IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 January 2023, accepted 15 January 2023, date of publication 3 February 2023, date of current version 9 February 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3241960

RESEARCH ARTICLE

Intelligent Warehouse Robot Path Planning Based on Improved Ant Colony Algorithm

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This work was supported in part by the National Natural Science Foundation of China under Grant 51705214 and Grant 51875003, and in part by the Natural Science Foundation of Jiangsu Province under Grant BK20170582.

ABSTRACT To improve the safety and accuracy of path planning of intelligent warehouse robots, this paper establishes a storage shelf model, incorporates Poisson Distribution to simulate the influence of unknown factors, and establishes a three-color raster map. The pheromone update mechanism is optimized by considering the path safety, path length, and turning elements under the influence of unknown factors. The two models based on the three-dimensional shelves are simulated separately, and the planned paths are de-pointed and smoothed. The simulation results show that the improved algorithm can design the optimal route safely and effectively in the storage environment under the influence of unknown factors. The proposed algorithm not only solves the blind search and deadlock problems, but also has better performances than other algorithms, i.e., 4 iterations compared to 22 and 30 iterations, 3 turns compared to 9 and 7 turns, 8.468s running time compared to 16.974s and 13.754s.

INDEX TERMS Intelligent warehouse robot, ant colony algorithm, path planning, poisson distribution, three-color grid map.

I. INTRODUCTION

With the development of technology and social progress, the traditional warehouse management warehouse has an unclear division of cargo space, disordered stacking, and unfavorable sorting, which makes the storage efficiency extremely low. [1]. Advanced technologies such as artificial intelligence, extensive data mining, and the industrial Internet of Things are playing an increasingly important role in the warehouse system to enhance the efficiency of delivery, processing, storage, and distribution of goods, thus solve the problem of inefficiency of storage system [2]. Therefore, the era of intelligent logistics is approaching. The development of warehouse management started from the manual stage, upgraded by mechanization, automation, and integration, and finally reached the competent stage [3]. The traditional logistics model is gradually upgrated to smart logistics. Warehouse management occupies a central position in logistics management, in which artificial intelligence equipment is an essential tool in intelligent storage, and intelligent storage robot is the most crucial part.

The essence of robot path planning is to find a safe and shortest path from the initial point to the target point in a working environment with obstacles according to the constraints. In the 1970s, Holland [4] proposed a Genetic Algorithm (GA) based on the evolutionary laws of living organisms in nature, but the search speed of this method was slow, and the time cost was high. In 1985, Liu [5] proposed an Artificial Potential Field (APF) method by introducing gravitation and repulsive fields, but this method suffered from the problem of local optimality. In 1992, Zhang [6] found that the ant colony could find the target quickly by secreting pheromones to exchange foraging information when searching for food, and proposed the Ant Colony Optimation (ACO) based on the principle of positive information feedback. However, this method converged slowly and was prone to deadlock and local optimum, In 1995, Zhang et al. [7] proposed the Particle Swarm Optimazation (PSO) algorithm,

The associate editor coordinating the review of this manuscript and approving it for publication was Sotirios Goudos.

which was initialized with a population of random solutions and searched for optima by updating generations. However, this method is prone to premature convergence in dealing with multi-peak search and has weak local optimal finding ability.

In recent years, path planning has also become a hot research topic. Yi et al. [8] improved the global search capability and convergence of the ACO through a multi-factor heuristic function strategy. Ning et al. [9] designed a new enhanced pheromone update mechanism based on the ACO, which reinforced the pheromones on the edges and improves the global search capability and convergence. Chen et al. [10] improved the ACO into a time-sensitive network (TSN), resulting in better convergence speed, optimization capability, and local optimum trap tendency than the traditional ACO. Miao et al. [11] proposed an improved adaptive ant colony algorithm (IAACO) for integrated global optimization of robot path planning. Dimitrios et al. [12] offered an improved fuzzy logic ant colony optimization that achieves better performance than the original ant colony algorithm. Hou et al. [13] proposed an enhanced ant colony algorithm with a communication mechanism to accelerate convergence by an expanded roulette wheel and to design adaptive sigmoid decay functions to optimize the heuristic information at different stages. Wang et al. [14] proposed an enhanced list-based simulated annealing (LBSA) algorithm for solving large-scale traveling salesman problem (TSP). An improved Tabu Search algorithm based on greedy algorithm is proposed for the stochastic vehicle routing problem [15]. Kala et al. [16] integrated fuzzy inference system with A* algorithm to solve the problem of robotic path planning.

