BACHELOR THESIS

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Serial Dependence in Verticality Perception

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Abstract

Keeping balance while walking and perceiving a stable visual image of the world at the same time is achieved by our ability to perceive the gravitational vertical and adjust to it. A Bayesian integration model for verticality perception has been suggested by Alberts et al.(2016). This model treats responses as independent, however, recently perceived stimuli and our decisions regarding those stimuli can influence the way we perceive the current moment. Two phenomena account for this interaction — adaptation and serial dependence. In this thesis I've explored the possibility of finding effects from those two phenomena in the data from the rod-and-frame task done by Alberts et al. (2019) and concluded that there is serial dependence.

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Chapter 1

Introduction

Verticality perception is of utmost importance for humans to be able to perceive and act in the world. It is achieved by a combination of multiple information sources — visual, vestibular and somatosensory[2]. One way to test the extent to which each information source weights in is the rod-and-frame task. This task consists of several stages - a square frame shows up on a screen followed by the addition of a rod within the frame. Subsequently, the participants indicate whether the perceived orientation of the rod was clockwise or counterclockwise from the perceived gravitational vertical. Figure 2.1 provides a visual illustration of the task. The frame and rod have different orientations relative to gravity which are randomly chosen from a set. The results from this experiment show that participants perceive the rod's orientation with a bias towards the orientation of the frame[1].

To account for this visual-vestibular interaction Alberts et al. (2016) have put forward a Bayesian inference model that incorporates the visual-frame cues with vestibular information and the *a priori* notion that head roll tilts are usually small, to approximate the perceived head-in-space orientation. From this head-in-space posterior the maximum *a posteriori* (MAP) is acquired. To obtain the perceived orientation of the rod in space, the MAP orientation is then transformed using the eye-in-head orientation and the retinal orientation of the rod estimate. This model is fitted to the data from the rod-and-frame experiment and has been shown to explain the rod-and-frame effect [1].

The current model treats responses as independent, however, we live in a world that is usually stable and continuous over time. As a result of that the recent past can be a good predictor of the current state of the world — recently perceived visual stimuli influence the way we perceive the present stimuli. However, there is an ongoing debate about whether this effect is positive or negative. Two partially competing theories can account for this interaction — adaptation and serial dependence[5].

Adaptation results in a negative correlation between the current percept and the adaptor. In the early 1900, it was already demonstrated that the orientation of a line with respect to the vertical and horizontal axes can be subject to this phenomenon[6]. A line initially perceived as somewhat tilted from one of the axes appears progressively less tilted with the duration of the exposure. The opposite effect was documented as well — a line initially perceived as vertical or horizontal appears tilted towards the other axis with time. This visual illusion called the tilt aftereffect is always negative and independent of initial orientation — clockwise or counterclockwise[8].

On the other hand, serial dependence is a positive correlation between the current stimuli and the preceding observed one. It results after short exposure to the previous stimuli and decays progressively with time[3]. These observations can explain why Fischer et al. (2014) put forward the idea that perception is attracted to the very recent past, repulsed from stimuli presented at short to medium timescales, and attracted to presentations further in the past.

To explain better the relation of those two phenomena, recent literature's center of attention is the dissociation between the effect of past stimuli and the effect of the subject's own past choices — a distinction between perception and post-perceptual processes[7][9][4]. Post-perceptual decisions about orientation tend to be repeated — a positive, attractive effect is found between the recent choice (trial n-1) and the current one (trial n). This bias is not strongly dependent on the spatial location of previous stimuli. Conversely, observers' perception is repelled away from previous stimuli — a negative effect is found between the recent stimulus (trial n-1) and the current one (trial n). This phenomenon is especially present when the exposure in the preceding trial is long compared to the time between trials, resembling low-level adaptation.

The focus of this thesis is to explore whether there is serial dependence in the data and to reason about how this dependence can be incorporated into the Bayesian integration model for verticality perception. Capturing these effects should improve the estimate of otolith noise, making it smaller, and thus improve the clinical value of the approach.

Chapter 2

Preliminaries

In this chapter I provide a more thorough overview of the rod-and-frame task and I will dive deeper into the formulas behind the Bayesian integration model. For more background reading — [1][2].

2.1 The data

The data that I'm working with for this project is from the paper "Age-related reweighting of visual and vestibular cues for vertical perception" by Alberts et al.(2019). It consists of the responses of 16 naive healthy subjects between the ages of 19 and 51 from the rod-and-frame task.

2.2 Rod-and-Frame Task

The rod-and-frame task is used to characterize the multi-sensory interactions between signals for verticality perception. Participants are seated in front of a black screen. At each trial a gray square frame is presented, subsequently, after 250 ms, a rod is briefly flashed for 33 ms in the center of the frame. Participants indicate, by pressing a button, whether they perceived the orientation of the rod to be clockwise (CW) or counterclockwise (CCW). After the response the screen turns black for 500 ms and a new trial begins. The frame orientation is randomly chosen from a set of 18 angles between -45°and 40°in steps of 5°, whereas the rod orientation is selected from a set of nine orientations centered around the perceived gravitational vertical (-7°,-4°,-2°,-1°,0°,1°,2°,4°, 7°) or (-15°,-10°,-5°,-2°,0°,2°,5°,10°,15°) depending on the experiment condition. Figure 2.1 provides a visual illustration of the task.

The perceived gravitation vertical is different for each subject - before performing the task participants perform a subjective visual vertical task without a frame. Every rod orientation is presented 10 times and the Point of Subjective Equality (PSE) is then estimated as the perceived orientation at which the subject responds 50% CW and 50% CCW. The PSE is then used as the orientation relative to which the rod orientations are centered.

