ANALYSIS ON PATH OPTIMIZATION OF AGRICULTURAL WAREHOUSE LOGISTICS HANDLING ROBOT BASED ON POTENTIAL FIELD ANT COLONY ALGORITHM

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基于势场蚁群算法的农业仓库物流搬运机器人路径优化研究

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ABSTRACT

In the layout of modern agricultural warehouse logistics handling industry, it was an inevitable way to realize industrial upgrading by replacing people with mobile robots. Aiming at the problems that the existing obstacle avoidance control algorithm of agricultural handling robot was easy to fall into local optimal solution, and the operation process of agricultural warehouse logistics handling robot was prone to collision, the obstacle avoidance control of agricultural warehouse logistics handling robot was studied. In addition, a control algorithm based on improved potential field ant colony was proposed. The moving trajectory of the agricultural warehouse logistics handling robot during the handling process was studied, and the spatial kinematics equation of the robot was given. The ant colony algorithm was used to optimize the classical artificial potential field algorithm to improve the global optimization ability and balance the interaction between gravity and repulsion. In the aspect of local area obstacle avoidance of agricultural storage and handling robots, the artificial potential field was optimized twice based on the strategy gradient algorithm. By analyzing the probability of the next action command, the randomness of the travel path selection when multiple robots work at the same time was improved. After testing, the path of the proposed control algorithm was the shortest, and under the condition of complex path planning, the number of collisions between robots was also significantly less than that of the traditional obstacle avoidance control algorithm. The practical application could meet the needs of improving the efficiency of warehouse logistics management.

摘要

在现代化农业仓库物流搬运产业布局中，通过移动机器人取代人来实现产业升级是一条必由之路。针对现有农业搬运机器人避障控制算法存在的路径寻优易陷入局部最优解，及农业仓库物流搬运机器人作业过程易发生碰撞等问题，对农业仓库物流搬运机器人的避障控制进行了研究，并提出一种基于改进势场蚁群的控制算法；对农业仓库物流搬运机器人搬运过程中的移动轨迹进行了研究，给出了机器人空间运动学方程；采用了蚁群算法对经典人工势场算法进行优化，提升全局寻优能力并平衡引力和斥力的相互作用关系；在农业仓储搬运机器人的局部区域避障方面，基于策略梯度算法对人工势场做二次优化，通过分析下一动作指令的发生概率，改善多机器人同时作业时行进路径选择的随机性；经测试，提出控制算法的路径最短，而且在复杂路径规划条件下，机器人之间发生碰撞的次数也显著少于传统避障控制算法，经实际应用能够满足提升仓储物流管理效率的需求。

INTRODUCTION

In the context of the rapid development of the logistics industry, the traditional manual or semi-manual warehouse logistics management methods obviously cannot meet the requirements of industry development. In recent years, with the advancement of robot technology, automation control technology and wireless sensor technology, warehouse logistics handling robots had been applied to warehouse logistics management activities on a large scale *(Chu et al., 2019)*. Warehouse handling robots were introduced into logistics management activities, which could not only save labor handling costs, but also effectively improved the efficiency and accuracy of logistics turnover. Usually large warehouse logistics center, would use multiple logistics robot at the same time, the robot in the process of transportation and handling must avoid storage shelves, other transport robots and various uncertain obstacles *(Yuan et al., 2021)*. This put forward higher requirements for the intelligent level of the warehouse handling robot, the economy of the transportation path selection and the emergency capability of the robot *(Ru et al., 2019)*.

With the rapid development of sensor technology and servo drive technology, high-performance real-time control has been able to meet the relevant needs of industrial control. Based on this, the warehouse handling robot can gradually meet the requirements of positioning and handling of heavy-duty components in modern intelligent digital factories. With the continuous improvement of the performance of the handling robot, it has been well applied in the field of agricultural engineering.

Agricultural handling robot was an intelligent robot that can carry out autonomous path planning and complete specific agricultural warehouse handling tasks *(Xu et al., 2021)*. As an indispensable part of the autonomous navigation of agricultural handling robots, path planning had received extensive attention from researchers. Its goal was to find a collision-free continuous solution that always meets specific performance indicators from the initial state to the target state. The quality of path cost and solution is an important factor to be considered when designing path planning algorithm *(Zhang et al., 2021)*. The quality of path planning of agricultural warehousing and logistics robot determines whether the robots can cooperate with each other, and also determines the safety and efficiency of robot driving. Therefore, it is of great safety and economic significance to study the path planning of agricultural warehousing and logistics handling robots. How to solve the problem of path navigation and obstacle avoidance in a more complex, boundary and extreme environment, so that agricultural handling robots can better serve production and life, has become a new research topic in the field of intelligent mobile robot technology.

