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Comparative Analysis of Path Planning Algorithms for Multi-UAV Systems in Dynamic and Cluttered Environments: A Focus on Efficiency, Smoothness, and Collision Avoidance

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ABSTRACT

This study evaluates the performance of various path planning algorithms for multi-UAV systems in dynamic and cluttered environments, focusing on critical metrics such as path length, path smoothness, collision avoidance, and computational efficiency. We examined several algorithms, including A*, Genetic Algorithm, Modified A*, and Particle Swarm Optimization (PSO), using comprehensive simulations that reflect realistic operational conditions. Key evaluation metrics were quantified using standardized methods, ensuring the reproducibility and clarity of the findings. The A* Path Planner demonstrated efficiency by producing the shortest and smoothest paths, albeit with minor collision avoidance limitations. The Genetic Algorithm emerged as the most robust, balancing path length, smoothness, and collision avoidance, with zero violations and high feasibility. Modified A* also performed well but exhibited slightly less smooth paths. In contrast, algorithms like Cuckoo Search and Artificial Immune System faced significant performance challenges, especially in adapting to dynamic environments. Our findings highlight the superior performance of the Genetic Algorithm and Modified A* under these specific conditions. We also discuss the potential for hybrid approaches that combine the strengths of these algorithms for even better performance. This study's insights are critical for practitioners looking to optimize multi-UAV systems in challenging scenarios.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have rapidly transformed various industries by providing innovative solutions for complex tasks [1]-[5]. These tasks range from agricultural monitoring and infrastructure inspection to more complex scenarios such as dynamic search and rescue operations in disaster-stricken urban areas UAVs are increasingly deployed in environments with challenging terrains, unpredictable weather, and dense obstacle fields [6]-[10]. In the logistics sector, UAVs offer a unique advantage, particularly in urban and rural areas with challenging terrains and limited infrastructure [11], [12]. These aerial vehicles can bypass ground-based obstacles, reduce delivery times, and provide access to remote locations [13], [14]. However, the integration of UAVs into logistical networks presents several challenges, foremost among them being the need for effective path planning to ensure safe and efficient navigation [15]-[18]. Path planning for UAVs involves determining the optimal route from a starting point to a destination while avoiding obstacles and minimizing travel time or distance [19]. Traditional deterministic algorithms, such as the A* algorithm, have been widely used in this domain. A* is renowned for its ability to find the shortest path in grid-based maps by systematically exploring nodes, which makes it effective in static environments with known obstacles [20], [21]. However, in dynamic or partially unknown environments, the rigidity of A* and similar algorithms can become a limitation [22]. These algorithms often struggle to adapt to real-time changes, such as moving obstacles or varying weather conditions, which can be critical in UAV operations [23].

The limitations of deterministic algorithms have led to the exploration of bio-inspired algorithms, which are based on natural phenomena and processes [24]. These algorithms, for instance, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA), offer adaptive and flexible solutions that can better handle the complexities of dynamic environments [25]. PSO, inspired by the social behavior of birds flocking or fish schooling, models each UAV as a particle in the swarm [26]-[28]. The particles move through the solution space, adjusting their trajectories based on individual and collective experiences. This approach allows for continuous adaptation and optimization of the path in response to changes in the environment. Similarly, GA, which emulates the process of natural selection, iteratively evolves a population of solutions through selection, crossover, and mutation, making it capable of exploring a vast and complex search space for optimal paths [29]-[31]. SA, inspired by the annealing process in metallurgy, employs a probabilistic mechanism to escape local optima and approximate global solutions, which is particularly useful in highly complex and multi-modal search spaces [32], [33].

As the deployment of UAVs becomes more widespread, the urgency of developing advanced path planning algorithms grows [34], [35]. UAVs are increasingly being used for critical applications, such as delivering medical supplies to disaster-stricken areas and providing last-mile delivery services in urban logistics [36]. In these scenarios, the ability to navigate efficiently and safely is paramount. The path planning algorithm must account for various factors, including energy consumption, payload capacity, regulatory restrictions, and the potential for dynamic obstacles [37]. These considerations necessitate the use of sophisticated algorithms capable of real-time decision-making and adaptation. The current state of research in UAV path planning has seen significant advancements, yet several challenges remain [38]. While deterministic algorithms provide a foundation for path planning, their application is limited to static and predictable environments. Bio-inspired algorithms, with their adaptive capabilities, offer a promising alternative, but they also come with their challenges, such as tuning parameters and ensuring convergence to optimal solutions [39]. Furthermore, the performance of these algorithms can vary significantly based on the specific characteristics of the environment and the UAV mission. For example, PSO may perform well in relatively simple environments but struggle in highly cluttered spaces, while GA may require extensive computational resources to explore large solution spaces effectively [40].

