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Genetic Algorithm-Based Approaches for Enhancing Multi-UAV Route Planning

Mohammed Abdulhakim Al-Absi[1], Hoon Jae Lee[2], Young-sil Lee[3,*]

[1]Dr, Department of Computer Engineering, Dongseo University, Busan, Korea
[2]Professor, Dongseo University, Division of Information and Communication Engineering, Korea
[3]Associate Professor, International College, Dongseo University, Busan, Korea
E-mail mohammed.a.absi@gmail.com, hjlee@dongseo.ac.kr, lys0113@gdsu.dongseo.ac.kr

Abstract

This paper presents advancement in multi- unmanned aerial vehicle (UAV) cooperative area surveillance, focusing on optimizing UAV route planning through the application of genetic algorithms. Addressing the complexities of comprehensive coverage, two real-time dynamic path planning methods are introduced, leveraging genetic algorithms to enhance surveillance efficiency while accounting for flight constraints. These methodologies adapt multi-UAV routes by encoding turning angles and employing coverage-driven fitness functions, facilitating real-time monitoring optimization. The paper introduces a novel path planning model for scenarios where UAVs navigate collaboratively without predetermined destinations during regional surveillance. Empirical evaluations confirm the effectiveness of the proposed methods, showcasing improved coverage and heightened efficiency in multi-UAV path planning. Furthermore, we introduce innovative optimization strategies, (Foresightedness and Multi-step) offering distinct trade-offs between solution quality and computational time. This research contributes innovative solutions to the intricate challenges of cooperative area surveillance, showcasing the transformative potential of genetic algorithms in multi-UAV technology. By enabling smarter route planning, these methods underscore the feasibility of more efficient, adaptable, and intelligent cooperative surveillance missions.

Keywords: *Genetic Algorithm, Multi UAV Route Plan, foresighted. Unmanned aerial vehicle*

1. Introduction

In the landscape of contemporary unmanned aerial vehicle applications, the optimization of multi-UAV route planning stands as a critical frontier, marked by the intersection of technological innovation and operational efficiency [1], [2]. As the utilization of multiple UAVs becomes increasingly pervasive across diverse domains such as surveillance, search and rescue, agriculture, and logistics, the imperative to orchestrate their trajectories with precision and foresight intensifies [3], [4]. The intricate task of multi-UAV route planning necessitates innovative approaches that transcend the limitations of traditional heuristic methods and optimization techniques [5], [6]. Among the repertoire of advanced optimization methodologies,

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Corresponding Authors: Young Sil Lee
E-mail: lys0113@gdsu.dongseo.ac.kr
Tel: +82 10-8229-9876
Author's affiliation (Associate Professor, International College Dongseo University, Busan, Korea)

