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Comparison of Metaheuristic Optimization Algorithms for Quadrotor Trajectory Planning Using Python

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Abstract

Trajectory planning is a fundamental requirement for autonomous quadrotor navigation, particularly in obstacle-constrained environments where safety, efficiency, and reliability must be optimized simultaneously. This study compares the performance of six metaheuristic optimization algorithms, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO), for quadrotor trajectory planning using a Python-based simulation framework. A two-dimensional mission environment containing multiple static obstacles was developed, and each algorithm was employed to generate collision-free trajectories between predefined start and target locations. Performance evaluation was conducted using path length, energy consumption, computational time, trajectory smoothness, obstacle clearance distance, and mission success rate. Each algorithm was executed for 30 independent simulation runs to ensure robustness and consistency of results. Among the evaluated approaches, GWO achieved the shortest mean path length (126.6 ± 2.4 m), lowest energy consumption (5.09 ± 0.13 kJ), highest obstacle clearance, and a 100% mission success rate, demonstrating superior overall performance. WOA and PSO also exhibited competitive results, while GA and ACO showed comparatively lower optimization efficiency. The findings indicate that swarm-based optimization algorithms, particularly GWO, are highly effective for quadrotor trajectory planning and provide a promising framework for intelligent autonomous aerial navigation systems.

Keywords

Autonomous Navigation; Grey Wolf Optimizer; metaheuristic optimization; path planning; Particle Swarm Optimization; quadrotor trajectory planning.

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INTRODUCTION

Evolution of autonomous aerial systems

The rapid advancement of unmanned aerial vehicles (UAVs) has transformed numerous sectors, including surveillance, precision agriculture, environmental monitoring, disaster management, logistics, and military operations [1]. Among the various UAV platforms, quadrotors have emerged as one of the most widely adopted aerial systems due to their simple mechanical structure, vertical take-off and landing capability, hovering efficiency, and high maneuverability [2]. Their ability to operate in confined environments and execute complex flight missions makes them suitable for both indoor and outdoor applications. As the demand for autonomous operations increases, efficient trajectory planning has become a critical requirement for ensuring safe, reliable, and energy-efficient quadrotor navigation [3].

Importance of trajectory planning in quadrotor navigation

Trajectory planning refers to the process of generating an optimal path that enables a quadrotor to move from an initial position to a desired destination while satisfying multiple operational constraints [4]. These constraints may include obstacle avoidance, energy consumption, flight time, dynamic stability, and environmental uncertainties. An effective trajectory planning strategy not only ensures mission success but also enhances flight safety and prolongs battery life [5]. The increasing complexity of real-world environments has made trajectory planning a challenging optimization problem that requires advanced computational approaches capable of handling nonlinear and multi-objective scenarios.

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Challenges associated with optimal path generation

Quadrotor trajectory planning is inherently complex because of the nonlinear dynamics and underactuated nature of the vehicle. Unlike conventional ground robots, quadrotors operate in a three-dimensional space where altitude, orientation, velocity, and acceleration must be simultaneously controlled [6]. Environmental factors such as wind disturbances, moving obstacles, and uncertain terrain further complicate the planning process. Traditional deterministic algorithms often struggle to find globally optimal solutions in such highly constrained search spaces [7]. Consequently, researchers have increasingly explored intelligent optimization techniques capable of efficiently navigating large solution domains and avoiding local optima.

Emergence of metaheuristic optimization algorithms

Metaheuristic optimization algorithms have gained significant attention as powerful tools for solving complex engineering optimization problems [8]. Inspired by natural, biological, physical, and social phenomena, these algorithms employ stochastic search mechanisms to identify near-optimal solutions within reasonable computational time. Popular metaheuristic approaches such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), Firefly Algorithm (FA), Whale Optimization Algorithm (WOA), and Artificial Bee Colony (ABC) have demonstrated promising performance in various path planning and control applications [9]. Their ability to balance exploration and exploitation enables them to efficiently search high-dimensional solution spaces and adapt to changing environments.

