# DWA vs RFA-Star: Choosing the Optimal Navigator

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***Abstract*—The aim of this paper is to provide a detailed comparison of two of the most widely used unmanned aerial vehicle(UAV) path planning algorithms: Dynamic Window Algorithm (DWA) and R5DOS Feature Attention A-star(RFA-Star). Both algorithms have been coded in Python and simulated on 2D grids with randomly scattered and densely clustered obstacle distributions, as well as on 3D terrains with complex features such as mountains. Performance metrics such as path length, computation time, reaction time, and obstacle avoidance have been calculated for the simulations. This study highlights the specific types of environment in which each algorithm performs best, along with the types of sensors typically required for their effective operation. The experiments indicate that DWA is best suited for highly dynamic and low or moderately clustered obstacles because of its reactive nature and adaptability, whereas RFA is more effective in dense structured obstacle environments where global optimality is essential. The results of this research provide a guideline on which path planning algorithm should be selected depending on the operational environment.**

***Index Terms*—UAV, Path Planning, Dynamic Window Approach, RFA-Star, Comparative Analysis**

## I. Introduction

Unmanned Aerial Vehicles (UAVs) have become essential, especially in domains that are hazardous or inaccessible for humans. They are widely used across various industries like:

- **Military and Defense:** conduct surveillance, combat operations and support missions.
- **Disaster Management:** help in assessing damage and providing emergency aid in disaster zones.
- **Search and Rescue:** help to locate missing people, help with excavation, and deliver supplies in tough terrains.
- **Infrastructure Monitoring and construction:** inspect bridges, dams, and power lines for structural issues or create 3D models and monitor construction progress.
- **Forest Restoration:** collect data to support forest recovery efforts.
- **Recreation and Media:** enable aerial photography in racing, media production.
- **Agriculture:** help to monitor crops, spray pesticides and manage irrigation.
- **Transportation and Delivery:** deliver packages, medical supplies and food. [1]

Their effectiveness is pivoted on robust path-planning algorithms. UAV path planning refers to the process of determining an optimal or reasonable path from a given starting point to a specific destination while avoiding obstacles and adhering to some limitations (Eg. maximum permitted altitude) [2]. Effective path planning is crucial for the autonomous, safe and efficient navigation of UAVs in complex dynamic environments.

### A. *Motivation*

Most real-world application use cases of UAVs utilize fundamental path planning algorithms like Dynamic Window Approach (DWA), R5DOS Feature Attention A-star (RFA-Star), Rapidly-exploring Random Tree (RRT) that are customized for the improvement of UAV performance in varied application domains. Additionally, as UAV technology continues to develop, coordinating multiple UAVs (swarms) is becoming essential for large-scale dynamic use. Swarm path planning is an extension of the principles of individual UAV navigation that allows groups of UAVs to work together to pursue common goals while preventing collisions within the swarm and with external obstacles. Swarm path planning methods incorporate centralized control to steer the group as an integrated whole and distributed control to coordinate local interactions between individual UAVs. Virtual forces - attraction brings UAVs closer to their destination and repulsion ensures proper spacing - adjust in real time to maintain efficient and safe navigation [3]. Key to the success of swarm path planning are advanced AI techniques like Reinforcement Learning (enables UAVs to adaptively learn optimal paths through trial and error), Evolutionary Computing (optimizes swarm trajectories by evolving solutions over generations), Swarm Intelligence (enables decentralized coordination drawing inspiration from natural systems), and Graph Neural Networks( represents complex environments and inter-UAV interactions for predictive path planning) [4]. These methods, based on strong individual path planning algorithms such as DWA, RFA-Star and RRT, improve swarm coordination and efficiency. Fundamentally, these swarm systems are based on the accuracy and flexibility of these algorithms, which allow individual UAVs to operate effectively within a collective system. Considering their extensive and successful application, it is essential to investigate these algorithms in detail, know how they operate, their limitations and strengths, and their performance under varying conditions. Thus, this paper provides a detailed study of two of the most prominently used UAV path planning algorithms: DWA and RFA-Star.

This foundational knowledge will enable development of more intelligent, trustworthy UAV systems for intricate real-world operations and lay the foundation for sophisticated swarm path planning, with an impact being felt in future multi-UAV technologies.

