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Route Planning of Intelligent Agricultural Inspection Robots Based on Improved Ant Colony Algorithm

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Abstract

Route planning for agricultural inspection robots is an extremely complicated combination optimization problem. The traditional optimization method cannot solve the problem of agricultural robot inspection routes, which is different from the classical TSP problem. The reason is that the coordinates of the agricultural robot inspection route are not completely connected. Therefore, an improved ant colony algorithm was proposed for route planning of agricultural inspection robots. First, the initial structure of ant colony pheromone was established, and the motion matrix of the target area was obtained. The kinematic constraints of the intelligent patrol robot were set, and the robot route planning evaluation function was constructed based on the improved ant colony algorithm. Second, an intelligent inspection robot route planning algorithm was designed by calculating the inspection completion of the inspection robot. Results show that, compared with those of the traditional ant colony algorithm, the average route length of the improved ant colony algorithm is reduced by 3.45%, and the efficiency of the algorithm is improved by 22.97%. Moreover, it has better stability and convergence and achieves better results in actual inspection tasks.

Keywords: Agricultural inspection robot, Route planning, Improved ant colony algorithm, Optimization

1. Introduction

Agricultural inspection robots, as a new type of robot, can autonomously run and complete various activities in the whole agricultural production process. These robots with different actuators and sensors can clearly perceive and respond to different signals and information in complex farmland environments and complete the detection and analysis of climate, soil, and crop growth state, which can help realize farmland management and production automation. Agricultural inspection robots can provide scientific and reasonable crop management suggestions for farmers by detecting environmental information, such as soil moisture, nutrient content, temperature, and humidity in farmland. In addition, they can monitor the growth of crops through cameras, infrared sensors, and other technologies, including growth height, stem diameter, and leaf color, and find problems in plant growth over time. Agricultural inspection robots can independently complete fertilization and spraying of drugs according to different needs of crops, avoid manual operation errors, and improve the efficiency and accuracy of fertilization and spraying [1].

In recent years, various robots used in agricultural production have gradually become an important part of equipment research and development and agricultural technology, which is indispensable for the development of concentrated agriculture [2]. To a certain extent, the development and application of agricultural robots have alleviated the problems of unreasonable rural structures and labor shortages, influenced the agricultural labor mode, and promoted the development of modern agriculture. Undoubtedly, agricultural robots will greatly contribute to the safe, high-efficiency, and green development and intelligent production of agriculture. Agricultural robots will gradually replace manual labor and reduce the labor intensity in agricultural production, and agriculture will also occupy a place in the robot industry [3]. Meanwhile, robots can improve labor efficiency and solve the labor shortage problem in many countries. These advantages have made agricultural robots increasingly concerned by countries all over the world.

In the intelligent fruit and vegetable greenhouses of demonstration farms in China and Israel, the first artificial intelligent agricultural robots officially started 24h production inspection [4]. The inspection agricultural robot is a white cartoon character with clear facial features and limbs. It can realize 360° rotation movement through the wheels and universal mechanism at the bottom and independently and smoothly conduct automatic inspection, automatic turning, fixed-point collection, automatic return, and automatic charging along the culture tank [5]. Various sensors of the inspection robot upload the data containing environmental temperature and humidity, soil humidity, soil temperature, and soil fertility in the agricultural production process to the cloud server in various networking ways and then feedback the optimal solution to the control organization through the integration, analysis, and processing of the data by the system. Finally, specific operations, such as sprinkler irrigation, light supplementation, drip irrigation, heating, shading, ventilation, and CO2 supplementation, will be performed.

2. State of the art

The rapid development of technologies, such as big data, cloud platforms, block chains, the Internet of Things, smart

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grids, and mobile communication, has driven the rapid growth of system information. Operation and maintenance personnel need to log in to specific equipment every day, check the inspection information of smart agriculture, and fill in the registration form manually. However, such a large amount of data may be omitted and filled in incorrectly, which will directly lead to untimely fault detection. Agricultural inspection robots can complete data collection and processing through mechanical equipment, which can eliminate possible human errors.

