AGRICULTURAL PLANT PROTECTION UNMANNED AERIAL VEHICLE SPRAY PATH PLANNING BASED ON ANT COLONY ALGORITHM
/
基于蚁群算法的农业植保无人机作物喷洒路径规划

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ABSTRACT
The farmland in the southwestern mountainous areas of China is mostly hilly terrain with multiple obstacles, and traditional manual spraying operations are time-consuming and laborious. The use of agricultural plant protection unmanned aerial vehicle (UAV) can reduce the problem of high manual operation costs. To solve the problem of optimizing the spraying operation path of plant protection UAVs, this study focused on the complex agricultural environment in the southwestern mountainous areas of China. First, a 2D agricultural map model with multiple obstacles was constructed using MATLAB. Second, the optimization requirements for job paths were analyzed, and a path optimization model based on the grid graph method was studied, aiming to shorten the total flight distance and reduce the number of paths. By applying the genetic algorithm, efficient optimization of the spraying path of plant protection UAV was carried out. Simulation verification showed that the optimized path significantly shortened the flight distance, accelerated convergence speed, and effectively avoided local repeated paths, thereby greatly improving the spraying efficiency of plant protection UAV.

摘要
中国西南山区农田多为含多个障碍物的丘陵地貌，传统人工喷洒作业费时费力，借助农业植保无人机可以减少人工作业成本高的问题。为解决植保无人机喷洒作业路径优化问题，本研究针对中国西南山区复杂农田环境，首先利用 MATLAB 构建了含多障碍物的二维农田地图模型。随后，分析了作业路径优化需求，研究了基于网格图法的路径优化模型，旨在缩短总飞行距离并减少路径数量。通过应用遗传算法，对植保无人机喷洒路径进行了高效寻优。仿真验证显示，优化路径显著缩短了飞行距离，加快了收敛速度，有效避免了局部重复路径，从而大幅提升了植保无人机的喷洒作业效率。

INTRODUCTION
The application of agricultural plant protection unmanned aerial vehicle (UAV) in foreign countries was first introduced in the United States. The fixed wing UAV produced by Huff Daland Company in 1932 has already been used in the agricultural field. According to statistics, over 9,000 UAVs are used in agricultural fields in the United States, and over 60% of them use UAVs to assist in planting management work. However, American agricultural UAVs mainly rely on fixed wing aircraft and helicopters, combined with advanced remote sensing and flight control technology, which is in line with the flat terrain and large-scale planting characteristics of their farmland. Among Asian countries, Japan was one of the earliest to apply UAVs to agricultural production. In 1958, Japan began using manned UAVs to control pests, diseases, and weeds in farmland. In 1983, the method of manned and unmanned driving working together on farmland was proposed. By 1987, the world's first agricultural UAV had been born in Japan, making it the first country to use crop protection UAV for crop protection operations *(Gago J. et al., 2020)*. Compared with large-scale farmland in the United States, Japan has a smaller per capita arable land area and complex terrain. In addition, the significant reduction in agricultural population and the high cost of manual labor caused by hilly terrain make the development of agricultural UAV in Japan relatively large. Japan's plant protection UAVs mainly rely on oil powered unmanned helicopters, and they have established a comprehensive plant protection service system around unmanned helicopters *(Xu C. et al., 2020)*. They have rich experience in the research and management of specialized pesticides for UAV.

The labels of their specialized pesticides include parameters such as weather restrictions, flight altitude, spray volume, and drift volume, making it convenient for the promotion and use of drugs.

The application of UAVs in China’s agricultural sector was relatively late compared with the United States and Japan. In 2010, the first commercial plant protection UAV appeared. In 2014, it began to enter a stage of rapid development. At present, China has over 100,000 types of agricultural crop protection UAVs, including fixed-wing and rotary-wing UAVs, with multi-rotor UAV being the main type in recent years. The well-known enterprise DJI UAV Company established DJI Agricultural Company in 2015, specializing in the agricultural field, and launched the T series of agricultural UAV. Its latest T50 can achieve the replacement of spraying and broadcasting modules to adapt to agricultural application scenarios. Its load capacity can reach up to 50 kg, and the dual atomization spraying system can make the droplets uniform and fine. When operating on fruit trees, centrifugal nozzles can be added to increase the spraying area and improve the adhesion rate of leaf back medicine. By carrying an active phased array radar and binocular vision system, terrain prediction and obstacle avoidance can be achieved. Some other companies have also launched similar plant protection UAVs *(Zhang H., et al., 2021)*.

