Decomposing spatial conflict BOLD activation using a drift-diffusion model framework

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Abstract

Drift-diffusion based models (DDM) have been recently adapted for analysis of behavior in spatial conflict tasks. However such DDM extensions are typically difficult to fit and compare because analytical solutions do not exist. We use a numerical method to estimate the likelihood function for fitting a Simon effect DDM to individual subject data, and use these fits to interpret blood-oxygen-level dependent (BOLD) responses. We find regions of BOLD activation that would be difficult to observe with methods that are not model based.

Keywords: Drift-diffusion; Simon effect; Conflict; fMRI

Introduction

The Simon effect (Simon & Rudell, 1967) is observed in spatial conflict tasks where the response time of subjects is increased if stimuli are presented in a lateralized manner so that they are incongruous with the response information that they represent symbolically.

In this study we fit a Simon effect drift-diffusion model (SE-DDM), a DDM (Ratcliff, 1978) extended for spatial conflict tasks (Ulrich, Schröter, Leuthold, & Birngruber, 2015; McIntosh & Mehring, 2017). The model includes specific estimates of conflict dependent (automatic) response bias and conflict monitoring based deployment of attention. Both of these parameters are needed because while a bias term captures the increased mean response time in conflict trials, the attention term is needed to capture a compensatory decrease in the standard deviation.

The power of the DDM is not only that it can model behavior but that it is cast at a level of abstraction where its specific components are directly interpretable under the assumption that it captures some core principles of decision making used in the brain. We therefore apply this approach for the Simon effect DDM parameters to interpret the BOLD response in terms of the overall parameter fits.

Methods

Data was obtained from the OpenfMRI database under an ODC Public Domain Dedication and Licence (PDDL). Its accession number is ds000101. Whole-brain functional volumes were obtained from 21 healthy adults as they performed the Simon task (Figure 1a).

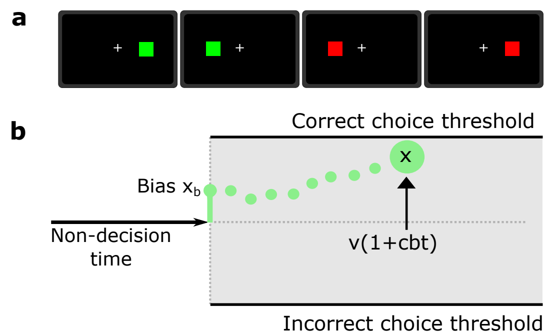

Figure 1: Simon task and model **(a)** Subjects should make a response with their left hand for a green square presentation, and right hand response for a red square presentation. Conflict trials are those where the side to which the square is presented to is inconsistent with the required response. **(b)** Example of a decision variable to bound in the SE-DDM for a non-conflict trial (parameters defined in text).

We introduce the accuracy coded SE-DDM shown in Figure 1b based on previous work (McIntosh & Mehring, 2017):

$$\Delta x = v \cdot (1 + c \cdot b \cdot d)\Delta t + s\xi\sqrt{\Delta t} \quad (1)$$

$$x_0 = x_b(1 - 2c) \quad (2)$$

Where the model is fit by finding parameters that maximize the log-likelihood for each subject's response time and choice. The variable x denotes the decision-variable that builds to a threshold. The stimulus conflict parameter c is set to take a value of 0 when there is no conflict present or 1 otherwise. Parameters v, s, and x_0 correspond to the drift, noise and starting point bias, while ξ represents draws from a Normal distribution and Δt corresponds to the model step size. Non-decision time and associated noise are also included. Parameters that are specific to the Simon task are b, a hypothesized attentional component that enhances the effective drift on conflict trials as its duration d increases, and x_b a parameter that captures the initial response bias caused by the Simon effect.

In order to specify the log-likelihood (maximized with a generalized pattern search algorithm) for a specific set of parameters and conditions we encoded the dynamics of the decision-variable into a transition matrix which is then evaluated over time. The transition matrix represents the probability of the decision-variable at the next time step given the current time step. Applying it involves discretizing time as well as the decision-variable x, and iteratively multiplying it with a vector corresponding to the current probability distribution of the decision-variable. In the SE-DDM, the transition matrix is fixed on non-conflict trials, and varies in a time dependent manner in conflict trials because of the $b \cdot d$ term. Outside the model threshold, transition matrix values take a value of zero except for along the diagonal where they take a value of one. The density function is then calculated by numerical differentiation of the sum of the iterated output above and below the model threshold. Weighted Akaike information criterion (w_{AIC}) values were calculated for the SE-DDM and simpler candidate models. The (w_{AIC}) can be interpreted as the probability of that model being the best model among the candidate set (Wagenmakers & Farrell, 2004).

