

# NeuroRobotics: A Spiking Neural Network Model of the Brain’s Spatial Navigation System for Autonomous Robots

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**Abstract: Orienting in an unknown, fast-changing environment is a crucial challenge met “effortlessly” by the brain. At ComBra Lab, we are developing the Gridbot, an autonomous neurobot controlled by a “bottom-up” Spiking Neural Network (SNN) model of brain networks that are associated with self-orientation and motor planning. By mimicking neurobiology, we developed an SNN that combined the neural representations of visual and self-motion cues and produced the behavior of accurately estimating head orientation. The SNN employed a spike-based Bayesian inference on the outputs of simulated head direction (HD) and border cells in a recursive way: The HD cell layer encoded in its spiking activity the HD likelihood distribution by integrating self-motion inputs; Similarly, the Border cell layer encoded the landmark likelihood distribution from visual observation and environmental mapping; Finally, a Bayesian inference layer generated a corrective distribution for the HD layer. Here we show results from implementing our model in the Robot Operating System and show how the SNN mimics the behavioral abilities observed in mammals, in localizing the HD and learning the environment.**

**Keywords:** Neuro-robotics; Spiking neural model; Head direction cells; Border cells.

## 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 (Hartley & Lever, 2014): *Grid cells* in the dorsomedial entorhinal cortex are related to speed integration and localization; *Place cells* in the hippocampus are related to path integration and planning; *Border cells* (BC) represent environmental information; *Head direction* (HD) *cells* are limbic neurons that provide orientation information to the spatial system. 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.

This paper describes our ongoing effort to develop a biologically constrained model of the brain’s navigation system that will be the controller of an autonomously moving robot. Specifically, here we describe a spiking neural network

(SNN) model where HD cells combine direction cues from both self-motion and environmental cues. We show how the SNN can use a dedicated layer to do Bayesian inference in integrating different cues encoded by HD cells and BCs and give an accurate neural representation of the HD.

## A Spiking Neuron Model of the Brain’s Navigational System

We developed a model of 3,900 LIF neurons. The layers of the recursive SNN as well as its inputs are shown in Fig. 1a. The HD layer consisted of 360 neurons forming a continue attractor neural network (CANN) model (Stringer & Trappenberg, 2002): Each HD cell had a single preferred head direction (with 1° resolution) for which it fired at a maximum rate (Fig 1b). Preserving spatial relationship, adjacent HD cells formed through their firing a distribution of possible HDs. Each HD cell connected to 2 rotation neurons (cyan blocks in Fig 1a) encoding angular velocity with additive Gaussian noise. The firing of these neurons shifted the attractor state of the HD cells towards left or right.

BCs were activated by border-like landmarks at a single preferred direction and distance. BCs are known to fire for landmarks *within* and *without* the field of view. To account for this, we first used an egocentric BC to encode visual information and then transformed the spiking activities from egocentric to allocentric, guided by the HD cell firing. Synaptic plasticity (long term potentiation-LTP) allowed the allocentric BC layer to *learn* the observed environment via persistent spike activity (Fig. 1g). We used a Bayesian inference (BI) layer to correct the neural representation of the head orientation in the HD cell layer. The BI layer received inputs from both visual landmark likelihood neurons and speed-driven HD cells (Fig. 1f) and drove strongly the HD cell layer every 1s to correct it (Fig. 1c; 1d). Neurons in the BI layer integrated the logarithmically decaying dendritic currents, approximating the nonlinear dendritic processes.

We developed our model in the Robot Operating System (ROS) simulating the Turtlebot 2 robot in two environments (Fig. 2e). Each SNN layer was a node in ROS, and different layers communicated with each other using topics with customized spiking or current messages. Neuron membrane voltages were updated using the Euler method every 10ms. The contribution of a spike to the post-synaptic current decaying exponentially with time.

