Flyintel – a Platform for Robot Navigation based on a Brain-Inspired Spiking Neural Network

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***Abstract*—Spiking neural networks (SNN) are regarded by many as the "third generation network" that will solve computation problems in a more biologically realistic way. In our project, we design a robotic platform controlled by a user-defined SNN in order to develop a next generation artificial intelligence robot with high flexibility. This paper describes the preliminary progress of the project. We first implement a basic simple decision network and the robot is able to perform a basic but vital foraging and risk-avoiding task. Next, we implement the neural network of the fruit fly central complex in order to endow the robot with spatial orientation memory, a crucial function underlying the ability of spatial navigation.**

***Keywords*—spiking neural network, navigation, robotics, Drosophila, central complex**

I. Introduction

In recent years, researchers and engineers in the field of robotic navigation have tried to realize SLAM (simultaneous localization and mapping) through various algorithms, optimization, modeling, or machine learning [1], [2]. However, most of the methods are computationally demanding and it is rather challenging to apply them in the low-powered mobile devices.

In contrast, biology-inspired spiking neural networks (SNN) provide a more efficient and flexible solution to many computation problems [3]. Several teams have started to develop robots that are controlled by SNN [4], [5]. In the present study, we build a robot platform that can flexibly implement any user-defined SNN, including those observed in small insects such as flies.

We start with the most basic innate behavior, foraging and risk-avoiding, by building a simple decision network. Next, we implement the central complex networks of fruit flies in the robot. The networks endow the robot with spatial orientation memory, allowing it to navigate even without the sensory input.

II. Methods

We construct a simple robotic car - "FlyintelBot" (Fig. 1a) that can receive and respond to environmental stimuli. The system consists of the following components:

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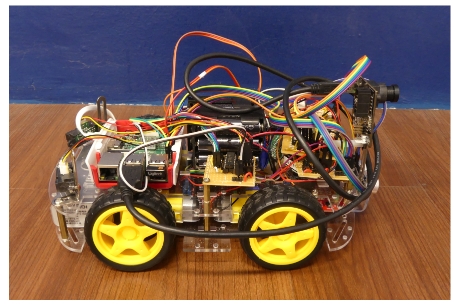
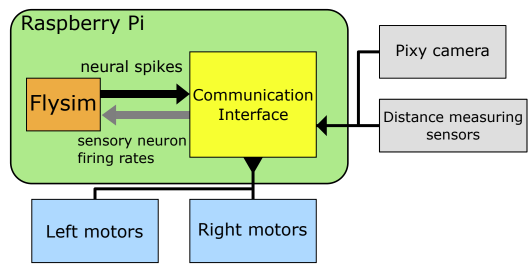


(a) Side view of the FlyintelBot.



(b) Overall architecture of the FlyintelBot.

Fig. 1. Flyintel simulates user-defined SNNs and interact with the real world.

A. Spiking Neural Network Model

For demonstration purposes, we implement a simple decision network model, which consists of 18 populations of neurons only (Fig. 2). There are three sensory neurons receiving visual stimuli and propagating the spikes to the downstream premotor neurons, and the premotor neurons immediately stimulate the corresponding motor neurons to achieve target-chasing. On the other hand, three risk-detecting sensory neurons, which receive distance-to-obstacle data from distance-measuring sensors, counteract the premotor neurons. Moreover, to improve the robustness of the motor output, a global inhibition neuron which shuts down other weakly activated neurons is required. The platform is highly flexible and we can easily edit the network parameters and configuration. The whole SNN is simulated on Flysim simulator [6], a lightweight and efficient SNN simulator developed in-house.

B. Hardware

The "brain" of the FlyintelBot system is a Raspberry Pi 3 single-board computer. The neural network simulator, communication interface and the SNN are all built on it (Fig. 1b).

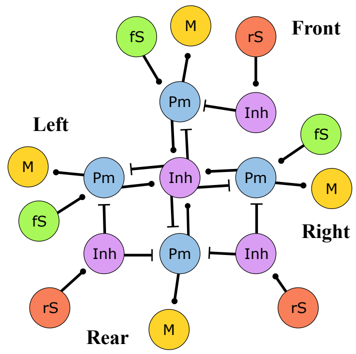


Fig. 2. The decision-making network implemented in Flyintel. “fS”stands for a foraging sensory neuron, “rS” stands for a risk-detecting sensory neuron, “M” stands for a motor neuron, “Pm” represents a premotor neuron and “Inh” is an inhibition neuron.

The input data are from the CMUcam5 Pixy vision sensor, which is able to learn and recognize multiple specific colored objects at the same time [7] and 3 distance-measuring sensors. The motor commands are executed by 4 DC motors.