In recent years, relevant scholars have carried out cutting-edge academic research on the optimal scheduling problem of handling robots in mobile shelf warehouses, and have made some research progress. The representative achievements include: *Lv et al. (2021)* proposed a robot allocation rule based on the processing speed of the picking station, constructed a semi-open queuing network and used a two-stage approximation method for performance evaluation. *Wang et al. (2020)* developed a stylized performance evaluation model based on a multi-class closed queuing network model. *Lv et al. (2020)* expressed the robot scheduling problem as an asymmetric traveling salesman problem, and extended the model by adding customer order priority constraints. By analyzing the order picking operation process of e-commerce logistics distribution center, Shang et al *(2022)* proposed two operation modes of synchronous and asynchronous picking of multiple picking stations, and established a robot scheduling model under two picking modes. *Bi et al. (2022)* proposed a random scheduling strategy in the case of batch order tasks. *Yang et al. (2020)* established a mathematical model for the problem of order allocation and shelf selection for multiple picking stations. *Tiseni et al. (2021)* proposed two mathematical methods for the problem of order and shelf allocation to pickers, and established an integer programming model for the shelf sequencing problem of the picking station.

The research on agricultural handling robot navigation technology in academia has reached a relatively mature stage. *Sarabu et al. (2019)* proposed a novel method for planning the path of an agricultural handling robot towards a target in an unknown environment, utilizing sensors to detect new obstacles along the way. This method numerically solves the partial differential equation of heat conduction to synthesize artificial temperature gradients within the entire known environment, where the heat encountered during robot navigation contrasts with the 'cold' target. The temperature at all other points on the known environmental grid was numerically calculated and continuously updated to account for new obstacles *(Sarabu et al., 2019)*. *Sehestedt et al. (2010)* proposed a multi-robot navigation method with heterogeneous capabilities. In this method, a single navigation had different translation and rotation speeds, accelerations, sensing distances and angles, while maintaining global connectivity to other robots. *Xia et al. (2016)* used unsupervised clustering to automatically detect the type of surrounding environment based on navigation complexity and limited the sampling space of local controllers. The methods described in the above literature all rely on laser to navigate and control the mobile robot. In a narrow environment, the movement of the robot is easily blocked by obstacles, resulting in the robot staying in place and the robot motion control is not flexible enough. According to the completeness of the agricultural robot's grasp of the working environment information, the robot path planning can be divided into global path planning and local path planning. Global path planning referred to planning a path from the starting point to the end point in a static environment when the environmental information was completely known *(Zhang et al., 2017)*. Commonly used methods included fast search random tree, topology, and intelligent methods such as particle swarm optimization and ant colony algorithm *(Dorigo et al., 2006)*. Local path planning referred to the planning of local driving paths in a dynamic environment when the environmental information was partially known. Common methods included rolling window method, artificial potential field method, and fuzzy strategy *(Mirjalili et al., 2016). Inbarani et al., (2014),* extended the 8-neighborhood grid to 24-neighborhood grid in the grid environment, and redefined the heuristic information and neighborhood selection probability.

The simulation results show that the proposed method has shorter planning path and better smoothness. Aiming at the problems existing in the A * algorithm, *Jahanbakht et al. (2021)* used the JPS algorithm to expand and jump the child nodes, which effectively improved the efficiency of the A * algorithm, and used the Bessel curve to improve the smoothness of the path. Aiming at the problems of local traps and unreachable targets in the artificial potential field method, *Patel et al. (2022)* proposed a multi-behavior strategy and a variable influence range potential field method, which had better planning performance in complex obstacle environments. The above research results have planned a better path in their respective settings, but the planning methods and planning objectives in different application scenarios are quite different. Therefore, the robot path planning problem is still a research hotspot of robot navigation.

Most of the existing warehouse logistics robot control algorithms were based on high-definition cameras *(Sawadwuthikul et al., 2022)*, radar sensors *(Yu et al., 2021)*, distance sensors *(Sami et al., 2020)*, etc. to correct the route and avoid obstacles along the way. *Cai et al. (2020)* proposed an AGV (Automated Guided Vehicle) robot that could achieve autonomous navigation and obstacle avoidance on the basis of manually setting control procedures. However, there were some problems in the global path optimization of AGV robot, which was easy to fall into local optimization, and then to choose non-economic path *(Cai et al., 2020)*. On the basis of neural network model and machine learning algorithm, *Zong et al. (2020)* proposed a path optimization algorithm based on Q learning, which selected a more economical path according to the instructions and avoided obstacles along the way. In summary, the artificial potential field model is an efficient global path optimization algorithm model, which has certain advantages in obstacle avoidance and global optimization. The principle of the artificial potential field algorithm is to simulate the force field in classical mechanics, that is, the gravitational force will be generated between the agricultural handling robot and the destination, attracting the agricultural handling robot to move towards the target point, and the repulsion will be generated between the robot and the obstacle, prompting the agricultural handling robot to avoid the obstacle. The agricultural handling robot will comprehensively evaluate the suction and repulsion, and choose the most economical path to move forward to the target. Based on the ant colony algorithm, this study optimizes the classical artificial potential field algorithm, overcomes the adverse effects of the repulsive potential field in the classical artificial potential field model, and improves the effect of global path optimization and obstacle avoidance.

