International Journal of Industrial Engineering, 32(1), 159-172, 2025

GLOBAL PATH PLANNING METHOD FOR AGV OF WAREHOUSING LOGISTICS BASED ON IMPROVED ANT COLONY ALGORITHM

Yan Liu

College of Economics and Management
Henan Polytechnic
Zhengzhou, China
*Corresponding author's e-mail: liuyan_0371@163.com

AGV for warehousing and logistics is an automatic guided vehicle that is used for cargo handling, storage, sorting and other operations in warehousing and logistics scenarios. Due to the complex warehousing logistics scenarios, AGV needs to deal with the complex environment and variable task requirements in warehousing logistics during operation, resulting in low efficiency of path planning. Therefore, a global path planning method for AGV of warehousing logistics based on an improved ant colony algorithm is studied. After analyzing the overall transportation path of warehousing logistics, according to the optimization algorithm of ants' foraging behavior in nature, the pheromone transmission mechanism and behavior rules are simulated, and relevant factors such as path length transportation efficiency. Obstacle avoidance and load balance are considered to adjust the parameters such as pheromone volatilization factor and heuristic information weighting so that the improved ant colony algorithm can better adapt to changes in the warehousing logistics environment and improve the accuracy and reliability of AGV path planning. Through experimental verification, the effectiveness and superiority of the method are proved, the AGV transportation efficiency is improved, and the algorithm has excellent stability and adaptability.

Keywords: Warehousing Logistics; AGV Global Path Planning; Ant Colony Algorithm; Improved Ant Colony Algorithm; Path Optimization.

(Received on March 12, 2024; Accepted on September 24, 2024)

1. INTRODUCTION

Storage and logistics AGV (automatic guided vehicle) is an automatic vehicle that is widely used in the storage and logistics field to realize the automatic handling and transportation of goods. In warehousing logistics, AGV is usually used for the handling, loading, unloading and transportation of goods. Typical AGV of warehousing and logistics includes chassis, control system, sensor, navigation system and charging system. The chassis is usually driven by a motor. The control system is responsible for directing the vehicle's movement. These sensors are used to raise environmental awareness, while navigation systems are used for path planning and positioning. The charging system is used for wireless charging or automatic charging.

Studying the global path planning of AGV in warehousing logistics is of great significance to e-commerce and warehousing logistics. It can not only improve the efficiency of warehousing operations but also reduce the transportation costs to a certain extent. With the rise of e-commerce, the volume of logistics warehousing business has increased dramatically, and manual sorting and handling methods have been unable to meet the demand for a large number of online shopping orders. With the help of intelligent logistics equipment, AGV can significantly improve the efficiency of warehousing operations. As the core technology of AGV scheduling, AGV global path planning is of great significance to shorten operation time and improve logistics efficiency. In warehousing logistics, transportation costs account for a considerable proportion. By studying the overall path planning of AGV and optimizing the operation path and task allocation of AGV, we can reduce transportation costs and improve the economic benefits of enterprises. However, due to the independence of customers, warehousing logistics has a high requirement for accuracy. Any sorting or transportation error will increase users' trouble and reduce convenience, and the warehousing logistics environment often changes, such as the change of cargo placement position or the emergence of temporary obstacles, which leads to the current path planning algorithm being unable to adjust the path in time to adapt to the dynamic changing environment, The path selection is not flexible enough. Therefore, it is necessary to study a rapid global path planning method for AGV of warehousing logistics.

In the research of wireless network traffic path planning (Huo, 2023), cloud computing services are realized through wireless communication, complex and changing traffic conditions are calculated under network storage conditions, and a variety of alternative paths are obtained. Path search is completed through data transmission and machine learning technology,

DOI: 10.23055/ijietap.2025.31.1.10007 ISSN 1072-4761

but the efficiency of path search and planning calculation is relatively low in 3D path planning; Han *et al*. (Han *et al.*, 2021) proposed a global motion planning for driving Unmanned Surface Vehicle (USV), taking into account all dynamic constraints of USV, tracking the global trajectory accurately through the maneuver system, executing A * search method to determine the effective trajectory, and achieving global path guidance and planning. However, the algorithm will give a large number of search tracks, and the final path planning accuracy is slightly lower. When studying path planning with low load and high efficiency (Sang *et al.*, 2021), an artificial potential field algorithm based on multiple sub-targets was proposed. According to the potential field trend, the algorithm was improved to ensure the optimality and rationality of the path planning. The optimal path was divided into multiple sub target points to form a sequence of sub target points. By switching target points, the probability of falling into a local minimum was reduced to achieve effective path planning. However, the under-driving problem was not taken into account when the heuristic function was applied in the research, so the actual path planning lacks direction constraints. Zhao *et al*. (2023) study put forward a hierarchical motion path planning framework, considering time-varying, unknown complex environments to the global trajectory optimization at the same time, adding local reactive collision strategy through adaptive elite genetic algorithm, analyzing the potential probability problems contained in the path planning, the application of virtual sensing vector seamless bridge transition path, strengthen the connection between global optimization and dynamic avoid, but in the use of genetic algorithm, the paper lacks the analysis of the path trajectory safety distance. Ait Saadi *et al*. (2022) used heuristic methods such as the artificial potential field method to create a potential field for drones, enabling them to avoid obstacles and move towards the target. However, the planning efficiency of this method in complex environments still needs to be further improved. Puente Castro *et al*. (2022) used reinforcement learning algorithms in UAV swarm path planning to simulate flight environments, enabling UAVs to learn how to plan paths optimally through trial and error. However, reinforcement learning requires a large amount of data and time to train models, and for complex environments and tasks, it requires complex models and high-performance computing resources. Han and Li (2023) achieved path planning for UAVs by combining dynamic weighted five neighborhood search A * algorithm and quadratic Bessel curve for path smoothing. At the same time, dynamic weighting is introduced into the heuristic function, and during the search process, the weight of the heuristic function can be adjusted based on the map situation and node attributes. This method makes path planning more targeted and can quickly find the optimal path. Although the five-neighborhood search reduces the redundancy of the search, the implementation of dynamic weighting and the calculation of quadratic Bessel curves can easily increase the complexity of the algorithm. From the above analysis, it can be seen that although path-planning technology has made significant progress in existing research, it still faces many challenges. Although Huo (2023) improved the flexibility of path search through cloud computing and wireless communication technology, the efficiency in three-dimensional environments is still insufficient. The A * search method proposed by Han *et al*. (2021) has achieved good results on unmanned surface vehicles, but there is still room for improvement in the accuracy and efficiency of path selection. The hierarchical motion planning framework proposed by Zhao *et al*. (2023) considers complex environments but lacks analysis in terms of path safety distance.

