ANALYSIS ON PATH OPTIMIZATION OF AGRICULTURAL HANDLING ROBOTS BASED ON ANT COLONY-IMPROVED ARTIFICIAL POTENTIAL FIELD METHOD
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基于蚁群-改进人工势场法的农业搬运机器人路径规划分析

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ABSTRACT
Aiming at the problems of low efficiency and slow function convergence of the ant colony algorithm in path planning of agricultural transport robots, a fusion algorithm combined with the artificial potential field method was proposed. Firstly, the function of each parameter was analyzed according to the mathematical model of the traditional ant colony algorithm, followed by the simulation analysis of the optimal parameters through grid map modeling in MATLAB and data recording. Secondly, the deficiency of the classical artificial potential field method in agriculture, i.e., it could not arrive at the endpoint or realize local locking, was improved by introducing the intermediate point and the relative distance of the target. Finally, the features of the two algorithms were combined and the improved artificial potential field method was integrated with the traditional ant colony algorithm so that the improved artificial potential field method could play a dominant role in the initial path planning stage of agricultural transport robots while the ant colony algorithm exerted the main effect in the later stage with the increase in the pheromone concentration. It was verified through simulation analysis, it was verified that the fusion algorithm of ant colony algorithm and improved artificial potential field method outperforms traditional ant colony algorithm in terms of farthest path, optimal path, running time, and iteration number.

摘要
*针对蚁群算法在农业运输机器人路径规划中效率低、函数收敛慢等问题，提出了一种与人工势场法相结合的融合算法。首先，根据传统蚁群算法数学模型对各参数的函数进行分析，并在 MATLAB 中通过栅格图建模对最优参数进行仿真分析，并记录数据。其次，通过引入中间点和目标相对距离的方法，改善了经典人工势场法在农业中无法到达终点和无法进行局部锁定的问题;最后，结合两种算法的特点，将改进的人工势场法与传统的蚁群算法相结合，使改进的人工势场法在农业运输机器人路径规划的初始阶段发挥主要作用，蚁群算法在后期随着信息素浓度的增加发挥主要作用。*通过仿真分析验证了将蚁群算法与改进的人工势场法相融合算法在最远路径、最优路径、运行时间、迭代次数各项数据都优于传统蚁群算法。

INTRODUCTION
With the development of society and the maturity of artificial intelligence technology, robots have gradually developed from industrial robots to intelligent agricultural handling robots, contributing to more convenient life *(Zhu et al., 2010)*. Agricultural handling robots involve the knowledge of various fields such as sensor technology, computer, automatic control, and communication technology. When located in an unknown environment, robots obtain external environmental information through external sensors and process it to realize their own positioning. Usually, the position and direction of the robot are controlled by real-time positioning and mapping of the surrounding environment *(Zhao et al., 2018)*. Generally speaking, agricultural handling robots use lidars, cameras, and inertial measurement devices as external sensors. These sensors integrate the advantages of small size, light weight, low cost, and rich image information. Vision sensors have been developing continuously *(Teng et al., 2018)*. At present, robot positioning generally includes ultrasonic navigation and positioning technology, visual navigation and positioning technology, and light reflection navigation and positioning technology of agricultural handling robots, GPS global positioning technology, etc. Robot positioning in indoor environments is the key and difficult point of

robot systems *(Wei et al., 2023)*. Because the positioning signal blocked by buildings is weakened, the outdoor lidar positioning cost is high, and the positioning signal of wireless sensors is easy to be attenuated, the positioning accuracy is affected by the navigation problem of robots, making it necessary for robots to plan an optimal collision-free path from the starting point to the endpoint in the environment according to the predetermined target *(Zhang et al., 2023)*. Before navigation, robots need to establish a map of the surrounding environment. Path planning is implemented in an unknown environment, and meanwhile, the obstacle avoidance ability of robots is also indispensable.

