Functional significance of shared brain state across various cognitive tasks

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Abstract:

Cognitive neuroscience aims to elucidate the neural mechanisms underlying cognitive functions. Classical fMRI studies have identified them by using specifically designed experimental tasks. Recently, a collaborative effort to establish a common ontology has enabled a broader understanding of cognitive functions beyond individual tasks. Despite progress, comprehensive insights of functions like sustained attention defined by task performance remain elusive due to variable brain activity patterns linked to performance across tasks. Recent computational advances offer data-driven estimation of brain states, independent of task performance. Studies using these methods frequently identify consistent brain states of the default mode network (DMN) and dorsal attention network (DAN), though their task-specific relevance and representation of cognitive functions are not fully understood. In this study, we estimated brain states in a data-driven manner using open fMRI data from about 100 participants who engaged in diverse cognitive tasks. Our findings indicate that both DMN and DAN states are common across tasks, with the DMN state associated with faster and more stable reaction times. However, accuracy differed by task and condition, suggesting that DMN and DAN may represent automatic processes and cognitive control, respectively. These data-driven approaches enable a unified analysis across tasks, enhancing our general understanding of cognitive functions.

Keywords: cognitive neuroscience; fMRI; data-driven approach; brain state

Introduction

A primary objective of cognitive neuroscience is clarifying the mechanisms that underlie cognitive functions. Classical neuroimaging research using fMRI has identified the neural correlates of specific function by contrasting experimental tasks that are carefully selected to vary with respect to only a key function of interest. Although each task probes only a small number of facets of cognition, the collaborative effort to establish a common ontology among experimental tasks emphasizes the critical importance of comparisons across these tasks [1]. This guides us to achieve a general understanding of cognitive functions without confining to specific cognitive task [2]. Despite these efforts, we lack a general understanding of cognitive functions, such as sustained attention that are defined by cognitive task performance. While the brain activation pattern associated with superior performance is regarded as reflecting focused state, one significant bottleneck is that brain activity associated with superior performance varies across cognitive tasks. Recent advances in computational methods offer a promising avenue for the data-driven estimation of brain states without relying on task performance. These advances consistently demonstrate the presence of the default mode network (DMN) and dorsal attention network (DAN) states [3–7]. However, since previous studies have primarily concentrated on specific tasks such as resting, movie viewing, and sustained attention tasks, it remains unclear whether these states are shared or specific to cognitive tasks, and what cognitive functions do these states represent. To solve these problems, we estimated brain states across various cognitive tasks and explored their correlation with task performance.

Methods

In this study, we applied a data-driven brain estimation method called energy landscape analysis [3,8] to an open fMRI dataset collected from 103 participants performing a variety of cognitive tasks [9]. For each cognitive task, reaction time (RT), RT variability, and accuracy in each brain state were evaluated.

Cognitive tasks

The open fMRI data consists of 103 healthy adults conducting attention network test (ANT), cued task switching (TwoByTwo), Columbia card task (CCTHot), dot pattern expectancy (DPX), delay discounting, simple and motor selective stop signal, Stroop, a towers task, and resting to examine the construct of self-regulation. Due to space limitations, we will only briefly describe the ANT, Stroop, DPX, and stop signal task, which are used to investigate the relationship between brain state and task performances. In the ANT, participants respond to arrows, indicated by a spatial cue (left or right), with congruent or incongruent flankers across 128 trials. In the Stroop task, subjects see color words printed in matching (congruent) or non-matching (incongruent) ink colors. Subjects are instructed to respond to the ink color of the word quickly and accurately. The task includes 96 trials. In the DPX task, subjects see a series of cue-probe stimulus pairs and make a speeded response after the probe. Each stimulus consists of dot patterns, with 6 possible cues and 6 possible probes. The “target cue” is 'A' and the “target probe” is 'X', and the others are ‘B’ and ‘Y’, respectively. Subjects must press one key if 'A' is followed by 'X' and a different key for any other cue-probe combination. The task consists of 160 trials and 55% of these trials are in the 'AX' condition (frequent) and 15% of these trials are in the other conditions (‘AY’, ‘BX’, ‘BY’), respectively. In the stop-signal task, subjects respond to simple cue with a key press. In some trials, a star appears after a delay, signaling the participant not to respond. There are a total of 125 trials, with 60% of the trials being go trials and 40% being stop trials. Task performance was evaluated in terms of RT, RT variability, and accuracy.

In the ANT and Stroop tasks, to investigate the relationship with attentional-control processes, we compared congruent and incongruent conditions. In the DPX task, to investigate the relationship with context processing, we compared the frequent (AX) and rare (AY) conditions. In the stop-signal task, to investigate the relationship with response inhibition process, we compared go and stop conditions.