Based on the above research results, a global path planning method for warehouse logistics AGV based on an improved ant colony algorithm is proposed. When not using a directed graph, the path-planning process is complex and difficult to quantify, making it difficult to determine the optimal path. This is because the directed graph model can clearly represent the path of AGV from the starting point to the ending point, as well as possible conflict points and diversion points, making path planning more accurate and quantifiable and can quickly finding the optimal path. In the case of numerous nodes and complex paths, it is difficult to find the optimal path, which can easily lead to low transportation efficiency. Therefore, considering the practical characteristics of modern large-scale warehousing logistics, an improved ant colony algorithm is used to achieve global path planning for warehousing logistics AGV. By optimizing path selection, ant foraging behavior can be better simulated. Through the accumulation and volatilization of pheromones, the AGV's actual operation status can be more accurately described, thereby optimizing path selection and improving the efficiency and accuracy of path planning. In order to improve the adaptability and application performance of global optimization, an improved ant colony algorithm is used to study the global planning path of warehousing logistics. The specific steps are as follows:

1) Globally analyze the current situation of warehousing and logistics, establish the corresponding raster model, clarify the elements such as warehouse, cargo space, path, etc., and set the relevant parameters according to the actual needs, such as the number of ant colonies, pheromone volatilization speed, and the number of iterations.
2) Initialize the colony: At the beginning of the algorithm, the colony needs to be initialized. This involves assigning a random start point to each ant and initial pheromones to each point on its path.
3) Pheromone update: In each iteration, the pheromone on the path is updated according to the ants' movement and pheromone volatilization rules. This can be done by calculating the path length and pheromone consumption of each ant in this iteration.
4) Selection of paths: When each ant selects the next node to move, it does so based on pheromone concentration and heuristic information (e.g., distance, direction, etc.). The ants will tend to choose the path with higher pheromone concentration and better heuristic information.

5) Iterative optimization: Repeat pheromone updating and path selection until a preset number of iterations is reached or stopping criteria are met. In the iterative process, the algorithm will continue to optimize the path to find the global optimal solution.
6) Output: Output the final global optimal solution found, that is, the global planning path of warehousing and logistics.
7) Post-processing and optimization: According to the actual operation and optimization goals, the algorithm is post-processed and optimized to improve the efficiency of path planning.

2. GLOBAL ANALYSIS OF TRANSPORTATION PATHS IN MODERN WAREHOUSING AND LOGISTICS

In the field of modern warehousing logistics, the automatic guided vehicle (AGV) system is widely used because of its automation, high efficiency and accuracy. In the AGV system, path planning and conflict shunting point analysis are the key factors to ensure efficient transportation.

(1) Path planning

Path planning is one of the core tasks of the AGV system, which involves determining the optimal route from the starting point to the ending point of AGV. Many factors, such as the weight and size of cargo, length and width of the path, and traffic density, should be considered in the planning process to ensure that AGV can complete the transportation task safely and stably in the shortest time.

In order to realize the path planning, a directed graph model is established, in which the vertices represent goods or transport nodes and the directed edges represent transport paths from one node to another. In this directed graph, we can define conflicts and shunt points. When two or more AGVs may meet or cross in the process of transportation, it is necessary to use diversion points to avoid conflict and ensure smooth transportation.

(2) Analysis of conflict diversion points

Conflict transfer point analysis is an important means to improve the efficiency of AGV transportation. Through analysis, it is possible to determine the reasonable location of diversion points and optimize each transportation path. This requires considering multiple factors, such as the AGV's driving speed, turning radius, and load capacity, as well as the spatial layout and cargo distribution within the warehouse.

In the design and management of diversion points, real-time monitoring and adjustment strategies can be adopted. By real-time monitoring of traffic flow and path congestion at diversion points, dynamic management and optimization of diversion points can be carried out to adapt to changes and demands in actual transportation.

(3) Weighted Directed Graph and Weighted Sorting

In order to more accurately describe the transportation path and weights of AGVs, the directed graph is transformed into a weighted directed graph. In a weighted directed graph, each edge between nodes has a weight value that represents a certain attribute of the path, such as distance, time, or cost. Find the optimal transportation route by calculating the minimum weight path between the starting node and the ending node (Li *et al.*, 2022; Yang *et al.*, 2022).

When GAV is transporting goods, the conflict point is represented by H, and the intermediate node between the starting and ending points is considered the core node, represented by G. The two adjacent nodes of goods transportation are connected to form a directed graph node route. In order to ensure the standardization of data in research, it is necessary to determine the corresponding weights of goods routes and sort adjacent node routes according to the weight sorting. During the process, the directed graph of warehousing and logistics goods transportation is directly converted into a weighted directed graph (Wang *et al.*, 2023), which can be expressed by the formula:

$$A = (W, [B]) \tag{1}$$

Among them, A is a weighted directed graph of the transportation paths of goods in the warehouse, and the W denotes the set of transportation path nodes contained within the warehouse, the $[B]$ describes a collection of path node connectors (Sun *et al.*, 2023; Hao *et al.*, 2022). In the process of weight value sorting ("the process of weight value sorting" refers to the process of classifying or sorting paths in a weighted directed graph based on the weight of each edge, such as distance, time, or cost, which helps to determine the optimal path or evaluate the advantages and disadvantages of different paths.), the corresponding weight of the goods route can be determined based on the actual situation (The actual situation of the warehousing and logistics environment, including the weight and size of goods, physical limitations of paths such as length, width, height, traffic density, AGV speed, turning radius, load capacity, as well as the spatial layout and distribution of goods in the warehouse.), and adjacent node routes can be sorted according to the weight. This helps to have a clearer understanding of the advantages and disadvantages of each path, providing a basis for path planning and optimization.