The working environment layout of agricultural handling robots is complex, which brings certain challenges to their path planning task. The traditional path planning algorithm has some shortcomings, such as low planning efficiency and poor operation safety of handling robots. For the identification and feature extraction of the surrounding environment during the movement of handling robots, therefore, the map of the surrounding environment is constructed, and the path planning of the handling robots is performed by using the artificial potential field method improved by ant colony, which will improve the path planning accuracy and speed up the learning efficiency of agricultural handling robots. It also provides accurate data for the operation of the robots in the process of movement. In this study, the global path planning and local path planning of agricultural transport robots were explored, and the low efficiency and poor security of transport robot planning algorithms were solved. Aiming at the low efficiency of transport robots, the path smoothing algorithm was studied. To solve the path tracking and control of handling robots, the path tracking research was carried out. The above work will provide certain reference significance and value for the path planning task of agricultural handling robots.

STATE OF THE ART

With the emergence of intelligent agriculture in recent years, agricultural handling robots have been widely studied and applied in the fields of industrial automation and intelligent factories. In the aspect of intelligent agricultural warehousing management, more efficient intelligent warehousing has gradually become the new direction of warehousing operation and development. How to plan the fast and energy-saving agricultural robot handling path is an important link to optimize the storage operation. As a typical engineering problem, the path planning of agricultural handling robots has great exploration space in improving robot positioning and mapping accuracy. Chinese and foreign experts and scholars have conducted extensive research from different angles, which can be roughly divided into two categories: traditional algorithms and bionic intelligent algorithms. Traditional algorithms, e.g., artificial potential field method, A* algorithm, and Dijkstra algorithm *(Das et al., 2016)*, have certain advantages in solving the path planning problem of agricultural handling robots in ideal environments. However, the artificial potential field method is easily disturbed by the external environment, accompanied by such problems as the increasing path length and the number of inflection points *(Mo et al., 2015)*. The real-time performance of the A * algorithm is poor, and the search efficiency of the algorithm is low due to the increase in the number of path nodes *(Tharwat et al., 2019)*. The Dijkstra algorithm is subjected to some problems such as low efficiency and high computational complexity *(Das et al., 2016)*. Moreover, the limitations of traditional algorithms often lead to local optimization and poor real-time performance in the path planning of agricultural transport robots. By observing the habits of natural creatures, bionic algorithms simulate the biological characteristics of group members, reduce the dependence on mathematical models, and exhibit strong global optimization and adaptability *(Zeng et al., 2016)*. Compared with the traditional path planning algorithm, therefore, intelligent optimization algorithms have higher efficiency and robustness in solving large-scale path planning problems. At present, swarm intelligence algorithms have been widely used in the field of path planning, among which the common ones are genetic algorithms, particle swarm optimization, and the ant colony algorithm. When used for path planning, genetic algorithms are easily influenced by the size of environmental grids, which leads to the long optimal path length, many inflection points, and slow convergence *(Ames et al., 2015)*. The Particle Swarm Optimization algorithm has a fast convergence speed in the initial iteration, but it is easy to fall into local optimization in the later iteration, which results in the unsmooth path and a large number of turns on the optimal path *(Yang et al., 2012)*. The ant colony algorithm is too random in the early iterative search, which gives rise to the low efficiency of the algorithm, and consequently, it will stagnate in the later centralized search, so the algorithm runs for a long time and is not suitable for large and complex maps *(Zhou et al., 2021)*. Therefore, the path planning problem of agricultural handling robots in complex environments and how robots can rapidly and effectively complete cargo transportation tasks have become the current research hotspots.

In the global path planning environment, there are mainly grid-based A* algorithm *(Yan et al., 2021)* and traditional Dijkstra algorithm *(Javidrad et al., 2017)*, which are mainly used for path search, with higher efficiency and smaller calculated quantity. Among the traditional reinforcement learning, the Q-learning algorithm *(Wang et al., 2020)* has been widely used. Xu et al. combined the lazy line of sight algorithm with distance transformation for path planning. The path planned by this algorithm is more robust and smoother, yet the running time is longer *(Xu et al., 2019)*. Sombolestan et al. regarded the robot as a point and connected it with the vertex, starting point, and endpoint of the convex obstacle to form an intuitive and accessible view that does not intersect with the obstacle area *(Sombolestan et al., 2019)*. If the robot can plan the path in any environment, path planning can be implemented using the ant colony algorithm and genetic algorithm, which can greatly improve the search efficiency *(Zhu et al., 2021)*. In order to realize the multi-robot cooperative work of handling robots in dynamic environment, Ma et al. adopted the ant colony algorithm to realize the multi-robot cooperative work task *(Ma et al., 2013)*. Kyaw et al. put forward an algorithm based on mixed ant colony and bee colony, which is suitable for complex mine environments and enables the robot to effectively carry out path planning in complex environments *(Kyaw et al., 2020)*. Duan et al. proposed a cooperative path planning method for multiple UAVs based on the improved particle swarm optimization algorithm, which solved the path planning problem of UAVs in three-dimensional space *(Duan et al., 2020)*.