Given that the main rice planting areas in China are concentrated in the south, the terrain is mainly irregular mountains and hills. The traditional method of spraying rice paddies mainly relies on individual farmers carrying portable equipment, which has the characteristics of high manual labor intensity and low work efficiency. With the development of UAV technology, using agricultural plant protection UAV for spraying operations has become a trend in modern agriculture. Compared with traditional methods of plant protection operations, plant protection UAVs not only have the characteristics of small size, easy portability, high safety, and the ability to hover freely, but they also can vertically take off and land in small work areas, allowing UAVs to perform spraying operations on various terrains. Therefore, the rational utilization of agricultural plant protection UAV has become a hot topic worthy of research in the current field of agricultural plant protection.

As the application scope of plant protection UAV continues to expand, the working environment faced by UAVs will gradually become complex, and the number of tasks will continue to increase, which may lead to some problems in path planning, such as missed or repeated operations, high energy consumption, long working paths, and inability to effectively avoid obstacles. Path planning is an essential part to improve the operational efficiency and reduce losses of plant protection UAV. Reasonably planning the operation path is the key to achieving safe and efficient operation of plant protection UAVs. In this process, factors such as terrain characteristics, vegetation information, and aircraft performance should be combined to develop path planning algorithms suitable for different terrains and farmland types by combining plant protection UAV with artificial intelligence to achieve efficient and energy-saving plant protection operations. This not only effectively reduces labor costs in agricultural production but also helps reduce pesticide spraying omissions and repetitions, thereby improving agricultural production efficiency and quality and ensuring food security.

At present, scholars at home and abroad have conducted extensive research on the path planning problem of plant protection UAVs. The methods used in the research can be generally divided into two types: one is path planning based on intelligent bionic algorithms. Commonly used examples are grey wolf optimization algorithm, ant colony algorithm, and genetic algorithm. These algorithms are mainly inspired by the intelligent phenomenon of natural biological populations and optimization algorithms were proposed by imitating the behavior of social animals. These algorithms are widely used in path planning research due to their efficient optimization speed and the need to consider too much initial information of the problem. Another type is path planning algorithms based on graph search, such as Voronoi diagram *(Asano H.et al., 2022)*, A* algorithm *(Kong X. et al., 2020)* and Dijkasta algorithm *(Zhang and Bai, 2024)*. These algorithms have strong path search capabilities and usually obtain accurate solutions, but the computational complexity of these algorithms increases with the increase in environmental complexity, resulting in a significant decrease in path planning performance.

When conducting plant protection operations, UAVs need to spray uniform medication on crops in the target area to ensure the effectiveness of the operation. In plain areas, the trajectory planning of plant protection UAV is full coverage path planning based on 2D planes, mainly limited by the battery capacity, load capacity, operation range, and plot shape of the UAV. The main focus is on indicators such as non-plant protection operation duration, plant protection operation trajectory length, operation repetition rate, and omission rate. The full coverage trajectory planning algorithm needs to plan an optimal trajectory that avoids obstacles and traverses the entire area within the region, mainly using the unit decomposition method and grid method.

The unit decomposition method divides the working area of the UAV into multiple accessible sub areas, and the coverage of each subarea becomes a simple reciprocating motion. The grid method decomposes environmental information into squares based on the motion speed and spraying width of the UAV. Each square represents a certain size of land, and it can be divided into idle or occupied squares based on whether there are obstacles in the land. The UAV can then find the optimal route to traverse all squares.

At present, there are mainly two methods for 3D trajectory planning. One is to obtain the height of the UAV relative to the ground and predict the slope of the work site through onboard sensors without obtaining a 3D map in advance to ensure that the UAV always maintains a relative height with the ground and completes the entire operation. Some research provided accurate positioning for UAV through RTK modules and used laser sensors to achieve obstacle avoidance, achieving trajectory planning for UAV under hilly terraced fields *(Wan Y. et al., 2022)*. Another approach is to obtain 3D terrain in advance and combine it with the constraints of the UAV itself for trajectory planning. And some other research rasterized the farmland based on its shape, height, and other information, established a 3D model of the farmland, and compared the planned trajectory of the same farmland on a 2D map and a 3D map. Their results showed deviations in the length of the trajectory and the position of the return point *(Xie H. et al., 2021)*. Using a 2D map for shortest path planning and then combining the performance of the UAV with its operating altitude through a 3D map, the waypoint position during the UAV's flight process can be optimized, thereby ensuring the safety of the UAV in terrain with large altitude changes. In hilly and mountainous environments, the round-trip distance of plant protection UAVs in non-operational situations cannot be ignored. Reducing energy consumption outside of work can prolong the overall operation time of UAVs and improve their work efficiency *(Lambertini A. et. al., 2022)*.