(4) Environmental modeling

In order to more intuitively describe and analyze the warehousing and logistics environment, a grid method is used to establish an environmental model. In the model, establish a Cartesian coordinate system and cut the entire spatial area horizontally and vertically based on the walking state of the AGV and the minimum space required for turning. This can divide the entire warehousing and logistics environment into several small areas (or grids), each grid representing a specific spatial location. The actual situation is shown in Figure 1.

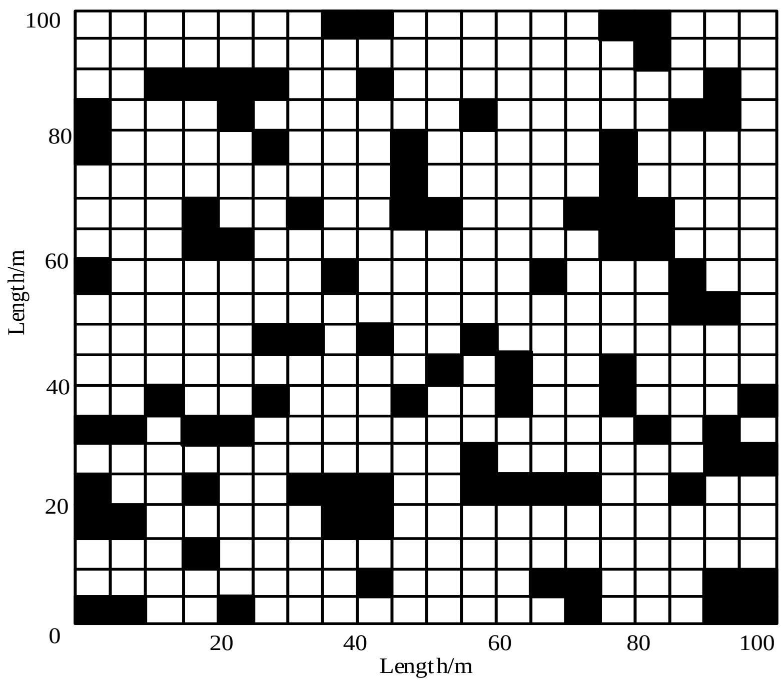

Figure 1. Modeling of Warehousing and Logistics Environment

Through environmental modeling, it is possible to more accurately simulate the movement trajectory and state of AGVs in the warehousing and logistics environment, providing important data support for path planning and conflict diversion point analysis. At the same time, the model can also be adjusted and optimized according to the actual situation (Zou *et al.*, 2023) to adapt to different transportation needs and scenarios.

3. PRINCIPLE ANALYSIS OF THE APPLICATION OF ANT COLONY ALGORITHM IN THE PATH PLANNING PROCESS

In warehouse logistics management, high-precision AGV global path planning is crucial for improving sorting efficiency, reducing errors, and ensuring the safety and stability of warehouse management. Ant colony algorithm, as a heuristic search algorithm, has been widely used in AGV global path planning problems due to its distributed parallel search characteristics.

3.1 Basic Principles of Ant Colony Algorithm

The ant colony algorithm simulates the behavior of ants searching for food sources in nature (Chen *et al.*, 2022). During the pathfinding process, ants release a chemical substance called "pheromones". Other ants are able to perceive this pheromone and tend to choose paths with higher pheromone concentrations. Through this positive feedback mechanism, the ant colony can find the optimal path from the nest to the food source.

3.2 Application of Ant Colony Algorithm in AGV Path Planning

In AGV global path planning, the ant colony algorithm simulates the pathfinding behavior of ants to achieve the search for the optimal path. The specific steps are as follows:

(1) Initialization

Set the number of ants in the ant colony and the initial position of each ant. At the same time, initial pheromone concentrations are assigned to each possible path, and these pheromone concentrations are set to equal values.

(2) Heuristic function

The heuristic function is used to evaluate the visibility or attractiveness between two nodes. In AGV path planning, the heuristic function is the reciprocal of the distance between two nodes, meaning that the shorter the distance, the higher the visibility. In the study, it is assumed that the distance between two nodes i and j is $d_{ij}(i,j = 1,2,\cdots,n)$, and the heuristic function between the two nodes in the search path is expressed as η_{ij}, then:

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{2}$$

$$d_{ij} = \left[\eta_{ij}(i_x - j_x)^2 + A\left(i_y - j_y\right)^2\right]^{1/2} \tag{3}$$

Among them, i_x、i_y and j_x、j_y denote the horizontal and vertical coordinates of the nodes i、j respectively.

(3) Path selection

Each ant selects the next node to be visited based on the pheromone concentration and heuristic function value at its current location (Ma *et al.*, 2022). During the selection process, the relative importance of pheromone concentration and heuristic function values will be considered (Han *et al.*, 2022), and the transition probability of ant k starting from node i and ultimately arriving at node j (Su *et al.*, 2023) will be calculated as p_{ij}^k:

$$p_{ij}^k = \begin{cases} \dfrac{\tau_{ij}(N_C+1)\eta_{ij}^{\beta}(t)}{\sum_{j\in allowed_k} \tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}, j \in allowed_k \\ 0, other \end{cases} \tag{4}$$

Among them, $N_C$represents node algebra, t indicates the information search time. $allowed_k$ represents the set of nodes that can be accessed during the path search phase of ants k, the α denotes the pheromone importance factor describing the ease or difficulty of path selection by ants (Xue, 2022). β is the importance factor that describes the heuristic function, when the value is larger, it indicates that the colony is more likely to select the nearest path node.

(4) Pheromone update

After all ants complete a path search, the pheromone concentration on each path is updated based on the length of the path they have walked and the search results. Pheromones will evaporate over time and also increase along the path that ants pass through.

(5) Iterative optimization

The process of repeating path selection and pheromone updates until the termination conditions are met (such as reaching the maximum number of iterations or finding the optimal path that meets the requirements).

By simulating the path-seeking behavior of ants using the ant colony algorithm, the algorithm has demonstrated good performance in the AGV global path planning problem. It can quickly find the optimal path from the starting point to the endpoint, effectively avoid vehicle congestion and conflicts, and improve the operational efficiency and stability of the warehousing system.

