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Analysis of path planning of UAV in short-distance logistics application

Shijia Guo[1, †], Xuan Li[2, †, 4]and Shuze Liu[3, †]

[1] College of Automotive Engineering, Jilin University, Changchun, 130000 China.
[2] College of Technology, Nanjing Agricultural University, Nanjing, 210031, China.
[3] School of Computer Science and Engineering, Sun Yat-sen University, Guangzhou, 510006, China.
[†] These authors contributed equally.

[4]9203012212@stu.njau.edu.cn

Abstract. China's e-commerce sector has grown quickly in recent years, and the logistics sector has grown to be a significant sector of the national economy. Meanwhile, the business volume of the logistics industry has also increased continuously. The characteristics of intelligence and informatization of short-distance logistics UAVs, advantages such as high efficiency and not being constrained by road grids and related technical applications can greatly save manpower and time in logistics and transportation, so that the goods can be transported to the receiving place faster. Therefore, UAVs are an important part of the logistics field, among them, the path planning of UAVs is an important technical component to ensure the transportation of goods. This article first introduces the importance of UAV path planning technology in the field of short-distance logistics. Secondly, the path planning of UAVs in short-distance logistics applications is divided into two categories. The overview and analysis are carried out from the two aspects of traditional mathematical algorithm and bionic algorithm. Meanwhile, based on the available information, the benefits and drawbacks of the available methods are examined. Then, based on MATLAB, two classical methods are selected from the traditional mathematical algorithm and the bionic algorithm to carry out path planning simulation experiments in scenarios of different complexity, and the results are analyzed. Finally, the advantages and disadvantages of the above two algorithms are summarized and analyzed, and the prospect of UAV citation in short-distance logistics is prospected.

Keywords: short-range UAV, path planning, comparative analysis, algorithmic induction.

1. Introduction

The e-commerce industry of China is developing rapidly in these years, and the logistics industry has become an important part of the national economy. Meanwhile, the business volume of the logistics industry has also increased continuously. According to third-party data, In 2022, China's "Double 11" event has reached a staggering 307.6 billion yuan in daily transaction volume and 1.225 billion parcels on the same day. As Chinese dividends continue to fade and labor costs continue to rise, this development has undoubtedly brought great pressure to the traditional human logistics model [1]. Due to traffic constraints, manpower and material resources and other factors, it is difficult to achieve the timeliness of logistics and door-to-door "last mile" transportation services. Therefore, systematic thinking and design of express collection and delivery service content, and improving the rationality of network settings and manpower allocation are urgent problems that need to be solved in the face of an increasingly large number of express shipments in the future [2].

UAVs have the characteristics of intelligence and informatization, as well as the benefits of compactness, lightness, affordability, and efficiency, strong mobility, and not constrained by road grids [3]. Therefore, drones have been frequently employed recently. in a variety of intelligent transportation systems, such as environmental protection detection, traffic monitoring, logistics distribution and other fields.

Based on these characteristics and advantages, the application of drones in the logistics industry will reduce the delivery time and improve the overall responsiveness and operational efficiency of the logistics system [4]. Therefore, the logistics industry urgently needs to use drone technology to free up labor and improve the quality and efficiency of the logistics industry in terminal distribution. At the same time, with the continuous update of today's "autonomous positioning and navigation" system and "UAV intelligent obstacle avoidance" technology, UAVs are seen to be a useful tool for addressing the "last mile" problem of distribution. Logistics drones will eventually become an essential component of the modern logistics industry infrastructure and aid in the sector's rapid growth [5].

Regarding UAV short-distance logistics delivery, although some UAV companies have begun to carry out commercial applications, there is still a lack of research on the dynamic scheduling of UAV distribution systems in the academic field. The current research on UAVs can be briefly divided into two directions: the first direction is the collaborative distribution of UAVs with other tools and manpower, such as the mode of "delivery vehicle + drone" and the mode of "truck + drone". Synergy tools can assign main feeder transport tasks with drones, and can even serve as ground mobile airports for drones [3]. The second direction is pure unmanned aerial system scheduling, which involves site planning, route planning, and path planning.