The agricultural inspection robot must move on the feasible route, which is different from the TSP problem in classical route planning. The traditional optimization algorithm can barely solve this problem. At present, the intelligent algorithms proposed for route planning in China and foreign countries include the neural network algorithm [6], particle swarm optimization algorithm [7], and ant colony algorithm [8]. The neural network algorithm has self-learning ability and can find the optimal solution at a high speed, but it easily falls into the local minimum and has low accuracy [9]. The ant colony algorithm has good robustness and can be combined with other methods, but it has some problems, such as a long calculation period and easy deadlock. The ant colony algorithm, as a global optimization method based on natural heredity and natural selection, has been widely used in the field of route planning [10]. Ma et al. introduced an improved ant colony algorithm with reverse mutation to avoid the mutation operation from generating new routes that do not meet the requirements [11]. Fan et al. [12] used distant mating in cross recombination, which can effectively prevent repeated routes of the next generation. However, Luo et al. and Chang et al. did not propose effective methods to prevent falling into a local optimal solution [13-14]. Behnck et al. and Zhong et al. introduced an elite reservation strategy into the ant colony algorithm to ensure that the algorithm jumps out of local extremum [15-16]. Luo M. et al. proposed a hierarchical route planning method combined with the Q-learning algorithm and ant colony algorithm [13]. Dian et al. proposed a method of adaptive adjustment of the crossover rate and mutation rate considering individual fitness to improve the convergence performance of the ant colony algorithm [17]. However, the abovementioned algorithms have the problem of gene stability in the mutation process. In the late iteration, some excellent genes will degenerate due to mutation, which will affect the convergence performance of the algorithm.

Route planning ability, in addition to the ability of information collection and processing, is also necessary for intelligent inspection robots [18-19]. Molina et al., Shao et al. and Song et al. all used the locust optimization algorithm, using the beta function as the initial solution in the population space, adjusting its distribution uniformity in space, and achieving the optimal design of control parameters [20-22]. Adhikary et al. and Jiang et al. used the hop search method to obtain the global route planning strategy and obtained the global optimal route with high smoothness at a faster speed combined with the optimized A* algorithm and the dynamic window method, which improved the application value of the algorithm [23-24]. Zhang et al. designed a route planning model based on discrete multi-objective cuckoo with multi-objective collaborative optimization as the core and defined and absorbed the update strategy of global optimization under a multilayer coding mechanism [25].

In view of the shortcomings of the traditional ant colony algorithm, such as poor convergence and local optimal solution, the concepts of adaptive mutation operator, elimination operator, and “distant mating” were introduced to improve the convergence speed and calculation accuracy. The advantages of the improved ant colony algorithm in the actual inspection task were verified by simulation. The experimental results show that the improved ant colony algorithm can optimize the mobile efficiency. On the basis of the abovementioned literature, this study designed a route planning method for intelligent inspection robots for power information network equipment based on an improved ant colony algorithm.

3. Construction of the route planning evaluation function of agricultural inspection robots

3.1 Locating search nodes of intelligent agricultural network equipment

In the route planning process of the intelligent inspection robot, multiple search nodes were set and located, which were the parts that the robot must pass through in the process of completing the task. After the robot avoided obstacles, it returned to the fixed route to avoid missing the positioning node. The trajectory of the inspection robot with a high-order polynomial was optimized by the subsection method to make it continuous. The route can be expressed as follows:

$$k_p(t)=\sum_{i=1}^{n}\left(\frac{f_n}{t_i}\right)^2 \tag{1}$$

where $k_p(t)$ is the polynomial programming result of the tth route, f_n is the curve of n short routes, and t_i is the time required for the ith route.

