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Chaotic Neural Oscillator for Navigation and Exploration of Autonomous Drones

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1 Introduction

Efficient exploration in unknown environments (e.g., indoors, caves, and tunnels) is an important basic behavior of autonomous drones for complex missions (e.g., indoor exploration, search and rescue, and goal-directed navigation). In such missions, the drones need to explore the overall area as much as possible within a short or given period. Typically, exploration control uses (Gaussian) random walk [1]. This control technique may lead to undesired behavior, such as overturning or looping. It causes the drone to repeatedly explore the same spots; thereby having a difficulty to cover the overall area. To overcome this problem, we propose here the use of a chaotic neural oscillator for efficient exploration of autonomous drones instead of Gaussian random walk. This technique is inspired by the chaotic (nonrandom) behavior of fruit flies, giving them efficient food searching [2]. We combine the chaotic neural oscillator (acting as our exploration control module) with reflex-based neural control for obstacle avoidance. By doing so, the drone is able to autonomously perform efficient exploration (covering the area larger than a exploratory random-walk strategy) in an autonomous and safe manner.

2 Materials and Methods

In this study, we used CoppeliaSim as an experimental platform to simulate a drone. The Robot Operating System (ROS) was used to provide communication between the simulated drone and the neural control system. The neural control system consists of two modules: a reflex-based control module for obstacle avoidance and a chaotic oscillator module for exploration (see Fig. 1). We use sensory feedback from the left and right distance detection sensors for the reflex-based obstacle avoidance control with fixed optimal control parameters [3]. The control outputs are used to command pitch and yaw control of the drone. The chaotic oscillator is used for generating a (nonrandom/unpredictable) chaotic output to allow the drone to explore a given area. Here, the chaotic oscillator is derived from a two-neuron recurrent ($C1$, $C2$) network [4] (Fig. 1). The neuron Ci of the network is modeled as discrete-time non-spiking neuron.

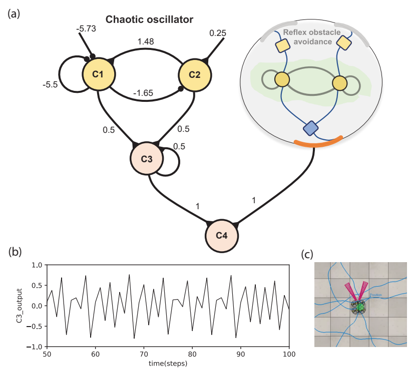

Figure 1: (a) A modular neural control system consists of reflex-based neural control for obstacle avoidance and a chaotic neural oscillator for efficient exploration. (b) The chaotic neural oscillator output ($C3$_activation, before thresholding). (c) The chaotic drone exploratory behavior (position tracking).

The activity a_i of each neuron develops according to:

$$a_i(t) = \sum_{j=1}^{n} W_{ij} \cdot o_j(t-1) + B_i \quad i = 1, \ldots, n \qquad (1)$$

where n denotes the number of neurons. B_i is an internal bias term or a sensory input to neuron i. W_{ij} represents the synaptic weight of the connection from neuron j to neuron i. The output o_i of all neurons is calculated using a tanh transfer function, except $C3$ which uses a threshold transfer function.

In this experiment, the chaotic neural oscillator module is computed at 50 times lesser frequency than the reflex obstacle avoidance control module which is computed at a frequency of 20 Hz. The chaotic neural oscillator output is combined with the yaw control output of the reflex obstacle avoidance control. Thus, the drone will perform oscillating behavior (turn left and right alternately) related to the oscillator output. We apply this behavior to allow the drone to explore the given area. To measure the exploration efficiency, we used an exploration diversity percentage ($\%E.D.$), which was defined as follow:

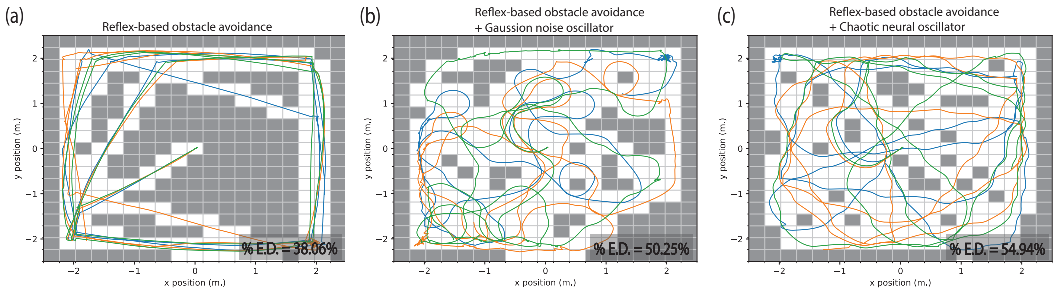

Figure 2: The tracked position of the drone exploring in the empty area is plotted by combining three exploring iterations (green, blue, and orange are first, second, and third iteration, respectively). (a) The reflex obstacle avoidance method. (b) The reflex obstacle avoidance plus a Gaussian noise oscillator, (c) The reflex obstacle avoidance plus the chaotic neural oscillator.