Despite these advancements, there remains a gap in the comprehensive evaluation of different path planning algorithms under a variety of conditions. Most existing studies have focused on specific algorithms or limited scenarios, providing a fragmented view of the field [20]. There is a lack of comparative studies that systematically assess the performance of multiple algorithms across diverse metrics, such as path length, smoothness, collision avoidance, and computational efficiency [41]. Additionally, many studies have not fully addressed the challenges posed by dynamic environments, where real-time adaptation and decision-making are crucial. This research addresses these gaps by systematically evaluating a broad spectrum of path planning algorithms for multi-UAV systems. The study considers a range of algorithms, from classical deterministic methods to advanced bio-inspired approaches, under various environmental conditions and constraints. By conducting a comprehensive analysis, this research aims to provide a detailed understanding of each algorithm's strengths and limitations, offering valuable insights for their practical application in real-world scenarios. The remaining structure of this journal article is organized as follows: Section 2 presents a detailed literature survey, discussing the historical development of path planning algorithms, their theoretical foundations, and their applications in UAV navigation. This section also explores the challenges and limitations encountered in previous research. Section 3 outlines the problem formulation, the specific algorithms implemented, and the evaluation metrics used to assess their performance. Section 4 details the research methodology, describing the simulated environments and the criteria for testing the algorithms. Section 5 presents the experimental results, providing a comparative analysis of the algorithms' performance across various metrics. Finally, Section 6 concludes the paper, summarizing the key contributions and emphasizing the significance of the research in advancing UAV path planning technologies.

2. Literature Survey

The evolution of path planning algorithms for Unmanned Aerial Vehicles (UAVs) has been marked by significant advancements, reflecting the growing complexity and diversity of UAV applications. The historical development of these algorithms can be traced back to classical deterministic methods, which provided the foundation for early UAV navigation systems. One of the earliest and most widely used deterministic algorithms is the A* algorithm, introduced by Hart, Nilsson, and Raphael in 1968 [42]. A* employs a best-first search approach that efficiently finds the shortest path by combining the benefits of uniform-cost search and pure heuristic search [43]. The algorithm uses a cost function that includes the cost from the start node to the current node and an estimated cost from the current node to the goal. This function ensures that A* is both complete and optimal, provided the heuristic is admissible. A* and its variants, such as Dijkstra's algorithm and D*, have been extensively applied in static and structured environments, such as indoor navigation and predefined routes [44], [45]. The theoretical foundation of these classical algorithms is grounded in graph theory and discrete mathematics, focusing on the representation of the environment as a graph where nodes represent possible positions, and edges represent possible movements [46]. The primary strength of deterministic algorithms lies in their precision and guarantee of finding the optimal path if it exists. However, these algorithms have inherent limitations, particularly in handling dynamic or uncertain environments [47]. The computational complexity increases exponentially with the state space, making real-time application challenging. Moreover, they require a complete and accurate map of the environment, which is often unavailable or constantly changing in real-world UAV operations [48].

The limitations of deterministic algorithms in dynamic and uncertain environments have led to the exploration of bio-inspired algorithms, which draw inspiration from natural phenomena and biological processes [49]. These algorithms offer a more flexible and adaptive approach to path planning, capable of coping with incomplete or dynamic information. Particle Swarm Optimization (PSO), developed by Kennedy and Eberhart in 1995, is one of the pioneering bio-inspired algorithms applied to UAV navigation [50]. PSO simulates the social behavior of bird flocking or fish schooling, where each UAV, considered a particle, adjusts its trajectory based on its own experience and the experiences of neighboring particles [51]. The algorithm optimizes the path by iteratively updating the position of each particle towards the best-known positions, balancing exploration and exploitation. Another significant bio-inspired algorithm is the Genetic Algorithm (GA), which is based on the principles of natural selection and genetic evolution [52]. Introduced by Holland in the 1970s, GA utilizes a population of potential solutions, evolving them over successive generations through selection, crossover, and mutation operations. In UAV path planning, GA has been used to optimize complex, multi-objective problems, such as minimizing travel distance while avoiding obstacles. The algorithm's ability to explore a vast solution space and adapt to changing conditions makes it suitable for dynamic environments [53]. However, GAs can suffer from slow convergence and require careful tuning of parameters, such as population size and mutation rate, to avoid premature convergence or excessive computational cost.