In summary, the current path optimization problem of agricultural plant protection UAVs mostly utilizes various methods for 2D map drawing. It is proposed to integrate the genetic algorithm, neural network algorithm, particle swarm optimization algorithm, artificial potential field method, and other algorithms to obtain the optimal algorithm for plant protection UAVs *(Liu Y. et al., 2022)*. On this basis, this study further designed a path optimization model based on the genetic algorithm for multi-obstacle avoidance scenarios in complex mountainous and hilly terrain to optimize the spraying operation path of agricultural plant protection UAV.

MATERIALS AND METHODS

The fitness function can calculate the cost of the track and compare the cost values of different tracks to determine the quality of the track. This article comprehensively balances three factors: track length, obstacle collision, and height change, and models the fitness function, as shown in formula (1):

$$F=\varphi_1 f_L+\varphi_2 f_C+\varphi_3 f_H \tag{1}$$

Among them: f_H represents the cost of height change, f_C represents the cost of obstacle collision, f_L represents the cost of track length, F represents the cost of track, $\varphi_1, \varphi_2, \varphi_3$ represents the weight values of different costs, and is a constant, and its proportion is related to the tasks performed by the drone.

Problem Description

The principle of path planning for commercial UAV is to traverse all points in point units to complete the task. The path planning of agricultural plant protection UAV is slightly different from commercial UAV. The purpose of the path planning is to start from the workstation, find a work path that traverses all grid lines in the target farmland area without crossing obstacles, and finally return to the work station. At this point, the task is completed. In summary, the goal of path planning for plant protection UAV is to find a Hamiltonian loop with the smallest weight, as shown in Fig. 1.

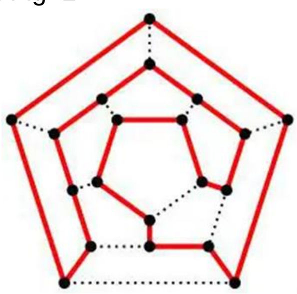

Fig. 1 - Hamiltonian circuit schematic diagram

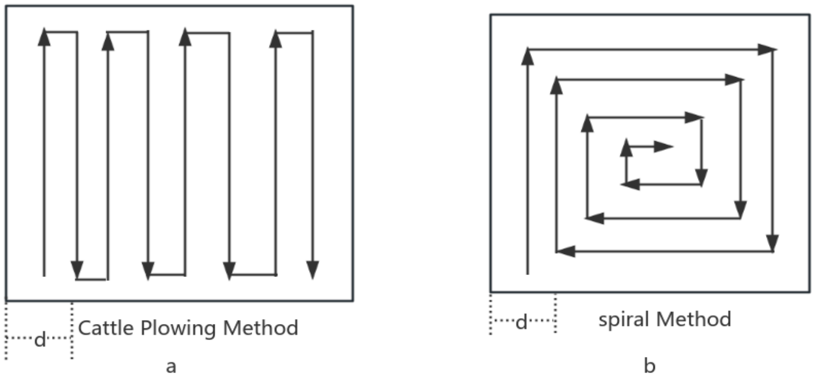

Fig. 2 -Schematic diagram of agricultural plant protection UAV operation coverage

The main problem faced by agricultural plant protection UAV serving farmland in southern China is how to achieve obstacle avoidance. The obstacles in agricultural areas come from two aspects. One is the actual obstacles in the agricultural area, such as power poles and signal towers; the other is the cruising altitude difference caused by the undulating terrain of hilly land. To address this issue, this study uses the ant colony algorithm to optimize the path of agricultural plant protection UAV while considering obstacle avoidance. As a result of the inability of plant protection UAVs to perform spraying operations when turning, to improve work efficiency, combined with the terrain characteristics of the target farmland area and the actual UAV model, this study abandoned the spiral (See Fig. 2 b) covering method and chose the cow plowing (See Fig. 2 a) method as the coverage method for plant protection UAV spraying operations.

Under the cow plowing method, the flight trajectory of the plant protection UAV is a unidirectional straight line. Therefore, the main method for optimizing its path is to determine the total sum of one-way paths, which is the total flight length. In addition, the UAV used in this study cannot perform operations during turns, so the optimization process should minimize the number of turns for the UAV.

Referring to XX's research, the total flight length SBou and total number of turns TBou of plant protection UAV are defined as Formulas (2) and (3), respectively.

$$S_{Bou} = L.ceil(\frac{M}{d}) + d.(ceil(\frac{M}{d}) - 1) \tag{2}$$

$$T_{Bou} = 2(ceil(\frac{M}{d}) - 1) \tag{3}$$

In the formula:

M - The horizontal length of the work area;

L - Vertical width of the work area;

D - The maximum width of UAV operation.

