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

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INTRODUCTION

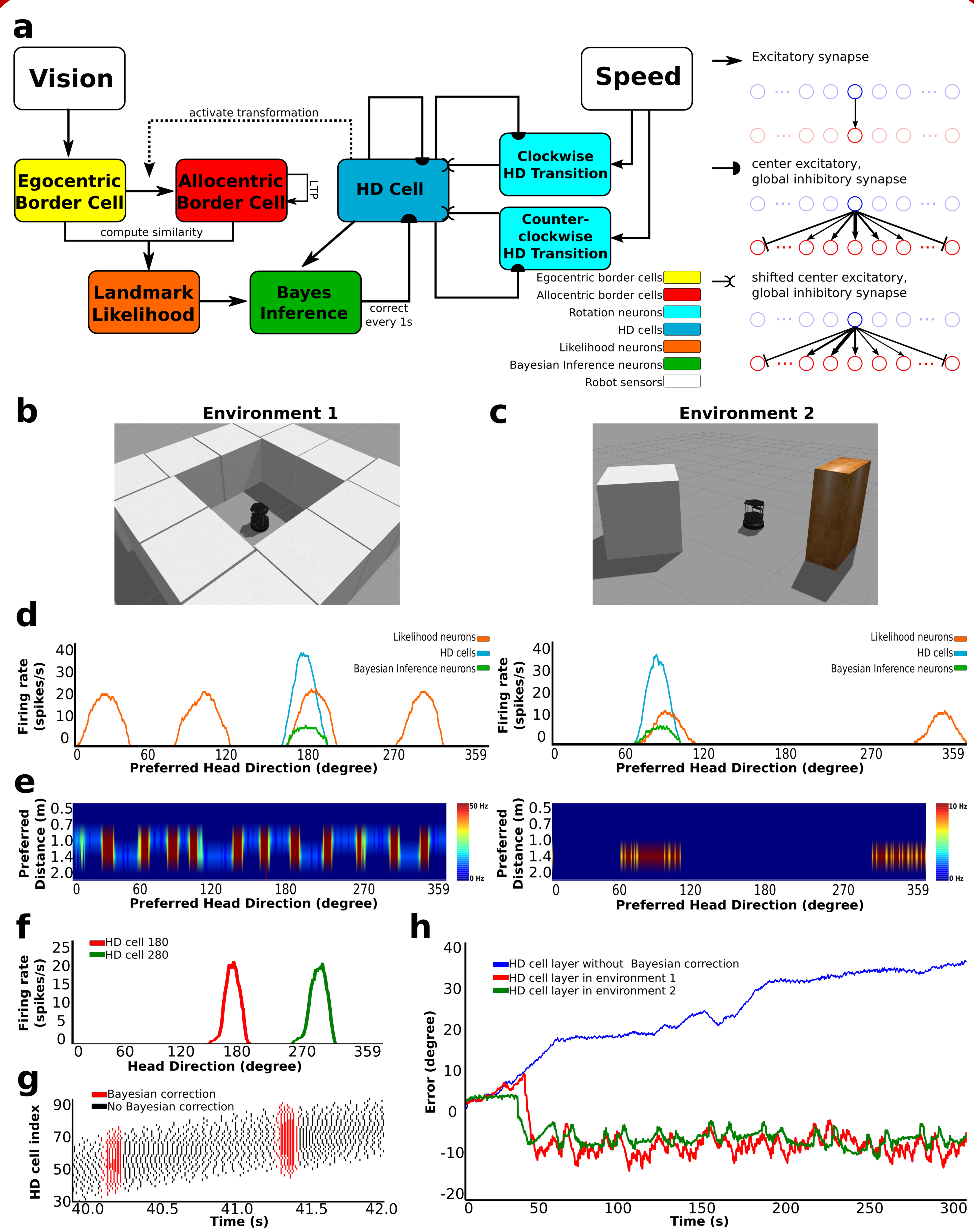
Navigating in a dynamic environment is a crucial task for the primitive brain. Animals and humans use esoteric cues from their body and external environment landmarks to locate themselves. Over the past decades, a large set of specialized neurons have been found to form a spatial localization system in the brain. Despite the multitude of experimental studies, how the observed behavior emerges from the interconnectivity among the aforementioned and other cells remains a mystery. Therefore, any bioinspired model employing these neurons needs to adhere to a number of extrapolations that will fill in the gaps of knowledge.

MODEL

We developed a model of 3,900 LIF neurons. The HD cell layer consisted of 360 neurons forming a continue attractor network. Each HD cell connected to 2 transition neurons encoding angular velocity with additive Gaussian noise. Border cells were activated by border-like landmarks at a single preferred direction and distance. We first encoded visual information using egocentric BCs and then transformed the spiking activities from egocentric to allocentric, guided by the HD cell firing. Synaptic plasticity (LTP) allowed the allocentric BC layer to learn the observed environment. We used a Bayes Inference layer to correct the neural representation of the head direction in the HD cell layer.

CONCLUSION

We showed our efforts in developing a neurobot that uses a neurobiologically constrained SNN to orient itself in an unknown environment and exercise intelligent behavior similar to the one found in animals. Our real-time spiking neural model mimics the behavioral abilities observed in mammals, in terms of localizing the HD and mapping the surrounding environment, while it compensated for the hardware limitations as well as its own intrinsic imperfections.



a) The proposed SNN employing Bayesian cue integration of external (vision) and internal (speed) information to estimate the HD.
b) Robotic simulation environment 1 in Gazebo simulator.
c) Robotic simulation environment 2 in Gazebo simulator.
d) Spiking activities of likelihood neurons, HD cells and Bayesian inference neurons during the experiment. Left for environment 1, right for environment 2.
e) Learned map of the environment represented by spiking activities of allocentric border cells. Left for environment 1, right for environment 2.
f) The tuning curves of 2 HD cells with preferred direction 180 and 280.
g) Spiking activities for HD cells when applying Bayesian correction on the HD cell layer.
h) Correction for the error drift through the Bayesian cue integration.