To sum up, common global path planning algorithms include A* algorithm, ant colony algorithm, genetic algorithm, and particle swarm optimization algorithm, while common local path planning algorithms include artificial potential field method, speed barrier method, and dynamic window algorithm *(Radwan et al., 2016)*. Among them, the ant colony algorithm integrates the merits of high stability, reliability, and independence. However, low search efficiency, long running time, and low convergence speed of the algorithm will be caused in case of a large search range and low pheromone concentration in the initial stage given its high dependence on pheromones. The artificial potential field method has the advantages of a simple mathematical model and fast response, but near the starting point, the repulsive force is ignored due to the excessive gravity, the intelligent vehicle collides with obstacles, and the target is unreachable, resulting in the local minimal point. Combining the characteristics of ant colony algorithm and artificial potential field method, the ant colony algorithm was firstly subjected to modeling and simulation analysis to obtain the optimal parameters, and the local minimum of the artificial potential field method was improved by introducing the relative target distance. Integrating the advantages of the ant colony algorithm and artificial potential field method, the improvement effect of the fusion algorithm was verified through mathematical modeling, theoretical analysis, and simulation experiments.

MATERIALS AND METHODS

Grid map modeling

According to the degree of obstacle information acquisition, the path planning of agricultural handling robots can be divided into local planning and global planning. In this study, global planning was discussed. In this study, the grid method was used to simulate the working environment of the robot, and the handling environment of the agricultural robot was decomposed into a series of equally-sized network units. The size of the unit depended on the size of the detection robot. Assuming that the inspection environment was a regular site with a length of L and a width of *w*, the environment was divided into m×n grids with a length of 1 and a width of *w*, respectively, each small grid is represented by N_{xy}, and the whole environment space is denoted as Φ, which is expressed by Equation (1).

$$\Phi = \sum N_{xy} | (x \in [1, m], y \in [1, n]) \tag{1}$$

The presence/absence of obstacle information in each grid is expressed by Equation (2).

$$N_{xy} = \begin{cases} 0, \text{No barriers} \\ 1, \text{Barriers} \end{cases} \tag{2}$$

Where: N_{xy} is the state information of each grid, N_{xy}=0 indicates that the obstacle-free area can be passed freely, and N_{xy}=1 means that the obstacle-containing area is forbidden to pass. By reference to the layout of substations in reality, multiple binary grid arrays were established to form the inspection environment for robots, and meanwhile, small grids (1×1) were set, as shown in Fig. 1.

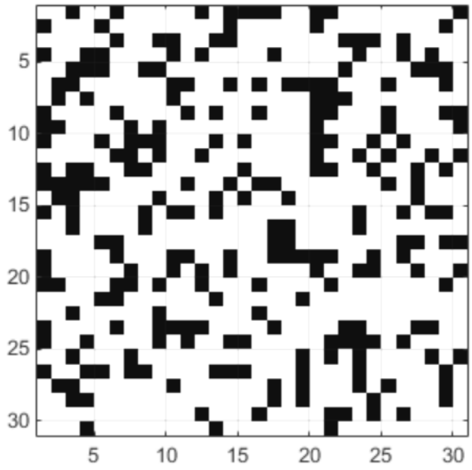

Fig. 1 - Grid map modeling

The grid method met the octree search strategy adopted in this study, that is, the robot could move between adjacent grids in eight directions in the search process.

