Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-20 (2025) 1569–1574

Bio-inspired neighbor selection mechanism and performance evaluation for UAV Swarm: An extended visual-attention model

Jun Zhang * **Liang Zhang** **

* *Sino-French Engineering School, Anhui University, Hefei 230093, China.*

** *the School of Electrical Engineering and Automation, Anhui University, Hefei 230093, China.(e-mail: liangzhang@ahu.edu.cn).*

Abstract:
Multi-unmanned aerial vehicle (UAV) swarms exhibit significant potential in collaborative tasks but face challenges in communication efficiency and neighbor selection, particularly in complex environments where global coordination is impractical. Inspired by biological flocking behaviors, this paper proposes an extended visual attention mechanism-based model for UAV swarm control, optimizing neighbor selection and maintaining balanced formations. By integrating bio-inspired communication strategies and evolutionary algorithms, our method reduces resource consumption while achieving robust swarm cooperation. Simulation results demonstrate that the proposed approach significantly improves energy efficiency, neighbor management, and formation stability, enabling effective task completion with minimized communication overhead. This study offers new insights into scalable and adaptive cooperative control for UAV swarms in diverse and dynamic environments.

Keywords: UAV swarm; Collaborative control;Distributed control strategies; Cooperative navigation; Swarm intelligence

1. INTRODUCTION

In recent years, multi-UAV formations have garnered significant attention due to their immense potential across a wide range of application fields (Zhou et al. (2020); Zhuo et al. (2023); Javed et al. (2024) The collaborative capabilities of multiple UAVs have introduced new possibilities for cooperative reconnaissance, area search, disaster relief, smart farming and environmental monitoring, such as Mukherjee et al. (2020) ,Carpentiero et al. (2017) , Xiaoning (2020). By leveraging the numerical advantage of the swarm, multi-UAV systems can accomplish tasks more efficiently and effectively than a single UAV. For instance, in disaster emergency rescue scenarios, UAV formations can swiftly cover large areas to locate survivors, assess damage, establish temporary communications, and transport relief supplies, thereby significantly enhancing the response time and effectiveness of rescue operations.

Despite the tremendous application potential of UAV formations, their large-scale and efficient deployment still faces numerous key challenges. To fully harness the advantages of UAV swarms, it is necessary to systematically address issues such as robust swarm modeling, efficient interaction mechanisms, advanced motion decision-making algorithms, and collaborative control strategies. Solving these problems relies on the deep integration and collaborative innovation across multiple disciplines, including computer science, control theory, and engineering. In the field of swarm robotics research, constructing an efficient internal communication topology for UAV swarms is a core challenge. Previous studies such as Gao et al. (2022) have provided important theoretical foundations for this field, but also highlighted the limitations of existing communication paradigms. Specifically, traditional low-power communication solutions (such as Bluetooth) face serious reliability bottlenecks in multi-node, long-distance communication scenarios, while high-power schemes lead to sharply increased deployment costs and energy consumption. Therefore, there is an urgent need to explore new methods for low-power, high-reliability swarm communication. To address these issues, this research aims to draw inspiration from nature to develop novel solutions.

Studies on biological swarms (such as birds and fish) have provided valuable inspiration for research on swarm UAV systems and control methods. The concept of UAV formations draws on the natural swarm behaviors of birds, fish, and insects, where simple interactions between individuals give rise to swarm intelligence, as discussed in Dutta (2010), Isaeva (2012), and Liang et al. (2021). For example, the V-formation flight of birds reduces air resistance and energy consumption, while the schooling behavior of fish confuses predators and enhances their survival capabilities. These natural swarm behaviors provide important references for the design and control of UAV formations and beyond (Zhang et al. (2024)).

