Gridbot: A Spiking Neural Network Model of the Brain's Navigation System for Autonomous Robots

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Introduction

Navigating in a dynamic environment is a crucial yet seamlessly "effortless" task for the brain. Animals and humans use esoteric cues from their body and external environment landmarks to locate themselves. Over the past decades, a large set of specialized brain cells have been found to form what is called the biological navigation system [1]: Grid Cells (GC) in the medial entorhinal cortex (mEC) are related to speed integration and localization; Place Cells (PC) in the hippocampus are related to path integration, planning and memory; Border cells (BC) represent environmental information; Head direction cells (HDC) are limbic neurons that provide orientation information to the spatial system. Goal cells (GoalC) represent different goal locations. Despite the multitude of experimental studies, how the observed behavior emerges from the interconnectivity among the aforementioned and other cells remains a mystery [2]. Therefore, any bioinspired model employing these neurons needs to adhere to a number of extrapolations that will fill in the gaps of knowledge [3].

A Spiking Neural Model for the Brain's Navigation System

In our ongoing effort to develop a biologically constrained model of the biological navigation system, we describe a spiking neural network (SNN) that has become the controller of an autonomous robot. Our SNN consists of 1321 spiking neurons that span the main areas associated with our effortless ability to recognize a new environment (Figure 2). Our proposed model encodes sensory information into distributed maps and different goals supported by different place cells in arbitrary environments, and uses allocentric and egocentric maps to guide the robot to search the environment. Spike-timing dependent plasticity (STDP) takes place at multiple neural layers: Egocentric border information from depth camera is first represented in BCs and memorized as synaptic weights between PCs and BCs; STDP is also employed to imprint goal information in the synapses between PCs and GCs. Self-motion information (from robotic sensors) was initially represented in GCs and generated new PCs with different place fields. To memorize the environment, the robot moved by motor cells without hitting the borders.

Implementation and Experiment

We implemented our SNN in the ROS environment in a distributed and modular framework [4], which is similar to a brain. The SNN moved the robot in an autonomous fashion as follows. The ROS nodes were packaged into separate threads and computed using parallel multithreads. Nodes communicated using messages in topics, similar to how neurons communicate via chemical signals in synapses. The

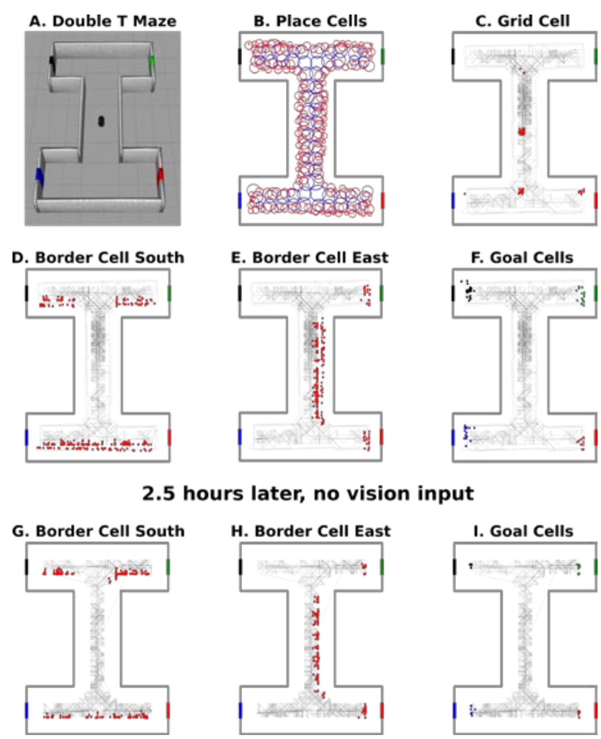

Figure 1. Experimental results in a double T maze environment. Representative neural cells are shown, each dot represents the associated neuron activity when the robot is at that location. B-F, cell activities during learning the environment. G-I, representative cell activities after learning (no vision input)