Establishment of the path planning model

In the path planning process of agricultural robots, the position coordinates updated by each iteration of the algorithm were set to represent a moving route of agricultural robots. In the optimization algorithm of the agricultural robot handling path, the optimal path from the starting point to the target point was found from the two-dimensional grid map. The constraint conditions were set as follows:

(1) Map boundary and obstacle constraints. The moving path of the agricultural robot must be limited within the grid map boundary, and the moving path of the agricultural robot is forbidden to cross the obstacle node in the movable area.

(2) Path continuity condition. It is necessary to avoid path overlap and detour when the agricultural robot moves in the traffic area. Assuming that the position coordinates of the agricultural handling robot at time t are (x_t, y_t), the position coordinates (x_{t+1}, y_{t+1}) of the agricultural handling robot at the next time need to meet $x_{t+1} > x_t$ or $y_{t+1} > y_t$.

(3) The shortest path condition. In order to realize path planning, the agricultural handling robot needs to find the shortest path from the starting point to the target point on the basis of satisfying the boundary constraints and path continuity conditions. Taking the Euclidean distance of the path as the fitness function of the algorithm, the path with the least fitness is the optimal path. The path length is calculated as shown in Equations (3) - (4).

$$L=S+L(i)+F \tag{3}$$

$$\begin{cases} S = X(1) - 1 \\ L(i) = \sum_{i=2}^{c} \left(\sqrt{(X(i) - X(i-1))^2 + 1} \right) \\ F = X(end) - c \end{cases} \tag{4}$$

Where L is the length of the robot's moving path, $X(1)$ is the position of the first node of the path, X(end) is the position of the last node of the path, and c is the number of columns of the grid map.

ALGORITHM DESIGN

Ant colony algorithm

The ant colony algorithm is implemented mainly depending on pheromone concentration, with its principle displayed in Fig. 2. Under the fixed concentration of pheromones released by ants and the fixed volatilization rate of pheromones, if the ant colony starts from point *A* to the endpoint *E* and the path from point *C* to point *F* is blocked, there are two paths—*ABCED* and *ABFDE*—for the ant colony from point *A* to point *E*. Given a fixed quantity of ant colonies, *BC*=*CD*=2 and *BF*=*FC*=2. When the experiment starts, therefore, the quantity of ants passing through the two paths was basically identical, but with the lapse of time, the quantity of ants on *ABFDE* gradually increased. This is because this path is short, the concentration of pheromones released by ant colonies grows within certain time, and thus ant colonies are inclined to this path.

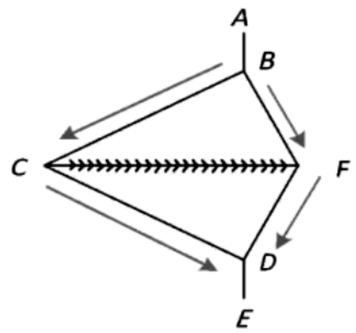

Fig. 2 - Principle of ant colony algorithm

By establishing the mathematical model of the ant colony algorithm to analyze the influence of various parameters on the algorithm, the following assumptions can be made for the ant colony search path: firstly, it is assumed that M ants participate in path search, the initial pheromone concentration of each path equals a constant *C*, and then the pheromone concentration *C* from X to Y can be expressed as $\tau_{AB}(0)=C$ (*C* is a constant). The *k*-th ant (*k*=1, 2, 3...., M) moves for t steps, and the probability for it to move from point X to point Y can be expressed as follows:

$$P_{XY}^{k}(t)=\begin{cases}\dfrac{\tau_{XY}^{a}(t)\eta_{XY}^{\beta}(t)}{\sum\limits_{s\in a_k}\tau_{AS}^{a}(t)\eta_{XS}^{\beta}(t)}, B\in a_k \quad a_k=\{1,2,\ldots,M\}-tabu(k)\\ 0, else\end{cases} \tag{5}$$

Where $\tau_{XY}^{a}(t)$ denotes the pheromone concentration on the path from *X* to *Y* at time t; a_k represents the set of places that the ant can reach at the next time; *tabu(k)* stands for the place previously passed by the ant; $\eta_{XY}^{\beta}(t)$ is the heuristic function from point *X* to point *Y*, which is an important parameter characterizing the probability for the ant to move from point *X* to point *Y* and can be expressed as below:

$$\eta_{XY}(t)=1/d_{XY} \tag{6}$$

Where d_{XY} indicates the distance between places. It is not difficult to see that a greater d_{XY} leads to the smaller distance and the smaller $P_{XY}^{k}(t)$; the greater the $\tau_{XY}^{a}(t)$, the smaller the $P_{XY}^{k}(t)$. The probability for ants to move from *X* to *Y* is negatively correlated with the distance between the two and positively correlated with the pheromone concentration.