MATERIALS AND METHODS

Spatial dynamics analysis

The agricultural storage and handling robot moves in three-dimensional space. Its position, direction, travel speed, acceleration, and steering angle in three-dimensional space have an important impact on obstacle avoidance and path selection. The robot searches the most economical optimization route in the global scope according to the pre-planned path planning, but it cannot avoid the occurrence of emergencies and needs to adjust the path temporarily. Therefore, the warehouse handling robot should also temporarily adjust the running speed and route according to the distribution of dynamic obstacles in the actual work, and actively avoid other robots to avoid collision with other robots. In this study, the four-wheel rear-drive rear-steering robot is taken as an example to analyze the spatial dynamics of the warehouse handling robot, as shown in Fig.1.

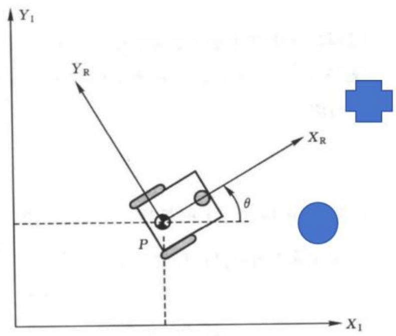

Fig. 1 – Spatial dynamics change of agricultural storage and handling robot

In the spatial coordinate system xOy, $O^{'}$ is the center of gravity of the storage and handling robot，A is the direction of the robot, β is the heading angle of the robot. If let $H=[x,y,\beta]^T$, $J=[v,\omega]^T$ (V and ω

are the speed and angular velocity of the robot respectively), the space kinematics equation of the robot is expressed as follows:

$$H=\begin{pmatrix}x\\y\\\beta\end{pmatrix}=\begin{pmatrix}\cos\beta & 0\\ \sin\beta & 0\\ 0 & 1\end{pmatrix}J \tag{1}$$

The movement of the agricultural storage and handling robot includes two degrees of freedom, namely, the current position and direction of the robot. The movement also includes three output variables, namely, position, direction of motion and steering speed. In terms of the control of the robot 's trajectory, the real-time correction of the trajectory of the agricultural storage and handling robot is realized by controlling v and ω ,and the obstacles in front are avoided in time. The spatial kinematics model of the storage and handling robot in the coordinate space is expressed as follows:

$$\begin{cases}\dot{x}=v\cos\beta\\ \dot{y}=v\sin\beta\\ \dot{\beta}=\omega^2\end{cases} \tag{2}$$

Because the four-wheeled warehouse handling robot is rear-wheel steering and rear-wheel drive in structural design, the position tracking and heading angle of the agricultural warehouse handling robot are synchronized, that is, the length and turning radius of the robot should be taken into account when the rear wheel is turned. At the same time, the heading angle is calibrated to ensure that the robot moves forward according to the specified path and can also avoid obstacles on the moving path. In order to better simulate the transportation and obstacle avoidance activities of agricultural storage and handling robots in warehouses, the target site is segmented based on the grille method. According to the volume of the storage robot and the size of the shelf, the entire warehouse site is divided into 46*46 small block areas, and then the robot 's travel channel is set according to the shelves and the placement of goods, and the size and location of obstacles (including moving obstacles such as shelves and other handling robots) are determined. Design the travel path and the trajectory of the robot. In large warehouse logistics centers, there are usually multiple warehouse handling robots working at the same time. For mobile agricultural warehouse handling robots, the three-dimensional shelves for storing items can be regarded as static obstacles, while other agricultural warehouse handling robots are regarded as moving obstacles.

Model construction

Assuming that the entire agricultural warehouse is a potential field, the current position coordinates of the agricultural warehouse handling robot are $P_o(x_o,y_o)$. The position coordinates of the target point are $P_d(x_d,y_d)$. The position coordinates of the obstacle are $P_b(x_b,y_b)$. Then the potential field function f_1 due to the existence of gravity, specifically expressed as follows:

$$f_1=\frac{1}{2}\delta\left(P_o-P_d\right)^2 \tag{3}$$

Among them is the δ gravitational gain coefficient, then the relationship between the pure gravitational function relationship g_1 and f_1 between the agricultural storage and handling robot and the target point is as follows:

$$g_1=-\nabla f_1=-\delta\tau\left\|P_o-P_d\right\| \tag{4}$$

Where, τ is the direction vector pointing to the target point, $\left\|P_o-P_d\right\|$ is the shortest distance between two points (Euclidean distance). Similarly, the repulsion potential field function between the agricultural storage handling robot and the repulsion field is defined.

$$f_2=\frac{1}{2}\delta\left(\frac{1}{\left\|P_o-P_B\right\|}-\frac{1}{\max\left|P_o-P_B\right|}\right) \tag{5}$$

Among them, $\left\|P_o-P_B\right\|$ is the Euclidean distance between the agricultural storage handling robot and the obstacle, $\max\left|P_o-P_B\right|$ is the maximum interference distance between the two. When $\left\|P_o-P_B\right\|$ exceeds $\max\left|P_o-P_B\right|$, the repulsion field is zero. In the artificial potential field environment, the final force of the agricultural storage and handling robot is the sum of the gravity of the object and the repulsion of the obstacle. The artificial potential field model is composed of the gravitational function of the potential field and the repulsion function of the potential field.