This paper mainly discusses the path optimization problem of UAV in short-distance logistics applications. Firstly, the path planning of UAVs in short-distance logistics applications is divided into two types, and the traditional mathematical algorithm and bionic algorithm are summarized and analyzed respectively. Subsequently, the advantages and disadvantages of the above method are analyzed based on the available data. Then, two classical methods are selected from the traditional mathematical algorithm and the bionic algorithm to carry out path planning simulation experiments in scenarios of different complexity and analyze the results. Finally, the advantages and disadvantages of the above two algorithms are summarized and analyzed, and the prospect of UAV citation in short-distance logistics is prospected.

2. Methods and techniques

2.1. Path planning based on traditional algorithms

2.1.1. A algorithm.* The A* algorithm is one of the most efficient direct search algorithm, a traditional heuristic algorithm. The A* algorithm is relatively efficient, has a straightforward structure, and is simple to read and write. At the same time, it is quite expandable and flexible to specific requirements. Hence, the shortest path issue under static conditions is frequently tackled using the A* algorithm. Based on the above reasons, the A* algorithm is frequently used to determine the ideal path for UAVs while solving path planning problems. The A* algorithm's clear drawback is that it has low search efficiency in a large range of high-dimensional spaces [6]. Therefore, the optimized A* algorithm is often used in research today [7].

The A* algorithm derivation breakthrough algorithm is a new algorithm summarized by combining other algorithms on its algorithm, which will produce new excellent properties and be more reasonable for path planning. The A* algorithm uses a cost function to represent the advantages and disadvantages of a node. In general, a small value of the cost function indicates a good planning effect. The cost function is expressed as:

$$f(n) = g(n) + h(n) \tag{1}$$

The specific cost function usually needs to be adjusted to the actual problem. Normally the path length is chosen as a cost function, but sometimes there are other factors to consider.

2.1.2. Simulated annealing algorithm. N. Annealing established the earliest concept for the simulated annealing algorithm (SA). Suggested by Metropolis et al. in 1953. S. Kirkpatrick et al. successfully applied annealing concepts to combinatorial optimization in 1983. It is a stochastic optimization algorithm built on the iterative Monte-Carlo solution approach. The strengths of the simulated annealing algorithm are reflected in the following aspects. Its process is simple, and it is also universal. Because of the parallelism of process it can be used to solve nonlinear optimization problems in parallel. The disadvantages are slow speed, long calculation time, and related to the initial data [8], [9].

Simulated annealing algorithms are often used in logistics drone path optimization problems to determine the delivery sequence of drones. In the logistics drone path planning problem, the drone needs to pass through each distribution point in the plan. Therefore, it is necessary to work out the optimal distribution sequence. However, in practical applications, it is not necessary to waste a lot of time to find the best solution for task distribution, just to find the relatively best solution. Therefore, an approximate solution can be obtained using a simulated annealing algorithm [10].

The steps to simulate the annealing algorithm are shown below. First, the initial temperature is set and the initial order is generated, and the evaluation value of this sequence is calculated according to the evaluation function. Subsequently, a new order is obtained based on the disturbance of the current temperature. At the same time, the evaluation values of the new order are calculated and compared with the evaluation values of the current order. If the rating value of the new shipping order is greater than the current review value, the new order is accepted. Conversely, the current order is determined whether to update according to the Metropolis acceptance criteria, where the Metropolis acceptance criteria such as expression (2) shown. Finally, repeat the above steps until the cooling is complete or the specified number of iterations is reached. It is worth noting that the evaluation function in the annealing algorithm usually needs to be adjusted according to the specific application situation.

$$p = \begin{cases} 1 & E_{new} > E_{old} \\ \mathrm{e}^{\frac{E_{new}-E_{old}}{kT}} & E_{new} < E_{old} \end{cases} \tag{2}$$

2.1.3. A- artificial potential field algorithm.* As mentioned above, A* algorithm is a typical intelligent heuristic algorithm. It can achieve global planning, but there are problems such as non-continuous curvature and excessive redundant points. This will lead to a certain impact on turning points and key points, which will greatly affect the accuracy of obstacle avoidance. The artificial potential field algorithm has the characteristics of short planning time and strong practicability, which can be used for real-time local planning. But this algorithm lacks global information in complex situations. After combining these two algorithms, the improved A* algorithm can be used for global planning of the path first, and it can be introduced into the artificial potential field algorithm as a yaw factor, and the final planning result can be obtained by using the artificial potential field method for secondary programming [7].