4. AGV GLOBAL PATH PLANNING BASED ON IMPROVED ANT COLONY ALGORITHM

In warehousing and logistics, the global path planning of AGVs (Automatic Guided Vehicles) is crucial for improving efficiency and reducing collision risks. Traditional ant colony algorithms perform well in the field of path planning, but they suffer from problems such as insufficient initial pheromones and susceptibility to local optima. To overcome these limitations, this paper proposes an improved ant colony algorithm that optimizes the path planning of AGVs by introducing directional coefficients and safe distance strategies.

(1) Introducing directional coefficients

The directional coefficient is an important parameter used to measure the correlation of entity motion in a certain direction. After introducing the directional coefficient μ, the algorithm can more intelligently select a path that matches the current motion direction, thereby improving the quality and effectiveness of path planning. To ensure accurate global route planning, it is necessary to avoid wasting a certain amount of search time due to excessively large route angles. Therefore, the operation guidance of AGV during cargo transportation is set up as shown in Figure 2.

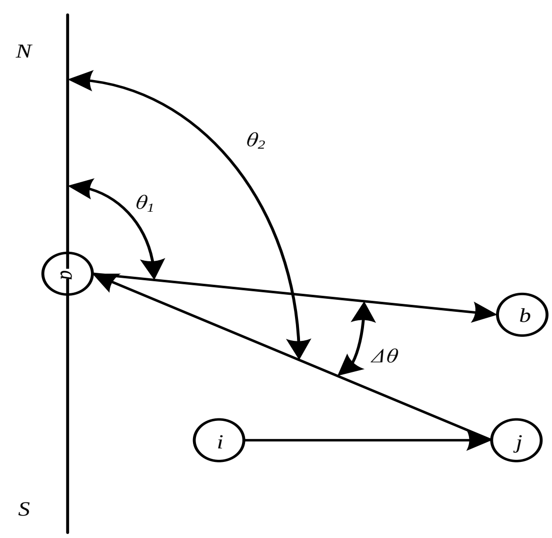

Figure 2. AGV Operation Guidance

In Figure 2, the path of AGV is indicated by the arrow, which is $i \to j \to a \to b$. At this point, each node not only serves as the arrival node, but also as the initial node for the next route. θ_1、 θ_2 represents the angle formed between the AGV and the motion boundary when it reaches the path node (Zhu *et al.*, 2022; Liu *et al.*, 2023; Liu *et al.*, 2022). The smaller the angle $\Delta\theta$, the closer the AGV is to the final node b. This proves that the closer the AGV's cargo transportation direction is to the target point, the shorter the distance it travels.

(2) Improve the heuristic function

Improve the heuristic function by combining directional coefficients. In study, set η_{ij}^* represent the improved path-finding expectation heuristic function (Wu *et al.*, 2023). By establishing a function relationship, we can get the following:

$$\eta_{ij}^{*} = \frac{1}{d_{ij} + \frac{\mu \Delta\theta}{\pi}} \tag{5}$$

where the heuristic function η_{ij}^{*} for the ant colony to find a path is greater than 0.

(3) Update of path transition probability

From the analysis of the above formula, it can be seen that when the transport path angle of the AGV is too large, the expected heuristic function value of the path will directly reduce, to a certain extent, reducing the loss of path selection probability due to the too large angle. At this time, calculated the path transition probability (Singh *et al.*, 2023) of the improved ant colony algorithm:

$$p_{ij}^{(k)}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}^{*}(t)\right]^{\beta}}{\sum_{s\in allow}[\tau_{is}(t)]^{\alpha}[\eta_{is}^{*}(t)]^{\beta}}, s \in allow \\ 0, otherwise \end{cases} \tag{6}$$

s represents the degree of path selection loss. After the above improvement of the heuristic function, the general structure of the path planning can be described more specifically by calculating the transfer probability of the ant colony in the path selection.

(4) Improving the pheromone update mechanism

But at this time, the path planning is not precise. The pheromone updating mechanism is further improved in the study due to the pheromone updating of the ant colony is relatively single, which leads to the algorithm cannot summarize and utilizing the shortest path pheromone obtained in the previous cycle well when it enters into the next cycle. The shortest path pheromone obtained in the previous cycle is not well summarized and utilized. Therefore, when updating and improving the pheromone mechanism, according to the cycle time and conditions of the ant colony, the pheromone on the nodes of paths passed by the ants is updated locally in actuality, and the pheromone on the optimal and worst paths can be obtained by establishing the following formulae after ants complete a cycle after a period of time:

$$\Delta\tau_{ij}(t, t+n) = \begin{cases} \dfrac{1}{L_{gb}, (i,j) \in T_u} \\ \left(\dfrac{1}{L_{gw}}\right) - \left(\dfrac{1}{L_{gb}}\right), (i,j) \in T_v \\ 0 else \end{cases} \tag{7}$$

In the formula, the n denotes the pheromone search time additive, the L_{gb} denotes the length of the optimal path in the current search path, and T_u denotes the set of all nodes contained in the searched optimal path, the L_{gw} denotes the length of the worst path in the current search path. T_v represents the set of all nodes contained in the worst path searched for. By introducing this updating mechanism, the pheromone in each round of the cycle can be utilized more efficiently. This means that those paths that proved to be superior in the past iterations will be more easily selected by the subsequent ants. This mechanism not only improves the performance of the path planning algorithm but also essentially avoids the problem of AGVs falling into local optimal paths during cargo transportation.

(5) Introducing a safe distance strategy

In the previous exploration, the effectiveness of global path planning has been ensured, providing a reliable path selection for AGV's cargo transportation (Shu *et al.*, 2023). However, in order to further improve the reliability and security of the global planning algorithm, it is recognized that the security of the path needs to be further optimized. In the next research, we will mainly focus on improving the safe distance strategy of the path. The safe distance refers to the minimum distance that should be kept between the AGV and the obstacles around it so as to ensure that the AGV will not collide with the obstacles during transportation. Research and improvement on how to calculate the safety distance more accurately and adjust the safety distance dynamically according to the shape, size and position of obstacles. In addition, how to effectively integrate the concept of safe distance into the global path planning algorithm is also a research topic, to ensure that AGV always considers the safety factor when planning the path.

