Adaptive Signal Processing Techniques for UAV Path Planning in Dynamic Urban Environments

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***Abstract*—Autonomous navigation of unmanned aerial vehicles (UAVs) in an urban area is a challenging research area these days. Planning of safe, optimized and collision free path are the basic challenges encountered in UAV mission. The major issue faced while planning a feasible path is to detect and avoid the obstacles encountered during a mission. This study uses a firefly algorithm for planning the shortest, optimal and collision free path in an urban environment. The key concept behind the working of firefly algorithm is the attraction of one firefly towards the other regardless of their gender. The proposed approach explores the environment and finds the shortest and safe path in the minimum time possible. The Firefly algorithm efficiently avoids obstacles and can also be implemented in a complex environment.**

Keywords—UAVs, firefly algorithm, path planning, autonomous navigation

I. Introduction

Recent advances in technology have made it possible to use unmanned aerial vehicles (UAVs), commonly known as drones across the number of applications in daily life among civil and military organizations. These autonomous aerial vehicles operate without direct human intervention and find diverse applications ranging from package delivery to enhancing communication networks. In hazardous or congested areas, UAVs play a crucial role in safeguarding human lives and have historically contributed to military operations and rescue missions. The evolving landscape of internet and technology has propelled notable advancements in UAV capabilities, expanding their utility across industrial and commercial domains. From mobile edge computing to precision agriculture, UAVs are deployed in a number of applications, each posing unique challenges, especially in dynamic urban environments [1-6].

Path planning, which is to provide a feasible path between two points with an optimal or near-optimal performance satisfying constraint requirements, is one of the most critical challenges in the autonomous navigation of UAVs. Despite substantial research efforts, accuracy in localizing and identifying targets remains a challenge, compounded by UAVs' high mobility. Effective path planning is critical for maximizing the utility of UAVs across various applications [7]. Researchers have developed optimization algorithms optimized for civil applications, reflecting the extensive use of UAVs in a variety of sectors. Studies have focused on analyzing collision-free path planning approaches under various obstacle scenarios while balancing computational efficiency and optimality.

Meta-heuristic algorithms have emerged as promising tools for real-time aerial path planning, providing near-optimal solutions, which is especially useful in cases where deterministic methods produce unsatisfactory results [8]. While the meta-heuristic algorithm cannot guarantee ideal results, it can provide reasonable and acceptable solutions by tweaking its parameters suitably. The Firefly algorithm (FA) is a meta-heuristic algorithm in which fireflies move based on their attraction to other fireflies. Recent research indicate that FA achieves promising performance on several benchmark functions and real-world issues [9]. Efforts to reduce path planning expenses, including fuel expenditure and mobility risks, have resulted in various ways. The authors of [10] provide a solution for the problem of minimum mission time to cover a set of target points in the surveillance area with multiple UAVs and propose an improved ant colony optimization (ACO) combining ACO with greedy strategy while the path planning problem is addressed in [10] using Particle Swarm Optimization (PSO). Furthermore, an improved Grey Wolf Optimization (IGWO) algorithm is proposed for path planning in UAVs in [12]. Adaptive signal processing methods present a viable way to improve UAV route planning in dynamic urban settings. Through the use of adaptive algorithms and real-time sensor data processing, UAVs are able to safely and efficiently alter their course when urban landscapes change. The application of the Firefly Algorithm in urban settings show the continued search for better path planning strategies tailored to dynamic urban situations.

The subsequent sections of the paper are structured as follows: Section II elaborates on the system model and the problem statement. Section III discusses the objective function, the algorithmic framework employed to address the stated problem using the mathematical modeling. Simulation outcomes are discussed and depicted in Section VI. Finally, the conclusion of the study is presented in Section V.

II. System Model

Fig. 1, highlights the operational dynamics within an urban environment where multiple UAVs (m) are deployed and serves as a system Model for this study. These UAVs undertake the mission of navigating from a predefined starting point to a designated endpoint while circumventing obstacles and accommodating the dynamic movement of other UAVs.