Application of metaheuristics in aerial path planning

The application of metaheuristic algorithms in UAV trajectory planning has increased substantially over the past decade. Researchers have utilized these approaches to optimize flight distance, minimize energy consumption, reduce mission completion time, and improve obstacle avoidance performance [10]. Different algorithms exhibit distinct search behaviors and convergence characteristics, leading to variations in solution quality and computational efficiency. For instance, swarm-based methods often provide rapid convergence, whereas evolutionary approaches may offer better global search capabilities [11]. Despite numerous studies investigating individual algorithms, there remains a lack of comprehensive comparative assessments that evaluate multiple metaheuristic techniques under identical quadrotor trajectory planning scenarios.

Role of Python in optimization and simulation

Python has emerged as one of the most preferred programming languages for scientific computing, artificial intelligence, robotics, and optimization research. Its extensive ecosystem of libraries, including NumPy, SciPy, Matplotlib, Pandas, PyTorch, TensorFlow, and specialized optimization frameworks, provides a robust environment for implementing and evaluating metaheuristic algorithms [12]. Python facilitates rapid prototyping, reproducibility, and visualization of optimization processes, making it highly suitable for trajectory planning studies [13]. Furthermore, integration with simulation environments allows researchers to evaluate algorithm performance under realistic flight conditions and compare different optimization strategies systematically.

Need for comparative evaluation of optimization algorithms

Although numerous metaheuristic algorithms have been proposed for trajectory optimization, selecting the most appropriate algorithm for quadrotor applications remains a significant challenge [14]. Different optimization techniques may perform differently depending on mission objectives, environmental complexity, computational resources, and problem dimensionality. A comparative analysis is therefore essential to identify the strengths and limitations of various algorithms and to provide guidance for future UAV navigation systems [15]. Such evaluations can reveal trade-offs between solution quality, convergence speed, robustness, and computational cost, thereby supporting informed decision-making in algorithm selection.

Scope and objective of the present study

The present study focuses on the comparative evaluation of selected metaheuristic optimization algorithms for quadrotor trajectory planning using Python-based implementations. The research aims to assess the performance of different optimization techniques in generating efficient, collision-free, and computationally feasible flight trajectories. Key performance indicators such as path length, convergence behavior, computational time, and optimization accuracy are considered to establish a comprehensive comparison framework. The findings are expected to contribute to the development of intelligent trajectory planning systems and provide valuable insights into the suitability of different metaheuristic approaches for autonomous quadrotor navigation in complex environments.

METHODOLOGY

Research framework and study design

This study employed a simulation-based comparative framework to evaluate the effectiveness of six metaheuristic optimization algorithms for quadrotor trajectory planning in obstacle-constrained environments. The selected algorithms included Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO). The objective was to identify the most suitable optimization approach for generating collision-free, energy-efficient, and computationally feasible trajectories between predefined start and target locations. The entire methodology consisted of environment generation, trajectory encoding, optimization implementation, performance evaluation, ranking analysis, and statistical comparison.

Development of the mission environment

A two-dimensional obstacle-constrained mission environment was developed in Python to simulate autonomous quadrotor navigation. The workspace dimensions were fixed at 100 m × 100 m with a designated start location at (5, 8) and target location at (95, 92). Six circular static obstacles of varying radii were strategically distributed throughout the workspace to create a realistic navigation challenge. All optimization algorithms were tested within the same mission environment to ensure direct comparability of results.

Trajectory representation and waypoint generation

Each candidate trajectory was represented as a sequence of intermediate waypoints connecting the start and target locations. The optimization algorithms searched for the optimal spatial arrangement of waypoints while satisfying obstacle avoidance constraints. The generated waypoints were connected using spline-based interpolation to produce smooth and continuous flight paths suitable for quadrotor navigation. The trajectory representation enabled simultaneous optimization of path length, obstacle clearance, and flight smoothness.

