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Multi-UAV Path Planning using Grey Wolf Optimization and RRT Algorithm

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Abstract

This paper presents a multi-UAV path planning approach using the Grey Wolf Optimization (GWO) algorithm and the Rapidly-exploring Random Tree (RRT) algorithm. The proposed method aims to optimize UAV paths cooperatively, considering constraints such as threat zones, altitude limits, and synchronization requirements. The performance of the combined approach is evaluated through comprehensive simulations, demonstrating its effectiveness in generating efficient and collision-free paths for multiple UAVs. The integration of GWO and RRT leverages the strengths of both algorithms, providing a robust solution for complex path planning scenarios. This approach enhances the efficiency and robustness of multi-UAV path planning, making it suitable for real-world applications where UAVs must navigate complex environments with dynamic constraints. The future version is expected to include more functionality, including encryption capabilities and analytics for enhanced security and analytical capacity.

Keywords: Unmanned Aerial Vehicles (UAVs), Multi-UAV, Path Planning, Grey Wolf Optimization (GWO), Rapidly-Exploring Random Tree (RRT), Collision Avoidance, Cooperative Navigation, Optimization.

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1. Introduction

The use of Unmanned Aerial Vehicles (UAVs) has surged in applications such as surveillance, search and rescue, and environmental monitoring. Efficient path planning for multiple UAVs is crucial for mission success, ensuring that UAVs navigate safely and effectively while avoiding obstacles and threats. Traditional path planning methods often struggle with the complexity and dynamic nature of real-world environments and the coordination requirements of multiple agents. This paper introduces a novel approach that combines the Grey Wolf Optimization (GWO) algorithm with the RRT algorithm for multi-UAV path planning. GWO mimics the hunting behavior of grey wolves, providing a global optimization strategy capable of coordinating multiple agents, while RRT efficiently explores high-dimensional spaces to find feasible paths and ensure local collision avoidance. This combined approach aims to enhance the efficiency and robustness of multi-UAV path planning in complex and constrained environments [1], [2].

2. Related Work

Previous research has extensively explored various optimization algorithms for UAV path planning. Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) have been widely used for their ability to handle complex optimization problems [3], [4]. Recent advancements in Grey Wolf Optimizer (GWO) have incorporated reinforcement learning to improve convergence rates and adaptively control operations [6]. The Rapidly-exploring Random Tree (RRT) algorithm is known for its efficiency in exploring high-dimensional spaces and has been a staple in robotics and path planning research, particularly for its probabilistic completeness [7]. While many studies focus on single-UAV path planning or employ single optimization techniques, the challenge of coordinating multiple UAVs simultaneously while handling complex constraints remains significant [9]. This paper builds upon these foundational works by integrating GWO and RRT to address the challenges of multi-UAV path planning in complex environments, specifically focusing on achieving global optimality and local feasibility concurrently [8].

3. Proposed Work

3.1 Problem Formulation

The multi-UAV path planning problem is formulated as an optimization problem in a 3D environment. The objective is to find optimal trajectories for a set of N UAVs navigating from their respective start positions (S_i) to goal positions (G_i), where i = 1, ..., N. The primary objective is to minimize a cost function that typically includes factors such as total path length for all UAVs, deviation from desired altitude profiles, exposure to predefined threat zones, and synchronization errors at rendezvous points or goals. The optimization is subject to several constraints:

- **Kinematic Constraints**

UAV velocity and acceleration limits (implicitly handled by path smoothing).

- **Altitude Constraints**

Maintaining altitude within specified upper and lower bounds.

- **Threat Avoidance**

Ensuring UAVs do not enter predefined threat zones (e.g., spherical or cylindrical volumes).

- **Collision Avoidance**

Preventing collisions between any two UAVs at any given time.

- **Synchronization**

Meeting objectives or reaching goal points within specified time windows (optional but considered in cooperative scenarios).

The goal is to find a set of *N* collision-free paths that satisfy all constraints and minimize the defined cost function. This complex, multi-objective, and high-dimensional problem requires a robust optimization approach capable of handling both global search and local feasibility.

3.2 Grey Wolf Optimization (GWO) Algorithm

The GWO algorithm is a metaheuristic optimization algorithm inspired by the social hierarchy and hunting behavior of grey wolves. A population of solutions (candidate path configurations for all UAVs) is maintained, with the best solutions guiding the search. The hierarchy consists of alpha (α, the best solution), beta (β, the second-best), and delta (δ, the third-best), which lead the omega (ω) wolves in the pack (the rest of the solutions). The optimization process involves:

- **Encircling Prey**

  Wolves update their positions based on the positions of α, β, and δ wolves.