The primary objective is to devise an optimized pathway to swiftly transport essential goods and provisions, particularly during adverse conditions like floods or earthquakes. Throughout the navigation process, UAVs encounter challenges such as obstacle detection, avoidance, and the unpredictable nature of their surroundings. The core focus of this study is to develop a path that ensures safety, efficiency, and obstacle-free traversal.

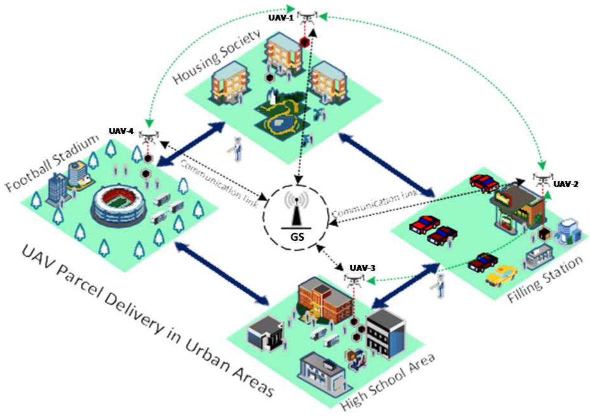

Figure 1: System Model for an urban environment

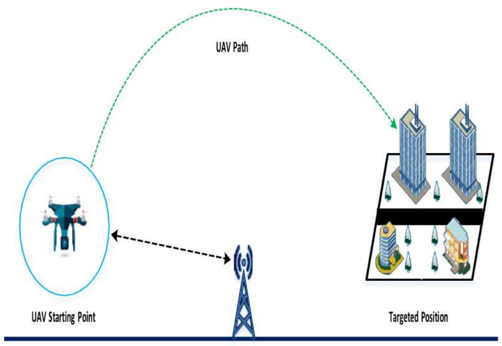

Figure 2: Navigation of UAV: No Oobstacles

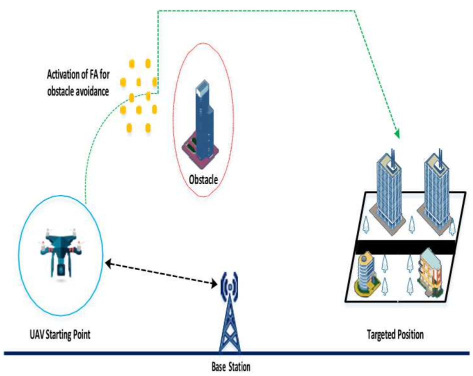

Figure 3: Navigation of UAV: Random Oobstacles

The model illustrates the utilization of UAVs for delivering goods and food items within an urban setting. Equipped with sensors, these UAVs possess the capability to perceive the size, shape, and spatial positioning of imminent obstacles, enabling informed path planning. During navigation, UAVs may encounter three potential scenarios:

- No obstacle
- Static obstacles.
- Both static and dynamic obstacles

The first two scenarios are specifically considered in this study. In circumstances with no barriers (Scenario-1), UAVs fly directly to the target point without using any cognitive algorithms, as seen in Fig. 2. In contrast, in cases including obstacles (Scenario-2), when there are random obstacles, the UAV activates the firefly method to identify its way to the target, as shown in Fig. 3.

A. *Problem Statement*

The aim of this study is to develop an optimized pathway within an urban environment utilizing the Firefly Algorithm, taking into account the dynamic nature of obstacles. In this context, environmental uncertainty stems from obstacles transitioning between static and dynamic states, although the research focuses solely on static obstacles. The primary objective is to devise the shortest, obstacle-free pathway for the efficient delivery of goods and essential items within a designated timeframe. The selected algorithm adeptly explores the environment and streamlines the search process within a reduced number of iterations. Notably, the Firefly Algorithm is chosen for its ability to generate an optimal pathway while effectively mitigating collisions. Two variables Z_1 and Z_2 act as decision variables for path safety and path length optimization, respectively. These are optimized together with the distance between the firefly and the objective and the intensity of light.

