PREREGISTRATION SPEED PERCEPTION DURING SELF-MOTION

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Motivation

To interact with our environment, humans need to extract the relevant information from the visual stimulus. While this is generally unproblematic for static observers, it has been shown that moving observers judge object motion both less precisely and less accurately for motion in depth (Wertheim, 2008). Simulated self-motion, that is, a visual stimulation that leads the observer to believe that they themselves are moving through an environment, has been an important tool to study this phenomenon. For example, it has been shown that the speed of approaching objects is overestimated when self-motion is simulated visually in the same direction as object motion. Furthermore, the direction of motion-in-depth is biased towards the focus of expansion of the flow pattern, and both biases are reduced during binocular viewing (Gray, Macuga, & Regan, 2004). Integrating self-motion into the final percept of object motion seems to increase accuracy, while decreasing precision, as demonstrated for example for direction judgments during self-motion (Dokka, MacNeilage, DeAngelis, & Angelaki, 2015). This may be due to the discounting of noisy self-motion information from less noisy object motion information.

This project thus aims to test the influence of self-motion on the perception of the speed of moving objects in our environment. Different sub-projects will test different variations over this theme. The present experiment focuses on the effects of visually perceived horizontal self-motion on the perception of horizontal motion.

Hypotheses

We expect prediction errors to reflect both accuracy and precision of the velocity estimate acquired during the visible part of the target trajectory. That is:

- 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** during object motion observation, we expect them to **overestimate the observed velocity**.
- When the observer is **moving in the same direction as the target** 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, and **higher when they are static**.

Participants

We aim to test 15 participants from a convenience sample of PhD and undergrad students from York University. Due to the low level nature of the phenomenon under study, we do not believe our results to be relevantly skewed by WEIRD people effects (Henrich, Heine, & Norenzayan, 2010). Our participants will be tested for stereovision and will have normal or corrected-to-normal sight.

Setup

Our experiment consists in a Two Interval Forced-Choice Task where participants are asked to answer by mouse button press which of two seen intervals presented the higher velocity. In one of the intervals, participants are presented one 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 are either static or move 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) is given by a cumulative Gaussian distribution with a mean of 0.25 and a standard deviation of 0.08. In the other interval, participants are shown a cloud of smaller moving balls as comparison. The speed of these smaller balls is controlled by a PEST staircase. We employ two staircases of each combination of self-motion (left, right or static) and object motion (-8, -6.6, 6.6 and 8 m/s), one of which starts 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). When participants answer that the ball cloud was faster, a lower velocity is displayed in the next trial of the same PEST, and vice-versa. The step sizes are governed by the following rules: the initial step size is 1.2 m/s. For the first five trials for each PEST, the step size is 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 is halved. After the second same answer, the step size is maintained. After the third same answer, the step size is either maintained, when the step size was doubled before the last reversal, or doubled when the step size was not doubled before the last reversal. After four same answers, the step size is always doubled. The PEST ends when it converges (five consecutive trials with step sizes lower than 0.1) AND participants have judged at least 20 trials of the staircase. If the staircase does not converge, the PEST is terminated after 35 trials. The experiment ends when all 24 PESTs (three self-motion profiles times four target motion profiles time staircase starting point above/below) have terminated.

Apparatus

We programmed the stimuli in Unity (2019.2.11f1), while object motion, self-motion and the staircase are controlled in C# via its integration with Unity. The Unity project is available on Open Science Foundation (https://osf.io/u7yhb/). Stimuli are presented in an Oculus Rift.

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 (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 ($\text{Velocity}_{\text{horizontal}}$, with values -8, -6.6, 6.6 and 8 m/s) as random effects with random intercepts, and self-motion profile (ternary variable "$Motion_{Subject}$" with the values "Congruent", "Incongruent" and "NoMotion") and difference in velocity between target and ball cloud ("$Difference$") and their interaction as fixed effects. In lme4 syntax, this corresponds to:

$$Motion_{Subject} * Difference + (1\ |Subject) + (1\ |\ Velocity_{Target})$$

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

$$Motion_{Subject} + Difference + (1\ |Subject) + (1\ |\ Velocity_{Target})$$

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 self-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 ("$Motion_{Subject}$") and the velocity difference between target and ball cloud ("$Difference$") as fixed effects (Moscatelli & Lacquaniti, 2012). The lme4 syntax is:

$$Motion_{Subject} + Difference + (1\ |\ Subject) + (1\ |\ Velocity_{Target})$$

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

$$Difference + (1\ |\ Subject) + (1\ |\ Velocity_{Target})$$

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 threshold. We vary the means of the Gaussian according to the self-motion profile: when the observer is static, we expect a mean of the presented velocity value, as no biasing factors should be present. When the observer moves opposite to the target, we expect the PSE to be higher, and when the observer moves with the target, we expect the PSE to be lower. We estimate this bias at 1/8 of the mean presented self-motion velocity. For the standard deviation, we part from a discrimination threshold of 10 % for the static condition, which corresponds roughly to a standard deviation of 15 % of the PSE. Where the observer is moving, we expect increased thresholds and therefore an increased standard deviation. We expect the standard deviation to be 1/3 higher than the standard deviation for a static observer. Additionally, we vary the PSE and SD per subject by multiplying them with random numbers 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 draw the stimulus strengths from a distribution centered around the respective PSE with a very high kurtosis. We draw 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 feed them into the cumulative Gaussian we established per condition and subject. This yields the answer probability for each trial. We then use these probabilities to draw binary answers (PEST faster yes/no) from a Bernoulli distribution for each trial.

We simulate 100 of these data sets, conduct the analyses described above over each and report the percentage where the Test Model is significantly better than the Null Model.

With the above values, we achieve a power of 85 % for the differences in thresholds, and a power of 99 % for the differences in PSE.

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

Prior to pre-registration, we collected data from six pilot subjects. Pilot results are largely in line with our predictions: In terms of JNDs, we find that our Test Model is significantly better than the Null Model ($p < 0.001$), and effects trend in the direction of our hypothesis (regression coefficients of -0.1, SE = 0.038, for the interaction between incongruent motion and self-motion and the difference in velocity, and of -0.005, SE = 0.04, for the interaction between congruent motion and self-motion and the difference in velocity; which corresponds to lower precisions for both). For the PSEs, we find that our Test Model is 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 is available under https://github.com/b-jorges/Motion-Perception-during-Self-Motion/blob/master/AnalysisPilotData.R.

The pilot data will not be included into the final analysis; we will recruit 15 new subjects.

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