From the beginning to the end of the ant colony, both the released pheromone $\Delta\tau_{XY}(t)$ and the volatilized pheromone should be considered. Assuming that the volatility coefficient is $\rho(0<\rho<1)$, the pheromone concentration can be updated as follows:

$$\tau_{XY}(t+1)=(1-\rho)\tau_{XY}(t)+\Delta\tau_{XY}(t) \tag{7}$$

$$\Delta\tau_{XY}(t)=\sum_{M}^{k=1}\Delta\tau_{XY}k(t) \tag{8}$$

According to Equation (8), the pheromone concentration update is equal to the volatilized pheromone concentration plus the newly added pheromone concentration, and the volatility coefficient ρ is negatively correlated with the pheromone concentration. In practical application, if the coefficient is too large, the pheromone concentration is volatilized at an accelerated speed, accompanied by the degraded global search ability of the robot and the slower algorithm convergence. When the coefficient is too small, the pheromone volatilization slows down, and the probability for the robot to choose different paths is reduced, which is not good for finding the optimal path.

$\Delta\tau_{XY}(t)$ is the pheromone released by the ant k from *X* to *Y*, which is expressed as follows:

$$\Delta\tau_{XY}^{M}=\begin{cases}\dfrac{Q}{L_k}, & \text{the } k^{th} \text{ant is on the path } XY\\ 0, else\end{cases} \tag{9}$$

L_k represents the distance of *XY*. Pheromone concentration *Q* refers to the total pheromone concentration after completing a cycle. After each iteration, the pheromones on all paths found by ants will be updated, which leads to the too rapid accumulation of pheromones and the local optimum of the algorithm. An appropriate pheromone concentration is the precondition ensuring the global search ability of the ant colony algorithm.

Artificial potential field method

The artificial potential field method is a common algorithm for robot local path planning. Its basic principle is to use artificial potential field to create a kind of attraction and repulsion, and use the physical principle of "like charges repel each other, unlike charges attract" to describe the effect generated by the target point and obstacles in the movement process of agricultural robots. Therein, attraction is the direction from agricultural robots to the target point and repulsion indicates the direction from obstacles to agricultural robots. The resultant force borne by agricultural robots in the potential field is the direction of forward motion.

Assuming that the attraction and repulsion borne by robots on the potential field are U_{att} and U_{rep}, respectively, the resultant force borne by robots can be expressed as follows.

$$U=U_{att}+U_{rep} \tag{10}$$

The attraction field function can be denoted as below.

$$U_{att}(X)=\frac{1}{2}K_{att}(X-X_g)^2 \tag{11}$$

Where X_g indicates the position of the target, X represents the current position of the agricultural handling robot, and K_{att} is an attraction constant. Then, the attraction borne by the robot can be expressed as follows.

$$\vec{F}_{att}=-grad[U_{att}(X)]=K_{at}d(X,X_g)\overrightarrow{e_g} \tag{12}$$

Where $d(X,X_g)$ is the distance between the endpoint and the agricultural handling robot, which is a unit vector with the direction from the agricultural handling robot to the endpoint. It can be obtained that the attraction is positively correlated with the distance from the robot to the target point. The attraction field intensity declines with the decrease in the distance between the robot and the target point until the robot reaches the target point when the attraction potential field is zero. The repulsion field function of the agricultural handling robot can be expressed as follows.

$$U_{rep}(X)=\begin{cases}\frac{1}{2}K_{rep}(\frac{1}{d(X,X_0)}-\frac{1}{d_0})^2, d(X,X_0)<d_0\\ 0, \quad d(X,X_0)\geqslant d_0\end{cases} \tag{13}$$

