Visual and Goal Vector Signals Interact to Shape Behavior and Spatial Representations

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Abstract

Spatial navigation relies on a variety of signals across different sensory modalities to guide movement towards a goal. While these signals can sometimes be redundant, they are crucial in the face of uncertainty, where navigating agents may have to switch between these signals or integrate them to determine the moving direction. We model these interactions in a deep reinforcement learning agent that uses two signals, vision and goal-vectors, to navigate. By analysing the agent's behavior and spatial representations, we show that it can successfully navigate using each signal independently or by integrating both. We show that this flexibility enables the agent to successfully cope with changing environments or with signals becoming contaminated with noise. Interestingly, our model also highlights a trade-off — when integration is unnecessary, such as in an unchanging environment, relying on a single stable signal improves navigation. We use this insight to explain counterintuitive experimental results. Additionally, we show that the place-cell-like spatial representations emerging in the network are shaped by both signals, albeit to varying degrees.

Keywords: spatial navigation; deep learning; reinforcement learning; signal integration; spatial representations

Background

Real-world navigation is inherently complex, involving dynamic and uncertain environments and intermittent access to sensory signals. A strategy for addressing these challenges is to integrate multiple sources of information. However, this integration is not trivial — signals vary in their reliability and susceptibility to noise. Effective navigation thus requires agents to flexibly combine these signals, weighting them dynamically, or relying on a single one when appropriate. Although animals demonstrate this capacity, the underlying mechanisms remain unclear. Experimental studies have mainly examined this question through the interaction of two key signals, vision and self-motion, and their influence on behavior and spatial representations (Chen, King, Burgess, & O'Keefe, 2012; Petrini, Caradonna, Foster, Burgess, & Nardini, 2016). We investigate the same question using a deep reinforcement learning (RL) model (Mnih et al., 2015) that uses both these signals to navigate.

Simulation setup

We simulate a task inspired by the Morris Water Maze (Morris, 1981), where the agent navigates to an unmarked goal in the environment from different starting points randomly assigned at the beginning of each trial. The walls are marked with distinct colors, serving as distal landmarks. We use the CoBeL-RL framework to generate the environments and train the agent (Diekmann et al., 2023). At each time-step, the agent receives visual input and a pre-computed goal vector, a proxy for the result of integrating self-motion, from the simulation environment (Fig. 1).

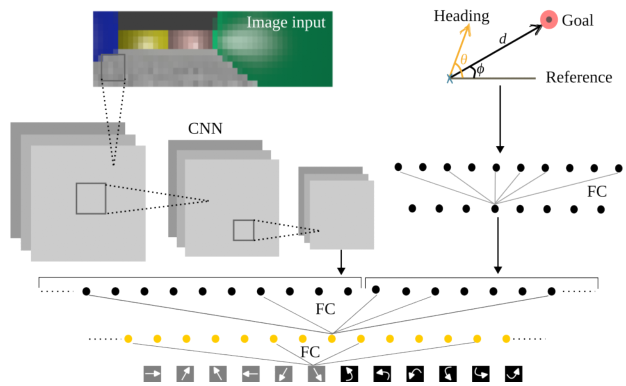

Figure 1: **Schematic of model architecture.** The network has two streams that process visual and goal-vector inputs before being combined. The output layer consists of action units that translate (grey icons) or rotate (black icons) the agent.

Results

We first test the ability of the agent to learn to navigate using each signal individually as well as integrate them. To this end, we periodically and randomly remove either input during training. The agent is able to successfully learn the task under these conditions, and test trials show that it can navigate using either input alone, even when the signals are subject to substantial noise. We next simulate a scenario common in experiments, where vision alone is sufficient for successful navigation. We hypothesize that in such cases, integrating a noisy signal with a reliable one may impair performance, and test our hypothesis, as we discuss below.

Combining multiple sensory signals Our findings indicate that when the task does not explicitly require the agent to navigate using each input independently, it relies more on the visual stream than on the vector stream (Fig. 2A). Further, when the agent is trained with increasing noise in the vector input, it begins to rely almost exclusively on the visual input, effectively disregarding the vector input, reflected in poor test performance when navigating using the vector stream alone (Fig. 2A, left, grey bars). In addition, the difference in test performance between using both inputs and visual input alone