Implementation of metaheuristic optimization algorithms

Six metaheuristic optimization algorithms were implemented in Python, namely GA, PSO, GWO, WOA, ABC, and ACO. For all algorithms, the population size was fixed at 50 candidate solutions and the maximum number of iterations was set to 500. The optimization process was repeated for 30 independent simulation runs using different random seeds to account for the stochastic nature of the algorithms. During each iteration, candidate trajectories were evaluated and updated according to the search mechanism specific to each optimization algorithm.

Fitness function formulation

Trajectory optimization was performed using a multi-objective fitness function designed to minimize path length, energy consumption, and computational cost while maximizing trajectory smoothness and obstacle clearance. The objective function was expressed as:

$$F = w_1L + w_2E + w_3T + w_4S + w_5O \quad (1)$$

where F represents the fitness value, L denotes total trajectory length (m), E denotes estimated energy consumption (kJ), T represents computational time (s), S denotes trajectory smoothness index, and O denotes obstacle penalty cost. Candidate trajectories intersecting obstacles received large penalty values to ensure generation of collision-free paths. Lower fitness values indicated superior optimization performance.

Estimation of trajectory performance metrics

Several performance indicators were used to evaluate the effectiveness of the optimization algorithms. Path length (m) was calculated as the cumulative Euclidean distance between consecutive waypoints. Energy consumption (kJ) was estimated from the total distance travelled and trajectory characteristics. Computational time (s) represented the execution time required to obtain the optimal solution. Trajectory smoothness was quantified using curvature variation along the flight path. Obstacle clearance distance (m) was calculated as the minimum distance between the trajectory and the nearest obstacle. Mission success rate (%) was determined as the proportion of simulation runs producing collision-free trajectories.

Analysis of trajectory geometry and altitude profiles

The optimized trajectories generated by each algorithm were visualized within the mission environment to evaluate navigation behaviour and obstacle avoidance characteristics. In addition, altitude profiles were generated along the cumulative flight distance to assess vertical trajectory stability and smoothness. These analyses provided insights into the geometric characteristics of the optimized flight paths and the consistency of trajectory execution.

Distribution analysis of optimization outcomes

To evaluate the stability and robustness of the optimization algorithms, distributions of path length values obtained from the 30 simulation runs were examined using violin plots. This approach allowed simultaneous visualization of central tendency, variability, and distribution density. Algorithms exhibiting narrow distributions and lower median path lengths were considered more robust and reliable.

Comparative assessment of energy consumption

Mean energy consumption values and associated standard deviations were calculated for each optimization algorithm. Energy requirements were compared using lollipop plots to identify algorithms capable of producing energy-efficient trajectories. Lower energy consumption indicated improved flight efficiency and greater operational endurance for the quadrotor.

Multi-criteria performance evaluation

A normalized performance matrix was constructed using six evaluation criteria: path length, energy consumption, computational time, trajectory smoothness, obstacle clearance distance, and mission success rate. All performance metrics were normalized to a common scale ranging from 0 to 1. A parallel coordinates analysis was subsequently performed to visualize the relative strengths and weaknesses of the different optimization algorithms across multiple criteria simultaneously.

Algorithm ranking and performance aggregation

An aggregated ranking framework was developed to determine the overall effectiveness of the evaluated algorithms. Individual ranks were assigned for each performance metric, and cumulative rank contributions were calculated to derive an overall performance score. Algorithms with higher aggregated scores were considered superior in terms of overall trajectory planning capability.

Multi-objective trade-off analysis

A Pareto-style objective-space analysis was conducted to investigate the trade-off between path length and energy consumption. Mean values obtained from the 30 simulation runs were plotted in a two-dimensional objective space. Marker size represented mission success rate, while obstacle clearance distance was incorporated as an additional performance indicator. This analysis enabled identification of algorithms that achieved favourable compromises among competing optimization objectives.