Most of the above methods are devoted to the convergence speed and local optimization of the algorithm, however, they do not take into account the unknown factors in the actual situation. For the path planning of intelligent storage robots, this paper firstly builds a three-dimensional shelf arrangement model, and incorporates the Poisson Distribution into the grid method to construct a three-color grid map. The security of the path is simulated by incorporating the pheromone update mechanism, and the planned path is de-pointed and smoothed. Our proposed algorithm not only integrates Poisson distribution into the traditional black-and-white grid map to simulate the influence of unknown factors, but also considers the path length, safety and turning factors to improve the traditional ACO algorithm. The simulation study shows that the improved ACO Algorithm performs well in terms of convergence speed, path safety, and algorithm running time under unknown factors.

II. RESEARCH BACKGROUND

A. ACO ALGORITHM

Path and pheromone updating [17] are the two cores of the ACO Algorithm. According to the roulette wheel model [18], the probability of path transfer from node i to node j of ant K can be expressed by Equation (1):

$$P_{ij}^{k}=\begin{cases}\dfrac{\tau_{\mathrm{ij}}^{\alpha}(t)\,\eta_{ij}^{\beta}(t)}{\Sigma_{s\in C}\,\tau_{\mathrm{is}}^{\alpha}(t)\,\eta_{is}^{\beta}(t)}, & j\in C\\ 0, & j\notin C\end{cases} \tag{1}$$

where C is the next feasible node set of the ant, τ_{ij} is the pheromone value of the path (i, j). α is the pheromone incentive factor, which reflects the influence of the pheromone concentration on the path selection. β is the expected heuristic factor, which reflects the impact of the heuristic information on the path selection. $\eta_{\mathrm{ij}}(t)$ is the heuristic function, which represents the expectation of the ants moving from node i to the target node j. The heuristic function plays a vital role in the search path, and the pros and cons of the heuristic function will directly affect the convergence iteration speed of the algorithm. Due to the traditional heuristic function has fewer constraints, the blind search phenomenon will occur in the early search of ants. Therefore, the algorithm has a slow convergence speed and a large number of iterations.

There are different calculation methods for the pheromone update strategy. The Ant-Cycle model used in this paper is calculated as:

$$\Delta t_{ij}(t)=\begin{cases}\dfrac{Q}{L_k}, & Ant\ K\ passes\ path(i,j)\\ 0, & others\end{cases} \tag{2}$$

where Q is the strength of the pheromone, L_k is the total length of the path taken by the ant K in this cycle. The heuristic function of the traditional ACO Algorithm only considers the path factor, i.e., path is the only constrain during path searching, which leads to unsatisfactory paths in a relatively complex environment. The traditional pheromone updating method will lead to the phenomenon of ant blind search, which increases the search cost of the algorithm. The traditional ACO Algorithm is widely applied in various scenarios. For example, terrain factors need to be considered in the path planning of robots in mountainous areas, marine factors should be considered in the path planning of uncrewed boats, and safety and turning factors should be considered in storage robots. Therefore, the ACO algorithm should be improved with unknown factors under different environment conditions.

B. MULTI-HEURISTIC ACO ALGORITHM

The path search constraint of the traditional ACO Algorithm only considers the distance length, which leads to the need to analyze the actual environment when solving the practical problems. Yi et al. [8] proposed a heuristic function based on the distance factor, turn factor, and terrain factor for the working environment of field operation robots, and used the integrated heuristic function to calculate the transfer probability. The heuristic function is improved as follows:

$$\eta_{ij}^{m}(t)=\psi(i,j,q)+\omega_{i,j}^{m}(t)+\varsigma(i,j) \tag{3}$$

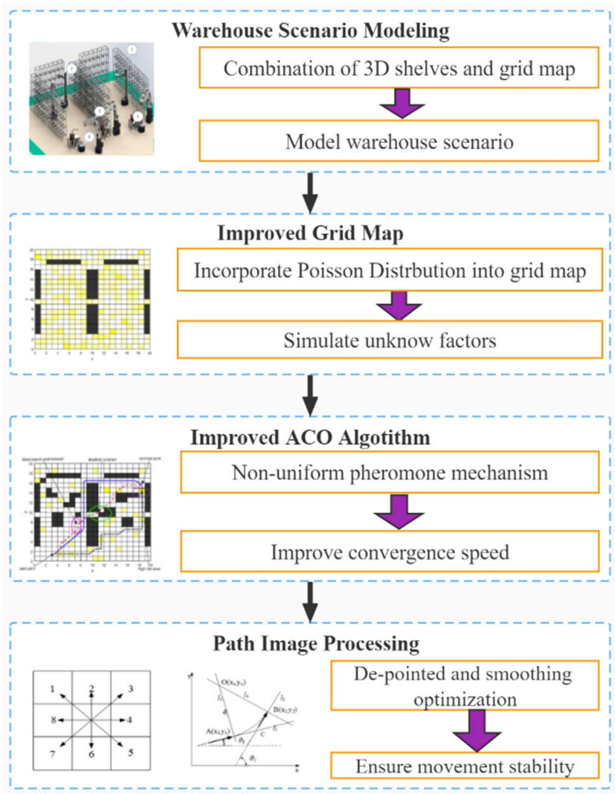

FIGURE 1. Flow chart of research methodology.

where $\psi(i, j, q)$ is the distance factor heuristic function, $\omega_{ij}^{m}(t)$ is the turn factor heuristic function, and $\varsigma(i, j)$ is the terrain factor heuristic function.

Through the improvement of multiple heuristic factors, the path of field operation robot is more safe and stable. The However, the research object of this paper is an intelligent storage robot, and this improvement method cannot be fully adapted to the intelligent storage environment. The storage environment is more about the efficiency of goods distribution and avoiding congestion caused by unknown factors. Also, it requires high accuracy of the path, and the smoothness of turns should be considered when planning the path. Therefore, this paper improves the multi-heuristic ACO Algorithm based on the unique application environment of warehouse robots.

III. RESEARCH METHODOLOGY

As shown in Fig. 1, this paper carries out the research of intelligent storage robot path planning through four steps, i.e., warehouse scenario modeling, improved grid map, improved ACO Algorithm, and path image processing. Fist, the modeling of warehouse environment mainly depends on the arrangement of the shelves. In this paper, three-dimensional warehouse scenario models of two combined shelves are constructed by using the grid map. Second, the improvement of grid map is mainly to integrate Poisson distribution into the traditional black-and-white grid method to simulate the influence of unknown factors on the path planning of warehouse robots. Third, the path length, safety and turning factors, the pheromone update mechanism adopts non-uniform distribution are considered to improve the traditional ACO algorithm. Fourth, the path image processing mainly considers the de-pointed and smoothing optimization.

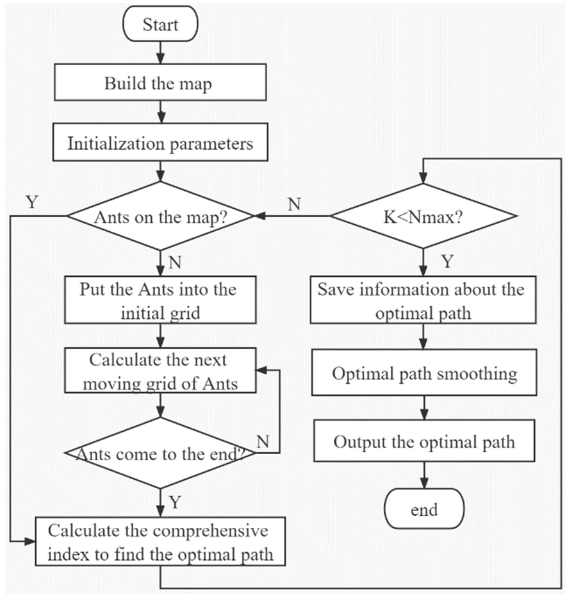

FIGURE 2. The improved ACO algorithm.

As shown in Fig. 2, four core steps are integrated together to develop the improved ACO algorithm of this paper as follows:

Step 1: According to the arrangement of the shelves in the intelligent warehouse environment, a three-color grid map is constructed. Parameters, and the coordinates of the starting and ending points are initialized and determined.

Step 2: Determine whether the ants are put into the grid map. If so, find the optimal path according to the comprehensive index. Otherwise, put the ants into the map and find the next grid according to the improved strategy of this paper.

Step 3: Judge whether the ant has reached the end. If so, find the optimal path. Otherwise, continue to find the following grid.

Step 4: Determine whether the algorithm has reached the maximum number of iterations. If so, save the optimal path information for smoothing, and output the optimal path and the iteration curve. Otherwise, move to Step 2.

