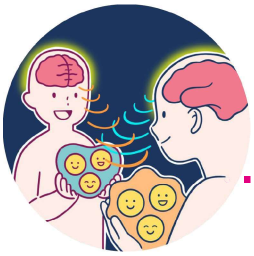
IoB Middleware

Moonshot Research and Development Program Goal 1 Kanai Project



Theory of Brain Control

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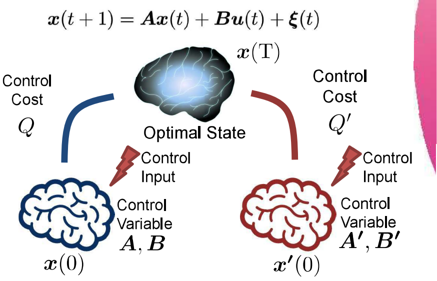
Overview

The brain can be considered a system that controls itself. If we can unravel the mechanisms of this control, it may become possible to guide the brain into desired states. We are currently working to elucidate the brain's controllability. For example, controllability during wakefulness should differ significantly from that during sleep or fatigue. One goal of this research is to investigate whether we can classify brain states based on these differences in controllability. Understanding the brain's controllability then allows us to approach the question of how to bring the brain closer to a desired state and what the optimal control might be. This represents another direction this research aims to pursue.



How the Brain can be Controlled?

1. System Identification via Perturbation (Ogino et al, bioRxiv, 2025): To realize brain control, it is necessary to model and estimate the temporal changes and dynamic characteristics of brain activity as accurately as possible. It has been found that achieving this accurate estimation is effective not only by observing brain activity but also by applying "perturbation inputs" and observing the brain's response. This is because perturbation makes the characteristics of dynamics that are inherently hidden and invisible become observable (Figure 1). We have developed a theory to investigate what kind of perturbation input should be applied to achieve the greatest improvement in identification accuracy. Based on this theory, system identification is most efficient when the frequency of the perturbation input matches the system's intrinsic frequency. These results also validate the effectiveness of brain state discrimination using stimulation techniques such as transcranial magnetic Stimulation (TMS). Moving forward, we will conduct verification studies, including the identification of effective perturbation inputs using real data.

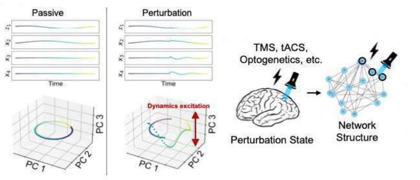


Figure 1. Excitation of invisible dynamics by stimulation Z

2. Classification of Brain States Based on Controllability (Shikauchi et al, bioRxiv, 2025): The brain can be viewed as a control system that transitions between states, such as shifting from a resting state to motor activity. This study proposed a simple method to estimate the controllability of brain states by introducing a control metric called the controllability Gramian (Figure 2). This method, grounded in control theory, utilizes the fact that the controllability Gramian is represented as the Gram matrix of the time-series data X during impulse stimulation. Introducing the controllability Gramian allows evaluation of both the ease of controlling a state (size of the Gramian eigenvalues) and the direction of control (direction of the Gramian eigenvectors). This enables a complete description of brain controllability along two axes: in which direction and to what extent control is possible. In data analysis, the proposed method was applied to transcranial magnetic stimulation (TMS)-electroencephalogram (EEG) data recorded during both active and resting states, characterizing a total of six distinct brain states from the perspective of controllability. The results revealed differences in the directionality of controllability across some brain states.

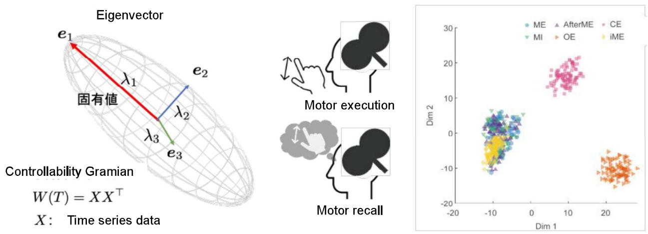


Figure 2. Eigenvalue decomposition of controllability Gramian and classifiability plot in motor tasks

Control Cost in Fluctuating Systems

3. Quantification of Stochastic Control Costs (Kamiya et al, Journal of Neuroscience, 2023): Quantifying control costs is essential for revealing how the brain can be controlled and which brain regions are most critical for regulating brain states. One challenge in elucidating brain controllability is that brain activity data are highly noisy and exhibit stochastic dynamics. Previous studies have largely ignored this probabilistic fluctuation, making accurate estimation of control costs difficult. This study constructs a new quantitative framework for control costs that accounts for the probabilistic fluctuation in neural dynamics. We established an analytical representation of the stochastic control cost and demonstrated that this cost can be decomposed into a mean control cost and a covariance control cost. The utility of the proposed metrics was confirmed using whole-brain imaging data from humans, identifying key brain regions involved in control transitions from the resting state to seven cognitive task states. Results revealed that the inferior visual cortex plays a common crucial role in average control across these transitions, while the posterior cingulate cortex plays a common crucial role in covariance control.

