Collaborative Path Optimization Method for Flood Control Material Storage

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Abstract. In order to reach its efficient storage and wide application, this paper analyzes and improves the outgoing efficiency of flood control material warehouse. Firstly, according to the characteristics of flood control material warehouse, the grid model of the warehouse is established, and the storage shelves are classified to store the goods with different use frequencies. Secondly, in view of the possible conflicts of robots in the operation of the warehouse, this paper proposes multiple strategies to improve the efficiency of goods delivery under the premise of avoiding conflicts. The reservation table is established to solve the problem of frontal collision of robots. Further, using the improved A* algorithm, each robot can transport goods along the shortest path. The dynamic weighting table is added to solve the multi-robot driving strategy of intersection conflicts, and the most urgent goods are guaranteed priority out of storage. Finally, the proposed program was verified by the simulation.

Keywords: A* algorithm · Appointment form · Dynamic weighting table

1 Introduction

With the development of logistics industry, intelligent storage has attracted more and more attention. The order allocation is one of the factors that affect the efficiency of warehouse [1]. In addition, how to distribute goods is also one of the research directions [2]. At the same time, the cooperation of multiple robots should also be considered to avoid collisions [3]. Given this premise, robots find the shortest path [4].

The characteristics of storehouses for flood control materials are obvious. Compared with the common warehouse, the sudden flood situation and the emergency of disaster relief make the warehouse of flood control materials have high requirements on the efficiency of outbound, but not excessive requirements

S. Wang et al. (Eds.): IoTCare 2021, LNICST 415, pp. 440–450, 2022.
https://doi.org/10.1007/978-3-030-94182-6_35

on the efficiency of inbound [5]. The materials of the same type or frequency of use are placed close to each other, which is convenient for management and can be transferred together when they are out of the warehouse [6].

In the process of warehouse delivery, multiple robots need to work at the same time to give full play to the advantages of warehouse space. Each robot searches for the shortest path and fetches its cargo. However, with the increase of robots, each robot cannot predict the route of other robots, so local optimal solutions and even conflicts often appear [7]. Therefore, when multiple robots are running in the warehouse, the central controller needs to coordinate the conflict uniformly, and then each robot calculates the shortest path according to the instructions of the central controller, so as to improve the overall efficiency [8].

In this paper, according to the characteristics of flood control materials and their intelligent storage, the warehouse needs to give priority to the transportation of materials in high demand according to the flood control work. So a storage model of flood control materials is established around the efficiency of warehouse delivery and the collaborative optimization of multi-robots.

This article will carry on the research through algorithm design and simulation. In section two, the reservation table and the improved A* algorithm are used to solve the path conflict problem of multi-robots, and the dynamic weight table is added to address the issue of prioritizing the transport of items in high demand in the event of a route conflict. In section three, the improved algorithm is compared with the simple A* algorithm, and the high efficiency of the algorithm is verified.

2 Algorithm Design

2.1 The Establishment of the Environment

Raster Map Building. This chapter proposes an efficient modular storage model to meet the storage requirements of different regions and materials. The small-scale storage model is adopted here, with a planned standard warehouse of 25 m long and 26 m wide. The most left row of the warehouse is the position of the picking table. The robot starts from the picking table, moves to the corresponding shelf to take down the goods, and sends the goods to the picking table, which is the end of the warehousing.

The warehouse is divided into 650 parts with each 1-m long and 1-m wide grid to form a standardized grid map, as shown in Fig. 1.

In the raster map, each shelf measuring 2 m long and 4 m wide occupies 8 grids. To ignore the problem of different pallet sizes caused by different materials, each pallet is set as a standard module with a length of 1 m and a width of 1 m, and the robot can only transport one pallet for each task. Each shelf is separated by a path with a width of 1 m, which serves as a transportation channel for warehouse robots and is distributed across the whole warehouse.