A. FLEXIBLE INTELLIGENT WAREHOUSE MODELING

The flexible warehouse area in this paper is mainly composed of three-dimensional shelves, loading and unloading work units, manipulator work units, handling work units, and warehousing platforms. The combination shelf is composed of multiple three-dimensional shelves, which can be combined arbitrarily according to the actual environment condition. According to different warehouse environments, shelves can be combined as shown in Figure 3 below. Where lable "1" are three-dimensional shelves, lable "2" means the loading

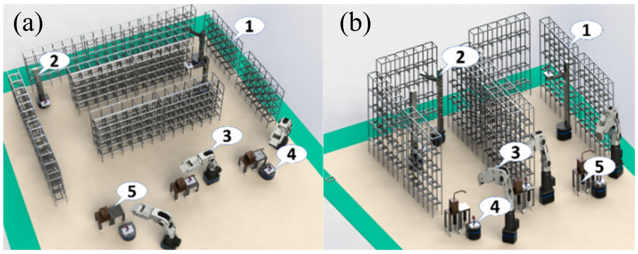

FIGURE 3. The shelf combination diagram of warehouse system. (a) Case 1 and (b) Case 2, respectively.

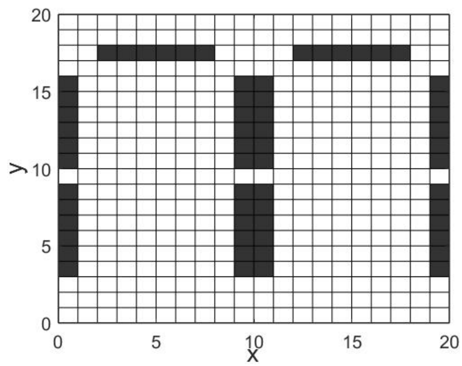

FIGURE 4. Traditional two-color raster map.

and unloading work unit, lable "3" refers to the manipulator work unit, lable "4" represents the handling work unit, and lable "5" is the warehousing platform. The loading and unloading steps of storage are completed by the loading and unloading work unit. Therefore, the path planning problem of intelligent warehouse robot in the three-dimensional shelf environment is reduced to a two-dimensional problem.

Grid method, visibility graph algorithm, topological method, free space method, etc. are commonly used two-dimensional map modeling methods [19]. The grid method has the advantages of simple creation, convenient modification, and controllable accuracy, so this paper adopts the grid method Map the warehousing environment in Fig. 3.

In this paper, we improve the traditional black and white raster method by incorporating a Poisson Distribution matrix to model unknown influences. The parameter λ of the Poisson Distribution [20] is the average number of occurrences of random events per unit time (or unit area) and also the expectation and variance of this distribution; therefore, λ is the only parameter of the Poisson Distribution. The physical meaning of λ in this paper is the number of occurrences per unit area of a busy grid affected by unknown factors, such as the need for temporary manual pickup to a particular extent due to the demand of other processes or the sudden failure of a stacker to stay in a grid. The smaller the value of λ, the more skewed the distribution, and as the value increases, the distribution becomes more symmetrical.

$$P(X=k)=\frac{\lambda^k}{k!}e^{-\lambda}, k=0,1,2\cdots,L \tag{4}$$

Therefore, this paper adopts the black, white, and orange raster method to model the map. The black raster represents

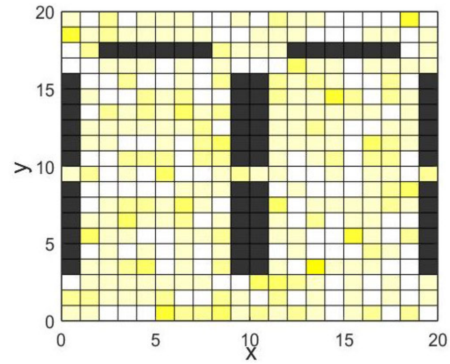

FIGURE 5. The improved three-color raster map.

the obstacles (including shelves, six consecutive black rasters in Fig. 4 represent shelves), and the white raster represents the feasible domain. In addition, the orange raster is used to simulate the change of unknown factors by using the Poisson Distribution matrix; the degree of orange shade indicates the strength of the unknown factors, where the yellow raster is the most vital unknown factor, which should be avoided as much as possible in path planning, and the orange raster with different degrees is the raster with weak unknown factors. By continuously adjusting the variable λ in Poisson's distribution, a storage map conforming to the environment of this paper is completed, as shown in Fig. 5.