The rod-and-frame task is repeated 3 times for head position at 0°, 15°and 30°. For the condition of head position at 0°the first rod orientation set is used, for the other two conditions the second rod orientation set is used.

Trials are presented pseudo randomly, with each set containing one repetition of each combination of frame and rod orientation. In total, 10 sets were tested, yielding 1620 trials per condition.

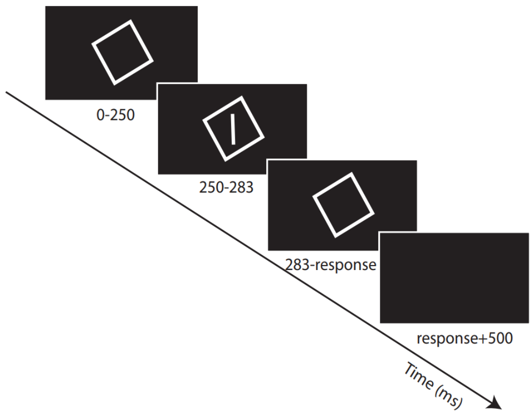

Figure 2.1: **Experimental procedure of the rod-and-frame task**. At each trial a frame is presented for 250ms, subsequently a rod is flashed for 33ms. The frame is then visible to the subject until a decision for the rod orientation, clockwise vs counterclockwise, has been indicated. The trial is ended with 500ms of black screen.

2.2.1 Rod-And-Frame Effect

Without a frame for reference and when seated upright people tend to overestimate small rod tilts and underestimate larger ones. This effect, however, is affected by the presence of a frame. The biases become cyclical — with a near-zero bias for upright and tilted ± 45°frame orientation, and for in-between frame orientations the bias is in the direction of the frame. The so-called rod-frame-effect (RFE) observed decreases when the frame size is bigger and increases with the tilt of the head[1].

2.3 The Model

The Bayesian optimal integration model provided by Alberts. et al. (2016), accounting for the observed bias and variability in the rod-and-frame task, consisting of prior, vestibular likelihood and contextual likelihood combined together with coordinate transformation, is discussed below in details.

2.3.1 The Head-in-space Prior

It is assumed that the head is usually in an upright position, so the prior is modelled by a Gaussian distribution centered around 0 with a standard deviation of σ_{HP}:

$$P(H_s) \sim N(0, \sigma_{HP})$$

2.3.2 The Vestibular likelihood

The vestibular likelihood is modelled by a Gaussian distribution centered around the true head orientation H_{true} and with a standard deviation of σ_{HV}. Due to the decrease of otoliths' sensitivity with larger head tilts, σ_{HV} is modeled by a linear equation. The noise of the otoliths is increasing as a function of the head orientation :

$$\sigma_{HV} = \alpha_{HV}(|H_{true}|) - \beta_{HV}$$
$$P(H_s \mid H_{true}) \sim N(H_{true}, \sigma_{HV})$$

2.3.3 The Contextual likelihood

The contextual likelihood is modelled by a sum of four von Mises distributions each with a peak at one of the four cardinal directions of the frame. First and foremost it is important to find where on the retina the frame falls — what is the observed frame orientation in retinal coordinates — θ_F^{ret}. In this and the following section the subscript denotes what we are observing — frame(F), rod(R), head(H), eye(E), and the superscript denotes in what context — retinal coordinates(ret), real-world(W) and head (H). It is important to be noted that the observed retinal orientation has a sign opposite that of the true spatial orientation. Thus, a frame of 20°spatial orientation would result in a retinal orientation of -20°given that the head is at 0°.

$$\begin{aligned}
\theta_F^{ret} &= -(\theta_F^W - H_{true}) - A_{OCR} * sin(|H_{true}|) \\
\phi &= [0, 90, 180, 270] \\
\kappa_1 &= \kappa_{ver} - [1 - cos(|2 * \theta_F^{ret}|)] * \tau * (\kappa_{ver} - \kappa_{hor}) \\
\kappa_2 &= \kappa_{hor} + [1 - cos(|2 * \theta_F^{ret}|)] * (1 - \tau) * (\kappa_{ver} - \kappa_{hor}) \\
\kappa &= [\kappa_1, \kappa_2, \kappa_1, \kappa_2] \\
P(\widehat{\theta_F^{ret}}|H_{true}) &= \sum_{i=1}^{4} vonMises((\phi_i - \theta_F^{ret} - H_{true}), \kappa_i)
\end{aligned}$$

The formula for frame on retina also takes into account eye torsion as $A_{OCR} * sin(|H_{true}|)$, where parameter A_{OCR} denotes uncompensated ocular counterroll.

2.3.4 The Head-in-space Posterior

To obtain the head-in-space posterior, which is what the subject estimates to be his head orientation, the prior is multiplied with the likelihoods resulting in :

$$P(H_s|H_{true}, \widehat{\theta}_F^{ret}) = P(H_s) * P(H_s \mid H_{true}) * P(\widehat{\theta}_F^{ret}|H_{true})$$

Figure 2.2 shows three examples of the Bayesian Integration Model with parameters taken from the Alberts et al. (2016) paper Table 1.

2.3.5 Probability of CW response

After obtaining the head-in-space posterior from the model we need to find what is the probability of CW response given a rod orientation. We need to use the formula for transformation from spatial to retinal coordinates and alter it to find the rod in space estimate given the true head, frame and rod orientations.

$$\begin{aligned} \theta_E^H &= A_{OCR} * sin(\mid \theta_H^W \mid) \\ \theta_R^{ret} &= -(\theta_R^W - \theta_H^W) - \theta_E^H \end{aligned}$$

Altering the equation above we get :

$$\widehat{\theta_R^W} = \widehat{\theta_H^W} - \theta_R^{ret} - \theta_E^H$$

Here I have substituted the head in space (head in real-world) with the estimate that we have obtained from the model's posterior.