Under the action of artificial potential field, the storage and handling robot will choose the best path according to the gravity and repulsion. However, if there are many robots of the same type in the field, these agricultural storage and handling robots will be transformed into moving obstacles, and the repulsion between agricultural storage and handling robots will also change randomly, which will eventually lead to the failure of agricultural storage and handling robots to choose the best path or fall into the local optimal solution. Therefore, this study optimizes the artificial potential field algorithm based on the global perspective and uses the ant colony algorithm to form a new potential field ant colony algorithm, which can ensure that all mobile robots in the site can find the best path in the existing coordinate dimension.

The ant colony algorithm simulates the foraging behavior of ant individuals in the ant colony. Through the propagation of pheromones and the superposition of pheromone concentrations, an optimal foraging path with the highest pheromone concentration is selected. The advantages of ant colony algorithm are high fault tolerance and global optimization. The two most important core elements in the algorithm are individual transfer probability and individual pheromone concentration. Suppose that the ant individual (corresponding to the agricultural storage and handling robot) in the ant colony at time t starts from the starting point b to the target place c for food, the initial pheromone concentration is τ_{bc}, and the heuristic information along the way is ξ_{bc}, then the path transition probability $P_{bc}^{A}(t)$ of the individual is expressed as follows:

$$P_{bc}^{A}(t)=\frac{\left[\tau_{bc}(t)\right]^{\zeta}\left[\xi_{bc}(t)\right]^{\eta}}{\sum\left[\tau_{bc}(t)\right]^{\zeta}\left[\xi_{bc}(t)\right]^{\eta}} \tag{6}$$

In the formula, ξ and η are weight parameters related to pheromone concentration and heuristic information. The larger the parameter value is, the greater the role of pheromone in ant individual path optimization is. The pheromone concentration $\tau_{bc}(t)$ on the route at time t is related to the number of ants passing through the route, and the heuristic information $\xi_{bc}(t)$ at time t is related to the Euclidean distance from the individual to the target:

$$\xi_{bc}(t)=\frac{1}{d(b,c)} \tag{7}$$

In the formula, $d(b,c)$ is the Euclidean distance between the starting point and the target point. In the warehouse area delineated based on the grille method, each moving agricultural warehouse handling robot can be regarded as an ant individual. Each delivery and handling behavior is regarded as an iteration in the global scope. Each ant individual moves towards the moving target, resulting in different pheromone concentrations on different paths. In the process of simulating ant foraging activities, the best path is selected according to the change of pheromone concentration, while avoiding the interference of other agricultural warehouse handling robots in the local area.

Algorithm design

In the traditional ant colony algorithm, the reciprocal of the distance between the current node and the next node is usually used as the heuristic function. The distance heuristic function has low visibility to the end point and does not consider the actual multi-path situation. In view of the above situation, this study first introduces the artificial potential field method to reconstruct the distance heuristic function, which overcomes the blindness of the early search of the ant colony algorithm, and then comprehensively considers the three factors of path length, path smoothness and smoothness to construct a new multi-factor heuristic function:

$$\eta_{ij}=aL_{ij}(t)+bH_{ij}(t)+cT_{ij}(t) \tag{8}$$

In the formula, a, b, c are the weight coefficients, $L_{ij}(t)$ is the distance heuristic function introduced by the potential field method, $H_{ij}(t)$ is the gentleness heuristic function, and $T_{ij}(t)$ is the smoothness heuristic function. This heuristic function overcomes the limitation of traditional path planning with distance as the index.

Improvement of the heuristic function

(1) Distance heuristic function. A new distance heuristic function $L_{ij}(t)$ is constructed by using the resultant force F_S constructed by the artificial potential field method. Because the artificial potential field has a guiding effect on the robot, the convergence speed of the ant colony is faster, but it is easier to obtain the local optimal solution. For the ant colony algorithm is easy to fall into the local minimum, this study adds the coefficient α to improve the potential field force, as shown below:

$$\alpha = 1 - \frac{N_k}{N_{\max}} \tag{9}$$

$$F_A = F_s \cdot \alpha \tag{10}$$

In the Equation (9), N_k is the number of iterations of the k-wave ants, N_{max} is the total number of iterations, and F_A is the improved potential force. Then the optimized distance heuristic equation is:

$$L_{ij}(t) = \begin{cases} \dfrac{aF_A \cdot \cos\theta}{d_{ij} + d_{jg}}, & j \in a_k \\ 0, & \text{else} \end{cases} \tag{11}$$

In the formula, it is the distance from d_{ij} node i to node j, and d_{ig} is the distance from node j to the target point g. When the potential force becomes 0, the distance heuristic function is used to search to avoid the algorithm falling into a 'deadlock'.