By improving the safety distance strategy, it is expected to significantly improve the reliability and safety of the global path planning algorithm so as to better protect AGV and cargo, and reduce the potential collision risk. It will provide a more robust and safe path-planning method for AGV cargo transportation in complex environments. Route ab、ij is the planned paths before and after the introduction of the safety distance, respectively, are shown in Figure 3.

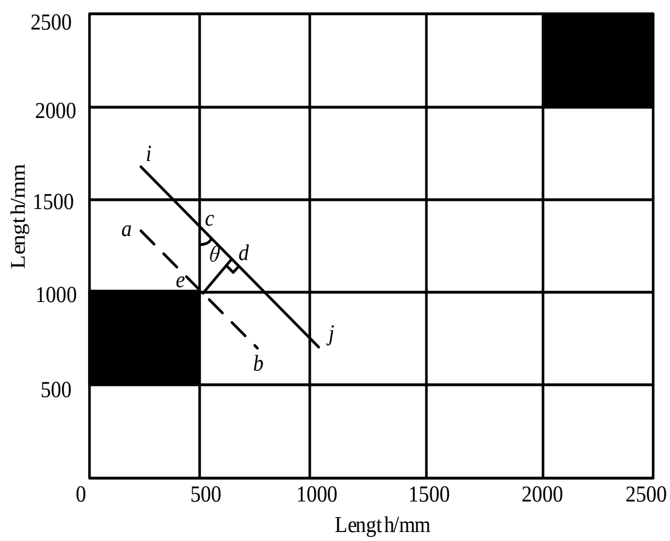

Figure 3. Path Safety Distance Simulation

In the set AGV motion direction, assume the coordinates of the edge point e of the obstacle is (x, y), the distance between point c and point e is 250mm. The coordinates of the point c can be expressed as $(x, y + 250)$, when AGV transports goods and runs to point c, at this point, the c point between obstacle edge points e and the end of the path j will form an angle θ, at which point the line segment l_{ed} is calculated as the safe distance between AGV and obstacles during operation:

$$l_{ed} = p_{ij}^{(k)}(t)\Delta\tau_{ij}(t, t+n)l_{ce}\sin\theta \tag{8}$$

In the formula, the l_{ce} denotes the actual length of the line segment ce, the θ denotes the angle between the line segment ce and cd, and the angle is less than 90°.

(6) Implement path planning

In global path planning, if the AGV chooses the path node and c point are the same when passing through the obstacle, the safe distance of cargo transportation can be ensured to the greatest extent. At this point, the overall improvement of the ant colony algorithm for global path planning is completed. The path planning process of warehousing logistics AGV is shown in Figure 4.

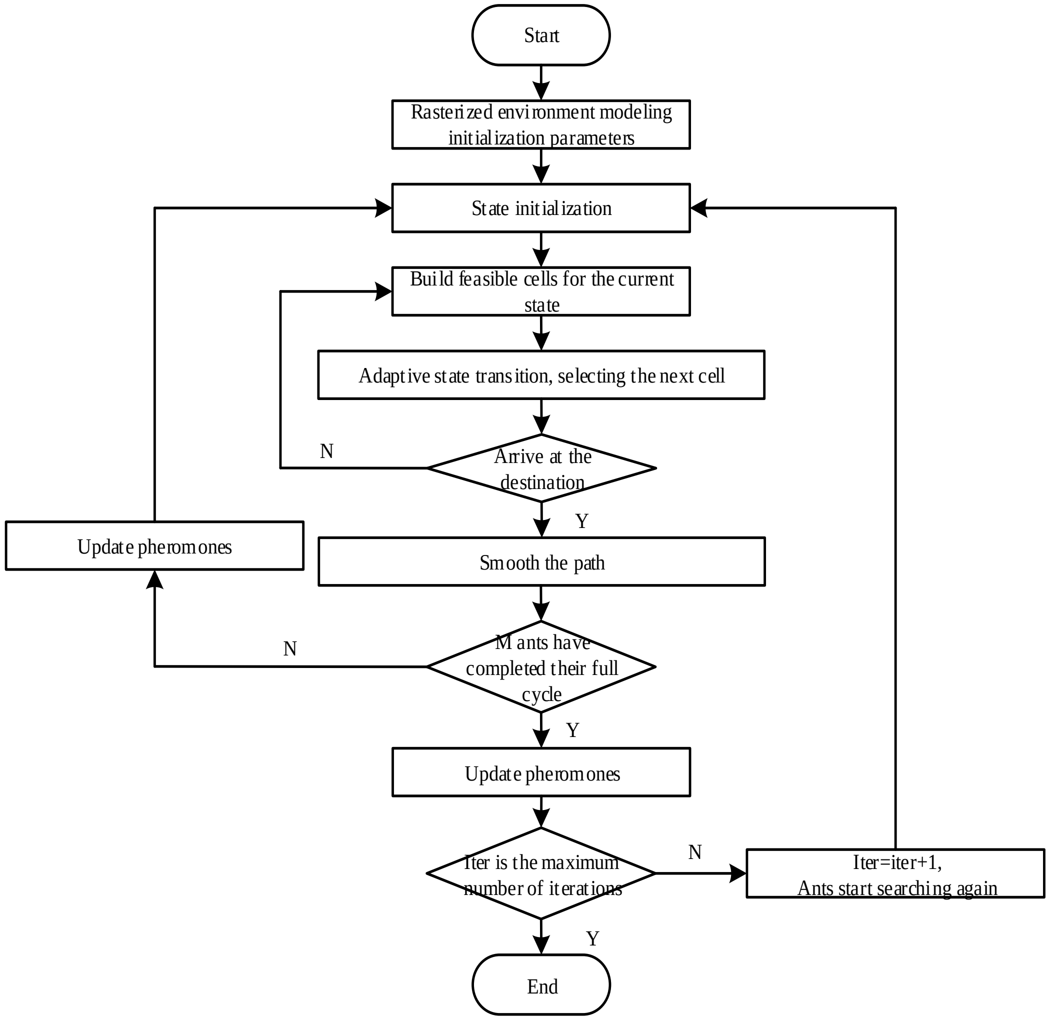

Figure 4. Improved ACO Algorithm Flow

5. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the specific performance of the proposed algorithm in practical applications, the storage logistics that meet the experimental conditions are selected, and the site situation is shown in Figure 5.

