Determining Mean and Standard Deviation of the Strong Gravity Prior through Simulations

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Abstract

Humans expect downwards moving objects to accelerate and upwards moving objects to decelerate. These results have been interpreted as humans maintaining an internal model of gravity. We have previously suggested an interpretation of these results within a Bayesian framework of perception: earth gravity could be represented as a Strong Prior that overrules noisy sensory information (Likelihood) and therefore attracts the final percept (Posterior) very strongly. Based on this framework, we use published data from a timing task involving gravitational motion to determine the mean and the standard deviation of the Strong Earth Gravity Prior. To get its mean, we refine a model of mean timing errors we proposed in a previous paper (Jörges & López-Moliner, 2019), while expanding the range of conditions under which it yields adequate predictions of performance. This underscores our previous conclusion that the gravity prior is likely to be very close to 9.81 m/s². To obtain the standard deviation, we identify different sources of sensory and motor variability reflected in timing errors. We then model timing responses based on

22 quantitative assumptions about these sensory and motor errors for a range of standard deviations of the

23 earth gravity prior, and find that a standard deviation of around 2 m/s² makes for the best fit. This value

24 is likely to represent an upper bound, as there are strong theoretical reasons along with supporting

25 empirical evidence for the standard deviation of the earth gravity being lower than this value.

Introduction

27 There is ample evidence that humans represent earth gravity and use it for a variety of tasks such as

28 interception (Ceccarelli et al., 2018; La Scaleia, Zago, Moscatelli, Lacquaniti, & Viviani, 2014; J McIntyre,

29 Zago, & Berthoz, 2001; Mijatovic, La Scaleia, Mercuri, Lacquaniti, & Zago, 2014; Senot et al., 2012; Zago

30 et al., 2004a, 2004b; Zago, La Scaleia, Miller, & Lacquaniti, 2011; Zago, McIntyre, Senot, & Lacquaniti,

31 2008; Zago & Lacquaniti, 2005a), time estimation (Moscatelli & Lacquaniti, 2011), the perception of

32 biological motion (Maffei et al., 2015) and many more. Recently, we have shown that gravity-based

33 prediction for motion during an occlusion matched performance under a 1g expectation not only

34 qualitatively, but also quantitatively (Jörges & López-Moliner, 2019). This was an important finding to

35 support our interpretation of the above results as a strong prior in a Bayesian framework of perception

36 (Jörges & López-Moliner, 2017). The results presented in (Jörges & López-Moliner, 2019) indicate that

37 temporal errors in a timing task were consistent with a mean of 1g (9.81 m/s²) when occlusions were long

38 enough. In the present paper, we extend the simulations brought forward in our previous paper: First, we

39 consider how accounting for the Aubert-Fleischl effect, which leads humans to perceive moving object at

40 about 80% of their actual speed when they pursue the target with their eyes (Aubert, 1887; Dichgans,

41 Wist, Diener, & Brandt, 1975; Fleischl, 1882), can extend our simple 1g-based model to shorter occlusions.

42 Furthermore, to fully characterize a prior, we need to not only indicate its mean, but also its standard

43 deviation. The second goal of the present paper is thus to determine the standard deviation of the strong

44 gravity prior. We aim to achieve this goal by simulations based on assumptions about the different sources

45 of noise relevant to the task at hand.

46 In this paper, we adopt a constructivist-computational framework (Marr, 1982; Nanay, 2014); we view

47 perception as a process by which humans acknowledge the state of the world around us based on both

48 prior knowledge and sensory online information in order to guide their interactions with the external

49 world. Please note that other psychological traditions, such as ecological perception (Gibson, 1986), deny

50 the necessity of prior knowledge. Within our constructivist framework, we envision (visual) perception as

51 a two-step process: Encoding and Decoding (Gold & Shadlen, 2007; Schneidman, Bialek, & Ii, 2003). During

52 Encoding, low level signals such as luminosity, retinal velocities or orientation are picked up by the

53 perceptual system and represented as neural activity. However, these low-level sensory signals, and the

54 neural activity they are represented as, can be ambiguous with respect to the state of the world: for

55 example, the same retinal velocities can correspond to vastly different physical velocities, depending on

56 the distance between observer and object. An object that moves 6 m in front of the observer in the fronto-

57 parallel plane with a physical speed of 1 m/s elicits a retinal speed of about 9.5°/s when fixation is

58 maintained. The same retinal speed could correspond to a target that moves at a physical speed of 1.2 m/s

59 7 m in front of the observer. Decoding is the process of interpreting optic flow information. In Decoding,

60 humans often combine sensory input with previous (prior) knowledge to obtain a more accurate and

61 precise estimate of the observed state of the world. For example, we use knowledge about the size of an

62 object to recover its most likely distance to the observer, thus providing a key to recover its physical

63 velocity from retinal motion. If we, for example, know that we are observing a basketball and know from

64 experience that its radius is 0.12 m, and we perceive that the target occupies a visual angle of 0.5°, we

65 know that the target moves at 7 m in front of as. We then also know that the physical velocity of the ball

66 is 1.2 m/s, not 1 m/s. In some, if not many instances, this combination occurs according to Bayes' formula:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

[1]

67   The probability of a state of the world A given evidence B is the probability of observing evidence B given

68   the state of the world A multiplied by the probability of the state of the world (A), divided by the

69   probability of the evidence (B). In a Bayesian framework, sensory input (Likelihood), corresponding to the