(2) Smoothness heuristic function. In the actual working environment of the robot, too bumpy road surface is easy to cause the rollover of the robot, and will affect the moving speed and energy consumption of the robot, so this study adds the gentleness heuristic factor to the heuristic function to guide the robot to choose a gentler path, so as to improve the gentle performance of the path and get a higher quality path.

$$H_{ij}(t) = \frac{h_{\max} - |h(i) - h(j)|}{h_{\max} - h_{\min} + Q} \frac{N_{\max} - N_k}{N_{\max}} M + N \tag{12}$$

$$h_{\max} = \max\{|h(i) - h[a_i]\} \tag{13}$$

$$h_{\min} = \min\{|h(i) - h[a_i]\} \tag{14}$$

In the formula, a_i represents the set of all reachable nodes near node i, h_{max} represents the maximum height difference between the current node i and the surrounding adjacent nodes, and h_{min} represents the minimum height difference between the current node i and the surrounding nodes. $h(i)$-$h(j)$ represents the height difference between node i and node j. N_{max} is the maximum number of iterations to prevent the denominator from being 0 when h_{max}=h_{min}, and M and N are stable correction parameters. When the ants choose a path with a smaller height difference, the greater the gentleness heuristic factor $H_{ij}(t)$, the gentler the path can be obtained.

(3) Smoothness heuristic function: In the process of path planning, the traditional ant colony algorithm tends to generate numerous inflection points, which can result in the robot needing to readjust its posture at these points, leading to unnecessary acceleration and deceleration, increased driving difficulty, and prolonged driving time for the robot. Therefore, in view of this phenomenon, the smoothness factor $T_{ij}(t)$ is added to the heuristic function, and the robot can choose the path with fewer turns.

$$T_{ij}(t) = \begin{cases} \rho u \dfrac{N_{\max} - N_k}{N_{\max}} + \sigma, & d_{mi} = d_{ij} \\ \dfrac{(1-\rho)u}{S(a_i)} \dfrac{N_{\max} - N_k}{N_{\max}}, & d_{mi} \neq d_{ij} \end{cases} \tag{15}$$

$$m = v_i(e - 1) \tag{16}$$

In the formula, $\rho(0 \le \rho \le 1)$ represents the importance of the ant going straight, u represents the flexibility constant of the robot, $N_{\max}$ is the total number of iterations, σ is the turning correction constant, v_i represents the set of all passing nodes of the ant from the starting point to the node i, $S(a_i)$ represents the number of all nodes in the set, $e-1$ represents the penultimate element in the set, that is, the last node m of the node i, d_{mi}, d_{ij} represents the movement direction of the ant from node m to node i and node i to node j, respectively. When the direction is the same, it means that the robot does not have to turn, the heuristic function is larger, and the ant is guided to the path with fewer turns.

Optimization of the pheromone update

(1) Initial pheromone allocation principle. In the early stage of path search, the ant colony algorithm will make the positive feedback effect of the algorithm not obvious because of the small difference in pheromone concentration of each node, resulting in large blindness, poor convergence and long search time

in the early stage of the algorithm. In order to solve this problem, this study proposes an uneven distribution method of initial pheromone, which redistributes the initial pheromone value between all the nodes found by the algorithm and the target point, and the pheromone value of the remaining nodes remains unchanged, thereby improving the convergence speed and search time of the algorithm in the early stage.

$$\tau_i = \begin{cases} \varphi D, i \in P \\ 1, else \end{cases} \tag{17}$$

In the formula, τ_i is the newly assigned initial pheromone value, $\varphi(\varphi > 1)$ is the initial pheromone concentration increase coefficient, *D* is the initial pheromone concentration, and *P* is the set of all nodes between the starting point and the target point. Because *P* contains the nodes in the optimal path, it is beneficial to improve the search speed of the search.

(2) Multi-factor pheromone update. Based on the results of multi-objective optimization, the pheromone update is determined by considering factors such as path smoothness, continuity, and overall path length.