10.1016/j.ifacol.2025.11.381

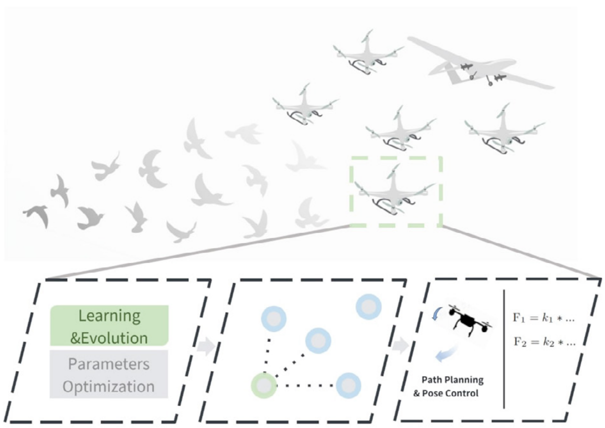


Fig. 1. From Bird Flocks to UAV Swarms: Learning from natural structure and evolution ,for enhancing the performance of UAV swarm .

Visual Attention Mechanism, developed based on biological visual phenomena, have laid the foundation for optimizing neighbor selection strategies in UAV formations. In biological vision, attention dynamically adjusts its spatial range to maintain focus on a central area while remaining vigilant of the surroundings. The mechanism retains this advantage, avoiding issues such as excessive communication objects and information redundancy. By applying this model to UAV formations, UAVs can selectively focus on key neighboring UAVs for communication and coordination, thereby improving the efficiency and effectiveness of neighbor selection.

Inspired by nature, this research proposes an extended swarm neighbor selection mechanism to address the aforementioned problems. This approach optimizes the communication topology through two key improvements: first, by reducing the required number of neighbor connections, and second, by minimizing communication distances. Notably, while optimizing the communication structure, the proposed mechanism maintains task performance comparable to traditional methods. These enhancements yield three significant benefits: reducing communication overhead and energy consumption, improving swarm communication efficiency, and enhancing the reliability of information exchange, thereby significantly improving the overall performance of UAV swarm systems. By building a simulation platform and testing the performance of each model on typical tasks, this research preliminarily addresses the problem of how to optimally select neighbors and construct efficient communication topologies for task execution under communication constraints. In the simulations, communication overhead was reduced by about half compared to traditional methods, while maintaining similar task performance. The results show that, under the same optimization algorithm, the visual attention-based model outperforms traditional methods in both neighbor selection efficiency and communication performance, demonstrating promising application prospects and theoretical value.

2. METHOD AND OPTIMIZATION

This section presents the methodologies and optimization techniques for UAV swarm coordination and control. The UAV swarm is categorized into multiple layers. First, neighbor selection models are introduced, as they are essential for swarm communication and coordination. Subsequently, the interactions, including velocity coordination and repulsion, among others, are elaborated. Next, position and attitude control are addressed using a second-order particle model. Finally, the optimization challenges of these models are tackled.

2.1 Models of Neighbor selection

Neighbor selection is a fundamental aspect of swarm intelligence, directly influencing the efficiency, robustness, and scalability of UAV swarm cooperation. In this section, we introduce two main categories of neighbor selection models: classical models and Visual Attention Mechanism.

(1) Classical Models:

a) Full Observation Model:

The Full Observation model assumes drones can access information from all nodes and communicate without restrictions. While ideal, this is hard to achieve in practice due to signal attenuation and obstacles. As swarm size increases, communication overhead and information redundancy also grow significantly which may bring catastrophic consequences such as network congestion.

b) Limited Field of View Model:

This model restricts a drone's perception to a specific angular sector, simulating scenarios where sensors or communication devices have directional limitations, such as cameras or directional antennas.For high-speed scenarios, such as FPV, this model is more applicable.

c) Limited Range of View Model:

Here, each drone communicates only with others within a limited circular range, reflecting practical constraints like signal strength and transmission power. While more realistic than the Full Observation model, it does not fully resolve communication overhead.

d) Topological Distance Model:

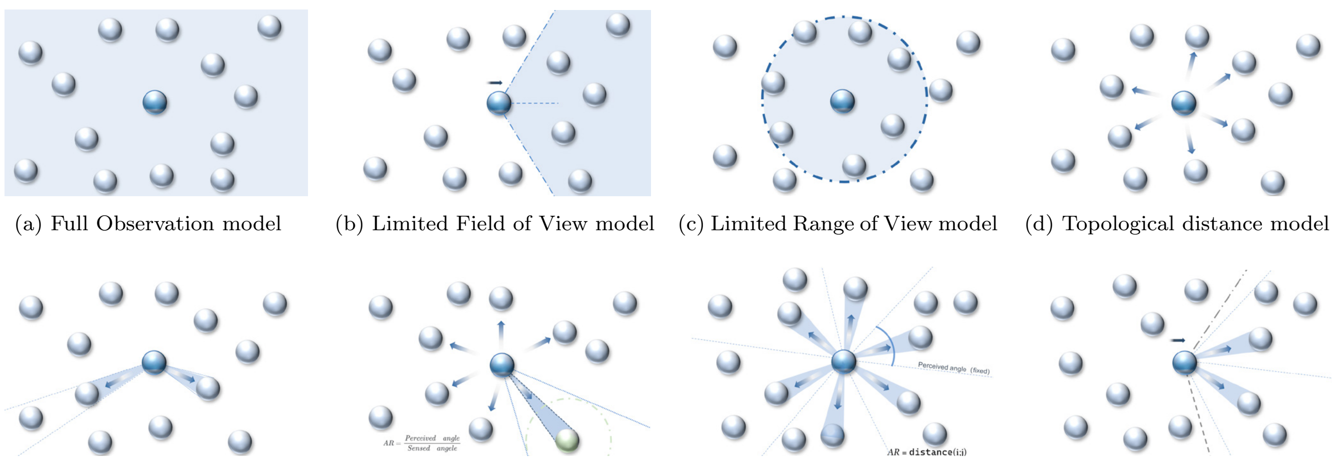
In this model, drones select a fixed number of nearest neighbors based on relative proximity, regardless of geometric distance. This approach is inspired by biological swarms, such as pigeon flocks, and can offer better information transmission and robustness in dynamic environments(Cavagna et al. (2010)).

e) Visibility Model:

Considering the physical volume of nodes, drones can only communicate with directly visible nodes, while obscured nodes remain inaccessible. This model is relevant for scenarios using cameras and visual algorithms for information acquisition.

(2) Visual Attention Mechanism:

Visual Attention Mechanism, inspired by biological visual systems, enable UAVs to efficiently select and focus on key neighboring nodes. The core parameter, Attention Ratio (AR), quantifies the balance between high-resolution focus and low-resolution peripheral perception. When AR = 1,



(a) Full Observation model (b) Limited Field of View model (c) Limited Range of View model (d) Topological distance model

(e) Visibility model (f) VAM with Fixed AR (g) VAM with Dynamic AR (h) VAM with Dynamic AR and Limited Field of View

Fig. 2. Illustrations of different neighbor selection models: From the simplest Full Observation model to the variants of VAM.

the model reduces to classic visibility-based interaction(Li et al. (2024)). These models simulate how drones allocate attention to specific nodes, prioritizing directions or nodes based on task requirements such as tracking targets or monitoring areas. The allocation of attention and perception angle may be dynamically adjusted according to real-time data or mission objectives.

f) Visual Attention Mechanism with Fixed AR:

In this model, AR is fixed. Each selected neighbor is assigned equal spatial weight, and the number of neighbors varies with swarm density.

g) Visual Attention Mechanism with Dynamic AR:

Here, AR varies with relative distance, keeping the number of neighbors approximately constant across different swarm densities,which means that the model is scale-free. This model is functionally similar to the topological model but is more computationally efficient, making it suitable for environments with varying densities.

h) Visual Attention Mechanism with Dynamic AR and Limited Field of View:

This model combines dynamic AR with a limited field of view, further constraining attention by sensor characteristics and directional limitations. It more accurately reflects UAV perception capabilities and exhibits unique performance characteristics.