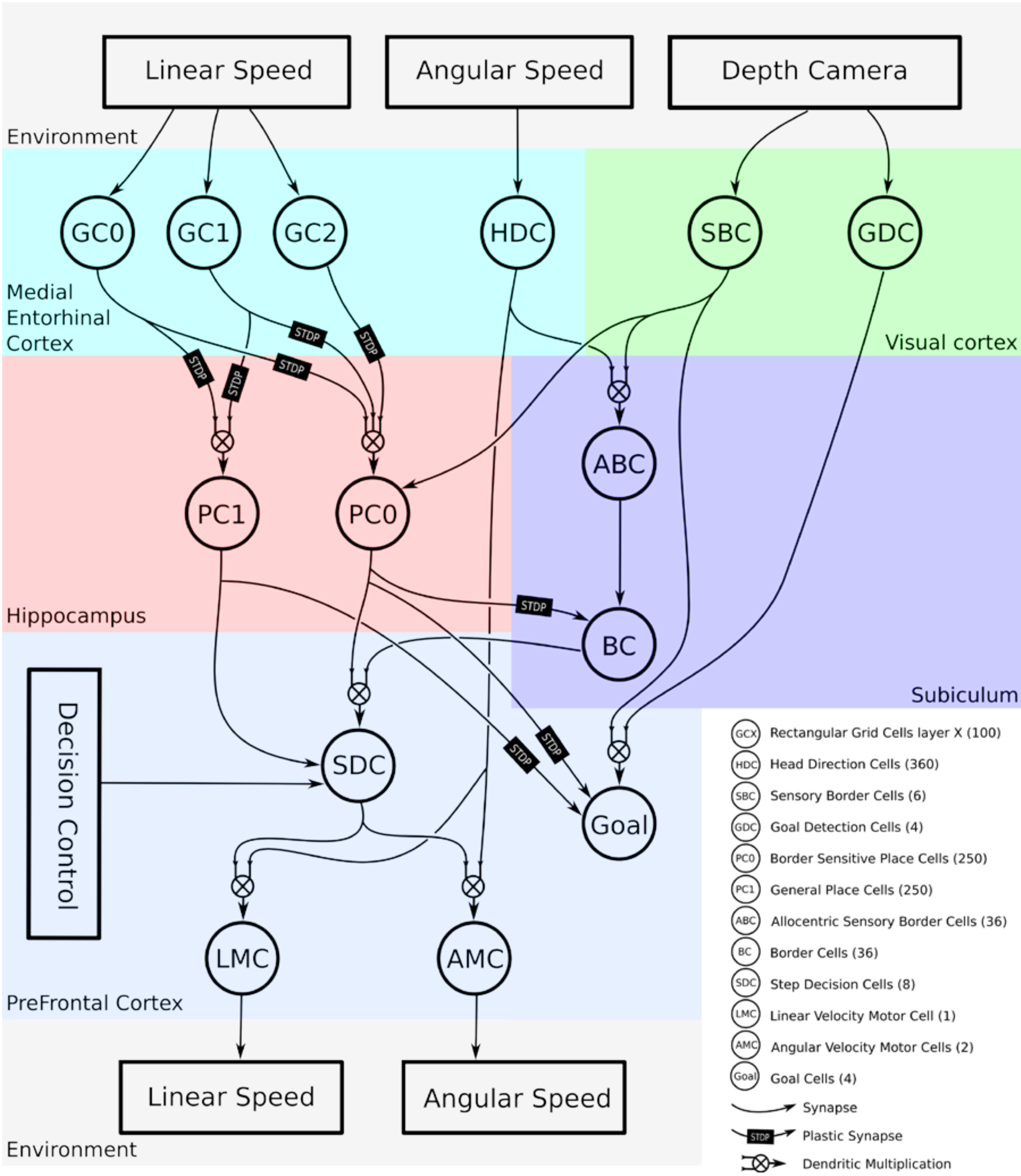

Figure 2. The proposed connectome among experimentally found neural cells that are associated with the brain's navigational system.

current work presents results from the Gazebo simulator (Figure 1.)

Discussion and Conclusion

To be effective in real-world, an autonomous robot should 1) be robust to a noisy neural representation, 2) adapt to a fast changing environment, and 3) learn with no or limited supervision or reinforcement. Working towards this direction, we are proposing a biologically constrained model of the brain's navigation system that controls an autonomously moving robot. Bringing brain-mimesis further down the cellular level, the built-in learning mechanisms of an SNN model of the biological spatial system show a potential to empower intrinsically adaptive robotic controllers that will also help further our understanding of brain function and dysfunction. This will catalyze efforts towards augmenting human cognitive abilities and engrafting them into intelligent robots.

References

[1] R. M. Grieves and K. J. Jeffery, "The representation of space in the brain," *Behavioural processes*, vol. 135, pp. 113-131, 2017.

[2] E. I. Moser, E. Kropff, and M.-B. Moser, "Place cells, grid cells, and the brain's spatial representation system," *Annual review of neuroscience*, vol. 31, 2008.

[3] M. Milford, G. Wyeth, and D. Prasser, "Efficient goal directed navigation using RatSLAM," in *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, 2005, pp. 1097-1102: IEEE.

[4] M. Quigley *et al.*, "ROS: an open-source Robot Operating System," in *ICRA workshop on open source software*, 2009, vol. 3, no. 3.2, p. 5: Kobe.