In this route, the starting and ending points of the search node can be obtained:

$$\begin{cases} k_1(t_0)=F_1 \\ k_{n+1}(t_n)=F_{n+1} \end{cases} \tag{2}$$

where $k_1(t_0)$ is the route of starting point k_1 at t_0 , F_1 is the distance traveled at this time, $k_{n+1}(t_n)$ is the route of end $k_{n+1}(t_n)$ at t_n , and F_{n+1} is the distance traveled during this time period.

Combined with the whole route, the following formula can be obtained:

$$k(t)=\begin{cases} k_1(t)=\sum_{i=1}^{n}\left(\frac{F_1}{t_0}\right)^2, t_0\le t\le t_1 \\ k_2(t)=\sum_{i=1}^{n}\left(\frac{F_2}{t_1}\right)^2, t_1\le t\le t_2 \\ \vdots \\ k_n(t)=\sum_{i=1}^{n}\left(\frac{F_i}{t_{n-1}}\right)^2, t_{n-1}\le t\le t^n \end{cases} \tag{3}$$

where $k(t)$ is the function value represented by each endpoint in the piecewise function and t_0, t_1, t_{n-1}, t_n is the time at each endpoint [8]. Under such a preset optimization problem, the time coefficient can be obtained according to a certain proportion:

$$t_n = \left(\frac{F_{\max}(t)}{G_m} \right)^{\frac{1}{n}} \tag{4}$$

where t_n is the time required for preset optimization in a certain proportion under the nth subsection, $F_{max}(t)$ is the maximum function value under the piecewise function in different time periods, and G_m is the expected value of the physical quantity. Combined with the abovementioned formula, the search node of the intelligent inspection robot can be located.

3.2 Construction of the evaluation function of agricultural inspection robot route planning

In the process of searching the route planning result, the extended nodes were used to decrease the complexity of the algorithm and the number of iterations. This way could shorten the running time of the algorithm and improve the efficiency. At this point, the search node of each intelligent agricultural network device was located. The actual cost of each node is as follows:

$$p(m) = \sqrt{\frac{(G_x - E_x)^2}{(G_y + E_y)^2}} \tag{5}$$

where $p(m)$ is the actual cost of each search node of intelligent agricultural equipment; G_x and G_y are the horizontal and vertical coordinates of the starting point, respectively; E_x and E_y are the horizontal and vertical coordinates of the end point, respectively. Combined with this cost function, the heuristic functions of intermediate nodes and target nodes can be redefined, and the pheromone of the ant colony algorithm can be initialized. In the improved ant colony algorithm, pheromone is generally used as the route information of the agricultural inspection robot during driving, and its storage structure is shown in Fig. 1.

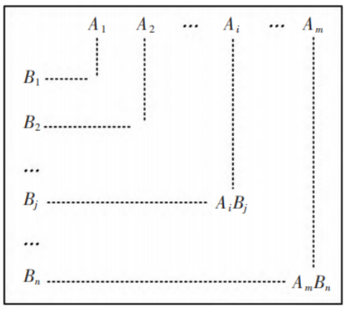

Fig. 1. Initialization structure of ant colony pheromone

In the initialization process of the ant colony pheromone, as shown in Fig. 1, the motion matrix of the agricultural inspection robot in the target area can be established:

$$f_{mn} = \left(\begin{bmatrix} \cos(\lambda_m) \\ \sin(\lambda_m) \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} \cos(\lambda_n) \\ \sin(\lambda_n) \\ \vdots \\ 0 \end{bmatrix} \right) \times H_{mn} \tag{6}$$

where f_{mn} is the motion matrix of the agricultural inspection robot in the target area $m \times n$; λ_m and λ_n are geometric constraint parameters of the target area on the horizontal and vertical coordinates, respectively; and H_{mn} is the circumferential curvature of the agricultural inspection robot. Combined with this motion matrix, the kinematic constraints of the intelligent inspection robot can be determined:

$$G(\lambda_m, \lambda_n)\text{Ö}0 \tag{7}$$

Where $G(\lambda_m, \lambda_n)$ is the constraint posture of the target area. Based on the improvement, the route planning evaluation function of the agricultural inspection robot is calculated:

$$k(x) = \sqrt{\frac{t(x)}{h(x) + b(x)}} \tag{8}$$

where $k(x)$ is the planning and evaluation function of the agricultural inspection robot in this route; $t(x)$ is the time parameter; $h(x)$ is the minimum cost function; and $b(x)$ is the route search function. Combined with the abovementioned formula, the route planning evaluation function of the agricultural inspection robot based on the improved ant colony algorithm can be obtained.

4. Design of the route planning algorithm of agricultural inspection robots

4.1 Motion model of agricultural inspection robots

Under the action of the improved ant colony algorithm, a complete motion model expression needs to be established according to the X-axis, Y-axis, and Z-axis coordinates of the current node of the robot to accurately grasp the global motion route of the agricultural inspection robot. If the agricultural inspection robot does not have the possibility of omnidirectional motion, then it can only complete simple rotation and forward motion in a given route area. Only the motion state difference of the robot at two adjacent moments needs to be considered when solving the motion model [4]. Given that the motion behavior of the agricultural inspection robot at adjacent moments satisfies the recording and marking of the linear motion behavior, the actual angular velocity and linear velocity of the robot will not be obviously different from the initial value given by the velocity vector under the condition that the rotation angle value is unchanged. θ is defined as the steering angle of the agricultural inspection robot, and its value must meet the definition condition of 0°<θ<90°. The motion model of the agricultural inspection robot is expressed as follows:

$$\begin{cases} X = \dfrac{\vec{X} \cdot \sin\theta}{M^2} \\ Y = \dfrac{M}{\vec{Y} \cdot \cos\theta} \\ Z = \dfrac{\sqrt{\vec{Z}} \cdot \tan\theta}{M} \end{cases} \tag{9}$$

where X is the X-axis definition condition, $\vec{X}$ is the X-axis normal vector, sinθ is the sine value of the steering angle θ, Y is the Y-axis definition condition, $\vec{Y}$ is the Y-axis normal vector, cosθ is the cosine value of the steering angle θ, Z is the Z-axis definition condition, $\vec{Z}$ is the Z-axis normal vector, and tanθ is the tangent value of the steering angle θ. The sine, cosine, and tangent values of the steering angle may be transformed. Thus, a transformation relationship also exists between the definition conditions of the X, Y, and Z axes of the robot motion model.

4.2 Sampling of the inspection speed of agricultural inspection robots

After the definition standard of the motion model of the agricultural inspection robot was determined, several different speed parameters were selected according to the improved ant colony algorithm to simulate the global motion trajectory of the agricultural inspection robot. Given that the robot speed sampling results corresponding to different speed parameters differed, the set space using speed indicators was infinite and recyclable. Under the action of the improved ant colony algorithm, the driving force of the agricultural inspection robot was completely provided by the motor components. Therefore, the robot will display faster when the physical value of the power driving coefficient is greater. The velocity vector in the X-axis direction is set as $\hat{X}$, the velocity vector in the Y-axis direction is set as $\hat{Y}$, and the velocity vector in the Z-axis direction is set as $\hat{Z}$, λ is the global adoption coefficient of the robot motion vector, and ϖ is the sampling feature of the velocity parameters based on the improved ant colony algorithm.

The sampling expression of the motion speed of the agricultural inspection robot is as follows:

$$s = \frac{X^2 \times Y^2 \times Z^2}{\sqrt{\lambda\left(\hat{X} + \hat{Y} + \hat{Z}\right)}} \tag{10}$$

To make the speed sampling results more in line with the global motion characteristics of the agricultural inspection robot, the $\hat{X}$, $\hat{Y}$, and $\hat{Z}$ vectors cannot be the maximum and minimum results simultaneously, and the values of the three index parameters cannot be zero simultaneously.