2.2 Swarm dynamic model

The acceleration of drone i is calculated as the sum of several forces:

(1) Velocity Alignment Force:

Velocity alignment is a fundamental concept in multi-drone systems, particularly in robotics and drone swarms, where drones aim to synchronize their velocities to achieve cohesive group motion. This principle is inspired by natural phenomena such as the flocking of birds and the schooling of fish, where individuals align their directions and speeds with neighbors to maintain group cohesion and avoid collisions. Mathematically, velocity alignment is often implemented through a consensus algorithm, where each drone adjusts its velocity based on the average velocity of its neighbors:

$$v_i(t+1) = v_i(t) + \frac{1}{|N_i|} \sum_{j \in N_i} (v_j(t) - v_i(t)), \tag{1}$$

where $v_i(t)$ is the velocity of drone i at time t, N_i is the set of neighbors of drone i, and $|N_i|$ is the number of neighbors. This approach ensures that drones gradually converge to a common velocity, enabling smooth and coordinated group movement.

The control input $U(t)$ can be defined as the velocity adjustment term, scaled by a time-dependent factor $\frac{1}{|t|}$. To further refine the control input, we introduce a scaling factor λ, which modulates the influence of the velocity alignment term:

$$U_{\text{va}}(t) = \lambda \cdot \frac{1}{|t|} \cdot \frac{1}{|N_i|} \sum_{j \in N_i} (v_j(t) - v_i(t)). \tag{2}$$

(2) Collision Avoidance (Cohesion Force):

$$\mathbf{F}_{\text{cohesion}} = \sum_{\substack{j=1 \\ j \neq i}}^{n} k_{\text{cohesion}} \left(\frac{1}{\|\mathbf{r}_{ij}\|} - \frac{1}{2R} \right) \frac{\mathbf{r}_{ij}}{\|\mathbf{r}_{ij}\|} \tag{3}$$

where k_{cohesion} is the parameter of the Cohesion Force, $\mathbf{r}_{ij} = \mathbf{x}_i - \mathbf{x}_j$ is the position vector between drone i and neighbor j, and R is the body size. This force maintains a comfortable separation distance between drones while preventing excessive dispersion.

(3) Basic Repulsive Force:

$$\mathbf{F}_{\text{repulsive}} = \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{k_{\text{rep}}}{\|\mathbf{r}_{ij}\|^3} \mathbf{r}_{ij} \tag{4}$$

where k_{rep} is the repulsive force gain parameter that determines the strength of the repulsive interaction between drones. This provides a strong short-range repulsion that decays rapidly with distance, ensuring that drones maintain a minimum separation and avoid collisions.

(4) Viscous Drag Force:

$$\mathbf{F}_{\text{viscous}} = -\xi \mathbf{v}_i \tag{5}$$

where ξ is the viscous coefficient. This force provides velocity damping, preventing unrealistic acceleration, and helping to stabilize the system. The total acceleration is then:

$$\mathbf{a}_i = \mathbf{F}_{\text{align}} + \mathbf{F}_{\text{cohesion}} + \mathbf{F}_{\text{repulsive}} + \mathbf{F}_{\text{viscous}} \tag{6}$$

2.3 Position update

Consider a swarm system composed of N drones, assuming all drones fly at the same altitude and simplifying the drone model to a 2-dimensional space. Under autonomous control, the following motion model is adopted:

$$\begin{cases} \dfrac{d\bar{p}_i(t)}{dt} = \bar{v}_i(t), \\ \dfrac{d\bar{v}_i(t)}{dt} = \bar{u}_i(t), \end{cases} \quad i = 1, 2, \ldots, N. \tag{7}$$

