



## Pre-stimulus functional networks modulate task performance in time-pressured evidence gathering and decision-making



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### ABSTRACT

Rapid perceptual decision-making is believed to depend upon efficient allocation of neural resources to the processing of transient stimuli within task-relevant contexts. Given decision-making under severe time pressure, it is reasonable to posit that the brain configures itself, prior to processing stimulus information, in a way that depends upon prior beliefs and/or anticipation. However, relatively little is known about such configuration processes, how they might be manifested in the human brain, or ultimately how they mediate task performance. Here we show that network configuration, defined *via* pre-stimulus functional connectivity measures estimated from functional magnetic resonance imaging (fMRI) data, is predictive of performance in a time-pressured Go/No-Go task. Specifically, using connectivity measures to summarize network properties, we show that pre-stimulus brain state can be used to discriminate behaviorally correct and incorrect trials, as well as behaviorally correct commission and omission trial categories. More broadly, our results show that pre-stimulus functional configurations of cortical and sub-cortical networks can be a major determinant of task performance.

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### Introduction

Pre-stimulus brain state, measured at a variety of spatial and temporal scales, has been shown to modulate upcoming task performance. For instance, studies in humans using electroencephalography (EEG) and magnetoencephalography (MEG) have shown that the power and/or phase of pre-stimulus alpha oscillations is correlated with performance (Hanslmayr et al., 2007; Linkenkaer-Hansen et al., 2004; Thut et al., 2006; Zhang et al., 2008). EEG and MEG, however are inherently limited by low spatial resolution. Their use for estimating current sources and scalp-level pre-stimulus modulators are biased toward the strongest cortical sources and typically ignore the interaction between these and weaker sources, as well as those that may be sub-cortical. Alternatively, the blood oxygen level dependent (BOLD) signal from functional magnetic resonance imaging (fMRI) provides whole-brain imaging that in theory provides a functional measurement of pre-stimulus brain state, albeit at a coarser temporal resolution. Most studies investigating pre-stimulus fMRI have largely limited their analyses to isolated regions of interest (ROIs) known *a priori* to be relevant for a given task (Hesselmann et al., 2008; Hsieh et al., 2012; Park and Rugg, 2010; Shibata et al., 2008).

Recently, functional connectivity analysis of BOLD signals during resting state and stimulus presentation has shown that distributed networks of neural substrates are engaged in both idle and active modes of attention (Hasson et al., 2012; Honey et al., 2007, 2009; McIntosh, 1999; McIntosh et al., 1997). For visually driven perceptual decision-making it has been shown that distributed neural substrates affect task difficulty and early visual perception (Hartstra et al., 2010; Philiastides and Sajda, 2007; Simmonds et al., 2008). However, characterization of the relationship between these substrates and how interactions between them may impact task performance has been lacking.

Here we used whole-brain imaging and graph-based network analysis to investigate the role of pre-stimulus brain state on task performance. Our rationale for this approach is that such a network characterization of task-relevant neural substrates would capture distributed BOLD activity across the entire brain. Graph theoretic approaches have been shown to be useful constructs for characterizing brain state, where changes in state are reflected in network parameters and configuration (Bressler and Menon, 2010; Bullmore and Sporns, 2009; Sporns, 2011). Features of the graph that can be measured and reflect graph/network configuration include, for example, the k-core decomposition which measures network properties related to node centrality and connectedness (Alvarez-Hamelin et al., 2008). Another commonly used approach to assess graph configuration is the random edge attack (REA), where selected structures of the network are systematically removed (Achard et al., 2006; Albert and Barabasi, 2002; van den Heuvel and Sporns, 2011).

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The specific graph theoretic approach we use is based on the work of Ekman et al. (2012). Specifically, Ekman et al. used a graph-based network analysis to study task related network configurations in motion/color perceptual decision making. While novel in its techniques and experimental design, this study utilized stimuli known to activate particular ROIs (e.g., V4 for color perception and MT for motion perception). These ROIs were found with a task-driven algorithm, so the computationally expensive and exploratory step of calculating pairwise connectivity between all fMRI voxels (>20,000 in standard MNI space) was not required. While the *a priori* functional information did not guide their algorithm, it provided a useful check on its veracity. Their graph-based approach further separated pre-stimulus networks into core and periphery sub-networks, showing that such distinctions could be used to isolate task-specific regions (e.g., V4 and MT) and task-general brain regions (e.g., frontal cortices), whose functional properties could be differentiated using standard graph theory measures, such as degree, efficiency and betweenness centrality. Such analyses build on the 'rich-club' concept that brain networks are functionally mediated by densely connected central hubs (van den Heuvel and Sporns, 2011).