Figure 5. Warehouse Logistics and AGV Freight Transportation Site

Set the initial parameters in the experiment, the number of initial ant colonies is 50, the pheromone importance factor is equal to 1, the expected degree factor is 8, the pheromone volatilization coefficient is 0.1, and the maximum number of iterations of the ant colony algorithm is 100. Select a more regular large obstacle storage environment for the experimental environment and compare the actual operation results of AGV under the improved algorithm with the walking path of the ant colony algorithm.

5.1 Analysis of the effectiveness of different methods of path planning

Experiments were conducted on the Vehicle path planning method under a dynamic unpredictable environment (Zhao *et al*., 2023), the unimproved algorithm and the improved ACO algorithm, and the results planned by the two algorithms were compared and analyzed. The results are shown in Figure 6.

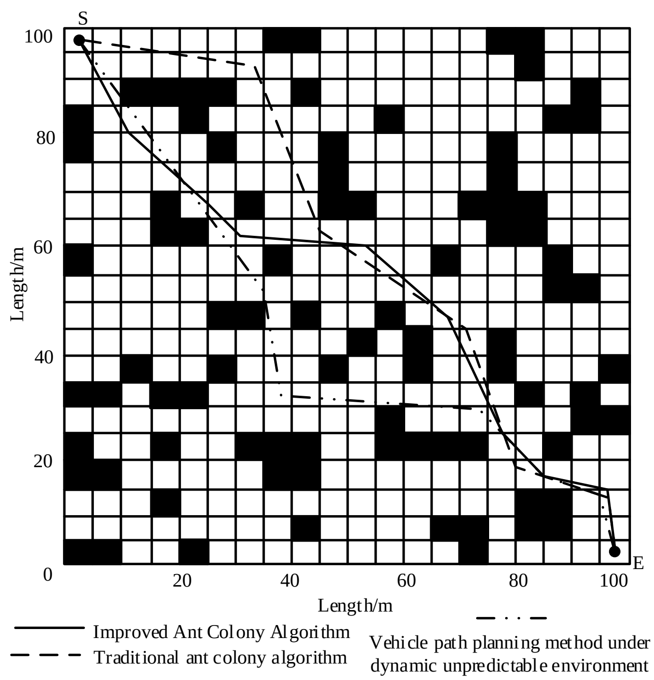

Figure 6. Large Rule-Barrier Storage Environments

It can be seen from Figure 6 that for the path planning results of the ant colony algorithm, the global planning path obtained by the improved ant colony algorithm is relatively smooth and can also ensure a certain safety distance when passing through obstacles. Although the path planned by the ant colony algorithm is also complete, the included angle of path changes generated when encountering obstacles is too large, and the safety distance from the edge of obstacles is too small. Therefore, a slight collision is likely to occur during the actual transportation of goods by AGV. On the other hand, the Vehicle path planning method under a dynamic unpredictable environment (Zhao *et al*., 2023) is prone to collision during the path planning process, and its security needs to be further improved.

5.2 Analysis of the path planning capabilities of different methods in a fragmented obstacle environment

The in-depth experiment was carried out against the scattered distribution environment existing in large-scale warehousing logistics. The environment contains many small obstacles. The comparison of AGV operation planning paths before and after improvement in the experiment is shown in Figure 7.

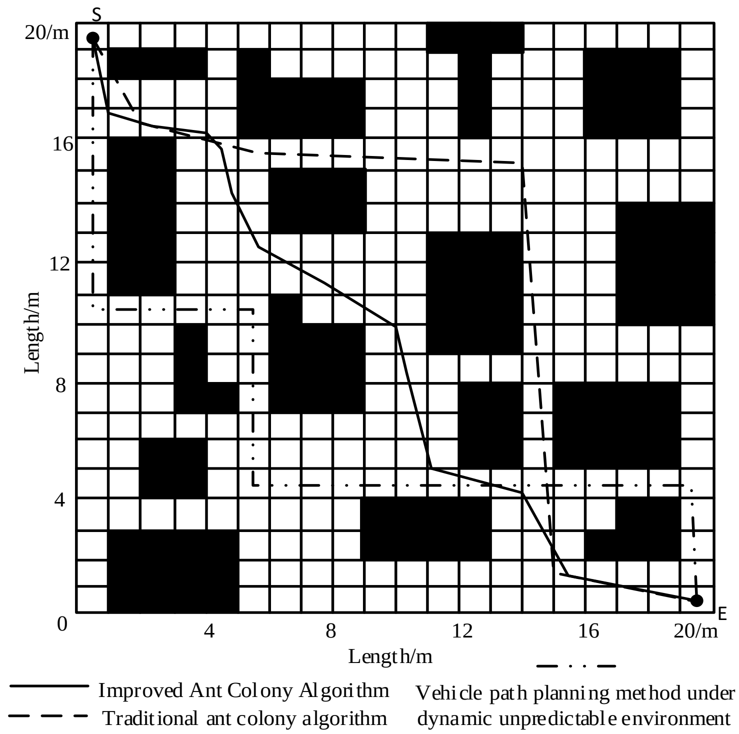

Figure 7. Small Scattered Distribution Barrier Environments

As can be seen from Figure 7, under the environment of small scattered distribution obstacles, the ant colony algorithm may have certain randomness in path planning, resulting in the path quality is not stable enough. The vehicle path planning method under a dynamic unpredictable environment (Zhao *et al*., 2023) plans a long path and has the problem of low planning efficiency, while the improved ant colony algorithm, due to the introduction of the optimization strategy, is able to make better use of the historical information and the heuristic information to derive the relatively shorter smoothing paths, and is able to adapt to different environments when changing the environment to deal with the more complex environment.

5.3 Path planning efficiency test of different methods

In order to ensure the accuracy of the experimental results of the ant colony algorithm and the improved ant colony algorithm, the number of experiments is set to be 20 times under the condition of ensuring that the algorithms are run independently and the length of the optimal path and the number of generations of convergence of the algorithms are taken as the indexes of the experiments, and the experimental results obtained are shown in Table 1.