B. IMPROVING THE PHEROMONE MECHANISM

1) INITIAL PHEROMONE OPTIMIZATION

The initial value of pheromone concentration in traditional ACO is fixed, so the ants are prone to deadlock or local optimum, so the initial pheromone is optimized as follows:

$$\tau_{i,j}(0)=f(s)+f(0) \tag{5}$$

$$f(s)=\frac{1}{C_U} \tag{6}$$

In Eqs. (5) and (6), $f(0)$ is a constant, $f(s)$ is an obstacle avoidance function, C_U is a complementary set of symbols, and U is the set of neighboring grids of this grid, i.e., the closer the ants are to the obstacle, the lower the initial pheromone concentration is, and the opposite is true. Improving the fixed initial pheromone to non-uniform according to the barrier, can significantly enhance the shortcomings of the traditional ACO algorithm of blind search and increase the convergence speed.

2) PHEROMONE UPDATE MODEL

The traditional pheromone update method is the ant-perimeter model; for the path length, turning cost, and unknown factors in the smart storage environment, the following changes are made in this paper:

$$\Delta\tau_{i,j}^m(t)=\begin{cases}\dfrac{Q}{B_m(t)}, & \{i,j\}\subset A_{m,t}^q\\ 0, & others\end{cases} \tag{7}$$

$$B_m(t)=uP_m(t)+vH_m(t)+wT_m(t) \tag{8}$$

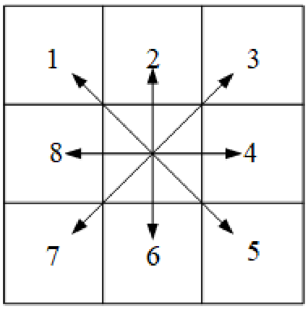

FIGURE 6. Adjacent grid steering and label.

In Eqs. (7) and (8), $A_{m,t}^{q}$ is the set of ordered grids traversed by ant m up to t iterations of grid q; $B_m(t)$ is the total pheromone index of ant m in the t-th iteration, and the size of the index is negatively correlated with the merit of the path, $P_m(t)$ is the path length, $H_m(t)$ is the path safety, $T_m(t)$ is the number of turns, and u, v, w are the adjustment coefficients of each factor. By substituting Equations (7) and (8) into Equation (2), we can obtain the improved pheromone calculation formula. By reasonably adjusting the factor control coefficients, the optimal paths under different constraints can be obtained, which makes the improved algorithm of this paper much more robust.

C. IMAGE PROCESSING

1) DE-POINTED PROCESSING

To ensure the accuracy and stability of the flexible intelligent storage robot, the path planned by the algorithm should be as far away from the obstacles as possible. Hence the path needs to remove the tip part. In this paper, we improve the way of storing map information, the movement trajectory of ants can be regarded as the process of transferring from the center point of the current grid to the center point of neighboring grids, and the whole path is finally planned by superimposing a finite number of grids transfers. There are 8 neighboring grids, and their directions and labels are shown in Fig. 6, among which the even numbers 2, 4, 6, and 8 are straight transfer grids, and the odd numbers 1, 3, 5, and 7 are oblique transfer grids. The principle of tip removal is that if the current grid is shifted to the oblique grid, only the grid adjacent to these two grids are free grids can be moved. For example, if the central grid is moving to grid 3, both grid 2 and grid 4 must be free for the ant to move. By improving the transfer strategy, the tip problem is effectively avoided.

2) OPTIMAL PATH SMOOTHING

For modeling with the grid method, the problem of path turning angle is unavoidable. If the turning tip is too large, it will reduce the kinematic performance of the warehouse robot and affect the handling efficiency. Therefore, secondary optimization is required. In this paper, the inscribed arc is used instead of the turning angle. As shown in Fig. 7, the direction of the arrow represents the movement direction of the robot. First, the coordinates of the starting point A (x_1, y_1) and the coordinates of B(x_2, y_2) are extracted; secondly, the corners of $\theta_1, \theta_2 (\theta_1 \neq \theta_2)$ the points A and B are extracted. The line passing through point A and the angle θ_1 with the X-axis is represented as l_1, and the line passing through point B and the angle θ_2 with the X-axis is denoted as l_2, and the linear equation is shown in Equation 9.