Simulated Annealing (SA), inspired by the annealing process in metallurgy, is another bio-inspired algorithm that has found application in UAV path planning. SA, introduced by Kirkpatrick, Gelatt, and Vecchi in 1983, uses a probabilistic technique to escape local optima and approximate global solutions [54], [55]. The algorithm simulates the cooling process of a material, where the temperature gradually decreases, reducing the probability of accepting worse solutions. This mechanism allows SA to explore a broader search space initially and focus on refining solutions as the temperature decreases. In the context of UAV navigation, SA has been employed to optimize flight paths in environments with multiple local minima, where traditional deterministic algorithms may struggle. Despite the advancements in bio-inspired algorithms, challenges and limitations persist. One of the primary challenges is the trade-off between exploration and exploitation. While these algorithms are adept at exploring diverse solutions, ensuring convergence to an optimal or near-optimal solution can be challenging, especially in large and complex search spaces. Additionally, bio-inspired algorithms often require extensive parameter tuning, which can be computationally expensive and time-consuming [56]. The stochastic nature of these algorithms also means that the quality of the solution can vary between runs, necessitating multiple runs to obtain reliable results.

The application of these algorithms in UAV navigation has been demonstrated in various scenarios, ranging from urban environments to disaster response. For instance, PSO has been used to optimize the deployment of UAVs in search and rescue missions, where the UAVs must efficiently cover a search area while avoiding collisions [57]. GA has been applied in multi-UAV systems for coordinated path planning, ensuring that multiple UAVs can complete their missions without interference [58]. SA has been employed in optimizing routes for UAVs delivering medical supplies in areas with uncertain and dynamic obstacles, such as in post-disaster scenarios [59]. The evolution of path planning algorithms reflects the growing complexity of UAV applications and the need for adaptive, robust solutions [60]. While deterministic algorithms provide a solid foundation for path planning in structured and predictable environments, bio-inspired algorithms offer the flexibility and adaptability required for dynamic and uncertain scenarios [61]. However, the challenges associated with these algorithms, such as parameter tuning, convergence issues, and computational cost, highlight the need for further research and innovation. This literature survey underscores the need for a comprehensive evaluation of path planning algorithms in diverse environments, guiding the research towards the development of more reliable and efficient solutions for UAV navigation. By addressing the limitations and challenges identified in previous research, this study aims to contribute to the field by providing a systematic comparison of various algorithms, exploring their applicability in real-world scenarios, and proposing novel approaches to enhance their performance. The findings from this research will inform the selection and implementation of path planning strategies, ensuring safe and efficient UAV operations in a wide range of applications.

3. Problem Formulation

The formulation of the path planning problem for multiple UAVs involves defining the environment, constraints, and optimization objectives based on the experimental code. The objective is to determine the optimal paths for multiple UAVs from their respective sources to their targets while avoiding obstacles and minimizing travel distance. The environment includes UAVs and their initial and target positions. $Let S_i = (x_{i,0}, y_{i,0}, z_{i,0})$ and $T_i = (x_{i,t}, y_{i,t}, z_{i,t})$ represent the initial and target positions of the *i-th* UAV, respectively, where $i \in 1,2, \dots, N$ and N is the number of UAVs. Obstacles in the environment are represented by $O_k = (x_{k,o}, y_{k,o}, z_{k,o}, r_k)$, where $k \in 1,2, \dots, M$ and M is the number of obstacles. Each UAV path is defined by a series of control points $P_{i,j} = (x_{i,j}, y_{i,j}, z_{i,j})$, where $j \in 1,2, \dots, n$ and n is the number of control points for each path. The path for the *i-th* UAV is represented as a spline curve passing through the control points, including the initial and target positions $P_i(t) = (X_i(t), Y_i(t), Z_i(t))$, where $t \in [0,1]$ is a parameter representing the position along

Vol. 4, No. 4, 2024, pp. 1602-1616

the path, and the spline functions $X_i(t), Y_i(t)$, and $Z_i(t)$ are defined by the control points. The objective is to minimize the total path length for each UAV while avoiding collisions with obstacles. The total path length L_i for the *i-th* UAV is given by equation (1).

$$L_i = \int_0^1 \sqrt{\left(\frac{dX_i(t)}{dt}\right)^2 + \left(\frac{dY_i(t)}{dt}\right)^2 + \left(\frac{dZ_i(t)}{dt}\right)^2}\, dt \tag{1}$$

To ensure collision avoidance, we define a penalty function V_i that measures the degree of violation of the collision constraints. For each obstacle k, the distance $d_{i,k}(t)$ between the *i-th* UAV and the *k-th* obstacle at time t is given by equation (2).

$$d_{i,k}(t) = \sqrt{\left(X_i(t) - x_{k,o}\right)^2 + \left(Y_i(t) - y_{k,o}\right)^2 + \left(Z_i(t) - z_{k,o}\right)^2} \tag{2}$$

The violation function for the *i-th* UAV with respect to the *k-th* obstacle is presented in equation (3).

$$\mathrm{v_{i,k}(t)} = \max\left(1 - \frac{\mathrm{d_{i,k}(t)}}{\mathrm{r_k}}, 0\right) \tag{3}$$

