Trends in Cognitive Sciences

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Spotlight

Bridging Motor and Cognitive Control: It's About Time!

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Is how we control our thoughts similar to how we control our movements? Egger *et al.* show that the neural dynamics underlying the control of internal states exhibit similar algorithmic properties as those that control movements. This experiment reveals a promising connection between how we control our brain and our body.

We often describe our mental states through analogy to physical actions. We hold something in mind or push it out of our thoughts. An emerging question in cognitive control is whether this relationship runs deeper than metaphor, with similar cognitive architectures underpinning our ability to control our physical actions and our mental states. For instance, recent work has shown that analogous control processes serve to optimize performance and regulate brain dynamics for both motor and cognitive actions [1,2]. A new study by Egger and colleagues [3] provides important new clues that the mechanisms supporting motor and cognitive control are more similar than previously shown.

These researchers tested whether the control of internal states exhibits a signature property of the motor system: the reliance on an internal model to guide adjustments of control [4]. To control one's actions, a person needs to maintain an internal model of their environment (e.g., potential changes in terrain or atmosphere) and of their own motor system (e.g., how successful they are at executing a motor com-

mand [5]). This model can be used to generate online predictions about the outcome of an action and to course-correct when there is a mismatch between that prediction and the actual outcome. This process is thought to be implemented via interactions between: (i) a simulator that makes predictions, (ii) an estimator that learns the current state, and (iii) a controller that implements actions. This new study investigated whether neural activity during the control of cognitive processes reflected this same three-part architecture.

To answer this question, Egger and colleagues recorded neural activity while monkeys performed an interval reproduction task (Figure 1). The monkeys observed two samples of a time interval and then timed a saccade to reproduce this interval. Previous work has shown that population-level neural activity in the dorsomedial frontal cortex (DMFC) during similar tasks systematically scales with the timing of an action [6]. If action timing in this task depends on an internal model, then this temporal scaling should already be present in DMFC activity prior to receiving a cue to respond. If the monkeys were not relying on an internal model, and the activity instead reflected the passive measurement of time ('open-loop' control), then DMFC activity during the second interval should not exhibit such temporal scaling.

The monkeys' behavior and neural activity demonstrated that they combined prior knowledge about the average interval duration with their perception of the current interval duration [7]. This behavior was well-captured by a near-optimal Bayesian algorithm that updated predictions in a way that was biased towards the average interval. By independently varying the duration of the two sample intervals, the authors

were further able to show that the monkeys incorporated both samples into their duration estimate.

Signatures of this biased updating process were also observed in DMFC neural activity. Replicating previous studies, individual neurons in the DMFC demonstrated ramping activity during the reproduction of an interval, with faster ramping when the monkey reproduced shorter intervals [6]. Critically, neural activity during the second sample interval exhibited the predicted simulation profile: neurons demonstrated interval-dependent ramping during this epoch, prior to the response cue.

Further support for an internal model hypothesis was found across different measures of neural activity, and in their relationship with subsequent behavior. Temporal scaling was evident not only at the level of DMFC single neurons but also in the population-level neural dynamics across this region. Unlike the transient single-unit responses, the rate of change in these population dynamics scaled consistently with interval length throughout the second sample interval. These dynamics reflected the same Bayesian biases observed in monkeys' behavior: an initial bias towards the average interval duration that became less biased with more samples. Critically, these population dynamics also predicted when the monkey would saccade on the upcoming response interval, and did so above and beyond what would be predicted by the lengths of the sampled time intervals alone. Collectively, these findings are consistent with the DMFC implementing an internal model to optimize the learning of task goals and the control of neural population dynamics.