Model Building

The path planning of plant protection UAV first requires a recognizable work environment information map. Currently, common model construction methods include grid graph method, visual graph method, and Voronoi graph method. Given the use of the ox plowing method in this study and considering the ease of achieving full coverage of farmland areas, the grid diagram method was chosen to simulate the establishment of a 2D operation plan for plant protection UAV via MATLAB simulation. When constructing the grid, the width of the UAV operation was set to a fixed spacing and then the path of the divided grid was planned based on environmental information. Compared with the two other modeling methods, the complexity of constructing a work environment using the grid graph method is relatively low, and the constructed graphics are clearer. To better implement the modeling process, this study determined the coordinates of the work area, as well as the coordinates of obstacles and workstations, to set or modify the work area of the plant protection UAV. MATLAB was used to establish a 2D environmental coordinate map including obstacles and workstations, as shown in Fig. 3.

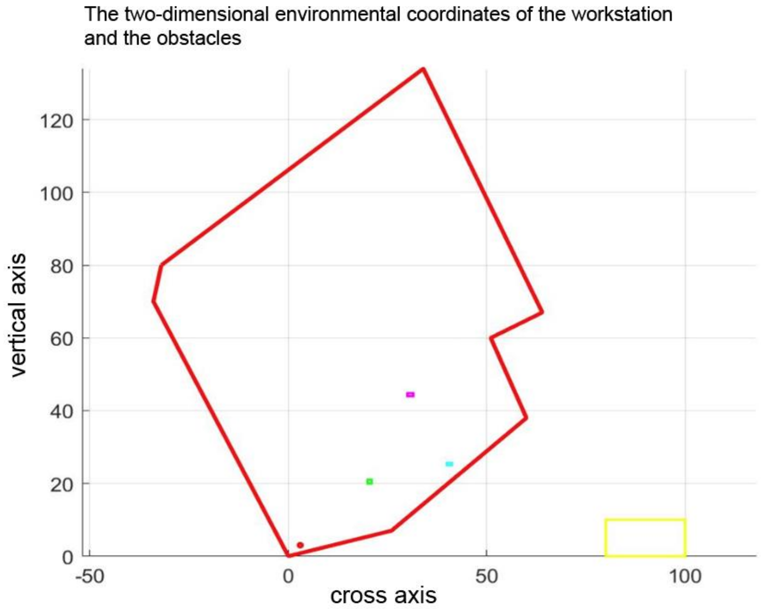

Fig. 3 - Two dimensional environmental coordinate map of plant protection area based on MATLAB simulation

In Fig. 3, the yellow area represents a dedicated workstation for UAV takeoff, landing, and maintenance. The red area is the experimental area selected for this study.

Design of Obstacle Avoidance Methods

Chinese farmland is mostly located in mountainous and hilly terrain, and common obstacles during spraying operations include telecommunications poles, large trees, and agricultural hardware facilities *(Khalilpour S. A. et al., 2020)*. These obstacles have different shapes and irregular distributions. During the process of using the ox plowing method, if there are no obstacles on the moving route, the plant protection UAV will walk between the two ends of the route during non-turning operations, with a distance of Euclidean distance. If there are obstacles on the moving route, the walking route of the plant protection UAV will be separated and obstacle avoidance is required *(Yin X. et al., 2021)*. Therefore, in the actual operation process, plant protection UAV must flexibly avoid obstacles according to their actual situation. On the basis of existing research findings, there are two principles for designing obstacle avoidance methods. One is to avoid crossing obstacles, that is, to stop moving forward when obstacles are detected. Another approach is to detour around obstacles. Considering the accuracy of grid graph simulation, this study adopted the obstacle avoidance design by bypassing obstacles. The principle of detour is shown in Fig. 4.