Given this equation we can substitute the θ_R^{ret} with the first formula :

$$\begin{aligned} \widehat{\theta_R^W} &= \widehat{\theta_H^W} - (-(\theta_R^W - \theta_H^W) - \theta_E^H) - \theta_E^H \\ &= \widehat{\theta_H^W} - (\theta_H^W - \theta_R^W - \theta_E^H) - \theta_E^H \\ &= \widehat{\theta_H^W} - \theta_H^W + \theta_R^W + \theta_E^H - \theta_E^H \\ &= \widehat{\theta_H^W} - \theta_H^W + \theta_R^W \end{aligned}$$

Given the rod in space estimate $\widehat{\theta_R^W}$, the probability of a CW response is then the integration of all the positive values — the rod orientation that should yield a CW response. This can also be obtained without the axis shift, directly, as an integration of the head-in-space posterior for the values that are bigger than $\theta_H^W - \theta_R^W$

$$P(CW|H_s, \theta_R^{ret}) = \int_{x=\theta_H^W - \theta_R^W}^{180} P(x \mid \widehat{\theta_H^W}, \widehat{\theta}_F^{ret}) dx$$

Figure 2.3 shows the probability of CW response for different rod orientations calculated from the three example posteriors from Figure 2.2. Figure 2.4 shows the bias shift represented by the change on the PSE for different frame orientations in the head upright condition.

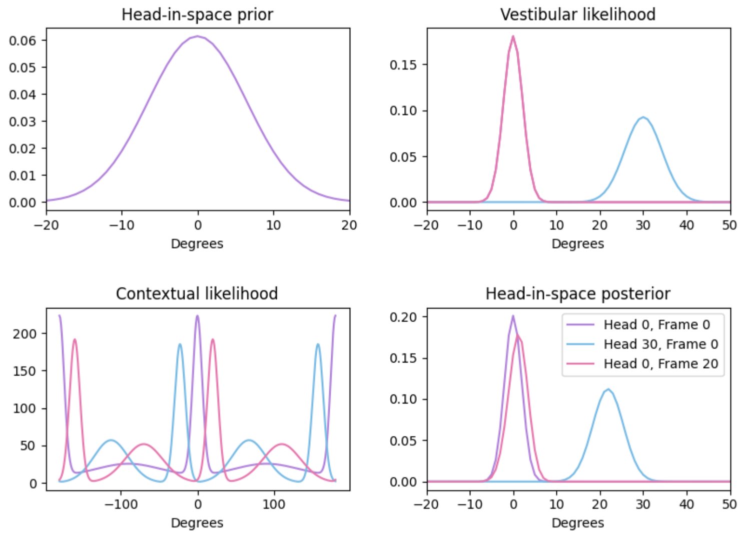

Figure 2.2: **Prior, likelihoods and posterior of three different cases** — 1) head and frame at 0°, 2) head at 30 °and frame at 0°, 3) head at 0°and frame at 20°. The parameters used in the model to generate the plots are taken from the Alberts et al. (2016) paper Table 1 [1]. Because the prior is that the head is at upright position all the cases have the same prior. For case 1) and 3) the head position is at 0°, thus the vestibular likelihood is centered around 0. For case 2) the vestibular likelihood is centered around the true head orientation — 30. We can see how the vestibular distribution for case 2) is wider compared to the distribution for case 1) and 3) — there is more uncertainly, noise from the otoliths, when the head is tilted. At the bottom left the the contextual likelihood for case 1) has two peaks : one at 0 degrees and one at 180 degrees, which becomes plotted as two half peaks at each side. The contextual likelihood for case 3) however has two main peaks and two smaller peaks which are in result of the horizontal sides of the frame — now that the frame is at 20°the horizontal lines weigh in more. The contextual likelihood for case 2) also have 4 peaks, two of which smaller — because of the head tilt of 30°the frame is perceived as $\sim -20°$. The frame is not perceived as -30, because of the ocular counter roll accounted for as A_{OCR}. Lastly, on the bottom right we can see the head-in-space estimation — the posterior. We can see for case 1) the probability distribution being centered around 0°and the uncertainly being the smallest of all three cases. For the third case we can see how the frame of 20°has slightly shifted the perceived orientation of the head towards it's orientation — as expected from the RFE explained in Section 2.2.1. The uncertainty in this scenario is also a bit larger than in case 1). Lastly for case 2) we can see how the contextual likelihood has shifted the vestibular estimate and the peak of the posterior is around 22°instead of 30°.

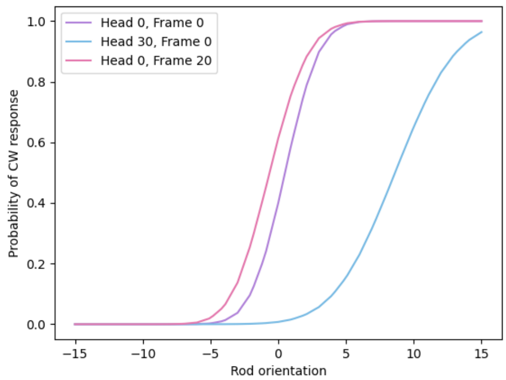

Figure 2.3: **Probability of CW response of three different cases** — 1) head and frame at 0°, 2) head at 30 °and frame at 0°, 3) head at 0°and frame at 20°. The parameters used in the model to generate the plot are taken from the Alberts et al. (2016) paper Table 1.As expected the PSE of case 1) is near 0°. The PSE of case 3) is smaller than the one in case 1), this can be explained by the frame orientation being positive and the RFE making the rod appeared as more tilted towards the frame. Lastly the curve for case 2) is shifted to the right because the positive head orientation makes the frame to be perceived as negative and thus the rods being tilted towards the negative orientation resulting in smaller chance of a CW response. We can see that the uncertainty in this case is larger than in cases 1) and 2) an that is due to the uncertainty from the head in space estimate as mentioned in Figure 2.3