Genetic algorithm-Based approaches have become a focal point for researchers addressing the inherent complexity of multi-UAV route planning. Drawing inspiration from the principles of natural evolution, genetic algorithm provides a powerful framework for solving intricate optimization problems [7]. The nuanced adaptability of GAs positions them promisingly for enhancing the efficiency and effectiveness of multi-UAV route planning [8]. In recent years [9], the rapid advancement of UAV technology has led to their widespread utilization across various domains [10]: surveillance, search and rescue, agriculture, and package delivery [11]. One key challenge in maximizing the efficiency and effectiveness of multiple UAV operations is the intricate task of route planning [12]. Efficient route planning for multiple UAVs is crucial to ensure optimal resource utilization, mission objective achievement, and avoidance of collisions and congestion [13]. Traditionally, route planning for multiple UAVs has relied on heuristic methods and optimization techniques [14]. However, as the complexity of the operational environments and mission requirements increases, these conventional methods often struggle to provide optimal solutions within reasonable time frames [15]. This has necessitated the exploration of advanced optimization techniques, among which GAs have emerged as a powerful tool for addressing the multi-UAV route planning problem [16], [17]. The fundamental concept of GAs involves iteratively evolving a population of potential solutions over generations, gradually improving the quality of solutions based on their fitness with respect to defined objectives [18]. In the context of multi-UAV route planning, GAs present an opportunity to discover solutions that are close to optimal, striking a balance between various goals such as minimizing travel time, maximizing mission coverage, and guaranteeing collision avoidance [19]. One significant issue in multi-UAV cooperative area surveillance is the inefficient route planning that hampers comprehensive coverage [20]. Traditional heuristic methods struggle to adapt to dynamic and complex environments, leading to suboptimal solutions within reasonable time frames [21]. In [22], the authors focus on optimizing the path planning for UAVs in complex three-dimensional (3D) urban environments. It introduces a new path planning method that efficiently finds optimal or quasi-optimal and collision-free paths by prioritizing high-probability spaces through the use of Constrained Polygonal Space (CPS) and an Extremely Sparse Waypoint Graph (ESWG). This approach significantly reduces path finding time complexity without compromising path length. In [23], the authors introduces a multi-objective coverage flight path planning algorithm designed for UAVs operating in complex 3D urban environments with multiple obstacles. The algorithm addresses the challenge of optimizing both inter-regional and intra-regional paths for UAVs required to cover spatially distributed regions while avoiding obstacles. In [24], the authors introduces an algorithm for flight path planning designed for small unmanned aerial vehicles (SUAVs) navigating 3D environments with fixed obstacles. Focused on optimizing energy consumption for low-altitude commercial SUAV applications, the algorithm employs a visibility roadmap based on the visibility graph approach. Its objective is to efficiently generate collision-free and energy-conscious flight paths within reasonable time complexity. In this paper, the authors concentrate on enhancing the methods for planning routes for multiple UAVs using genetic algorithms. This study aims to overcome the limitations of traditional heuristic approaches by leveraging the capabilities of GAs. The goal is to provide more reliable and efficient solutions for the complex challenges of coordinating multiple UAVs in dynamic environments. Therefore, our contributions stand at the forefront of addressing critical challenges in multi-UAV cooperative area surveillance. Traditional heuristic methods often falter in dynamic and complex environments, leading to suboptimal solutions within reasonable time frames. In response, this paper introduces genetic algorithm-based approaches, showcasing transformative potential. The proposed Foresightedness and Multi-step methods present innovative solutions to the inefficient route planning challenge, offering distinct advantages in different scenarios.

This research is structured as follows: In the first section, we explore the background of genetic algorithms.

The section concludes by highlighting the motivation behind our work and the contributions made in this paper. The second section focuses on the enhancement of the multi UAV route planning methods through the introduction of foresighted and multi-step approaches. Section three discussed the simulation experiment and result analysis and concludes by highlighting the limitations and challenges. In the last section, conclusions, and future opportunities to improve the UAV route are discussed.

2. Improvement of multi-UAV route planning method based on genetic algorithm

2.1 Foresighted approach

In response to the potential advantages of observing forthcoming surveillance coverage changes during UAV flights within the target area, we introduce a foresighted approach. This approach is based on the concept that, during patrol flights, a group of drones can increase their coverage potential by extending their flight radius beyond the traditional arc distance. Rather than relying on the original flight radius, which is constrained by a predefined value, our approach permits the drone group to amplify the radius by a factor of μ (where $\mu > 1$). To implement this approach, consider a drone positioned at point A; previously, it could fly up to the boundary of arc BD. In contrast, it can now fly an extended distance along the arc to $B'D'$. Importantly, the node on arc $B'D'$ coincides with the arc center node on BD. Through evaluating node adaptability along arc $B'D'$, we select the node exhibiting the highest adaptability value. Notably, this node's coordinates are denoted as (x', y'). Despite this selection, the drone's ultimate target node remains the node (x, y) on arc BD, ensuring that the drone operates within the route planning's set speed and interval parameters. Essentially, this method extends the drone's operational foresight, allowing it to survey a more extensive area by assessing adaptability values for farther nodes—while maintaining the drone's actual flight conditions in practice.

