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To compare the performance of ant colony algorithm and artificial bee colony algorithm in UAV track planning

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Abstract:

In the field of unmanned aerial vehicle (UAV) trajectory planning, the optimization of intelligent algorithms is crucial. This paper compares and analyzes the search ability, convergence, and environmental adaptability of the Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithms in UAV path planning. The study finds that the ABC algorithm demonstrates strong global search ability but lower local search efficiency, with fast initial convergence but a tendency to fall into local optima. The ACO algorithm excels in local search and adaptability to complex environments, though its performance declines in high-dimensional problems. Through literature review, the study reveals differences in their dynamic environment performance and proposes optimizing the local search mechanism of ABC and improving the heuristic function of ACO to enhance UAV path smoothness. This research fills the gap in traditional algorithm comparison and provides references for UAV trajectory planning algorithm optimization.

Keywords: Unmanned Aerial Vehicle, Ant Colony Optimization, Bee Colony Algorithm, Trajectory Planning

1. Introduction

In today's society, drones (Unmanned Aerial Vehicle) have been widely used in civilian and military fields, and can be applied in disaster relief, geological detection, photography, or to perform a series of dangerous and complex tasks on behalf of humans.

At the same time, the technology in the field of drone trajectory planning (UAV track planning) is becoming increasingly advanced. It is also a key part of drone mission allocation and can be achieved through many intelligent algorithms, such as ant colony algorithm, artificial bee colony algorithm, genetic algorithm, particle swarm algorithm, etc., each with its own advantages and disadvantages. They can be connected to drones at the hardware or software level. The author of this paper is particularly interested to research further into the algorithms of the ant colonies and the artificial bee colonies. After reviewing a large number of papers on drone trajectory planning, it was found that several researchers have published papers on the artificial bee colony algorithm.

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Studies found in literature exhibit a method that make the convergence speed of the traditional ABC algorithm improved by combining the grey Wolf algorithm and the ant colony algorithm [1].The heuristic function is improved in ant colony algorithm to make the flight path of UAV smoother [2]. It was found that few papers compared these two algorithms. Most research papers only studied the application of a certain algorithm or to propose improvements to an algorithm. Therefore, this study will to compare the advantages and disadvantages of the two algorithms after reviewing the literature and materials, optimize the disadvantages of the two algorithms, and fill this research gap. This paper will make a series of comparisons between artificial bee colony algorithm and ant colony algorithm in terms of search ability, convergence, adaptability, and path planning effect (planning accuracy and speed of their planned paths).

Based on this research gap, the first step is to search, screen and read the literature. After this the process will include summarizing the performance of the two algorithms in drone trajectory planning and their advantages and disadvantages, understand the different parameters, calculation methods and processes of the two algorithms, And the different performance of artificial bee colony algorithm and ant colony algorithm in static environment, dynamic environment and complex environment. Quantitative analysis and qualitative analysis were carried out respectively. And review the existing ways to optimize the two algorithms for comparison.

2. Literature Review

2.1 Overview and Basic Principles of Ant Colony Optimization

Ant Colony Optimization (ACO) is a heuristic optimization algorithm inspired by the foraging behavior of ants in nature. It is also a probabilistic algorithm with a positive feedback mechanism, capable of effectively solving numerous optimization problems. First proposed by Italian scholar Marco Dorigo et al. in 1991 [3].ACO belongs to the category of swarm intelligence algorithms. Due to its strong optimization capabilities and adaptability, ACO has been widely applied in various fields. For example, in robotics, it is used to find optimal paths from starting points to targets; in logistics and supply chain management, it optimizes delivery routes to reduce transportation costs and improve efficiency; it is also utilized in combinatorial optimization problems.

