New virtual rodent environments and dimensionality reduction: Improved computational tractability for autonomous navigation

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Today's autonomous vehicles are trained specifically for the well-structured environment of roads and require significant advances in perception, intelligence, and efficiency to operate in unstructured, dynamic settings. Yet, the capabilities envisioned for next-generation autonomous vehicles — learning on-the-fly and adapting to novel environments — are already exhibited by biological organisms, animals, and humans. Inspired by these observations, this research simulates rodents' capabilities through reinforcement learning and works to advance the science of autonomy to include novel domains. Prior research in this field has enabled the creation of a virtual rodent that supports advanced kinematics, joint angles, forces, and perceptive inputs in several complex environments. Despite improvements in the performance of state-of-the-art RL algorithms such as Proximal Policy Optimization, training Google DeepMind's virtual rodent remains computationally intensive.

We provide two mechanisms for simplification: developing arena-task pairs on which the rodent can be more efficiently trained and reducing the rodent's action space dimensionality from 38 to 24 without significantly affecting performance. Specifically, we create a locomotion task, rewarding the rodent for maintaining a nonzero constant velocity, and a food collection task, rewarding the rodent for collecting items that spawn and despawn on fixed time intervals. Furthermore, we analyze simulation data and identify the subset of virtual actuators that are most crucial to accomplishing the locomotion task by determining those with least variability across simulations.

Our simplified environments and virtual rodent enable more efficient testing of neuroscience hypotheses and faster prototyping of novel RL algorithms for autonomous navigation. Testing learned policies against real-world biological experiments would achieve autonomous goal-directed navigation in novel environments and motivate methodology improvements.