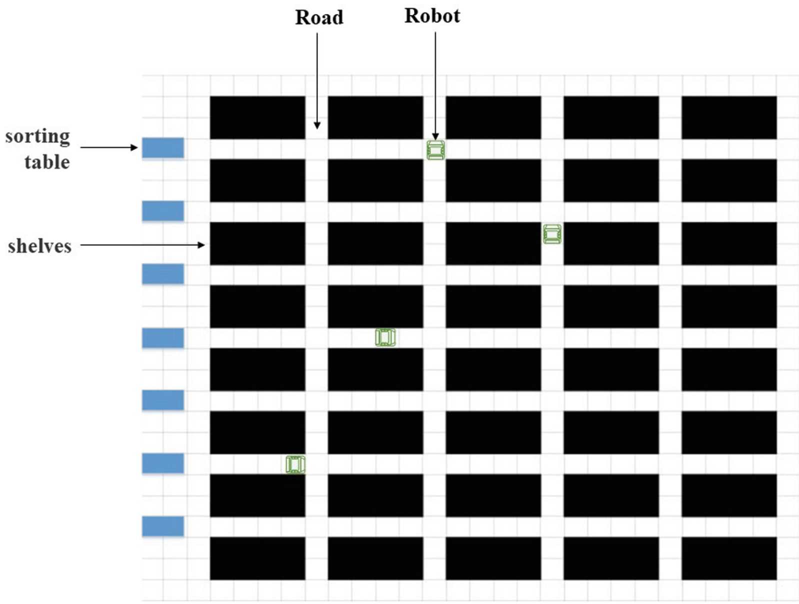

Fig. 1. Raster map and warehouse structure.

In order to minimize the carrying distance of shelves in the picking process, all the shelves in the warehouse are divided into three parts according to the frequency of use, as shown in Fig. 2. The two rows of shelves near the picking platform are high-frequency storage areas for storing goods with high frequency of use such as life jackets and tents. The third and fourth rows of shelves are medium frequency storage areas, which store oil, inspection lights and other goods. The last row of shelves for low-frequency storage areas, storage generators and other low-frequency and large goods.

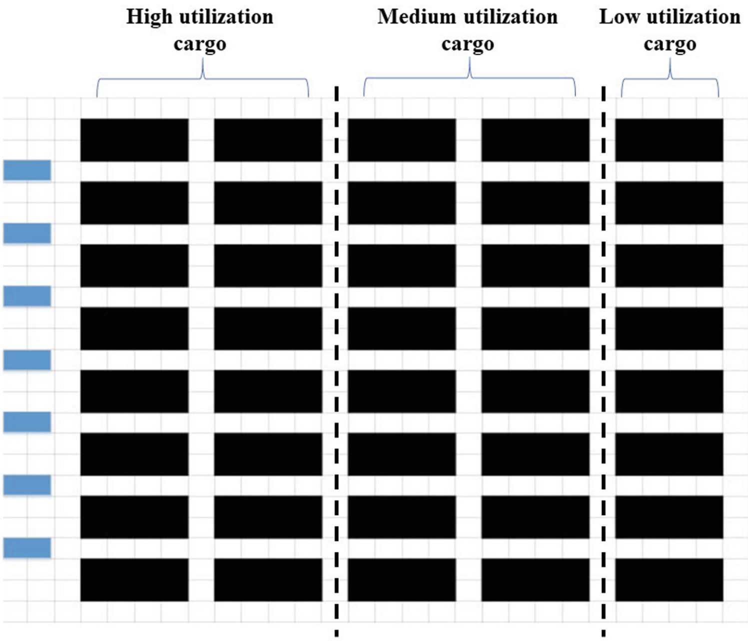

Fig. 2. The division of shelf area.

Appointment Form. In the intelligent storage system, multiple robots participate in the transportation of goods in and out of the warehouse at the same time. The environment is dynamic and changeable, and there will be congestion, collision and even deadlock. Typical situations can be divided into the following four categories, as shown in Fig. 3.

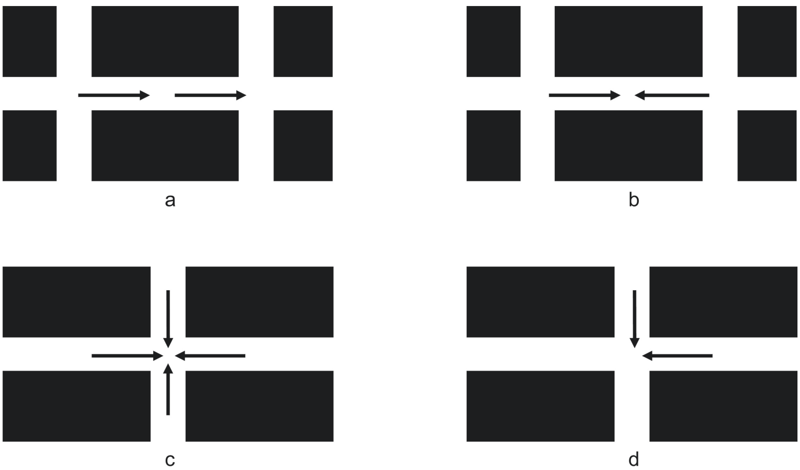

Fig. 3. Conflicting situations.

In case A, the risk of rear-end collision can be avoided by installing a distance sensor on the head of the robot and slowing down in advance after receiving the information.

