Behavioral Data Validation of Attractor Network Mechanisms in Multi-alternative Decision Tasks

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Abstract: Drift diffusion model (DDM) is a classic psychophysical model for explaining binary decision-making, but its extension to multi-alternative decisions and its neural implementation mechanisms remain to be validated. We designed a six-alternative forced-choice decision task to investigate key behavioral predictions of the ring attractor network as a neural implementation of multi-alternative DDM. By analyzing behavioral data, we found significant neighbor error effects, positively skewed reaction time distributions, and classic psychophysical laws. These results consistently support the ring attractor model proposed by [1], indicating that multi-alternative decision-making relies on neuronal population coding and lateral inhibition mechanisms, rather than simple independent evidence accumulation.

1 Introduction

In the field of perceptual decision-making, the classic drift diffusion model (DDM) successfully describes the evidence accumulation process in binary decisions. It assumes that decision-making is an evidence accumulation process: the brain continuously accumulates evidence related to the options until the evidence for one option reaches a preset threshold, triggering a decision response. However, when the number of alternatives increases, how the brain processes multiple competing options remains theoretically debated. Currently, there are two main competing hypotheses: the independent race model assumes that each option accumulates evidence independently without mutual interference, while the ring attractor network model suggests that options compete through lateral inhibition, and decision-making is a dynamic evolution of population activity.

Theoretical work by [2] shows that n-alternative decision-making can be modeled as an (n-1)-dimensional drift diffusion process, and the ring attractor network is precisely the neural implementation of this multidimensional DDM. This model predicts: (1) decision errors should mainly occur in neighboring directions, forming a "Mexican hat" error distribution pattern; (2) reaction time distributions should exhibit long-tailed characteristics, reflecting decision deadlocks in nonlinear dynamics.

We designed a six-alternative random dot motion task to behaviorally validate two key predictions of the ring attractor network as a neural implementation of multi-alternative DDM. This not only helps distinguish between competing theoretical models but also provides an empirical basis for understanding the neural computational mechanisms of multi-alternative decision-making.

2 Ring Attractor Network

The ring attractor network, proposed by [1], is a computational neuroscience model for explaining how the brain processes continuous variables (such as direction selection) during perceptual decision-making. The core idea is to map the decision space onto a continuous neural population code, where neurons are organized into a ring topology according to their preferred directions.

In this network, neurons with adjacent preferred directions support each other through local excitatory connections, while neurons with distant preferred directions compete through global inhibitory connections. This connectivity pattern forms the so-called "Mexican hat" interaction profile: center excitation, near-neighbor inhibition, and distant weak inhibition. When external stimulus inputs are applied, the network forms a stable activity "bump" whose location corresponds to the direction currently most supported by accumulated evidence.

The ring attractor network provides a neural computational framework for multi-alternative decision-making, extending the linear evidence accumulation of traditional DDM to a continuous neural population activity space. In this architecture, decision errors are no longer random but follow specific spatial tuning patterns. Additionally, reaction time distributions exhibit nonlinear dynamic characteristics, providing testable predictions at the behavioral level.

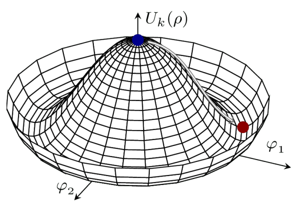

Figure 1: Mexican hat diagram of interaction profile

3 Our Experiment

We used a six-alternative random dot motion paradigm to validate the behavioral predictions of the ring attractor network. The experimental task required participants to judge the overall motion direction of random dot clouds, with six possible direction options (0°, 60°, 120°, 180°, 240°, 300°), and responses were made via keypresses. Each direction corresponded to multiple key options, including letter and number keys, to reduce response bias. We designed low, medium, and high coherence levels, with each direction repeated multiple times under each coherence condition. Data from five participants were collected, totaling 756 trials.

After collecting the behavioral task data, we performed data analysis. First, we examined the spatial error distribution across all trials, calculating the deviation between the response direction and the target direction for each error trial, and statistically analyzed the proportions of neighbor errors (±60°) and opposite errors (180°). Next, we analyzed the reaction time distribution for all trials, plotting RT histograms and calculating skewness and long-tail characteristics. Finally, we plotted psychometric curves to reflect changes in accuracy and reaction time with coherence.

4 Experimental Results

Psychometric curves (Fig. 2) show that accuracy increased with coherence, and average reaction time decreased with coherence. This aligns with general perceptual decision-making laws, validating the effectiveness of the behavioral task. The spatial distribution of error trials exhibited a significant neighbor effect (Fig. 3). Among 212 error trials, neighbor errors accounted for 60.8%, significantly higher than the random guessing level (40%). This result is consistent with the predictions of the ring attractor network, indicating that decision evidence diffuses along adjacent directions in the neuronal network rather than being randomly distributed. The reaction time distribution showed a clear positive skew (Fig. 4), with a skewness of 0.8, a mean significantly higher than the median, and obvious long-tail characteristics. This suggests that in some difficult trials, decision processes encountered deadlocks, with the system among multiple attractors, leading to abnormally prolonged reaction times—consistent with predictions from nonlinear dynamic systems [3].

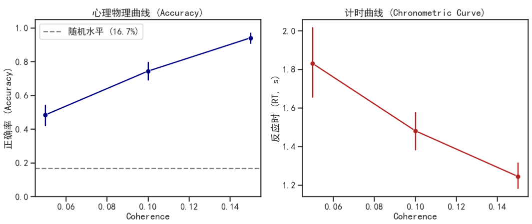

Figure 2: Psychometric curves: accuracy and reaction time vs. coherence

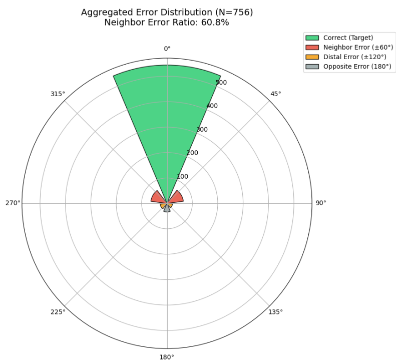

Figure 3: Spatial distribution of error trials

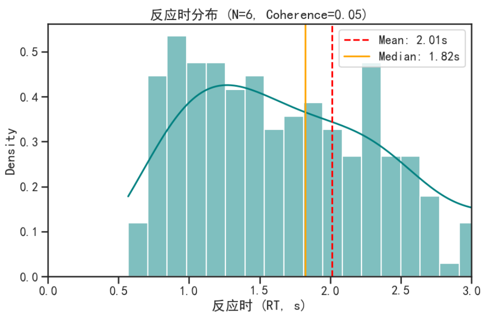

Figure 4: Reaction time distribution histogram

5 Conclusion

This study behaviorally validates the ring attractor network as a neural implementation mechanism for multi-alternative decision-making [1]. The observed neighbor error effects and long-tailed reaction time distributions are consistent with predictions from nonlinear attractor dynamics, supporting the Wong & Wang (2006) model. These findings suggest that multi-alternative decisions rely on population coding and lateral inhibition, with evidence diffusing continuously rather than accumulating independently across discrete channels. This work provides empirical support for attractor-based theories of decision-making and offers a foundation for future neuroimaging studies and applications in cognitive assessment and interface design.

References

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Appendix:Teammates Contribution

Rank doesn't stand for amount of contributions:

- 231880101 Junhui Sun: write the experiment report and collect data.
- 231880207 Xiao Liu: code and analyse the results of the experiment.
- 231880387 Ziyue Wang: design the experiment and collect data.