There are many improvements that can be made to the A* algorithm. It can be designed according to actual problems, based on constraints such as the range and turning radius of the UAV, so as to achieve the effect of screening out some nodes and improving the speed of the algorithm. This paper takes the A*-artificial potential field method as an example, and its improved algorithm cost function expression is:

$$f(x) = g(x) + h(x) \tag{3}$$

In expression (3), $f(x)$ means the estimated total cost of node X. $g(x)$ means the actual cost spent from the starting point F to the node X, called the actual cost function. $h(x)$, called the heuristic function, is the estimated cost from node X to the termination point G.

$$g(x) = \alpha_1 L + \alpha_2 E + \alpha_3 R_1 + \alpha_4 R_2 \tag{4}$$

In the urban environment, the path planning of logistics drones focuses on avoiding obstacles and urban no-fly zones, so the Euclidean distance is selected as the heuristic function, and its expression is:

$$h(x) = N_{length\sqrt{(x_n-x)^2+(y_n-y)^2+(z_n-z)^2}} \tag{5}$$

Then use the artificial potential field method to carry out secondary programming. The superimposed resultant force formed by the sum of the gravitational force and the repulsive force vector is the guiding direction of the UAV, so that it can avoid obstacles and reach the terminal take-off and landing point. The expressions are:

$$\begin{gathered} F_{att1}(x) = \frac{k_1(C_g-C_t)}{|C_g-C_t|} \\ \mathrm{F}_{att2}(x) = k_2\left(C_p - C_t\right) \\ \mathrm{F}_{rep}(x) = k_3\left|\frac{1}{d(C_t-C_{ob})} - \frac{1}{d_0}\right|\frac{C_{ob}-C_t}{d(C_t-C_{ob})} \end{gathered} \tag{6}$$

The expression of the resultant force on the UAV is:

$$F_{sum}(x) = F_{att1}(x) + F_{att2}(x) + \sum_{i=1}^{n} F_{rep}(x) \tag{7}$$

In expression (6), $k_1, \mathrm{k}_2, \mathrm{k}_3$ are target gravitational gain coefficient, yaw gravitational gain coefficient, repulsion gain coefficient. $C_g, \mathrm{C_t}, \mathrm{C_p}, \mathrm{C_{ob}}$ are Termination point coordinates$\left(X_g, Y_g, Z_g\right)$, Drone's current location coordinates(X_t, Y_t, Z_t), The coordinates of the closest point on the initial route to the current position of the drone $\left(X_p, Y_p, Z_p\right)$, obstacle coordinates (X_{ob}, Y_{ob}, Z_{ob}), $d\ (C_t - C_{ob}) = |C_t - C_{ob}|$ measures the separation between the drone's current location and potential hazards, d_0 is the repulsion effective distance threshold. Relevant experimental findings demonstrate that this strategy can produce reliable navigational outcomes in urban settings [11].

2.2. Path planning based on bionic algorithm

2.2.1. Genetic algorithm. John Holland first proposed Genetic Algorithm (GA) in the United States in the 1970s. The algorithm was created in accordance with the natural rule of evolution that governs creatures. By imitating the natural evolution process, it is an algorithm for looking for the optimal solution. A computer is used to give the simulation operations of the algorithm. It transforms the process of working out the problem into a process similar to the selection, cross and variation in biological evolution. Its main advantage is that there are not many mathematical requirements for the optimization problem, and there are no type requirements for the objective function and constraints. The UAV path planning problem is limited, though, and real-time planning with a genetic algorithm is challenging [12].

The following describes the fundamental workings of a genetic algorithm. The evolution algebra counter should first be set to 0. Second, Set the largest evolution algebra T, and create M individuals at random for the starting population P(0). Third, determine each individual's level of fitness in the population P(t). The selection operator is then applied to the population. The goal of selection is to either produce new individuals by paired crossover and then inherit them to the next generation, or to directly deliver the optimized individuals that they are for the next generation. The process of selection operation among them is based on how fit each individual of the group is. Following that, the population is subjected to the crossover operator and the mutation operator.