## II. Related Work

Majority of the existing UAV path planning algorithms are adapted from the core UAV algorithms to address the real-world challenges. A summary of such works is summarized in table I. Based on different use-case scenarios, the existing works are presented below:

**Disaster Management** : During Hurricane Harvey, camera- and thermal imaging-equipped UAV drones had been instrumental in disaster management by finding stranded persons, evaluating damage, and directing rescue operations. They offered real-time views and high-resolution images to identify inaccessible zones, map and survey flood areas, and evaluate structural damage. UAV information aided emergency planning, resource deployment, and even offered homeowners visual information on their property [5].

**Precision Agriculture**: In California's San Bernabe Vineyards, the RCATS UAV was employed. It took high-resolution RGB and hyperspectral images,allowed detailed crop health monitoring, canopy vigor, soil exposure. Combined with GIS and ground sensor data, it detected low-vigor zones, diagnosed problems like inadequate irrigation or nutrient deficiency, assisted precision agriculture by optimizing water and resource consumption.It was found to be a cheap, timely, accurate solution for enhancing vineyard management decision-making [6].

**Construction**: UAVs, equipped with high-resolution cameras and LiDAR sensors, generate accurate 3D models, orthomosaics, point clouds and enhance site planning, design verification, and construction tracking.For instance, in high-rise building monitoring, UAVs captured multi-angle images to generate a 3D model which enabled the comparison of the construction progress against the plan. In bridge construction inspection, UAVs inspected prefabricated components; verifying alignment and connection without having to physically access the place, which enhances safety [7].

**Transportation and Delivery**: In the COVID-19 emergency in Valencia, UAVs (DJI Mavic 2 Enterprise and Matrice 300 RTK) were used over rural, peri-urban, and urban environments to quickly transport medical aid such as PPE, test kits, and mock sample vials. From distribution points to hospitals and clinics, they facilitated quick, two-way transportation, even in remote locations, thereby assisting in overcoming ground logistics hurdles. UAVs took automated routes using safety protocols [8].

**Search and Rescue** : In two scenarios of tests conducted in South Korea, a fixed-wing UAV by the name of Sky Observer was used to find a simulated survivor sending inconsistent radio signals autonomously. Over a 4×4 km and a 1×1 km space, it moved zigzag or circular patterns, scanned signals, and estimated and fine-tuned the location of the survivor based on RSSI and ToA using a genetic algorithm. The UAV automatically updated its flight path without ground control.It performed reliably in severed or low-visibility conditions effectively dodging obstacles, assisting in minimizing search time and directing rescue teams efficiently [9].

**Recreational Activity**: In recreational videography, drones such as the DJI Phantom IV Pro and Skydio R1, with capabilities such as automated landing, target tracking, and obstacle avoidance, autonomously capture outdoor activities by tracking subjects, navigating around obstacles, and maintaining targets in-frame. The Skydio R1, with sophisticated sensors, visual SLAM, and deep-learning-based object detection, performs well in challenging environments such as wooded trails [10].

**Military and Defense** : UAVs such as the Parrot AR.Drone 2.0 [11] and Harpy [12] were employed for autonomous reconnaissance and region defense. The Parrot drone scanned a simulated battlefield, took pictures, identified hostile assets with the help of AI, pinpointed their locations with the help of EKF and Pinhole algorithms, and created a highly detailed map, assisting real-time intel without endangering human lives. The Harpy UAV demonstrated a combat mission—patrolling a specific area, independently detecting enemy radar emissions, and carrying out predictive pursuit and dive attacks to neutralize the threats.

TABLE I: UAV Algorithm Choices and Modifications

| Works by | Scenario | Algorithm | Modification to core Algorithm |
|---|---|---|---|
| Greenwood et.al. [5] | Disaster Management in hurricane Harvey | DWA | Integrate real-time sensor fusion (e.g. thermal imaging, LiDAR) to adapt to evolving disaster conditions and detect survivors |
| L.F.Johnson [6] | Agriculture in California Vineyards | RFA-Star | Utilize features from multi-spectral imagery, such as vegetation patterns for efficient coverage and monitoring |
| W.W. Greenwood [7] | Construction in buildings, bridges | RFA-Star | Incorporate predefined inspection waypoints |
| D. Oh and J. Han [9] | Search and Rescue (SAR) (hostile environment) | DWA | Utilize probability maps to prioritize search areas and integrate real-time image recognition for survivor detection |
| D.Oh and J. Han [9] | SAR (non-hostile environment) | RFA-Star | Integrate multi-sensor data (e.g. thermal, RGB, sonar) for efficient target detection and optimal systematic coverage |
| M.A. Ma'Sum [11] [12] | Military surveillance and combat | DWA | Incorporate real-time threat detection and avoidance, adjusting paths to minimize exposure or engage targets as needed |
| I.Quintanilla Garc´ıa [8] | Transportation and delivery | DWA | Integrate traffic prediction models to anticipate and avoid congested areas or moving obstacles, ensuring timely delivery |
| I. Mademlis [10] | Recreation (outdoor filming) | DWA | Integrate subject tracking algorithms to maintain focus on moving targets while ensuring smooth, collision-free paths |