III. MATHEMATICAL DESCRIPTION

The objective function of the path planning optimization problem in this study is formulated as given in (1)

$$f_x = Z_1 \frac{1}{\min o_r \in o_p \|D_{bo}\|} + Z_2 \|D_{ft}\| \quad (1)$$

where,

O_r= r number of obstacles

x_{or}, y_{or}= Corresponding coordinate positions of Obstacles

o_p= Number of obstacles detected by the sensors

Z_1 , Z_2= Decision variables

The function $\min o_r \in o_p \|D_{bo}\|$ depends on the distance of fireflies from the obstacle. Its value increases with increase in distance and decreases with decrease in distance. The achievement of the desired value of the objective function depends on the selection of control parameters. To achieve the desired value of f_x, the value of $\|D_{ft}\|$ will be less. The UAV can safely avoid obstacles with a maximum value of Z_2 , but the odds of colliding with obstacles rise as Z1 decreases. Similarly, the smallest value of Z_1 increases the path length, while the path length decreases with higher value of Z_2.

A. *Firefly Algorithm*

The Firefly Algorithm, draws inspiration from the behavior of fireflies, which emit light from their lower abdomen to attract other insects, a phenomenon known as bioluminescence. This natural behavior serves as the foundation for the development of the Firefly Algorithm, a nature-inspired meta-heuristic algorithm. The flowchart depicting the operational framework of the Firefly Algorithm is presented in Fig. 4. The algorithm operates based on three fundamental rules:

1. There is no gender discrimination because all fireflies are unisex, which means that one firefly will be attracted to another regardless of gender.
2. The Fireflies' attractiveness grows with brightness and decreases with distance. In a pair of flashing fireflies, the less luminous one gravitates towards the brighter one. If there are no brighter fireflies, a single firefly will go randomly over the space.
3. The objective function depends upon the brightness.

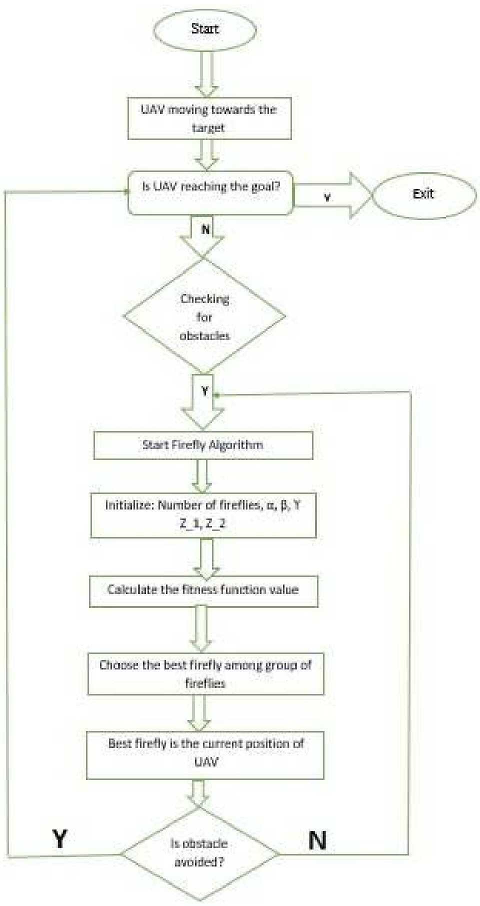

Figure 4: Flow Chart of Firefly Algorithm

Distance between two fireflies and attractiveness of the fireflies is given by (2) and (3), respectively:

$$\gamma_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_i^k - x_j^k)^2} \quad (2)$$

$$\beta(r) = \beta_o \exp(-\gamma r^m)\,; m \geq 1 \quad (3)$$

The movement of the firefly depending on brightness is given as (4):

$$x_i^k(t+1) = x_i^k(t) + \beta_o \exp(-\gamma r_{ij}^2)((x_{ij}^2(t) - x_i^k(t) + \alpha(r - \tfrac{1}{2}) \quad (4)$$

where,

$\beta(r)$= Attractiveness of firefly
β_o= Attractiveness of firefly at r=0
i, j =Representing two fireflies
x_i, x_j= Relative position of fireflies
k = dimension
α = randomization parameter, for random number r