Finally, the above operations are iterated continuously. After going through the evolution process, the member with the highest fitness level is output as the optimal choice, and the calculation is then complete. Genetic operations have three basic genetic operators: selection, crossover, and mutation. Its expression method is as follows.

$$GA = (C, E, P0, M, \phi, \Gamma, \psi, \mathrm{T}) \tag{8}$$

The corresponding meanings of the parameter in the above equation are shown in Table 1.

Table 1. Parameter description.

Parameter description	Meaning	Parameter description	Meaning
C	Individual coding scheme	ϕ	Select operator
E	Individual fitness evaluation function	Γ	Crossover operator
$P0$	Initial population	ψ	Mutation operator
M	Population size	T	Genetic algorithm termination condition

2.2.2. Improved genetic algorithm introducing hill climbing algorithm. The mountain climbing algorithm is a heuristic algorithm. Its design idea is derived by simulating the climbing action of monkeys in the process of climbing mountains in nature. It aims to design its corresponding optimal search process. It has strong local search ability but global search the characteristics of poor ability. Combining it with the traditional genetic algorithm can make the new algorithm not only have the advantages of the global search of the genetic algorithm, but also have the advantages of the local search of the hill-climbing algorithm [13], [14]. The introduction of the hill-climbing operator can act on the shrinking space of the algorithm, resulting in the effect of optimizing the population before the genetic algorithm.

Next, a genetic algorithm that is improved by using hill-climbing operator is introduced. The search space of the initial population is $[a_i, b_i]$. Individuals with spatial dimension i in the population are denoted by x_i. The dimension of the initial population is denoted by m. The population size is represented by n. The shrinkage space ratio in the population is denoted by e [15]. The solution expression is as follows:

$$\begin{gathered} e = \frac{(b_i - a_i)m}{2n} \\ \mathrm{a}_{i+1} = max(a_i, x_i - e_i) \\ \mathrm{b}_{i+1} = max(b_i, x_i + e_i) \end{gathered} \tag{9}$$

The following are the key steps of hill climbing algorithm. First, suppose the population is $X = (x_1, x_2, \dots, x_n)$, and set $i = 1$. Then, according to the search space of individuals in the population$[a_i, b_i]$ and its corresponding shrinkage ratio e, a new shrinkage space can be calculated, which is defined as $[a_{i+1}, b_{i+1}]$. Then, use the golden section method to optimize the individual search space in the population, and obtain excellent individuals in the new shrinking space$[a_{i+1}, b_{i+1}]$. Then, replace the old individuals of the previous generation with new excellent individuals to form a new population, and set $i = i + 1$. Finally, step determination is performed by judging the value of i. If the judgment result satisfies the condition of i\len, proceed to the second step. Otherwise, output the result and end the operation.

2.2.3. Ant colony optimization algorithm. Ant colony algorithm is a probabilistic algorithm. It is a bionic intelligent optimization algorithm that is built by modeling ant colony collaboration [16]. This algorithm has problems such as slow convergence, easy-falling to partial optimum and some iterations. So, the current ant colony algorithm has been further optimized, such as using the principle of wolf group assignment to soften the path curve, adding an intelligent gain algorithm to improve the convergence speed, using the grid map method, modifying the ant colony algorithm's transition probability, and adding dead zone judgment. These methods can effectively reduce "ineffective ants" [17], [18].

The key part of this algorithm is the update of the pheromone matrix, and the updated result directly leads to the optimal route of the ant colony algorithm. The transmission probability of the traditional ant colony algorithm is as follows:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}}{\sum_{s\in J_k(i)}[\tau_{is}(t)]^{\alpha}\cdot[\eta_{is}(t)]^{\beta}} & j \in J_i(k) \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

α stands for the pheromone significance factor in expression (10). The crucial component of the heuristic function is represented by β. The collection of the ant named k from position i to the reachable path point is represented by $J_k(i)$. $\tau_{ij}(t)$ displays the pheromones from I to j at time t. The heuristic factor is $\eta_{ij}(t)$. Its value is the reciprocal of the distance from position i to j at time t.