## III. Overview of DWA and RFA-Star

### A. *Dynamic Window Approach (DWA)*

DWA is a velocity-based local path planning technique that performs well in dynamic environments [13].
DWA evaluates viable velocity pairs $(v, \omega)$, samples short-term paths, and picks the best with a weighted cost function:

$$\begin{aligned}\text{Total Cost} = {} & \text{goal\_weight} * \text{goal\_cost} + \\ & \text{obstacle\_weight} * \text{obstacle\_cost} + \\ & \text{speed\_weight} * \text{speed\_cost} \qquad (1)\end{aligned}$$

where:

- goal_cost measures the alignment towards the goal,
- obstacle_cost assesses proximity to obstacles,
- speed_cost encourages higher speeds for efficiency.

The algorithm works as below:

1: *Initialize*: Define start/goal positions, initial velocity, and parameters (e.g., max/min speeds, yaw rates, cost weights).
2: *Sense*: Identify obstacles in sensing radius (e.g. 4 units) and update local map.
3: *Calculate Window*: Determine feasible $(v, \omega)$ pairs within dynamic constraints, safe stopping.
4: *Simulate*: Estimate trajectories for every pair of velocities for a brief horizon (e.g. 3 s) via motion equations.
5: *Evaluate*: Compute cost of every one of the trajectories according to Equation (1).
6: *Select*: UAV employs the cheapest trajectory to travel to its next state.
7: *Check*: Halt if UAV has reached within goal threshold (e.g. 0.5 units); otherwise, loop from sensing.

#### *Core Characteristics*

DWA is preferred in such scenarios because of the following capabilities:

**Reactive Local Planning**: DWA works at high frequency, making use of real-time sensor inputs to respond immediately to dynamic obstacles such as moving cars, people, or hostile agents.

**Velocity Space Optimization**: It analyzes feasible translational and rotational velocities within dynamic constraints for safe, goal-oriented, and efficient motion—well-suited for cluttered or constrained environments.

**On-the-Fly Mapping (Octo-map Integration)**: DWA dynamically builds and continuously updates a 3D occupancy map from onboard sensor data, allowing navigation in the absence of pre-existing maps—particularly applicable in disaster situations and GPS-denied environments. environments.

**Tunable Multi-Objective Function**: By adjusting the relative weights assigned to goal proximity, obstacle avoidance, and velocity, DWA can be tailored for task-dependent priorities, e.g. prioritizing lateral avoidance in deliveries in urban areas or vertical clearance in inspecting infrastructure.

#### *Sensor Suite*

DWA utilizes a dense sensor suite to sense and respond to its environment:

**LiDAR**: Produces 3D point clouds for obstacle mapping and collision avoidance.

**RGB Cameras**: Offer visual context to feature detection in media or traffic scenarios.

**Radar**: Detects and locates dynamic targets like automobiles and pedestrians in urban or battlefield environments.

**Thermal Cameras**: Detect heat signatures, important for finding survivors or equipment malfunction.

**EMF and UV Sensors**: Enable power line inspection by detecting anomalies and corona discharges.

#### *Operating Environments*

[14]DWA excels in:

**Dynamic Environments**: With rapid and unpredictable changes (e.g. city traffic, construction areas).

**Confined Spaces**: With tight spaces requiring accurate, collision-free navigation (e.g. ruins, indoor spaces).

**Partially Known or Unknown Areas**: Where real-time map construction is required (e.g. caves, underground structures).

**GPS-Denied Locations**: Where onboard sensing and mapping must perform navigation.

DWA guarantees adaptive and secure exploration while balancing goal-seeking, obstacle avoidance, and optimality. Essentially, its strength lies in its rapid adaptability, sensor fusion, and spatial awareness, making it a robust choice for UAV operation in highly dynamic, real-world environments.