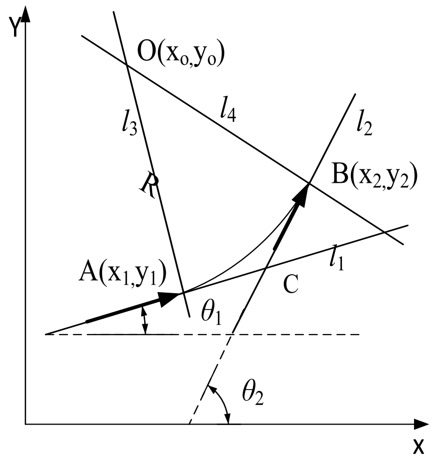

FIGURE 7. Schematic diagram of path smoothing processing.

$$\begin{aligned} l_1 &: (x - x_1)tan\theta_1 - y + y_1 = 0 \\ l_2 &: (x - x_2)tan\theta_2 - y + y_2 = 0 \end{aligned} \tag{9}$$

Make a vertical line l_1 through point A, denoted l_3, and a vertical line l_2 through point B, denoted l_4, and the linear Equation is shown in Equation (10).

$$\begin{aligned} l_3&:(x - x_1)cot\theta_1 + y - y_1 = 0 \\ l_4&:(x - x_2)cot\theta_2 + y - y_2 = 0 \end{aligned} \tag{10}$$

The Equation of the straight line l_3, l_4 can be found immediately by joining the intersection point O with the site-mark (x_o, y_o), whose expression is shown in equation (11).

$$\begin{aligned} \mathrm{x_o} &= \frac{\mathrm{y_2 - y_1} + x_2 \cot\theta_2 - \mathrm{x_1}\cot\theta_1}{\cot\theta_2 - \cot\theta_1} \\ \mathrm{y_o} &= \frac{\mathrm{y_1}\cot\theta_2 - \mathrm{y_2}\cot\theta_1 + (\mathrm{x_1 - x_2})\cot\theta_1\cot\theta_2}{\cot\theta_2 - \cot\theta_1} \end{aligned} \tag{11}$$

Then draw a circle with point O as the center and R as the radius. The expression of R is shown in formula (12). Because the arc AC is tangent to l_1 and l_2, the final path is smooth. Through the path quadratic planning process, the smoothness of the planned way is improved, thereby improving the motion stability of the intelligent warehouse robot.

$$\begin{aligned} R &= \sqrt{(\Delta x)^2 + (\Delta y)^2} = \sqrt{(x_o - x_1)^2 + (y_o - y_1)^2} \\ &= \left| \frac{csc\theta_1\left[(y_1 - y_2) + cot\theta_2\,(x_1 - x_2)\right]}{cot\theta_2 - cot\theta_1} \right| \end{aligned} \tag{12}$$

IV. SIMULATION EXPERIMENTS

To verify the feasibility of the algorithm in this paper, the parameters are continuously adjusted and optimized based on a large number of experiments. Finally, a set of parameters

TABLE 1. Input parameters.

Symbol	Description	Values
m	Number of ants	100
n	Number of iterations	50
Q	Pheromone intensity	110
α	Heromone heuristic factor	1
β	Expected heuristic factor	8
ρ	Pheromone evaporation rate	0.3
u	Routing factor	100
v	Safety factor	1
w	Turning factor	100
λ	Poisson Distribution parameters	1

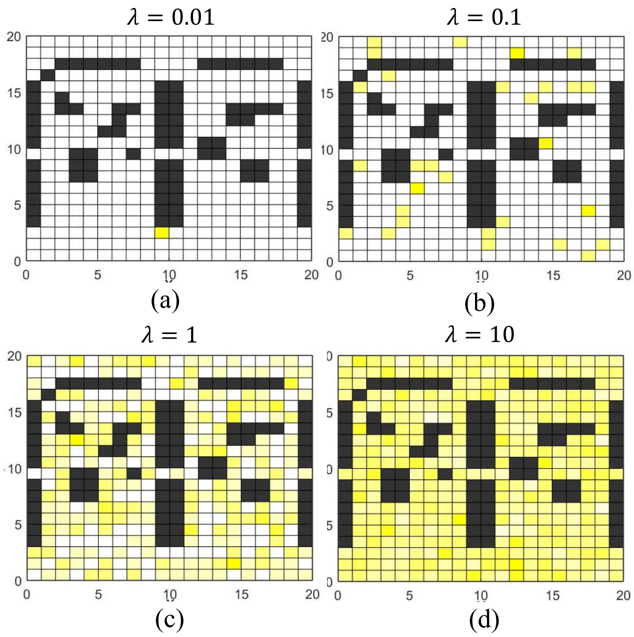

FIGURE 8. Comparison of simulation results of the Poisson Distribution parameter λ equals to (a) 0.01, (b) 0.1, (c) 1 and (d) 10, respectively.