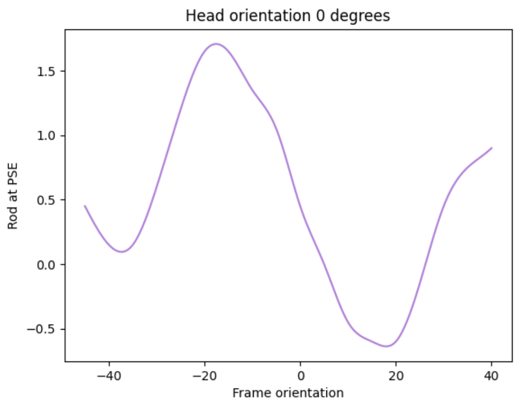

Figure 2.4: **Frame induced biases for head at upright position**. For each frame orientation the point of subjective equality is shown. The bias is highest for ± 20°frame orientation. The parameters used in the model to generate this plot are taken from the Alberts et al.(2016) paper Table 1. As expected the PSE is a a direct reflection of the RFE discussed in Section 2.2.1.

Chapter 3

Methods

Before revisiting the model, initial data analysis is needed to determine whether there is a significant difference between trials following previous clockwise (CW) vs counterclockwise (CCW) responses. To this end I split the data based on the previous trial's response, resulting in a set with a CW response on the previous trial and another set with a CCW response on the previous trial.

For every combination of frame and rod, the proportion of CW responses is calculated. Subsequently, for every frame orientation a psychometric curve is fitted to the data using a cumulative Gaussian.

$$P(CW) = \lambda + (1 - 2\lambda)\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{x} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

Where λ denotes the lapse rate (i.e., guess rate), accounting for non-informed responses of the subject. x represents the rod orientation and μ and σ represent the subjects' perceived orientation of gravitational vertical and response variability.

The fitting was performed using Python's *scipy.minimize* function, which finds the parameters λ, μ and σ that minimize the negative log-likelihood of obtaining the participant's responses for the frame and rod.

For every subject all frames are fitted simultaneously together with a single lapse rate because non-informed responses do not depend on external factors such as frame and rod orientation. This results in 37 parameters to be optimized in parallel for each subject for each condition — 18 μ, 18 σ and 1 lapse rate.

The initial values used in the minimization function are as follows — for the bias μ I've used the gravitational vertical — zero, for σ I've used two, based on the results illustrated in Figure 3. from Alberts et al. (2019) and for the lapse rate I've used 0.05, based on information from the same paper Table 2.

The boundaries I've set for the parameters are also based on information from the aforementioned paper — μ should be between -20 and 20, given that the maximum rod orientation in the tilted head condition is 15°, sigma between 0.1 and 8 and lapse rate between 0 and 0.1.

The resulting data contains 576 μ and σ for each of the three head conditions — 16 subjects, 18 frames, CW and CCW μ and σ. Combined together that scales up to 1728 entries. To determine if there is a significant difference between the means of the CW previous vs CCW previous response a three-way repeated measures ANOVA is used on the combined dataset. The dependent variable is the bias — μ and the factors are frame orientation with 18 levels, previous response with two levels (CW and CCW) and condition with three levels (head at 0°, head at 15°and head at 30°) and participant as a random factor.

To further determine the significance of the previous response on the current one and unravel the interaction between frame orientation and previous response I conducted three separate two-way ANOVA measurements including partial eta squared measurement on each of the three head-orientations datasets.

Chapter 4

Results

4.1 Psychometric results

In Figure 4.1 the raw data of a representative subject is plotted as the proportion of CW responses for each rod orientation for all 18 frame orientations for a head at 0 °separated based on the response on the previous trial — CW or CCW. To quantify the bias and response variability in each case a psychometric curve was fitted to the data as explained in Section 3.

It can be noticed that the overall bias (μ) increases starting from frame orientation 0°and peaks around frame orientation 20°, from which it then decreases. Similarly to that, in the other direction it decreases with a peak around frame orientation of -20°after which it goes slowly back to the same value of near 0 for frame orientation of -45°. This is a direct result of the frame-and-rod effect described in Section 2.2.1. The bias is in the direction of the frame for frame orientations between the two extremes of ± 45 and 0. The variability also increases with the frame tilt in either direction showing how the contextual cues (frame orientation) affect the uncertainty.

Comparing the two psychometric curves it is clear to notice that the bias in the CW case is always lower than the one for the CCW case, showing that there is a higher chance of a CW response if the previous response was also CW.

Similar and more extreme results can be observed for head orientation of 15°(Figure 4.2) and 30°(Figure 4.3).

Comparing the differences in biases per frame in the three conditions it can be noted that the gap between the two curves becomes larger with the increase of the head tilt. This can be a result of the growing unreliability of the vestibular information due to the head tilt, which triggers a post-perceptual effect of positive serial dependence.