### B. *R5DOS Feature Attention A-star(RFA-Star)*

RFA-Star enhances A* with reactive capabilities and feature attention for efficient, real-time navigation in dynamic, complex environments [15].

RFA-Star optimizes A* path finding with the R5DOS model and feature attention for UAVs to navigate through dense obstacle fields. The R5DOS model categorizes spatial relations (E.g. Discrete, Partial Overlap) to mark obstacles as safe, warning, or hazardous. Its feature attention mechanism prefers effective routes through salient features, prioritizing obstacles' edges, corners and important points, adapting the A* cost function as:

$$F(n) = G(n) + H(n) - \lambda * \text{feature}(n) \qquad (2)$$

where:

- G(n) : Cost from start to current node
- H(n): Heuristic estimate to goal
- feature(n): Feature attention value
- $\lambda$: Weight factor for feature attention

The algorithm works as below:

1: *Initialize:* Initialize 2D grid, start/goal positions, UAV detection range, and cost weights.
2: *Apply R5DOS:* Divide space into four quadrants; classify obstacles (e.g., Discrete, Partial Overlap); compute DOS count (obstacles per quadrant). If DOS_count $\geq 4$, flag as cluttered.
3: *Detect Features:* Identify obstacle edges(more than 3 neighbours), corners (1-3 neighbors), and critical points (nearest to UAV/goal).
4: *Execute A*:* Plan path using the cost function in Equation (2), preferring feature-rich paths.
5: *Select Path:* UAV chooses the lowest-cost path, balancing distance and feature efficiency.
6: *Terminate:* Stop when goal is reached or no path exists.

### *Core Characteristics*

RFA-Star succeeds in these areas because of the following core characteristics [15]:

**Global Path Planning:** As an enhanced version of A*, RFA-Star calculates a best full-environment path from origin to destination—good for large-scale tasks like bridge inspection or field surveying.

**Feature Attention Mechanism:** It attends to important obstacle features (e.g., vertices, edges) to limit the search space, speeding up planning without sacrificing path quality in cluttered spaces such as forests or orchards.

**R5DOS Spatial Topology Model:** Employing a 3D topological structure, it intelligently chooses potential nodes and facilitates effective obstruction evasion in complex, static environments.

**Computational Efficiency:** By minimizing node expansion, RFA-Star balances optimality and speed, making it suitable for large-scale maps like forest zones or agricultural fields.

### *Sensor Suite*

RFA-Star is based on high-resolution sensor technologies for effective mapping and world comprehension:

**LiDAR:** Creates high-resolution 3D maps for obstacle detection in infrastructure or agricultural land.

**Multi-spectral Cameras:** Facilitate vegetation analysis and environmental monitoring.

**RGB Cameras:** Offer visual mapping for inspection and navigation.

**Sonar:** Facilitates underwater obstacle detection in certain situations.

**GPS:** Helps with accurate geolocation in open, structured environments.

### *Operating Environments*

RFA-Star is most effective in:

**Static Environments:** With fixed, predictable obstacle layouts (e.g. bridges, crop fields).

**High Obstacle Density Areas:** Such as forests or orchards, where the feature-based approach is more efficient.

**Large-Scale Maps:** Requiring comprehensive planning (e.g. ecological restoration).

**Structured Layouts:** Like power line corridors or plantation rows, where predefined path planning is possible.

RFA-Star ensures efficient navigation in dense environments by reducing search space via spatial analysis and feature focus. Overall, RFA-Star's global planning ability, spatial understanding, and computational efficiency position it as a prime candidate for UAV missions within stable, ordered environments.

Table II summarizes various UAV application areas, their corresponding environment types, commonly used navigation algorithms in those environment, and the sensors utilized by these algorithms.

