Real-time Mapping on a Neuromorphic Processor

Guangzhi Tang
Computational Brain Lab
Rutgers University
New Brunswick, New Jersey
gt235@cs.rutgers.edu

Konstantinos P. Michmizos
Computational Brain Lab
Rutgers University
New Brunswick, New Jersey
michmizos@cs.rutgers.edu

ABSTRACT

Mapping is a critical component for developing a simultaneous localization and mapping (SLAM) system in mobile robots. We draw from the brain's dedicated network that solves the spatial navigation problem by learning a cognitive map of the surrounding environment using networks of specialized neurons, such as place cells, grid cells, head direction cells, and border cells. We further integrated our neuro-inspired network into a neuromorphic processor, namely Intel's Loihi chip. Here, we proposed an SNN that used Winner-Take-ALL (WTA) structure and heterosynaptic competitive learning for place field generation and dendritic trees for reference frame transformation. The network learned distributed sub-maps on place cells, that, when combined, they encode accurately a unified map of the environment. By using an efficient interaction framework between the Robot Operating System (ROS) and Loihi, we showcase how our SNN may run in real-time interacting with a mobile robot equipped with a 360-degree LiDAR sensor. These results pave the way for an efficient neuromorphic SLAM solution on Loihi for robots operating in unknown environments.

CCS CONCEPTS

• **Computer systems organization → Neural networks**;

KEYWORDS

Mapping, Robotics, Neuromorphic Processor, Spiking Neural Network, Robot Operating System

ACM Reference Format:
Guangzhi Tang and Konstantinos P. Michmizos. 2020. Real-time Mapping on a Neuromorphic Processor. In *Neuro-inspired Computational Elements Workshop (NICE '20), March 17–20, 2020, Heidelberg, Germany.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3381755.3381780

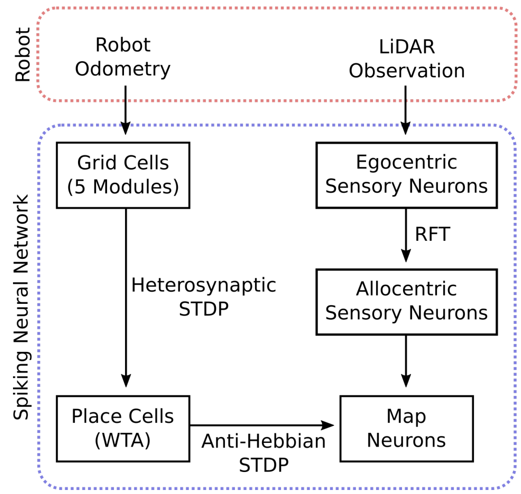

Figure 1: The proposed SNN for real-time robotic mapping on Loihi. Head direction cell network conducting reference frame transformation is not shown here.

1 INTRODUCTION

Navigation is so crucial for our survival that the brain hosts a dedicated network of neurons to map our surroundings. Place cells, grid cells, border cells, head direction cells and other specialized neurons in the hippocampus and the cortex work together in planning and learning maps of the environment [5]. When faced with similar navigation challenges, robots have an equally important need for generating a stable and accurate map. In our ongoing effort to translate the biological network for spatial navigation into a spiking neural network (SNN) that controls mobile robots in real-time, we first focused on simultaneous localization and mapping (SLAM), being one of the critical problems in robotics that relies highly on the accuracy of map representation [3]. Our approach allows us to leverage the asynchronous computing paradigm commonly found across brain areas and therefore has already demonstrated to be a significant energy-efficient solution for 1D SLAM [7], that can spur the emergence of the new neuromorphic processors, such as Intel's Loihi [2] and IBM's TrueNorth [4].

In this paper, we expand our previous work by proposing a SNN that forms a cognitive map of an unknown environment and is seamlessly integrated to Loihi (Fig. 1).