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \tag{11}$$

The optimized ant colony method can raise the likelihood that there will be fewer ants in the dead zone by using the following equation:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}(t)]^{\beta}\cdot[\text{allow}_{ij}(t)]^{\varphi}}{\sum_{s\in J_k(i)}[\tau_{is}(t)]^{\alpha}\cdot[\eta_{is}(t)]^{\beta}\cdot[\text{allow}_{is}(t)]^{\varphi}} & j \in J_i(k) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

In expression (12), $\text{allow}_{ij}(t)$ represents the number of feasible nodes in the next section selected by ants. This expression allows the UAV to preferentially choose directions with more feasible nodes, optimizing the efficiency of path planning.

2.3. Comparative analysis

Combined with the existing relevant literature, this paper compares the advantages and disadvantages of the algorithm mentioned in the above content, as shown in Table 2.

Table 2. Algorithm comparison.

Algorithm	Update mechanism	Advantage	Disadvantage
Genetic algorithm	Select, mutate	More mature, Wide application	Difficult to plan in real time
Simulated annealing algorithm	Random optimization based on Monte-Carlo iterative solution strategy	The calculation process is simple, Ggeneral	Long calculation time, The quality of the solution is related to the initial data
A* algorithm	Update according to the heuristic function	The structure is simple, Run fast	Calculation efficiency is low when the model is complex
A* - artificial potential field algorithm	Plan twice	Precise	
Monkey herd optimization algorithm	Climbing mechanism	Solving some problems is very advantageous	The result may be only a local optimal solution, not a global one
Ant colony optimization algorithm	Ant colony cooperation mechanism	Having a positive feedback mechanism, Can be improved by fusing different algorithms	Converging slowly, Easy to fall into local optimum

3. Experimental results and analysis

In this paper, a path simulation model is established on MATLAB platform, and the road conditions are divided into three categories: simple road condition (10*10), more complex road conditions (20*20) and most complex road condition (20*20). In these three road conditions, the difference between the two

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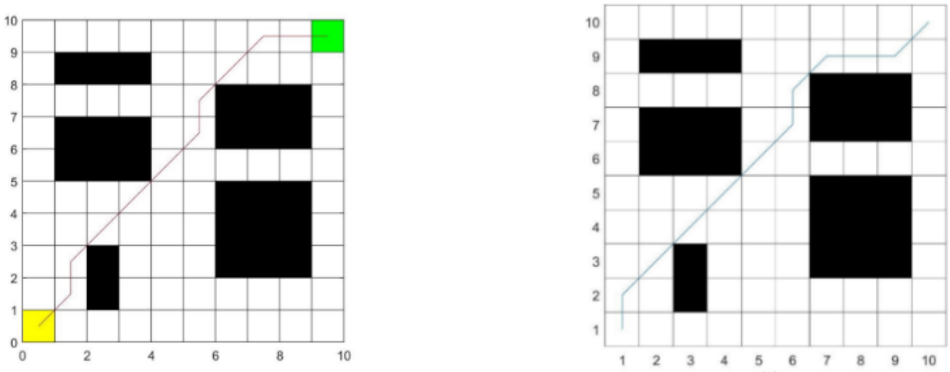
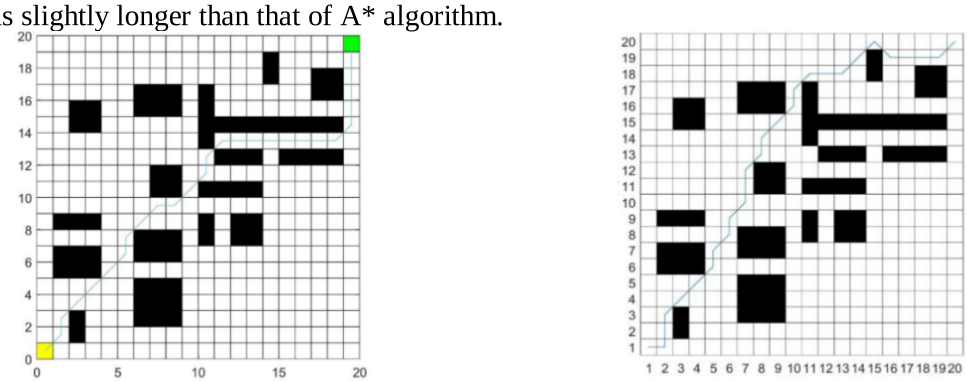
algorithms is obtained by comparing genetic algorithm and A* algorithm. The specific path plan is shown in the following figure:



(a) (b)

Figure 1. Simple road condition.