However, case B, C and D still cannot be avoided by using distance sensor, so this paper uses reservation table to solve this problem. When two robots meet at an intersection, it must be decided that one robot first occupies the intersection and passes through it, while the other robot waits in place and continues to move after this robot passes. In other words, each grid can only be occupied by one robot at a certain time. The raster occupied by the robot in the raster map at the current time is recorded in the same table to form the reservation table, as shown in Fig. 4. The reservation table takes the warehouse grid model as the horizontal and vertical coordinates, and uses a two-dimensional array to record the state of each cell. The idle table is 0, otherwise it is 1. The grid occupied by the robot at each moment records the corresponding robot number, and other robots can decide to move forward or wait for another robot to pass by querying the reservation table at the current moment.

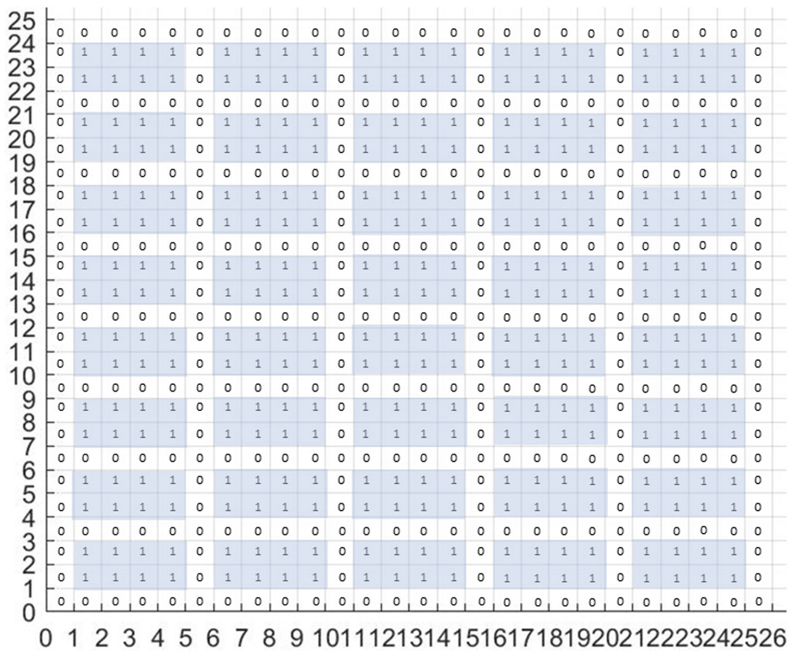

Fig. 4. Appointment Form.

2.2 Improved A* Algorithm

A* algorithm is A heuristic algorithm, which is the most effective direct search method to solve the shortest path in the static map. It sort the neighboring nodes according to the evaluation function, and then select the optimal neighboring nodes for the next search until the target point. The warehouse map used in this paper is simple and neat, which is suitable for using A* algorithm to calculate the shortest path.

A starting point and a target point are first set. The robot starts from the starting point and expands the grid around the current grid point. Extended search mechanism usually has two kinds, four neighborhood search and eight neighborhood search. In this paper, the robot in the warehouse can move up, down, left and right, so the neighborhood search method is chosen. The robot calculates the cost of raster paths in the four directions of the current location extension, which is called the parent node. Select the direction with the least cost to move, and the position after moving becomes the new parent node, and continue to expand the grid with the new parent node as the center. Repeat this step until the robot reaches the target point. In this way, we can get an optimal path from the starting point to the target point with the least cost. The cost estimation function of A* algorithm is expressed as:

$$f(n) = g(n) + h(n) \tag{1}$$

In the formula, $g(n)$ represents the actual cost from the starting point to the current node n, which is generally expressed by distance or time. In this paper, time is used as a unified scalar to compare the cost of function $f(n)$. The expression $g(n)$ is

$$g(n) = \frac{d}{v} \tag{2}$$

Variable d is the actual moving distance of the robot from the starting point to the current node n, and v is the speed at which the robot travels at constant speed.

Variable $h(n)$ represents the heuristic estimated cost from the current node n to the target point, expressed as

$$h(n) = \frac{d_n}{v} \tag{3}$$

Variable d_n is the estimated shortest distance of the robot from the current node n to the target point, which is usually represented by Euclidean distance, Chebyshev distance and Hamandon distance. Here, the Hamilton distance is used.

$$d_n = abs(n.x - goal.x) + abs(n.y - goal.y) \tag{4}$$

Hamilton distance is the sum of the transverse and longitudinal distances between the current node n and the target point.

However, in the actual operation process, robots, especially the four-way shuttle robots commonly used in logistics warehouses, need a certain amount of time to complete the reversing action in the turning process, as shown in Fig. 5(a). Compared with the linear movement, the reversing time of the robot needs to be taken into account.

