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From model-based perceptual decision-making to spatial interference control

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Model-based neuroscience is aimed at understanding latent cognitive processes using quantitative cognitive models in combination with neuroscientific measures. This approach has been successful in the domain of perceptual decision making, in which the properties of accumulator models of choice tasks have been related to neural networks that are involved in decision making. Here, we propose that this approach can also be applied to spatial interference control such as required in the Simon task. Spatial interference control is essential for understanding cognitive control processes. A model-based approach may aid in understanding the latent cognitive processes in spatial interference control. Ultimately this approach may uncover the relationship between decision making that requires interference control and default decision making such as perceptual choice.

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Introduction

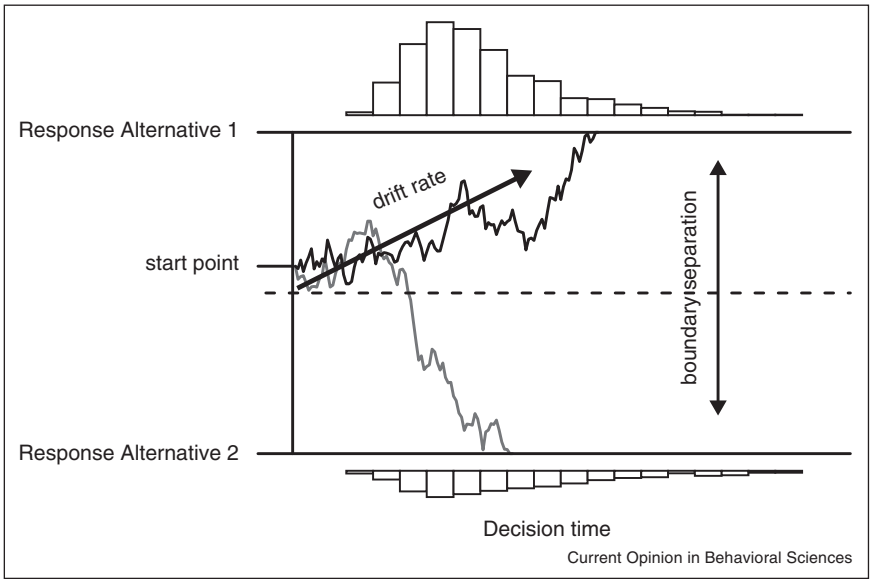
A recent trend in the cognitive neurosciences is the use of formal models of cognition to inform analyses of neural data [1•,2••]. Essentially, this trend entails that theories about the cognitive processes under consideration are explicated in mathematical or computational form, and these formal models are used to make inferences about the neural data. The model-based approach has been successfully applied in perceptual decision neurosciences [3••]. Perceptual decision neurosciences study the neural networks underlying simple perceptual choices. By relating these networks to properties of cognitive models, the model-based neuroscience approach has greatly increased our understanding of how the brain controls the behavioral outcome of simple choices.

A prominent model that has been instrumental in the success of model-based perceptual decision neurosciences is the diffusion model of choice reaction time [4••]. Essentially, the diffusion model assumes that the difference in evidence for two response alternatives is represented by a biased random walk process (Figure 1). The bias in this process is referred to as drift rate. Decisions are made as soon as the random walk hits one of two boundaries, with each boundary representing one response alternative. Because the drift is a random walk process, each boundary can in principle be reached. However, a positive drift rate means that it is more likely that the random walk will be towards the upper boundary, making the associated response more likely. The time required to reach a boundary represents the decision time, which is a function of both the drift rate and the boundary separation. That is, higher drift rates as well as boundaries that are closer together lead to lower decision times. The observed response time is then the sum of the decision time and the time required for additional, non-decision related processes. Crucially, because of the stochastic nature of the random walk process, the diffusion model predicts the proportion in which each boundary is reached, and the distributions of finishing times of the process. Thus, when fit to experimental data, the diffusion model explains both the proportion of correct and erroneous responses, as well as the distribution of response times of each of these response types.

Only recently, the diffusion model and related models have been applied to more complex cognitive behaviors in which control is exerted over a decision (e.g. [5,6•, 7–10]). That is, certain paradigms require that decision makers ignore an interfering irrelevant stimulus feature and focus on a task-relevant feature instead. Often, the irrelevant feature relates to a direct mapping between stimulus and response, making the task to ignore this feature difficult [11].