70   term $\frac{P(B|A)}{P(B)}$ in Equation 1, and prior knowledge (Prior), corresponding to $P(A)$ in Equation 1, are

71   combined according to their respective precisions to yield a more precise and more accurate final percept

72   (Posterior). Under many circumstances, Prior, Likelihood and Posterior can be represented as normal

73   distributions whose standard deviations correspond to the representation's reliability. If an organism has

74   a high sensitivity to the sensory input, that is, when they are able to reliably distinguish one stimulus

75   strength from a very similar stimulus strength, the standard deviation of the Likelihood would be very low,

76   which corresponds to a very narrow distribution. On the other hand, if the organism has a very precise

77   representation of the most likely state of the world, the Prior would be very narrow. Finally, the standard

78   deviation of the Posterior would depend on the precision of Likelihood and Prior. Usually, both the Prior

79   and the Likelihood contribute to the Posterior; for example when we know that our opponent in a tennis

80   match *usually* serves in the right corner of the court, but *not always*, (Prior) and we have good visibility of

81   their serving motion, but since the motion is so quick, we do not have a lot of time to acquire evidence

82   (Likelihood). We thus take sensory input (e. g. about their body posture while serving) into account only

83   to some extent (see "Normal Prior" scenario in Figure 1). However, in the case of gravity it seems that the

84   expectation of Earth Gravity overrules all sensory information that humans collect on the law of motion

85   of an observed object (La Scaleia, Zago, & Lacquaniti, 2015; McIntyre et al., 2001; McIntyre, Zago, Berthoz,

86   & Lacquaniti, 2003; Zago & Lacquaniti, 2005b; Zago et al., 2008). On a theoretical level, this is a sensible

87   assumption, since all of human evolution and each human's individual development occurred under Earth

88   Gravity. In Bayesian terms, the Prior is extremely precise and thus overrules all sensory information

89   represented as the Likelihood. According to our interpretation, we would thus expect an extremely low

90   value for the standard deviation of the earth gravity prior ("Strong Prior" scenario in Figure 1). We would

91   expect this value to be represented more precisely than linear velocities, which generally elicit Weber

92   Fractions of 10%, which corresponds to a standard deviation of about 15% of the mean represented

93   stimulation.

94   In the following, we use the data from our previous study (Jörges & López-Moliner, 2019) to simulate the

95   variability of responses under different assumptions about the standard deviation of the gravity prior.

Methods

97   In this paper, we use previously published data (Jörges & López-Moliner, 2019). The pre-registration for

98   the original hypotheses can view viewed on Open Science Foundation (https://osf.io/8vg95/). All data

99   relevant to this project are available in our GitHub repository (https://github.com/b-jorges/SD-of-Gravity-

100   Prior).

Participants

102   We tested ten participants (n = 10) overall, including one of the authors (BJ) who was excluded from the

103   analyses in this paper. The remaining participants were between 23 and 34 years old and had normal or

104   corrected-to-normal vision. Three (n = 3) of the included participants were women and six (n = 6) were

105   men. All participants gave their informed consent. The research in this study was part of an ongoing

106   research program that has been approved by the local ethics committee of the University of Barcelona.

107   The experiment was conducted in accordance with the Code of Ethics of the World Medical Association

108   (Declaration of Helsinki).

Stimuli

110   Participants were shown targets of tennis ball size (r = 0.033), shape and texture in an immersive 3D

111   environment (see Figure 2). The 3D environment should help participants to perceive the stimulus at the

112 correct distance and activate the internal model of gravity (Zago et al., 2011). The targets moved along

113 parabolic trajectories in the fronto-parallel plane 6.15 m in front of the observer. The trajectories were

114 determined by the simulated gravity (0.7g, 0.85g, 1g, 1.15g, 1.3g or -1g), the initial vertical velocity (4.5 or

115 6 m/s) and the initial vertical velocity (3 or 4 m/s). Air drag was simulated in line with the air drag at the

116 location of the experiment (Barcelona in Spain, at sea-level), and the ball did not spin. Targets always

117 moved from left to right. When gravity acted downwards, the target started 0.5m above the simulated

118 ground and when it acted upwards, the target started out 3.5m above the ground. The final positions

119 were marked with tables for downwards gravities and by lamps hanging from the ceiling for upwards

120 gravities. The total flight time was the time it took for the ball to return to its initial height. The target

121 disappeared either between 75% and 80% (Short Occlusion) or between 50% and 55% (Long Occlusion)

122 of the total flight time. Each of the conditions was repeated 24 times, for a total of 1344 trials across four

123 blocks. Within each block, the kinetic profiles were presented in a random order. From the participant's

124 perspective, the trajectories always unfolded in front of the white wall, that is, low level cues such as

125 contrast and brightness were equal across all trajectories and conditions. Figure 2 shows the trajectories

126 projected on the visual scene.

127 ## Apparatus
128 We used two Sony laser projectors (VPL-FHZ57) to present overlaid images on a back-projection screen

129 (244 cm high and 184 cm wide). The images had a resolution of 1920 x 1080 pixels and were refreshed at

130 85Hz. Participants were wearing glasses with polarizing filters to provide stereoscopic images. They stood

131 2 m in front of the screen. The disparity between the two projectors' images was adapted to each

132 participant's interocular distance. The stimuli were programmed in PsychoPy (Peirce et al., 2019). The

133 projectors introduced a delay of 0.049259 s (SD = 0.001894 s) that we accounted for in the analysis of

134 timing responses. For another hypothesis, eye-tracking data was acquired; see (Jörges & López-Moliner,

135 2019).