The Firefly Algorithm offers several advantages for solving optimization problems. Firstly, it can solve linear, nonlinear, and multi-model optimization problems, making it versatile across various domains. Additionally, the computational cost associated with the Firefly Algorithm is low, enabling efficient optimization even with complex problem spaces. One notable feature of the FA is that its iteration process does not necessitate a precise initial start, enhancing its usability

Algorithm 1 :Pseudo Code of FA

Objective function $f(k), k = (k_1, k_2, ...k_d)^T$
Initialize: Number of fireflies,γ, α, Z_1, Z_2
light intensity I_i at k_i is determined by $f(k_i)$
while $t \leq$ maximum population **do**
  for $i = 1 : n$ all n fireflies **do**
    for $j = 1 : n$ all n fireflies **do**
      if $(I_i \leq I_j)$ **then**
        move firefly i towards j
      end if
      Vary attractiveness with distance r via exp [-gamma r^2]
      find new solutions and change light intensity accordingly
    end forj
  end fori
  Rank the fireflies and select the global best firefly
end while

and robustness. Moreover, the FA demonstrates high convergence speed, facilitating quick attainment of optimal solutions. Furthermore, the FA can easily integrate with other optimization techniques to form hybrid approaches, enhancing its adaptability and effectiveness in addressing diverse optimization challenges. Overall, these advantages position the Firefly Algorithm as a powerful tool for tackling optimization problems across different applications and domains.

B. *Mathematical Modeling*

The operation and navigation of a UAV in an urban environment is not an easy task. Due to the number of obstacles in an urban environment, UAV may encounter both static and dynamic obstacles. For safe navigation, the UAV needs to maintain a safe distance from all obstacles. The group of points along the path that connects a source to a destination is called a way point collection. These are dispersed around a region at various locations. Firefly is an algorithm used to connect these waypoints and plan an optimal safe path. A random number of fireflies are produced close to the obstruction by the firefly algorithm, and one firefly is chosen at random from the group based on brightness.

The nearest barrier should be as far away from the chosen brighter firefly as is safe. The brighter firefly is displaced by the UAV, and the process of looking for it begins anew until the UAV finds the best and safest route. The euclidean distance between the firefly and the nearest obstacle provides the information for the brightness of the firefly, and it is computed using (5).

$$D_{BO} = \sqrt{(x_o - x_{bi})^2 + (y_o - y_{bi})^2} \tag{5}$$

where,

D_{BO}= distance of the firefly from obstacle

x_o, y_o = coordinates of the obstacle

x_b, y_b= coordinates of the firefly position

For safe navigation it is necessary to adopt the optimal path with the information of the nearest obstacles in crowded urban environment. The distance between the UAV and nearest obstacles (D_{UO}) is calculated by (6):

$$D_{UO} = \sqrt{(x_o - x_u)^2 + (y_o - y_u)^2} \tag{6}$$

where, x_o, y_o, x_u, y_u are the corresponding coordinates of the nearest obstacle and UAV position respectively.

The choice of the brighter firefly is determined by the distance from the obstacle and the goal. Specifically, the maximum and lowest distances from the obstacle and target point, respectively. This is an iterative process that will continue until the firefly reaches the target. The distance between the firefly and target is determined by (7).

$$D_{ft} = \sqrt{(x_t - x_{fi})^2 + (y_t - y_{fi})^2} \tag{7}$$

where,

D_{ft}= distance between the firefly and the target

x_t, y_t= coordinates of the target

IV. PERFORMANCE EVALUATION

The proposed algorithm is implemented and evaluated in an urban environment using MATLAB with the following parameters given in Table 1.