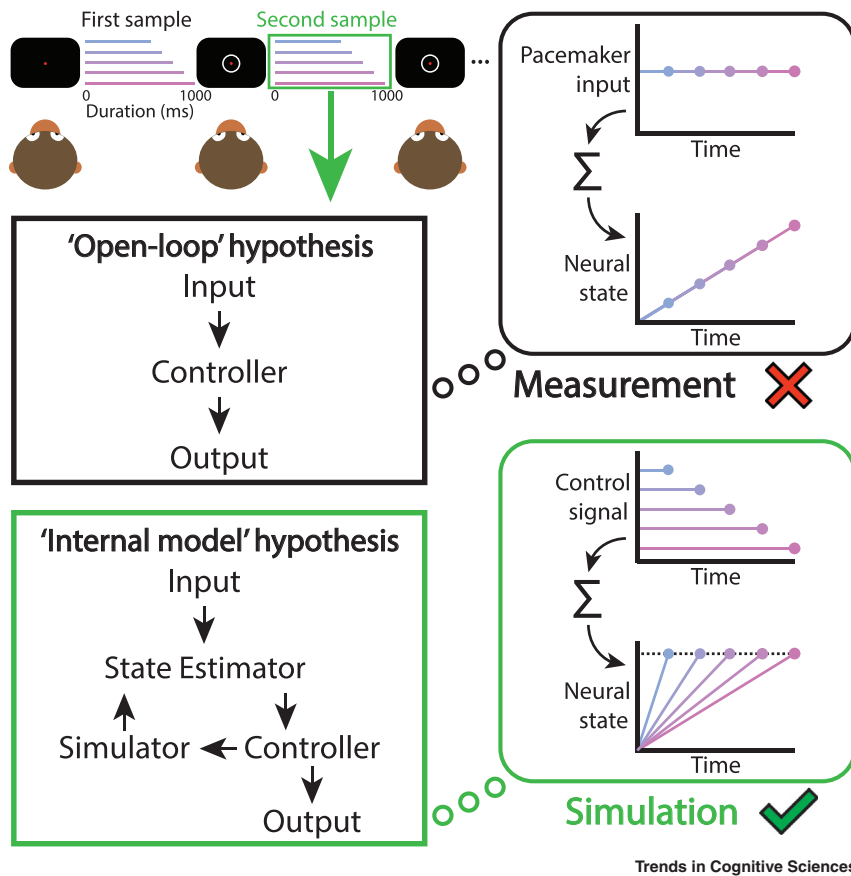This study provides evidence that DMFC mediates the influence of prior

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Figure 1. Alternative Hypotheses for Internal State Control.
Monkeys observed two sample time intervals (top) and then tried to reproduce the interval (not shown). There were two competing hypotheses for the form brain dynamics would take during the second sample interval. Under the 'open-loop' hypothesis, neural activity should not distinguish between expected durations, instead reflecting passive measurement of time. Under the 'internal model' hypothesis, neural activity should distinguish between expected durations, producing a simulation that aids in learning and control. The authors observed that neural responses were consistent with the internal model hypothesis, aligning the control of internal states with prominent theories of motor control. Task figure adapted from [3].

and noisy environment) and that they are also both constrained by some underlying cost, limiting the amount of control that individuals can engage at a given time. As a consequence, decisions about how to allocate one's control are sensitive to whether the reward for goal achievement outweighs these costs [10]. To the extent computational and neural architecture for motor and cognitive control allocation mirror one another, the behavior and neural dynamics observed in the current task should demonstrate sensitivity to performance incentives for both forms of control.

In spite of their abundant bodies of research, the obstacle to bridging our understanding of motor and cognitive control have been similarly abundant, including limitations of tasks, measurement tools, and model organisms. This study demonstrates how a combination of computational modeling and measures of neural dynamics in the monkey can be leveraged towards this goal and, in doing so, provides a valuable path forward in mapping the joints between these two domains of control.

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predictions and incoming sensory evidence on planned actions, and lays the groundwork for critical tests of this proposed mechanism using causal manipulations (i.e., stimulation or inactivation). Such causal tests can also help to rule out alternative accounts of neural dynamics during the sample intervals, for instance, whether they reflect a simulated motor plan (as the authors infer) or an interval expectation (e.g., predicting the onset of the interval cue [8]). Nevertheless, by elaborating on the neuronal dynamics within DMFC

during a task that requires online adjustments of learning and control, this study builds on a growing literature that implicates regions along this dorsomedial wall in the control of motor and cognitive commands [9,10].

More generally, this research provides compelling new evidence that motor and cognitive control share a common computational toolbox. Past work has suggested that both forms of control serve similar objectives (achieving a goal state within a dynamic, uncertain,

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