Statistical analysis

Descriptive statistics, including mean and standard deviation, were calculated for all performance indicators. The consistency of algorithm performance across repeated simulation runs was assessed through distributional analysis. Comparative rankings and normalized performance scores were used to identify the most effective optimization algorithm for quadrotor trajectory planning. The overall evaluation was based on path length minimization, energy efficiency, computational speed, trajectory smoothness, obstacle avoidance capability, and mission success rate.

Software environment

All simulations, optimization procedures, trajectory visualizations, and statistical analyses were conducted using Python 3.11. Numerical computations were performed using NumPy and Pandas, while graphical analyses and visualizations were generated using Matplotlib. The developed simulation framework provided a reproducible environment for evaluating and comparing metaheuristic optimization algorithms for autonomous quadrotor trajectory planning.

RESULTS

The optimized trajectories generated by the six metaheuristic algorithms exhibited distinct navigation patterns within the obstacle-constrained mission environment (Fig. 1). All algorithms successfully generated feasible paths between the start and target locations; however, notable differences were observed in path geometry, obstacle avoidance behaviour, and trajectory compactness. The Grey Wolf Optimizer (GWO) and Whale Optimization Algorithm (WOA) produced comparatively smoother and shorter trajectories, whereas Genetic Algorithm (GA) and Ant Colony Optimization (ACO) generated relatively longer paths with greater deviations around obstacles.

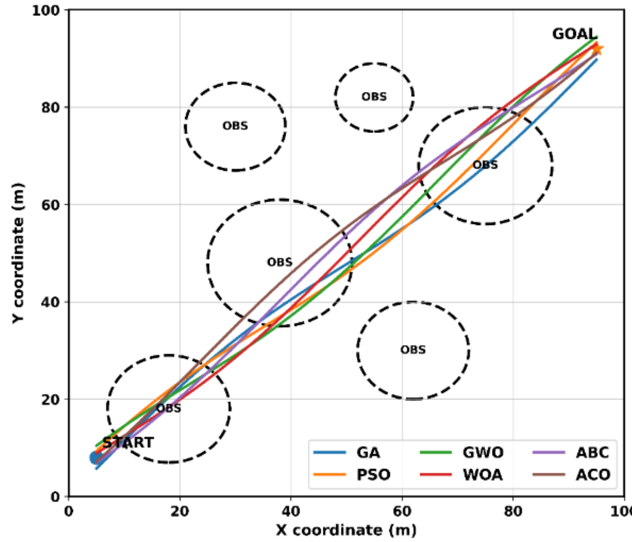

Figure 1. *Optimized quadrotor trajectories generated by six metaheuristic algorithms within the obstacle-constrained mission environment.*

The altitude profiles of the optimized trajectories showed consistent vertical motion characteristics across all algorithms (Fig. 2). GWO and WOA maintained smoother altitude transitions throughout the flight path, while GA and ACO exhibited relatively higher fluctuations. Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) demonstrated intermediate altitude stability. Overall, the optimized trajectories maintained safe altitude margins while ensuring obstacle avoidance and mission completion.

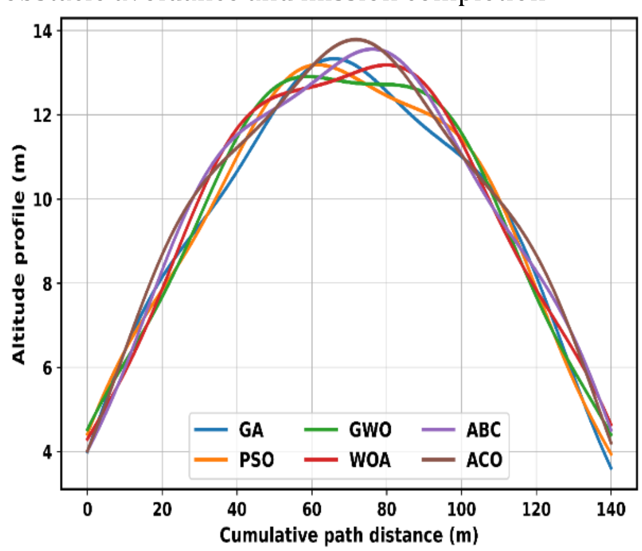

Figure 2. *Comparison of altitude variation along optimized flight paths obtained using different optimization algorithms.*