The total violation V_i for the *i-th* UAV is presented in the equation (4).

$$V_i = \int_0^1 \sum_{k=1}^{M} v_{i,k}(t)\, dt \tag{4}$$

The overall cost function to be minimized for the *i-th* UAV is a weighted sum of the path length and the collision violation penalty $J_i = L_i + \lambda V_i$, where λ is a weighting factor that balances the importance of path length and collision avoidance. The optimization problem for the *i-th* UAV is formulated as equation (5).

$$\min_{P_{i,j}} J_i = \min_{P_{i,j}} \left(\int_0^1 \sqrt{\left(\frac{dX_i(t)}{dt}\right)^2 + \left(\frac{dY_i(t)}{dt}\right)^2 + \left(\frac{dZ_i(t)}{dt}\right)^2}\, dt + \lambda \int_0^1 \sum_{k=1}^{M} \max\left(1 - \frac{d_{i,k}(t)}{r_k}, 0\right) dt \right) \tag{5}$$

The control points must satisfy the boundary conditions, $P_{i,0} = S_i and P_{i,n+1} = T_i$. To solve the optimization problem, various algorithms such as PSO, GA, SA, ACO, ABC, FA, BA, CS, DE, GWO, HS, WOA, TS, BBO, and others are used. Each algorithm employs different strategies to explore and exploit the solution space, updating the control points to minimize the overall cost function. For instance, in the Particle Swarm Optimization (PSO) algorithm, the position of each UAV (particle) is updated based on its own experience and the experiences of neighboring UAVs equation (6).

$$P_{i,j}^{t+1} = P_{i,j}^{t} + v_{i,j}^{t+1} \tag{6}$$

Where $\boldsymbol{v_{i,j}^{t+1}}$ is the updated velocity of the particle, considering the particle's best-known position and the swarm's global best-known position. In the Genetic Algorithm (GA), a population of potential solutions evolved through selection, crossover, and mutation to find the optimal paths. The selection process favors solutions with lower costs, while crossover and mutation introduce diversity and enable exploration of the solution space. Each algorithm has its unique approach to navigating the optimization landscape, balancing exploration and exploitation to achieve efficient and collision-free paths for multiple UAVs. By formulating the path planning problem mathematically and employing diverse optimization algorithms, this research aims to provide a comprehensive evaluation of their performance, guiding the development of robust and efficient path planning strategies for UAVs in dynamic environments.

4. Research Methodology

4.1. Problem Definition and Environment Setup

The problem involves finding optimal paths for multiple UAVs in a three-dimensional space with obstacles. Each UAV must travel from a specified source to a target while avoiding obstacles and minimizing travel distance. The environment includes the UAVs' initial and target positions and spherical obstacles characterized by their centers and radii. Let $(S_i = (x_{i,0}, y_{i,0}, z_{i,0}))$ and $(T_i = (x_{i,t}, y_{i,t}, z_{i,t}))$ represent the initial and target positions of the $(i) - th$ UAV, respectively, where $(i \in \{1, 2, \dots, N\})$ and (N) is the number of UAVs. Obstacles are represented by $(O_k = (x_{k,o}, y_{k,o}, z_{k,o}, r_k))$, where $(k \in \{1, 2, \dots, M\})$ and (M) is the number of obstacles. The path for the $(i) - th$ UAV is represented as a spline curve passing through control points, including the initial and target positions $P_i(t) = (X_i(t), Y_i(t), Z_i(t))$ where $(t \in [0,1])$ is a parameter representing the position along the path. In addition, the environment includes urban and rural scenarios with varying levels of complexity, such as narrow urban alleyways with dynamic obstacles (e.g., moving vehicles) and open rural landscapes with unpredictable weather changes. The UAVs' initial and target positions are randomly generated within these environments, with obstacles modeled as either static (e.g., buildings, trees) or dynamic (e.g., moving vehicles, weather changes).

4.2. Data Representation and Initialization

The initial paths for UAVs are generated using random control points within the defined environment's boundaries. The control points, including the UAVs' start and end positions, ensure the paths connect the specified points. Obstacles' positions and radii are also initialized. The path for the $(i) - th$ UAV is defined by the control points $P_{i,0} = S_i$ extend $P_{i,n+1} = T_i$ where (n) is the number of control points. On the other hand, for the cost Function and collision avoidance, the objective is to minimize the total path length for each UAV while avoiding collisions with obstacles. In terms of cost function, the total path length (L_i) for the $(i) - th$ UAV is given by equation (7).

$$[L_i = \int_0^1 \sqrt{(racdX_i(t)dtight)^2 + (racdY_i(t)dtight)^2 + (racdZ_i(t)dtight)^2}\ dt] \tag{7}$$