Where d_0 indicates the farthest distance between the agricultural handling robot and the obstacle. If the distance between the robot and the obstacle is greater than d_0, the effect of repulsion can be omitted. The repulsion borne by the robot in the repulsion field can be acquired through the negative gradient operation of the repulsion field function, expressed as follows.

$$F_{rep}=-grad[U_{rep}(X)]=\begin{cases}K_{rep}(\frac{1}{d(X,X_0)}-\frac{1}{d_0})\frac{1}{d^2(X,X_0)}\overrightarrow{e_0}, d(X,X_0)<d_0\\ 0, \quad d(X,X_0)\geqslant d_0\end{cases} \tag{14}$$

Therefore, the resultant force borne by the agricultural handling robot in the potential field can be expressed as below.

$$\vec{F}_{tol}=\vec{F}_{att}+\vec{F}_{rep} \tag{15}$$

It can be concluded from the above analysis that the artificial potential field method has many advantages. But there are also some problems in some specific situations, specifically as follows:

(1) Target inaccessibility. When the agricultural robot draws close to the endpoint, the repulsion may be greater than attraction so that the target point cannot be reached;

(2) Local minimum. The direction in which the agricultural robot bears the resultant force in the potential field determines the moving direction. If the resultant force received by the agricultural handling robot is zero at a certain point, that is, the attraction is equal to the repulsion, the agricultural robot cannot move, or wander about.

Improved artificial potential field method

(1) Target inaccessibility. When the agricultural handling robot reaches one point, it fails to reach the target point since the repulsion is greater than the attraction. By introducing the relative distance $d(X,X_g)$ of the target point, the new target point can add attraction to the agricultural handling robot so that the direction of the resultant force borne by the agricultural handling robot will change. The repulsion field function is redefined as follows.

$$U_{rep}(X)=\begin{cases}\frac{1}{2}K_{rep}(\frac{1}{d(X,X_0)}-\frac{1}{d_0})^2 d(X,X_g)^n, d(X,X_0)<d_0\\0, \quad d(X,X_0)\geqslant d_0\end{cases} \tag{16}$$

The following can be acquired through the negative gradient operation of the repulsion field function (16).

$$\vec{F}_{rep}=\begin{cases}\vec{F}_{rep1}+\vec{F}_{rep2}, d(X,X_0)<d_0\\0, \quad d(X,X_0)\geqslant d_0\end{cases} \tag{17}$$

In Equation (17).

$$\vec{F}_{rep1}=K_{rep}[\frac{1}{d(X,X_0)}-\frac{1}{d_0}]\frac{1}{d^2(X,X_0)}d(X,X_g)^n\vec{e_0} \tag{18}$$

$$\vec{F}_{rep2}=\frac{n}{2}K_{rep}[\frac{1}{d(X,X_0)}-\frac{1}{d_0}]^2 d^{n-1}(X,X_g)\vec{e}_g \tag{19}$$

In Equation (18), the direction of the unit vector $\vec{e_0}$ is from the obstacle to the robot, which is the direction of the repulsion borne by the agricultural handling robot. In Equation (19), the unit vector $\vec{e}_g$ is the direction in which the robot points to the target point and the direction of the attraction borne by the agricultural handling robot. Therefore, $\vec{F}_{rep1}$ denotes the repulsion borne by the agricultural handling robot and $\vec{F}_{rep2}$ represents the component of the attraction borne by the agricultural handling robot.

By introducing the relative distance of the target point, the attraction borne by the agricultural handling robot grows, the direction of the resultant force changes, and the robot can continue to move towards the target point. In this case, the direction of the resultant force borne by the agricultural handling robot can be expressed as below.

$$\vec{F}_{tol}=\vec{F}_{att}+\vec{F}_{rep1}++\vec{F}_{rep2} \tag{20}$$

(2) Local minimum. When the robot is unable to move due to the force balance in the potential field, the method of obstacle transfer can be used to make the robot get rid of the current situation that the attraction is greater than the repulsion. The specific operation steps are as follows:

Step1: When the robot can't move, the robot is connected into a line after confirming the positions of the robot and the target point;

Step2: Taking the path from the agricultural handling robot to the target point as the bottom, a perpendicular line is drawn through the obstacle, and the point *P* nearest to the obstacle on the perpendicular line is marked;

Step3: The robot is connected to point *P*, and this path is namely the path temporarily passed by the agricultural handling robot.