2 NEUROMORPHIC REAL-TIME MAPPING

The map of the environment was distributed in a network of randomly generated place cells whose learned place fields represented unique positions within the environment, in analogy to their biological counterparts. We utilized the Winner-Take-All (WTA) structure for constructing the place cell network and introduced heterosynaptic competitive learning for synaptic plasticity between grid cells and place cells. Egocentric sensory neurons encoded the distance observation and the reference frame transformation (RFT) network transformed the observation from the sensory reference frame to the world reference frame using the dendritic tree operation, that

NICE '20, March 17–20, 2020, Heidelberg, Germany

ACM ISBN 978-1-4503-7718-8/20/03.
https://doi.org/10.1145/3381755.3381780

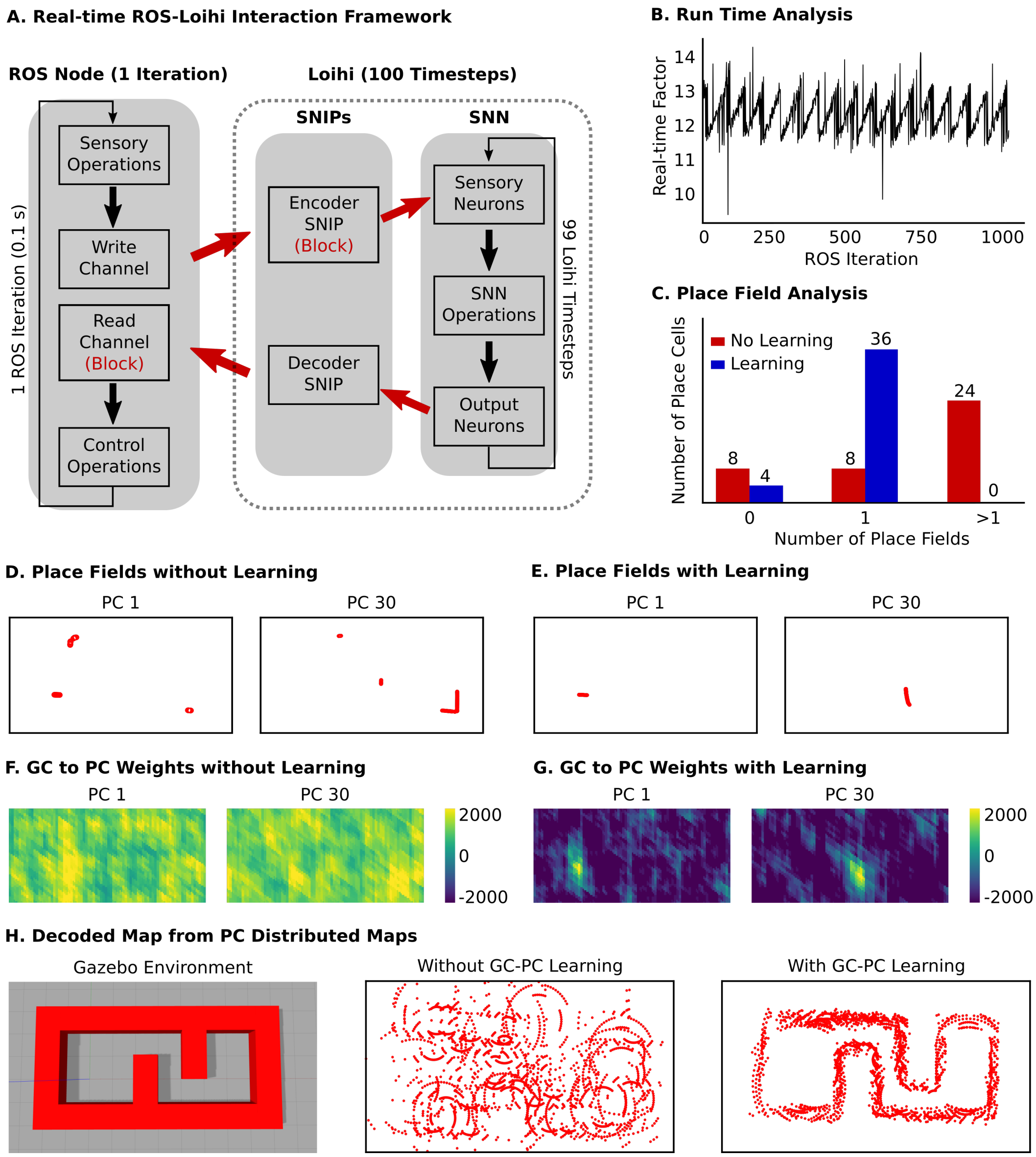

Figure 2: . A. General ROS-Loihi framework for arbitrary SNN running on Loihi. B. The real-time factor for the robotic mapping task based on time recordings from each ROS iteration. C. Comparison of the number of place fields between place cells with and without learning on synapses from grid cells. D and E, spike locations of place cells. F and G, the summation of weights from grid cells projected to each position within the environment. H. Environment and decoded maps from place cell anchored distributed maps.

we have recently introduced [7]. The place cell memorized the observation by using Spike-Timing-Dependent Plasticity (STDP) on the synapses between the place cells and map neurons. This way, place cells built a distributed sub-map surrounding the position represented by their place field.