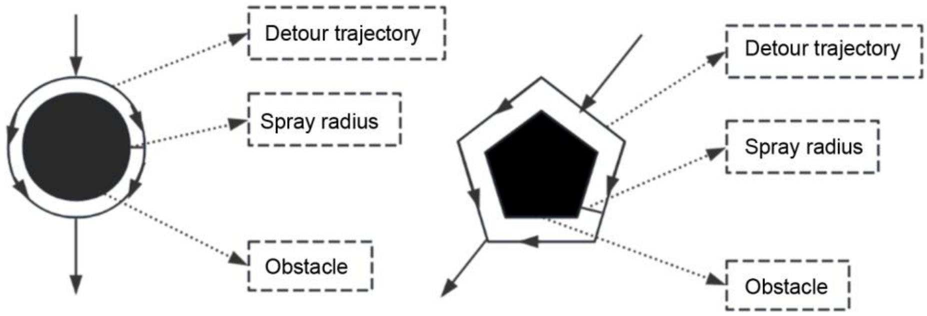

Fig. 4 - Schematic diagram of obstacle avoidance and detour for plant protection UAV

Calculation of Distance Matrix

The obstacle avoidance scheme used in this study requires calculating the shortest path between any two points on the map *(Ampatzidis Y. et. al., 2020)*. For irregular obstacles, there are multiple detours to choose from. Appropriate algorithms must be used to select and calculate the distance between the pre-set endpoints of opposite obstacles, and a short path should be selected for the operation. Therefore, the key to designing obstacle avoidance methods is to determine the shortest distance between endpoints on the route.

The Floyd algorithm was used in this study to calculate the shortest path between any two points in the map. The Floyd algorithm has a time complexity of $O(n^3)$ and a spatial complexity of $O(n^2)$, which can limit the computational complexity to an allowable range *(Xie P. et al., 2024)*. As a result of its compact triple-loop structure, the algorithm performs well in planning dense graphs and can handle problems with positive or negative edge weights. Compared with the Dijkstra algorithm, this algorithm has higher execution efficiency and is simple and effective.

In the Floyd algorithm, a directed graph is first constructed based on known conditions and the intrinsic relationships between nodes, and the shortest distance matrix d is generated based on the weight information between each node. In the distance matrix, $D(i, j)$ represent the weight of the shortest path directly connecting point i and point j. If point i and point j cannot be directly reached, $D(i, j)$=inf. In a directed graph, generally $D(i, j) \neq D(j, i)$.

The routing matrix P is used to record the information of intermediate nodes generated in the distance matrix d. When the sum of the weights of $d[i, k]$ and $d[k, j]$ is less than the previous weight of $d(i, j)$, update the weight of $P[i, j]$ to the intermediate node k. When the sum of the weights of $d[i, k]$ and $d[k, j]$ is greater than the weight of $d(i, j)$, the weight of $P[i, j]$ is not updated. At the end of the loop, the shortest path between any two points can be found in the routing matrix P. Finally, through the obtained routing matrix P, calculate the shortest path length from any point i to point j according to the constructed job area. Let the point set consisting of all endpoints of the grid line be V_1, and the point set consisting of all vertices of obstacles be V_2. The starting point of the UAV is v^* , and all the above points from the point set V, as shown in formula (4):

$$V = V_1 \cup V_2 \cup \{v^*\} \tag{4}$$

Calculate the distance matrix D between any two endpoints based on the point set V, as shown in formula (5), where $Dij \in D$.

$$D_{ij} = \begin{cases} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} & \text{Accessibility between } i \text{ and } J \\ M & \text{otherwise} \end{cases} \tag{5}$$

$M \in R+$, A sufficiently large positive real number.

The distance Dij calculated according to Formula (5) is the direct distance between any two points in the graph, that is, the distance between the two points without obstacles. Correspondingly, it is the indirect distance between two points, which is the shortest path when there are obstacles between the two points. When there are obstacles between two points, the Floyd algorithm proposed in this article needs to be used to calculate the shortest path of the detour. To achieve effective obstacle avoidance of UAV and achieve the optimization goal of minimizing the length of operations, this paper used the following algorithm to construct the shortest path matrix, as shown below:

Input: Point set V

Output: Shortest path matrix R between two points.

1) Calculate the direct distance D in point set V using formula (5).

2) Using the Floyd algorithm, calculate the shortest path matrix R between any two points in set V based on the distance matrix D.

3) Due to the fact that the vertices of obstacles do not necessarily belong to the vertices of the grid lines. Therefore, by removing all rows and columns corresponding to points (V_2-V_1) included in V_2 but not in V_1 from R, the matrix R is obtained.

4) Output the shortest path matrix R.

RESULTS

Determination of the Shortest Path

The traditional ant colony algorithm was initially used to solve the traveling salesman problem, which requires traversing all points during planning *(Tian H. et al., 2023)*. The path planning problem of plant protection UAV is based on line segments as the basic unit of operation, which requires traversing all grid lines in the operation area to complete the task of full coverage of the operation area. When using the ant colony algorithm for path planning, first, set the endpoints of the grid lines to ensure that the plant protection UAV can operate based on line segments.

