A Hierarchical Bayesian Model for Measuring Motion Adaptation

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24 January, 2014

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Introduction

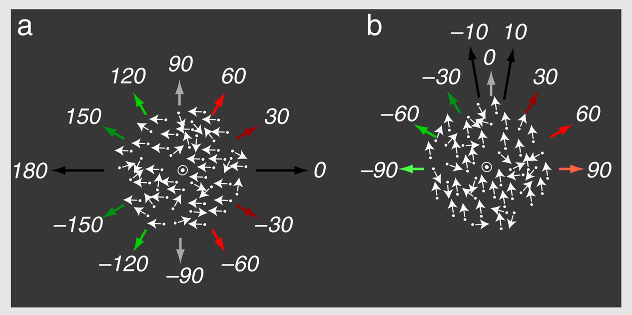
Previous research has shown that motion imagery draws on the same neural circuits that are involved in perception of motion, thus leading to a motion aftereffect (Winawer et al., 2010). Imagined stimuli can induce a similar shift in participants' psychometric functions as neural adaptation due to a perceived stimulus. However, these studies have been criticized on the grounds that they fail to exclude the possibility that the subjects might have guessed the experimental hypothesis, and behaved accordingly (Morgan et al., 2012). In particular, the authors claim that participants can adopt arbitrary response criteria, which results in similar changes of the central tendency μ of psychometric curves as those shown by Winawer et al. (2010).

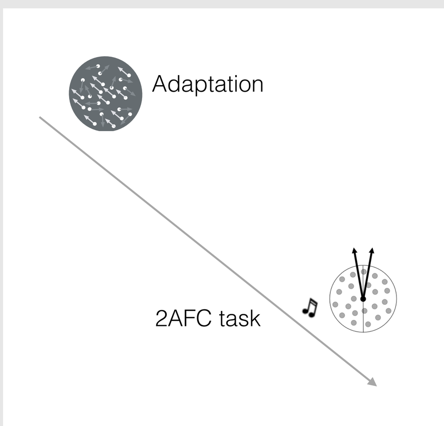
Goal of the study

The goal of this study is to demonstrate a novel paradigm for investigating the behavioural effects of motion adaptation, which is not susceptible to demand characteristics, based on a model of motion discrimination (Jazayeri & Movshon, 2006). Furthermore, we introduce the use of Bayesian techniques and multi-level modelling to obtain group-level and individual parameter estimates simultaneously, rather than using the traditional two-step approach to psychophysical data analysis.

Random Dot Task

Jazayeri & Movshon (2007) describe a version of the random dots paradigm in which subjects perform a fine discrimination task. In this task, the two alternatives are 10° to the left and right of the decision boundary.





According to Jazayeri & Movshon (2006), the contribution of neurons tuned to flanking motion directions increases when computing the most likely direction, as the alternatives approach the decision boundary. In this experiment, participants performed a random dot fine discrimination task. For each participant, we determined an individual coherence level prior to experiment, at which the participant achieved an accuracy rate of 75%. Before the 2AFC task, whose onset was indicated by a tone, there was a 3 second adaptation period, during which participants passively viewed a cloud of coherently moving dots in one of 5 directions (L90, L45, 0, R45, R90), whilst maintaining central fixation. Participants were instructed to respond as quickly as possible to the direction of the dots after the tone.