In the algorithm, individual ants act as simple agents that move through the problem's search space to construct solutions. The inspiration for ACO comes from observing how ants in nature leave a chemical substance called pheromone. This pheromone guides other ants in path selection and marks nodes that can be detected by the highly developed olfactory systems of other ants. Ants tend to follow paths with higher pheromone concentrations. Over time, pheromones accumulate more on shorter paths, with concentration levels reflecting path length—higher concentrations indicate shorter paths, while lower concentrations indicate longer ones. Ants probabilistically choose paths with higher pheromone concentrations and continue depositing pheromones on their traveled paths, forming a positive feedback mechanism [4]. Once all ants locate the food source, iteration is completed. After multiple iterations, an optimal path from the starting point to the food source emerges.

In addition to pheromones, ants also consider problem-specific features when selecting nodes, such as the distance between the starting point and the food source or the cost of reaching the target. These factors are termed "heuristic information".

As for the core principles of ACO lie in path selection and pheromone updating mechanisms. First, the algorithm initializes parameters such as pheromone concentration, heuristic factors, number of ants, and maximum iterations. In traditional ACO, pheromones are uniformly distributed initially to ensure equal starting concentrations across all paths, while distinguishing accessible nodes from obstacle nodes.

The path selection is about each ant starts from the origin and independently constructs a solution within the search space. The probability of selecting the next node is determined by both pheromone concentration and heuristic information. At each node, an ant calculates transition probabilities for all feasible neighboring nodes and selects the next node using a roulette wheel method based on these probabilities [5].

In addition pheromone update is the core mechanism of ACO, enabling global optimization through dynamic pheromone updates. To prevent excessive accumulation, pheromones undergo evaporation after each iteration. During iterations, existing pheromones evaporate while ants traversing the path deposit new pheromones. Thus, pheromone concentrations are updated after each iteration [6]. Updates are categorized into two types, the first is local update pheromones evaporate during ant movement to avoid premature convergence.

Another is the global update which means after each iteration [7], pheromones are reinforced based on path quality (e.g., path length). Higher-quality paths receive greater pheromone increments.

2.2 Overview and Basic Principles of Artificial

Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence optimization algorithm that mimics honeybee foraging behavior. Proposed by Turkish scholar Karaboga in 2005.ABC simulates the division of labor and cooperation among bees to solve complex optimization problems. It has been widely applied in fields such as function optimization such as nonlinear functions. Combinatorial optimization likes traveling salesman problem, knapsack problem, and path planning with drones or robots [6].

Inspiration and roles illustrate that the ABC algorithm is inspired by the natural process of bees searching for nectar. This process is a complex and efficient behavior, reflecting the high degree of collaboration and division of labor of bees as social insects. A bee colony is divided into three roles:

Firstly, Employed Bees responsible for exploring known food sources and evaluate their quality (e.g., nectar quantity). They generate new candidate solutions near current food sources and replace inferior ones.

Onlooker Bees that's select high-quality food sources reported by employed bees using a roulette wheel method, where selection probability is proportional to fitness. They further search around chosen sources. Scout Bees charge of randomly searching for new food sources if existing ones stop after multiple iterations, preventing local optima.

In global and local search, the most of the improved artificial bee colony algorithms, the current global optimal nectar source provides the guiding direction for local search, ensuring the fast convergence of search [8]. The algorithm balances exploration for scout bees and exploitation for employed and onlooker bees.

Initialization is also the first step in the operation of the algorithm; the initial honey source is generated in a random way in the artificial bee colony algorithm. The aim is to provide an initial search starting point for the algorithm, thus laying the foundation for the subsequent optimization process. Generate random food sources (initial solutions) within predefined bounds to ensure diversity and avoid premature convergence.

Iterative Optimization is step that also a key step for algorithm optimization. The role of the update and iteration mechanism includes improving the current solution, the current path, and exploring new Spaces through stochastic perturbation and global search, balancing global and local search. Employed bees perform local searches. Onlooker bees probabilistically enhance high-quality solutions. Scout bees replace stagnant solutions with random ones after exceeding a limit [9].

Finally, termination is the algorithm stops when reaching maximum iterations, achieving preset fitness thresholds, or observing no significant fitness improvement. That ensure the algorithm is optimized in a limited time. Through collaborative efforts, the bee colony gradually converges toward the global optimal solution.

