Functional Role Division in Working Memory Emerges from Intrinsic Neural Timescale Diversity

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Abstract

Neural activity spans a wide range of timescales, both across and within cortical areas. However, the functional significance of this temporal diversity remains poorly understood. In this study, we investigate how heterogeneity in neural timescales within the frontal cortex—a hub for higher cognitive functions—supports performance in a context-dependent working memory task. Specifically, we model a delayed match-to-sample task with context cues, which requires the maintenance of information over time and flexible adaptation of behavior based on contextual input.

We construct a recurrent neural network (RNN) composed of units with varying intrinsic time constants to perform this task. Our analysis reveals that task performance is optimized when neural timescales are appropriately balanced, consistent with experimental observations. Notably, neurons with slower dynamics play a causal role in improving task performance despite not showing stronger selectivity to task-relevant signals compared to faster neurons. In contrast, fast neurons encode task-relevant information more precisely but only transiently.

These findings suggest that diversity in neural timescales supports a functional division of labor, enabling stable memory maintenance and flexible signal encoding. This work provides a mechanistic account of how temporal heterogeneity in neural populations can support complex cognitive computations.

Keywords: working memory, intrinsic neural timescales

Introduction

The neural system is a complex network composed of components that operate over a wide range of timescales. While slow synaptic dynamics—such as synaptic plasticity—shape long-term connectivity and learning, faster neural dynamics are crucial for executing cognitive functions. Recent experimental studies have shown that neural activity exhibits a wide distribution of intrinsic timescales, both across cortical areas(Murray et al., 2014; Runyan, Piasini, Panzeri, & Harvey, 2017) and within individual areas(Cavanagh, Wallis, Kennerley, & Hunt, 2016; Cavanagh, Hunt, & Kennerley, 2020; Perez-Nieves, Leung, Dragotti, & Goodman, 2021).

Although intrinsic timescales have been linked to perception and working memory processes(Wasmuht, Spaak, Buschman, Miller, & Stokes, 2018; Cavanagh et al., 2016), the precise role of neurons with different timescales in ongoing information processing remains unclear. Some studies suggest that intrinsic timescales observed during resting states are preserved during task performance, and that timescale diversity may enhance learning(Perez-Nieves et al., 2021). However, the functional contributions of neurons with distinct temporal dynamics—such as how their representations differ or how they support task performance—remain largely unresolved. In this study, we investigate the functional roles of intrinsic neural timescales in a context-dependent working memory (CWM) task(Kurikawa, 2025), which requires the sustained maintenance of contextual information throughout each trial (Fig. 1). To this end, we train an artificial recurrent neural network (ARNN) composed of neurons with two distinct time constants and analyze how temporal diversity supports task performance.

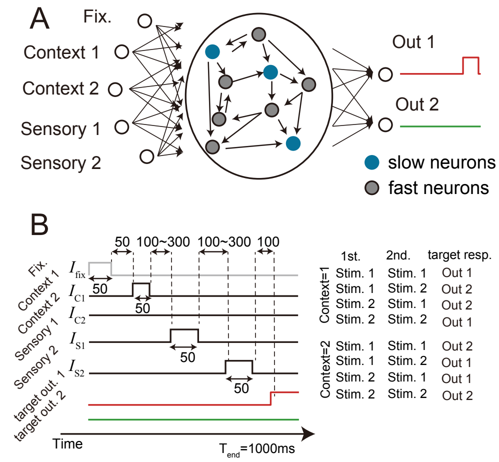

Figure 1: Schematic image of our model and task. A: Network image. B Left: Task procedure showing a trial with context 1. B Right: A table showing the mapping between the inputs and target outputs, depending on the context.

Methods

Network Model

The recurrent network has $N_{in} = 5, N = 200$, and $N_{out} = 2$ neurons in an input, hidden, and output layers, respectively. In the hidden layer, N rate coding neurons follow the equation

$$\tau_i \frac{dx_i}{dt} = \tanh\Big(\sum_{j\neq i} J_{ij}x_j + \sum_j W^{in}_{ij} I_j + b_i\Big) - x_i, \qquad (1)$$

where x_i $(i = 1,,,N)$ is the activity of i-th neuron with its time scale τ_i and J is a connectivity matrix in the recurrent network. W is a connectivity matrix from the input neurons to the recurrent network and I represents the activities of input neurons,

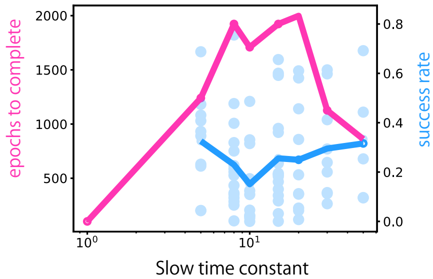

Figure 2: Learning performance with the time constant varied.