Brain state analysis

The fMRI data were preprocessed using fmriprep 21.0.1 [10]. We extracted the activities from 8 networks (Fronto parietal control network divided into A and B in Yeo 7 network)[11,12] based on previous study [3]. We integrated these activities of all participants, and applied energy landscape analysis to estimate the stable brain state for each cognitive task. This analysis labels each time point as a stable brain state. The brain state is represented by one of 256 (2^8) patterns with 8 networks ACTIVE and INACTIVE. By knowing the brain state at each time point, we could evaluate the task performance during participants spend in the brain state.

Results

Brain state results

We found that a total of 12 stable brain states existed across all tasks (Figure1A). Notably, State1 (DMN active state) and State2 (DAN active state) were dominant across a range of tasks including ANT, Stroop, DPX, and both stop signal tasks. Furthermore, we discovered for the first time that State1 and State2 were shared brain states present in all tasks except for the delay discount task (Figure1B). This novel finding underscores the ubiquitous nature of DMN and DAN states, aligning with and extending previous research that has consistently reported on these states [3,5].

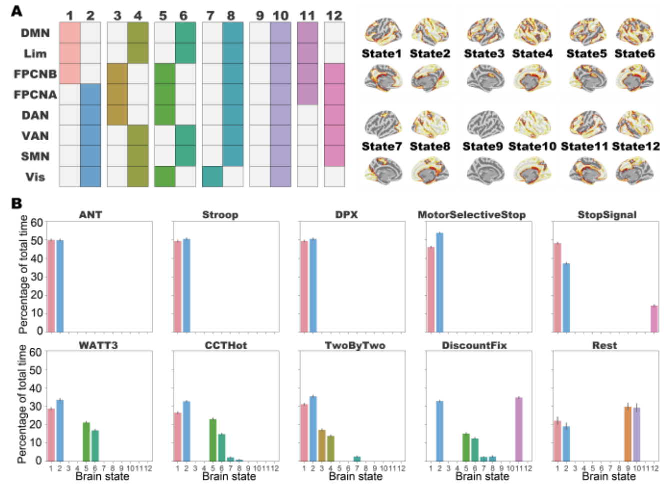

Figure 1: Estimated brain states. The colored cell represents ACTIVE network (A) and their dwell time (B) in 10 cognitive tasks. DMN: Default mode network; Lim: Limbic; FPCN: Fronto-parietal control network; DAN: Dorsal attention network; VAN: Ventral attention network; SMN: Somato-motor network; Vis: Visual

Relationship between state and behavior

We explored the link between cognitive processing and State1 and State2 by analyzing their influence on performance in ANT, Stroop, DPX, and stop signal tasks where both states were dominant. Using a generalized mixed effects model, we analyzed interactions between condition and brain state, treating participant effects as random in each task. We found that average RTs in State1 were significantly faster and more stable across all task conditions compared to those in State2 (State effect, all $p < 0.05$, no significant interaction). This finding aligns with the performance observed in sustained attention tasks from previous studies [3,5]. Surprisingly, however, the brain states associated with high accuracy varied depending on the task condition (interaction effect in Stroop and DPX, $p < 0.005$, Figure 2). Specifically, the accuracy was significantly higher in State2 in the incongruent condition of Stroop, the rare condition of DPX, and the stop condition of stop signal task, while the accuracy was significantly higher in State1 in the other conditions except for stop signal go condition. The conditions associated with higher accuracy in State 2 were task conditions in which cognitive control is important [13,14]. This suggests that State 2 represents a cognitive control process. Furthermore, faster RT but low accuracy during State1 in those conditions suggests that State1 represents automatic process.

In this study, we found that two brain states, common across various cognitive tasks, consistently associated with the speed and variability of RT but differently associated with accuracy. Using data-driven methods allows for unified analysis across tasks, improving our general understanding of cognitive functions.

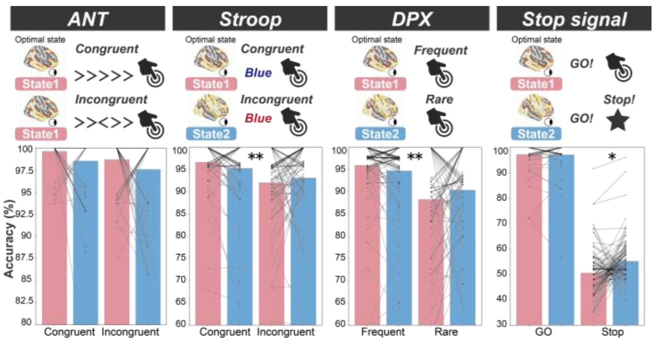

Figure2. Relationship between brain state and behaviors in cognitive tasks. ** $p < 0.005$, significant interaction effect. * $p < 0.05$, significant state effect.

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