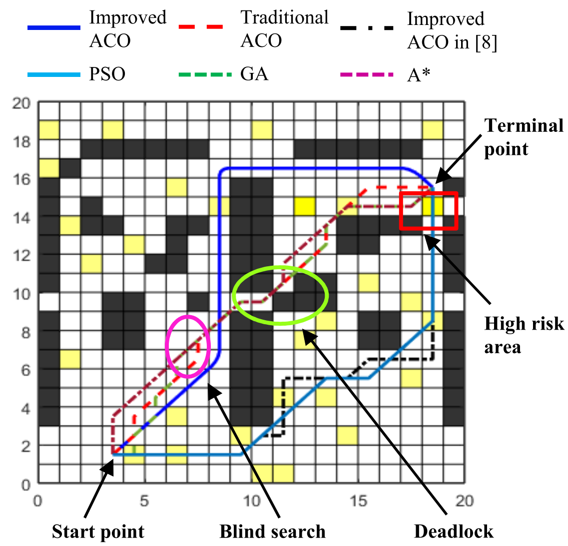

FIGURE 9. Comparison of optimal paths of different algorithms.

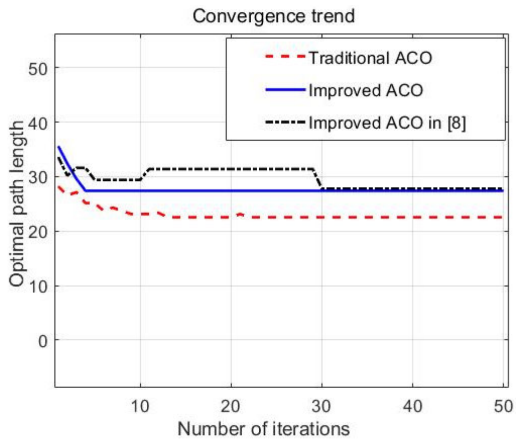

FIGURE 10. Convergence trend of three different ACO algorithms.

with excellent simulation results is obtained. The raster map is built, and the algorithm is run in the following environment: Windows10_64bit; Matlab2018a; processor Intel(R) Core(TM) i5-3230M with 2.60GHz main frequency memory; 4GB of memory.

A. PARAMETER SELECTION

Since the Poisson Distribution is incorporated into the improved raster map, this paper only shows the process of taking the parameter λ in the Poisson Distribution. The values of the input parameters are shown in Table 1.

The values of λ in Fig. 8 are 0.01, 0.1, 1 and 10, respectively. The simulation results show that. When λ is taken as 0.01, the influence factor is almost negligible when λ is taken as 10, the influence factor is too strong and not suitable for the environment of this paper, and when λ is taken as 0.1 or 1, the storage environment of this paper is satisfied. A set of optimal parameters suitable for the simulation environment can be continuously adjusted in the simulation study.

B. ALGORITHM COMPARISON IMITATION

1) CASE 1 COMBINED SHELF

The 20 × 20 combined shelf is simulated to verify the performance of the improved algorithm in this paper. Different algorithms, i.e., the improved algorithm of this paper (the path is the solid blue line), the traditional Ant Colony Algorithm (the path is the dotted red line), the improved Ant Colony Algorithm in [8] (the path is the dotted black line), Particle Swarm Optimization (PSO) Algorithm (the path is the solid cyan line), Genetic Algorithm (GA) (the path is the dotted green line) and A* Algorithm (the path is the dotted purple line), are applied to the simulated Case 1 combined shelf.

As shown in Fig. 9, the blind search of three algorithms, i.e., the traditional ACO, GA and A* algorithm, in the early stage will appear the chaotic path state marked by the pink ellipse. It will pass through a large number of obstacles tip points, especially the center point marked by the green ellipse in Fig. 9. If these two grids are real obstacles, the intelligent warehouse robot will be deadlocked, thus affecting

TABLE 2. Simulation results of case 1 combined shelf.

	Traditional ACO	Improved ACO in [8]	Improved ACO
Number of iterations	22	30	4
Number of turns	9	7	3
Optimal path length	22.56	27.8	27.4
Path Reliability	Low	Low	High
Running Time (s)	16.974	13.754	8.468

TABLE 3. Input parameters of different groups.

	Group 1	Group 2	Group 3
Routing factor u	100	100	1
Safety factor v	1	100	100
Turning factor w	100	1	100

TABLE 4. Simulation results of different groups.