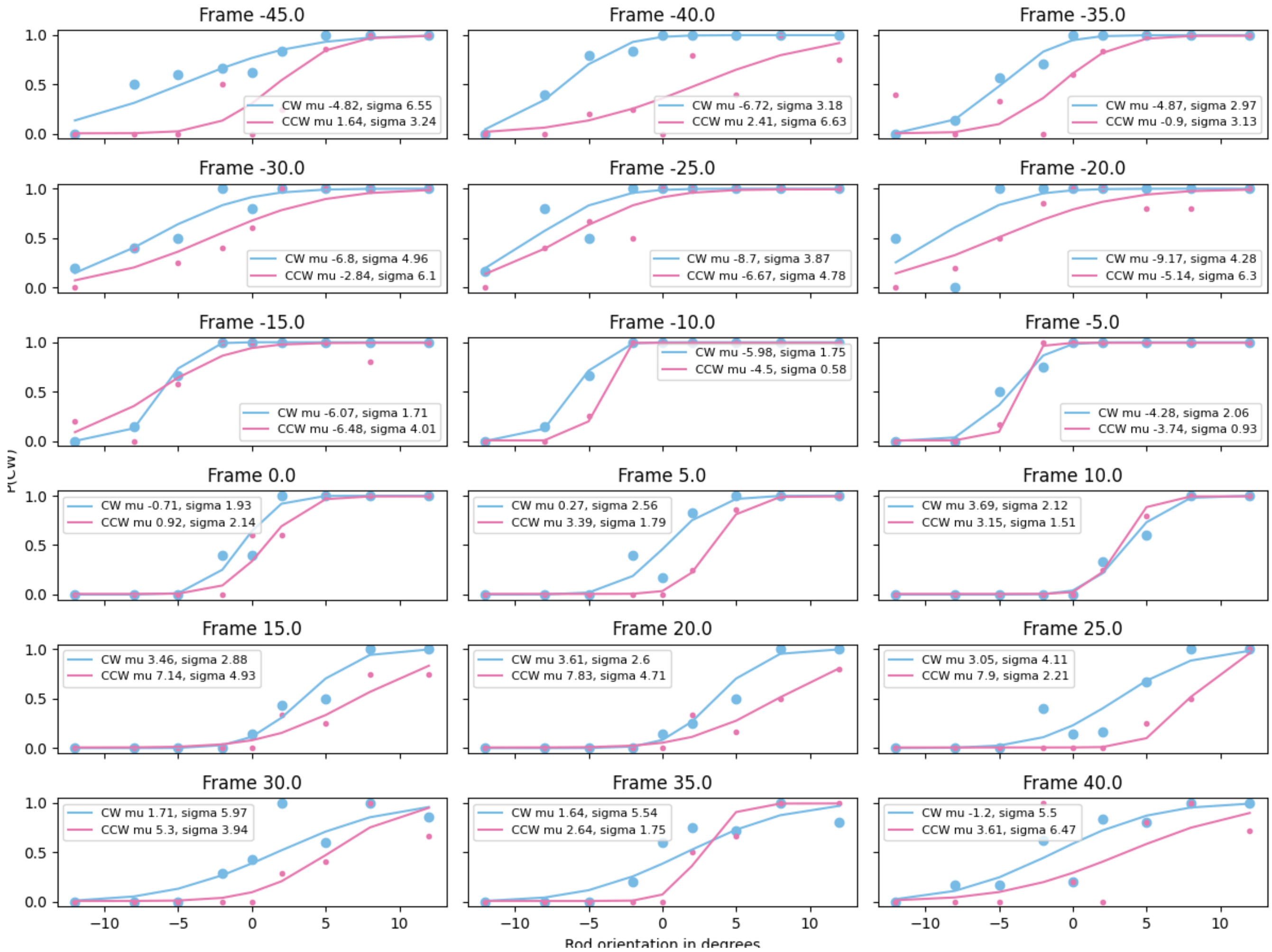

Figure 4.1: Probability of CW responses plotted against rod orientation for each of the 18 frame orientation for head position of 0°for a representative subject (number 8). The data is separated based on response on the previous trial resulting in two datasets and thus two curves.