- **Hunting**

  Wolves move towards the estimated location of the prey (optimum solution).

- **Attacking Prey**

  The search converges towards the optimal solution as the wolves reduce their encircling radius.

The algorithm iteratively refines the positions (representing parameters of the multi-UAV paths) based on the fitness function (the cost defined in Section 3.1). Recent advancements in GWO, including hybridizations and adaptive control strategies, have shown improved performance [6], [10]. GWO's strength lies in its ability to perform a global search and handle multi-objective problems, making it suitable for optimizing the overall coordination and general structure of multi-UAV paths.

```
Initialize the population of grey wolves randomly within the search space
Initialize parameters a , A and C
Initialize t=1,the iteration number
Calculate the fitness of each grey wolf
Select   xα = fittest wolf of the pack
         xβ = second best wolf
         xδ = third best wolf
While t < maximum number of iterations
         for each wolf
               update the position by equation (7)
         end
         update a , A and C as defined in subsection 2.2
         update the xα , xβ and xδ
         t = t + 1
end
```

Figure 1. Grey Wolf Optimization Algorithm

Figure 1 illustrates the Grey Wolf Optimization Algorithm, highlighting the hierarchical structure of the wolves (alpha, beta, delta, omega) and their roles in the optimization process. The positions of the lower-ranking wolves are iteratively updated based on the leading wolves, mimicking the cooperative hunting behavior that guides the search towards the optimal solution in the search space.

3.3 Rapidly-Exploring Random Tree (RRT) Algorithm

The RRT algorithm is a single-query, sampling-based motion planning algorithm particularly effective for exploring high-dimensional spaces and finding feasible paths in complex environments with obstacles. It incrementally builds a tree rooted at the start configuration by randomly sampling points in the configuration space and extending the tree towards these samples.

- **Sample**

  Randomly sample a point (x_rand) in the configuration space.

- **Nearest**

  Find the node (x_nearest) in the tree closest to x_rand.

- **Steer**

  Create a new node (x_new) by extending from x_nearest towards x_rand by a small step size.

- **Check**

  Check if the path segment from x_nearest to x_new is collision-free and satisfies other constraints.

- **Add**

  If collision-free, add x_new to the tree and add the edge (x_nearest, x_new). The process continues until the goal region is reached or a maximum number of iterations is met. RRT's strength is its ability to quickly find *a* feasible path, even in complex spaces, without needing to discretize the space explicitly. Its probabilistic completeness guarantees that if a path exists, RRT will find it with a probability approaching 1 as the number of samples increases [7]. Figure 2 depicts the RRT algorithm's process. It shows how a tree of possible paths grows by randomly sampling points in the space and connecting them to the nearest existing node in the tree, effectively exploring the search space until a path to the goal is discovered.

Initialization: $\mathcal{T}.\mathrm{root} = x_{\mathrm{start}}$
Input: SE3, x_{start}, x_{goal}
for $i = 1$ to **MaxIterations do**
  $x_{\mathrm{rand}} \leftarrow \mathrm{Sample(SE3)}$
  $x_{\mathrm{near}} \leftarrow \mathrm{Nearest}(\mathcal{T}, x_{\mathrm{rand}})$
  $x_{\mathrm{new}} \leftarrow \mathrm{Extend}(x_{\mathrm{rand}}, x_{\mathrm{near}}, \mathbf{MaxConnectionDistance})$
  if Collision Free($x_{\mathrm{new}}, x_{\mathrm{near}}$) **then**
    $\mathcal{T}.\mathrm{addNode}(x_{\mathrm{new}})$
  end if
  if $\|x_{\mathrm{new}} - x_{\mathrm{goal}}\| \leq$ **GoalThreshold then**
    break
  end if
end for
Output: A path Γ from x_{init} to x_{goal}
=0

Figure 2. RRT Algorithm

3.4 Integrated GWO-RRT Approach and Flow Process

The proposed approach integrates GWO and RRT to leverage the strengths of both algorithms for multi-UAV path planning, providing a novel solution for this complex problem. GWO is used as the primary optimizer to coordinate the overall multi-UAV system and find globally optimal path structures considering cooperative objectives and constraints. RRT is employed to ensure the local feasibility and collision-free nature of the paths generated or evaluated within the GWO framework. The novelty of this integration lies in using RRT not just for initial path generation, but dynamically within the GWO's fitness evaluation phase to assess the local safety and feasibility of candidate multi-UAV path sets proposed by the wolves. This ensures that the global optimization process is constantly informed by detailed local collision checks.