	Group 1	Group 2	Group 3
Number of iterations	2	17	4
Number of turns	6	10	5
Optimal path length	28.8	28.8	28.8

the efficiency of cargo handling. Although the improved algorithm in Reference [8] and PSO algorithm avoid the deadlock problem, they pass through the area marked by the red rectangle in Fig. 9, i.e., the yellow area where unknown factors have a greater impact, and these paths have certain risks. The improved Ant Colony Algorithm in this paper not only solves the deadlock problem but also bypasses the high-risk area, helping the warehouse robot to complete the handling task. Fig. 10 shows the convergence trend of three different ACO algorithms. As shown in Fig. 10, the improved ACO algorithm in this paper has the best performance compared to the traditional ACO and improved ACO algorithm in [8].

Table 2 shows the simulation results of Case 1 combined shelf. The traditional ACO algorithm converges for 22 iterations, the improved algorithm in Reference [8] converges for 30 iterations, and the improved ACO algorithm in this paper converges after 4 iterations. The traditional ACO, improved ACO in [8] and improved ACO in this paper turn 9, 7 and 3 times, respectively. In terms of the optimal path length, the traditional ACO does not consider the deadlock and has the lowest length of 22.56. Moreover, the improved ACO in this paper shows the lowest running time of 8.468s, compared to 16.974s of traditional ACO and 13.754s of the improved ACO in [8]. The simulation results, i.e., number of iterations, number of turns, optimal path length, path reliability, and running time, show that the improved ACO algorithm in this paper outperforms the other two algorithms.

2) CASE 2 COMBINED SHELF

The Case 2 combined shelf is simulated to further verify the applicability of the improved algorithm in this paper with a complex storage environment. Three groups of parameters, i.e., route factor, safety factor and turning factor, are simulated in Table 3.

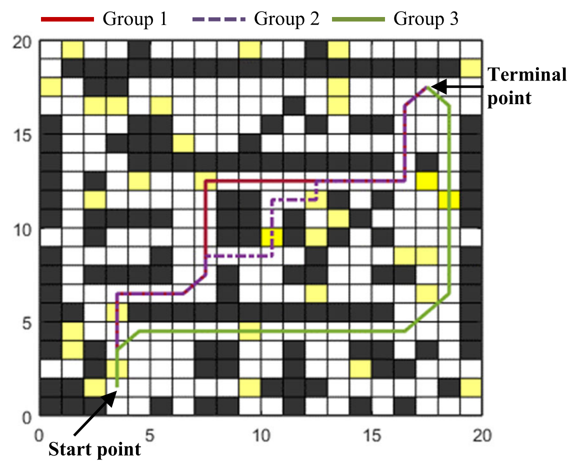

FIGURE 11. Comparison of optimal paths with different parameters.

Table 4 shows the simulation results of different groups. The improved ACO in this paper shows the same optimal path length of 28.8 with three groups of parameters. Moreover, it can obtain the optimal path with faster convergence speed by adjusting the routing factor u. The safety factor v affects the safety of path searching.We can adjust the turning factor w in order to obtain the path with the least turning cost. Therefore, the improved ACO algorithm in this paper can meet the needs of different scenarios. It is only necessary to adjust the corresponding parameters in order to obtain the optimal path with comprehensive factors. Fig. 11 shows the comparison of optimal paths with different groups of parameters.

V. SUMMARY AND PROSPECTS

In this paper, the intelligent storage robot is taken as the research object. Based on the traditional black-and-white dichroic grid map, Poisson distribution is integrated into the three-color grid map to simulate the storage environment caused by unknown factors. Aiming at the problems of traditional ACO algorithm, such as low search efficiency, slow convergence speed and poor obstacle avoidance strategy. This paper improves the pheromone updating mechanism by taking the routing factor, turning factor and safety factor into account.

The simulation results of Case 1 combined shelf show that the improved algorithm in this paper can quickly find the optimal path under the influence of unknown factors, which solves the problem of deadlock and poor security in the literature. The de-pointed and smoothing process will greatly improve the motion stability of the intelligent warehousing robot. The proposed algorithm reduces the number of iterations from 22 and 30 to 4. The number of turns is reduced from 9 and 7 to 3. Also, the running time of proposed algorithm has 50.11% and 38.43% reduction compared with other two ACO algorithms, respectively. The simulation results of Case 2 combined shelf show that the improved algorithm can obtain the optimal path under complex storage environment by adjusting different parameters. Moreover, dynamic obstacles can be further considered to conduct future research on robot-human cooperation work.

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