4.3 Estimation of the inspection step value of agricultural inspection robots

Step size estimation is also called trajectory measurement of agricultural inspection robots. In the global route trajectory, the physical interval between adjacent route nodes is greater when the absolute value of the step value index is larger. If the absolute value of the step value index is relatively small, then the physical interval between adjacent route nodes is small. $\tilde{X}$ is the numerical component of the motion step value of the agricultural inspection robot in the X-axis direction, $\tilde{Y}$ is the numerical component of the motion step value in the Y-axis direction, $\tilde{Z}$ is the numerical component of the motion step value in the Z-axis direction, X_0 is the initial assignment of the motion index in the X-axis direction, Y_0 is the initial assignment of the motion index in the Y-axis direction, and Z_0 is the initial assignment of the motion index in the Z-axis direction.

The estimation results of the global motion step value of the agricultural inspection robot are as follows:

$$d = \frac{\sqrt{\left(\tilde{X} - X_0\right)^2 + \left(\tilde{Y} - Y_0\right)^2 + (\tilde{Z} - Z_0)^2}}{\psi \cdot s} \tag{11}$$

Where ψ is the movement step of the robot. When implementing the global route planning of agricultural inspection robots, we should not only refer to the improved ability of the ant colony algorithm but also pay attention to the appropriate value of the step value index. This way not only can avoid the excessive stride movement of the robot but also can effectively control the deviation between the actual detection trajectory and the preset motion trajectory.

4.4 Route planning algorithm of agricultural inspection robots

By combining the position of the search node and the evaluation function, the route planning algorithm of the agricultural inspection robot can be obtained by combining the position of the search node and the evaluation function. First, the initial node was input, and the loss function in the network was calculated by the improved ant colony algorithm. Second, the relative characteristics of the target node and the search node were determined by the loss function. The inspection completion degree of the agricultural inspection robot was obtained:

$$U_m = \frac{F_1(e_m - e_m^{'})}{\sum_{i=1}^{m}(d_i - d_j)^2} \tag{12}$$

Where U_m is the inspection completion coefficient. When U_m >0, the agricultural inspection robot has completed the overall inspection work, and no obstacle prevents it from entering the target area. When U_m =0, the agricultural inspection robot has not completed the normal work.   is the weight parameter. e_m and $e_m^{'}$ are the actual inspection point and the updated inspection point, respectively. d_i and d_j are the completion degrees of the ith and jth maintenance operations, respectively. The abovementioned contents can be used as the route planning algorithm of the agricultural inspection robot, and the driving route of the agricultural inspection robot in actual operation can be obtained through this algorithm.

The improved ant colony algorithm was used on the basis of the abovementioned obstacle avoidance route planning objectives to obtain the optimal obstacle avoidance route planning results. In the application process of the improved ant colony algorithm, the pheromone updating method is important to determine whether the best obstacle avoidance route can be found quickly. Therefore, the pheromone updating method should be changed correspondingly. The improved pheromone updating formula is as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{\alpha=1}^{m}\Delta\tau_{ij}^{\alpha} + \Delta * \tau_{ij} - \Delta ** \tau_{ij} \tag{13}$$

Where $\tau_{ij}(t+1)$ and $\tau_{ij}(t)$ are the pheromone concentration on the obstacle avoidance route $<i,j>$ at $t+1$ and time, respectively; $\Delta\tau_{ij}^{\alpha}$ is the volatilization coefficient of pheromone; is the pheromone concentration of the α ant on the obstacle avoidance route; m is the total number of ants; $\Delta*\tau_{ij}$ and $\Delta**\tau_{ij}$ are the pheromone concentrations on the local optimal and worst obstacle avoidance routes, respectively, and their calculation formulas are as follows:

$$\Delta^{*}\tau_{ij}=\begin{cases}\delta(Q/L^{*}), \textit{Local optimal obstacle avoidance route passes} <i,j> \\ 0, other\end{cases} \quad (14)$$

$$\Delta^{**}\tau_{ij}=\begin{cases}\omega(Q/L^{**}), \ \textit{Local worst obstacle avoidance route passes} \ <i,j> \\ 0, other\end{cases} \quad (15)$$

where δ and ω are the number of ants needed to find the local optimal and worst obstacle avoidance routes, respectively; Q is the total route length; and L^{*} and L^{**} are the lengths of the local optimal and worst obstacle avoidance routes, respectively.