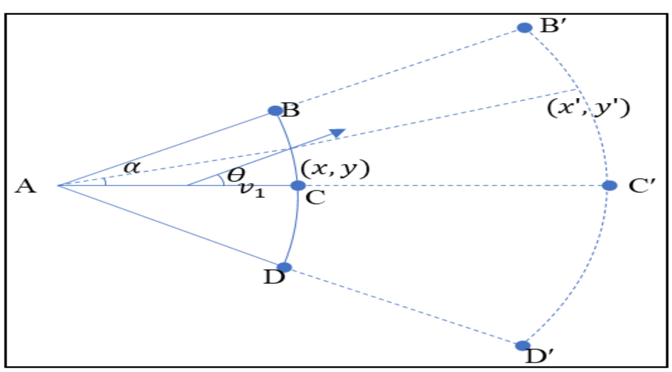

Figure 1. The foresighteness method

Since the target node for drone flight searching differs from the selected target node, we present the formula for calculating the target node as follows:

$$x' = x_A + \mu * v_p * \Delta t * \cos(\alpha + v_1) \quad (1)$$

$$y' = y_A + \mu * v_p * \Delta t * \sin(\alpha + v_1) \quad (2)$$

The horizontal and ordinate coordinates of the target nodes x' and y'obtained in the far-sighted situation of the drone, x_A and y_A represent the horizontal coordinates and ordinates of the starting point A,respectively.

The variable μ signifies the extent of farsightedness, v_p is the drone flying speed, Δt represents the time interval, α is the deflect angle of the target node relative to the starting point A and v_1 is the angle at starting point A (Figure1).

The calculation formula of the target node information of the actual selection flight is the same as the formula before: For the extended foresighted scenario, the horizontal and vertical coordinates of the target nodes (x' and y') are derived from the drone's starting point A, considering the factor μ for extended range, drone speed v_p, time interval Δt, the deflection angle α of the target node from the starting point, and the angle v_1 at starting point A. Conversely, for the selected flight's actual target node, the formula remains consistent with the preceding formulation:

$$x = x_A + v_p * \Delta t * \cos(\alpha + v_1) \tag{3}$$

$$y = y_A + v_p * \Delta t * \sin(\alpha + v_1) \tag{4}$$

Furthermore, the angle v_2 at the subsequent target node, v_1 at starting point A are determined. Additionally, the deflection angle α of the actual target node's flight relative to A, and the angle θ indicating the drone's speed change from the start to the actual next target node are defined as:

$$v_2 = v_1 + \theta \tag{5}$$

The relationships elucidated within these equations enable precise determination of target nodes during both foresighted and selected flight situations. These relationships account for factors such as speed, angle variation, and deflection angles, which are vital for optimizing UAV path planning.

2.2 Multi-step

The existing route planning approach for multi-UAV cooperative area monitoring, based on genetic algorithms, operates as a single-step planning method. This means that at each iteration, the method only plans the immediate next step from the current node, selecting the optimal node for the UAV in the given feasible positions. However, this approach is not without its limitations. It may result in UAVs predicting solely the next step, potentially leading to extreme reactionary behavior based on the current state. Although the fitness value might increase at each step, it can later become evident that this step's behavior yields unfavorable outcomes. To address these limitations, we propose an alternative route planning method rooted in the multi-step cooperative flight of UAVs. In this approach, the UAV group engaged in patrol flight no longer selects the node with the highest fitness value according to the fitness function after each UAV flight step. Instead, considering the constraints of UAV flight and after T flight steps, the mean fitness of the previous T steps is calculated. Subsequently, the route with the highest mean fitness value is chosen. The sequence of nodes in this route, encompassing T nodes, becomes the UAV's next flight nodes. This process repeats iteratively for subsequent nodes until the termination criteria are met. This innovative multi-step cooperative flight approach holds promise in circumventing the limitations of single-step methods, potentially enabling more informed decision-making for UAV reactions during surveillance missions. By considering the broader context of past flight steps, the proposed method seeks to strike a balance between predictive accuracy and avoiding extreme reactions, contributing to more effective cooperative area monitoring.

Based on the two-step route planning method (Figure 2), we assume that the current UAV is located at point A, the position that the UAV can fly after one step flight is located on arc BD. Currently, it is uncertain which node has the maximum fitness value but takes a random node as the current node and flies one step under the constraint conditions. For example, it flies to node M first and then M is used as the initial node of UAV flight in the next step. At this time, the feasible position of UAV in the next step is located on arc EF.Assuming flying to node N, then the fitness values of point M and point N are obtained and their mean values are used to judge the advantages and disadvantages of this section of route. Any point on arc BD can be like point M in multi-step and the feasible position of the next node can be determined at this node again under the constraint of turning of UAV. The flying situation considered in such arrangement and combination is geometrically higher than that in hyperopia. At the same time, the calculation amount of multi-step prediction will increase with the predicted value. The number of steps increases exponentially, and the route planning time will also increase greatly.