2.3 Overview of Contemporary UAV Technology and Its Path Planning

In recent years, with the continuous advancement of algorithms and technologies, UAV (Unmanned Aerial Vehicle) technology has rapidly evolved, achieving significant improvements in flight performance and functional practicality. It integrates multidisciplinary technologies from aviation, communications, electronics, and artificial intelligence, demonstrating broad application prospects and societal impact [10].The core components of UAVs include many components.

The first is the flight control system. It utilizes components such as GPS sensors to monitor flight status and make real-time adjustments. Next the communication system facilitates data exchange between the UAV and ground stations, enabling real-time transmission of commands, algorithmic outputs, and flight data. Thirdly, power system ensures sustained energy supply for operations [10].

Current trends in UAV technology focus on enhancing performance and endurance, advancing intelligent and autonomous capabilities, and integrating with emerging technologies.

UAV path planning refers to the autonomous navigation capability that allows UAVs to intelligently select flight paths based on environmental changes and mission requirements. This ensures operational efficiency and improves flight safety, making it a critical factor in achieving autonomous UAV operations and as a key to research specific area in navigation and guidance.

The primary objectives of UAV path planning are to achieve safe, efficient, and precise flight operations. It requires balancing external factors such as obstacle avoidance, environmental perception, and mission demands with internal constraints like UAV performance and energy consumption.

Path planning algorithms can be categorized into two main types based on methodology. For intelligent optimization algorithms, the evolutionary algorithms include Genetic Algorithms (GA).

In addition variety of swarm intelligence algorithms, such as Particle Swarm Optimization (PSO), Ant Colony Optimization, and Artificial Bee Colony [11] simulate natural evolution or physical phenomena to search for optimal paths. Machine learning algorithms can leverage

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data-driven approaches for adaptive path planning.

Algorithm selection is also an important factor. The optimal solution for UAV path planning depends on specific mission requirements and environmental conditions. Recent studies highlight that A* and D* algorithms which excel in static or low-dynamic environments. The RRT (Rapidly-exploring Random Tree) performs well in high-dimensional and complex environments.

This technological progression underscores the importance of selecting context-appropriate algorithms to maximize UAV operational effectiveness.

3. Methodology

A comprehensive literature search was conducted. Investigations were performed on China National Knowledge Infrastructure (CNKI) using the following keywords: artificial bee colony algorithm, ant colony algorithm, unmanned aerial vehicles (UAVs), path planning, etc.

Initially, the search scope was limited to publications from 2020 to 2024 for two primary reasons: To begin with, rapid technological advancements mean older studies cannot adequately reflect current research trends in UAV applications; Secondary continuous emergence of new algorithm improvement methods by researchers makes earlier data less relevant. Subsequently, preliminary screening was conducted by reviewing article abstracts and conclusions, with supplementary scanning of main content. The CRAAP (Currency, Relevance, Authority, Accuracy, and Purpose) evaluation framework was then applied to select appropriate literature for in-depth analysis. And summarize their advantages and disadvantages in the field of UAV flight path planning, as well as their search ability, adaptability, convergence and specific planning effects.

The search also intentionally included studies comparing other algorithms such as Genetic Algorithms (GA) - “a search algorithm mimicking natural evolutionary principles [12]” - and Particle Swarm Optimization (PSO) - “which simulates natural bird flocking behavior [13]” - in UAV path planning applications. These bio-inspired algorithms share conceptual similarities with bee and ant colony algorithms that providing valuable comparative insights into current UAV algorithm research and practical implementations. During analysis, literature was categorized based on specific algorithm type (bee colony and ant colony). Presence of algorithm improvements either through cross-algorithm hybridization or intrinsic optimization .Direct relevance to UAV path planning applications versus general theoretical discussions. Particular attention was paid to studies proposing innovative modifications while maintaining practical applicability to UAV trajectory planning challenges.

4. Results&Discussion

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4.1 Search ability

In the trajectory planning of unmanned aerial vehicles (UAVs), the search ability of an algorithm refers to the ability of the algorithm to search for the optimal path or to meet specific task conditions within a certain specific space.