136   Participant responses were collected with a regular computer mouse. It has been shown that commodity

137   input devices often lack in temporal accuracy and precision for response capture (Plant & Turner, 2009).

138   To mitigate such issues, we use the openGl engine in python (pyglet) devoted to gaming, which aims to

139   reach maximum precision both for stimulus frames and input recording. We access the mouse time

140   stamps directly iohub python libraries (which merges with PsychoPy) which circumvents the main system

141   events loop and uses the clock_gettime(CLOCK_MONOTONIC) in unix-like systems (like os x, the one we

142   use). The precision is sub-milliseconds. Iohub can be used with or without PsychoPy real-time access to

143   input devices. Importantly, it runs its own thread devoted to continuously sampling the input device state

144   independently of the video (stimulus) thread.

145   ## Procedure
146   We asked participants to follow the target closely with their gaze and indicate with a mouse click when

147   they believed the target had returned to its initial height. Participants first completed 48 familiarization

148   trials in which the balls reappeared when they pressed the button, which allowed them to assess the

149   spatial error. Then, the main experiment followed. It consisted of four blocks: 3 blocks with 320 trials each

150   (the five positive gravities – 0.7g, 0.85g, 1g, 1.15g, 1.3g –, two initial vertical velocities, two initial

151   horizontal velocities, two occlusion conditions, eight repetitions per condition) and one block with 384

152   trials (as the other block, but 1g and -1g as gravities, and 24 repetitions per condition). Each block took

153   15-20 minutes and participants could rest after each block. We counterbalanced across participants

154   whether the -1g block or the 0.7g-1.3g blocks was presented first.

155

156   # Results

157   We have reported mean difference in a previous paper (Jörges & López-Moliner, 2019). In the following,

158   we thus limit ourselves to analyzing the influence of gravity on the *precision* of responses in preparation

159　for the simulations we are conducting after. We used a slightly different, more liberal outlier analysis for

160　this project to make sure that we do not lose any variability present in participants' responses. We also

161　exclude all data collected from the author (s10; all 1344 trials). Further, we exclude all trials where subjects

162　pressed the button before the target disappeared (38 trials) or where the temporal error was greater than

163　2 s (178 trials). Overall, we excluded 1.6% of all trials from the nine participants included in the analysis.

164　To make it easier to compare temporal errors across conditions, we then computed the error ratio:

$$Error\ Ratio = \frac{Error + Occluded\ Duration}{Occluded\ Duration} \qquad [4]$$

165　In Figure 3, we illustrate the response distributions. For an analysis and interpretation of the effect of

166　gravitational motion on accuracy, please see our previous paper (Jörges & López-Moliner, 2019).

167　While we used Linear Mixed Modelling to assess accuracy, assessing precision differences between

168　conditions is not straight-forward with this method. Therefore, we employ Bayesian Linear Mixed

169　Modelling to assess whether gravity has an impact on the precision of the timing responses. The R package

170　brms (Bürkner, 2018), which provides user-friendly interface for the package rstan (Stan Development

171　Team, 2016), uses a very similar syntax to the more well-known lme4 (Bates, Mächler, Bolker, & Walker,

172　2015). In addition to mean differences, this type of analysis also allows us to test for variability differences

173　between conditions. We thus fit a mixed model to explain both means and standard deviations of the

174　response distributions, with gravity as a fixed effect and varying intercepts per participant as random

175　effects. In lme4/brms syntax, the test model is specified as:

$$Error\ Ratio \sim Gravity + (1\ |Subject)$$
$$Sigma \sim Gravity + (1\ |Subject)$$
$$[5]$$

176   Where the first line corresponds to the statistical structure that corresponds to the means of the response

177   distributions and the second line corresponds to the standard deviations of the response distributions.

178   Unlike regular Linear Mixed Models, Bayesian Linear Mixed Models do not need to be compared to a Null

179   Model. We can use the hypothesis() function from the R Core package (R Core Team, 2017) to test

180   hypotheses directly. We found a posterior probability of >0.999 that a lower gravity value is related to

181   lower variability, the sigma coefficient for Gravity being 0.057 (SE = 0.004; 95% Confidence

		0.7g-1.3 Block					-1g/1g Block	
		Long Occlusion						
v_{yi}		*0.7g*	*0.85g*	*1g*	*1.15g*	*1.3g*	*-1g*	*1g*
4.5 m/s	*Mean*	1.12	1.11	1.20	1.24	1.30	1.33	1.17
	SD	0.47	0.49	0.53	0.42	0.44	0.53	0.38
6 m/s	*Mean*	1.05	1.11	1.17	1.24	1.32	1.23	1.16
	SD	0.49	0.55	0.57	0.54	0.57	0.56	0.46
		Short Occlusion						
v_{yi}		*0.7g*	*0.85g*	*1g*	*1.15g*	*1.3g*	*-1g*	*1g*
4.5 m/s	*Mean*	1.22	1.31	1.34	1.41	1.52	1.68	1.35
	SD	0.64	0.65	0.65	0.56	0.88	0.86	0.58
6 m/s	*Mean*	1.26	1.33	1.37	1.47	1.49	1.51	1.35
	SD	0.65	0.77	0.77	0.88	0.75	0.80	0.76

Table 1: Means and standard deviations observed for the temporal errors divided by gravities and initial vertical velocities

182   Interval = [0.051;0.064]) in the log space. In the regular space, this corresponds to a standard deviation of

183   0.296 (95 % CI = [0.282;0.313]) for 0.7g, 0.321 (95% CI = [0.303;0.344]) for 0.85g, 0.350 (95%

184   CI = [0.326;0.378]) for 1g, 0.382 (95% CI = [0.351;0.416]) for 1.15g and 0.413 (95% CI = [0.378;0.458]) for

185   1.3g. Table 1 lists all mean temporal errors and the respective standard errors across participants. Note

186   that, unlike the results from the Bayesian Mixed Model, the variability values from Table 1 also include

187   variability that the Mixed Model assigns to the individual.