To ensure collision avoidance, a penalty function (V_i) measures the degree of violation of the collision constraints. The distance $(d_{i,k}(t))$ between the $(i) - th$ UAV and the $(k) - th$ obstacle at time (t) is given by equation (8).

$$d_{i,k}(t) = \sqrt{\left(X_i(t) - x_{k,o}\right)^2 + \left(Y_i(t) - y_{k,o}\right)^2 + \left(Z_i(t) - z_{k,o}\right)^2} \tag{8}$$

The violation function for the $(i) - th$ UAV with respect to the $(k) - th$ obstacle is $v_{i,k}(t) = \max(1 - racd_{i,k}(t)r_k, 0)$. The total violation (V_i) for the $(i) - th$ UAV is presented in the equation (9). The positions of UAVs are represented as vectors in 3D space, with their start and end points defined within the environment. Each UAV's movement is constrained by its maximum speed and turning radius, reflecting real-world UAV capabilities. In addition, static obstacles are represented as fixed spheres in the environment, while dynamic obstacles have predetermined movement paths or randomized patterns reflecting real-world scenarios like moving vehicles or fluctuating weather conditions.

4.3. Optimization Problem

The overall cost function to be minimized for the $(i) - th$ UAV is a weighted sum of the path length and the collision violation penalty $J_i = L_i + \lambda V_i$ where (λ) is a weighting factor that balances the importance of path length and collision avoidance. After that, the algorithm implementation will be conducted, the study employs various optimization algorithms to solve the path planning problem, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing (SA), A*, Modified A*, Ant Colony (ACO), Bee Colony (ABC), Firefly Algorithm (FA), Bat Algorithm (BA), Cuckoo Search (CS), Differential Evolution (DE), Grey Wolf Optimization (GWO), Harmony Search (HS), Whale Optimization (WOA), and Artificial Immune System. Each algorithm follows specific strategies to explore and exploit the solution space, updating control points to minimize the overall cost function. Furthermore, simulations are run to optimize UAV paths by iterating through each algorithm's process, adjusting control points to minimize the cost function. During each iteration, the algorithms evaluate the fitness of the paths based on the cost function, which includes path length and collision penalties. The optimization process continues until a stopping criterion is met, such as a maximum number of iterations or convergence threshold. The algorithms iteratively refine UAV paths, aiming to reduce travel distance and ensure safe navigation around obstacles.

$$V_i = \int_0^1 \sum_{k=1}^{M} v_{i,k}(t)\ dt \tag{9}$$

4.4. Evaluation Metrics and Implementation

Simulations were conducted in a high-fidelity environment using Python and relevant libraries like NumPy for numerical computations and Matplotlib for visualizations. The environment was simulated multiple times to account for variability in dynamic obstacles, ensuring the robustness of the algorithms. The performance of each algorithm is evaluated using metrics such as total path length, smoothness (measured by changes in direction along the path), number of collisions, and computational efficiency (time taken to converge). The algorithms' outputs are analyzed to determine the most effective methods for UAV path planning in complex environments. Visualizations of optimized paths show UAV trajectories and their proximity to obstacles, helping assess the feasibility and safety of proposed paths. Statistical analyses compare the algorithms' performance, providing insights into their strengths and weaknesses.

5. Results and Analysis

5.1. Results Explanation

This section provides a comprehensive analysis of the multi-UAV path planning performance across different algorithms. The evaluation metrics include path length, path smoothness, collision violations, and feasibility. The results are summarized in four tables representing the performance of each algorithm. The path lengths for UAVs 1, 2, and 3 are presented in Table 1. The A* Path Planner consistently delivered the shortest path lengths, indicating its efficiency in finding direct routes. Specifically, A* achieved path lengths of 0.7659, 0.6828, and 0.4626 for UAVs 1, 2, and 3 respectively. The Genetic Algorithm and Modified A* Path Planners also showed competitive results, providing relatively short paths. For instance, the Genetic Algorithm achieved path lengths of 1.2216, 0.8969, and 0.7832, while Modified A* achieved 1.0933, 0.8769, and 0.5207 for the respective UAVs. In contrast, the Cuckoo Search algorithm produced abnormally high path lengths, likely due to numerical issues, with values such as 4216687618.042575, 7.2029e+16, and 2.0685e+16, indicating a significant discrepancy in performance.

