Gridbot: Spike-Based Head Direction Cells Employing Bayesian Inference

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Introduction

Localization – knowing one's position – and mapping – knowing the surrounding landmarks' positions – have long been at the forefront of mobile robotic research. The main challenge is to produce accurate estimates from noisy signals that are also susceptible to errors due to hardware constraints and environmental conditions. Interestingly, localization and mapping are "effortless" characteristics exhibited with great accuracy by most mammalian brains, even in the absence of visual, auditory, olfactory, or tactile cues. A discovery of a neural mechanism that dynamically computes self-position based on real-time information of position and direction has revealed the existence of a series of specialized neurons in the brain (Moser and Moser 2008): *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* keep representations of environment information; *Head direction cells* (HDCs) are limbic neurons that provide orientation information to the spatial system.

Although we are still missing a complete theory on how the above and other neurons interact to solve the localization and mapping problem, interesting navigation methods inspired by the observed behavior have been proposed (Milford, Wyeth et al. 2004, Erdem and Hasselmo 2012, Bush, Barry et al. 2015). At ComBra Lab, we are developing the Gridbot, a biomimetic robotic system that follows a "bottom-up" approach and relies on neural spiking to self-orient autonomously and on real-time. Here, we present the first steps towards our goal, namely a fully functional HDC layer that can provide an accurate head direction representation using the real-time spiking of neurons.

A Spiking Neuron Model of a Head Direction Cell System

HDCs change their spiking activity with respect to the current direction of the head of the animal (Taube 1998). An HDC has a single preferred direction for which it fires at a maximum rate. This directional coding provides an allocentric heading that is independent of location. To simulate the HDCs, we used the continue attractor neural network (CANN) model (Stringer, Trappenberg et al. 2002). The attractors of CANN lie on a continuous manifold in the phase space allowing for increased stability and reasonably fast dynamics. The HDC layer was driven by a visual and a speed layer and the Bayesian filtering layer (Fig. 1a, b). The contribution of spikes to the post-synaptic current decayed exponentially with time. In the CANN, the neurons had stable Gaussian tuning curves (Fig. 1c) which were dynamically changed by rotational speed. In other words, each HDC was connected to 2 rotation neurons that received angular velocity input with additive Gaussian noise, which could shift the attractor state of the HDCs in a single direction.

Implementation

We implemented our model (Fig. 1a, b) in the Robot Operating System (ROS), which uses nodes as its basic computation unit to control a Turtlebot 2, which is an open-source robot development kit. Each layer of our model was a node in ROS, and different layers communicated with each other using topics with customized spiking or current messages. The neurons were simulated as a leaky Integrate-and-Fire (LIF) model. For the HDC layer, we used 360 LIF neurons to allow for a directional resolution of 1 deg. Neuron membrane voltages were updated using the Euler method every 10 ms. The Bayesian Inference layer sampled both inputs over time, and drove strongly the HDC layer every 500 ms to correct it (Fig. 1d, e). We also assume that the visual information error at each time step is independent.

Discussion

Here we propose a spike-based neural architecture of a HDC system that is inspired by recent neurobiological studies. Our method could be seen as the spike-based analogy to the extended Kalman filter (EKF) method (Julier and Uhlmann 1997), which is a non-linear realization of Bayesian inference that uses noisy environment observations and noisy transition functions to estimate the hidden Markov state, which in this case is the head direction.

The importance of the vision input to the HDCs depicted by our results is further reinforced by experimental studies showing that the visual information contributes to the accuracy of the direction representation in HDCs. Specifically, just like in our simulated HDC system (Fig. 1e), the absence of visual input to the biological HDCs introduces a gradual drift due to an error accumulation (Goodridge, Dudchenko et al. 1998). However, visual information can't provide the ground truth of head direction, since it is also a noisy signal. In our Bayesian inference model, the visual input is the likelihood of the observed environment.