188   Interestingly, precision seems to be higher for 1g trials than for -1g trials. To test this observation

189   statistically, we fitted a second Bayesian Linear Mixed Model to the -1g/1g data, where gravity as fixed

190   effect factor and subjects as random effects predict the timing error:

191 $Error\ Ratio \sim Gravity\ + (1\ |Subject)$

192 We tested the hypothesis that Gravity would lead to lower variability. The posterior probability of this

193 hypothesis being true was > 0.999, with a sigma coefficient for Gravity of -0.011 (SE = 0.004; 95 %

194 Confidence Interval = [-0.014,-0.009] in the log space. That is, the standard deviation of distribution of -

195 1g responses in regular space is 0.426 (95% Confidence Interval = [0.414;0.439]), while the standard

196 deviation of the distribution of 1g responses in regular space is 0.344 (95% Confidence Interval =

197 [0.334;0.353]). This indicates that the absolute error is lower and thus the precision is higher for 1g than

198 for -1g. On a theoretical level, this is in line with previous findings (Indovina et al., 2005) showing that the

199 internal representation of gravity is not activated when upwards motion is presented, even when the

200 absolute value of acceleration impacting the object is equal to the absolute value of earth gravity

201 (9.81 m/²). The precision may thus be higher for 1g than for -1g because the internal model of gravity is

202 utilized for 1g, but not for -1g trials.

203

204 Simulations

205 The physical formula for distance from initial velocity and acceleration (Equation 4) is the base for both of

206 our simulation procedures. This reflects the assumption that humans perform the task at hand accurately

207 – under most circumstances. This assumption is supported by our data, which show a high accuracy for

208 the earth gravity conditions.

209 We furthermore neglect the air drag for these simulations and use the equation for linearly accelerated

210 motion as an approximation.

$$d_y = \frac{g}{2} * t^2 + v_y * t \qquad\qquad [6]$$

$$t_{1/2} = \frac{-v_y \overset{+}{-} \left(v_y{}^2 - 4 * \frac{g}{2} * d_y\right)^{0.5}}{2 * \frac{g}{2}}$$
[7]

211 As evidenced by a comparison between equations (1) and (2) and equations (3) and (4), the computational

212 complexity increases significantly if we want to accommodate air drag, while the gains in accuracy are

213 marginal (0.02 s in the condition with the most extreme differences).

214

Mean of the Gravity Prior

216 To characterize the mean Strong Gravity Prior, we build upon our model the mean timing errors presented

217 in our previous data (Jörges & López-Moliner, 2019). Importantly, the predictions of our model matched

218 the observed data only for the Long Occlusion condition. In the Long Occlusion condition, subjects

219 displayed a tendency to respond slightly too late, while their responses should be centered around zero.

220 Our ad hoc explanation of this discrepancy was that subjects were often executing a saccade when the

221 ball returned to initial height, which may have interfered with the predictions (Jörges & López-Moliner,

222 2019). An alternative explanation may be, however, that our subjects underestimated the target's speed

223 at disappearance due to the so called Aubert-Fleischl phenomenon: humans estimate the speed of a

224 target that they pursue with their eyes at about 80% of its actual speed (Aubert, 1887; de Graaf,

225 Wertheim, & Bles, 1991; Fleischl, 1882; Spering & Montagnini, 2011; Wertheim & Van Gelder, 1990). Our

226 subjects were specifically instructed to follow the target with their eyes, and the eye-tracking data we

227 collected that they generally did pursue the target (Jörges & López-Moliner, 2019). An underestimation

228 of the velocity at disappearance could explain the tendency of subjects to respond too late in the Short

229 Occlusion condition. For the Long Occlusion condition, on the contrary, the vertical speed at

230 disappearance is very low and has a nearly neglectable influence on the final prediction. Setting the

231 perceived velocity at 80% of the presented velocity should thus yield more accurate predictions for the

232   Short Occlusion condition, while the accuracy for the Long Occlusion condition would be largely

233   maintained. We thus employ the same procedure laid out in (Jörges & López-Moliner, 2019), but add a

234   coefficient of 0.8 to the perceived velocity at disappearance to account for the Aubert-Fleischl

235   phenomenon.