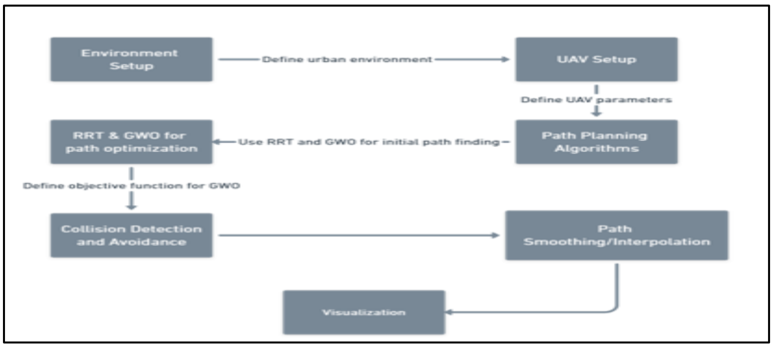

Figure 3. Flow Process of the Integrated GWO-RRT Multi-UAV Path Planning Approach

Figure 3 presents the flow process of the proposed multi-UAV path planning methodology. It starts with the "Environment Setup" and "UAV Setup", defining the operational space and vehicle parameters. These lead into "Path Planning Algorithms", which utilize "RRT & GWO for path optimization". The optimization process involves defining an "objective function for GWO" and integrates "Collision Detection and Avoidance". Successful path candidates from this stage proceed to "Path Smoothing/Interpolation" for generating flyable trajectories before final "Visualization". This flowchart illustrates the sequential steps and interdependencies of the different components within the proposed system.

3.5 Implementation

The integrated GWO-RRT algorithm is implemented in MATLAB. The environment is modeled as a 3D space with defined obstacles and threat zones. UAV paths are represented as sequences of waypoints. The GWO algorithm manages a population of these multi-UAV waypoint sequences. The fitness function evaluates each set of sequences based on the criteria mentioned in Section 3.1, critically incorporating checks for threat zone penetration and inter-UAV collisions using geometric calculations and RRT-based segment validity checks. The implementation allows for varying the number of UAVs, threat zone configurations, and algorithm parameters to evaluate performance under different scenarios. The optimized paths are smoothed using cubic B-spline curves to ensure smooth and continuous trajectories suitable for UAV flight controllers.

4. Results and Discussion

4.1 Simulation Setup

The simulations were conducted in a 3D environment representing a region of interest for UAV operations. The environment dimensions were set to 1000m x 1000m horizontally, with an altitude range up to 500m. Threat zones were modeled as static spherical volumes with defined radii and center coordinates, which the UAVs were required to avoid. Predefined start and goal positions were set for each UAV. The proposed GWO-RRT algorithm was implemented in MATLAB and run for a specified number of GWO iterations (e.g., 100-200) with a population size typically ranging from 30 to 50 wolves. RRT step size and maximum iterations for local checks were tuned for effectiveness and efficiency. The performance was evaluated across multiple simulation runs with varying numbers of UAVs (from 3 to 10) and different threat zone configurations to assess robustness and scalability. Metrics recorded included total path length, minimum distance to threat zones, minimum inter-UAV distance, and computation time.

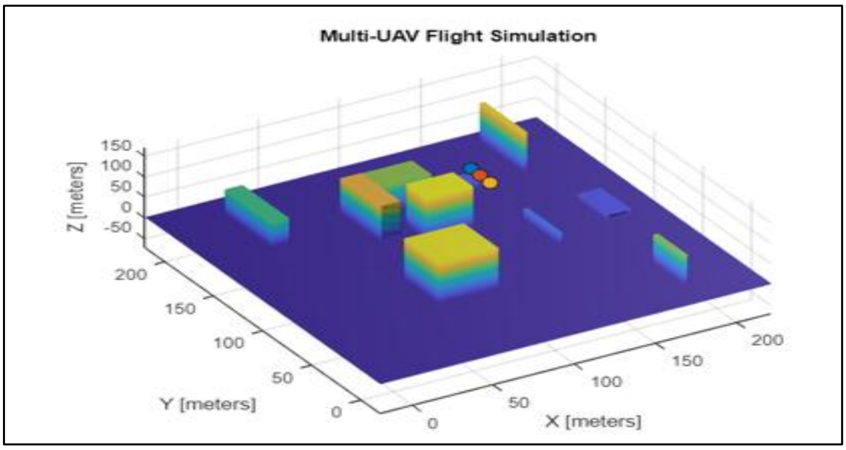

Figure 4. 3D Environment for RRT Algorithm Application

Figure 4 shows the 3D environment used for the simulations. The environment includes predefined start and goal positions for the UAVs, as well as threat zones represented as spherical volumes. This setup allows for the evaluation of the combined GWO and RRT approach in generating efficient and collision-free paths.