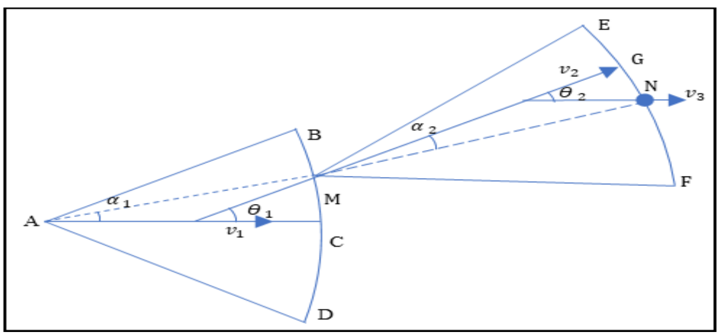

Figure 2. The two-step route planning method

We assume that point M and point N are the optimal route after two flight steps. The position speed information update formula of point M and point N is the same as that of target node position information and velocity method information given before. The position speed update formula of point M is as follows: In the context of the two-step route planning approach, let us consider the scenario where the current UAV is positioned at point A, and the potential locations reachable after one step of flight lie along arc BD. At this point, the optimal node with the maximum fitness value remains uncertain. To address this, we randomly select a node within the feasible positions and proceed with a one-step flight, adhering to constraint conditions. For instance, let's assume the UAV first flies to node M, which then becomes the starting node for the subsequent flight step. Consequently, the feasible positions for the next step are situated along $arc\ EF$. Upon reaching node M, the process is replicated for point N and the fitness values of both points M and N are acquired. The mean of these fitness values is used to assess the quality of the route segment. This procedure can be applied to any point on arc BD, resembling the multi-step process. This approach offers a geometrically broader exploration compared to hyperopia. However, it's important to note that as the number of predicted steps increases, the computational complexity and planning time grow exponentially. For the scenario where points M and N emerge as the optimal route after two flight steps, the position and speed information update formulas for these points are similar to the target node's previously provided position and velocity updates. For point M, the position update formulas are given by:

$$x_M = x_A + v_p * \Delta t * \cos(\alpha_1 + v_1) \tag{6}$$

$$y_M = y_A + v_p * \Delta t * \sin(\alpha_1 + v_1) \tag{7}$$

$$v_2 = v_1 + \theta_1 \tag{8}$$

Similarly, the position update formulas for the subsequent point N are:

$$x_N = x_M + v_p * \Delta t * \cos(\alpha_2 + v_2) \quad (9)$$

$$y_N = y_M + v_p * \Delta t * \sin(\alpha_2 + v_2) \quad (10)$$

$$v_3 = v_2 + \theta_2 \quad (11)$$

These equations embody the position and speed updates for points M and N, driving the multi-step route planning method and showcasing its complexity in capturing a broader search space for optimized routes. When the drone is at point M, its starting velocity angle is determined by the updated velocity angle v_2 from point A to M, along with the angles $\theta_1$and the θ_2 found using the genetic algorithm for the two steps. α_1 and α_2 are just half of these angles. For updating the drone's speed direction towards the target node's position, we use a formula that calculates the average fitness value across both steps. However, it's important to understand that this averaging doesn't mean the drone follows both steps fully towards the optimal path. Instead, the drone only takes one step towards the optimal path, even though the average fitness value considers both steps. This reflects the complexity of our multi-step approach.

3. Simulation experiment and result analysis

Our multi-UAV cooperative surveillance adapts to diverse operating environments, including urban and rural terrains. Unlike traditional path planning, explicit obstacle modeling is bypassed in favor of real-time adaptability. Genetic algorithms drive dynamic path planning, emphasizing coverage and turning angles, inherently addressing collision avoidance. This probabilistic approach considers potential dynamic obstacles within the operational environment, ensuring the responsiveness needed for efficient surveillance without relying on detailed a priori modeling. Real-world environments present a spectrum of obstacle shapes, ranging from convex structures to non-convex entities. Our methodology embraces the inherent adaptability of genetic algorithms to navigate these complexities without relying on detailed geometric obstacle models. The genetic algorithms utilized encode turning angles and employ coverage-driven fitness functions, enabling UAVs to dynamically adjust paths in response to the presence of obstacles. The adaptability of genetic algorithms inherently addresses both convex and non-convex obstacles, allowing for effective cooperative surveillance without explicit obstacle shape specifications.