TABLE II: UAV Application Areas, Environments, Algorithms, and Sensors Used

| **Application Area** | **Environment** | **Algorithm** | **Sensors Used** |
|---|---|---|---|
| Infrastructure Monitoring | Complex 3D, static (bridges, dams, power lines) | RFA-Star | LiDAR, thermal, RGB, multi-spectral |
| Construction Management | Dynamic, cluttered (construction sites, moving workers) | DWA | LiDAR, RGB, radar |
| Forest Restoration | Static, high-density (forests, tree zones) | RFA-Star | Multi-spectral, RGB, LiDAR |
| Recreation/Media | Dynamic, varied (racing, filming) | DWA | RGB, radar |
| Transportation/Delivery | Dynamic, urban/rural (buildings, vehicles) | DWA | LiDAR,RGB, radar, GPS |
| Disaster Management | Dynamic, unpredictable (debris, floods) | DWA | LiDAR, thermal, RGB, multi-spectral |
| SAR (Hostile) | Dynamic, hazardous (mountains, forests, caves) | DWA | LiDAR, radar, thermal, RGB |
| SAR (Non-Hostile) | Static, structured (fields, meadows) | RFA-Star | LiDAR, RGB, multi-spectral, GPS |
| Medical Services | Dynamic, crowded (urban, hospitals) | DWA | LiDAR, RGB, thermal |
| Agriculture | Static, structured (farms, crop rows) | RFA-Star | Multi-spectral, RGB, LiDAR, hyperspectral |
| Military/Defense | Dynamic, adversarial (battlefields, enemy zones) | DWA | LiDAR, thermal, radar, EMF, UV |

## IV. Comparative Analysis of DWA and RFA-Star

### A. *Simulation Environments*

The two algorithms were evaluated in the following configurations and their perfromance was compared:

*Grid World*

Figures 1a and 1b illustrate a 2D grid world with 49 obstacles densely packed in clusters.

*Random Obstacles*

Figures 1c and 1d illustrate a 2D environment with 25 randomly distributed point obstacles.

*3D Terrain*

Figures 1e and 1f illustrate a 3D terrain simulating real-world mountainous terrain with Perlin noise.

### B. *Evaluation Metrics*

In order to enable a balanced and inclusive comparison, the following parameters for both DWA and RFA-Star on all simulation setups was monitored:

- **Path Metrics**:
  - Path Length: Total distance from start to goal.
  - Path Optimality: degree of deviation from ideal path.
- **Computational Efficiency**:
  - Total Execution Time: Time to complete navigation.
  - Max and Avg. Planning Time per Step
  - Number of Planning Steps: Number of re-planning instances.
- **Responsiveness**:
  - Avg. Reaction Time: Time to respond to obstacles.
  - Obstacles Detected:Fraction of obstacles detected.
- **Goal Achievement**:
  - Final Position Error: Distance of final position from goal.

These metrics evaluate efficiency, safety, computational cost, and goal accuracy.

### C. *Comparative Performance Analysis*

The computed metrics in different settings, clearly shown in table III, reflect the differences in the performance of the two algorithms in diverse environments:

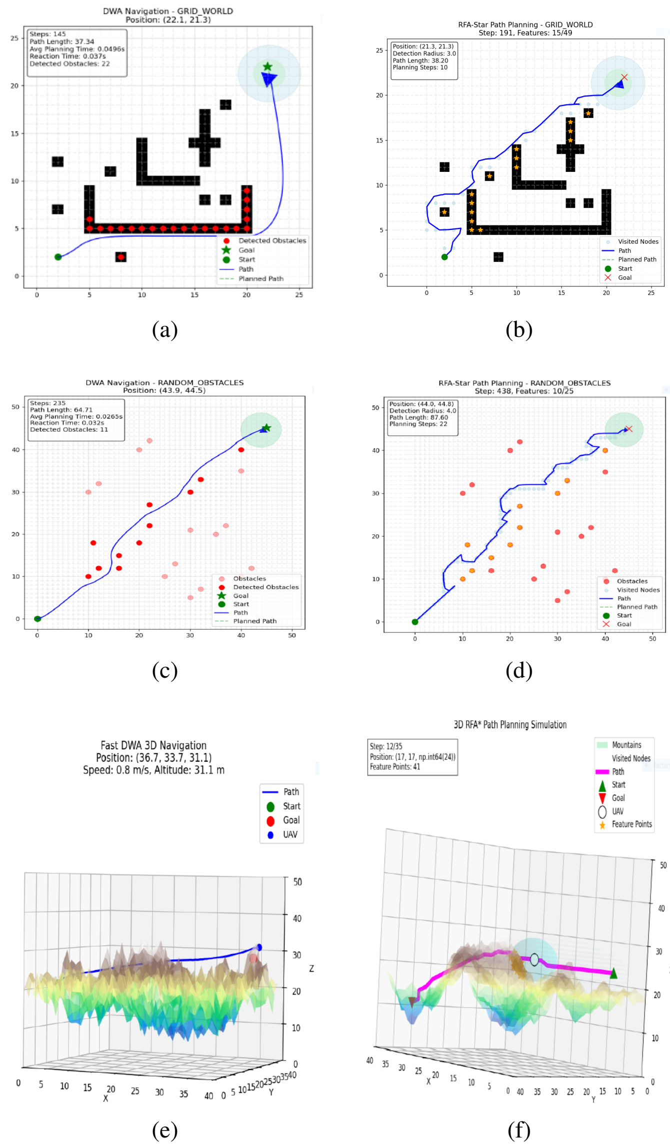


Fig. 1: (a) DWA in grid world environment, (b) RFA-Star in grid world environment, (c) DWA in randomly scattered obstacle environment, (d) RFA-Star in randomly scattered obstacle environment, (e) DWA in complex 3D environment, (f) RFA-Star in complex 3D environment.