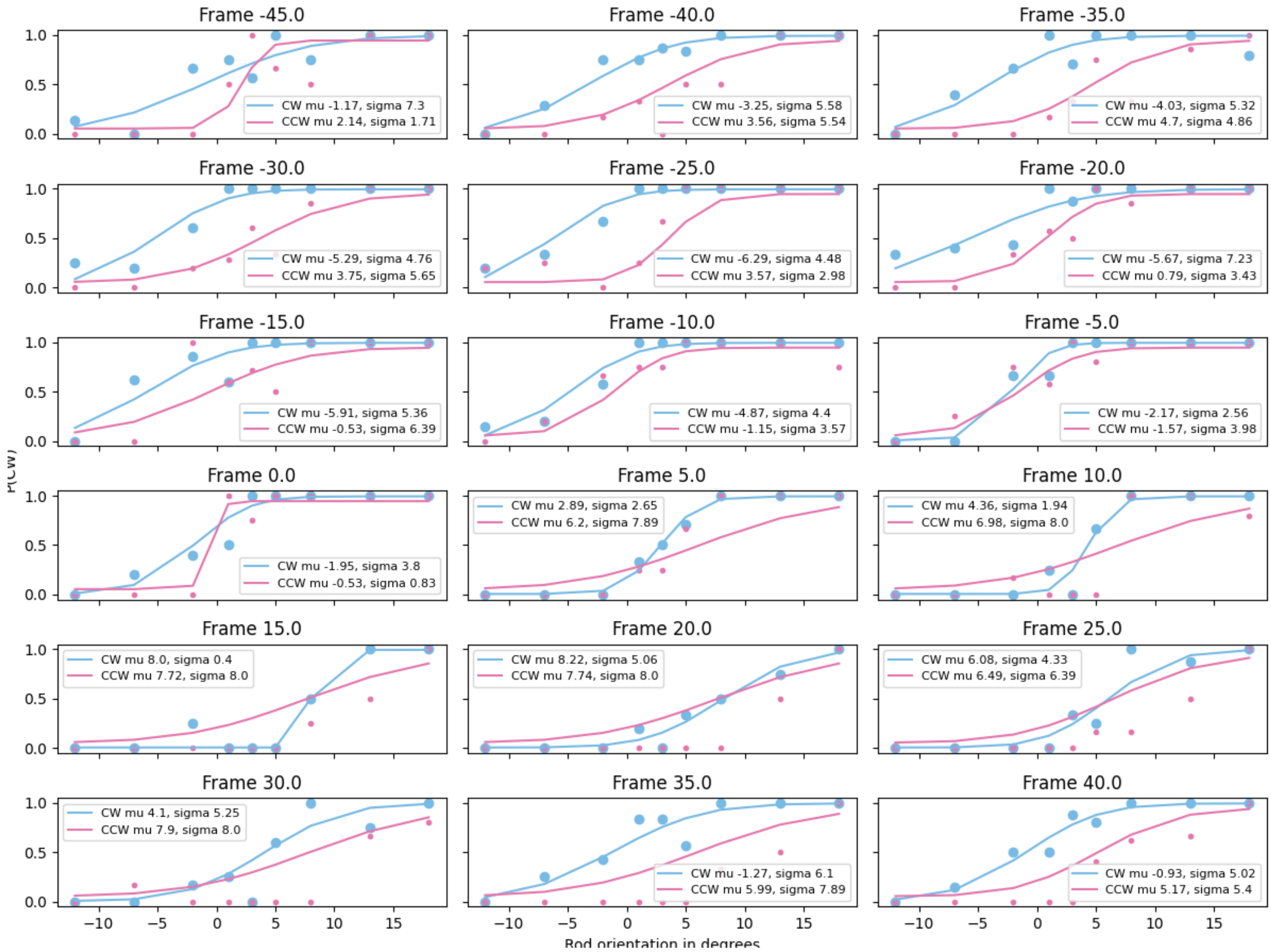

Figure 4.2: Probability of CW responses plotted against rod orientation for each of the 18 frame orientation for head position of 15°for a representative subject (number 8). The data is separated based on response on the previous trial resulting in two datasets and thus two curves.

