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Model-based functional neuroimaging using dynamic neural fields: An integrative cognitive neuroscience approach

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HIGHLIGHTS

- Interactive cognitive neuroscience approach is demonstrated using DFT.
- DNF models fitted trends in behavioral and neural data to response selection task.
- Neural population dynamics in DNF model were mapped to particular brain regions.

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ABSTRACT

A fundamental challenge in cognitive neuroscience is to develop theoretical frameworks that effectively span the gap between brain and behavior, between neuroscience and psychology. Here, we attempt to bridge this divide by formalizing an integrative cognitive neuroscience approach using dynamic field theory (DFT). We begin by providing an overview of how DFT seeks to understand the neural population dynamics that underlie cognitive processes through previous applications and comparisons to other modeling approaches. We then use previously published behavioral and neural data from a response selection Go/Nogo task as a case study for model simulations. Results from this study served as the 'standard' for comparisons with a model-based fMRI approach using dynamic neural fields (DNF). The tutorial explains the rationale and hypotheses involved in the process of creating the DNF architecture and fitting model parameters. Two DNF models, with similar structure and parameter sets, are then compared. Both models effectively simulated reaction times from the task as we varied the number of stimulus–response mappings and the proportion of Go trials. Next, we directly simulated hemodynamic predictions from the neural activation patterns from each model. These predictions were tested using general linear models (GLMs). Results showed that the DNF model that was created by tuning parameters to capture simultaneously trends in neural activation and behavioral data quantitatively outperformed a Standard GLM analysis of the same dataset. Further, by using the GLM results to assign functional roles to particular clusters in the brain, we illustrate how DNF models shed new light on the neural populations' dynamics within particular brain regions. Thus, the present study illustrates how an interactive cognitive neuroscience model can be used in practice to bridge the gap between brain and behavior.

1. Introduction

Although great strides have been made in understanding the brain using data-driven methods (Smith, Fox, Miller, Glahn, Fox, & Mackay, 2009), human neuroscience will need sophisticated theories (Gerstner, Sprekeler, & Deco, 2012). *But what would a good theory of brain function look like?* Addressing this question requires theories that bridge the disparate scientific languages of neuroscience and psychology.

Turner, Forstmann, Love, Palmeri, and Van Maanen (2016) described three categories of approaches to this issue using model-based cognitive neuroscience that bridge the gap between brain and behavior by bringing together fMRI data and cognitive models (Turner et al., 2016). The first approach uses neural data to guide and inform a behavioral model, that is, a model that mimics

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features of responses such as reaction times and accuracy. One example of this approach is the Leaky Competing Accumulator model by Usher and McClelland (Usher & McClelland, 2001). This is a mechanistic model for evidence accumulation, which incorporates well-known properties of neuronal ensembles such as leakage and lateral inhibition. The model provides a good fit for a range of behavioral data, for example, time–accuracy curves and the effects of the number of alternatives on choice response times. Unfortunately, as remarked by Turner et al., this mechanistic approach stops short of establishing any direct connection to the dynamics of particular neural circuits or brain areas.

The second type of approach uses a behavioral model and applies it to the prediction of neural data. One example of this approach is Rescorla and Wagner's (1972) model of learning conditioned responses. In this model, the value of a conditioned stimulus is updated over successive trials according to a learning rate parameter. The model produces trial-by-trial estimates of the error between the conditioned and unconditioned stimuli. This measure can then be used in general linear models to detect patterns matching the model predictions within fMRI data. The method potentially allows one to identify neural processes that are not directly measurable through behavioral results (Davis, Love, & Preston, 2012; Mack, Preston, & Love, 2013; Palmeri, Schall, & Logan, 2015). However, a drawback of this model-based fMRI approach is that it does not explain cognitive states encoded by patterns of activation distributed over multiple voxels in the brain.

The last, and most difficult approach is an *integrative* cognitive neuroscience approach where a model simultaneously predicts behavioral and neural data. That is, the model explains what the brain is doing in real-time to generate specific patterns of fMRI *and* behavioral data. Turner et al. acknowledge that there are relatively few examples in this category. For instance, they highlight recent papers that use cognitive architectures such as ACT-R ('Adaptive Control of Thought-Rational') to capture simultaneously fMRI and behavioral data (Anderson, Matessa, & Lebiere, 1997; Borst & Anderson, 2013; Borst, Nijboer, Taatgen, Van Rijn, & Anderson, 2015). Although we agree that this approach has immense potential, this is a relatively limited example of an integrative cognitive neuroscience approach because ACT-R is not a neural process model. Thus, ACT-R does not capitalize on constraints regarding how real brains actually work.