Based on the improved ant colony algorithm, a process for detecting the obstacle avoidance route planning of robots is developed as follows:

(1) The working environment information of the agricultural inspection robot is transformed into a matrix, and the internal element value is 0 or 1. A value of 0 represents a normal environment, and 1 represents obstacles.

(2) Initialization improves the parameters of the ant colony algorithm, such as the maximum number of iterations and pheromone volatilization coefficient. Ants search for obstacle avoidance routes from the starting point.

(3) The inspection route is determined. If obstacles are present on the next route, then other routes will be searched. If no obstacle is present on the next route and the target point is not reached, then the inspection robot continues moving. If the end point of the next route is the target point, then the obstacle avoidance route will not be searched.

(4) The pheromone concentration value is updated according to Formula (2).

(5) Whether the number of iterations has reached the maximum is determined. If the maximum number of iterations is reached, then the center point smoothing method is used to address the obstacle avoidance route. Instead, step 3 is continued.

(6) The optimal obstacle avoidance route planning result of the inspection robot is output.

5. Route planning of agricultural inspection robots based on the improved ant colony algorithm

5.1 Simulation experiment

This study assumes that 34 agricultural inspection robots are present at the agricultural inspection points, and their positions are represented by the values of coordinates X and Y. The speed of the agricultural inspection robot is known, and the coordinates of 34 inspection points are shown in Table 1. The layout of 34 inspection points is shown in Fig. 2.

Table 1. Coordinates of inspection points

Inspection point	Coordinate X	Coordinate Y	Inspection point	Coordinate X	Coordinate Y
1	13.04	23.12	18	40.61	23.7
2	36.39	13.15	19	37.8	22.12
3	41.77	22.44	20	36.76	25.78
4	37.12	13.99	21	40.29	28.38
5	34.88	15.35	22	42.63	29.31
6	33.26	15.56	23	34.29	19.08
7	32.38	12.29	24	35.07	23.67
8	41.96	10.04	25	33.94	26.43
9	43.12	7.9	26	34.39	32.01
10	43.86	5.7	27	29.35	32.4
11	30.07	19.7	28	31.4	35.5
12	25.62	17.56	29	25.45	23.57
13	27.88	14.91	30	27.78	28.26
14	23.81	16.76	31	23.7	29.75
15	13.32	6.95	32	29.31	36.76
16	37.15	16.78	33	19.08	40.29
17	39.18	21.79	34	5.11	12.44