236   We will briefly summarize the procedure and then present how this tweak affects the results of our

237   simulations. We used the physical formula for distance from accelerated motion (Equation 4, with d being

238   the height as disappearance, v_y the vertical velocity at disappearance and g being gravity). For our

239   simulations, we assume that humans use an earth gravity value of 9.81 m/s² independently of the

240   presented gravity value, as long as the display is roughly in line with a real-world scenario. We furthermore

241   assume that we perceive the vertical velocity at disappearance at 80% of the presented velocity. Equation

242   7 thus becomes

$$t_{1/2} = \frac{-v_{y,perceived} \overset{+}{-} \left(v_{y,perceived}^2 - 4 * \frac{g_{earth}}{2} * d_y\right)^{0.5}}{2 * \frac{g_{earth}}{2}} \qquad [8]$$

243   With $v_{y,perceived} = 0.8 * v_{y,presented}$ and $g_{earth} = \frac{9.81\,m}{s^2}$.

244   We use this formula to simulate the timing error for each trial separately without adding noise. We

245   furthermore also simulate the responses without accounting for the Aubert-Fleischl phenomenon to

246   compare performance for both models. Figure 4 shows the mean errors observed in our participants

247   ("Obs. Error"), the mean errors when accounting for the Aubert-Fleischl phenomenon ("Sim. Error (AF)"),

248   and the mean errors when not accounting for the Aubert-Fleischl phenomenon ("Sim. Error (No AF)").

249   The overall Root Mean Squared Error between AF model predictions and observed behavior is 0.2, and

250   for the non-AF model predictions substantially higher, at 0.265. Table 2 shows the error for each of the

251   conditions. Including the AF phenomenon thus vastly improves the model's generalizability..

$\mathbf{v_{yi}}$	Long Occlusion		Short Occlusion	
	AF	*No AF*	*AF*	*No AF*
4.5 m/s	0.150	0.160	0.236	0.333
6 m/s	0.148	0.158	246	0.344

Table 2: Root Mean Squared Errors (RMSEs) between simulated and observed mean errors for simulations including the Aubert-Fleischl phenomenon (AF) and simulations that don't (No AF). Lower values signify a better fit.

This improvement upon our previous model lends further support to the idea that the mean of a strong gravity prior is at or very close to 9.81 /s².

Standard Deviation of the Gravity Prior

The second value needed to characterize a normal distribution, which we assume the strong gravity prior to be represented as, is its standard deviation. There are two different ways to approach this problem: First, we can simulate the temporal responses of our subjects assuming different standard deviations for the gravity prior and minimize the difference between the standard deviations of the responses we observed in our subjects and the model standard deviations. In this case, we would draw the values for v_y, d_y and g_{earth} from distributions with given means and standard deviations, and compute a simulated temporal response from these values. The mean for v_y would be the last observed velocity in y direction, corrected by a factor of 0.8 for the Aubert-Fleischl phenomenon, and the standard deviation can be computed based on Weber fractions for velocity discrimination from the literature. The mean for d_y is the distance in y direction between the point of disappearance and the reference height. The mean for g_{earth} is 9.81 m/s², and we optimize over its standard deviation to match the standard deviation observed in the subjects' temporal responses.

270   A second approach would be to solve equation (3) for g_{earth}, and then compute its mean and standard

271   deviation analytically based on the means and standard deviations of t, v_y and d_y. For the addition,

272   subtraction and multiplication of two normal distributions, there are analytic solutions to compute mean

273   and standard deviation of the resulting distribution.

$$g_{earth} = \frac{2(d_y - v_y * t)}{t^2}$$ [8]

274   However, as evident from Equation 5, this method requires computing the standard deviation of the

275   quotient of two distributions. To our knowledge, this is not possible in an analytical fashion and would

276   entail simulations by itself. We will thus focus on the simulation approach.

277

278   Assumptions

279   For this approach, we need to make several assumptions. In the following, we will outline each and

280   provide the rationale for the chosen values. Please note that we conduct these simulations in absolute

281   terms (i.e., absolute errors) to mimic the processes more closely, but convert quality metrics (such as

282   model fits) and results into relative terms (i.e., error ratios).

283   **Use of Equation (3)** – In our previous paper, we have shown that predictions based on Equation 3 fit

284   observed temporal errors reasonably well (Jörges & López-Moliner, 2019). This is particularly the case

285   when subjects extrapolated motion for larger time frames in the Long Occlusion condition. The difference

286   in predictions for this equation with regards to Equation (2) is at most 3 ms, and the added computational

287   complexity does not justify the added accuracy, especially since our main concern is precision.

288    $\boldsymbol{v_y}$ – The velocity term in Equation 4 ($v_y * t$) refers to the part of the full distance the target moved

289   because of its initial velocity. Our targets disappeared right after peak, therefore their initial velocity was

290   very low. The velocity term thus contributes less to the full estimate than the gravity term, especially in

291   the Long Occlusion condition (see also Figure 5C). Importantly, the vertical velocity component is not

292   perceived directly. Rather, it has to be recovered from the tangential speed ($v_{tan,perceived}$) and the angle

293   between the tangential speed vector and the vertical speed vector ($\alpha_{perceived}$) by means of the equation:

$$v_{y,perceived} = \cos(\alpha_{perceived}) * v_{tan,perceived} \qquad [9]$$

294   Weber fractions for the discrimination of angular velocities reported in the literature are about 10%

295   (Kaiser, 1990). To calculate the standard deviation of the distribution of perceived velocities from the

296   Weber fraction, we have to find that normal distribution where a difference of 10% from its mean leads

297   to a proportion of responses of 25/75%. For a standardized normal distribution with a mean of 1, this is a

298   standard deviation of 0.148. Note that, by using a standardized normal distribution, we assume that

299   Weber fractions are constant across the relevant range of stimulus strengths. Figure 5C shows how

300   predictions vary with varying variability in perceived vertical velocity: The effect is negligible for the Long

301   Occlusion condition, while it increases response variability uniformly across gravities. Further variability is

302   incurred in estimating $\alpha_{perceived}$. Following (Schoups, Vogels, & Orban, 1995), the JND for orientation

303   discrimination in untrained subjects is around 6° for oblique orientations. This corresponds to a standard

304   deviation of 0.089.