## V. Results and Discussion

DWA and RFA-Star exhibit distinct performance profiles, with each being tailored for specific environmental conditions. Their strengths and weaknesses, analyzed through path metrics, as shown in table III, guide their application in UAV navigation.

**DWA** performs better in dynamic, uncertain environments with its real-time velocity-space optimization, allowing smooth trajectories and tight control in narrow spaces. It generates near-optimal paths with lengths only 2% greater than theoretical optima. Continuous re-evaluation of velocity guarantees flexibility to moving obstacles, making it suitable for applications such as disaster response or urban delivery. But DWA's computational overhead and increased latency (0.027s reaction time in grid environments) is a disadvantage. It is also vulnerable to local minima in dense obstacle configurations and parameter tuning, especially cost function weights, can compromise its performance in structured environments.

**RFA-Star** excels in static, feature-rich environments through its use of feature attention to focus on important navigational landmarks like obstacle edges and corners. With low

TABLE III: Comparative Performance of DWA and RFA* Algorithms

| Metric | Grid | | Random | | 3D | |
|---|---|---|---|---|---|---|
| | **DWA** | **RFA*** | **DWA** | **RFA*** | **DWA** | **RFA*** |
| Time (s) | 25.40 | **23.44** | **35.86** | 57.42 | 72.88 | **26.29** |
| Path (units) | **37.34** | 38.20 | **65.13** | 87.60 | **44.70** | 50.83 |
| Optimality | **1.32×** | 1.35× | **1.02×** | 1.38× | **1.04×** | 1.15× |
| Plan Time (s) | 7.11 | **0.06** | 6.45 | **0.28** | 44.35 | **26.29** |
| Plan Steps | 145 | **10** | 240 | **22** | **114** | 3932 |
| Avg Plan/Step (s) | 0.049 | **0.006** | 0.027 | **0.013** | 0.389 | **0.007** |
| React Time (s) | 0.027 | **0.007** | 0.025 | **0.015** | 0.389 | **0.007** |
| Max React (s) | 0.067 | **0.014** | 0.042 | **0.040** | 0.493 | **0.028** |
| Obstacles Detected | **22/49** | 15/49 | **11/25** | 10/25 | 0 | **5316** |
| Position Error | **0.76** | 0.97 | **0.76** | 1.00 | 1.94 | **0.00** |
| **Better performance** | **RFA*** | | **DWA** | | **RFA*** | |

computational overhead, quick response time (0.007 seconds in grid-based environments), and 63.9% quicker completion of tasks in densely clustered obstacle environments, it is efficient in high-density applications like agriculture or infrastructure monitoring. Nevertheless, its performance decreases in random or unstructured situations, in which it produces routes that are, on average, 38% longer than optimum. Its reliance on precise feature detection and abrupt changes in path at feature points constrain its versatility in dynamic or unforeseen conditions.

DWA performs best in dynamic, uncertain environments, beating RFA-Star by 37.5% in random obstacle fields because of its reactive planning. RFA-Star, on the other hand, is 7.7% faster in structured grids because of its feature-driven nature for optimal navigation. It also performs better in dense obstacle fields, where computational load for DWA increases. These complementary strengths suggest that algorithm choice should be environment-dependent, allowing optimal UAV deployment in different scenarios.

## VI. Conclusion

This research highlights the need to choose a suitable path planning algorithm depending on the particular nature of the operational environment. By extensive simulations of the DWA and RFA-Star under different scenarios, the strengths and weaknesses of each approach have been outlined. The findings inform rational decision-making to maximize UAV performance in various real-world applications, ranging from emergency response to precision agriculture. By providing unambiguous guidelines for algorithm choice, this work makes an important contribution towards the successful design and deployment of autonomous UAV systems that can successfully navigate the nuances of real-world missions.

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