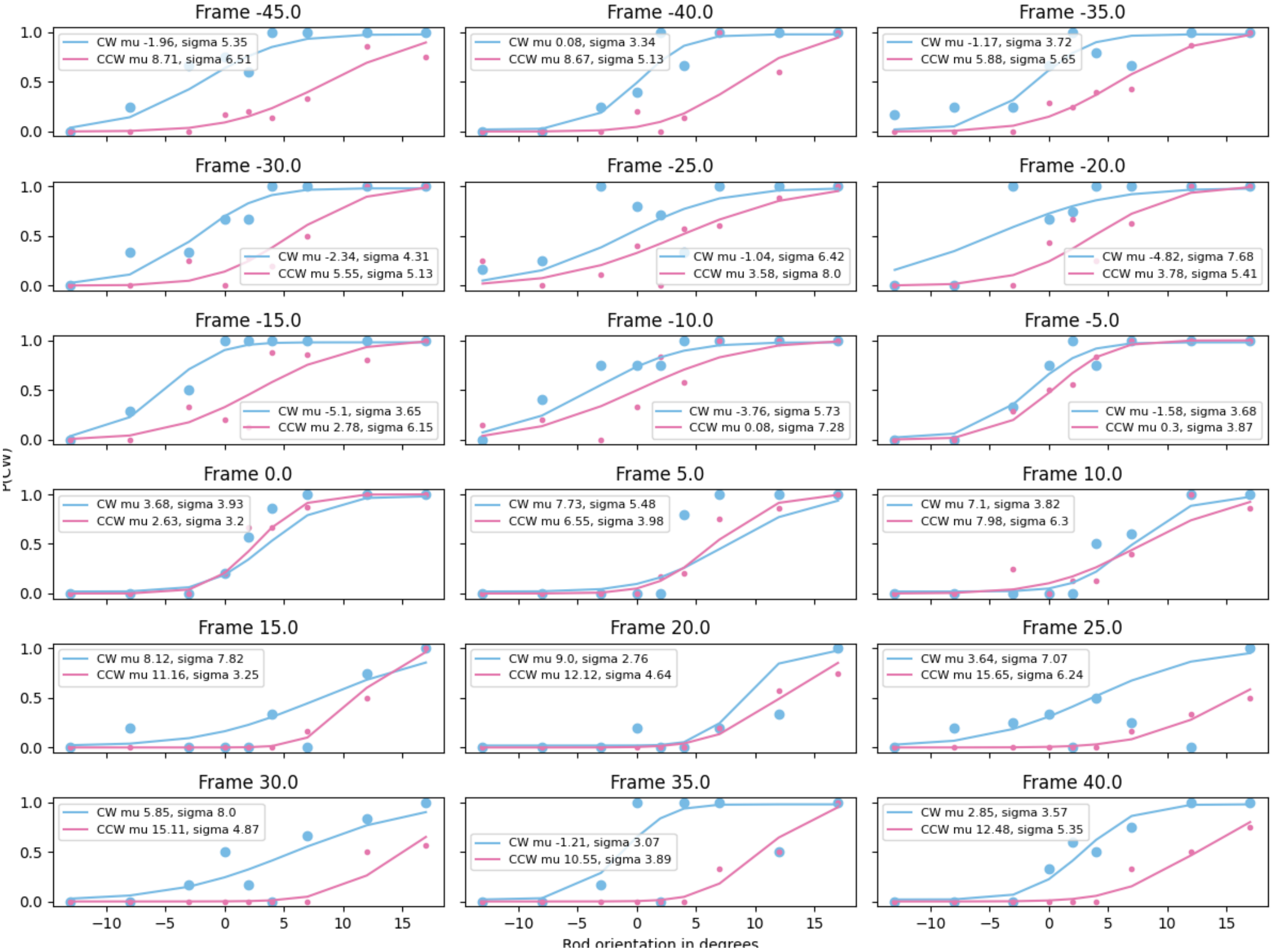

Figure 4.3: Probability of CW responses plotted against rod orientation for each of the 18 frame orientation for head position of 30°for a representative subject (number 8). The data is separated based on response on the previous trial resulting in two datasets and thus two curves.

Figure 4.4 summarizes the shifts in μ and increases in variability across all participants. The bias (μ) and variability (σ) for CW and CCW previous response are plotted against the frame orientation for each of the three conditions — head orientation of 0°, 15°and 30°. As mentioned above for all three conditions the bias in the CW data is smaller than the one in the CCW, this comes to show that the psychometric curve for CW previous response is shifted to the left, meaning participants tend to repeat their choices.

There are two main things to be noted here. Firstly, the mean difference between the two cases increases with the head tilt. For head at 0°the average difference is 1.82, for head at 15°is 3.34 and for head at 30°is 5. Secondly, in all three cases we can see that the mean difference also increases with the frame tilt.

Those interactions might be a result of the growing uncertainty connected to the head and frame tilt resulting in a need for another information source. Assuming that the world is usually stable and continuous over time repetition of the previous choice becomes an adequate substitute for the missing confidence.

As expected there is no significant difference in variability between the CW and CCW cases.

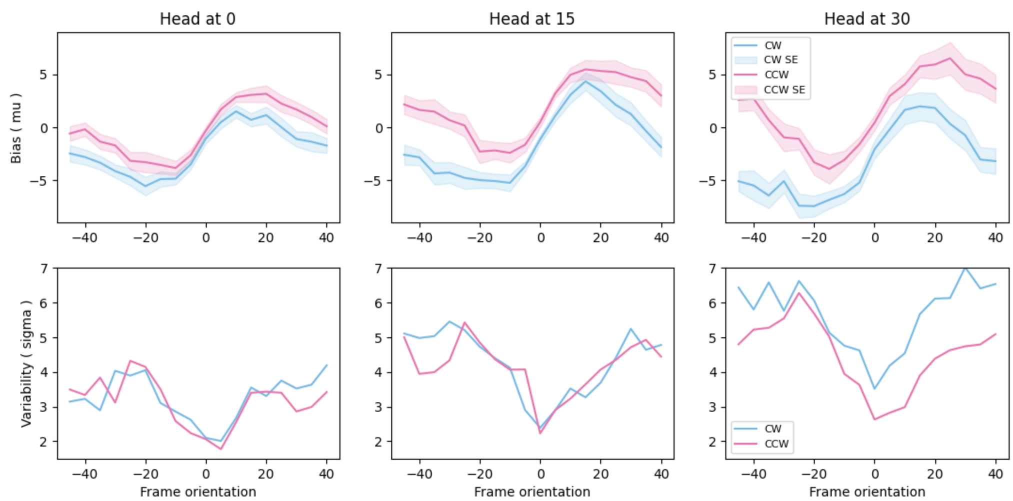

Figure 4.4: **Bias and variability plotted against frame orientation for the three conditions** — head orientation of 0°, 15°and 30°, for both cases CW and CCW previous response. The shaded areas represent the standard error across subjects.

4.2 Statistical significance

To quantify the effects observed in the figures above, the results of the three-way repeated measures ANOVA are presented in Table 4.1. This analysis shows that the previous response has a main effect on the bias (μ). However, the effect the frame orientation has on the response is also significant — in the last column the P-value of the frame orientation is near 0.

All three two-way interactions show significant results. The strong interaction between previous response and head orientation reflects the increasing difference between the means of CW bias and CCW bias with the increase of the head tilt, as mentioned in the previous section. In addition to that, the interaction between previous response and frame orientation also shows significance — as noticed in Figure 4.4 with the frame tilt in either direction the difference between the means increases. Lastly, the interaction between frame orientation and head orientation refers back to Section 2.2.1 mentioning that the rod-and-frame effect increases with the tilt of the head.

To further unravel those interactions, the results of the separate ANOVA analysis on the three head conditions are provided in Tables 4.2, 4.3, 4.4. In those tables a partial eta squared is also included under column "Effect" as a measurement of the effect size of the different factors. In all the conditions both factors have significant effect on the bias, however, there is a shift of effect from frame orientation to previous response. In Table 4.2 we can see that the effect of frame orientation and previous response is respectively 0.69 and 0.62. In Table 4.3 and Table 4.4 we can see the increase of effect of both factors, but the increase of effect of previous response is larger. The effect of the interaction between previous response and frame orientation also increases with the tilt of the head.