Experimental Hypotheses

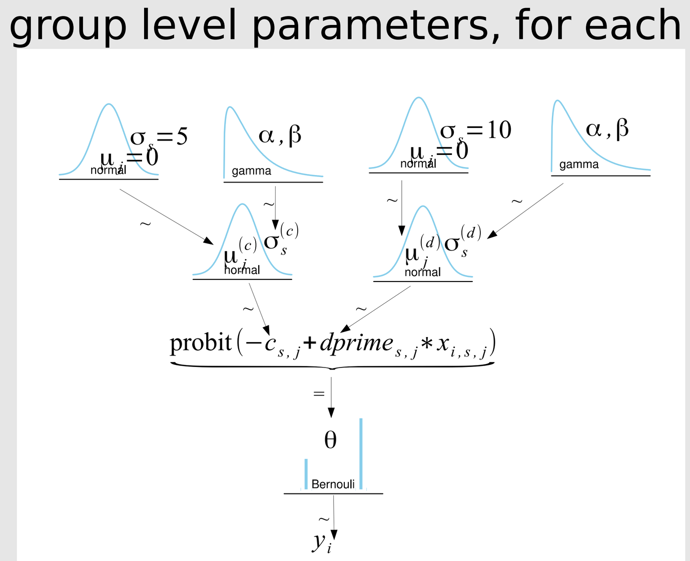
- *H1*: Adaption to L45 and R45 directions should induce strong biases toward the opposite direction.
- *H2*: Adaptation to L90 and R90 directions should induce weak biases toward the opposite direction.
- *H3*: Sensitivity should be high for L90 and R90 directions, and should be reduced after adaptation to L45 and R45 directions.

Methods

We implemented an equal-variance Signal Detection Theory model as a hierarchical Bayesian Generalized Linear Model with a probit link function, in order to estimate group level bias and sensitivity parameters under each adaptation condition. The probability of a rightward response is given by:

$$Pr(Response = Right|Right) = \phi(-c + d * X) \tag{1}$$

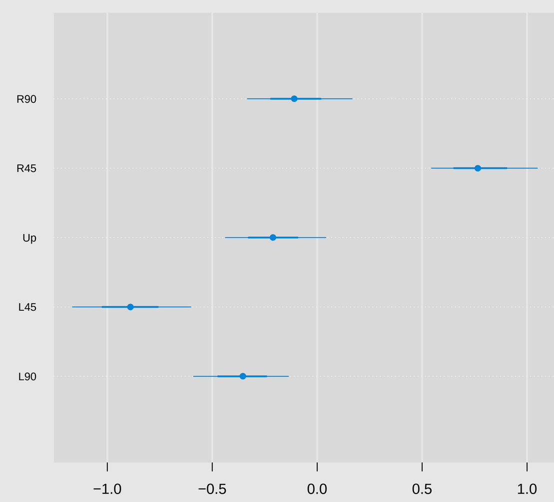
where the inverse link function ϕ is the inverse standard normal cumulative density function, c is a measure of bias, and d is a measure of sensitivity. If the stimulus is coded with the values -0.5 and 0.5 for left-ward and right-ward directions, respectively, this Generalized Linear Model corresponds to a traditional equal-variance Signal Detection model (DeCarlo, 1998). The following graphical model can be used to infer c (bias) and d' (sensitivity) parameters jointly for J participants, and to simultaneously infer group level parameters, for each adaptation condition.

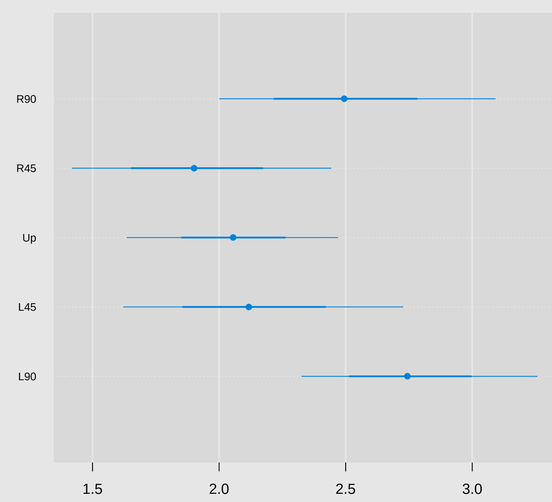


The joint posterior probability of all the parameters in the model was estimated using Markov Chain Monte Carlo sampling in R (R Core Team, 2013) and JAGS (Plummer, 2003). 50,000 samples were drawn from each of 3 independent chains, and convergence of the chains was monitored. All parameters were given minimally informative reference prior distributions (David Lunn, 2013).

Results

In the left panel, marginal posterior estimates for the group level bias parameters $\mu_j^{(c)}$ for each condition are shown ; the right panel depicts the same for the group level sensitivity parameters $\mu_j^{(d)}$ ($N = 10$).