In this domain, applying the diffusion model holds great promise, because evidence suggests that conflict tasks are best understood when studying the response time distributions [12•]. This is particularly clear for the Simon task. In this task, participants are asked to respond with a left or right hand response to a certain stimulus feature, typically the color of a circle [11]. The stimuli are presented left or right of a central fixation cross. This spatial outline creates a condition in which the location of the stimulus (e.g. left of the fixation cross) is congruent with the required

Figure 1



A graphical representation of the diffusion model. The predicted response time on each trial is the finishing time of the random walk process and an additional parameter representing non-decision related processes such as perception and the motor response.

response (e.g. the color blue should yield a left button press), and a condition in which the location of the stimulus and the required response are incongruent (e.g. a blue circle to the right of the fixation cross, requiring a left button press). The Simon task is demanding because on incongruent trials, participants are confronted with interfering information in the form of the spatial location, but have to respond to the task-relevant feature only. The response time distributions of the Simon task deviate from other conflict tasks in that the time cost of resolving the interfering information is mostly associated with relatively fast responses. That is, most conflict tasks show a greater interference effect for slower responses, but the Simon task shows the greater interference effect for faster responses [13]. This pattern of interference is atypical for most conflict tasks. It suggests that in terms of the cause of interference, more processes are involved than in for example a flanker task [14].

While it is clear that an accumulator model of spatial interference control such as in the Simon task would greatly increase our understanding of cognitive control, as yet no such model has been published. The aim of the current article is to pave the way to use accumulator models to understand latent processes in spatial interference control. That is, based on previous model-based approaches towards the neural basis of perceptual decision making, and previous functional Magnetic Resonance Imaging (fMRI) studies in spatial interference control, we aim to outline the important processes in an accumulator model of spatial interference.

The neural basis of perceptual decision making

In this section we review basic perceptual decision making experiments that have sought to relate diffusion model properties to Blood Oxygen Level Dependence (BOLD) responses. In fact, the two most important properties of the diffusion model can be identified in the brain [3••]. The rate of evidence accumulation has been shown to be positively related to BOLD in dorsolateral prefrontal cortex (DLPFC, e.g. [15–17]) and anterior Insula (aI, e.g. [15–18]). Thus, a high accumulation rate elicits a stronger BOLD response than a low accumulation rate, suggesting that easier perceptual decisions yield a stronger BOLD response in DLPFC than hard perceptual decisions. In addition, some studies report a correlation between the rate of evidence accumulation and the BOLD signal in right inferior frontal gyrus (rIFG, [19,20•]). In particular, in the context of a go/no-go task, White and colleagues [20•] found that accumulation rate and rIFG activation correlated negatively, suggesting that less selective inhibition yields a faster response.

The amount of evidence that is required seems to be modulated by cortical regions such as presupplementary motor area (pre-SMA) and anterior cingulate cortex (ACC, e.g. [21•,22,23,24•,25]). Many studies report that individual differences in pre-SMA BOLD responses correlate with individual differences in boundary setting of diffusion models (e.g. [21•,22]). Also, trial-by-trial fluctuations in pre-SMA BOLD correlate with trial-by-trial estimates of boundary settings under speed-stress [24•]. This means that if there is a need to respond

quickly, participants' ability to adjust the amount of evidence required for a response is reflected in the BOLD response in the pre-SMA. The ACC, an area that is in close spatial proximity to the pre-SMA, has also been associated with the amount of evidence. Van Maanen and colleagues [24•] found that trial-to-trial fluctuations in BOLD response correlated with boundary settings in an accumulator model, but only when the task instruction switched. Similarly, Mansfield *et al.* [22] found a correlation between ACC activation and boundary setting in a task switching paradigm, and Mulder *et al.* [23] found a correlation between ACC activation and the amount of required evidence in a two-alternative forced choice task in which the probability of the choices was manipulated.

Additionally, subcortical nodes in the basal ganglia have been found to be related to boundary settings. In particular, similarly to the pre-SMA, neural activation in striatum has been found to correlate with the boundary setting in the diffusion model or related models. Also, there is some evidence that the subthalamic nucleus plays a role in setting response thresholds [26,22].

The neural basis of spatial interference control

The previous section focussed on studies in which diffusion model properties were related to various regions of interest. In this section, we review work that has studied the BOLD response in spatial interference control tasks. The aim of this section is to identify which diffusion model processes can be expected to be important in an explanation of spatial interference control, given the overlap in regions of interest.

The brain area that is most often reported in relation to interference control is the ACC (for a review see [27]). Although ACC activation is often associated with conflict monitoring or detection [28,29] and therefore should be active during interference tasks, the debate on the specific role of ACC is still open. Besides conflict monitoring [30••,31], people have argued that the ACC is active during anticipatory activation [32–34], in response to errors [35], as an indicator of the likelihood of an upcoming error [36,37], and during task switching [38,39].