In the equation:

$$\bar{p}_i(t) = [x_i y_i], \bar{v}_i(t) = \begin{bmatrix} v_{x_i} \\ v_{y_i} \end{bmatrix}, \bar{u}_i(t) = \begin{bmatrix} u_{x_i} \\ u_{y_i} \end{bmatrix}$$

represent the position, velocity, and control input vector of the drone i, respectively, that satisfy the kinematic constraints of the drone, that is, $\|\bar{v}_i(t)\| \leqslant v_{\max}$, $\|\bar{u}_i(t)\| \leqslant u_{\max}$. While more complex dynamics (e.g., 3D motion with attitude dynamics) could be considered, this fundamental model captures the essential swarm coordination mechanisms while permitting analytical insight. Such simplified models have been widely adopted in both theoretical swarm intelligence and path planning and so on. Under local interaction rules, each UAV achieves swarm movement by exchanging position and velocity information exclusively with its neighbors as defined by the interaction topology N_i

2.4 Parameters Optimization for Models

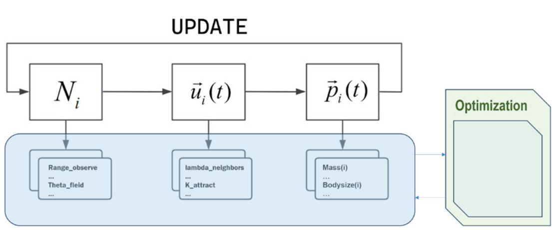


Fig. 3. Each model contains dozens of parameters. To compare the effectiveness of the models, optimization should be conducted first.

The system involves a multitude of parameters across different levels, and these parameters exhibit complex interdependencies. Achieving optimal performance in various task scenarios requires carefully tailored parameter combinations. It is important to emphasize that meaningful model comparisons can only be made when all models are evaluated under their respective optimal parameter configurations. In our research, we initially selected the Covariance Matrix Adaptation Evolution Strategy (CMA-ES), a widely used and robust optimization algorithm. CMA-ES is particularly effective for solving unconstrained or bound-constrained optimization problems and has demonstrated strong performance in search spaces ranging from three to one hundred dimensions (Jastrebski and Arnold (2006); Igel et al. (2007)). However, it is important to distinguish between parameters that can be freely optimized and those that are fundamentally constrained by hardware or environmental factors. For example, parameters such as the opening angle on both sides of the field of view (FOV), communication range, observation range, and air resistance coefficient are typically determined by the physical characteristics of the UAVs and their sensors. Unlike parameters such as the velocity alignment coefficient or repulsion strength, these fundamental parameters cannot be easily adjusted in practice. Therefore, they should be set to match real-world conditions as closely as possible, rather than being included in the optimization vector space. This distinction ensures that the optimization process remains both realistic and relevant to practical deployment scenarios.

3. SIMULATION AND DATA ANALYSIS

In this section, we present the simulation setup and the performance metrics used to evaluate the proposed models and optimization techniques for UAV swarm coordination.

3.1 Simulation Setup

The simulation framework is designed to validate the models under various scenarios. We aim to identify the most effective strategies for UAV swarm coordination, and provide insights into their practical implementation.

The simulation framework is configured with a time step of $\Delta t = 0.1$ seconds, including velocity variations, formation adjustments, and collision avoidance maneuvers. with the complete simulation spans $T = 200$ seconds of operational time. The drones are initially randomly distributed in the deployment area and are guided to reach the designated area.

We demonstrate our framework using representative models: the Limited Field of View model, the Visibility model, and the Visual Attention Mechanism with configurations including Fixed AR, Dynamic AR, and Limited Field of View.

Flocking is one of the simplest and most representative swarm behaviors. We start with Flocking and discuss the performance of different models and their parameters.

3.2 Performance Metrics

Having established the simulation setup, we now evaluate the swarm performance under three key metrics: Average Neighbor Count, Average Neighbor Distance, and Required Energy Consumption at the Transmitter.