305   Furthermore, we need to account for the Aubert-Fleischl phenomenon, which consists in an

306   underestimation of the velocity of a moving target during smooth pursuit (Aubert, 1887; de Graaf et al.,

307   1991; Fleischl, 1882; Spering & Montagnini, 2011; Wertheim & Van Gelder, 1990). While this effect should

308   in principle be partially offset by improved predictions for motion coherent with earth gravity – an

309   empirical question that has, to our knowledge, not been addressed so far –, our simulations show that a

310   Aubert-Fleischl correction factor of 0.8 yields an excellent fit for the observed mean errors. We thus

311   proceed with a value of 0.8 also for the simulations concerning the standard deviation.

312     $\boldsymbol{d_y}$ – For the distance term (d_y), we choose the stimulus value as mean distance, as we don't expect any

313   biases. In terms of precision, Weber fractions of 3% to 5% are observed for distance estimates in the front

314   parallel plane (Norman, Todd, Perotti, & Tittle, 1996). However, since subjects have to estimate the

315   distance not between two well defined points, but rather the height above the simulated table, the

316   precision of these estimates is likely lower than reported for the above task. We thus work with a Weber

317   fraction of twice the reported value (10%). Using the above method, we determine that the standard

318   deviation for this value is 0.148. Figure 5A shows how predictions vary with variability in perceived

319   distance: There is a slight logarithmic pattern, where response variability added by higher variability in

320   perceived distance increases with decreasing gravity.

321   **t** – The response time t is measured directly in our task, both in mean and variability.

322   **Remaining Variability** – For our simulations, we rely on accounting for every source of variability in the

323   responses. One source of error beyond perceiving and representing **g**, v_y and $\boldsymbol{d_y}$ is the motor response.

324   Motor responses are likely to vary strongly between tasks, for which reason variability reported in the

325   literature is of limited use. To estimate the error introduced by these further factors, we thus take

326   advantage of previous results indicating that the gravity model is not activated for upside-down motion

327   (Indovina et al., 2005), a hypothesis which is also supported by our data.

328

329   Under this assumption, we can use the responses for the inverted gravity condition to estimate the errors

330   introduced by motor variability. An inactivation of the gravity prior would mean that the gravity acting

331   upon the object should be represented with the same precision as arbitrary gravities. We previously found

332   Weber fractions of between 13% and beyond 30% for arbitrary gravities (Jörges, Hagenfeld, & López-

333   Moliner, 2018), which is in line with those found for linear accelerations (Werkhoven, Snippe, &

334   Alexander, 1992). We thus proceed with a value of 20%, which corresponds to a normalized standard

335   deviation of 0.295 (see procedure above).

336   There are further constraints: First, the motor variability should be lower than the overall variabilities

337   observed for the absolute error in each condition (the minimum is just over 0.08 s for the short occlusion

338   condition with 1.3g and an initial vertical velocity of 4.5 m/s). Second, the motor variability should be

339   equal across conditions and be independent of gravity, initial velocity and Occlusion category (see

340   Figure 5B).

341   We put these values for g, v_y and d_y into Equation 4 to stimulate the temporal responses for each trial

342   1000 times. We minimize the Root Mean Square Errors (RMSE) between the standard deviations of the

343   simulated timing error and the observed timing errors, separately for each combination of gravity, initial

344   vertical velocity, Occlusion condition and participant. We collapsed the error across initial horizontal

345   velocities because results for both values were virtually the same, mostly likely because the horizontal

346   velocity barely influences overall flight duration in the presence of air drag, and not at all in the absence

347   of air drag. After visualizing a relevant range of candidate values for the standard deviation of the

348   remaining errors (see Figure 6), we use the optim() function implemented in R with a lower bound of

349   0.01 s and an upper bound of 0.06 s to find the best fit for the observed data. We found the best fit for a

350   standard deviation of 0.058 s, with an RMSE of 0.04.

351

352   The Standard Deviation of the Gravity Prior

353   We then proceed to apply these values to simulate data sets based on the above assumptions, get the

354   standard deviations for the timing error and compare them to standard deviations of the observed timing

355   errors (Method 1). We restrict this comparison to the 0.7g/0.85g/1g/1.15/1.3g condition, as we expect

356   the gravity model not to be activated for inverted gravitational motion. For a discussion of factors

357   impacting the performance of the model for short occlusions, see (Jörges et al., 2018). We first simulate

358   a range of sensible standard deviations (from 0, corresponding to an impossibly precise representation,

359   to 0.28, corresponding to a quite imprecise representation with limited impact on the final percept, in

360   steps of 0.03) to determine the lower and upper bounds of the optimization interval (see Figure 6B). Figure

361   5D furthermore highlights how changes in the simulated variability of the represented gravity changes

362   response variability.

363

364   We find the errors to be lowest around 0.21, and choose thus 0.16 as the lower bound and 0.26 m/s² as

365   the upper bound. We then search for that standard deviation that minimizes the error between simulated

366   and observed timing errors, using the optim() function implemented in R (R Core Team, 2017). For each

367   iteration, we simulate 1000 data sets and minimize the Root Mean Square Error (RMSE) between the

368   standard deviations of simulated and observed timing errors across these 1000 data sets. The R code we

369   used for these simulations can be found on GitHub (https://github.com/b-jorges/SD-of-Gravity-Prior),

370   including extensive annotations. We found a normalized standard deviation of 0.208 for the gravity prior,

371   which corresponds to a standard deviation of about 2.04 m/s² for a mean of 9.81 m/s², and a Weber

372   fraction of 14.1%. The RMSE is 0.024. In Figure 7, we illustrate how the simulated standard deviations

373   relate to the observed ones. The light red dots correspond to this method ("Simulated (Method1)"); as

374   evident from the figure, the fits are better for the Long Occlusion condition, while the SDs are generally

375   overestimated for the Short Occlusion condition.