In algorithms, it is usually divided into local search ability and global search ability. For the artificial bee colony algorithm, it usually has strong global search ability, because it benefits from the unique mechanism of this algorithm and the division of labor and cooperation among various bee colonies. During the search process of the algorithm, the balance between global search and local search is achieved through the cooperation of employed bees and onlooker bees.

Among them, the employed bees are responsible for searching near the currently known nectar sources, and they use the method of random perturbation to search for new solutions. This enables the algorithm to conduct extensive exploration in the solution space, avoiding getting stuck due to premature convergence to a local optimum, thus ensuring the global search ability of the artificial bee colony algorithm. One of the literatures mentions that the search is carried out within the corresponding nectar source neighborhood according to the following formula to generate new nectar sources:

$$g'_{ij}=g_{ij}+rand(-1,1)\times(g_{ij}-g_{kj}) \quad (1)$$

In the formula: g'_{ij} is the new nectar source, rand(-1,1) is a random number within the range of [-1, 1], $k \in \{1,2,\ldots,N\}$, and $k \neq i$.

Regarding the global search ability of the Ant Colony Optimization (ACO) algorithm, due to the relatively high evaporation rate of the pheromone evaporation coefficient, the accumulation of pheromones is reduced, making it easier and quicker for ants to explore new paths. Moreover, the distributed search method of the ACO algorithm and its probability-based path selection mechanism both endow the algorithm with good global search ability. However, once the UAV (Unmanned Aerial Vehicle) mission involves high-dimensional problems, the search performance of the ACO algorithm will decline, because the parameters of the ACO algorithm are highly sensitive. In contrast, the Artificial Bee Colony (ABC) algorithm has fewer parameters, and the randomness and diversity mechanisms of the division of labor among various types of bees endow this algorithm with a better ability to search in high-dimensional spaces. Generally speaking, both the ABC algorithm and the ACO algorithm perform well in terms of global search ability for common path planning problems. However, the ABC algorithm has a better ability to search in high-dimensional spaces compared to the ACO algorithm.

On the contrary, the ABC algorithm has the problems that the distribution of initial nectar source positions is random, and there is blindness and randomness in the local search process, which reduces the search efficiency of the algorithm [14]. At the same time, each update of the algorithm only focuses on one dimension, resulting in relatively weak local search ability.

Compared with the ACO algorithm, the ACO algorithm can quickly reflect the quality of the path due to the pheromone mechanism when ants move. It can optimize and quickly search the paths in the local area. Moreover, the introduction of heuristic information in the ACO algorithm enables the algorithm to more efficiently select better paths in the local areas of the entire search space, thus enhancing its local search ability. Based on the above reasons, the local search ability of the ACO algorithm is stronger than that of the ABC algorithm.

4.2 Convergence

The convergence in an algorithm refers to whether the algorithm can find the global optimal solution within a certain period of time, or how close it can get to the optimal solution. It also reflects the efficiency of the algorithm in generating the optimal path. Firstly, for the artificial bee colony algorithm, it has a relatively fast convergence speed in the initial stage of the algorithm. This is because, as mentioned above, the artificial bee colony algorithm benefits from the efficient local search ability of the employed bees. Moreover, in the initial stage of the algorithm, the global search ability and the local search ability are relatively balanced, which accelerates its convergence speed. Additionally, the onlooker bees make optimal selections based on the information searched by the employed bees [1].And the onlooker bees make probabilistic selections according to the quality of the nectar sources, and choose the nectar sources through the roulette wheel selection method.

For example, the probability that the i-th nectar source is selected by the follower bee is:

$$P_i = \frac{fit_i}{\sum_{k=1}^{N} fit_k} \tag{2}$$

according to [15] as cited by [10].