When a UAV reaches a certain endpoint, the primary problem to be solved in path planning is how to select the other end point of the line segment that this endpoint is facing. On the basis of the above issues, this article proposes the following solutions for the application of the ant colony algorithm in plant protection UAV.

To ensure that the plant protection UAV traverses all grid lines in a basic unit of line segments, the first step is to process the line segments formed by the two endpoints of the grid lines. Therefore, this article processed the shortest path matrix R, as shown in Formula (6):

$$\overline{R_{ij}} = \begin{cases} 0 \quad i \neq j, \quad \text{Endpoints belonging to the same network cable} \\ \qquad R_{ij} \qquad\qquad \text{otherwise} \end{cases} \tag{6}$$

After processing, the UAV will inevitably pass through another endpoint of the same grid line when it first reaches one end of the grid line. Thus, the plant protection UAV can traverse all line segments during operation and complete the full coverage task.

Ant Colony Algorithm Process

This study defined all grid lines as a set L, and any grid line $L_i \in L$, $i = 1,2,3,\cdots,n$. The two endpoints of Li are v_{i1} and v_{i2}, respectively (where $v_{ij} \in V1$, $j = 1, 2$, V_1 is the set of points formed by all endpoints of the grid lines shown in the previous section). The specific implementation steps of the ant colony algorithm based path planning for plant protection UAV proposed in this article are as follows:

Step 1: Construct the operation map of the plant protection UAV.

Step 2: Initialize the number of ants m in the ant colony algorithm, the maximum number of iterations *NC- max*, the pheromone constant *Q*, the pheromone weight factor *α* , the heuristic function weight factor *β*, and the volatility coefficient *Å*.

Step 3: Randomly select v_{ij} as the starting point for the ants, and set a variable *tabuk* to store the points that the ants have passed.

Step 4: The ant starts from point $v_i \in V_1$ and selects the next point v_j from *Allowedk* based on the concentration of pheromones on the path and the heuristic function. The calculation formula is shown in Formula (7).

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \times \left[\eta_{ij}(t)\right]^{\beta}}{\sum\left[\tau_{is}(t)\right]^{\alpha} \times \left[\eta_{is}(t)\right]^{\beta}} & s \in Allowed_k \\ 0 & else \end{cases} \tag{7}$$

In the formula:

$P_{ij}^{k}(t)$: The probability of ant *k* from point *i* to j at time *t*;

$\tau_{ij}(t)$: The intensity of pheromones on the connection path from point i to point j at time t;

α : Pheromone weight factor;

$\eta_{ij}(t)$: The expected degree of ant transfer from point *i* to point *j*;

β : Heuristic function weight factor;

$Allowed_k$: Stores the points that ants are waiting to access;

Step 5: Check if there are any points in the $Allowed_k$ that need to be accessed. If not, record the current route. Otherwise, return to step 4.

Step 6: When ants choose the next line segment to work on, they will release pheromones along their path, and the concentration of pheromones that have already walked along the path will evaporate over time. Therefore, when all ants traverse all line segments, the pheromone concentration on the job path must be updated, as shown in Formulas (8) and (9).

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \\ \Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \end{cases} \tag{8}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q / L_k \quad , \quad ant \quad K \quad from \quad i \quad to \quad j \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad else \end{cases} \tag{9}$$

In the formula:

$\rho(0<\rho<1)$: Volatility coefficient of pheromones;

$\Delta\tau_{ij}(t)$: The total concentration of pheromones released by all ants on paths *i* to *j*;

$\Delta\tau_{ij}^{k}(t)$: The concentration of pheromones released by the k-th ant on paths *i* to *j*;

Q: Constant, representing the total amount of pheromones released by ants in one cycle;

L_k: The path length of ant k after traversing all the job grid lines.

Step 7: Check if the number of times the ant has traversed has reached the maximum number of iterations. If it has, output the optimal solution. Otherwise, return to step 3.

The flowchart of the application of ant colony algorithm in plant protection UAV is shown in Fig. 5.