The average number of neighbors reflects swarm connectivity, provides insight into the overall connectivity and interaction within the swarm. For drone i at time t, neighbors $N_i(t)$ are defined as drones within the communication range r_c:

$$\bar{N}_{\text{n}} = \frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} |N_i(t)| \tag{8}$$

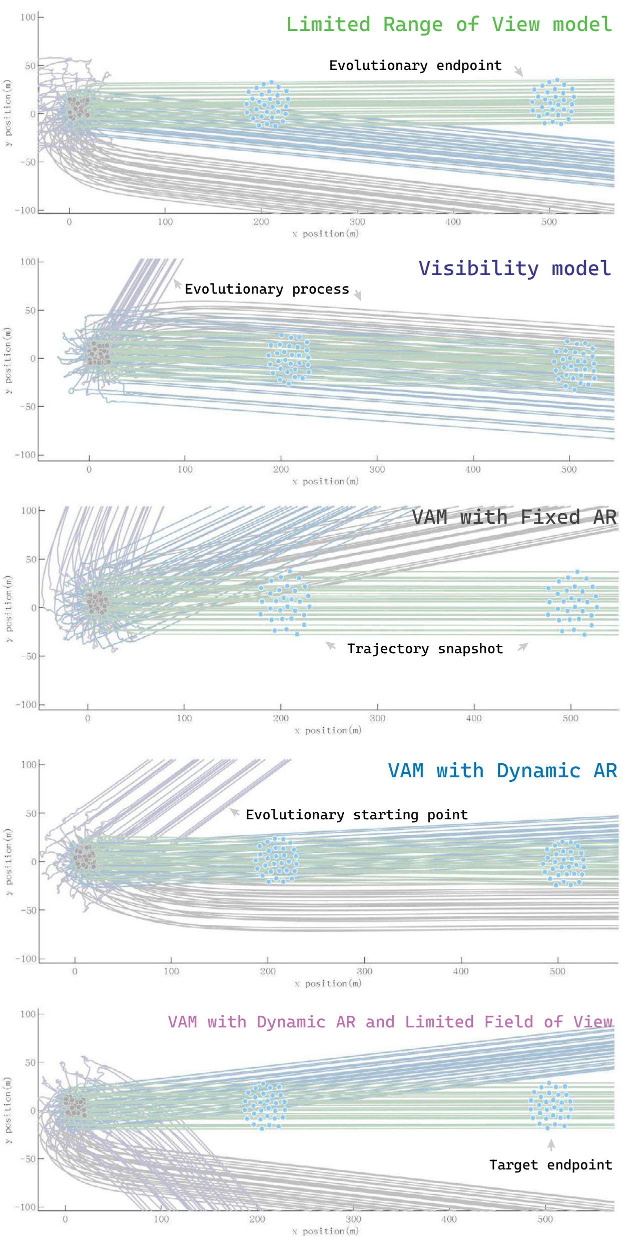


Fig. 4. Swarm trajectories under different neighbor selection models are shown by the process of evolution and optimization. Different colors indicate various stages of evolution: the purple line represents the initial parameter setting; grey and blue lines correspond to trajectories obtained using two sets of sampled parameters during the evolution/optimization process, and the green trajectory shows the final result.

where N denotes the number of UAVs, and $\mathcal{N}_i(t)$ denotes the set of neighbors of drone i at time t.

To quantify how effectively the swarm maintains balanced formations and adequate communication distances,we employ the mean relative neighbor distance metric for the UAV swarm:

$$\bar{D}_{\mathrm{n}} = \frac{1}{TN} \sum_{t=1}^{T} \sum_{i=1}^{N} \frac{1}{|N_i(t)|} \sum_{j \in N_i(t)} \|\mathbf{p}_i(t) - \mathbf{p}_j(t)\| \tag{9}$$

As a widely adopted short-range communication protocol, Bluetooth exemplifies the challenges and opportunities in drone swarm networking, the received signal power requirement is typically between -70 dBm and -90 dBm (Rondón et al. (2019)). Here, we consider the case where the received signal power requirement is -70 dBm. The free-space path loss (FSPL) can be calculated using the formula:

$$\text{FSPL (dB)} = 20\log_{10}(d) + 20\log_{10}(f) + 20\log_{10}\left(\frac{4\pi}{c}\right) \tag{10}$$

where d is the distance between the transmitter and receiver (in meters), f is the frequency of the signal (in Hz), c is the speed of light in vacuum (approximately 3×10^8 m/s).