Table 1. Considered Simulation parameters

Parameter	Value
Number of drones N	6
Network Size	200Km*200Km
Surveillance radius	70Km
Speed v_p	150m/s
Flight time per step Δt	20s
Maximum turning angle	45°
Selection probability p_c	0.9
Mutation probability p_m	0.1
Crossover probability p_s	0.5
Generation	80
Population Size	200

In optimizing multi-unmanned aerial vehicle cooperative area surveillance, the selection of an effective fitness function is paramount. Our strategy for the Genetic algorithm centers around key objectives outlined in this paper. First and foremost, the fitness function prioritizes coverage maximization, rewarding solutions that contribute to extensive surveillance coverage across the designated target area. Efficiency enhancement is also a critical consideration, with metrics such as total travel distance, time taken, or fuel consumption guiding the GA toward more efficient UAV route planning solutions. Collision avoidance is addressed by penalizing solutions that lead to close encounters between UAVs, considering factors like minimum separation distance, potential conflict points, or collision probabilities. Given the real-time dynamic path planning nature of our approach, Dynamic adaptability is emphasized, encouraging solutions that can dynamically adjust paths in response to changing conditions or obstacles. The fitness function incorporates the Foresightedness introduced in our paper, rewarding solutions demonstrating a proactive approach to surveillance by preemptively covering areas with potential future interest. Lastly, to address the complexities of multi-UAV route planning, a multi-objective Optimization strategy is employed. This involves combining metrics related to coverage, efficiency, collision avoidance, and foresightedness, with assigned weights based on mission priorities. This comprehensive fitness function strategy aligns with the challenges and goals outlined in our paper, providing a robust foundation for enhancing the efficiency and effectiveness of multi-UAV cooperative surveillance missions. In our experiments, we used a setup detailed in Table 1. We set up a coordinate system with the starting point at the lower left corner of the task area. The table also includes information about how fast the UAVs fly and the radar's monitoring radius. In our experiment, the drones began at different spots: (0, 50), (60, 0), (120, 0), (160, 200), and (200, 150). They all flew at the same speed v_p, and took their first step after a certain time. When they reached their 30th step, here's what we observed in the simulation:

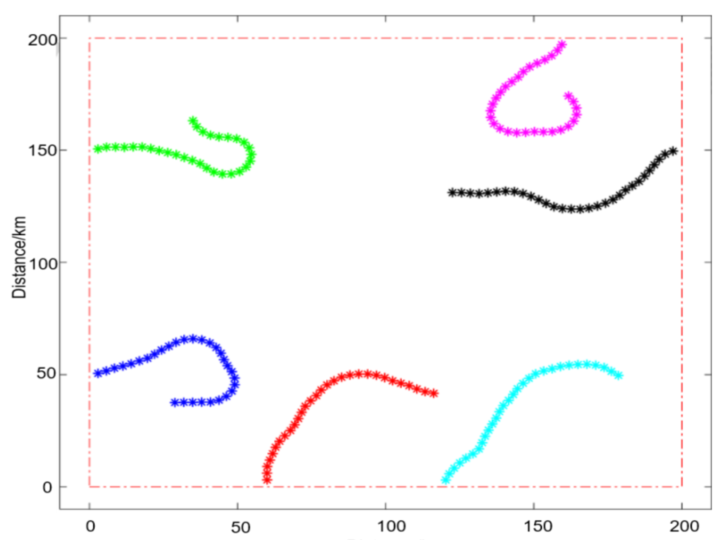

Figure 3. The route diagram of six UAVs flying 30 steps

In Figure 3, you can see the route map created using the genetic algorithm for all the UAVs. In Figure 4, we show the monitoring range of the six UAVs at the 30th step. The red dots indicate where each UAV is located, and the shaded arc areas represent the coverage of the radar surveillance by these drones. The results clearly demonstrate that the radar coverage of all the UAVs effectively spans the entire mission area. In summary, these simulation outcomes confirm that the genetic algorithm-based flight routes for the multi-UAVs enable comprehensive and continuous monitoring across the designated target area.

