Neuro-Lorenz Oscillator with Bias Adaptation for Adaptive Searching and Exploring Behaviors of Flying Systems

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1 Introduction

Searching and exploring behaviors of animals in nature are important for their existence (i.e., food foraging). The complex behaviors basically emerge from a combination of searching to collect food nearby (local search) and moving across a large area to explore new food resources (global search). Several attempts have been made to realize efficient searching and exploring behaviors of animals [1]. Among them, the most common and effective method appears to be the Lévy flight (Lévy walk) models which can reproduce the movements of albatrosses [2] and Drosophila larvae [3] for food foraging. Existing Lévy models, based on mathematical formulas with the Lévy distribution, are difficult to relate to a biological neural system of animals. From this point of view, this study proposes an alternative Lévy model based on a synthesized recurrent neural system. Through its synaptic weights and biases, the neural system is programmed to become a so-called neuro-Lorenz oscillator, which exhibits the Lorenz attractor dynamics. The attractor dynamics acts as a ground state for basic (rhythmic) searching and exploring behavior generation and, by adapting the biases, adaptive searching and exploring behaviors can be achieved with local search and global search strategies, comparable to Lévy flights/walks. The neural system is applied to a flying robot to evaluate the performance of the generated searching and exploring behaviors. Additionally, the neuro-Lorenz oscillator with neuro-adaptive obstacle avoidance control is combined to enable obstacle avoidance while searching and exploring in an obstacle-filled environment.

2 Materials and Methods

In this study, we used CoppeliaSim to simulate the experiment with a quadcopter drone as the experimental platform. The Robot Operating System (ROS) was used for communication between the simulated drone and our neural control system, consisting of two modules: the proposed neuro-Lorenz oscillator and a neuro-adaptive obstacle avoidance control (Fig. 1). Due to the different inherent neurodynamics of each module, they are updated at varying frequencies. The adaptive obstacle avoidance control module

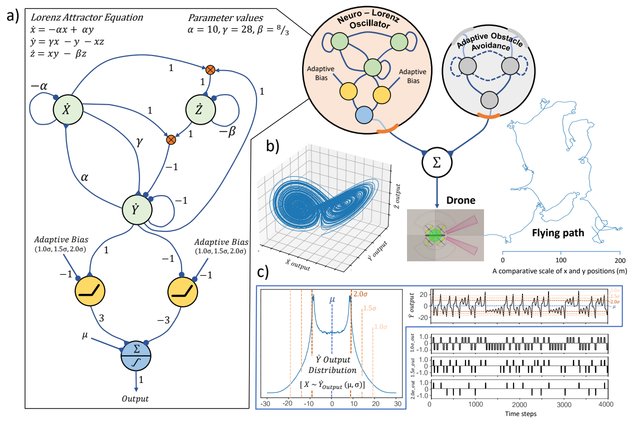

Figure 1: (a) Neuro-Lorenz oscillator and neuro-adaptive obstacle avoidance control for adaptive searching and exploration behaviors with obstacle avoidance in a flying robot and its flying path. (b) Lorenz attractor dynamics. (c) $\dot{Y}$ neuron output signal, the output distribution where its mean (μ) is 0.085, standard deviation (σ) is 9.167, and the neuro-Lorenz oscillator final output used under different biases (1.0σ, 1.5σ and 2.0σ).

with slow neurodynamics operates at a normal frequency of 20 Hz, while the neuro-Lorenz oscillator with fast neurodynamics (Fig. 1b) operates at a rate 50 times slower. This ensures that the drone can follow the obstacle avoidance control and oscillator commands (outputs). Additionally, we use sensory feedback from the front-left, front-right, left-side, and right-side distance detection sensors for adaptive obstacle avoidance control [4]. The neuro-Lorenz oscillator is used for the adaptive searching and exploring behavior control. Its structure is synthesized as a recurrent network with three neurons (green, Fig. 1c) based on the Lorenz system [5], where the parameters are described as the synaptic weights of the network (Fig. 1a). An output neuron ($\dot{Y}$) is projected to the final output neuron with the tanh activation function (blue, Fig. 1c) through two hidden neurons using the ReLU activation function (yellow, Fig. 1c). At the hidden neurons, we introduce adaptive bias terms based on the standard deviation (σ) of the output signal ($\dot{Y}$, Fig.