The preferential selection mechanism of this artificial bee colony algorithm based on fitness enables it to quickly approach good solutions in the early stage of the algorithm, and it has higher convergence efficiency than the ant colony algorithm. However, after the artificial bee colony algorithm has been calculated for a period of time, it is prone to fall into the situation of local optimality in the later stage, resulting in poor convergence of the algorithm. One of the reasons is that the scout bee mechanism has certain limitations, because the condition for it to avoid falling into local optimality through random search is that the nectar source has not been updated in multiple iterations. The triggering condition is harsh and difficult to achieve, so that the solution of the algorithm keeps hovering near the optimal path in the later stage. At the same time, in the problem of multi-dimensional path planning, the search range of employed bees and onlooker bees gradually shrinks, and the diversity of optional paths decreases, which indirectly leads to the slowdown of the convergence speed of the artificial bee colony algorithm.

For the ant colony algorithm, its convergence performance is relatively poor. Especially when dealing with a large amount of problem information, it takes a relatively long time for the search. This is because in the early stage, the ant colony algorithm adopts the strategies of pheromone evacuation distribution and the random search of the ant colony. Therefore, to a certain extent, the convergence speed of the ant colony algorithm is slower than that of the artificial bee colony algorithm in the early stage. In the middle stage of the ant colony algorithm, the pheromone concentration and heuristic information will jointly act on the path selection of the unmanned aerial vehicle (UAV). This combination improves the efficiency of the probability of the ant colony searching for the flight path in the middle stage of the algorithm as a whole, enabling it to find a high-quality path more quickly, thus accelerating the convergence efficiency. A recent literature mentions that the specific transition probability formula is:

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_j(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum_{s\in\alpha_k}\left[\tau_S(t)\right]^{\alpha}\left[\eta_{is}(t)\right]^{\beta}} \; j\in\alpha_k \\ 0 \; j\notin\alpha_k \end{cases} \tag{3}$$

Where: α is the pheromone influence factor; β is the heuristic function influence factor; τ_j is the pheromone concentration at node j; τ_S is the pheromone concentration at nodes; η_{ij} is the distance heuristic function.The expression of η_{ij} is usually $\eta_{ij} = 1/d_{ij}$ [16].

In the later stage of the ACO algorithm, due to the positive feedback mechanism of pheromones, when the evaporation rate of pheromones is low or the initial value is too high, the algorithm may converge prematurely to a local

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optimal path and fall into a local optimal solution. At the same time, the increase in the number of iterations leads to a reduction in the diversity of the ant colony's path selection, making the algorithm prone to getting trapped in a local optimum.

In summary, in terms of the convergence results in the later stage, the Ant Colony Optimization algorithm and the ABC algorithm have certain similarities, and both are likely to fall into a local optimal state. In the middle stage, the Ant Colony Optimization algorithm has a faster convergence speed compared to the Artificial Bee Colony algorithm. However, in the early stage, due to the optimization mechanism of the scout bees in the Artificial Bee Colony algorithm, the convergence performance is more efficient than that of the Ant Colony Optimization algorithm.

4.3 Adaptability

The complex environment refers to an environment where a large number of obstacles exist, which will hinder the flight of the UAVto a certain extent, or an environment that is not conducive to the UAV performing its corresponding tasks. In such an environment, the difficulty of the algorithm in searching for the optimal path is greatly increased, and situations such as the failure of the path planning task may even occur. Adaptability refers to the accuracy of the UAV's path planning in different complex environments, the time taken for the planning, and whether it can provide the optimal path[17].

For the artificial bee colony algorithm in the dynamic environment of UAV path planning and obstacle avoidance, the algorithm will monitor the surrounding environment in real time to update the initial path distribution in its algorithm. At the same time, due to the random search mechanism of the scout bees in the artificial bee colony algorithm, it can effectively adapt to environmental changes and avoid falling into local optimality.

The formula for the random search of the scout bee is:

$$g_{ij} = L_{ij} + rand\left(0,1\right) \times \left(U_{ij} - L_{ij}\right) \tag{4}$$

In this formularand(0, 1) is a random number in the interval [0, 1]. U_{ij} and L_{ij} are the upper and lower bounds of g_{ij} respectively according to [9] .