Assuming a frequency of 2.4 GHz (common for BLE), the FSPL at a distance d can be simplified to:

$$\text{FSPL (dB)} = 20\log_{10}(d) + 40.024 \tag{11}$$

To ensure reliable communication, a link margin of 10 dB is considered to account for interference and other losses. Therefore, the required transmitted signal power P_t can be calculated as:

$$P_t(\text{dBm}) = \text{FSPL (dB)} + P_r(\text{dBm}) + \text{Link Margin (dB)} \tag{12}$$

Transforming P_t(dBm) into P_t(mW), then we obtain the Required Energy Consumption at the Transmitter:

$$E(\text{mJ}) = \sum_{t=1}^{T} P_t(\text{mW}) \cdot \Delta t \tag{13}$$

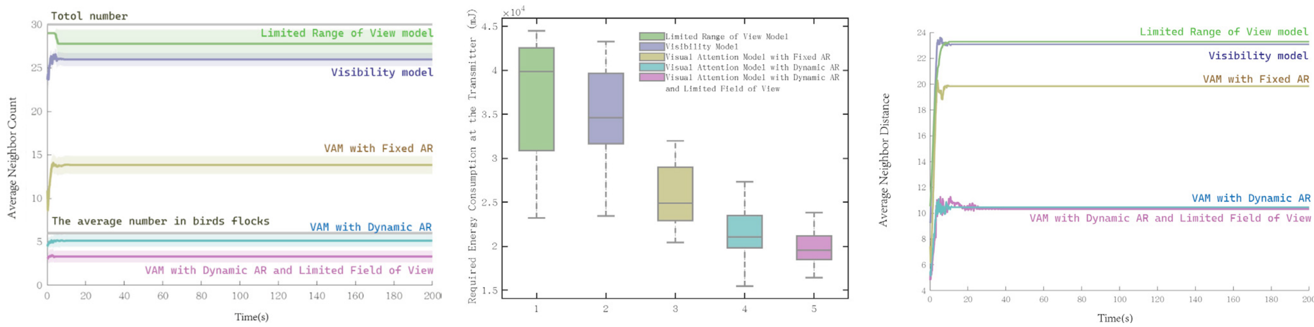
3.3 Result Analysis

As shown in Figure 5a, the use of visual attention mechanisms results in fewer neighboring drones in the same scenario. This not only aligns with the number of neighbors observed in natural starling flocks, but also suggests that a communication network can be constructed using more affordable, general-purpose devices.

Figures 5b and 5c further demonstrate that visual attention mechanisms significantly reduce transmitter energy consumption. This indicates that lightweight communication modules can be employed instead to achieve the same objectives, or, under the same hardware conditions, missions with larger spatial scales can be executed.

These data and figures illustrate that different neighbor selection models can affect swarm performance under the same objectives. Comparative analysis reveals that visual attention mechanisms not only enhance energy efficiency, but also improve the overall performance of UAV swarms by optimizing neighbor selection and maintaining balanced formations.

In conclusion, by applying biologically inspired communication methods and evolution algorithms, UAV swarms can achieve the same or similar functions with reduced resource



(a) Average Neighbor Count with time (b) Required Energy Consumption at the Transmitter (c) Average Neighbor Distance with time

Fig. 5. Under evolutionary conditions, the performance metrics of each model differ, which verifies the effectiveness of our model in reducing communication overhead and energy consumption.

4. CONCLUSION

In this paper, we propose an extended visual attention mechanism-based control method that optimizes neighbor selection and maintains balanced formation in UAV swarms. Simulation experiments show that our method significantly improves energy efficiency, neighbor management, and formation stability, aligning with natural flocking behaviors observed in biological systems. In conclusion, by leveraging bio-inspired evolutionary algorithms and streamlined communication, UAV swarms can achieve similar capabilities while minimizing resource consumption.

