

Embodied Memory Through Gaze Control

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Abstract

To tackle complex natural tasks, one must maintain an accurate internal model of the environment to support actions. However, neural representations of the environment are noisy and rarely accurate. Fortunately, animals with fovea and acute vision can quickly scan the environment and foveate locations relevant to the task, enabling the updating and maintenance of an accurate internal model. We hypothesize that eye movements can be used as embodied memory to locate the evolving latent goal, and this mechanism benefits both biological and artificial intelligence. To investigate this, we developed a deep reinforcement learning (RL) agent with free eye movements and trained both the agent and macaques in a navigation task. We found that, without explicit instruction, both the agent and macaques naturally developed the use of eye movements as embodied memory for the latent goal to support navigation, resulting in better performance. The agent’s artificial neurons also explained posterior parietal cortex (PPC) data from macaques.

Keywords: deep reinforcement learning; embodied memory; neuro-inspired artificial intelligence; eye movements

Introduction

Our memory is fallible. We leverage mnemonic strategies to help us: we jot down notes, we count on our fingers, and we keep track of hidden objects by pointing to where they should be. These strategies use our bodies or the external world to retain information when needed. We hypothesize that we use our eyes as an embodied memory in the same way.

Active vision facilitating natural tasks is easy to fathom. Eyes swiftly parse the task scene, actively interrogating and efficiently gathering useful information to construct an internal belief of the outside world (Schroeder, Wilson, Radman, Scharfman, & Lakatos, 2010). For example, in navigation, subjects might compute their bearing with respect to visible landmarks. Even more remarkable is that eye movements contribute to landmark-free navigation: dynamic beliefs about latent goal location can be reflected in macaques’ oculomotor behavior (Lakshminarasimhan et al., 2020).

Although eye movements are a well-honed neural machinery in the brain, they are still largely overlooked in artificial intelligence (AI). To bridge neuroscience and AI, here, we developed a deep RL agent equipped with eye movements and trained both this agent and macaques in a navigation task. Our result showed that the agent developed behaviors and neural computations similar to macaques, leveraging gaze as embodied memory to facilitate task-solving—an example of using AI models to understand the brain. Flipping the sign of inspiration, our agent with eye movements also achieved better performance than without this brain mechanism.

Results

Macaques and the agent controlled a joystick to steer to a transiently cued goal location in a VR environment. Self-location is not directly observable due to the lack of stable landmarks; instead, the subject needs to use optic flow cues on the ground to perceive self-motion and perform path integration. At the start of each trial, a target briefly blinked at a random location within the field of view on the ground before disappearing. The joystick controlled forward and angular velocities, allowing free movement in 2D. The objective was to steer to the memorized target location. A reward was provided if stopped in the reward zone, a region centered at the target.

Deep RL agents with eye movements

Navigation as a sequential decision process can be modeled through the RL framework (Sutton & Barto, 2018). Briefly, RL represents the task as a Markov Decision Process (MDP), consisting of states (e.g., locations), feasible transitions between states based on the subject’s actions (e.g., steering), and rewards associated with states and actions (e.g., stopping in the reward zone). Optimal performance involves computing the expected value of potential actions at a given state and selecting the action with the highest value. However, real-world scenarios, as in our task, typically render the states partially observable (e.g., the target is observable only in the trial beginning). Consequently, MDP-based models must incorporate a *belief* that estimates the state to support decision making. Our model formulation (Fig. 1A) has states representing a combination of physical states in the world and the subject’s beliefs. Transitions between states now encompass both

physical locomotion and changes in beliefs, with beliefs maintained through noisy working memory [via a recurrent neural network (RNN)] and updated by gaze and other observations. Thus, actions used to reach goals include both locomotory actions (causing transitions in environment) and eye movement oculomotory actions (causing transitions in beliefs). Consequently, values of reaching the target can be assigned not only to locomotory actions that steers to the target but also to eye movements that aid the navigation process.

Gaze as embodied memory of navigation goal

The RNN integrates evidence to form an internal belief of the target to support behaviors (Fig. 1A). Using available information as inputs, along with the sparse reward signal when reaching the reward zone, our agent learned steering behaviors (Fig. 1B) and eye movement behaviors (Fig. 1C) that closely aligned with those of monkeys (Fig. 1D). Note that eye movements for both the agent and monkeys were not explicitly guided, and both were free to select any eye actions that aided steering to the goal. This behavioral similarity suggests the same role of eye movements in this task. One way to investigate this role is to restrain eye movements during navigation (Fig. 1E): by decreasing the RNN's working memory capacity (via imposing higher noise in RNN's hidden state), the eye-moving agent maintained good performance while the eye-fixed agent without eye movements cannot. This result suggests that gaze control is another form of memory.