Due to the complete randomness and independence of this algorithm, and the fact that the sampling of information is uniformly distributed throughout the entire space, it will not be biased towards a certain region. However, since the overall performance of the artificial bee colony algorithm depends to a large extent on the parameter settings within it, this will lead to a lack of sufficient flexibility when parameters need to be adjusted. For example, the limit parameter directly affects the performance of the algorithm. If the solution has not been updated after the number of exploitation reaches the maximum exploitation number limit, it is considered that the corresponding solution has fallen into a local optimum, and this nectar source is discarded, and the employed bee becomes a scout bee. In addition, the maximum number of iterations of the algorithm needs to be adjusted according to different obstacles, terrains, etc. in different environments. However, these parameters of the traditional artificial bee colony algorithm are highly fixed, making it difficult to quickly adapt to different environments. This is also the reason why the response speed of this algorithm is not high, so that situations such as slow UAVtrajectory planning and planning errors are likely to occur. Therefore, to a certain extent, its adaptability is not high.

On the contrary, the ant colony algorithm has good robustness and excellent adaptability in complex environments. The pheromone in the ant colony algorithm will volatilize and then be dynamically adjusted, effectively preventing the algorithm from falling into a local optimum. The pheromone on the trajectory will be continuously released and volatilize, while enhancing the adaptability to complex environments.

The pheromone update function is shown in the following equation.

$$\tau_{ij} = \left(1-\rho\right)\tau_{ij} + \rho\Delta\tau_{ij} \tag{5}$$

In this formula ρ is pheromone volatilization factor, $0 < \rho < 1; \Delta\tau_{ij}$ is the concentration of pheromones released by ants on the paths they have traversed [18].

The ant colony algorithm is also a distributed algorithm. Each ant can be regarded as an independent individual and can exchange information with each other through pheromones. Due to the large number of ants, it has a high fault tolerance rate and computational efficiency, thus having good adaptability to different environments and showing higher efficiency in path planning in complex environments.

In conclusion, the ant colony algorithm has higher adaptability than the artificial bee colony algorithm in terms of the performance of UAV path planning in different complex environments. This is because of the good computational mechanism of the ant colony algorithm and the characteristics of pheromones, as well as reasons such as the computational complexity of the artificial bee colony algorithm and its insufficient sensitivity in parameter adjustment.

4.4 Summary and Implications

In conclusion, in the problem of UAV path planning, both algorithms have their own advantages and disadvantages. From the perspective of search ability, both the artificial bee colony algorithm and the ant colony algorithm have good global search capabilities. However, the ant colony algorithm has better local search ability than the artificial bee colony algorithm. For high-dimensional search problems, the artificial bee colony algorithm shows better search performance and more accurate path planning.

In terms of the convergence of the two algorithms, in the early stage, the convergence of the ant colony algorithm is slightly worse than that of the artificial bee colony algorithm. In the middle stage, the ant colony algorithm converges faster. In the later stage, due to the respective defects of the two algorithms, they are both prone to fall into local optimality, resulting in poor convergence.

From the perspective of the adaptability of the two algorithms, the ant colony algorithm is more adaptable to complex environments and outperforms the artificial bee colony algorithm, showing better path planning performance in such situations.

Regarding the respective disadvantages of the two algorithms, different optimization directions can be proposed. The artificial bee colony algorithm is prone to falling into a local optimum during its application, which leads to the problem of reducing the search and convergence speed. This can be optimized by optimizing the search method for the position of local nectar sources. A recent study utilized the oscillatory changes of a sine wave to exert a disturbing effect during the process of the onlooker bees searching for the positions of nectar sources, thereby improving the local search ability of the ABC algorithm.

$$x_{ij}^{t+1} = \omega x_{ij}^{t} + r_1^* |\alpha|^* maparange_j \tag{6}$$

$$\alpha = sin(2\pi) * rand(0,1) \tag{7}$$

$$\omega = \frac{e^{\frac{t}{iter_{max}}-1}}{e-1} \tag{8}$$

$$r_1 = \alpha - \frac{\alpha t}{iter_{max}} \tag{9}$$

Inthisformula t is the number of iterations, $iter_{max}$ is the maximum number of iterations; α is a constant taken as 1; ω is the weight factor [19]).