Path smoothness, which reflects the continuity and lack of abrupt changes in the generated paths, is summarized in Table 2. The A* Path Planner achieved the lowest path smoothness values, suggesting it generates smoother paths. This is crucial for practical UAV operations to minimize abrupt maneuvers, with A* achieving smoothness values of 8.8327, 12.7154, and 31.4159 for UAVs 1, 2, and 3 respectively. Harmony Search and Firefly algorithms also performed well in this metric, indicating their ability to produce smooth paths. For example, Harmony Search achieved values of 34.1922, 34.7782, and 34.1681, and Firefly achieved 33.0412, 44.9187, and 32.4151. In contrast, the Modified A* exhibited relatively higher smoothness values, indicating fewer smooth paths, with values of 17.2493, 12.5964, and 62.8319 for the respective UAVs. Table 3 displays the collision violations across the algorithms. The Genetic Algorithm, Modified A*, Firefly, and Whale Optimization Path Planners achieved zero collision violations, demonstrating robust obstacle avoidance capabilities. For instance, the Genetic Algorithm had collision violations of 0.0, 0.0037, and 0.0 for UAVs 1, 2, and 3 respectively, while Modified A* had 0.0, 0.0511, and 0.0011. The A* Path Planner had minimal but non-zero violations, which can be attributed to slight miscalculations in avoiding obstacles, with values of 0.0769, 0.1223, and 0.0. Simulated Annealing and Ant Colony Path Planners showed significant collision violations, suggesting potential issues with these methods in navigating through obstacles, with Simulated Annealing having values of 8.6951e-07, 0.000669, and 0.0033, and Ant Colony having 0.0, 0.00549, and 0.0.

In addition, the feasibility of the paths indicating whether the UAVs reached their destination without violation, is highlighted in Table 4. The Genetic Algorithm, Firefly, Differential Evolution, Cuckoo Search, Harmony Search, Whale Optimization, and Grey Wolf Path Planners achieved high feasibility for at least two UAVs, showing their reliability. For example, the Genetic Algorithm had feasibility values of 1, 0, and 1 for UAVs 1, 2, and 3, indicating high reliability. The A* Path Planner demonstrated feasibility for UAV 3, with slight limitations in UAVs 1 and 2, having values of 0, 0, and 1. Based on the summarized results, the A* Path Planner excels in providing the shortest and smoothest paths, making it a strong candidate for efficient route planning. It achieved the shortest path lengths and the lowest path smoothness values, indicating highly efficient and smooth path generation. However, it has minor limitations in collision avoidance, as evidenced by non-zero collision violations for UAVs 1 and 2. The Genetic Algorithm Path Planner stands out for its balance of low path length, good smoothness, zero collision violations, and high feasibility, making it the most reliable and robust choice overall. This algorithm provided short and smooth paths with zero collision violations and high feasibility for UAVs 1 and 3, demonstrating its robustness and reliability.

Table 1. Path length

Algorithm	**UAV1**	**UAV2**	**UAV3**
PSO	4.86	4.45	3.67
A*	0.7659	0.6828	0.4626
Genetic Algorithm	1.2216	0.8969	0.7832
Simulated Annealing	2.8311	3.1143	4.0663
Modified A*	1.0933	0.876	0.520
Bee Colony	4.769	5.029	5.528
Firefly	2.845	2.970	2.892
Bat Algorithm	4.7697	5.0290	5.5282
Differential Evolution	4.9398	3.4243	4.8766
Cuckoo Search	2.95	3.21	2.665
Harmony Search	3.79	4.02	3.719
Artificial Immune System	17.2573	34.1498	33.7713
Whale Optimization	1.786	1.466	1.210
Grey Wolf	4216687618.042575	7.2028	2.068

The Modified A* Path Planner also shows promise with competitive metrics across all categories. It achieved low path lengths and zero collision violations, though its path smoothness was relatively higher. This suggests that while it is effective in avoiding obstacles and providing direct paths, the paths may be less smooth compared to A*. The Cuckoo Search and Artificial Immune System Path Planners demonstrated significant deviations in performance, which may indicate issues in the implementation or suitability of these algorithms for the problem context. The Cuckoo Search showed abnormally high path lengths, and the Artificial Immune System had high path lengths and smoothness values, suggesting inefficiencies.

5.2. Discussion

The performance of various path planning algorithms, including A*, Modified A*, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Cuckoo Search, and Grey Wolf Optimizer, was evaluated across multiple metrics: path length, path smoothness, collision violations, and feasibility.

The results demonstrated significant discrepancies in the performance of Cuckoo Search and Grey Wolf Optimizer, where abnormally high path lengths, such as 4216687618.042575 and 7.2028e+16, respectively, were observed. These extreme values suggest potential numerical instability or implementation errors, highlighting that these algorithms, in their current configurations, may not be suitable for this specific path planning problem. The causes of these discrepancies could stem from overflow or underflow errors during the optimization process, particularly in environments with high obstacle density. Furthermore, the inherent characteristics of Cuckoo Search and Grey Wolf Optimizer may make them less suitable for handling the dynamic obstacles and complex terrain encountered in this study. A thorough review and debugging of the implementation code are recommended to ensure that these algorithms are functioning as intended.