The multi-factor pheromone update method is as follows:

$$\tau_{ij}(t+1) = (1-\phi)\tau_{ij}(t) + \phi\Delta\tau_{ij}^{k}(t) \tag{18}$$

$$\Delta\tau_{ij}^{k}(t) = \Delta\tau_{ij}^{\mathrm{L}}(t) + \Delta\tau_{ij}^{\mathrm{H}}(t) + \Delta\tau_{ij}^{\mathrm{T}}(t) \tag{19}$$

$$\Delta\tau_{ij}^{\mathrm{L}}(t) = \begin{cases} \dfrac{A \cdot Q}{L_{k(t)}}, & j \in a_i \\ 0, & else \end{cases} \tag{20}$$

$$\Delta\tau_{ij}^{\mathrm{H}}(t) = \begin{cases} \dfrac{B \cdot Q}{100 H_k(t)}, & j \in a_i \\ 0, & else \end{cases} \tag{21}$$

$$\Delta\tau_{ij}^{\mathrm{T}}(t) = \begin{cases} \dfrac{C \cdot Q}{T_k(t)}, & j \in a_i \\ 0, & \text{else} \end{cases} \tag{22}$$

$$L_k(t) = \Sigma d(B, \cdots i, j, \cdots G) \tag{23}$$

$$H_k(t) = \sqrt{\frac{1}{p-1}\sum_{i=1}^{p}\left(h(i) - \bar{h}\right)^2} \tag{24}$$

$$p = s(p), T_k(t) = c(B, \cdots, i, j, \cdots G), d_{mi} \neq d_{ij} \tag{25}$$

In the formula, $\Delta\tau_{ij}^{\mathrm{L}}(t)$, $\Delta\tau_{ij}^{\mathrm{H}}(t)$ and $\Delta\tau_{ij}^{\mathrm{T}}(t)$ represent the pheromone increments of the distance factor, the smoothness factor, and the continuity factor, respectively. In order to expand the influence of road conditions on the path, the height mean square error is increased by 100 times. A, B and C are the weights of each factor, which are used to adjust the adaptability of the robot in different environments, so as to achieve the optimal effect of the path. Q represents the pheromone strength, $L_{k(t)}$ represents the length of the path obtained by the artificial potential field method. The pheromone strength diminishes as the distance increases. $H_k(t)$ represents the height mean square error of the path, where *h(i)* denotes the height of the current node, $\bar{h}$ represents the average height, and p denotes the number of nodes. A smaller mean square error corresponds to a greater $\Delta\tau_{ij}^{\mathrm{H}}(t)$, indicating stronger pheromone intensity for the path. $T_k(t)$ represents the number of turns in the path, and c(B, …, i, j, …G) records the turning nodes.

Improvement of the grid map

When the agricultural warehouse handling robot performs the handling task in the agricultural product warehouse, it has high safety requirements. Therefore, it is proposed that in the grid map, even the vertex of the obstacle cannot be touched, so that agriculture can ensure the absolute safety of the robot and obtain a path of better quality. The improved map information storage method is used to update the vertex anti-collision strategy, as shown in Fig. 2.

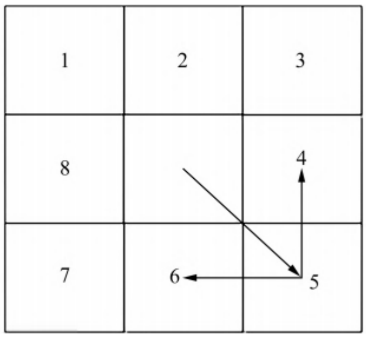

Fig. 2 – Improvement of the map information storage method to update the vertex anti-collision strategy

This study stipulates that the even number label is the robot 's straight label, and the odd number label is the robot's oblique label. Only when there are no obstacles in the oblique direction and the two straight grids are perpendicular to the direction, can the oblique movement be carried out. As shown in Fig. 4, when turning to the 5th grid, when there are no obstacles in the 4th and 6th grids perpendicular to the 5th grid, the robot will carry out oblique transfer. In order to store the feasible information of the ant, the transfer distance matrix D is established as follows:

$$D(i,j)=\begin{cases} l, & \operatorname{mod}(j,2)=0\ \&\ G(i_1)=0 \\ \sqrt{2}l, & \operatorname{mod}(j,2)=1\ \&\ G(i_2)=G(i')=G(i'')=0 \\ \infty, & \text{else} \end{cases} \tag{26}$$

In the formula, i_1 is the straight grid, mod is the remainder function, i_2 is the oblique grid, i' and i'' are the grids in two directions perpendicular to the oblique grid, and l is the side length of the grid.

Selection of the experimental parameters

In this study, the simulation analysis is carried out in Matlab, and the path optimization of the agricultural warehouse logistics handling robot is verified in the 46×46 scale grid environment. The layout of the shelves and the scene diagram are shown in Fig. 3.