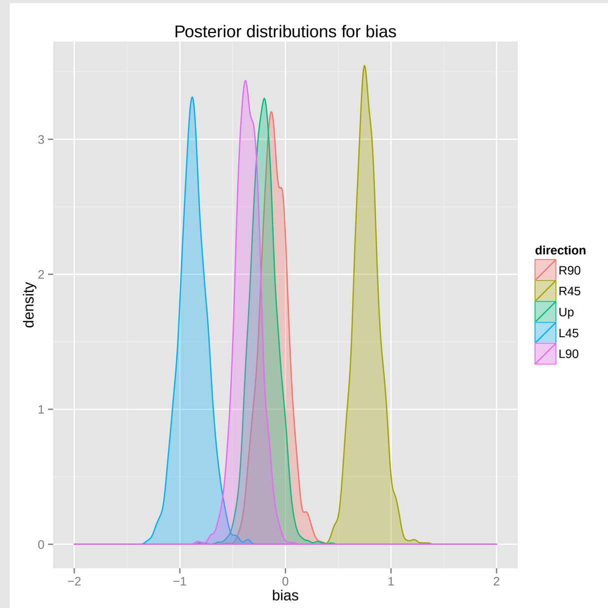


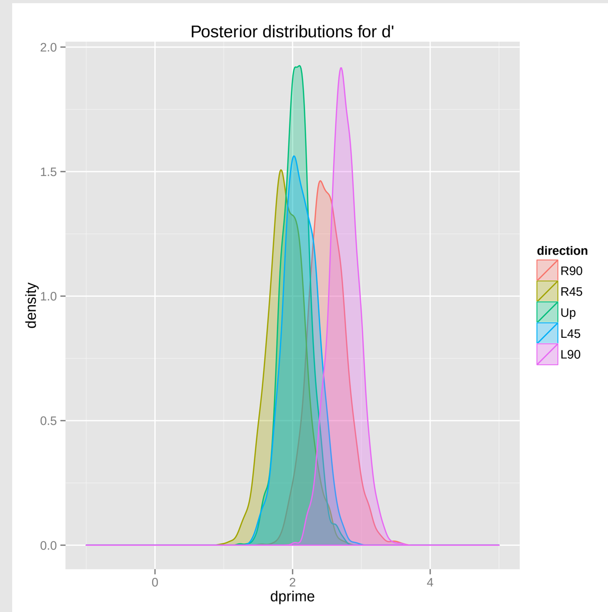


Results (continued)

The dots show the medians, the thick lines show the 68% credible intervals, and the thin lines show the 95% credible intervals for the parameters. Negative values for c indicate a bias to give a 'right' response, positive values indicate a bias towards 'left' responses.

- The hypotheses *H1* and *H2* are clearly borne out by the results: Under both left and right conditions, adaptation to random dot motion at $\pm$ 45°of the decision boundary induces a far greater bias to give a response in the opposite direction than adaptation to motion at $\pm$ 90°.
- Hypothesis *H3* is not conclusively supported by the data, although a tendency can be detected that adaptation to random dot motion at $\pm$ 45°as well as motion along the decision boundary reduce participants' sensitivity to discriminate between left and right ward motion directions, compared to adaptation to motion at $\pm$ 90°. However, the parameter estimates are very uncertain, resulting in an overlap of the distributions.





The smoothed histograms offer an alternative view of posterior distributions of the group level parameters; in the left panel, there is very little overlap between the smoothed histograms of the $\pm$ 45°conditions and the $\pm$ 90°conditions for the bias estimates, whilst in the right panel the overlap between the $\pm$ 45°conditions and the $\pm$ 90°conditions is much greater.

Conclusions

- We have provided behavioural evidence from a motion adaptation task which shows that participants' performance is in agreement with predictions from a model of motion discrimination (Jazayeri & Movshon, 2006).
- These results provide an improved baseline with which to compare participants' performance in a task designed to measure adaptation to imagined motion.
- We have introduced a Bayesian multi-level modelling approach to estimating group-level parameters. This approach is very flexible, and can be extended to allow for modelling of contaminant processes (e.g. attentional lapses), as well as model comparison.
- We are currently using the paradigm to investigate neural adaptation due to imagined motion.

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