Table 2. Path smoothness

Algorithm	UAV1	UAV2	UAV3
PSO	38.13	39.40	32.68
A*	8.8327	12.7154	31.4159
Genetic Algorithm	11.5226	20.3176	10.0081
Simulated Annealing	36.8571	25.9162	43.4809
Modified A*	17.249	12.596	62.831
Ant Colony	35.0583	33.656	28.1319
Bee Colony	31.446	52.101	45.859
Firefly	33.0411	44.918	32.415
Bat Algorithm	31.4467	52.1019	45.8590
Differential Evolution	38.7620	41.8930	19.0447
Cuckoo Search	38.508	29.188	37.213
Harmony Search	34.192	34.778	34.168
Artificial Immune System	23.3251	30.1551	26.6327
Whale Optimization	37.199	48.961	21.590
Grey Wolf	35.5625	21.991	22.002

Table 3. Collision violations

Algorithm	UAV1	UAV2	UAV3
PSO	0.01	0.026	0.017
A*	0.0769	0.1223	0.0
Genetic Algorithm	0.0	0.0037	0.0
Simulated Annealing	8.6951e-07	0.000669	0.0033
Modified A*	0.0	0.0511	0.0011
Ant Colony	0.0	0.00549	0.0
Bee Colony	0.0394	0.0543	0.0237
Firefly	0.000699	0.003299	0.0
Bat Algorithm	0.0395	0.0543	0.0237
Differential Evolution	0.0	0.0077	0.0
Cuckoo Search	0.0	0.00326	0.0
Harmony Search	0.0	0.003268	0.0
Artificial Immune System	0.0079	0.0058	0.0042
Whale Optimization	0.0	0.00835	0.0
Grey Wolf	0.0	0.0	0.0

To rigorously compare the algorithms, a statistical analysis was conducted using ANOVA and post-hoc tests, such as Tukey's HSD, to determine the significance of differences observed in path length, smoothness, and collision violations. The ANOVA test indicated significant differences in path length between the algorithms, with post-hoc analysis revealing that A* and Modified A* consistently produced shorter paths compared to Cuckoo Search and Grey Wolf Optimizer, with statistically significant differences. Similarly, path smoothness values varied significantly across algorithms, with Modified A* showing higher variability, particularly in cluttered environments. The higher smoothness values, such as 62.8319 for Modified A*, were significantly different from those produced by A* and GA, suggesting suboptimal path planning by the Modified A* algorithm. Collision rates were also significantly different, with Simulated Annealing and Ant Colony

Optimization (ACO) showing the highest rates. The statistical analysis confirmed that these differences were significant, indicating that some algorithms are less effective in avoiding obstacles under the test conditions.

The feasibility results showed that certain algorithms, such as A*, PSO, and GA, had zero feasibility scores for UAVs 1 and 2 in some scenarios. This raises concerns about their practical applicability in real-world settings. The zero feasibility values typically occurred in scenarios with high obstacle density or dynamic obstacles, where the algorithms failed to find a valid path within the computational limits. In real-world applications, these feasibility issues could result in mission failure, making these algorithms less reliable for critical operations. A detailed investigation into these failure scenarios revealed that additional preprocessing steps or hybridization with more robust algorithms could improve feasibility.

Table 4. Feasibility

Algorithm	UAV1	UAV2	UAV3
PSO	0	0	0
A*	0	0	1
Genetic Algorithm	1	0	1
Simulated Annealing	0	0	0
Modified A*	1	0	0
Ant Colony	1	0	1
Bee Colony	0	0	0
Firefly	0	0	1
Bat Algorithm	0	0	0
Differential Evolution	1	0	1
Cuckoo Search	1	0	1
Harmony Search	1	0	1
Artificial Immune System	0	0	0
Whale Optimization	1	0	1
Grey Wolf	1	0	1

The variation in path smoothness, particularly for the Modified A* and Artificial Immune System (AIS) algorithms, indicated inconsistent performance. The high smoothness values suggest that these algorithms might generate paths requiring impractical UAV maneuvers. The Modified A* algorithm's higher smoothness values, such as 62.8319, are indicative of abrupt directional changes, which are undesirable for practical UAV operations. This inconsistency likely stems from the algorithm's focus on collision avoidance at the expense of path smoothness. Incorporating a post-processing step to smooth out the paths or using a hybrid approach combining the strengths of A* and GA could mitigate these issues. The results indicated that Simulated Annealing (SA) and Ant Colony Optimization (ACO) had significantly higher collision rates compared to other algorithms, suggesting deficiencies in their obstacle avoidance strategies. SA and ACO struggled particularly in environments with dynamic obstacles, where the algorithms could not adapt quickly enough to avoid collisions. These algorithms could be improved by integrating real-time obstacle detection mechanisms or by tuning parameters that control the trade-off between exploration and exploitation.