Table 1. Comparison of Experimental Results before and after Improvement

Barrier environments	Contrasting approaches	The optimal path length			Convergent algebra		
		Min	Max	Mean	Min	Max	Standard deviation
20×20	Ant colony algorithm	28.667	28.667	29.877	21	34	1.368
	Improving the ant colony algorithm	26.451	27.418	27.451	12	16	0.567
100×100	Ant colony algorithm	167.12	152.36	156.58	34	38	2.698
	Improving the ant colony algorithm	141.98	143.586	142.456	28	31	1.124
150×150	Ant colony algorithm	289.77	313.65	299.63	67	72	4.075
	Improving the ant colony algorithm	243.58	268.79	252.77	42	55	2.976

According to Table 1, it can be seen that the optimal path length of the improved ant colony algorithm is obviously shorter than that of the ant colony algorithm in a 20×20 environment. Due to the improvement of the heuristic function and the updating of the pheromone, it can complete the convergence of the path searching and planning more quickly and ensure stable path planning, and the number of convergence generations is shortened by half compared with that of the ant colony algorithm. Comparing the path planning in 100×100 and 150×150 environments, we can find that the improved ant colony still has good advantages. The average value of the optimal path of the improved algorithm is shorter, and the convergence is more stable. Through the adjustment of the pheromone volatility factor, heuristic information weighting, etc., the improved ant colony is able to converge to the more optimal solution faster and improve the search efficiency, which proves that the improved ant colony algorithm is more advantageous, with better performance and path planning efficiency. It is proved that the improved ant colony algorithm has more advantages, better performance and faster path planning efficiency.

The next experiment took a warehouse logistics center goods as the experimental object. The goods from the logistics center were transported to A, B, C, D, E, F, G, and H in eight locations using the improved method and the unimproved method. The optimal route of freight transportation in the logistics center is planned. Eight directed graphs of freight transport are established, with the number of nodes being 11, 14, 16, 15, 18, 19, 18 and 21, respectively. The number of conflict nodes is 3, 2, 6, 4, 3, 1, 2, 4, and each freight transportation path is determined, and then the path is constrained by constraint conditions. The weight of each path is determined according to the actual situation. Finally, the optimal path was selected, and the actual transportation time of AGC in the improved algorithm and the unimproved algorithm was recorded and analyzed in depth as experimental data, as shown in Table 2.

Table 2. The Optimal Route for Warehouse Logistics and Cargo Transportation

Logistics and transportation serial numbers	Time weights	Time/min		Congestion time/min		Road weights
		Unimproved	Improvements	Unimproved	Improvements	
1	0.54	7.64	6.25	1.26	1.01	0.26
2	0.42	8.69	7.46	0.48	0.01	0.53
3	0.56	9.41	8.8	1.06	0.56	0.24
4	0.45	9.14	8.4	1.05	0.45	0.36
5	0.30	8.26	7.8	0.65	0.32	0.28
6	0.287	9.12	7.9	0.48	0.22	0.46
7	0.48	10.13	8.9	1.06	0.48	0.36
8	0.29	10.36	9.6	1.08	0.36	0.29

According to Table 2, according to the planning path of the improved ant colony algorithm, in the actual warehousing logistics, AGV can make corresponding judgments and analyses on the actual road conditions according to the warehouse environment so as to minimize congestion time. The overall cargo transportation time and congestion time are smaller than the ant colony algorithm, and the path planning effect is better.

6. CONCLUSION

With the continuous progress of technology, intelligence and automation will become the development trend of warehousing logistics. Studying the AGV global path planning will help enterprises lay out in advance and adapt to the changes and challenges of the future market, which has become an inevitable development trend. In warehousing and logistics, the path planning problem of AGV is very important. In order to ensure that AGV can complete the transportation task efficiently and safely, we adopt a grid modeling method to model the path planning problem of AGV. This method divides the environment into a series of grids, and each grid represents a unit that AGV can move. Based on this modeling method, a new improved ant colony algorithm for the AGV obstacle avoidance path is designed. This algorithm has undergone a series of optimizations on the basis of the unimproved ant colony algorithm. By improving the path selection parameters, a weight mechanism based on distance and obstacle information is introduced so that the ants can more accurately evaluate the pros and cons of each path when selecting the path. Secondly, the transfer rules and pheromone update conditions are optimized. In the ant colony algorithm, the movement of ants and pheromones update are independent, but in our improved algorithm, we introduce obstacle information so that ants can fully consider the impact of obstacles when moving and pheromone update so as to better avoid collisions. In addition, the path results are smoothed. By introducing a series of smoothing algorithms, we optimize the planned path to ensure that the AGV travels more smoothly, reducing energy consumption and shortening the distance. At the same time, the smooth processing also makes the AGV walk more stable and improves the safety performance. In order to improve the performance and stability of the algorithm, the path selection and pheromone volatilization coefficient are adjusted in the iterative process. As the iteration progresses, these parameters are gradually adjusted to achieve rapid convergence while ensuring the optimality of the global search.

Experimental results show that the algorithm is effective and superior. Compared with the original path planning algorithm, the proposed algorithm has significant advantages in convergence speed, path quality and stability. At the same time, the route after smoothing is more consistent with the walking conditions of AGV in the actual environment, which can significantly reduce energy consumption, shorten distance and improve safety. To sum up, the AGV global path planning of warehousing and logistics is of great significance for improving the warehousing operation efficiency of the pharmaceutical industry, reducing transportation costs, enhancing warehousing security, improving system stability and adapting to future development trends.

REFERENCES

Huo, L. (2023). The Global Path Planning for Vehicular Communication Using Ant Colony Algorithm in Emerging Wireless Cloud Computing. *Wireless Networks*, 29(2):833-842.

Han, S., Wang, L., Wang, Y. and He, H. (2021). An Efficient Motion Planning Based on Grid Map: Predicted Trajectory Approach With Global Path Guiding. *Ocean Engineering*, 238(Oct.15):109696.1-109696.14.