$$\% E.D. = (\frac{C_A}{A})(\frac{C_G}{A}) \times 100\% \tag{2}$$

where A denotes the total exploration area (grid count). C_A is the largest covered area. C_G is the total covered grid or covered density. Please note that grid resolution is directly affecting the exploration diversity percentage.

3 Experimental Results

To evaluate the system's exploratory performance, we let the drone explore in an empty area size $25\,\mathrm{m}^2$ (5 m x 5 m) using three different experimental navigation methods: reflex obstacle avoidance, reflex obstacle avoidance plus a Gaussian noise oscillator, and reflex obstacle avoidance plus the chaotic neural oscillator. The result in Fig. 2 shows the drone tracked position exploring in the empty area, which is plotted by combining three exploring iterations for each navigation method. According to the drone tracked position in Fig. 2, we computed the exploration diversity percentage using grid size $0.0625\,\mathrm{m}^2$ (0.25 m x 0.25 m) for each navigation method. The results are 38.06, 50.25, and 54.94 %, respectively, which shows that the drone can explore the area efficiently utilizing the reflex obstacle avoidance plus the chaotic neural oscillator navigation method. Additionally, the exploratory behavior comparison between the Gaussian noise oscillator and the chaotic neural oscillator is presented through the turning count, and turning steps (Fig. 3). The result indicates that the chaotic neural oscillator can produce a higher variance of turning behavior (see Fig. 3(a)) and less looping behavior (over turn right or left, see Fig. 3(b)) compared to the other method. This allows the drone to be able to explore more effectively.

4 Conclusion

In this study, we exploit the chaotic dynamics embedded in a minimal two neuron-recurrent network for an efficient exploration strategy of autonomous drones. This strategy follows the food searching/exploratory behavior of fruit flies. While the chaotic behavior is set as the ground state, the reflex obstacle avoidance behavior is activated based on

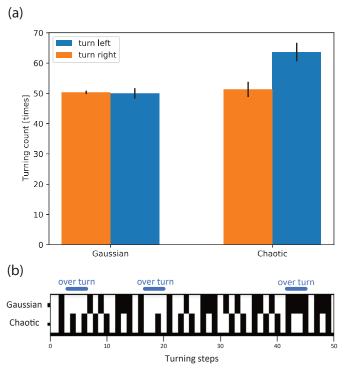

Figure 3: (a) The turning count comparison between applying the Gaussian noise oscillator and the chaotic neural oscillator used raw data from the three iterations in Fig. 2. (b) The sample turning- step comparison (white: turn right, black: turn left).

the left and right distance detection sensors for safe navigation. The result shows the effectiveness of the proposed chaotic method allowing the drone to explore the area larger and denser than a traditional Gaussian random walk method. It is important to note that the used two neuron-recurrent network can also exhibit other rich neurodynamics (e.g., stable periodic patterns and hysteresis effects) by modifying neural control parameters. Thus, in the future, we will explore and exploit the rich neurodynamics for generating complex behaviors of autonomous drones. We will also investigate the performance of the control approach in complex environments with many obstacles and real drone applications.

References

[1] Antonio L. Alfeo, Mario G. C. A. Cimino, Nicoletta De Francesco, Alessandro Lazzeri, Massimiliano Lega, and Gigliola Vaglini. Swarm coordination of mini-uavs for target search using imperfect sensors. *CoRR*, abs/1901.02885, 2019.

[2] Alexander Maye, Chih-hao Hsieh, George Sugihara, and Björn Brembs. Order in spontaneous behavior. *PLOS ONE*, 2(5):1–14, 05 2007.

[3] C.K.Pedersen and P. Manoonpong. Neural control and synaptic plasticity for adaptive obstacle avoidance of autonomous drones. In *From Animals to Animats 15. SAB 2018*, pages 177–188. Springer, 2018.

[4] S. Steingrube, M. Timme, F. Wörgötter, and P. Manoonpong. Self-organized adaptation of a simple neural circuit enables complex robot behaviour. *Nature Phys*, 6:224–230, 2010.