Table I: Simulation Parameters

Parameters	Range
γ	0.1-1
α	0.1-1
β	0.1-1
Z_1	0.1-1
Z_2	0.01-0.0001

Developing an efficient FA controller involves meticulously selecting parameters tailored to address specific issues. Key parameters, ranging from 0 to 1, include the randomization parameter (α), attraction (β), and light absorption coefficient (γ). Additionally, specifying the quantity of firefly and maximum generation helps reduce computational effort. The number of fireflies typically ranges from 10 to 100, while iterations can vary between 50 and 100, determining the algorithm's convergence and efficiency. The FA operates based on the attraction of fireflies, driven by differences in brightness intensity. When the attraction parameter β is set to zero, fireflies exhibit random movement. Simulation experiments are conducted in a 2D space measuring 150cm by 150cm, populated with static obstacles. Through varied values of the randomization constant α, the optimal and safe path for the UAV is determined, with α = 0.75 yielding favorable results.

Fig. 5 provides a comprehensive pictorial representation of the distribution of 200 users, depicted as blue dots, and the deployment of UAVs, shown as red blocks. This figure encompasses three distinct scenarios, each highlighting different deployment outcomes. In the first scenario, a total of 16 UAVs have been deployed in the field, out of which only 6 UAVs are successful in providing connections to users. In the second scenario, 9 UAVs have been deployed, with 4 UAVs effectively establishing connections with the users. The third scenario mirrors the first in terms of UAV deployment, with 16 UAVs placed in the field, but here, only 4 UAVs manage to establish user connections. Once the UAVs have been successfully placed and have established connections with users, the subsequent phase involves meticulous path planning for the UAVs. This step is essential to determine the most effective trajectories for the UAVs to follow. Effective path planning is crucial as it helps the UAVs to navigate the medium efficiently and assess any environmental or circumstantial factors they might encounter. This planning ensures that the UAVs can maintain stable connections and optimize their performance in providing reliable service to the users.

Fig. 6 provides a detailed visualization of the outcomes, showcasing the effectiveness of the Firefly Algorithm in planning an optimal and feasible path. This figure includes multiple sub-figures that illustrate how the fireflies' movements and behaviors change with different α values, thereby demonstrating the algorithm's dynamic adaptability. In Fig. 6(a), observed at α = 0.45, the fireflies exhibit random movement patterns. At this stage, less bright fireflies are attracted to their brighter counterparts, but their overall motion remains largely unpredictable and disordered. This randomness indicates that the algorithm is still in an early phase of processing, where the fireflies are exploring space without a clear direction toward the destination. In Fig. 6(b), with α set at 0.55, and in Fig. 6(c), with α at 0.65, the fireflies continue to display random movements. These movements are characterized by a lack of clear alignment towards the destination, suggesting that while there is some degree of attraction between fireflies, it is insufficient to guide them effectively towards an optimal path. However, a significant shift is observed in Fig. 6(d) at α = 0.75. Here, the fireflies begin to align more consistently towards the destination, marking the emergence of a more structured and optimal path. This alignment indicates that the algorithm is reaching a critical threshold where the fireflies' movements become more coherent and directed. As the value of α increases further, this trend continues. Fig. 6(e) and 6(f), corresponding to α = 0.85 and α = 0.95 respectively, show a pronounced alignment of fireflies towards the destination. Despite the increased randomness observed at these higher α values, the effectiveness of the Firefly Algorithm in planning an optimal and feasible path is clearly reaffirmed. The fireflies' alignment at α = 0.75 and above underscores the algorithm's ability to adapt to changing conditions and effectively navigate UAVs in dynamic urban environments. These results collectively support the adaptability and reliability of the Firefly Algorithm for UAV navigation. The algorithm's performance, particularly at higher α values, demonstrates its robustness in guiding UAVs through complex and dynamic urban landscapes, ensuring efficient path planning and optimal trajectory alignment.