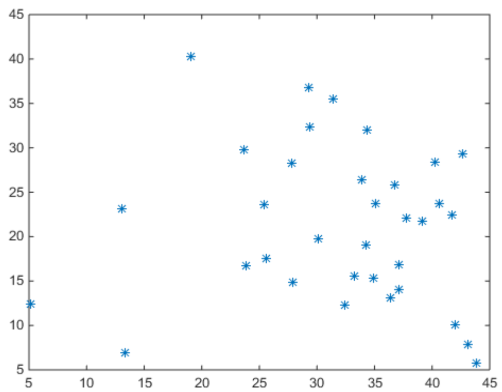

Fig. 2. Layout of inspection points of agricultural robots

This study conducted experiments on an Intel i7 processor using MATLAB 2014a and solved the optimization model of the inspection route of agricultural robots through the improved ant colony algorithm. The related parameters are set as follows: the number of ants m=50; pheromone importance factor alpha=1; importance factor of heuristic function beta=5; pheromone volatilization factor rho=0.1; constant coefficient Q=1; heuristic function Eta=1./D; pheromone matrix Tau=ones(n,n); initial value of iteration number iter=1; route record table = zeros(m,n); maximum number of iterations iter_max=200; optimal route_best=zeros(iter_max,n); length of the best route of each generation Length_ best =zeros (iter_max,1); and average length of each generation route Length_ave=zeros(iter_max,1). Agricultural robots must stop at all monitoring points during the inspection. The improved ant colony algorithm and the traditional ant colony algorithm were used to simulate and test, respectively, and the corresponding calculation results were compared.

5.2 Result analysis

The improved ant colony algorithm was used to optimize the detection route of the agricultural inspection robot for 200 times for eliminating the influence of various random factors and verifying the advantages and disadvantages of the improved ant colony algorithm. The convergence curve of the improved ant colony algorithm is shown in Fig. 3, and the optimal route of the agricultural inspection robot is given in Fig. 4.

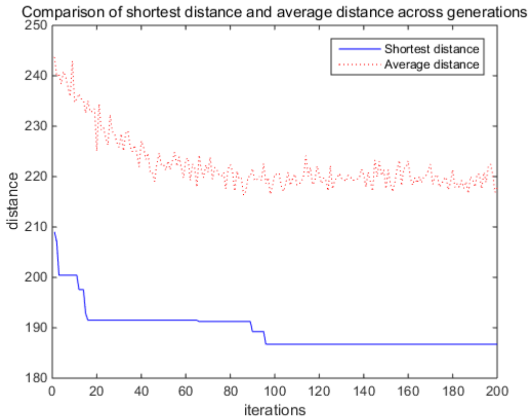

Fig. 3. Convergence curve of the improved ant colony algorithm

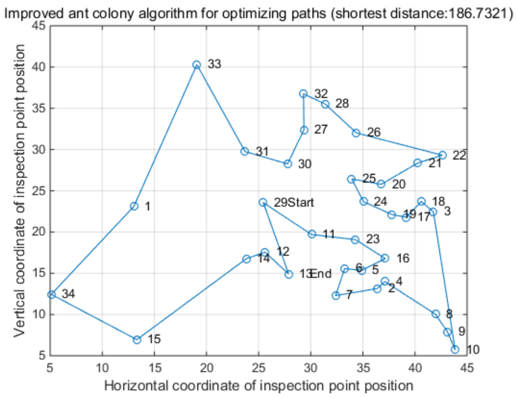

Fig. 4. Optimal path of the agricultural inspection robot.

The traditional ant colony algorithm was applied on the same platform to verify the effectiveness of the model and the algorithm, and the proposed optimization model was solved with the same parameters. The maximum number of iterations of the traditional ant colony algorithm was also set to 200 to make the experimental results more scientific and effective. The convergence curve of the improved ant colony algorithm is given in Fig. 5, and the optimal route of the agricultural inspection robot is shown in Fig. 6.

Fig. 5. Convergence curve of the traditional ant colony algorithm

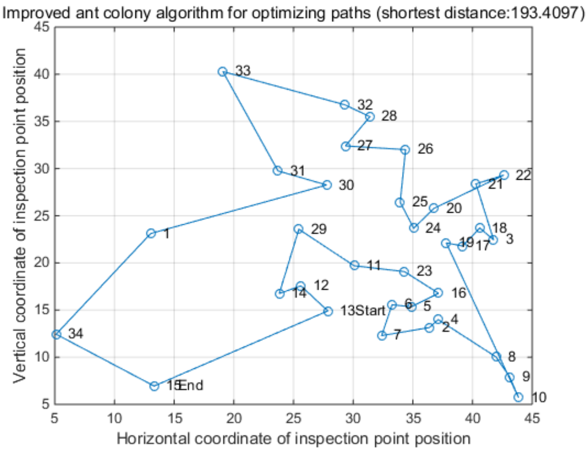

Fig. 6. Optimal path of agricultural inspection robot

The improved ant colony algorithm and the traditional ant colony algorithm were compared in terms of the inspection route, the total distance traveled by the agricultural inspection robot, and the convergence time of the algorithm. The comparison results are listed in Table 2.

