

Tasks as controllers: Engineering real-time fMRI to validate Resting State Network Dynamics

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Introduction

¹Resting-state networks (RSNs) are central to cognition and brain health, but their functional roles remain difficult to test experimentally. Conventional task fMRI can show that RSN activity changes during cognitive demands, yet it rarely provides falsifiable input-output models that predict how coordinated RSN states should change under defined task inputs. Here, we ask whether fMRI tasks can be modeled formally as a controller that moves the brain through a low-dimensional RSN state space. Our objective is to use state-space modeling and controllability analysis to characterize task-driven RSN dynamics and motivate closed-loop real-time fMRI adaptations of tasks. We demonstrate the concept of fMRI tasks acting as controllers of RSN dynamics using the multisource interference task (MSIT) is a robust executive-control task. The MSIT reliably modulates default mode network (DMN) activity and engages cognitive-control systems.

Methods

We analyzed MSIT fMRI data from 150 participants who also completed a prior DMN neurofeedback study. RSN activity was decoded using support vector regression models trained to a 10-network set of RSN templates. For each participant, decoded 10-dimensional RSN time series were modeled using Sparse Identification of Nonlinear Dynamics (SINDy; **Fig. 1A**), with congruent and incongruent MSIT task timing modeled as control inputs. We estimated coupled state equations of the form $\dot{x} = Ax + Bu$, where x represents RSN activity, A captures intrinsic RSN coupling, and B captures task input effects. We then computed the controllability matrix $C = [B \ AB \ A^2B \ \dots \ A^{n-1}B]$ to determine whether MSIT inputs could theoretically steer the RSN system through the modeled state space. Finally, we projected single-subject RSN activity onto leading controllability directions to evaluate whether these directions separated congruent and incongruent task states and could support adaptive real-time task control.

Results

Results are shown in Figure 1. **Fig. 1B** shows SINDy results, with Bonferroni-corrected RSN dynamics during MSIT. Specifically, we find statistically significant coefficients estimating $\dot{x} = Ax + Bu$ across 150 participants (McDonald et al., 2017) for the MSIT. The controllability matrix C was full rank, indicating a controllable system. **Fig. 1B** also shows the first two eigenvectors of C . **Fig. 1C** demonstrates MSIT acting as an RSN controller. Shown are the mean of all participants' congruent and incongruent 10-D RSN activity for every TR projected onto the first two eigenvectors of the group controllability matrix (from **Fig. 1B**). Arrows indicate the mean coordinates for a single individual. Also shown is every TR of the same individual's MSIT blocks, demonstrating the robustness of MSIT's RSN control. Finally, ROC curves using the group GLM as the gold standard supports the feasibility of an adaptive, rtfMRI-controlled MSIT task. **Fig. 1D** demonstrates numerical integration (red) compared mean response from McDonald et al. (2017) MSIT model (blue). This demonstrates that the SINDy models can accurately predict RSN dynamics in independent experimental data. **Fig. 1E** shows reproducibility scatter plots of MSIT vs. DMN NF from A matrix coefficients showing both a high degree of reproducibility as well as a major task-specific difference (red arrow) between the medial visual network and its dependence on the DMN.

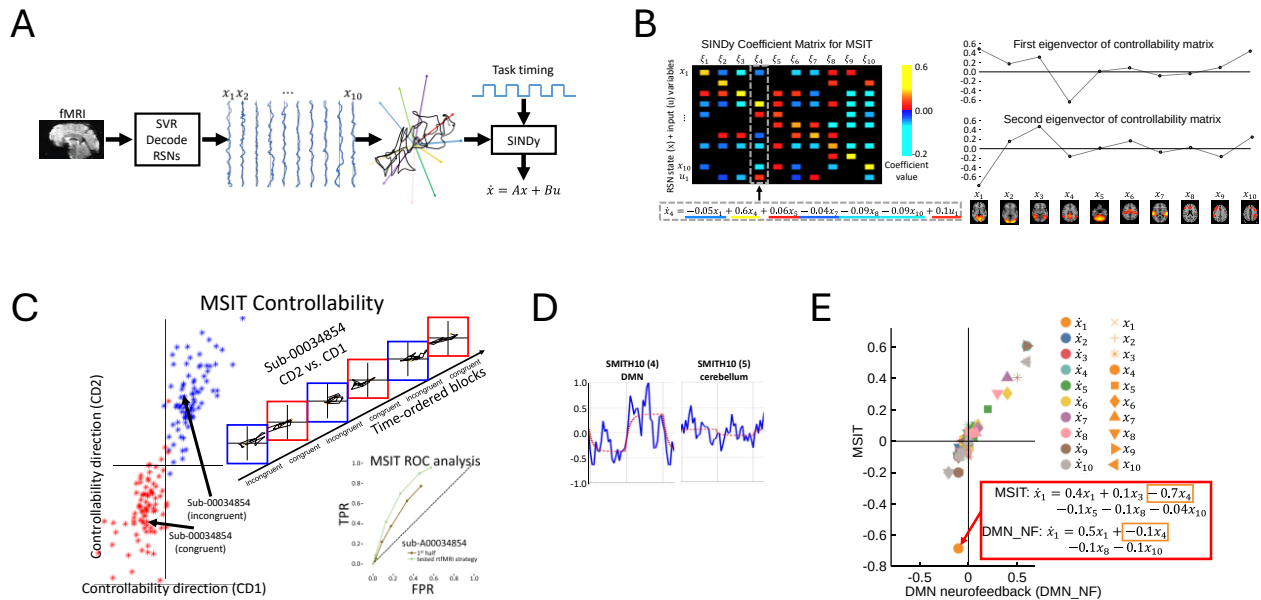
To summarize, MSIT-controlled RSN dynamics were highly consistent across participants. The estimated state-space coefficients survived conservative Bonferroni correction across the 10 coupled equations, indicating reproducible intrinsic and task-driven RSN interactions. The MSIT controllability matrix was full rank, suggesting that the task defines a controllable RSN system within the modeled 10-dimensional state space. Projection of decoded RSN time series onto leading

controllability directions separated congruent and incongruent MSIT states at the single-subject, TR-by-TR level. These results identify an MSIT-specific control basis for RSN dynamics. Preliminary offline simulations further support Rapid-MSIT: early termination of congruent or incongruent blocks once the projected RSN state crosses a controllability threshold can match or improve conventional MSIT mapping accuracy using the same or fewer time points.

Conclusions

These findings support a new interpretation of task fMRI: MSIT can be modeled as an experimental controller of coordinated RSN dynamics, rather than only as a task that evokes regional activation or DMN suppression. State-space modeling yields explicit, falsifiable predictions about how executive-control demands should move RSN activity, while controllability analysis identifies task-specific directions that can guide real-time stimulus adaptation. Rapid-MSIT will test whether closed-loop fMRI can prospectively validate these predictions by switching task conditions when target RSN states are achieved. More broadly, this work provides a scalable framework for engineering fMRI tasks that test, rather than merely observe, coordinated network function.

Figure 1



References

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