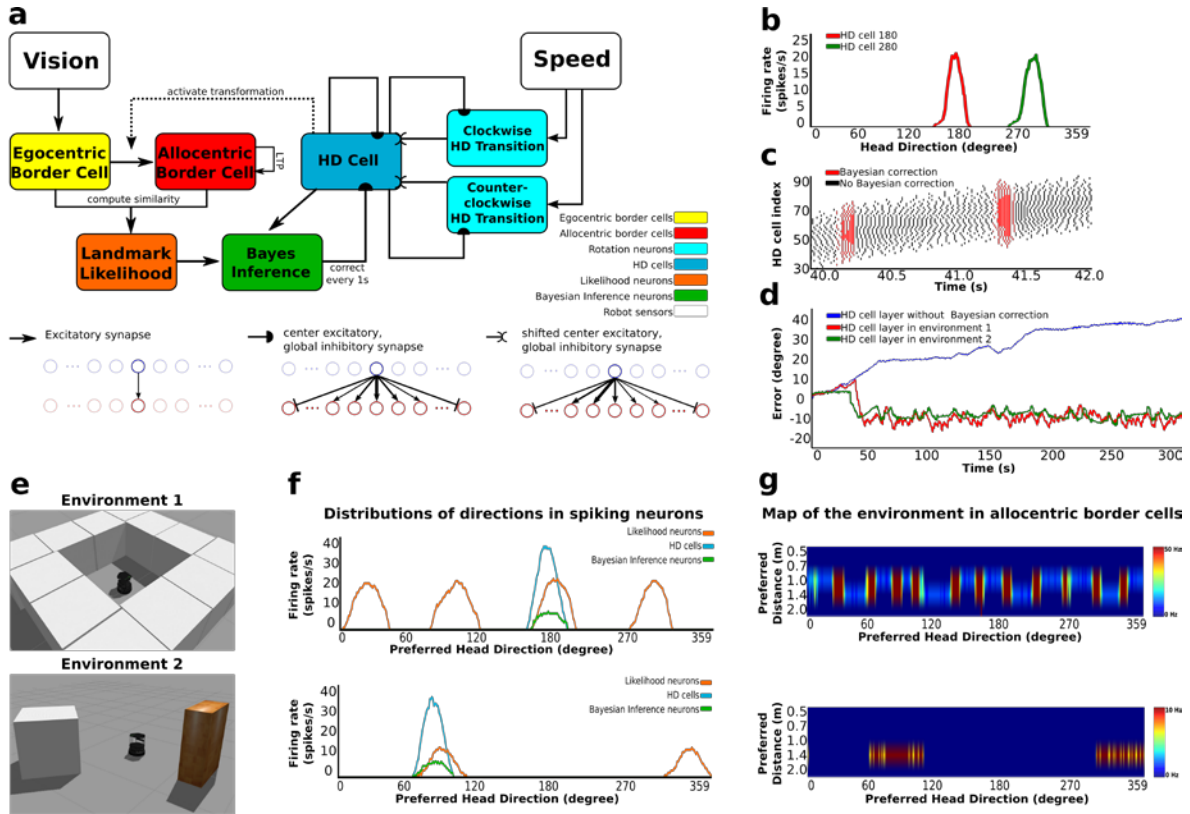


Figure 1: a) The proposed SNN employing Bayesian cue integration of external (vision) and internal (speed) information to estimate the HD. b) The tuning curves of 2 HD cells with preferred direction 180 and 280 degrees. c) Spiking activities for HD cells when applying Bayesian correction on the HD cell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

## Discussion and Conclusion

We briefly presented our efforts in developing a neurobot that uses a neurobiologically constrained SNN to autonomously orient itself in an unknown environment and therefore exercise intelligent behavior similar to the one found in animals. To fully solve the problem of localization at the neural level, we described how an SNN model employing HD cells and BCs need to be reinforced by a BI layer. This allowed us to accurately estimate HD and learn a map of the visually observed environment. The biological relevance of the visual cue integration to the HD representation via BCs is further reinforced by experimental studies showing that the visual information contributes to the accuracy of the direction representation in HD cells. In agreement with our results (Fig. 1d), the absence of visual input to the biological HD cells introduces a gradual drift due to an error accumulation (Taube, 1998). However, the visual information by itself can't provide the ground truth of HD, since it is also a noisy signal. Interestingly, reinforced by neurobiological and behavioral evidences, our proposed SNN model offers an alternative to normal weighted cue integration methods (Taube, 2007). Overall, 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 compensates for the hardware limitations as well as its own intrinsic imperfections.

## References

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