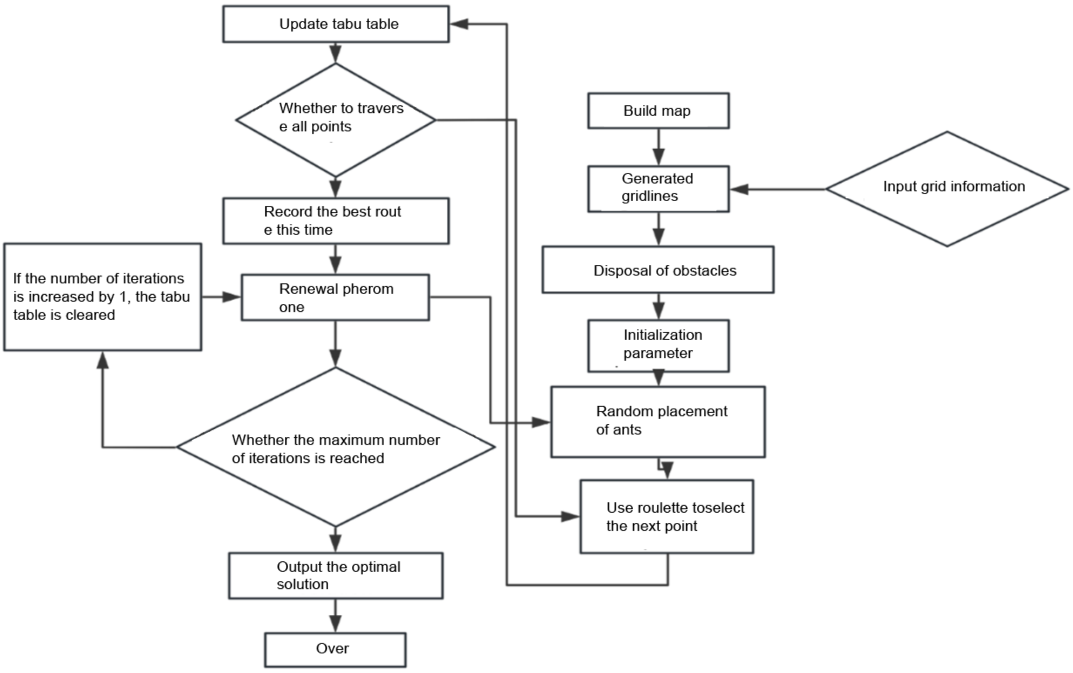

Fig. 5 - Algorithm flow

Simulation Results and Analysis

In general, changes in pheromone weight factor, number of ants, heuristic function weight factor, maximum number of iterations, pheromone volatility coefficient, and total pheromone quantity can all affect the optimization effect of ant colony algorithm. To date, there is no mathematical method that can directly solve for the most parameter settings, and the parameters need to be set through empirical or experimental methods. This study referred to the former research to set the parameters of the ant colony algorithm *(Liu Lu et al., 2024; Tian H. et al., 2023)*, with specific values shown in Table 1.

Table 1

Parameter Settings of Ant Colony Algorithm

Parameter	Parameter value setting
Maximum number of iterations	500
Ant count	100
Heuristic function weight	10
Pheromone weighting factor	1.0
Total amount of pheromones	200
Volatility coefficient	0.9

The software system for this simulation experiment was WIN10 and M atlab2021; the hardware platform was Intel (R) Core (TM) i5-6200U CPU @ 2.30GHz, with 8GB of memory. The experimental plot is located in Guang'an, southwestern China, and its shape and obstacle distribution are shown in Figure 3. According to Figure 3, the coordinates of the plot are arranged counterclockwise as (−32, 80), (−34, 70), (0, 0), (26, 7), (60, 38), (51, 60), (64, 67), (34, 134), and the coordinates of the workstation are (−10, −40), (10, −40), (10, −50), (−10, −50). Adjust the unit as needed in meters. The relevant information about obstacles is shown in Table 2.

Table 2

Obstacle Information

Obstacle name	Grid 2D coordinates
Basic farmland facilities	(40,27), (41,27), (41,28), (40,28)
Water storage well	The center coordinates are (3, 2) with a radius of 0.5
Telecommunications facilities	(18,20), (19,20), (19,21), (18,21)
Power facilities	(35,44), (36,44), (36,45), (35,45)

The spraying width of the local plant protection UAV was 6 m. Considering the departure position of the UAV from the workstation, it entered the experimental site in a 135° operation direction for work and finally returned to the UAV departure workstation. Therefore, in the simulation experiment, initial settings were made based on the above conditions, and the obstacle avoidance method of this study was adopted. The experimental results are shown in Fig. 6. The new path enabled the plant protection UAV to effectively avoid all obstacles and plans an optimal path from the starting point to traverse all trajectories before returning to the starting point, verifying the effectiveness of the proposed algorithm.

