Disentangling mental imagery and perceptual expectation

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Highlights

- We investigate mental imagery within the computational framework of control theory and state estimation.
- Mental imagery and perception are thought to rely on similar neural circuits; however, on more theoretical grounds, imagery seems to be closely related to the output of forward models (sensory predictions).
- We reanalyzed data from a study of imagined self-motion.
- Bayesian modeling of response times may allow us to disentangle the effects of mental imagery on behavior from other cognitive (top-down) effects, such as expectation.

Theoretical Background

- Mental imagery and perception are thought to rely on similar neural circuits, and many behavioral studies have attempted to demonstrate interactions between actual physical stimulation and sensory imagery.
- Nigmatullina et al. (2015) asked subjects to imagine self-motion prior to performing a motion detection task on a motorized chair. If the direction of imagined motion was congruent with the actual motion direction, subjects required less intense motion for correct detection. Similar effects were found for the vestibular-ocular reflex (VOR) at the earliest stages of vestibular processing.
- However, their data analysis is inconclusive, and in the light of recent computational models of vestibular processing, the results may be attributable to perceptual expectation.

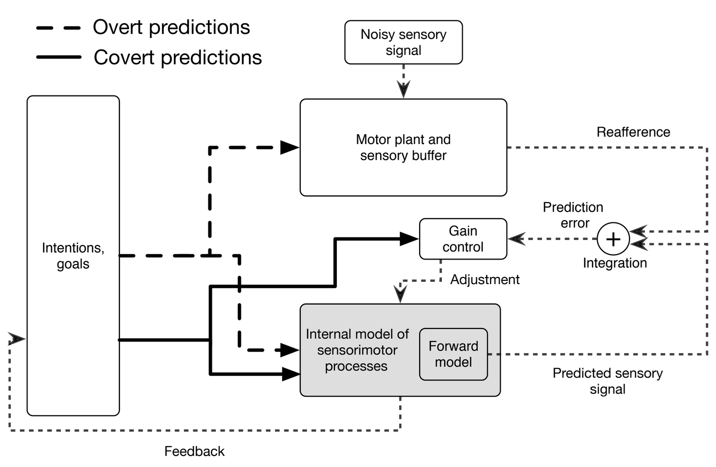

Figure 1: Dynamic state estimation model

Fig. 1 shows a Kalman filter (KF) model of vestibular processing, based on Laurens & Droulez (2006); Karmali & Merfeld (2012), as discussed in Mast & Ellis (2015). An important component is the forward model, which is responsible for continuous prediction of future sensory signals. The goal of such a model is, e.g., to estimate the system's velocity from noisy semi-circular canal (SCC) measurements.

- Fig. 2 shows the output of a Kalman filtering algorithm in response to a sudden increase in velocity. The dark grey lines show the SCC afferent signal, and the light grey lines show the estimated velocity (Fig. adapted from Karmali & Merfeld (2012)

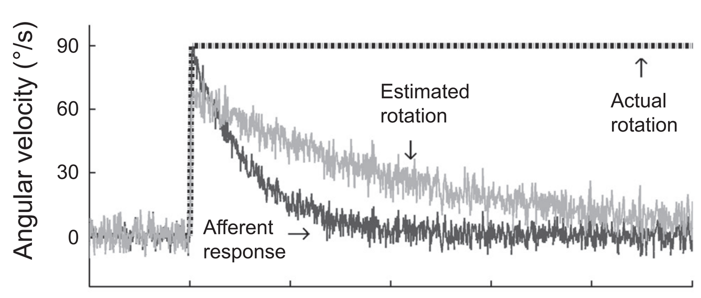

Figure 2: Effects of imagined motion on subsequent motion detection

The KF reproduces the velocity storage, and demonstrates that, at the earliest stages of vestibular processing, complex internal models are required for state estimation. It is unclear how an interaction, as reported by Nigmatullina et al. (2015), may be explained in terms of such a model.

- Subjects were required to imagine self-motion prior to detection an actual motion; this could have the effect of increasing the state estimate (angular velocity), leading to an elevated starting point for the accumulation of evidence for actual angular motion.
- A simple model of detection of angular motion: the estimated velocity during the rotation is simply summed over time, and the subject responds when this sum crosses a threshold. The response times generated by such a process can be analyzed using a drift diffusion model (DDM) (Vandekerckhove et al., 2011).