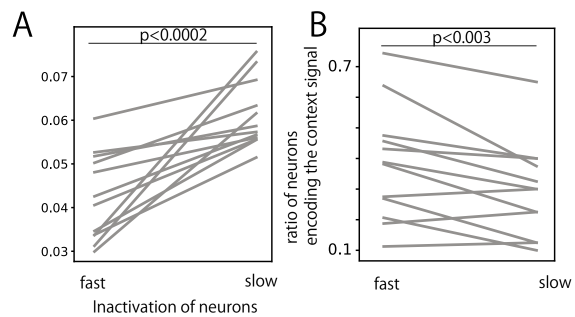

Figure 3: The role of diverse timescales. A: Inactivation of fast and slow neurons increases the deviation of the output from the target. Without inactivation, the deviation is less than 0.01. B: The number of neurons that encode the context signal scaled by the number of neurons.

which will be explained later. N_{out} neurons in the output layer are received the input from the hidden neurons through a fully connecting weight matrix W^{out} as $x_{out}(t) = W^{out}x + b_{out}$. We train the network (trainable parameters: $J, W^{in}, W^{out}, b, b_{out}$) with the back-propagation algorithm with the adam optimizer to perform the CWM task after discretizing Eq. (1).

The time scale parameters τ_i have two values (fast and slow neurons) in this study. Fast neurons comprise 80% of the hidden units, while slow neurons make up the remaining 20%. The time scale parameters are not trainable and are fixed during training, $\tau_{fast} = 1, \tau_{slow} = 10$ except of analysis of dependence of τ_{slow}.

Context-dependent Working memory task (CWM)

The input consists of five types of signals, each represented by a dedicated input neuron (see Fig. 1A). The fixation, context, and two sensory cues are activated sequentially. Context is randomly chosen between contexts 1 and 2; sensory cues are also randomly selected from two options. In context 1 trials, the network is required to produce output 1 when the first and second sensory signals are identical, whereas in context 2 trials, it must produce output 2 under the same condition, as shown in Fig. 1B.

Results

Optimal balance between the fast and slow timescales

First, we explore whether the balance between the fast and slow timescales affects training performance. Fixing $\tau_{fast} = 1$ and varying τ_{slow}, we measured training success rates and epochs to complete training (Fig. 2). Success is defined as completing training within 2000 epochs. Performance peaked around $\tau_{slow} \sim 10$, both in terms of speed and accuracy. These timescale values correspond to membrane time constants. Notably, biological studies in monkeys and humans report membrane constants ranging from 10 ms to 70 ms(Perez-Nieves et al., 2021), suggesting that biological systems may be tuned for optimal cognitive performance.

Inactivation of neurons with different timescales impairs the performance differentially

To uncover the functional role of the fast and slow neurons, we conduct the inactivation of some neurons and analyze how the behavior of the network differs. Throughout the inference process (namely, recall process after training without change in the parameters), values of randomly chosen 10 fast (or slow) neurons are clamped at 0. For this process, we measure the mean square error between the target behaviors and the actual behaviors generated by the network with the inactivation and plot it in Fig. 3A. Inactivation of slow neurons led to a larger increase in MSE than that of fast neurons, indicating a greater contribution of slow neurons to task performance.

Interestingly, more fast neurons encoded task-relevant signals—context, stimuli, and output choice—compared to slow neurons (Fig. 3B). Additionally, the encoding magnitude (defined as the activity difference between signal on/off conditions) was greater for fast neurons. Thus, fast neurons provide stronger signal encoding, but slow neurons are more critical for performance.

Conclusion

This study demonstrates that an optimal balance between fast and slow neural timescales is crucial for effective task performance in context-dependent working memory. Slow neurons, despite small encoding performance for task-relevant signals, play a significant causal role in task success, highlighting their contribution to stable memory maintenance, whereas fast neurons encode task signals more strongly. This finding implies a reasonable information flow: the task-relevant signal is, first, encoded in the fast neurons and then the encoded information is transferred to the slow neurons, giving the stable memory throughout the trial. Thus, our study demonstrates that diversity in neural timescales supports a functional division of labor, where slow and fast neurons specialize in different aspects of task execution, ultimately improving overall cognitive performance.

Acknowledgement

The present work is supported by JSPS KAKENHI (No 25H02622) and Special Research Expenses in Future University Hakodate.

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