The observed overlap in convergence spaces among UAVs, as shown in Figure 4, raises concerns about potential collisions and suboptimal surveillance coverage. To minimize this overlap, an adaptive convergence space adjustment mechanism is proposed, dynamically modifying spaces based on real-time conditions and neighboring UAV positions. Additionally, collision avoidance maneuvers are integrated into the route planning algorithm, triggering proactive actions to prevent collisions when overlap is detected. These strategies ensure safer separation distances and optimized surveillance coverage, addressing the identified drawbacks of the proposed approaches.

The computational complexities of the proposed approaches stem from the use of Genetic Algorithm-Based Methods, introducing additional computation overhead compared to traditional heuristic methods. Genetic algorithms involve iterative evolution of populations, which can be resource-intensive. However, the proposed Foresighted and Multi-step methods aim to strike a balance between solution quality and computational time. While GAs bring advantages in optimizing multi-UAV routes, it's acknowledged that heuristic methods are traditionally favored in UAV pathfinding due to their perceived advantage of lower computational complexity. The challenge is to harness the benefits of genetic algorithms while managing their computational demands effectively for real-time applications in UAV path planning.

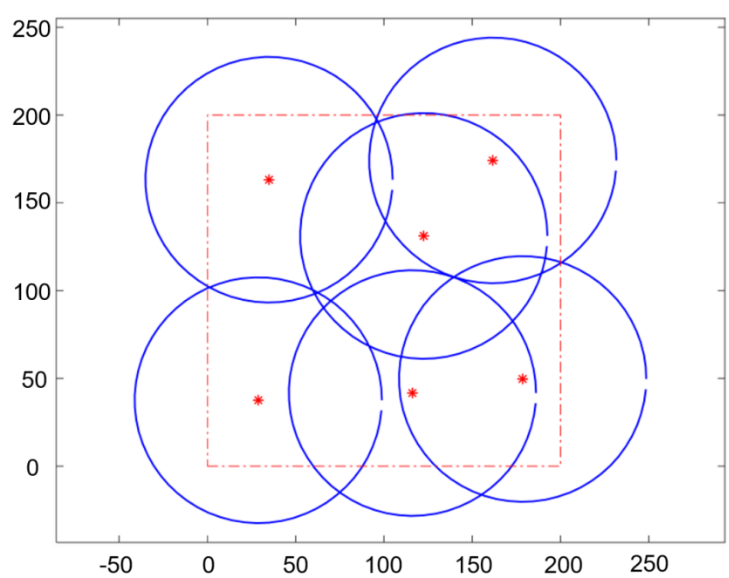

Figure 4. Monitoring ranges of 6 UAVs at 30 steps

Limitations and Challenges

The computational complexities of the proposed approaches stem from the use of Genetic algorithm-based methods, introducing additional computation overhead compared to traditional heuristic methods. Genetic algorithms involve iterative evolution of populations, which can be resource-intensive. However, the proposed foresighted and multi-step methods aim to strike a balance between solution quality and computational time. While GAs bring advantages in optimizing multi-UAV routes, it's acknowledged that heuristic methods are traditionally favored in UAV pathfinding due to their perceived advantage of lower computational complexity. The challenge is to harness the benefits of genetic algorithms while managing their computational demands effectively for real-time applications in UAV path planning.

As with any technological advancement, it is essential to recognize the inherent challenges and limitations that accompany the proposed genetic algorithm-based approaches for multi-UAV route planning. While these methodologies showcase remarkable promise in enhancing efficiency and adaptability, a nuanced understanding of their constraints provides valuable insights into areas for improvement and future research directions.

- Computational complexity: The proposed methodologies, particularly the "multi-step" approach, exhibit increased computational complexity as the number of predicted steps rises. Future research could explore optimization techniques to mitigate computational challenges and enhance real-time applicability.
- Predictive accuracy: The foresighted and multi-step methods rely on predictions and assumptions about future surveillance coverage and UAV behavior. Uncertainties in real-world scenarios may impact the accuracy of predictions, requiring further refinement of models.
- Parameter sensitivity: The performance of genetic algorithms is influenced by the sensitivity of parameters such as crossover and mutation rates. Fine-tuning these parameters for optimal results may pose a challenge, necessitating additional research on adaptive parameter tuning strategies.