Sang, H., You, Y., Sun, X., Zhou, Y. and Liu, F. (2021). The Hybrid Path Planning Algorithm Based on Improved A* and Artificial Potential Field for Unmanned Surface Vehicle Formations. *Ocean Engineering*, 223(Mar.1):108709.1-108709.16.

Zhao, L., Bai, Y. and Paik, J.K. (2023). Global-Local Hierarchical Path Planning Scheme for Unmanned Surface Vehicles Under Dynamically Unforeseen Environments. *Ocean Engineering*, 280(Jul.15 Pt.2): 114750.1-114750.22.

Ait Saadi, A., Soukane, A., Meraihi, Y., Benmessaoud Gabis, A., Mirjalili, S. and Ramdane-Cherif, A. (2022). UAV Path Planning Using Optimization Approaches: A survey. *Archives of Computational Methods in Engineering*, 29(6):4233-4284.

Puente-Castro, A., Rivero, D., Pazos, A. and Fernandez-Blanco, E. (2022). A Review of Artificial Intelligence Applied to Path Planning in UAV Swarms. *Neural Computing and Applications*, 34(1):153-170.

Han, C. and Li, B. (2023). Mobile Robot Path Planning Based on Improved A* Algorithm. *In2023 IEEE 11th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, 8(11):672-676.

Li, H., Zhao, T. and Dian, S. (2022). Forward Search Optimization and Subgoal-Based Hybrid Path Planning to Shorten and Smooth Global Path for Mobile Robots. *Knowledge-Based Systems*, 258(Dec.22):110034.1-110034.10.

Yang, X.F., Shi, Y.L., Liu, W., Ye, H., Zhong, W.B. and Xiang, Z.R. (2022). Global Path Planning Algorithm Based on Double DQN for Multi-Tasks Amphibious Unmanned Surface Vehicle. *Ocean Engineering*, 266(Dec.15 Pt.1):112809.1-112809.14.

Wang, H.L., Lu, L.Y., Li, T.S. and Wang, A.Q. (2023). Multi-AUG Three-Dimensional Path Planning and Secure Cooperative Path Following Under DoS Attacks. *Ocean Engineering*, 274(Apr.15): 113864.1-113864.14.

Sun, X., Zhang, L., Song, D. and Wu, Q.M.J. (2023). A Novel Path Planning Method for Multiple USVs to Collect Seabed-Based Data. *Ocean Engineering*, 269(Feb.1):113510.1-113510.12.

Hao, K., Zhao, J.L., Li, Z.S., Liu, Y.L. and Zhao, L. (2022). Dynamic Path Planning of A Three-Dimensional Underwater AUV Based on An Adaptive Genetic Algorithm. *Ocean Engineering*, 263(Nov.1): 112421.1-112421.21.

Zou, A.W., Wang, L., Li, W.M., Cai, J.C., Wang, H. and Tan, T.L. (2023). Mobile Robot Path Planning Using Improved Mayfly Optimization Algorithm and Dynamic Window Approach. *The Journal of Supercomputing*, 79(8):8340-8367.

Chen, X., Bose, N., Brito, M., Khan, F., Millar, G., Bulger, C. and Zou, T. (2022). Risk-Based Path Planning for Autonomous Underwater Vehicles in An Oil Spill Environment. *Ocean Engineering*, 266(Dec.15 Pt.4):113077.1-113077.13.

Ma, D.F., Hao, S.F., Ma, W.H., Zheng, H.R. and Xu, X.L. (2022). An Optimal Control-Based Path Planning Method for Unmanned Surface Vehicles in Complex Environments. *Ocean Engineering*, 245(Feb.1):110532.1-110532.11.

Han, S., Wang, L., Wang, Y. and He, H. (2022). A Dynamically Hybrid Path Planning for Unmanned Surface Vehicles Based on Non-Uniform Theta* and Improved Dynamic Windows Approach. *Ocean Engineering*, 257(Aug.1 Pt.2):111655.1-

111655.11.

Su, Y.M., Luo, J., Zhuang, J.Y., Song, S.Q., Huang, B. and Zhang, L. (2023). A Constrained Locking Sweeping Method and Velocity Obstacle Based Path Planning Algorithm for Unmanned Surface Vehicles in Complex Maritime Traffic Scenarios. *Ocean Engineering*, 279(Jul.1):113538.1-113538.14.

Xue, H. (2022). A Quasi-Reflection Based SC-PSO for Ship Path Planning with Grounding Avoidance. *Ocean Engineering*, 247(Mar.1):110772.1-110772.10.

Zhu, H.R., Wang, Y.H. and Li, X.T. (2022). UCAV Path Planning for Avoiding Obstacles Using Cooperative Co-Evolution Spider Monkey Optimization. *Knowledge-Based Systems*, 246(Jun.21):108713.1-108713.19.

Liu, C., Wu, L., Xiao, W.S., Li, G.X., Xu, D.P., Guo, J.J. and Li, W.T. (2023). An Improved Heuristic Mechanism Ant Colony Optimization Algorithm for Solving Path Planning. *Knowledge-Based Systems*, 271(Jul.8):110540.1-110540.19.

Liu, Y., Zheng, Z., Qin, F., Zhang, X. and Yao, H. (2022). A Residual Convolutional Neural Network Based Approach for Real-Time Path Planning. *Knowledge-Based Systems*, 242(Apr.22):108400.1-108400.12.

Wu, X., Hirota, K., Jia, Z., Ji, Y., Zhao, K. and Dai, Y. (2023). Ameliorated Equilibrium Optimizer with Application in Smooth Path Planning Oriented Unmanned Ground Vehicle. *Knowledge-Based Systems*, 260(Jan.25): 110148.1- 110148.16.

Singh, M.K., Choudhary, A., Gulia, S. and Verma, A. (2023). Multi-Objective NSGA-Ⅱ Optimization Framework for UAV Path Planning in An UAV-Assisted WSN. *The Journal of Supercomputing*, 79(1):832-866.

Shu, J.Q., Shi, W. and Wang, Y.Y. (2023). Trajectory Tracking of Rescue AGV Based on Fuzzy-Model Predictive Control. *Computer Simulation*, 40(6):474-479+527.