376   If the gravity prior was discarded completely for upwards motion, we might observe even larger errors for

377   -1g motion. We elaborate on this issue in the discussion. As there is thus some reason to believe that the

378   gravity prior is not completely inactive in upwards motion, which may bias to above method to

379   overestimate the standard deviation of the gravity prior, we furthermore conducted simulations where

380   both the motor variability and the strong gravity prior are fitted to the data (Method 2). To this end, we

381   use the optimize() function implemented in R which uses the Nelder and Mead method (Nelder & Mead,

382   1965) to determine those values for the motor standard deviation and the standard deviation of the

383   gravity prior that yield the smallest errors between simulated and observed variability. This is suitable

384   because variability in the gravity prior and motor variability affect the final variability differentially (see

385   Figure 5): a higher motor variability leads to uniformly higher standard deviations for the observed error,

386   while a higher gravity variability affects longer trajectories (Long Occlusion, higher initial vertical velocity

387   and lower gravities) more strongly than shorter ones. Based on above results, we chose 0.04 and 0.2 as

388   starting parameters, but did not limit the parameter space. This method allots variability in slightly

389   different proportions: the standard deviation for the motor error is 0.06 s and the standardized standard

390   deviation of the gravity prior is 0.211 (which corresponds to a non-standardized standard deviation of

391   2.07 m/s² and a Weber fraction of 14.2%), with an RMSE of 0.024. These values are extremely close to the

392   values found with Method 1. While it is worth noting that fitting both parameters to the data makes this

393   method more susceptible to overfitting, this lends additional support to the tentative conclusion that the

394   standard deviation of the gravity prior is just above 2 m/s² or a Weber Fraction of 14.2% The simulated

395   standard deviations for these conditions are depicted in solid red in Figure 7 ("Simulated (Method 2)"):

396   The fits are much better for the long occlusions, at the cost of a slight overestimation of the variability for

397   the short occlusions.

398

399   Discussion

400   Humans assume in many tasks and circumstances that objects in their environment are affected by earth

401   gravity. It has thus been suggested that we maintain a representation of this value, which we then recruit

402   to predict the behavior of objects in our environment. We recently interpreted this representation as a

403   Strong Prior in a Bayesian framework (Jörges & López-Moliner, 2017). A "Strong Prior" is a prior with a

404   reliability so high that it overrules any sensory input represented in the likelihood. Based on data from

405   timing task (previously reported in Jörges & López-Moliner, 2019), we make an attempt at determining

406   the standard deviation of a hypothetical Strong Earth Gravity Prior. Our general approach is to account

407   for other sources of perceptuo-motor variability in the task based on thresholds reported in the literature,

408   and attributing the remaining variability to the Gravity Prior. Based on this approach, we find a standard

409   deviation of 2.13 m/s² (Method 1) or 2.07 m/s² (Method 2), for a prior with a mean of 9.81 m/s², which

410   corresponds – mathematically – to a Weber fraction of 14.1% or 14.2%, respectively. This is considerably

411   lower than Weber fractions generally observed for acceleration discrimination, but above Weber fractions

412   for the discrimination of constant speeds (McKee, 1981).

413   Interestingly, when we simulated the timing errors with a fixed value of 9.81 m/s² (i.e., in a non-Bayesian

414   framework where the value of earth gravity is not represented as a distribution, but rather a value set at

415   1g; see Jörges & López-Moliner, 2019 and also above), we found that our results fit the observed timing

416   error quite nicely for each gravity value. That is, the observed gravity (corresponding to the Likelihood)

417   had no discernable influence on the final percept (Posterior). However, in a Bayesian framework, this is

418   only possible if the Likelihood is extremely shallow and the Prior is extremely precise. A Weber fraction of

419   about 30% for the likelihood (which we assume for acceleration discrimination), and a Weber fraction of

420   14.1% or 14.2%. for the prior (as modelled) would not result in discarding the likelihood completely (see

421   also Figure 1; even for a strong prior and a rather shallow likelihood, the likelihood attracts the posterior

422   to some extent). Our results thus reveal a mismatch between the means observed in our experiment, the

423   modelled standard deviation and a Bayesian explanation.

424   We see two possible ways to explain this mismatch. Firstly, our observed standard deviation for the gravity

425   prior could be an upper bound. Our method relies on identifying all sources of variability and allotting

426   variability in the response accordingly. Since we did not measure our participants' Weber fractions for

427   velocity and distance discriminations individually, but rather used averages reported in the literature for

20

428 somewhat different tasks, this may have distorted how much variability perceived distances and velocity

429 at disappearance introduced in the response. Furthermore, when estimating the variability introduced in

430 the motor response, we part from the premise that the internal model of gravity is not activated at all for

431 -1g motion. However, we observe a bias to respond too late in this condition, suggesting that humans

432 expect objects to accelerate less when moving upwards. This could be taken as evidence that the internal

433 model of gravity is still activated to some extent. In this case, we would need to allot more variability to

434 the motor error, which in turn would lead to a lower standard deviation for the gravity prior. However,

435 this pattern in our data is also consistent with humans taking arbitrary accelerations into account

436 insufficiently in perceptuo-motor tasks, which has been reported repeatedly for tasks where the gravity

437 prior is highly unlikely to be recruited (Benguigui, Ripoll, & Broderick, 2003; Bennett & Benguigui, 2013;

438 Brenner et al., 2016; Werkhoven et al., 1992). The values of 14.1% or 14.2% obtained above may thus be

439 an upper bound for the standard deviation of the Earth Gravity Prior.