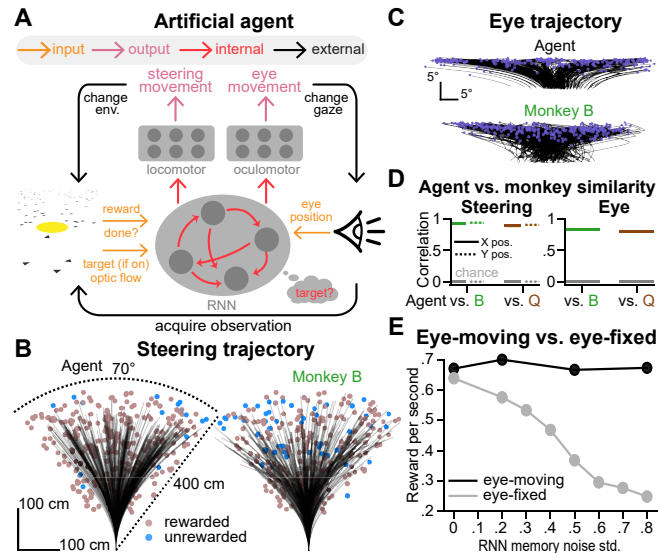


Figure 1: **A.** Agent. **B.** Overhead view of the spatial distribution of targets (dots) and subjects' trajectories. **C.** First-person view of the eye movement trajectories. Purple dots: initial eye position in each trial. **D.** Similarity of steering (in **B**) and eye movement (in **C**) trajectories between the agent and two monkeys for the same set of targets. **E.** Performance for two types of agents, one allowing eye movements and the other not, trained with varied noise uncertainties in the RNN's working memory.

To further investigate the role of eye movements, we measured how closely the eyes tracked the target. We found that both monkeys and the agent tightly tracked the target in the trial beginning, with tracking accuracy decreasing over time after the target became invisible (Fig. 2A). This target tracking error (the difference between the gaze and target position) highly correlated with the steering error (the difference between the target and stop location; Fig. 2B), indicating that subjects' belief about goal location (stop location) becomes more inaccurate when gaze does not track the target well. Indeed, gaze correlated more closely with the steering stop location over time than with the true target position (Fig. 2C), and both macaques' PPC neurons and the agent's RNN neurons encoded the stop location more prominently than the target location (Fig. 2D). These findings suggest that gaze dictates the navigation goal. Another more direct way to investigate is through causal manipulation: we perturbed agents' eye movements and found that the steering error matched the perturbation direction and magnitude applied on gaze, further confirming the embodied memory role of eye movements for locating navigation goals (Fig. 2E).

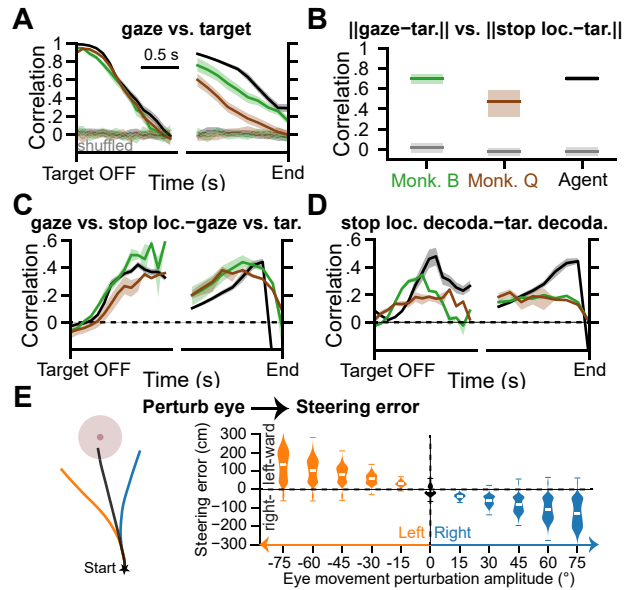


Figure 2: Gaze is embodied memory of the navigation goal. **A.** Target-tracking (correlation between gaze and target position) decreased over time. **B.** Target-tracking error correlated with steering error. **C.** Correlation between gaze and stop location minus correlation between gaze and target location. **D.** Linear decodability of stop location minus linear decodability of target location. **E.** Perturbing eye position biased steering to the perturbation direction.

Conclusion

We demonstrated that eye movements in both biological and artificial systems can serve as embodied memory for task goals. Our model with eye movements gained better perfor-

mance and can explain animal's behaviors and neural computations.

Acknowledgments

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