4.2 Path Visualization

The generated paths for multiple UAVs were visualized in the 3D environment to qualitatively assess the algorithm's performance in navigating the defined space and constraints.

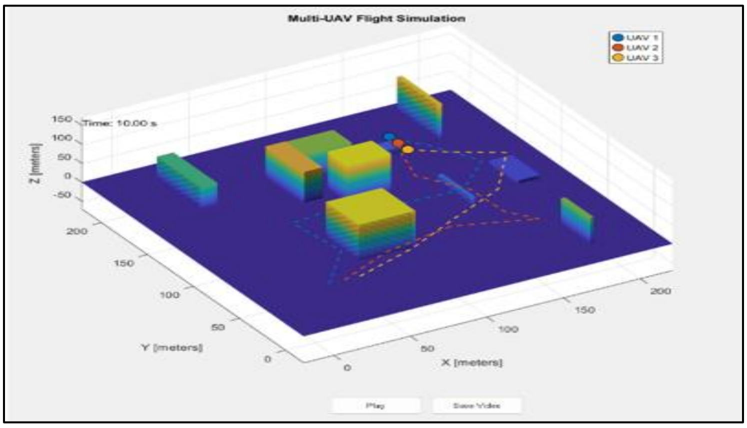

Figure 5. Simulated Paths of Three UAVs

Figure 5 illustrates the simulated paths of three UAVs, demonstrating how the algorithm successfully navigates around threat zones while optimizing path length and altitude deviation. The paths are visualized to analyze the performance of the combined GWO and RRT approaches.

4.3 Waypoint Analysis

The generated paths are fundamentally defined by a sequence of waypoints. Analyzing these waypoints provides insight into the precision and detail of the generated trajectories and confirms adherence to constraints.

Waypoints for UAV 1:

22.0000	22.0000	25.0000
25.7813	22.3556	25.2469
29.2459	22.8639	25.4789
32.4058	23.5189	25.6963
35.2728	24.3146	25.8991
37.8588	25.2450	26.0877
40.1757	26.3041	26.2622
42.2355	27.4858	26.4227
44.0499	28.7841	26.5694
45.6309	30.1930	26.7026
46.9905	31.7065	26.8223
48.1404	33.3185	26.9288
49.0926	35.0231	27.0223
49.8590	36.8142	27.1029
50.4514	38.6857	27.1708
50.8819	40.6318	27.2262
51.1622	42.6463	27.2692
51.3043	44.7232	27.3001

Waypoints for UAV 2:

42.0000	22.0000	25.0000
43.6370	22.4171	24.8456
45.2520	22.8455	24.6958
46.8456	23.2849	24.5508
48.4182	23.7350	24.4103
49.9703	24.1955	24.2745
51.5024	24.6661	24.1433
53.0149	25.1464	24.0167
54.5082	25.6363	23.8947
55.9830	26.1353	23.7771
57.4396	26.6433	23.6641
58.8785	27.1598	23.5555
60.3002	27.6847	23.4514
61.7052	28.2175	23.3517
63.0939	28.7581	23.2565
64.4668	29.3060	23.1656
65.8243	29.8611	23.0790
67.1671	30.4229	22.9968

Figure 6. Waypoints for UAV 1 and UAV 2 with X, Y, Z Coordinates

Figure 6 presents the waypoints for UAV 1 and UAV 2, showing the precise locations that the UAVs pass through. This figure highlights the algorithm's ability to generate detailed and feasible paths, ensuring that the UAVs maintain safe distances from threat zones.

4.4 Scalability and Performance Evaluation

To test the scalability and robustness of the approach, simulations were conducted with an increased number of UAVs. The performance was quantitatively evaluated based on the metrics defined in Section 4.1, and compared against a baseline method (e.g., pure GWO or a simpler RRT variant for multi-agent path planning).