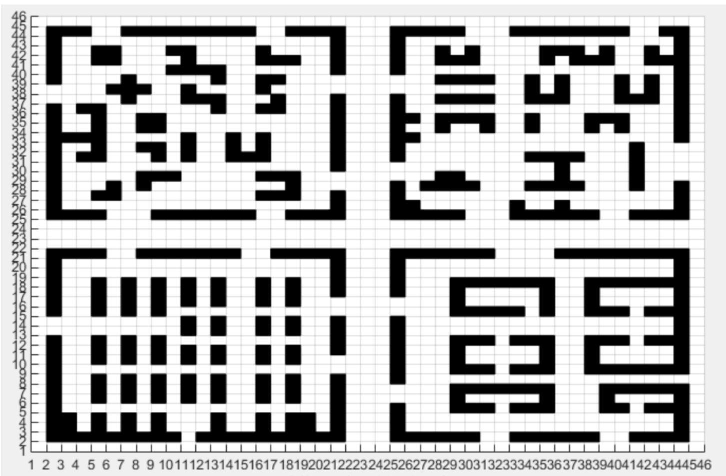

Fig. 3 – Warehouse site diagram based on grid method

The black square in Fig.4 represents the immovable shelf, and the white area is the channel. The length, width and height of the logistics handling robot used in the experiment are 0.9 m, 0.6 m and 0.4 m respectively. The warehouse logistics handling robot itself has the function of telescopic lifting, and the maximum bearing capacity is 0.5 tons.

RESULTS

Results analysis

In this study, two modes of warehouse area and cross warehouse area are set up to verify the model and algorithm, and the shortest path of the two algorithms in 46×46 environment is compared.

Analysis of the handling path of agricultural warehouse logistics robots in the warehouse area

The two algorithms are used to plan 10 times in a 46×46 environment, and the shortest paths planned by the two algorithms are selected for comparison. The potential field ant colony algorithm is used to carry the agricultural warehouse logistics robot in the warehouse area and the path is shown in Fig. 4. The traditional ant colony algorithm is used to carry the agricultural warehouse logistics robot in the warehouse area and the path is shown in Fig. 5.

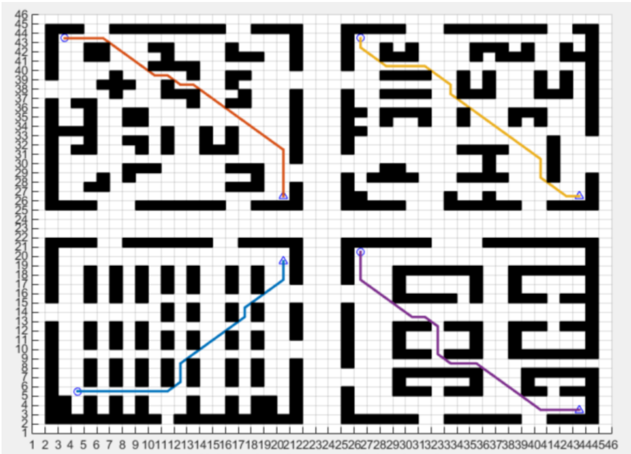

Fig. 4 - Potential field ant colony algorithm in warehouse area agricultural warehouse logistics robot handling path

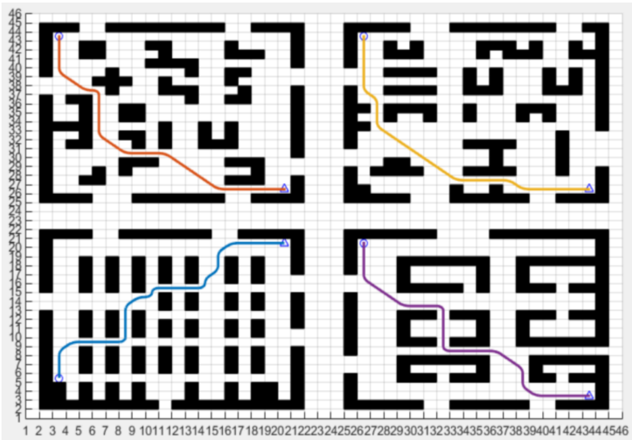

Fig. 5 – The traditional ant colony algorithm in the warehouse area of agricultural warehouse logistics robot handling path

Comparing the paths planned by the two algorithms in Fig. 5 and Fig. 6, it can be seen intuitively that the traditional algorithm has more inflection points and the corresponding length is larger. The potential field ant colony algorithm has fewer inflection points and shorter path length. In order to further compare, the length of the planned path, the number of inflection points, and the number of iterations of the two algorithms are counted, as shown in Table 1.

Table 1

Comparison of planning path results in each algorithm warehouse area

Algorithm type	Warehouse area	Path length	Number of inflection points	Number of convergences
Potential field ant colony algorithm	Path 1	26.9706	6	76
	Path 2	26.3848	8	77
	Path 3	27.5563	8	79
	Path 4	26.6820	6	75
Traditional ant colony algorithm	Path 1	28.7872	15	90
	Path 2	29.0018	16	91
	Path 3	29.7441	13	90
	Path 4	28.3184	15	92

Analysis of the handling path of agricultural warehouse logistics robots across warehouses

The two algorithms are used to plan 10 times in a 46×46 environment, and the shortest paths planned by the two algorithms are selected for comparison. The potential field ant colony algorithm is used to carry the agricultural warehouse logistics robot in the warehouse area and the path is shown in Fig. 6. The traditional ant colony algorithm is used to carry the agricultural warehouse logistics robot in the warehouse area and the path is shown in Fig. 7.