However, our research has several limitations. The simulation experiments are conducted under ideal conditions, whereas in practical applications, environmental uncertainties may affect performance. In the future, we aim to refine these mechanisms and validate their effectiveness in real-world scenarios. We will also explore the application of the model in more complex tasks, such as multi-UAV cooperative target tracking and area coverage, to further expand its scope.

ACKNOWLEDGEMENTS

This work was partly supported by the State Key Laboratory of Micro-Spacecraft Rapid Design and Intelligent Cluster under grant No. MS01240110, the National Natural Science Foundation of China under grant No. 62303002, and the Key Program of Natural Science Foundation of Anhui Higher Education Institutions of China under grant No. 2022AH050068.

REFERENCES

Carpentiero, M., Gugliermetti, L., Sabatini, M., and Palmerini, G.B. (2017). A swarm of wheeled and aerial robots for environmental monitoring. In *2017 IEEE 14th international conference on networking, sensing and control (ICNSC)*, 90–95. IEEE.

Cavagna, A., Cimarelli, A., Giardina, I., Parisi, G., Santagati, R., Stefanini, F., and Viale, M. (2010). Scale-free correlations in starling flocks. *Proceedings of the National Academy of Sciences*, 107(26), 11865–11870.

Dutta, K. (2010). How birds fly together: The dynamics of flocking. *Resonance*, 15(12), 1097–1110.

Gao, N., Liang, L., Cai, D., Li, X., and Jin, S. (2022). Coverage control for uav swarm communication networks: A distributed learning approach. *IEEE Internet of Things Journal*, 9(20), 19854–19867.

Igel, C., Hansen, N., and Roth, S. (2007). Covariance matrix adaptation for multi-objective optimization. *Evolutionary computation*, 15(1), 1–28.

Isaeva, V. (2012). Self-organization in biological systems. *Biology Bulletin*, 39, 110–118.

Jastrebski, G.A. and Arnold, D.V. (2006). Improving evolution strategies through active covariance matrix adaptation. In *2006 IEEE international conference on evolutionary computation*, 2814–2821. IEEE.

Javed, S., Hassan, A., Ahmad, R., Ahmed, W., Ahmed, R., Saadat, A., and Guizani, M. (2024). State-of-the-art and future research challenges in uav swarms. *IEEE Internet of Things Journal*, 11(11), 19023–19045.

Li, K., Li, L., Groß, R., and Zhao, S. (2024). A collective perception model for neighbor selection in groups based on visual attention mechanisms. *New Journal of Physics*, 26(1), 012001.

Liang, H., Fu, Y., and Gao, J. (2021). Bio-inspired self-organized cooperative control consensus for crowded uuv swarm based on adaptive dynamic interaction topology. *Applied Intelligence*, 51, 4664–4681.

Mukherjee, A., Misra, S., Sukrutha, A., and Raghuwanshi, N.S. (2020). Distributed aerial processing for iot-based edge uav swarms in smart farming. *Computer Networks*, 167, 107038.

Rondón, R., Mahmood, A., Grimaldi, S., and Gidlund, M. (2019). Understanding the performance of bluetooth mesh: Reliability, delay, and scalability analysis. *IEEE Internet of things journal*, 7(3), 2089–2101.

Xiaoning, Z. (2020). Analysis of military application of uav swarm technology. In *2020 3rd International Conference on Unmanned Systems (ICUS)*, 1200–1204. IEEE.

Zhang, X., Wang, Y., Ding, W., Wang, Q., Zhang, Z., and Jia, J. (2024). Bio-inspired fission–fusion control and planning of unmanned aerial vehicles swarm systems via reinforcement learning. *Applied Sciences*, 14(3), 1192.

Zhou, Y., Rao, B., and Wang, W. (2020). Uav swarm intelligence: Recent advances and future trends. *Ieee Access*, 8, 183856–183878.

Zhuo, Z., Kunfeng, L., Zhaolei, W., and Zheng, Y. (2023). Analysis and prospects of cooperative control technology for aircraft clusters. *Journal of Astronautics*, 44(4), 538–545.