C. Communication Interface

The input data from the sensors cannot be read directly by the SNN, which requires spike inputs. Therefore, we design a communication interface which encodes the data into spike trains as the inputs for the sensory neurons. A similar issue occurs for the SNN output as well. The outputs of the SNN are spike trains, and the interface also needs to decode them into motor operation commands, i.e., voltage.

III. Results and Discussion

FlyintelBot is highly adaptive to different types of environments it is trained for, since the vision sensor only picks up the colors we taught. The foraging and risk-avoiding task work fairly well, and all the processes are totally autonomous. In addition to the simple decision network, we are also in the process of implementing a more complex and powerful network model inspired by *Drosophila* (fruit fly) brain, which is one of the most intensively studied species in brain science, onto FlyintelBot.

In primates, the most famous navigation system is the grid cell and place cell network [8], however there is no report on a similar system in a *Drosophila* brain. Nevertheless, a *Drosophila* central complex model was proposed (Fig. 3a) to explain how a fruit fly remembers the orientation of the target relative to itself [9]. Hence, we are implementing the model on FlyintelBot. We have already simulated the model on the computer, and the result shows that the model can maintain spatial orientation even after the landmarks disappear (Fig. 3b). This approach may lead to a biologically realistic and power-efficient SLAM technique if the SNN models are implemented in neuromorphic chips in the future.

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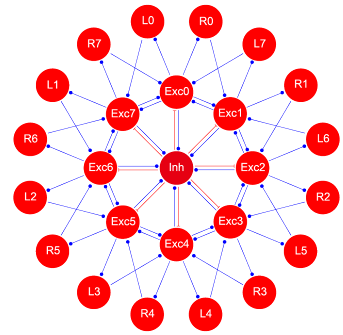
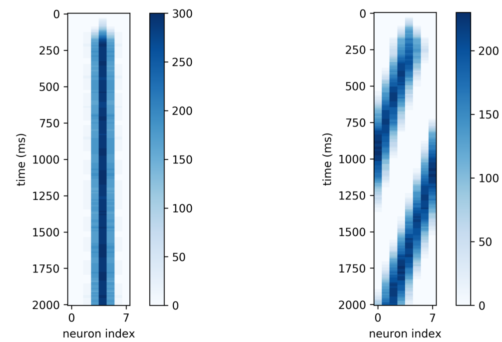


(a) The simplified model of *Drosophila* central complex depicts a three-ringed model.



(b) The simulation result of the central complex model. Left: When the fly faces the same direction all the time, the bump is fixed. Right: When the fly rotates counterclockwise, the bump rotates clockwise to update the memory of the target direction.

Fig. 3. A *Drosophila* brain stdudy suggests a model that the ring structures inside the central complex play an important role in spatial memory and navigation.

References

[1] E. Fernandes, P. Costa, J. Lima, and G. Veiga, “Towards an orientation enhanced astar algorithm for robotic navigation,” in *2015 IEEE International Conference on Industrial Technology (ICIT)*, March 2015, pp. 3320–3325.

[2] Z. Meng, H. Sun, H. Qin, Z. Chen, C. Zhou, and M. H. Ang, “Intelligent robotic system for autonomous exploration and active slam in unknown environments,” in *2017 IEEE/SICE International Symposium on System Integration (SII)*, Dec 2017, pp. 651–656.

[3] W. Maass, “Networks of spiking neurons: The third generation of neural network models,” *Neural Networks*, vol. 10, no. 9, pp. 1659 – 1671, 1997.

[4] G. Tang and K. P. Michmizos, “Gridbot: An autonomous robot controlled by a spiking neural network mimicking the brain’s navigational system,” in *Proceedings of the International Conference on Neuromorphic Systems*, ser. ICONS ’18. New York, NY, USA: ACM, 2018, pp. 4:1–4:8.

[5] R. Kreiser, M. Cartiglia, J. N. P. Martel, J. Conradt, and Y. Sandamirskaya, “A neuromorphic approach to path integration: A head-direction spiking neural network with vision-driven reset,” in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*, May 2018, pp. 1–5.

[6] Y.-C. Huang, C.-T. Wang, T.-S. Su, K.-W. Kao, Y.-J. Lin, C.-C. Chuang, A.-S. Chiang, and C.-C. Lo, “A single-cell level and connectome-derived computational model of the drosophila brain,” *Frontiers in Neuroinformatics*, vol. 12, p. 99, 2019.

[7] Pixy PixyCam. [Online]. Available: https://pixycam.com/pixy-cmucam5/

[8] 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, no. 1, pp. 69–89, 2008.

[9] T.-S. Su, W.-J. Lee, Y.-C. Huang, C.-T. Wang, and C.-C. Lo, “Coupled symmetric and asymmetric circuits underlying spatial orientation in fruit flies,” *Nature Communications*, vol. 8, no. 1, p. 139, Jul. 2017.