Standard pre-processing of fMRI data was implemented in FSL (Smith et al., 2004), and FEAT was used for event-related analysis. Parameters of interest were added as 100ms long pulses and motion parameters were added to the model as confounds of no interest. FEAT was set to use a double-gamma haemodynamic response function to convolve with a single set of regressors representing stimuli. Beta values were extracted after averaging across blocks (level 2), and taken into MNI space. Threshold-free cluster enhancement (Smith & Nichols, 2009) implemented in MatlabTFCE[1] was used to generate permutation corrected statistics. Corresponding p-values then represent the correlation between SE-DDM parameters and BOLD activation across subjects at each voxel.

Results and discussion

Figure 2a shows the w_{AIC} for the SE-DDM and less complex candidate models. The model incorporating a conflict dependent bias term was well supported (M3: largest w_{AIC} for 8/21 subjects), and so was the full SE-DDM (M4: largest w_{AIC} for 9/21 subjects). We take this to imply that the full SE-DDM is the preferable generic model, although some subjects exhibit low values of b and hence are better fitted by M3.

Correlations with bias x_b across subjects (Figure 2b, yellow) were present in multiple regions of cortex. Particularly prominent were precuneus, lingual gyrus and posterior cingulate. Correlations with attention b were found in postcentral gyrus, insular cortex, anterior cingulate and SMA. Additionally, we found opercular, planum temporale, and superior temporal gyrus activation. We hypothesize that the features of conflict are represented in precuneus and these are made use of by standard regions of cognitive control such as the supplementary motor area (SMA) and anterior cingulate. We confirmed that repeating this analysis with response time or response time difference between conflict and non-conflict conditions did not yield any detectable activation at ($p < 0.05$), highlighting the strength of the model based approach.

In the future we will investigate how these regions integrate more broadly into a circuit of cognitive control that is likely engaged in the Simon task, as well as using our fitting procedure to test other candidate models for the Simon effect, and extending them into a hierarchical Bayesian framework.

[1] https://github.com/markallenthornton/MatlabTFCE

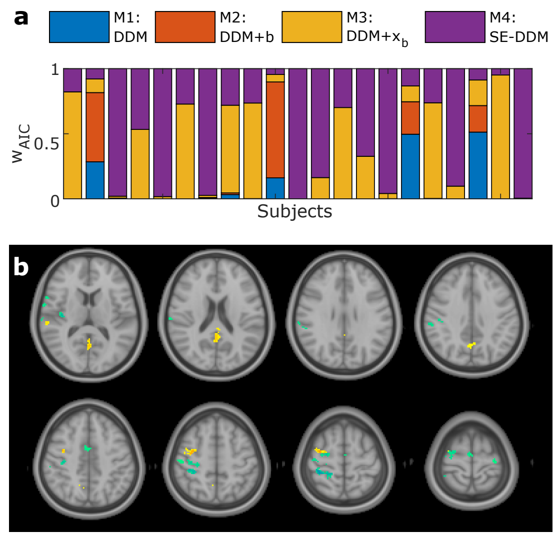

Figure 2: Model comparison and BOLD activation **(a)** w_{AIC} for candidate models. M1: basic DDM; M2: DDM with attention parameter b; M3: DDM with bias parameter x_b; M4: SE-DDM. **(b)** Statistically significant ($p < 0.05$), correlations between subject parameters and BOLD activation for attention parameter b (green) and bias x_b (yellow).

References

McIntosh, J. R., & Mehring, C. (2017). Modifying response times in the simon task with transcranial random noise stimulation. *Scientific Reports*, *7*(1).

Ratcliff, R. (1978). A theory of memory retrieval. *Psychol Rev*, *85*.

Simon, J. R., & Rudell, A. P. (1967). Auditory S-R compatibility: The effect of an irrelevant cue on information processing. *J Appl Psychol*, *51*.

Smith, S. M., Jenkinson, M., Woolrich, M. W., Beckmann, C. F., Behrens, T. E., Johansen-Berg, H., ... Matthews, P. M. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *NeuroImage*, *23*.

Smith, S. M., & Nichols, T. (2009). Threshold-free cluster enhancement: Addressing problems of smoothing, threshold dependence and localisation in cluster inference. *NeuroImage*, *44*(1).

Ulrich, R., Schröter, H., Leuthold, H., & Birngruber, T. (2015). Automatic and controlled stimulus processing in conflict tasks: Superimposed diffusion processes and delta functions. *Cognit Psychol*, *78*.

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using akaike weights. *Psychonomic Bulletin & Review*, *11*(1).