3 REAL-TIME ROS-LOIHI INTERACTION

Since real-time operation is arguably vital for robotic exploratory applications, we first needed to develop a framework for real-time interaction between the Robot Operating System (ROS) and Loihi (Fig. 2A). Within this framework, Loihi communicates with the robot by using a specialized ROS node that writes compact sensory signals to Loihi and reads Loihi's computation. Loihi and ROS ran parallelly, with communication taking place every 100 Loihi timesteps. Our framework ran 12 times faster than real-time for the robot mapping, as described below.

4 EXPERIMENTS AND RESULTS

To validate our network, we used the Turtlebot 2 mobile robot equipped with a 360-degree LiDAR simulated in the Gazebo simulator. We controlled the robot to explore a maze (Fig. 2H). We show that, with heterosynaptic learning, the number of place cells with a single place field significantly increased compared to place cells that were activated by the randomly initialized weights (Fig. 2C). We analyzed the heterosynaptic learning by generating a position-based weight projection image. Weights from grid cells to place cells were projected to positions within the environment based on the grid cells' firing fields. We observed the weights transformed from a random distribution in the initial state to a single modal distribution after learning (Figs. 2F, G). As each place cell learned a fraction of the environment, we combined these distributed submaps to form a unified map (Fig. 2H). Since place cells anchored sub-maps, stable place fields were essential for the accuracy of the map. In Fig.2H, we compared the unified map from networks with and without place field learning.

5 DISCUSSION

In this paper, we expanded our biologically constrained SNN to include 2D robotic mapping and described its real-time implementation on Loihi. Our approach gave an accurate map of the environment using the error-free odometry signals from the Gazebo simulator. This work also suggests how episodic memories of where and what may be formed in the brain, in real-time, in contrast to other computational models doing offline simulations [1, 6]. This work supports our ongoing efforts towards an active-SLAM neuromorphic system for robotic navigation in real-world.

ACKNOWLEDGMENTS

This research is funded by Intel's NRC Research Award.

REFERENCES

[1] Andrej Bicanski and Neil Burgess. 2018. A neural-level model of spatial memory and imagery. *ELife* 7 (2018), e33752.

[2] Mike Davies, Narayan Srinivasa, Tsung-Han Lin, Gautham Chinya, Yongqiang Cao, Sri Harsha Choday, Georgios Dimou, Prasad Joshi, Nabil Imam, Shweta Jain, et al. 2018. Loihi: A neuromorphic manycore processor with on-chip learning. *IEEE Micro* 38, 1 (2018), 82–99.

[3] Giorgio Grisetti, Cyrill Stachniss, and Wolfram Burgard. 2007. Improved techniques for grid mapping with rao-blackwellized particle filters. *IEEE transactions on Robotics* 23, 1 (2007), 34–46.

[4] Paul A Merolla, John V Arthur, Rodrigo Alvarez-Icaza, Andrew S Cassidy, Jun Sawada, Filipp Akopyan, Bryan L Jackson, Nabil Imam, Chen Guo, Yutaka Nakamura, et al. 2014. A million spiking-neuron integrated circuit with a scalable communication network and interface. *Science* 345, 6197 (2014), 668–673.

[5] Steven Poulter, Tom Hartley, and Colin Lever. 2018. The neurobiology of mammalian navigation. *Current Biology* 28, 17 (2018), R1023–R1042.

[6] Trygve Solstad, Edvard I Moser, and Gaute T Einevoll. 2006. From grid cells to place cells: a mathematical model. *Hippocampus* 16, 12 (2006), 1026–1031.

[7] Guangzhi Tang, Arpit Shah, and Konstantinos P Michmizos. 2019. Spiking neural network on neuromorphic hardware for energy-efficient unidimensional SLAM. In *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 4176–4181.