440 A second possibility is that prior knowledge and online perceptual input are combined in a non-Bayesian

441 fashion (and we should thus avoid the terminology "Prior", "Likelihood" and "Posterior"), where the mean

442 of the final percept is set according to an acceleration of 9.81 m/s², while its standard deviation is

443 determined by a (not necessarily Bayesian) combination of prior knowledge and online sensory

444 information.

445

446 Conclusion

447 In this paper, we build upon a simple model for coincidence timing of gravitational motion brought

448 forward in (Jörges & López-Moliner, 2019). By accounting for the Aubert-Fleischl phenomenon, we extend

449 the domain of our model to also include shorter extrapolation intervals. Furthermore, we propose a

450 procedure to determine the standard deviation of a potential gravity prior, and apply it to pre-existing

451   data from a timing task. Standard deviations of 2.13 m/s² or 2.07 m/s² (depending on the method)

452   explains the behavior observed in our task best. However, considering the literature we would expect an

453   even lower standard deviation, as a Prior with a mean of 9.81 m/s² and standard deviations of 2.13 m/s²

454   or 2.07 m/s² should not attract the Posterior as strongly as has been commonly observed. We thus believe

455   that we are not able to fully disentangle different sources of noise in our data; the value we find for the

456   standard deviation of the earth gravity prior is thus more likely an upper bound, and follow-up

457   experiments may find lower values.

458

Author Contributions and Notes

460   BJ conducted the simulations and wrote the paper. BJ and JLM established the research question in a joint

461   effort. JLM provided advice at every step of the project.

462   The authors declare no conflict of interest.

463

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467

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588

589 *Figure 1: Graphical illustration of Likelihood, Prior and Posterior in a Bayesian framework, for both a normal, relatively shallow*
590 *Prior, and a strong, extremely precise Prior.*

591 *Figure 2: 2D depiction of the visual scene used as environment for stimulus presentation. The stimulus was always presented in*
592 *front of the white wall and never crossed other areas (such as the lamps of tables) that could introduce low level differences in*
593 *contrast etc. The lines denote the different parabolic trajectories that along which the targets travelled. Figure from (Jörges &*
594 *López-Moliner 2019).*

595 *Figure 3: Temporal errors in the 0.7-1.3 g conditions. The wings of each structure indicate the distribution of responses, while the*
596 *boxplot in the middle of each structure indicate the 75% percentiles and the mean per condition.*

597 *Figure 4: Mean temporal errors that we observed in our participants (across participants in blue, and for each participant*
598 *separately in shades of grey), simulated taking the Aubert-Fleischl phenomenon into account (light red) and simulated without*
599 *taking the phenomenon into account for the different conditions. The right column represents values for the Long Occlusion*
600 *condition, while the left column represents the Short Occlusion condition. The upper row shows values for an initial vertical velocity*
601 *of 4.5 m/s, while the lower row represents initial vertical velocities of 6 m/s. Note that the standard errors for the observed errors*
602 *are so small that all error bars fall well within the area covered by the dots.*

603 *Figure 5: Predictions for different standard deviations chosen for different parameters in our model. Dots represent the standard*
604 *deviation for each gravity (0.7g-1.3g), divided by Occlusion category (Long and Short) and initial vertical velocities (4.5 and 6 m/s).*
605 *The color gradient indicates different values of the (standardized) standard deviation for the perceived distance, the perceived*
606 *velocity, the represented gravity and the remaining error. The baseline values are 0.148 for distance and velocity, 0.1 for gravity*
607 *and 0.05 for the remaining (motor) error. A. Predictions for five standardized standard deviations for the perceived distance (0.1-*
608 *0.3 m). B. Predictions for five standard deviations for the remaining (motor) error (0.02-0.1 s), modelled as independent of and*
609 *constant across initial velocities, gravities and occlusion conditions. C. Predictions for five different standardized standard*
610 *deviations for the last perceived velocity (0.1-0.3 m/s). D. Predictions for five different standardized standard deviations for the*
611 *represented gravity (0.02-0.18 m/s²).*

612 *Figure 6: A. Root mean square errors (RMSE) between the standard deviation of timing errors simulated based on different motor*
613 *errors (between 0.00 and 0.07 s) and the standard deviation of observed timing errors. B. Root mean square errors (RMSE)*
614 *between the standard deviation of timing errors simulated based on different standard deviations of the gravity prior between*
615 *0.15 and 0.25*9.81 m/s² and the standard deviation of observed timing errors.*

616   *Figure 7: Observed and Simulated Standard Deviations separated by Occlusion Condition, initial vertical velocity and presented*
617   *gravity. Blue indicates the observed standard deviations across subjects, while the standard deviations simulated through the two-*
618   *step process (Method 1) are coded light red and the standard deviations simulated through the two-parameter fit (Method 2) are*
619   *coded solid red.*

620