Artificial potential field method combined with ant colony algorithm

(1) The basic principle of the algorithm. In the initial stage of path planning, the improved artificial potential field method is used to avoid the inaccessibility of the target point and the local minimum, and the early-stage blind search of the ant colony algorithm is improved. Meanwhile, the improved fusion algorithm increases the pheromone concentration difference. As the pheromone concentration increases, the effect of the artificial potential field method is weakened, and the effect of the ant colony algorithm is fully exerted so that the agricultural handling robot can achieve the global optimal path within the shortest time.

In the traditional ant colony algorithm, the probability of ant k to move from point *X* to point *Y* can be expressed as.

$$P_{XY}^k(t)=\begin{cases}\frac{\tau_{XY}^a(t)\eta_{XY}^\beta(t)}{\sum_{s\in a_k}\tau_{AS}^a(t)\eta_{XS}^\beta(t)}, B\in a_k\\0, else\end{cases} \tag{21}$$

In Equation (21), the heuristic factor is $\eta_{XY}(t)=1/d_{XY}$, which represents the probability for the ant to move from point X to point Y and is negatively correlated with the distance. Another factor is then introduced so that the heuristic factor is correlated with the resultant force borne by the agricultural handling robot and the number of iterations, expressed as follows.

$$\eta_{Ftol} = \frac{D_{\max}}{D_{\max} \times a^{F_{tol}\cos\theta}} \tag{22}$$

In Equation (22), D represents the current number of iterations of the ant colony; $D_{\max}$ stands for the maximum number of iterations of the ant colony; $\cos\theta$ is the cosine value of the included angle between the movable direction of the agricultural handling robot and the direction of the resultant force borne.

In this case, the probability for the ant k to move from point X to point Y can be expressed as below.

$$P_{XY}^{k}(t) = \begin{cases} \dfrac{\tau_{XY}^{a}(t)\eta_{XY}^{\beta}(t)\eta_{F_{tol}}^{\gamma}}{\sum\limits_{s \in a_k} \tau_{XS}^{a}(t)\eta_{XS}^{\beta}(t)\eta_{F_{tol}}^{\gamma}}, Y \in a_k \\ 0, else \end{cases} \tag{23}$$

In Equation (23), γ is the regulatory factor. It is not difficult to find that in case of a small number of iterations in the early stage, this factor exerts a great effect on the path planning of the agricultural handling robot, and the artificial potential field plays a dominant role. In the above equation, the resultant force is:

$$\vec{F}_{tol} = \vec{F}_{att} + \vec{F}_{rep1} + +\vec{F}_{rep2} \tag{24}$$

(2) In the fusion algorithm, the stress analysis of the agricultural handling robot in the grid map and the possible movement direction analysis of the robot are described as follows: in case of no external force, the robot can move towards eight directions. When the mobile robot bears a resultant force of F_{tol}, the robot may move leftward or lower leftward. According to the relationship of the cosine value of the included angle between the direction of the resultant force and the movable direction with η_{Ftol}, it can be known that the robot will move towards a direction with a smaller angle, namely, it will move bottom leftward.

RESULTS

Example simulation

The improved fusion algorithm was subjected to the simulation experiment via MATLAB2014B. In general, parameter optimization is realized through expert experience or repeated experiments, and the control variable method is adopted to optimize the ant number M, pheromone influencing factor, heuristic information influencing factor β, volatility coefficient ρ, and pheromone strength Q. ditu.qishi=[1,1], ditu.mubiao=[30,28], ditu.daxiao=30. It was acquired through repeated simulations in the preceding part that when the ant number M was set to 100, pheromone factor to 1.5, heuristic factor β to 3.0, volatility coefficient ρ to 0.5, and pheromone constant Q to 1, the simulated trajectory diagram acquired based on the ant colony-improved artificial potential field method is as shown in Fig. 3.