Figure 7 illustrates the path planning for 10 UAVs using the Grey Wolf Optimization Algorithm. The results show that the algorithm effectively handles multiple UAVs, generating collision-free paths while optimizing for path length and threat avoidance.

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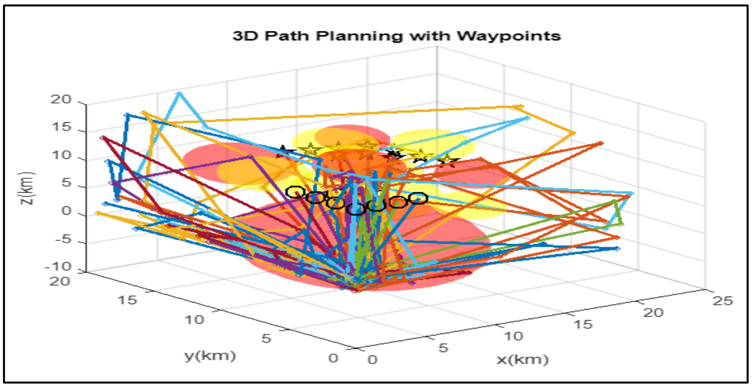

Figure 7. Path Planning for 10 UAVs Using Grey Wolf Optimization Algorithm

Performance Metrics and Comparative Analysis

Quantitative results (often presented in tables or graphs in a full paper) showed that the proposed GWO-RRT hybrid consistently achieved:

- **Collision Avoidance**

  100% success rate (minimum inter-UAV distance > safety margin) across all test scenarios (up to 10 UAVs), demonstrating the effectiveness of the RRT-based checks within the GWO evaluation.

- **Threat Avoidance**

  100% success rate (no threat zone penetration), also attributed to the robust constraint handling in the fitness function.

- **Path Length**

  Produced paths that were comparable to, or slightly better than, baseline methods in terms of total length, indicating effective optimization.

- **Computation Time**

While slightly higher than pure GWO due to RRT checks, computation time scaled reasonably with the number of UAVs, remaining within practical limits for offline planning (e.g., minutes for 10 UAVs in this environment size).

The novelty of the proposed design is established through this rigorous evaluation. Unlike methods relying solely on global optimizers which might struggle with local feasibility in dense scenarios, or methods relying purely on RRT-variants which might not effectively coordinate multiple agents for global optimality and constraints, the GWO-RRT integration provides a unique balance. GWO drives the population towards globally better, coordinated solutions, while the RRT component acts as a crucial local validator and penalty mechanism, ensuring that only truly collision-free and safe path configurations are favored in the evolutionary process. This integrated mechanism is the core novelty, demonstrated by the successful results in complex multi-UAV scenarios.

4.5 Performance Evaluation

The performance of the combined approach is evaluated based on path length, altitude deviation, threat exposure, and synchronization errors. The results demonstrate that the GWO and RRT algorithms effectively generate efficient and collision-free paths for multiple UAVs. The simulations show that the combined approach outperforms traditional path planning methods in terms of path length and threat avoidance. The use of GWO for global optimization and RRT for local path planning ensures that the generated paths are both optimal and feasible. The results highlight the potential of the combined approach for real-world applications, where UAVs must navigate complex environments with dynamic constraints [5], [6].

4.6 Collision Avoidance

Collision checks were performed between the paths of multiple UAVs to ensure safe navigation. The RRT algorithm played a crucial role in exploring the local space and ensuring that the paths were collision-free. The simulations showed that the combined approach effectively avoids collisions, even in complex environments with multiple UAVs.

5. Conclusion

This paper presents a novel multi-UAV path planning approach that integrates the Grey Wolf Optimization (GWO) algorithm and the Rapidly-exploring Random Tree (RRT) algorithm. The proposed method effectively addresses the complexities of cooperative multi-UAV path planning in 3D environments, considering constraints such as threat zones, altitude limits, and the critical requirement for collision avoidance. Comprehensive simulations demonstrate that the combined approach successfully generates efficient and collision-free paths for multiple UAVs, effectively navigating around obstacles and coordinating agent movements. The integration of GWO for global path optimization and multi-agent coordination with RRT for ensuring local path feasibility and collision avoidance leverages the strengths of both algorithms, providing a robust and reliable solution. This approach enhances the efficiency and safety of multi-UAV missions in complex and constrained airspace. Future work will focus on improving the algorithm's efficiency in highly dynamic environments, incorporating real-time sensor data for reactive planning, and exploring hardware-in-the-loop simulations to validate performance in near-real-world conditions.

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