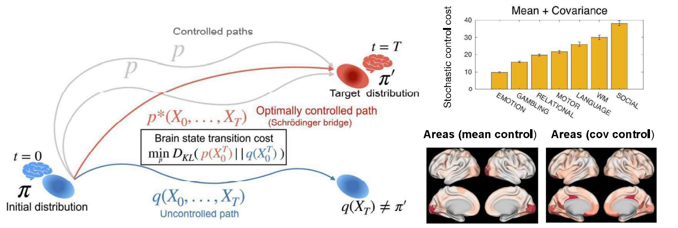


Figure 3. Control cost in brain state transitions and probabilistic systems

4. Thermodynamic Maintenance Cost (Sekizawa et al, Physical Review X, 2024): While the brain incurs control costs when changing from its current state to another state, it also incurs control costs to maintain its current state. This maintenance cost can be quantified by applying stochastic thermodynamics. We derived the relationship between neural oscillations in the brain and the entropy production rate used in stochastic thermodynamics. First, we mathematically demonstrated that the "housekeeping entropy production rate," which relates to maintaining the probability distribution within the total entropy production rate, can be decomposed into an independent positive contribution in an oscillatory representation (Figure 4). Specifically, the sum of the square of the oscillation frequency multiplied by the amplitude corresponds to entropy production. This means that faster oscillating waves incur higher maintenance costs. Furthermore, applying the proposed method to monkey EEG data revealed clear differences in the contribution of oscillations between the awake and anesthetized states. Specifically, the contribution of delta waves increased in the anesthetized state, while the contribution of higher frequency components like theta waves decreased. This demonstrates that the characteristics of neural oscillations accompanying changes in brain state can be interpreted from a physical perspective involving thermodynamic dissipation and the limits of information processing.

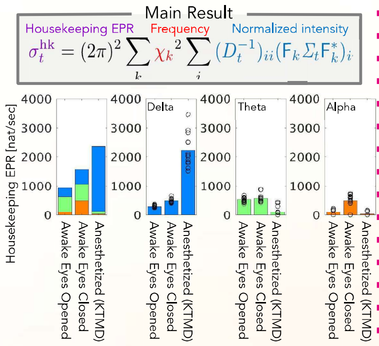


Figure 4. Decomposition of entropy production rate and its application to monkey EEG data

Summary of Results

This study yielded the following results:

[1] Designing optimal perturbation inputs for system identification in neuroscience (Ogino et al, bioRxiv, 2025)

[2] Quantifying state-dependent control properties of brain dynamics from perturbation responses.→ Applied to EEG data for motor state discrimination (Shikauchi et al, bioRxiv, 2025)

[3] Optimal Control Costs of Brain State Transitions in Linear Stochastic Systems→ Applied to human fMRI data to quantify transition costs between task states and identify contributing regions (Kamiya et al, Journal of Neuroscience, 2023)

[4] Decomposing thermodynamic dissipation of linear Langevin systems via oscillatory modes and its application to neural dynamics→ Characterization of Arousal and Anesthesia States Using Monkey ECoG Data (Sekizawa et al, Physical Review X, 2024)

Future Prospects

We will apply the theoretical framework we have developed to actual neural data to verify whether brain states—such as fatigue levels and arousal levels—can be distinguished from the perspective of controllability. Furthermore, we believe this could lead to optimal intervention methods for guiding the brain into specific states and clinical applications for correcting abnormal controllability in the future.

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Graduated from the Department of Physics, Faculty of Science, The University of Tokyo. Earned a Ph.D. from the Laboratory of Masato Okada, Graduate School of Frontier Sciences, The University of Tokyo. Assumed current position in April 2019. After obtaining his Ph.D., he was a member of the Shunichi Amari Team at the RIKEN Brain Science Institute until March 2017. From October 2011 to October 2013, he was a member of Giulio Tononi's laboratory at the University of Wisconsin-Madison. From April 2015 to October 2016, he was a member of Naotsugu Tsuchiya's laboratory at Monash University, Australia.From March 2017 to March 2019, he was a member of the Basic Research Group, Technology Department, at Araya Corporation.

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Internet of Brains