	F Value	Num DF	Den DF	PR >F
previous response	71.0044	1.0000	15.0000	0.0000
frame orientation	47.2705	17.0000	255.0000	0.0000
head orientation	2.2376	2.0000	20.0000	0.1242
pr : fo	11.3490	17.0000	255.0000	0.0000
pr : ho	31.6240	2.0000	30.0000	0.0000
fo : ho	3.4248	34.0000	510.0000	0.0000
pr : fo : ho	2.6369	34.0000	510.0000	0.0000

Table 4.1: **Results of three-way rmANOVA analysis on the whole dataset containing all the head orientations.** Abbreviations "pr", "fo" and "ho" stand for "previous response", "frame orientation" and "head orientation". "Num DF" are the degrees of freedom in the numerator and "Den DF" are the degrees of freedom in the denominator

	F Value	Num DF	Den DF	PR >F	Effect
previous response	25.5249	1.0000	15.0000	0.0001	0.629857
frame orientation	33.8244	17.0000	255.0000	0.0000	0.692776
pr : fo	1.6861	17.0000	255.0000	0.0455	0.101048

Table 4.2: **Results of two-way rmANOVA analysis on head orientation of 0°** Abbreviations “pr” and “fo” stand for “previous response” and “frame orientation”. “Num DF” and “Den DF” are the degrees of freedom in respectively the numerator and the denominator. “Effect” represents partial eta squared effect size.

	F Value	Num DF	Den DF	PR >F	Effect
previous response	50.2540	1.0000	15.0000	0.0000	0.770129
frame orientation	39.0636	17.0000	255.0000	0.0000	0.722549
pr : fo	5.5587	17.0000	255.0000	0.0000	0.270380

Table 4.3: **Results of two-way rmANOVA analysis on head orientation of 15°** Abbreviations “pr” and “fo” stand for “previous response” and “frame orientation”. “Num DF” and “Den DF” are the degrees of freedom in respectively the numerator and the denominator. “Effect” represents partial eta squared effect size.

	F Value	Num DF	Den DF	PR >F	Effect
previous response	85.7331	1.0000	15.0000	0.0000	0.851092
frame orientation	32.8857	17.0000	255.0000	0.0000	0.686754
pr : fo	7.2315	17.0000	255.0000	0.0000	0.325282

Table 4.4: **Results of two-way rmANOVA analysis on head orientation of 30°** Abbreviations “pr” and “fo” stand for “previous response” and “frame orientation”. “Num DF” and “Den DF” are the degrees of freedom in respectively the numerator and the denominator. “Effect” represents partial eta squared effect size.

Chapter 5

Discussion

The focus of this thesis was to explore response dependence in the rod-and-frame task and determine if there is a positive or negative interaction between consecutive trials. The information gained from this analysis would in turn be used in the revision of the visual-vestibular model by Alberts et al.(2016) for a more precise diagnosis of patients with vestibular diseases. From the data analysis I found that there are significant results to support the hypothesis that there is serial dependence and participants tend to repeat their choices. This post-perceptual dependency occurs when there is increased uncertainty introduced by the vestibular signal or the contextual information as a way of compensation. However, more research is needed to dissociate the effects of adaptation and serial dependence.

5.1 Adding reaction time

The main drawback of my analysis is the lack of consideration of reaction time. Perceptual adaptation and post-perceptual serial dependence depend heavily on time. Serial dependence is believed to occur after short exposure to the stimuli and the effect of it to decrease with reaction time. Inversely the effect of adaptation increases with the exposure time[9].

To dissociate the effects of the two phenomena the data needs to be first separated based on reaction time and then based on previous response. The results of the short reaction time should resemble the results in the current analysis but amplified, whereas the results of the long reaction time group should show smaller effects of previous response and decreased interaction between previous response and frame and head orientation.

5.2 Adaptation to frame orientation

Due to the presence of two stimuli in the rod-and-frame experiment — rod and frame — it would only be natural to take into account adaptation to the frame orientation. There is no decision related to the frame orientation so I am not expecting there to be positive serial dependence.

I would expect the contextual effect to linearly decrease with reaction time when the frame orientation is away from the gravitational vertical. My expectation is based on the results from experiments done by Gekas et. al [5].

5.3 Revision of the model

Given the nature of the two phenomena different approaches are needed for their implementation. The current model proposed by Alberts et al. (2016) is symmetric around the gravitational vertical for the head at 0°condition. If I fit the model to the CW and CCW split data, the estimated noise parameters would increase to capture the variance introduces by the bias shifts and would not be able to actually produce the bias shifts.

Setting aside serial dependence, incorporating adaptation to the frame as proposed in the previous section would be possible by changing the way the contextual likelihood is modelled. Referring back to Section 2.3.3 the equation for variable θ_F^{ret}, accounting for the retinal perception of the frame, could be changed from

$$\theta_F^{ret} = -(\theta_F^W - H_{true}) - A_{OCR} * sin(|H_{true}|)$$

to

$$\theta_F^{ret} = -(\theta_F^W - H_{true}) - A_{OCR} * sin(|H_{true}|) - \delta * (|\theta_F^W| * reactionTime)$$

where δ would be a parameter to be optimised, and $(|\theta_F^W| * reactionTime)$ would account for the linear increase of adaptation dependent on frame orientation and reaction time.

On the other hand, serial dependence is on post-perceptual level, meaning that the change might be included after the head-in-space posterior is estimated. It can be similar to the coordinate transformation used to obtain the probability of CW response in Section 2.3.5. However, incorporating not only the previous response but also the associated stimuli into the model would require a more fundamental approach for which more research is needed.

5.4 Conclusion

The present work suggests that incorporating serial dependence and adaptation into the existing model of verticality perception by Alberts et al.(2016) would make the estimation of the vestibular noise more accurate. By doing so the clinical value of the approach of using psychometric assessment of the RFE to estimate the degree of neurological diseases would improve.

Chapter 6

Appendix

The implementation of the model, as well as the code used to analyze the data and make the plots can be found on GitHub. There you can also find the plots for the other participants. The participant whose results were presented in this report is number eight. Reference the ReadMe file for a more detailed information on the content and file structure of my code.

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