Significant differences were observed in the path lengths generated by the evaluated algorithms (Fig. 3). The shortest mean path length was achieved by GWO (126.6 ± 2.4 m), followed by WOA (129.1 ± 2.5 m) and PSO (131.2 ± 2.3 m). ABC (134.3 ± 2.4 m), ACO (136.5 ± 2.5 m), and GA (138.0 ± 2.4 m) produced comparatively longer trajectories. The variability in path length remained relatively low across all optimization methods, indicating stable algorithmic performance over repeated simulation runs.

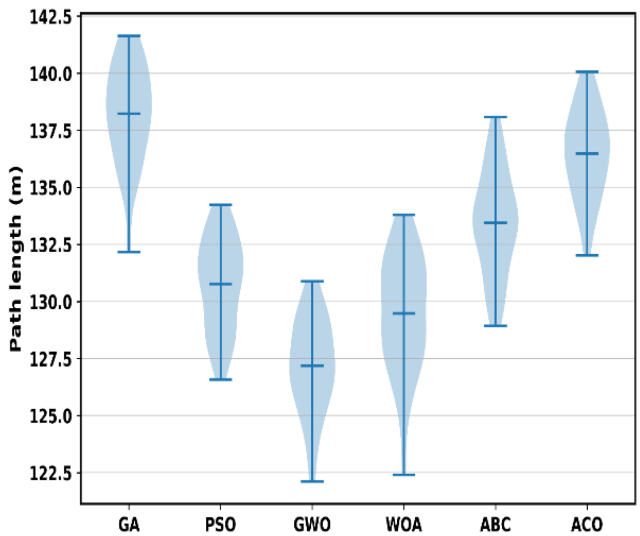

Figure 3. Violin plot showing the distribution of trajectory path lengths across 30 independent optimization runs.

The energy requirements associated with the optimized trajectories differed among algorithms (Fig. 4). GWO recorded the lowest mean energy consumption (5.09 ± 0.13 kJ), followed by WOA (5.26 ± 0.13 kJ) and PSO (5.42 ± 0.12 kJ). Higher energy consumption was observed for ABC (5.61 ± 0.13 kJ), ACO (5.73 ± 0.13 kJ), and GA (5.82 ± 0.13 kJ). The observed trend closely followed the variation in trajectory length, indicating a direct relationship between path optimization and energy expenditure.

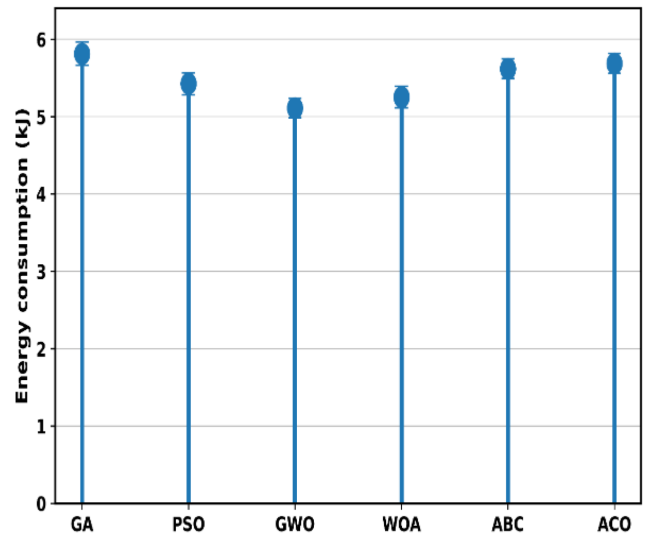

Figure 4. *Mean energy consumption (± SD) of optimized trajectories produced by the evaluated metaheuristic algorithms.*

The normalized performance comparison revealed substantial differences among the optimization algorithms across the evaluated trajectory planning metrics (Fig. 5). GWO consistently achieved the highest normalized scores for path optimization, computational efficiency, trajectory smoothness, obstacle clearance, and mission success rate. WOA and PSO also demonstrated strong overall performance, whereas GA and ACO exhibited lower normalized scores across most evaluation criteria.