An alternative approach that does capitalize on neural constraints was proposed by Deco, Rolls, and Horwitz (2004). These researchers used integrate-and-fire attractor networks to simulate neural activity from a 'where-and-what' task. The model includes several populations of simulated neurons to reflect networks tuned to specific objects, positions, or combinations thereof. The authors then define a local field potential (LFP) measure from each neural population by averaging the synaptic flow at each time step. To generate a BOLD response, they convolved the LFP measure with an impulse response function. Although one version of the model was able to approximate single neuron recordings from a prior study, as well as a measured fMRI pattern in dorsolateral prefrontal cortex, other fMRI patterns from the ventrolateral prefrontal cortex were not modeled. Moreover, comparisons to fMRI data were made qualitatively via visual inspection. No attempt was made to quantitatively relate the measures. Finally, behavioral data from this study were not a central focus. Such issues are relatively common when modeling relies on biophysical neural networks due to the immense computational challenges of simulating such networks. Appropriate partitioning of the parameter space and estimation of model parameters are, in general, difficult steps of this approach (see Anderson, 2012; Turner et al., 2016).

Inspired by this work, Buss, Wifall, Hazeltine, and Spencer (2013) adapted this approach to simultaneously model behavioral and fMRI data from a dual-task paradigm (Buss, Wifall, Hazeltine, & Spencer, 2013). They first constructed a dynamic neural field (DNF) model of the dual-task paradigm reported by Dux and colleagues (Dux et al., 2009). The model quantitatively fit a complex pattern of reaction time changes over learning, including the reduction of dual-task costs over learning to single task levels. These researchers then generated a LFP measure from each component of the neural model and convolved the LFPs with an impulse response function to generate BOLD responses from the model. The DNF model captured key fMRI results from Dux et al., including the reduction of the amplitude of the hemodynamic response in inferior frontal junction in dual-task conditions over learning. Moreover, Buss et al. contrasted competing predictions of the DNF model and ACT-R, showing that changes in hemodynamics over learning predicted by the DNF model matched fMRI results from Dux et al., while predictions from ACT-R did not.

It is important to highlight several key points achieved by Buss et al. (2013). First, the DNF model simulated neural dynamics in real time. The dynamics created robust 'peaks' of activation that were directly linked to behavioral responses by the model, and these responses quantitatively captured a complex pattern of reaction times over learning. Second, the same neural dynamics that quantitatively fit behavior also simulated observed hemodynamics measured with fMRI. Finally, Buss et al. demonstrated the specificity of these findings by contrasted predictions of two theories. Thus, their work constitutes a notable example of an integrative cognitive neuroscience approach using a neural process model that capitalizes on constraints regarding how brains work.

The current paper builds on the above example, by formalizing an integrative cognitive neuroscience approach using dynamic neural fields. Our paper is tutorial in nature, walking the reader through each step of this model-based cognitive neuroscience framework. We extend the work of Buss et al. (2013) by (1) formalizing several steps regarding the calculation of LFPs from dynamic neural fields and the generation of BOLD predictions; (2) adding new methods to quantitatively evaluate BOLD predictions from dynamic neural field models using general linear models (GLM), inspired by other model-based fMRI approaches; and (3) adding new methods to identify model-based functional networks from group-level GLM results. These methods allow for effectively identifying where particular neural patterns live in the brain, as well as specifying their functional roles.

The paper proceeds as follows. We begin with a brief introduction to dynamic field theory. This places our model-based approach within a broader context for readers who might be less familiar with this theoretical approach. Next, we introduce the particular case study we will use throughout the paper, that is, the particular behavioral and fMRI dataset that serves as the basis for the tutorial. We then discuss the DNF model that we used to capture simultaneously behavioral and neural data from this study, explaining where this model comes from and how we approached the simulation case study. The presentation will highlight key issues that theoreticians face when adopting an integrative cognitive neuroscience approach. Next, we present behavioral fits of the data and discuss strengths and limitations of the DNF model at this level of analysis.

After considering the behavioral data, we introduce a step-by-step guide to generating hemodynamic predictions from dynamic neural field models. We then discuss how to evaluate these predictions using general linear modeling (GLM). We first evaluate the model predictions at the individual level. We then move to the group level, showing how our approach can be used to identify model-based functional networks. To evaluate these networks, we compare our approach to standard fMRI analyses, highlighting examples where the DNF model sheds interesting light on the functional roles of particular brain regions. The tutorial concludes with a general evaluation of our model-based approach, highlighting strengths, weaknesses, and future directions.

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