Table 2. Comparison between the improved ant colony algorithm and traditional ant colony algorithm

Algorithm	Inspection route	Distance (m)	Time (s)
Improved ant colony algorithm	29→11→23→16→5→6→7→2→4→8→9→10→3→18→17→19→24→25→20→21 →22→26→28→32→27→30→31→33→1→34→15→14→12→13→29	186.7321	60.17
Traditional ant colony algorithm	13→12→14→29→11→23→16→5→6→7→2→4→8→9→10→19→17→18→3→21 →22→20→24→25→26→27→28→32→33→31→30→1→34→15→13	193.4097	78.11

As shown in Table 2, the improved ant colony algorithm has better optimization ability and convergence than the traditional ant colony algorithm. The convergence curve of the algorithm indicates that the optimal route length obtained by the improved ant colony algorithm is better than that obtained by the traditional ant colony algorithm in terms of the total inspection distance of agricultural robots. The total inspection distance of the improved ant colony algorithm is shortened by 6.78 m and 3.45% compared with that of the traditional genetic algorithm. The traditional ant colony algorithm has a longer convergence time than the improved ant colony algorithm. The convergence time of the improved ant colony algorithm is 17.94 s shorter and 22.97% higher than that of the traditional genetic algorithm.

The servo motor power of the agricultural inspection robot is approximately 2200 W, and the total power of the other equipment is approximately 80 W. The agricultural inspection robot stops at each stop point and rotates the tripod head for inspection. The average residence time of each inspection point is approximately 4 s, and the average driving speed of the inspection robot is approximately 1 m/s. The inspection robot is equipped with a 50 Ah lithium battery pack and uses an AC charger with a charging power of 200 W. After each inspection, the agricultural inspection robot needs to return to the charging room for charging and then conduct the next inspection. Therefore, the total time of each inspection includes two parts: task and charging times. The inspection time and weekly inspection frequency of inspection robots using the traditional ant colony algorithm and improved ant colony algorithm are shown in Table 2. The improved algorithm shortens the detection route by approximately 3.45% compared with the traditional ant colony algorithm by reducing the task and charging times. The operational reliability of the agriculture equipment will be significantly improved due to the increase in inspection times per unit time.

6. Conclusions

This study designed a route planning method for intelligent agricultural inspection robots based on the improved ant colony algorithm. This method not only can effectively solve the problem of low inspection efficiency of intelligent equipment and avoid missed inspection and incorrect inspection reports in the inspection process but also can perfectly achieve the expected optimization effect. However, the development time of the route planning method is relatively short, and multithreading route processing is not used in the algorithm. Therefore, the proposed method is inefficient in stimulating resources and has not reached the maximum. In future studies, the problems existing in the operation and maintenance of power information network equipment can be solved, and the learning and analysis ability of inspection robots can be further improved. In this study, the application of an improved ant colony algorithm in agricultural route planning was investigated, and the following conclusions could be drawn:

(1) Constructing an environmental model is important for the route planning of agricultural inspection robots. Subsequent algorithms can be implemented more easily by simplifying the environment model.

(2) The improved ant colony algorithm is prone to jump out of the local optimal solution compared with the traditional ant colony algorithm. This algorithm with better convergence and stability can effectively solve the route planning problem of agricultural inspection robots. In addition, the improved ant colony algorithm can shorten the interval between each inspection task. Compared with those of the traditional ant colony algorithm, the inspection route is reduced by 3.45%, and the convergence speed is increased by 22.97%. The operational reliability of agricultural equipment is improved to some extent.

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