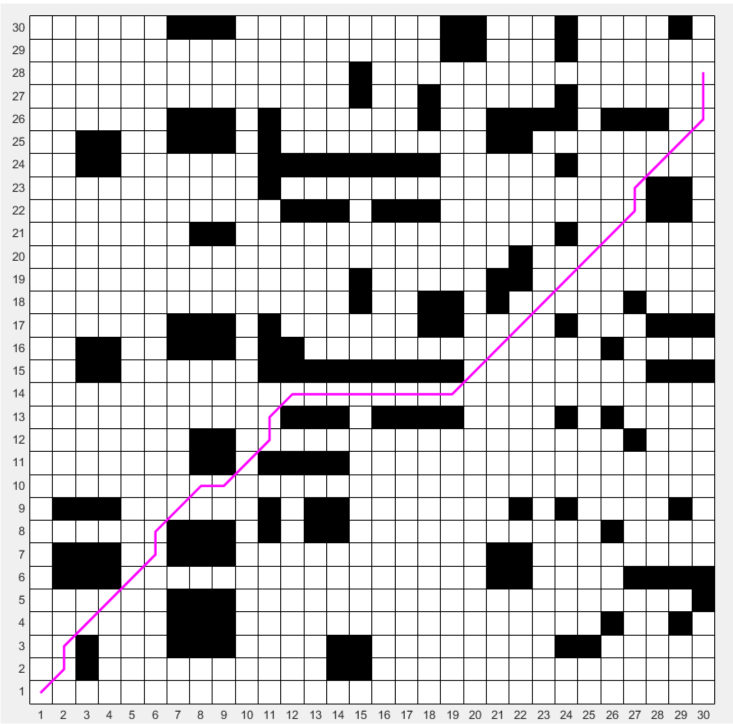

Fig. 3 - Simulated motion trajectory obtained through ant colony-improved artificial potential field method

Discussion of results

In this chapter, the problems of target inaccessibility and local minimum in the local path planning of the agricultural handling robot were mainly solved. The repulsion function was improved by adding an adjustment factor to the repulsion field function so that the target point became the lowest potential field and the target inaccessibility of the robot could be solved. The agricultural handling robot was prevented from local minimum by applying an external force towards another direction. When the agricultural handling robot encountered a dynamic obstacle in the dynamic environment, an improved repulsion field function was adopted to make the repulsion field function change with the local environment of the robot. Then, the feasibility of the improved algorithm was verified through experimental simulations. Next, the improved artificial potential field algorithm was combined with the ant colony algorithm. This mixed algorithm not only had the global path planning ability but also it was capable of avoiding temporary obstacles and dynamic obstacles in local path planning. In addition, the mixed algorithm achieved the shortest path and exhibited the stronger obstacle-avoiding ability.

CONCLUSIONS

In this study, a path planning model for the agricultural handling robot based on ant colony and improved artificial potential field method was established. By introducing the relative distance of the target and the intermediate point method, the repulsion field function of the agricultural handling robot was improved, and the problems of target inaccessibility and local minimum encountered by the artificial potential field method were solved. Moreover, the advantages and disadvantages of the ant colony algorithm were analyzed through grid map modeling and simulation. The improved potential field function was introduced based on the traditional ant colony algorithm, and a complex function containing the potential field factor and pheromone concentration was reconstructed. In addition, the slow search speed and local optimum of the ant colony algorithm were solved. Finally, the feasibility of the ant colony-improved artificial potential field method was further verified via MATLAB simulation analysis.

(1) The ant colony-improved artificial potential field algorithm can solve the local minimum and target inaccessibility of the robot. Local path planning is implemented using the artificial potential field method. The path is a random point in the environment instead of coordinate points on the environmental map. When road stiffness planning is carried out through the improved artificial potential field method, the robot will joggle on individual paths due to the defects of the artificial potential field method itself. With limited ability to process external environmental information, the artificial potential field method is generally applicable to local path planning, local environmental information processing, and decision-making.

(2) When working in a dynamic environment, the agricultural handling robot will encounter temporary stacking obstacles, which will hinder the robot’s forward movement, that is, the object that suddenly blocks the robot appears on the working path of the robot. Under this circumstance, the robot needs to avoid dynamic obstacles through local path planning, followed by local path planning once again so as to complete the remaining path planning.

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