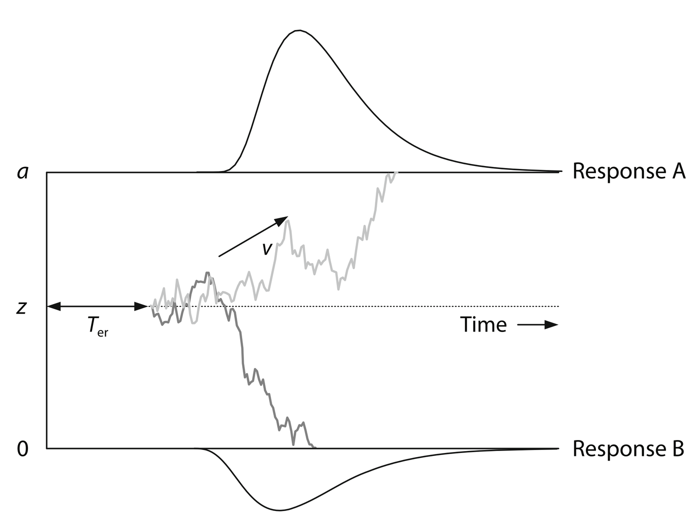

Figure 3: Parameters of drift diffusion model for choices and response times.

Fig. 3 shows the parameters of the DDM: of particular interest are z, the starting point for evidence accumulation (bias), and v, the rate of evidence accumulation. If mental imagery influences the bias z, the it could be tricky to distinguish from other manipulations, e.g. expectation.

Imagined Self-Motion Experiment

- We reanalyzed data from experiment 1 in (Nigmatullina et al., 2015). 16 subjects were instructed to imagine a cued self-motion prior to detection a physical rotation, which was either congruent or incongruent with the direction of imagined motion. The original data analysis amounted to a comparison of mean response times between congruent and incongruent trials, aggregated over subjects.
- Due to unsuitability for analysis using a DDM, we fitted ex-Gaussian distributions to subjects' response times and VOR onsets for congruent and incongruent trials, using Bayesian parameter estimation.
- The ex-Gaussian results from the convolution of a normal and an exponential distribution. The parameters of the ex-Gaussian are μ and σ^2, the mean and variance of the normal component, and λ, the rate of the exponential component. In particular, μ shifts the distribution along the x-axis, and λ affects the tail behavior.
- We fit all ex-Gaussian models in Stan (Stan Development Team, 2015), placing mixed-effects model on the μ and λ parameters (Preuss et al., 2015).

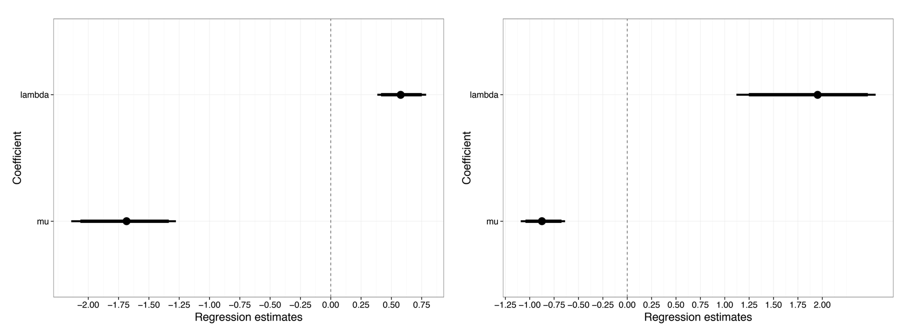

Figure 4: Parameter estimates of the ex-Gaussian distribution

Fig. 4 shows the additive fixed effect of congruent trials, in comparison with incongruent trials. For both choice response times (left panel), and VOR onset (right panel), the mean μ of the Gaussian component is decreased for congruent trials, indicating a shift along the x-axis.

- In addition, the rate parameter λ is increased, indicating that both subjects' choices and VOR onset were less variable for congruent trials relative to incongruent trials. This represent a significant finding, which would not be possible using a repeated measures ANOVA of mean response times.
- Although Matzke & Wagenmakers (2009) warn against comparing parameters of the ex-Gaussian distribution with those of the DDM, it is conceivable that the shift in μ might correspond to a change in the bias parameter, similar to the effects of perceptual expectation.
- An increase in λ might be due to increased drift rate (rate of evidence accumulation) , and a decrease in boundary separation.

Next steps

- Further work is required to experimentally dissociate the effects of mental imagery on perception of physical stimuli form those of perceptual expectation. This will require a combination of theoretical work, computational modeling, and careful experimental design.
- It is becoming increasingly clear that mental imagery is related to expectation (Clark, 2012); future experiments need to take this into consideration.
- Bayesian modeling of response times allows us to place complex regression models on individual parameters of response time distributions. This allows us to avoid aggregating over subjects, and restricting analysis to mean response times, both of which are known to be problematic.

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