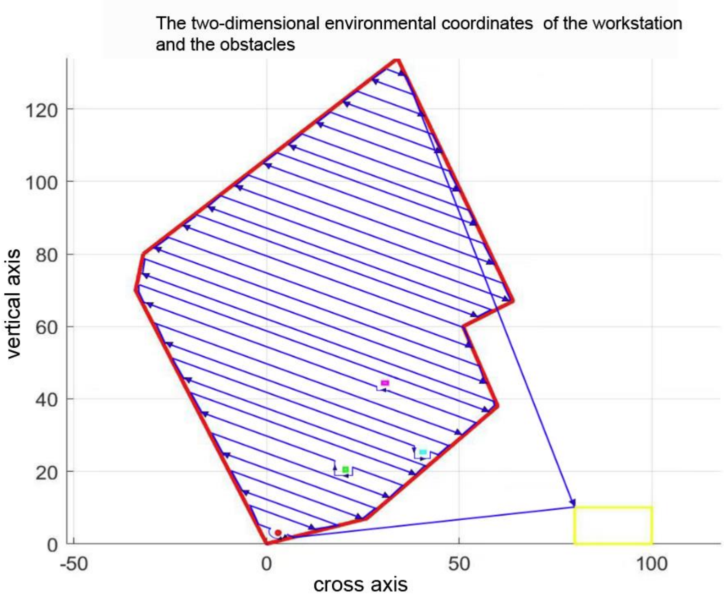

Fig. 6 - Results of Path Optimization Operation

The red curve in Fig. 6 represents the average path length planned by the ant colony algorithm, whereas the blue line represents the shortest path length. The graph shows that the ant colony algorithm had relatively small fluctuations in the overall average data when planning the path of plant protection UAV. The algorithm could quickly converge to the optimal path, as shown in Fig. 7.

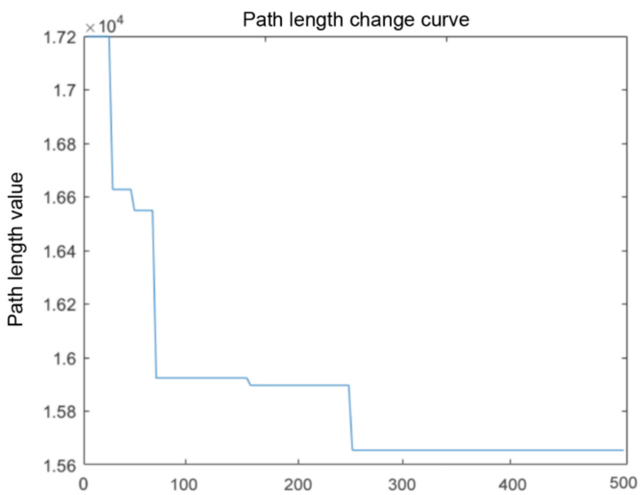

Fig. 7 - Algorithm iteration diagram

To further verify the performance of the ant colony algorithm in path planning of plant protection UAV, this paper compared the operation path of plant protection UAV with that of traditional cattle plowing method in the grid graph. Path planning of plant protection UAV with obstacles reduced the repetition of local paths compared with the traditional cattle plowing method (from 15% of repeated paths to 2.7% occasionally), and the spraying coverage rate was 100%. These data showed that the ant colony algorithm remarkably optimized the operation path of the plant protection UAV, effectively improving its operational efficiency. Further observation of the variance data of the shortest path planned by the ant colony algorithm in the table revealed that the optimal path length planned by the ant colony algorithm was relatively stable. The above analysis indicated that the ant colony algorithm was superior in path planning for plant protection UAV.

CONCLUSIONS

This study mainly optimized the spraying operation path of plant protection UAV in a certain farmland area of a southwestern city in China. First, considering reasonable obstacle avoidance, the shortest detour distance was calculated using the Floyd algorithm to construct the optimal path model for plant protection UAV. Second, the ant colony algorithm was used for experimental design, and MATLAB was used for simulation experiments. Results showed that the path planning method based on the ant colony algorithm proposed in this section was feasible, and its coverage range and total operation path were better than traditional ox plowing methods. Given the topography of the research object, the proposed approach is mainly applicable to farmland with small hilly terrain. When the land area is large, multiple plant protection UAVs may be simultaneously deployed for optimal path planning. In addition to mature applications in the agricultural field, UAV path planning has the feasibility of further expansion in commercial fields (such as UAV express delivery routes), cultural tourism, and sports (such as optimizing the performance paths of UAVs in sports stadiums and spraying operations on football fields). The limitations of further application of the results of this study mainly lie in two aspects: first, some geomorphic environmental wind fields in the mountainous areas of southwest China change greatly in real time, and the UAV may be interfered with in the process of plant protection operation; second, this study mainly considers the operation scenario of contiguous farmland area, and does not consider the operation scenario of non-contiguous multi-farmland area. In the future, the application of this path optimization model in plant protection operations of multiple farmland under complex wind field environment in mountainous areas will be further verified.

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