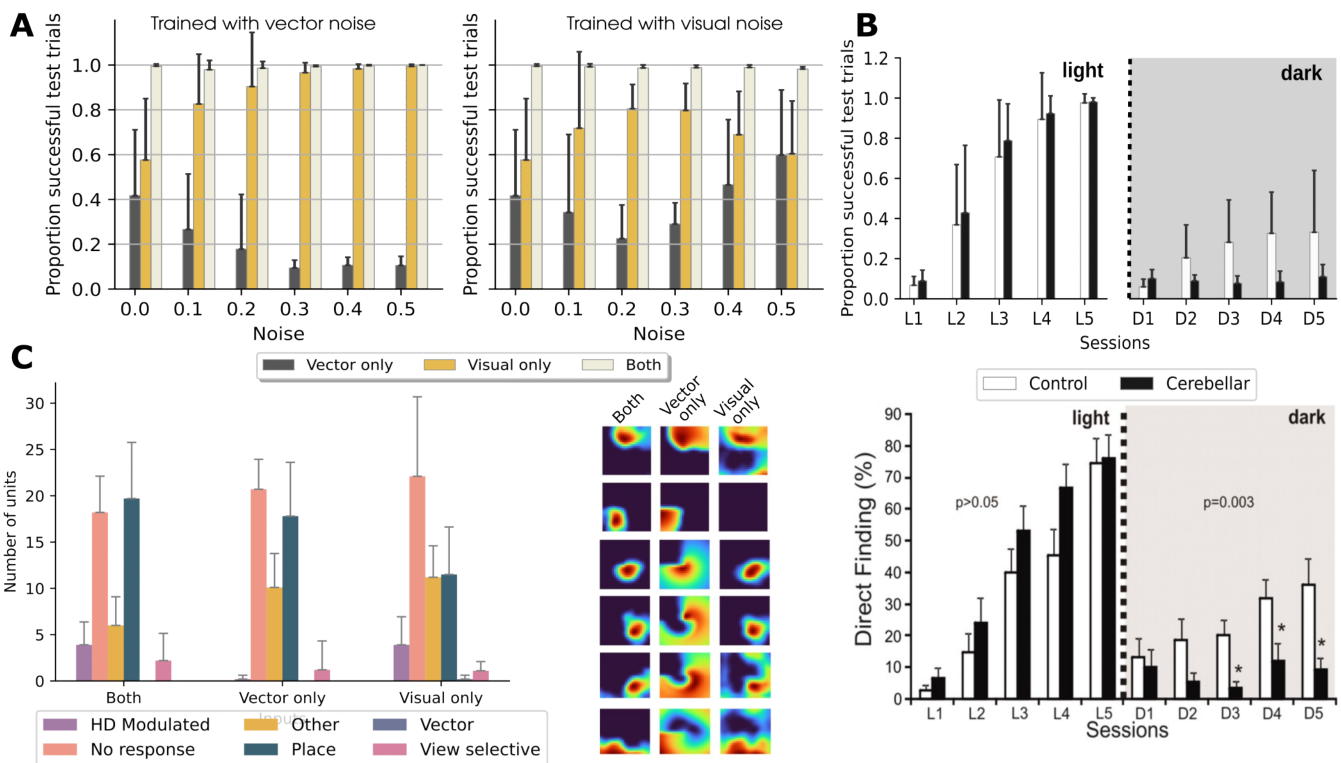

Figure 2: **Behavior and spatial representations in the agent. A:**Test performance of agents trained with noise in vector input (left) and visual input (right). Agents learned to ignore the vector input for higher levels of noise. **B:** Model (top) and experimental (bottom) results for navigation in light and dark conditions **C:** Spatial representations in the model. Left: Place-like units emerge in the model, and are affected by the removal of either input. Right : Examples of place-like units and the effect of removing each input on the firing field.

diminishes, becoming negligible at high noise levels (Fig. 2A, left, yellow and white bars). In contrast, noise in the visual stream does not lead the agent to completely disregard it, even with higher noise (Fig. 2A, right, yellow bars). Instead, the agent continues to integrate both streams, albeit to varying degrees.

We apply this finding to model the experimental findings of Rochefort et al. (2011), who examined navigation in cerebellar-lesion and control mice under light and dark conditions. The authors hypothesize that the cerebellum supports navigation through its role in path integration. In our model, control mice are represented by agents with low vector noise ($\sigma = 0.2$), while cerebellar-lesion mice are modeled as agents with high vector noise ($\sigma = 0.5$), simulating impaired path integration. When tested under light conditions, both agents improve navigation over time, in line with the experimental results (Fig. 2B). Our model also accounts for the small but consistent advantage observed in cerebellar-lesion mice under light conditions. This effect arises in our model because agents with high vector noise rapidly learn to disregard the unreliable vector input when visual cues are available, whereas agents with lower noise continue to integrate both inputs, resulting in slower learning. However, this advantage comes at the cost of robustness, as shown by the inability of high-noise agents and cerebellar-lesion mice to learn in the absence of visual input.

Spatial representations in the model We also examined the spatial representations that emerged in the network to support navigation, and the extent to which these representations are influenced by the two input streams. To assess this, we selectively removed each input and examined the impact on the spatial representations. We found several place-cell-like units in the network. Removal of either input stream led to varying degrees of disruption of these units. Some units required the integration of both input streams to maintain their spatial tuning, while others preserved their firing fields with access to only one input stream (Fig. 2C).

In conclusion, we demonstrate that a deep RL agent can learn to navigate using multiple sensory signals, and flexibly integrate them based on their reliability. Our model replicates experimental findings and offers insight into how animals may navigate in the face of uncertainty with noisy or missing inputs.

Acknowledgments

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