V. CONCLUSIONS

This study addressed the aadaptive signal pprocessing for UAV Path Planning in dynamic urban environment using Firefly Algorithm. The mathematical description for this meta-heuristic approach is described. This approach simplifies the finding of an optimal, collision-free, and shortest path for UAVs using Firefly Algorithm , resulting in minimal time consumption and computational expense. The algorithm adeptly explores the environment and streamlines the search process within a reduced number of iterations

The study has limitations as the algorithm solely targets static obstacles within two-dimensional predetermined settings. However, the proposed approach exhibits potential for UAV navigation amid urban settings with random obstacles. This underscores the adaptability and agility of the Firefly Algorithm in addressing UAV path planning challenges across diverse and challenging urban environments. Future work aims to mitigate algorithmic time complexity by addressing sorting frequency, considering both distance and brightness weights using both static and dynamic barriers.

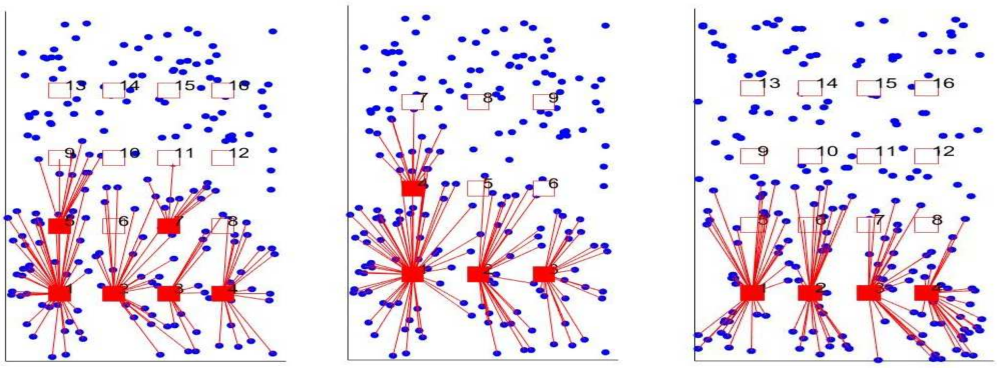

Figure 5: Placement of UAV, Distribution of Users and Users-UAV Connectivity

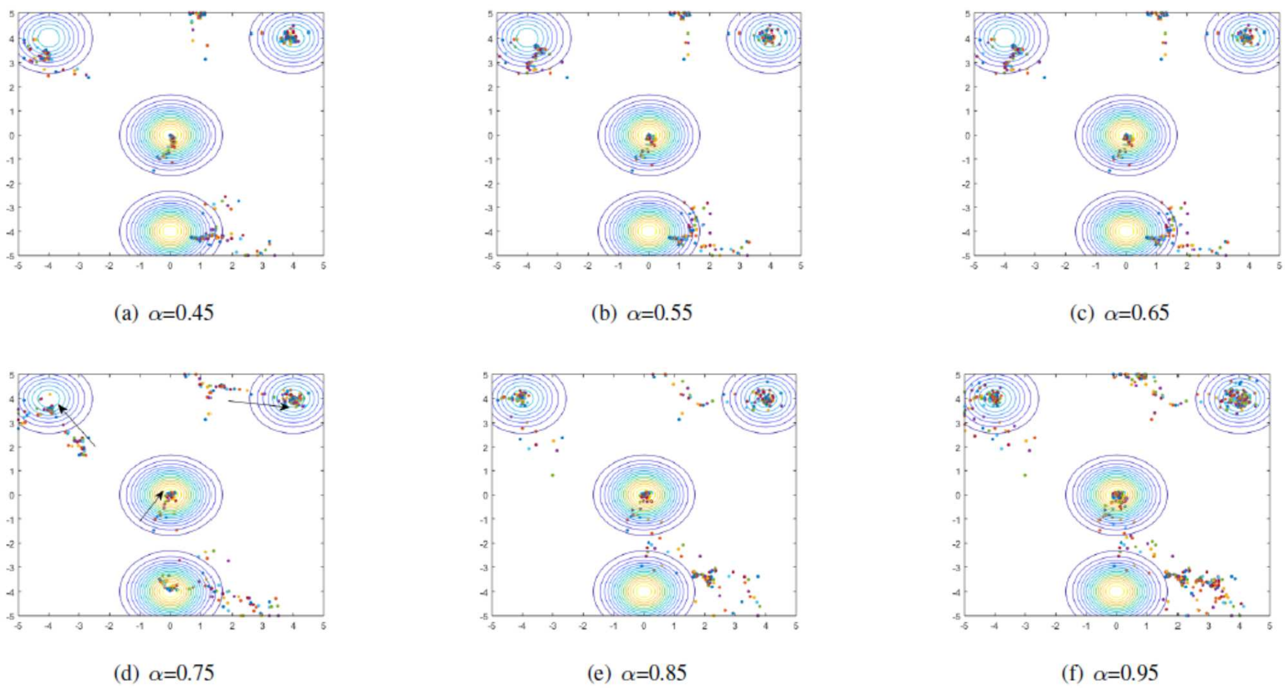

Figure 6: Visualization of Firefly Algorithm's Effectiveness in UAV Path Planning

REFERENCES

[1] Q. Yang and S.-J. Yoo, "Optimal UAV path planning: Sensing data acquisition over IoT sensor networks using multi-objective bio- inspired algorithms," IEEE Access, vol. 6, pp. 13 671–13 684, 2018.

[2] Qadir, Z., Ullah, F., Munawar, H. S., & Al-Turjman, F. Addressing disasters in smart cities through UAVs path planning and 5G communications: A systematic review. Computer Communications, 168, 114-135.2021.

[3] Mohsan, S. A. H., Othman, N. Q. H., Li, Y., Alsharif, M. H., & Khan, M. A. . Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. Intelligent Service Robotics, 16(1), 109-137. 2023.