Figure 1 (a) and (b) are the paths planned by A* algorithm and genetic algorithm in simple road condition. According to the experimental findings, the A* algorithm's overall path length is around 13.899, and its running time is approximately 0.2313s. And while the total path length of genetic algorithm is about 13.899 and the running time is about 0.3080s. It can be seen that in the case of simple road conditions, both algorithms can obtain the optimal solution, but the planning time of genetic algorithm is slightly longer than that of A* algorithm.



(a) (b)

Figure 2. More complex road condition.

Figure 2 (a) and (b) are the paths planned by A* algorithm and genetic algorithm in more complex road condition. The experimental results show that the A* algorithm has an overall path length of about 27.556 and a running time of about 0.3263s. And while the total path length of genetic algorithm is about 32.385 and the running time is about 0.2440s. It can be seen that in more complex road condition, A* algorithm takes longer, but finds a better solution than genetic algorithm.

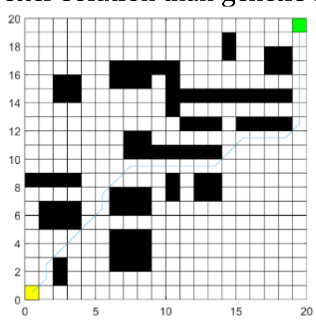


Figure 3. A* algorithm Most complex road condition.

At the same time, in order to further study the difference between the two algorithms, obstacles are added when the starting point and end point remain unchanged. Figure 3 is the path planned by A* algorithm. A* algorithm can still plan a path. Genetic algorithms, on the other hand, cannot solve a solution. It may be because genetic algorithm falls into local optimum. The comparison of experimental results is shown in Table 3:

Table 3. Comparison of experimental results

Road condition	A* algorithm	Genetic algorithm
Simple road condition	Find the optimal solution, Less time	Find the optimal solution, More time
More complex road condition	Shorter path, Less time	Longer path, More time
Most complex road condition	Find the optimal solution	No solution

Analysing the second set of results, it can be concluded that genetic algorithm takes less time. It may be because genetic algorithm has the characteristic of population search to avoid searching for some unnecessary points. At the same time, genetic algorithms are based on probabilistic rules, not deterministic rules. It makes the genetic algorithm more flexible. Analysis of the third set of results shows that genetic algorithm is difficult to plan paths in complex situations. It may be because of the premature phenomenon of genetic algorithm, which leads to the earlier convergence of the algorithm to local optimal solution. Based on the three groups, it can be seen that A* algorithm has a stronger ability to find the optimal solution. This is because the algorithm chooses the path based on the evaluation function's minimum value. As a result, finding the ideal solution is simpler by using A* algorithm.

4. Conclusion

The level of consumption has been steadily rising in recent years, and the logistics sector has grown to play a significant role in the national economy. At the same time, the logistics industry has also ushered in continuous growth, which in turn has increased the demand for logistics capabilities. The advantages of short-distance logistics UAV such as intelligence, high informatization and high efficiency, and not being constrained by road grid and related technology applications can greatly save manpower and time in logistics transportation and make goods transported to the receiving place faster, so UAV has important application value in the field of logistics. This article first introduces the importance of UAV path planning technology in the field of short-distance logistics. Secondly, the path planning of UAVs in short-distance logistics applications is divided into two types, and the traditional mathematical algorithm and bionic algorithm are summarized and analyzed from two aspects: traditional mathematical algorithm and bionic algorithm. Subsequently, the advantages and disadvantages of the above method are analyzed based on the available data. Finally, based on MATLAB, two more classical methods are selected from traditional mathematical algorithms and bionic algorithms to carry out path planning simulation experiments in scenarios of different complexity, and the results are analyzed.

In summary, UAV path planning is an important part of UAV short-distance logistics, and a suitable path planning algorithm can improve UAV logistics efficiency, reduce UAV logistics costs, and make large-scale application of UAVs in the logistics field possible. Both traditional algorithms and bionic algorithms have their corresponding advantages and disadvantages, and they will show different results for different scenarios. Therefore, the author believes that with the continuous refinement of application scenarios in the future, different path planning algorithms will be selected according to the corresponding problem requirements to achieve better results.

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