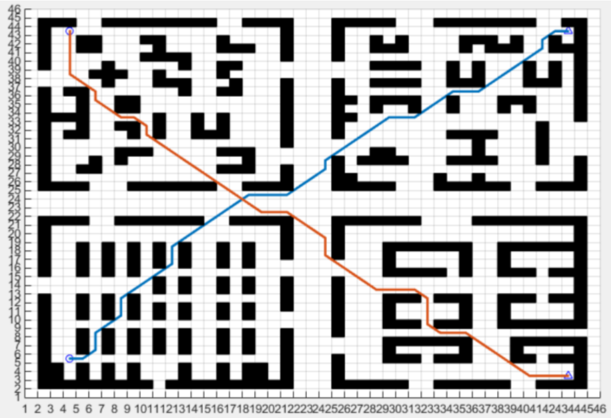

Fig. 6 – Potential field ant colony algorithm cross warehouse agricultural warehouse logistics robot handling path

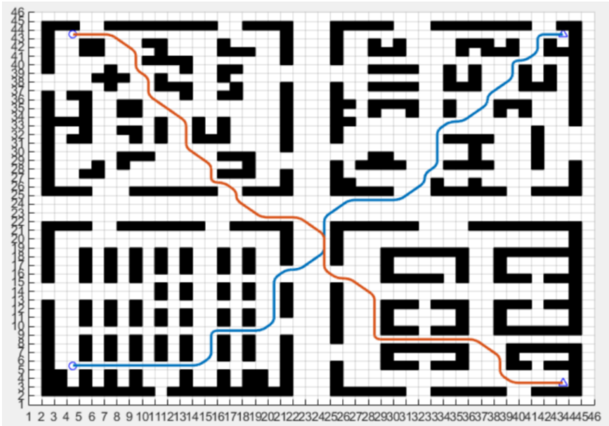

Fig. 7 – Traditional ant colony algorithm cross warehouse agricultural warehouse logistics robot handling path

From Fig.7 and Fig.8, it can be seen that the simulation experiment of the cross-warehouse handling path of the agricultural warehouse logistics robot is carried out in the grid environment. The differences between the two algorithms in the three dimensions of path length, number of corners and average number of iterations are compared. The experimental results are shown in Table 2.

Table 2

The comparison of the results of the cross-warehouse area planning path of each algorithm

Algorithm type	Cross warehouse area	Path length	Number of inflection points	Number of convergences
Potential field ant colony algorithm	Path 1	59.4264	18	85
	Path 2	62.5980	18	88
Traditional ant colony algorithm	Path 1	65.8400	36	101
	Path 2	66.2972	39	106

It can be seen from Table 1 and Table 2 that the pheromone of the potential field ant colony algorithm uses the gradient initialization method, and the early search efficiency of the algorithm is high, which greatly reduces the number of algorithms. The pheromone gradient initialization method makes the ants more efficient in selecting the path, and the path planned by the ants is more concentrated in the optimal area. Based on the strategy gradient algorithm, the collision between the warehouse handling robot and the shelf is effectively avoided.

The strategy gradient algorithm will adjust the movement direction and speed of the robot in time according to the local obstacle distribution of the site, which not only ensures the overall progress of the path planned by the potential field ant colony algorithm, but also effectively realizes the obstacle avoidance of local moving obstacles. Based on the above analysis, it can be seen that the potential field ant colony algorithm has certain advantages in the path planning in the grid environment.

CONCLUSIONS

In recent years, with the rapid development of agriculture and logistics industry, the scale of the industry has expanded simultaneously, which objectively requires the management level and management efficiency of agricultural warehouses to be improved. At present, in order to cope with the large-scale, centralized and digital agricultural logistics management mode, agricultural warehouse handling robots are widely used in warehouse logistics management activities. When multiple warehouse handling robots work at the same time, while planning the travel path of each robot, it is also necessary to avoid local path conflicts between logistics robots, thereby avoiding collisions between logistics robots. In this study, the classical artificial potential field model was optimized, and the global optimization ability of ant colony algorithm was used to accurately determine the position of obstacle robot, and the economic path of robot was comprehensively planned from a macro perspective. At the same time, the strategy gradient algorithm was used to overcome the randomness in the local motion of the robot and avoid collisions due to path overlap. The experimental data showed that the obstacle avoidance ability, path planning ability and obstacle avoidance ability of the potential field ant colony algorithm were better than those of the traditional algorithm. It can be seen that the robot random planning algorithm based on local probability is an important research direction in the future, which is helpful to better realize the obstacle avoidance in complex scenes.

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