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Modeling the Effect of Prior Information on Human Tactile Object Recognition Using Recurrent Neural Networks

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I. Introduction

Sensory information from touch is essential for human survival. Through touch, humans learn about the shape of an object in the three-dimensional space. However, depending on the size of the object, only a portion of its shape can be perceived at any given moment. To form a comprehensive representation, the brain must accumulate tactile information both spatially and temporally. Recent studies [1], [2] have shown that the prior information from other modalities–such as visions, auditions, or previous tactile experiences–can enhance tactile representation at the primary somatosensory areas. However, little has been known about the mechanism by which prior information influences tactile object recognition in human.

Since the brain remains largely a black box, behavioral modeling provides a more practical approach to investigate such mechanism. Traditionally, tactile behavior has been modeled using machine learning methods such as Ridge Regression and Support Vector Machine (SVM). However, these models assume a direct and often linear relationship between sensory stimuli and human responses. They lack the capacity to capture the temporal and sequential nature of tactile processing. As a result, such models may not reflect how the brain integrates and interprets tactile information over time.

In neuroscience, modern data-driven approaches using neural networks have been emerging [3]. The idea is to develop deep neural networks that can accurately predict individual behavior, then use these models as a "digital twin" to explore the underlying computational mechanisms. In terms of temporal processing, recurrent neural networks (RNNs) have been considered a gold standard in fields like computer vision. Numerous studies have demonstrated their capacity to capture sequential processing in both the artificial system [4] and in the biological brain [5] .

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In this study, we leverage the intrinsic architecture of RNN to model the effect of prior information on human tactile object recognition. We conducted a behavioral experiment and subsequently developed the computational models to simulate the participant's responses.

II. Methods

A. Behavioral experiment

33 participants were recruited for a behavioral experiment in which their right palm is stimulated by an in-house developed pneumatic array haptic display. The task involves recognizing ten types of dot-digit stimuli, from 0 to 9 (see [6] for details). All participants practiced for approximately 1 hour prior to the experiment. The experiment consists of three sessions with 18 trials. In each session, every digit was repeated three times in a randomized order. The presentation sequence was shuffled for each session to minimize order effects.

B. Models

We developed and evaluated several types of models to simulate the participant's tactile recognition behavior. The first model is a simple frequency model (FM) that predicts responses based on the most frequently associated outcome for each stimulus. This model serves as a basic statistical baseline.

The second model comprises the conventional machine learning methods, specifically SVM and Ridge Regression. All input pixels were used as features, with input dimensions of (5, 224, 224) for each stimulus. Model parameters were optimized using 5-fold cross-validation.

The third model is a RNN, which consists of two Long-Short-Term Memory (LSTM) layers followed by one fully connected (FC) output layer. The LSTM was selected for its ability to capture the temporal accumulation of sensory input, mimicking how tactile information is integrated over time.

To incorporate the influence of prior information, we constructed variants of the RNN that concatenate the latent representation of n-back stimuli into the model's hidden layers. The value of n ranged from 1 to 4, allowing us to explore how varying amounts of prior input affect recognition performance.

C. Evaluation

Model performance was assessed based on averaged classification accuracies across all digits using a left-out test dataset. Paired t-tests on accuracy scores were performed to determine whether the differences are statistically significant between models.

III. Results

Figure 1 shows that all models performed significantly above the chance level, confirming their overall validity and predictive power.

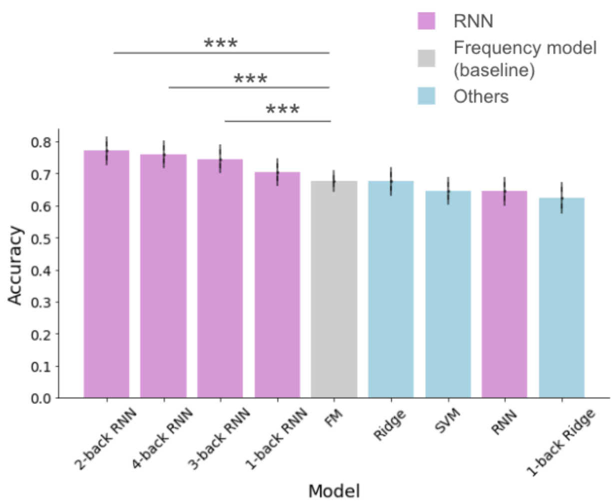

Fig. 1. Comparison of behavioral models. Whiskers indicate the standard error of the mean. Colors indicate different classes of model. ***: $p < 0.001$, paired t-test.

The n-back RNN demonstrated a statistically significant improvement over other classes of models (paired t-test, $p < 0.001$ for $n > 2$). This result suggests that incorporating prior information enhances the behavioral model's ability to replicate participant's responses. We suspected that the participant may base their responses on memorized sequences or pairing of presented stimuli. Thus, we analyzed the frequency of stimulus pairs and used them to predict responses. This approach yielded an overall accuracy of 0.33–only slightly above chance–indicating that simple pair memorization does not account for the improved performance of the n-back RNN.

To further explore how prior information alters internal processing, we performed UMAP visualization on the latent representation extracted at the final FC layer. Figure 2 shows that the inclusion of prior information leads to more distinct and separable clusters, enabling better computational classification. In contrast, representations from those without prior information were highly overlapping.

IV. Discussion and Conclusion

The main finding in this study is that incorporating prior information significantly enhances the performance of the behavioral model in tactile recognition. This result underscores the importance of prior information in modeling tactile

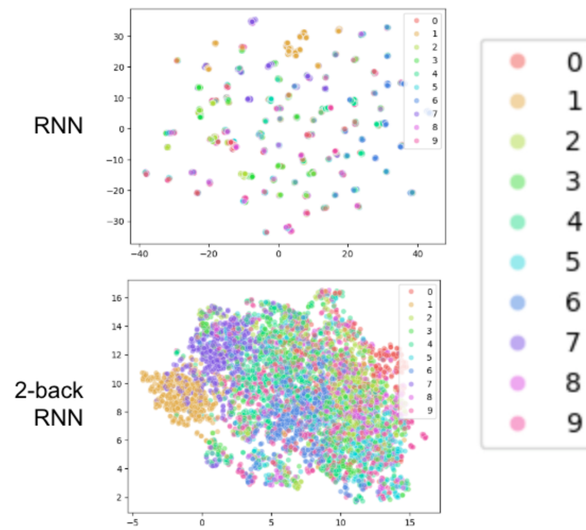

Fig. 2. UMAP visualization of the latent representation of RNN with and without prior information. Colors indicate the stimulus.

processing. Among all tested approaches, only n-back RNN demonstrated a performance level that closely approximated human behavior. This highlights the potential of RNNs as tools for investigating the computational principles underlying human tactile processing.

Notably, the best performance was found in the n-back model with n greater than 2. A slight decrease in accuracy was observed in 3-back and 4-back models. This trend may reflect the capacity limits of human working memory, which is thought to involve regions such as the dorsolateral prefrontal cortex. Previous research involving visually impaired participants [7] suggested a working memory capacity of approximately 3–5 items, recommending 2 items as optimal for applied tasks. Our findings are consistent with this estimate. To further explore the neural basis of the prior information effect, we plan to employ n-back RNN as an encoding model in future functional magnetic-resonance imaging (fMRI) studies.

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