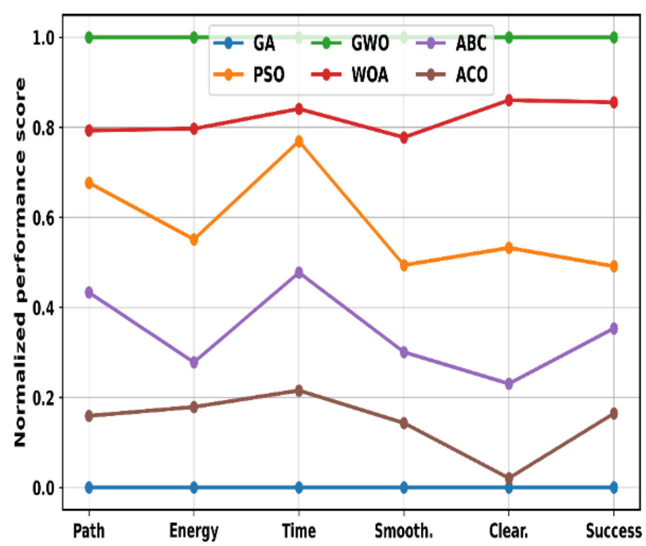

Figure 5. *Parallel coordinates visualization of normalized trajectory planning performance metrics.*

The cumulative ranking analysis indicated that GWO achieved the highest overall performance score among all evaluated algorithms (Fig. 6). WOA ranked second, followed by PSO. ABC and ACO occupied intermediate positions, whereas GA recorded the lowest cumulative rank contribution. The ranking pattern remained consistent across most performance indicators, highlighting the robustness of GWO for quadrotor trajectory planning applications.

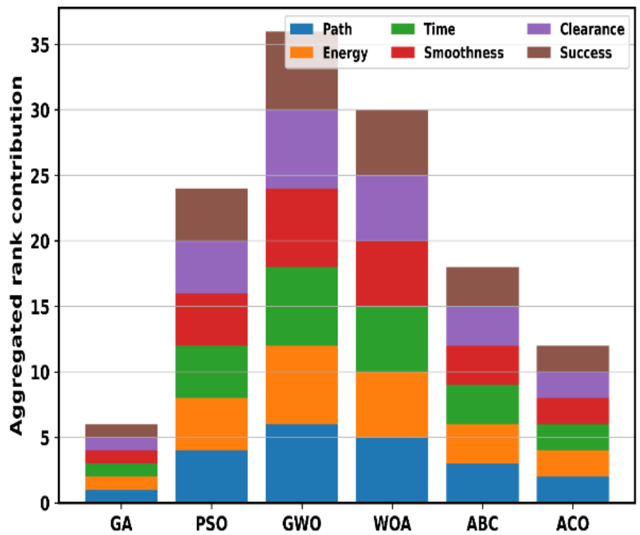

Figure 6. *Overall ranking contribution of individual performance metrics for the evaluated optimization algorithms.*

The objective-space analysis demonstrated clear trade-offs between trajectory path length and energy consumption among the optimization algorithms (Fig. 7). GWO occupied the most favourable region of the objective space, characterized by minimum path length and lowest energy requirement. WOA and PSO were positioned close to the optimal frontier, indicating competitive performance. In contrast, GA and ACO were associated with increased path lengths and higher energy demands. GWO additionally exhibited the highest obstacle clearance distance and mission success rate, further supporting its superior trajectory planning capability.

