this power analysis is available online under <https://github.com/b-jorges/Motion-Perception-during-Self-Motion/blob/master/PowerAnalysisMotionEstimation.R>.

**Pre-existing Data**

We collected data from six pilot participants. Pilot results are largely in line with our predictions: In terms of JNDs, we found that our Test Model is significantly better than the Null Model (p = 0.02), and effects trended in the direction of our hypothesis (regression coefficients of -0.078, SE = 0.034, for the interaction between self-motion present and the difference in velocity, which corresponds to a lower precision). For the PSEs, we found that our Test Model was significantly better than the Null Model (p < 0.001), and the effects go largely in the expected direction (regression coefficients of 0.072, SE = 0.05, for the main effect of congruent motion, and -0.25, SE = 0.053, for the main effect of incongruent motion; which corresponds to a lower perceived speed for congruent motion and self-motion, and a higher perceived speed for incongruent motion and self-motion). The code used for this analysis as well as the pilot data are available under <https://github.com/b-jorges/Motion-Perception-during-Self-Motion/blob/master/AnalysisPilotData.R>.

The pilot data were not included into the final analysis; we recruited 16 new subjects.

Open Data

We will publish all raw data collected during this project in the GitHub repository <https://github.com/b-jorges/Motion-Perception-during-Self-Motion/>.

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