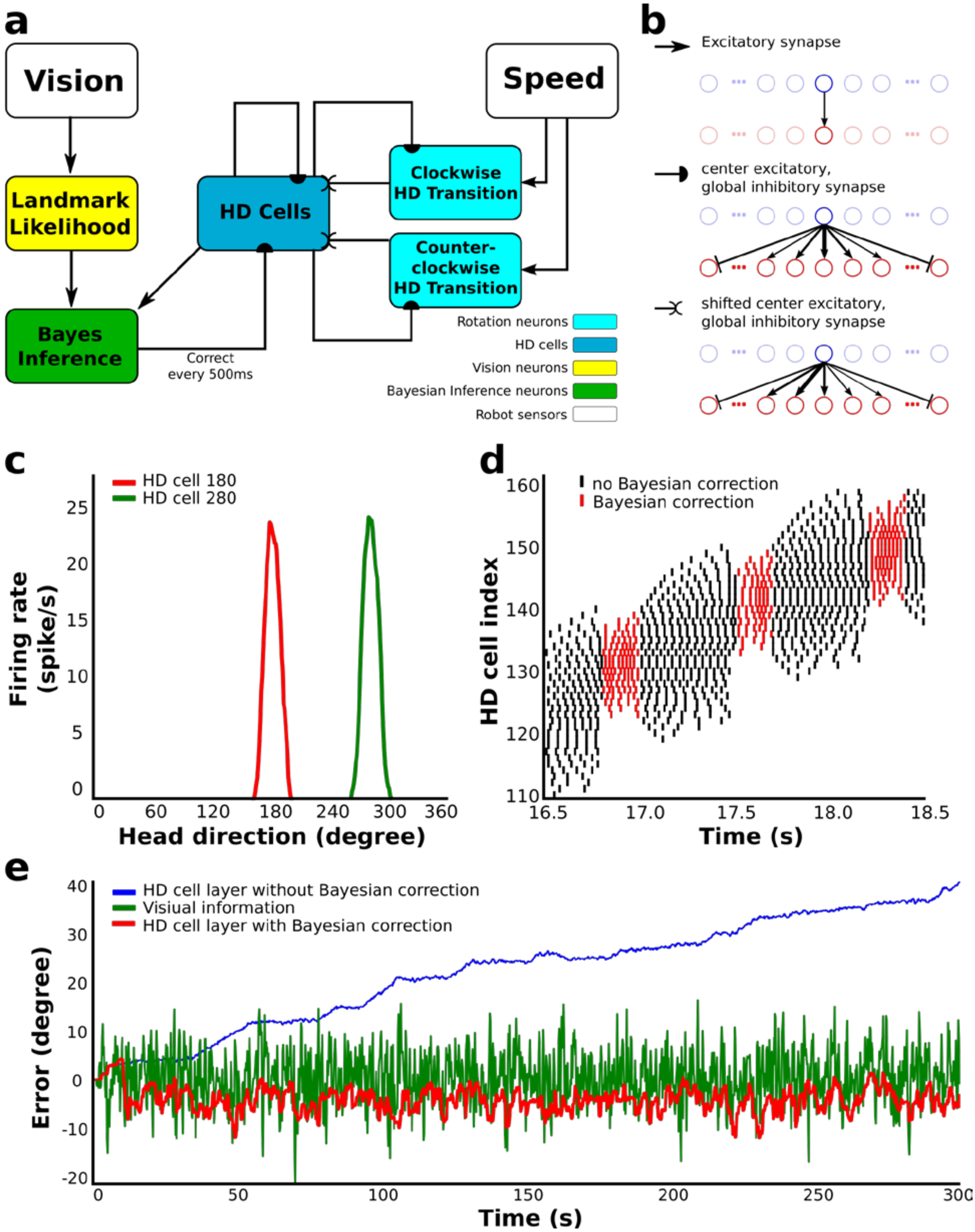

Figure 1 a) The proposed neuro-mimicking HDC model combining vision and speed to estimate the head direction. **b)** The three different types of synaptic connectivity used between layers. **c)** The tuning curves of two neurons that are sensitive to a head direction of 180 and 280 degrees, respectively. **d)** The effect of a Bayesian correction on the HDC network firing. **e)** a long experiment where the robot rotates with angular velocity of 10 deg/s; The drift in the error was corrected through the proposed Bayesian Inference layer. Note that the variance of the corrected prediction is smaller than the vision; A similar drift has been experimentally found in animal studies.

Conclusion

We showed that a model of an HDC system, reinforced by a neural layer that performs Bayesian filtering, can combine stimulus from a self-motion speed sensor and a visual sensor to accurately assess on the direction of the head. The addition of the visual information improved the head direction representation in the presence of noise. Although still its infancy, our robotic system mimics the behavioral abilities observed in mammals, at least in terms of localizing its head direction.

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