In addition to the ACC, it has been argued that the DLPFC is involved in the resolution of conflict [30••,40–43]. However, in general, the DLPFC seems to be involved whenever a decision between multiple difficult stimuli has to be made. For example during a face/house discrimination task, DLPFC activation increases with increasing noise levels of the stimuli [17]. Thus, as the decision becomes more difficult, the DLPFC is more involved.

While many researchers have studied conflict tasks, only a few fMRI studies have focussed on the Simon task, rather than the flanker or Stroop tasks or similar paradigms [44]. However, as argued before, the marked differences between response time distributions in the Simon task relative to these related paradigms warrant a separate discussion. Kerns [43] and Strack and colleagues [34] performed fMRI studies of the Simon task and found that in addition to the ACC and the DLPFC, the pre-SMA also played an important role. Strack and colleagues found that when cued with a symbol indicating the congruency of the upcoming stimulus (i.e. congruent or incongruent), activation was higher in the pre-SMA than in the ACC, as compared to cues indicating the spatial location of the stimulus. Forstmann and colleagues [45,46] studied the relation between various properties of the response time distributions and the BOLD response in the Simon task. They found that BOLD activation in the pre-SMA correlated with the proportion of fast incorrect responses [45]. Additionally, Forstmann and colleagues reported that the decrease in interference for slower responses (i.e. a negative-going *delta plot*, [12•]) was predictive of the amplitude of the BOLD response in rIFG [45,46]. The slope of the delta plot that reflects slow responses has been associated with selective response inhibition [12•]. Thus, this result suggests a role for inhibitory processing for the rIFG in the Simon task, which seems consistent with the literature on the function of the rIFG [47–49].

A subset of studies focussed on the overlap in the BOLD response between the Simon task and related interference tasks [50–52]. These studies found a common involvement of DLPFC, pre-SMA, ACC, and rIFG for both Simon and Stroop tasks. However, these studies reported slight differences in the amplitude of the activation in these areas. The pre-SMA and ACC were found to be more active during the Simon task than the Stroop task; the DLPFC and the rIFG were more activated during the Stroop task than the Simon task. One study also considered the time course of the BOLD response in both the Simon task and the Stroop task [52]. This study found that the increased activation for bilateral IFG during the Stroop task was mainly driven by the first 1.65 s of a trial, whereas the activation in (pre-)SMA that was observed in the Simon task was mainly driven by a later BOLD response.

A diffusion model analysis of the Simon task

Because of the complexity of the response time distributions observed in the Simon task, a formal accumulator model is not straightforward [14]. To deal with this complexity, we hypothesize that the architecture of such a model should align with our understanding of the neural networks involved in spatial interference control. That is, given the involvement of the DLPFC and the rIFG in interference control, we hypothesize that the rate of accumulation, specifying how fast evidence is accrued in favor of a (correct) alternative, is lower for incongruent trials. This would reflect that because the activation in the

DLPFC is increased on incongruent trials — which is associated with conflict resolution — the drift rate is decreased. Moreover, the negative correlation between drift rate and rIFG activation suggests that an increase in the rIFG as observed for slow responses — associated with increased selective suppression — relates to a decrease in the rate of accumulation for incongruent trials as well.

Given the hypothesized role of the pre-SMA in setting response thresholds [3••], the findings by Forstmann and others [45,46] suggest that on incongruent trials in the Simon task, fast errors are made due to an incorrect accumulation towards a low threshold. That is, if the threshold is close to the starting point of accumulation, a fast yet error-prone response is likely to occur, similar to an error in the speed-accuracy trade-off paradigm [53]). The involvement of the ACC suggests a role for model parameters representing the amount of evidence required to make a choice. While typically, this entails boundary setting, preliminary results from fitting accumulator models to data of the Simon task suggest that there exist a differential response caution towards the different response options. This would shed a new light on the specificity of the ACC with respect to response caution.

Conclusion

According to model-based analyses of perceptual decision making, the regions of interest in the Simon task may be the DLPFC, rIFG, pre-SMA, and ACC. BOLD activation in the DLPFC and the rIFG correlates with the accumulation of evidence, which may be hampered in the Simon task due to interfering location information. Activation in the pre-SMA and the ACC correlates with the amount of evidence that is required. This may also vary in the Simon task, for example, due to the congruency of the previous trial, which is thought to play a prominent role in interference tasks [54]. This suggests that the Simon task involves at least two separate processes, represented as two different parameters in a diffusion model. However, a review of the literature on neural activation in conflict tasks also suggests considerable overlap between spatial and non-spatial interference. Consequently, although the behavioral outcome differs between paradigms, the neural networks that mediate a response may be shared.

Conflict of interest statement

The authors declare no conflict of interest.

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