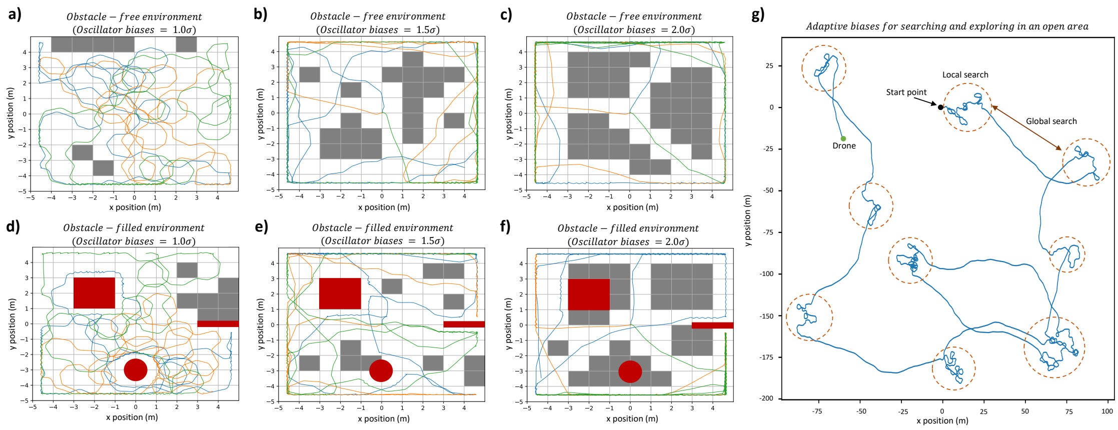

Figure 2: The tracked position of the drone exploring the given areas both without (a, b, c) and with (d, e, f) obstacles (red blocks). The biases of the neuro-Lorenz oscillator are set to different values (1.0σ, 1.5σ, and 2.0σ). Three colored lines (orange, green, and blue) present three tests where the gray grids refer to the unexplored grid and the red blocks are obstacles. (g) Adaptive searching and exploring behaviors, which include both local and global search, exhibit patterns similar to those of a Lévy flight. A video of the experiments can be viewed at `www.manoonpong.com/AMAM2023/NeuroLorenz/Video.mp4`

1c). By adapting the biases to different values (e.g., 1.0σ, 1.5σ, and 2.0σ), we can obtain different ReLU activation function thresholds to adapt the final output. The output is combined with the yaw control output of the obstacle avoidance control module. By doing so, the drone turning behavior is driven by the internal neuro-Lorenz oscillator and the sensor-driven obstacle avoidance control. This results in adaptive searching and exploring behaviors with obstacle avoidance.

3 Experimental Results

The adaptability of the proposed control system was demonstrated by flying the drone in a given area measuring $100\,\mathrm{m}^2$ (10 m x 10 m) with and without obstacles using three different bias values (1.0σ, 1.5σ, and 2.0σ). Fig. 2 shows the tracked position of the drone when flying to explore the given area. The tracked position shows that using different bias values causes the drone to vary its search and exploring behaviors. A low bias value (1.0σ) made the drone frequently turn; thus, the drone flew in a circular pattern and mainly focused on some parts of the area (Fig. 2a, 2d). This can be described as a local search. In contrast, setting the biases to high values (i.e., 1.5σ and 2.0σ), the drone turned less and flew forward more (Fig. 2b, 2c, 2e, 2f). Due to the closed area, the drone exhibited a kind of wall-following behavior. However, in an open area, the drone flew or searched over a greater distance; representing a global search. From this point of view, when adapting the biases to small and large values, we can automatically obtain adaptive searching and exploring behaviors with local and global search strategies. The results are shown in Fig. 2g where we implemented a simple bias adaptation mechanism by adapting the biases to small and large values at certain periods based on the standard deviation (σ) of the neuro-Lorenz oscillator output distribution.

4 Conclusion

In this study, we exploit the Lorenz attractor dynamics embedded in a recurrent neural network with a bias adaptation strategy for generating adaptive searching and exploring behaviors of an autonomous drone. This strategy follows the food-foraging behaviors of animals [2, 3] in nature. The results also show the effectiveness of the neuro-Lorenz system combined with the neuro-adaptive obstacle avoidance control system, allowing the drone to perform search and exploration in closed and open areas. By simply adapting the biases of the neuro-Lorenz system from small to large values and vice versa, a local search (looking for information in the immediate vicinity) and a global search (moving across a broad area) can be obtained. However, the bias adaptation strategy used here is a simple internally driven mechanism. Thus, in the future, we will further extend and optimize the bias adaptation strategy by using sensory feedback and learning mechanisms. This will enable the implementation of goal-directed behavior.

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