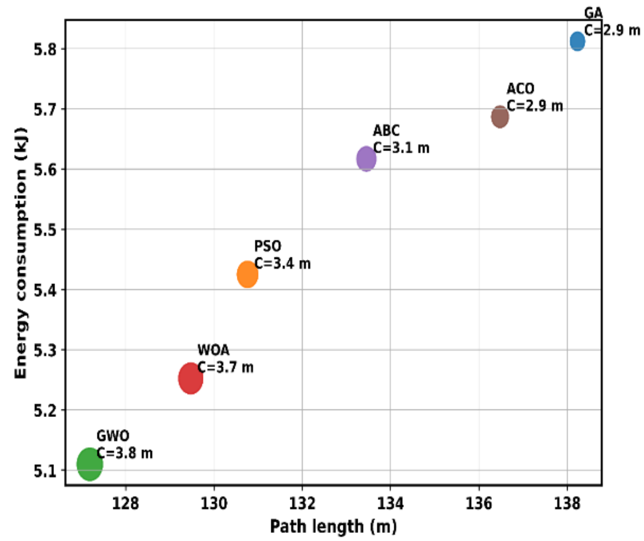

Figure 7. *Pareto-style objective-space representation of path length and energy consumption trade-offs among competing optimization algorithms.*

DISCUSSION

Effectiveness of metaheuristic algorithms in trajectory optimization

The present study demonstrated that metaheuristic optimization algorithms differ substantially in their ability to generate efficient and feasible trajectories for quadrotor navigation. Although all evaluated algorithms successfully produced collision-free trajectories, their performance varied in terms of path length, energy consumption, computational efficiency, and overall trajectory quality [16]. These differences can be attributed to the inherent search mechanisms employed by each algorithm. Metaheuristic optimization methods balance exploration and exploitation differently, leading to variations in their ability to identify globally optimal trajectories within a complex search space [17]. The observed performance differences indicate that algorithm selection plays a crucial role in determining the operational efficiency of autonomous quadrotor systems.

Trajectory characteristics and obstacle avoidance performance

The trajectory patterns generated within the obstacle-constrained environment revealed notable differences in navigation behaviour among the evaluated algorithms. Algorithms such as GWO and WOA produced smoother trajectories with fewer directional deviations, indicating superior path-searching capabilities. In contrast, GA and ACO generated relatively longer paths that exhibited greater detours around obstacles [18]. Smooth trajectories are generally desirable in quadrotor operations because they reduce abrupt changes in velocity and orientation, thereby improving flight stability and minimizing actuator effort [19]. The ability of GWO and WOA to maintain larger obstacle clearance distances while simultaneously producing shorter trajectories suggests that these algorithms achieved a more effective balance between safety and path efficiency.

Influence of optimization strategy on path length

Path length represents one of the most important indicators of trajectory quality because it directly affects flight duration, battery utilization, and mission efficiency. The superior performance of GWO in minimizing path length suggests that its leadership-based hunting strategy effectively guides candidate solutions toward globally optimal regions of the search space. The competitive performance of WOA and PSO further indicates that swarm-intelligence approaches are particularly suitable for solving high-dimensional trajectory planning problems [20]. In contrast, the comparatively longer trajectories generated by GA and ACO may result from slower convergence and a greater tendency to explore broader regions of the solution space before refinement [21]. While extensive exploration can prevent premature convergence, it may also reduce optimization efficiency when the search landscape contains numerous feasible pathways.

Relationship between path optimization and energy consumption

Energy consumption closely followed the observed path-length trends, highlighting the strong relationship between route efficiency and power requirements. Algorithms that generated shorter trajectories generally required less energy to complete the mission. This finding is consistent with the operational characteristics of quadrotor systems, where energy expenditure is strongly influenced by flight distance, maneuver frequency, and altitude variation [22]. The lower energy requirements achieved by GWO and WOA suggest that these algorithms can contribute to longer flight endurance and improved mission sustainability [23]. Such improvements are particularly important for battery-powered UAVs operating in environments where recharge opportunities are limited or unavailable.