The pursuit of optimizing multi-UAV route planning through genetic algorithms introduces a realm of possibilities and transformative potential. However, this journey is not without its share of challenges, each providing valuable insights and avenues for future exploration. As scholars delving into the intricate domain of cooperative area surveillance, understanding and addressing these challenges become imperative for the advancement of both theory and practical implementation.

- Computational complexity (navigating the balance): One of the foremost challenges lies in managing the computational complexity introduced by the 'multi-step' optimization approach. As the number of predicted steps increases, so does the complexity, presenting a delicate balance between computational efficiency and predictive accuracy. Scholars in this field face the ongoing task of refining algorithms to ensure real-time applicability while preserving the integrity of route planning predictions.
- Uncertainties in predictive accuracy: The reliance on predictions and assumptions about future surveillance coverage and UAV behavior introduces uncertainties. Real-world scenarios are dynamic and often unpredictable, posing a challenge in achieving precise predictive accuracy. This challenge necessitates ongoing research to enhance the robustness of models, making them adaptable to the complexities of dynamic operational environments.
- Parameter sensitivity (optimal performance): Genetic algorithms are sensitive to parameter adjustments, particularly in crossover and mutation rates. Achieving optimal performance requires intricate parameter tuning, a process that demands ongoing attention and exploration. Scholars engaged in this research must grapple with the challenge of finding the delicate balance that ensures the algorithm's adaptability across diverse scenarios.
- Dynamic environmental changes (adapting in real time): In the face of dynamic environmental changes, such as sudden obstacles or alterations in mission requirements, scholars encounter the

challenge of developing adaptive algorithms. Ensuring that the genetic algorithm-based approaches can respond to real-time changes in the environment is a critical area for ongoing research and innovation.

- Optimal fitness function design (balancing objectives): Crafting a fitness function that comprehensively captures the multifaceted objectives of multi-UAV route planning is a persistent challenge. Scholars must navigate the complexities of balancing conflicting objectives and constraints to develop fitness functions that offer a holistic optimization perspective.
- Human-in-the-loop optimization (avenues for collaboration):The integration of human operators into the optimization loop introduces challenges and opportunities. Leveraging human intuition and expertise requires innovative approaches to incorporate human preferences and constraints into the route planning process. This challenge opens avenues for collaborative research at the intersection of artificial intelligence and human-machine collaboration.

As we look towards the future, potential avenues for further research include the integration of machine learning techniques and real-world implementations to validate and extend the applicability of these findings. Exploring collaborations between artificial intelligence and human-machine interactions could open new dimensions for enhancing multi-UAV technologies.

Conclusion

This work has explored and demonstrated the significant potential of genetic algorithm-based approaches for enhancing multi-UAV route planning in the context of cooperative area surveillance. Through the development and analysis of innovative methodologies, we have made substantial progress in addressing the intricate challenges associated with orchestrating multiple UAVs to achieve efficient and effective surveillance over wide regions. The presented research has illuminated the advantages of leveraging genetic algorithms in optimizing multi-UAV routes in real-time scenarios. By dynamically adjusting routes based on genetic encoding of turning angles and coverage-driven fitness functions, our approaches have showcased notable improvements in coverage percentages and operational efficiency. The integration of adaptive strategies, such as the "hyperopia" and "multi-step" optimization methods, further highlights the versatility of genetic algorithms in addressing diverse objectives and constraints. The empirical validations conducted through comprehensive simulations reaffirm the robustness and efficacy of the proposed approaches. Improved coverage, enhanced efficiency, and adaptability to real-time changes have been consistently demonstrated, validating the efficacy of genetic algorithms in multi-UAV path planning.

As we reflect on the journey undertaken in this research, it is evident that genetic algorithm-based methods hold promise as transformative tools for multi-UAV cooperative area surveillance. The innovative strategies put forth in this manuscript underscore the capacity of genetic algorithms to optimize complex interactions and solve real-world challenges. We believe that the insights gained through this research will contribute to the ongoing advancement of UAV technology and pave the way for more efficient and intelligent cooperative surveillance missions. Future research avenues might explore the integration of machine learning techniques and real-world implementation to further validate and extend the applicability of these findings.

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