[4] Aggarwal, S., & Kumar, N.. Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges. Computer communications, 149, 270-299.2020.

[5] A. Alihodzic, E. Tuba, R. Capor-Hrosik, E. Dolicanin, and M. Tuba,"Unmanned aerial vehicle path planning problem by adjusted elephant herding optimization," in *2017 25th Telecommunication Forum (Telfor)*. IEEE, 2017, pp. 1–4.

[6] Shahid, N., Abrar, M., Ajmal, U., Masroor, R., Amjad, S. and Jeelani, M. Path planning in unmanned aerial vehicles: An optimistic overview. *International Journal of Communication Systems, 35*(6), p.e5090, 2022.

[7] X. Zhang, J. Chen, B. Xin, and Z. Peng, "A memetic algorithm for path planning of curvature-constrained UAVs performing surveil- lance of multiple ground targets," *Chinese Journal of Aeronautics*, vol. 27, no. 3, pp. 622–633, 2014.

[8] J.-S. Lee and K.-H. Yu, "Optimal path planning of solar-powered UAV using gravitational potential energy," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 53, no. 3, pp. 1442–1451, 2017.

[9] Kumar, V. and Kumar, D. A systematic review on firefly algorithm: past, present, and future. Archives of Computational Methods in Engineering, 28, pp.3269-3291, 2021.

[10] Li, J., Xiong, Y. and She, J. March. An improved ant colony optimization for path planning with multiple UAVs. In 2021 IEEE International Conference on Mechatronics (ICM) (pp. 1-5), 2021.

[11] Yu, Zhenhua, Zhijie Si, Xiaobo Li, Dan Wang, and Houbing Song. "A novel hybrid particle swarm optimization algorithm for path planning of UAVs." *IEEE Internet of Things Journal* 9, no. 22: 22547-22558 2022.

[12] Zhang, Wei, Sai Zhang, Fengyan Wu, and Yagang Wang. "Path planning of UAV based on improved adaptive grey wolf optimization algorithm." IEEE Access 9: 89400-89411.2021.

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