The work we present here uses this graph-based approach to investigate the role of pre-stimulus network configuration on task performance given a rapid evidence accumulation decision-making (READ-M) paradigm. The READ-M paradigm requires subjects to employ visual memory, motion assessment, and a rapid behavioral response or inhibition of response, all while under time pressure. We refer to this as 'the baseball paradigm' as it requires the subject to judge whether a simulated trajectory of a circular object matches or does not match a pre-stimulus trajectory cue. As in the game of baseball, the subject – or 'hitter' – must rapidly decide his/her course of action (or inhibition of action) given a fast-moving visual stimulus. This entire process typically takes less than half a second. Previous studies have shown that this paradigm engages anatomically separated neural substrates during stimulus perception and subsequent decision formation (Ekman et al., 2012; Sherwin et al., 2012). This paradigm also falls into the general class of Go/No-Go tasks, which have been shown to involve local and distant brain regions, such as the inhibition network for No-Go and an execution network for Go decisions (Simmonds et al., 2008). Our hypothesis is that the pre-stimulus configuration of brain networks, represented *via* these graphical constructs, switch configuration based on the subject's anticipation of the trajectory cue and that this switch subsequently predicts task performance.

## Materials and methods

### Subjects

Eleven subjects participated in the study (all male, mean age = 21.6 years, range = 18–30 years). None of the subjects had professional or collegiate baseball experience. All subjects reported normal or corrected vision and no history of neurological problems. Informed consent was obtained from all participants in accordance with the guidelines and approval of the Columbia University Institutional Review Board.

### Stimuli overview

For the visual stimulus, subjects viewed 5 blocks of 90 simulated baseball pitches (see pitch simulations below) on a computer monitor with a mean jittered inter-stimulus interval (ISI) of mean = 3000 ms, SE = 225 ms. The ISI and stimulus presentation was optimized using *optseq2* program (Dale, 1999). This program is a tool for automatically scheduling events for rapid-presentation event-related fMRI experiments and it jitters the events such that the overlap in estimated hemodynamic response is removed. Subjects viewed the paradigm through VisuaStim Digital System (Resonance Technology) 600 × 800 goggle display. The simulated view was that of where the catcher would sit on a standard baseball diamond, *i.e.*, at the end point of the pitch trajectory (horizontal view 3.93°, vertical view 1.12°).

### Pitch simulations

Each simulated pitch was identified only by its trajectory, although in real-life baseball hitting the pitch is identifiable by other features, such as spin. Henceforth, we refer to 'pitch' and 'trajectory' synonymously. This trajectory moved within the plane of the screen and simulated movement in the direction perpendicular to this plane. For each frame of the simulated pitch, an isoluminant green circle was plotted on a gray background. The size of the circle increased as it approached the viewer, so as to give the illusion of depth. When the ball crossed 'home plate,' the circle disappeared.

As in previous work (Muraskin et al., 2013; Sherwin et al., 2012) using a related paradigm, each pitch was created in three dimensions of space using a differential equation solver in Matlab 2010a (Mathworks, Natick, MA, USA) (see pitch simulations below) and presented *via* PsychToolbox (Brainard, 1997; Pelli, 1997).

Most baseball pitches can be simulated using 6-coupled differential equations (Adair, 1995; Armenti, 1992) and we used these equations to simulate each pitch.

Equations of motion for simulated pitch trajectories:

$$\frac{dx}{dt} = v_x \quad (1)$$

$$\frac{dy}{dt} = v_y \quad (2)$$

$$\frac{dz}{dt} = v_z \quad (3)$$

$$\frac{dv_x}{dt} = -F(v)v_x + B\omega(v_z \sin\phi - v_y \cos\phi) \quad (4)$$

$$\frac{dv_y}{dt} = -F(v)v_y + B\omega v_x \cos\phi \quad (5)$$

$$\frac{dv_z}{dt} = -g - F(v)v_z - B\omega v_x \sin\phi \quad (6)$$

$$F(v) = 0.0039 + \frac{0.0058}{1 + e^{(v-v_d)/\Delta}} \quad (7)$$

The first three equations specify the change in spatial location in each direction, which equals the velocity of the baseball. The last four equations specify the accelerations due to the drag ( $F(v)$ ), the Magnus force ( $B$ ), and gravity ( $g$ ) acting on the baseball. After specifying the initial conditions ( $x_0, y_0, z_0, v_{x0}, v_{y0}, v_{z0}, \omega$  (rotational frequency)), the 6 ordinary differential equations were solved in MATLAB.

We simulated three different pitch categories with these equations. The three pitch categories – fastball, curveball, and slider – have well-defined individual initial conditions. To create each pitch category, we varied the initial velocity and the rotation angle. We also varied pitches within each category so that no two pitches from the same category followed the exact same trajectory. To this end, the initial conditions of the trajectory were also jittered within each pitch category.

### Behavioral paradigm

Subjects were presented with a pitch chosen at pseudorandom from the three pitch categories (here, 'fastballs', 'curveballs' and 'sliders'). Preceding the pitch, a horizontal bar (horizontal extent 3.93°, vertical extent 0.28°) appeared onscreen for a mean time of 819 ms, SD = 3.1 ms, during which time the horizontal length of the bar shrank at a constant rate until it disappeared. For pitches coming from a right-handed pitcher, the horizontal bar shrank in size to the left; *vice versa* for pitches from a left-handed pitcher. Once the bar shrank completely

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