For the ant colony algorithm, in order to avoid the unnecessary energy consumption caused by the frequent turns of the unmanned aerial vehicle (UAV), the heuristic function therein can be improved. A piece of literature mentions that the magnitude of the heuristic function should be within a reasonable range, and it is chosen to use the exponential function as the heuristic function.

That is $\eta_{ij}^{\alpha g} = e^{sin\theta}$

Considering that the UAV flight has an angular constraint,

that is $\theta < \theta_{max}$, therefore, an angle constraint heuristic factor S is added on the basis of the above content.

$$S = \begin{cases} 1\theta < \theta_{max} \\ 0other \end{cases} \tag{10}$$

The final heuristic factor is $\eta_{ij} = S \cdot \frac{1}{d_{ij}} \cdot \eta_{ij}^{\alpha g}$ [2] .

This improvement method has greatly enhanced the stability of the UAV path planning.

5. Evaluation

5.1 Highlights

Firstly, the above-mentioned research encompasses a great deal of research on UAV (Unmanned Aerial Vehicle) trajectory planning algorithms and references numerous literatures in the aspects of algorithms and trajectory planning. These literatures include various types of journals as well as master's and doctoral theses. Through systematic screening, a part of them are selected for in-depth reading and analysis. Meanwhile, the above research also adheres to a complete structural framework, owing to the comprehensive methodology.

In addition, this paper makes a comparison of the performance of the Artificial Bee Colony Algorithm and the Ant Colony Algorithm in UAV trajectory planning, thus filling the gap that most literatures and journals have not made such a comparison. Moreover, this paper also lists and analyzes the optimization methods that can be implemented for the two algorithms.

5.2 Limitations

The above research has compared the two algorithms in terms of the trajectory planning problem, and each algorithm has its own characteristics, advantages and disadvantages. However, the performance of the algorithms is largely influenced by the performance of the unmanned aerial vehicles (UAVs) used. A recent piece of literature mentions that the performance ofUAV sensors, such as the detection range and accuracy, determines their environmental perception ability, and it requires the algorithms to have stronger environmental adaptability and dynamic adjustment ability to achieve the goals [10].

This paper cannot cover all the factors that may affect the performance of the algorithms. Therefore, only the key factors that lead to the above-mentioned performances of the two algorithms are mentioned and cited in the paper. In reality, there are more and more complex issues to be

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considered when performing planning tasks.

6. Conclusion

This paper aims to explore the performance of the artificial bee colony algorithm and the ant colony algorithm in terms of convergence at different stages, adaptability to complex environments, and search capabilities in the field of UAV (unmanned aerial vehicle) trajectory planning. The research results show that these two algorithms have their respective advantages and disadvantages in these aspects. Meanwhile, they also have certain similarities in terms of global search capabilities. However, there are some differences in their performance in terms of convergence and adaptability to the task environment. Through a series of literature searches, it is found that few documents compare the traditional artificial bee colony algorithm with the ant colony algorithm. Therefore, the content mentioned in this paper can, to a certain extent, fill the current research gap. At the same time, it analyzes and summarizes the characteristics, advantages, and disadvantages of the two algorithms in trajectory planning.

This paper also puts forward suggestions for improvement and optimization of these two algorithms respectively. It mentions improving the convergence and search capabilities of the artificial bee colony algorithm, as well as reducing the unnecessary energy consumption of UAVs during flight when using the ant colony algorithm. However, there is still a large room for optimization of these two algorithms that has not been mentioned in this paper. For example, integrating other algorithms can make up for their disadvantages and enhance the performance of the algorithms. It is believed that in the future, there will be more documents researching the artificial bee colony algorithm and the ant colony algorithm, more simulation experiments and comparative experimental data. Moreover, better and more concise improvement methods will be proposed, and the convergence and search capabilities of the two algorithms will also be significantly improved.

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