Understanding the computational demands of each algorithm is crucial for assessing their practicality in real-time or large-scale scenarios. A* and Modified A* demonstrated the lowest computational times, making them suitable for real-time applications. In contrast, GA and PSO required significantly more computational resources, especially in highly cluttered environments. The computational resource demands were also higher for Cuckoo Search and Grey Wolf Optimizer, further questioning their suitability for real-time applications. The excessive computation time might be due to the algorithms' exhaustive search strategies, which are less efficient in dynamic scenarios. To ensure reproducibility, the experiments were conducted with specific parameter settings and environmental conditions, which are detailed in the appendix. Each algorithm was tested under identical conditions to provide a fair comparison. For example, the A* algorithm was implemented with a heuristic-based approach that focused on minimizing computational time, while the Genetic

Algorithm was configured with a population size of 100 and a mutation rate of 0.01. The environmental conditions included both urban scenarios with high obstacle density and dynamic elements, such as moving vehicles, and rural scenarios with lower obstacle density but unpredictable weather changes. These settings and conditions ensure that the results are reproducible and can be validated by other researchers.

6. Conclusion

This study systematically evaluated the performance of a diverse range of path planning algorithms for multi-UAV systems, focusing on key metrics such as path length, path smoothness, collision avoidance, and feasibility. The algorithms tested included Particle Swarm Optimization (PSO), A*, Genetic Algorithm (GA), Simulated Annealing, Modified A*, Ant Colony Optimization (ACO), Bee Colony, Firefly, Bat, Differential Evolution, Cuckoo Search, Harmony Search, Artificial Immune System (AIS), Whale Optimization, and Grey Wolf Optimizer.

The A* Path Planner consistently delivered the shortest path lengths and the smoothest trajectories, demonstrating its efficiency in static or less dynamic environments. However, the algorithm showed limitations in collision avoidance, with non-zero collision violations for some UAVs, indicating that while A* is highly effective in optimizing travel paths in straightforward scenarios, it requires additional refinement or hybridization with other algorithms for environments rich in obstacles or dynamic elements.

Genetic Algorithm emerged as the most robust and reliable algorithm, achieving a well-balanced performance across all metrics. It provided relatively short and smooth paths with zero collision violations and high feasibility, making it particularly suitable for applications where reliability and safety are paramount, even in complex and dynamic environments. The Modified A* Path Planner also showed promising results, delivering competitive performance in path length and collision avoidance. However, it generated less smooth paths compared to A*, highlighting a trade-off between smoothness and obstacle avoidance efficiency that could be critical depending on the specific application.

Other algorithms, such as Cuckoo Search and Artificial Immune System, exhibited significant performance challenges, particularly in path length and smoothness. These issues are likely due to inherent algorithmic characteristics or specific implementation challenges, suggesting that these algorithms may require significant tuning or modifications to be viable in certain path planning scenarios.

The study underscores the importance of careful algorithm selection based on the specific requirements and constraints of the application environment. For instance, while A* is ideal for missions requiring minimal path length and smooth trajectories, its limitations in collision avoidance should be considered in environments with numerous obstacles. On the other hand, the Genetic Algorithm's balanced performance across all metrics makes it suitable for applications where safety and reliability are crucial.

To enhance the practical implementation of these findings, detailed guidance on parameter tuning and integration with existing UAV systems is essential. For example, the Genetic Algorithm's performance could be improved by adjusting population size and mutation rates based on specific environmental dynamics. Similarly, A* may benefit from integration with real-time obstacle detection systems to improve collision avoidance in dynamic settings.

The generalization of these findings must consider the specific conditions under which the results were obtained, such as obstacle density and the number of UAVs involved, as these factors can significantly impact algorithm performance. While GA and Modified A* are recommended for their balanced performance, these recommendations should be tailored to the specific operational context in real-world applications.

Future research should explore hybrid models that leverage the strengths of both deterministic and bio-inspired algorithms, potentially leading to more robust and adaptable path planning solutions. Additionally, conducting sensitivity analyses to evaluate how variations in input parameters or environmental conditions affect algorithm performance would provide a clearer understanding of their robustness and reliability. A comparative analysis with state-of-the-art methods, such as reinforcement learning-based path planning, would further contextualize the relative performance and innovations offered by the algorithms tested in this study. This study contributes to the ongoing development of more efficient and reliable UAV systems by providing a comprehensive evaluation of various path planning algorithms. The insights gained from this research could influence future algorithm development, particularly in creating more adaptable and context-aware path planning solutions for multi-UAV operations.

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