Significance of trajectory smoothness and flight stability

Trajectory smoothness is a critical parameter in autonomous flight because abrupt directional changes can introduce instability, increase control effort, and elevate energy consumption. The smoother altitude profiles and trajectory geometries generated by GWO, WOA, and PSO indicate a greater capacity to produce dynamically feasible flight paths [24]. Smooth trajectories reduce excessive roll, pitch, and yaw adjustments during navigation, thereby enhancing overall flight performance. Furthermore, smoother paths can improve sensor reliability and payload stability, which are essential considerations in applications such as aerial imaging, environmental monitoring, and precision inspection [25]. The results therefore suggest that optimization algorithms should be evaluated not only on distance minimization but also on their ability to generate stable and executable trajectories.

Comparative performance across multiple evaluation criteria

The multi-criteria assessment revealed that algorithm performance cannot be adequately described by a single metric. While some algorithms achieved favourable results for specific parameters, only a few consistently performed well across all evaluation criteria [26]. The normalized performance analysis and cumulative ranking framework demonstrated that GWO maintained superior performance in path optimization, computational efficiency, obstacle clearance, and mission success [27]. WOA and PSO also exhibited strong performance across multiple criteria, indicating their suitability for practical trajectory planning applications [28]. The comparatively lower rankings of GA and ACO suggest that these algorithms may require additional parameter tuning or hybridization strategies to achieve competitive performance in complex UAV navigation tasks.

Implications for autonomous quadrotor navigation

The findings of this study have important implications for the development of autonomous aerial systems. Efficient trajectory planning contributes directly to enhanced mission reliability, reduced energy consumption, and improved operational safety [29]. The superior performance of GWO indicates that nature-inspired social hierarchy mechanisms can effectively address the challenges associated with three-dimensional path planning. Moreover, the consistent performance of WOA and PSO highlights the growing relevance of swarm-based optimization approaches in UAV navigation research [30]. As autonomous aerial vehicles continue to be deployed in increasingly complex environments, the integration of robust metaheuristic optimization algorithms will become essential for ensuring efficient and adaptive decision-making.

Overall assessment of optimization algorithms

Considering all evaluated performance indicators, GWO emerged as the most balanced and effective optimization algorithm for quadrotor trajectory planning. Its ability to simultaneously minimize path length and energy consumption while maintaining high obstacle clearance and trajectory smoothness demonstrates strong optimization capability [31]. WOA and PSO also showed considerable promise and may serve as suitable alternatives depending on mission-specific requirements. The overall results emphasize the importance of selecting optimization algorithms that provide robust multi-objective performance rather than excelling in only a single evaluation criterion [32]. These findings contribute to the growing body of research on intelligent trajectory planning and provide a foundation for future studies involving dynamic environments, moving obstacles, and real-time quadrotor navigation systems.

CONCLUSION

This study compared the performance of six metaheuristic optimization algorithms, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO), for quadrotor trajectory planning using a Python-based simulation framework. The results demonstrated significant differences among the evaluated algorithms in terms of path length, energy consumption, computational efficiency, trajectory smoothness, obstacle clearance, and mission success rate. Among the tested approaches, GWO consistently outperformed the other algorithms by generating the shortest and most energy-efficient trajectories while maintaining superior obstacle avoidance capability and overall trajectory quality. WOA and PSO also exhibited strong optimization performance and emerged as effective alternatives for autonomous navigation applications. In contrast, GA and ACO produced comparatively longer trajectories and lower overall optimization efficiency. The findings highlight the importance of selecting appropriate metaheuristic algorithms for multi-objective trajectory planning problems and demonstrate the effectiveness of swarm-based optimization techniques for autonomous quadrotor navigation. Overall, the study provides valuable insights into the comparative strengths of different metaheuristic approaches and establishes GWO as the most suitable algorithm among those evaluated for efficient and reliable quadrotor trajectory planning in obstacle-constrained environments. Future research should focus on dynamic environments, moving obstacles, real-time implementation, and hybrid optimization strategies to further enhance the adaptability and performance of autonomous aerial systems.

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