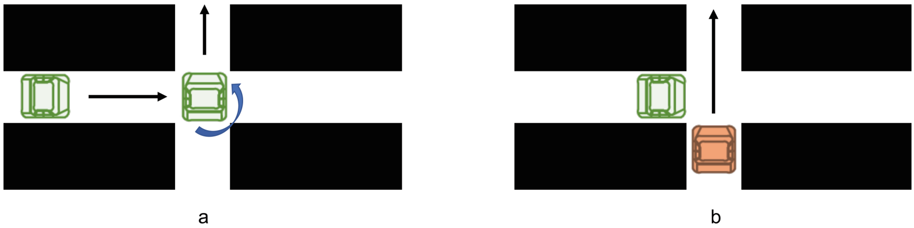

Fig. 5. Robot reversing and waiting actions.

In addition, when the robot encounters path conflict, if its weight is small, it needs to pause and wait for other robots to pass before continuing to move, as shown in Fig. 5(b). The waiting time should also be taken into account. Therefore, this paper improves the A* algorithm and updates the cost formula as follows:

$$f(n) = g(n) + h(n) + \sum_{j=1}^{m} t_{j(turn)} + \sum_{j=1}^{m} t_{j(wait)} \quad (5)$$

where, $\sum_{j=1}^{m} t_{j(turn)}$ is the sum of the extra time taken by the robot to turn from the starting point to the target point, and $\sum_{j=1}^{m} t_{j(wait)}$ is the extra time taken by the robot to wait in place due to path conflict. The improved A* algorithm reduces the turning times and path conflict times of the robot's moving path, and improves the overall efficiency of all robots in the storage model.

2.3 Dynamic Weighting Table

Under the joint action of the reservation table and A* algorithm, the frontal collision of robots is avoided. However, when multiple robots are about to pass the same intersection at the same time, the sequence of robots passing cannot be effectively determined by the control of the reservation table alone.

The general warehouse is determined according to the remaining time for the robot to reach the target point from the current conflict point, but in the flood control warehouse, this scheme may not be able to give priority to the most needed materials and affect the progress and efficiency of the flood control work. As shown in Fig. 6, at this conflict point, robots transporting low-demand materials are preferred to pass through, while robots transporting high-demand materials can only wait in place and then continue to move, resulting in lower efficiency.

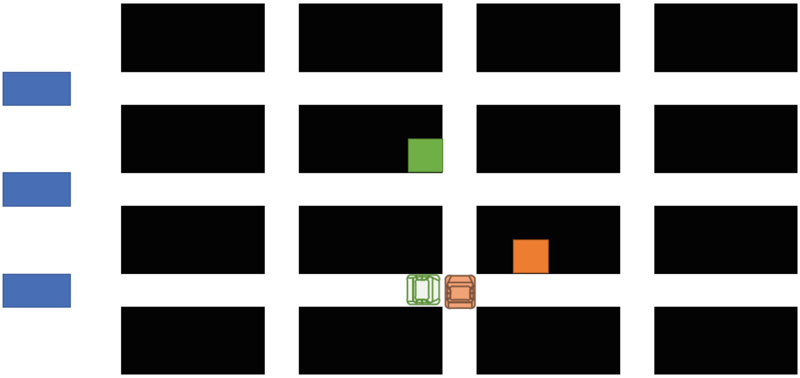

Fig. 6. Intersection conflict.

Combined with the timeliness and priority of flood control warehousing, this paper innovatively puts forward a dynamic weighting table to solve the problem of crossing order and ensure that the materials with the highest demand will be given priority for delivery.

The dynamic weighting table is a matrix table composed of robot label and corresponding dynamic weights, as shown in Table 1.

Table 1. Dynamic weighting table

Robot ID (r_i)	Weight (W_i)	Resource (R_i)	Journey (J_i)	$h_{(n)_i}$
r_1	$W_1 = [R_1, J_1, h_(n)_1]$	R_1	J_1	$h_{(n)_1}$
r_2	$W_2 = [R_2, J_2, h_(n)_2]$	R_2	J_2	$h_{(n)_2}$
...	...	...	...	...
r_i	$W_1 = [R_i, J_i, h_(n)_i]$	R_i	J_i	$h_{(n)_i}$

The dynamic weight is represented by W_i, which refers to the weight of robot r_i at the current moment. The matrix composition of weight W_i is as follows:

$$W_1 = [R_i, J_i, h_(n)_i] \tag{6}$$

where, R_i represents the priority level of materials in the transportation task currently performed by robot r_i. After receiving the task, the robot will get the weight R_i according to the type of goods until the end of the task. According to the classification of shelves, goods are also divided into three types here. R_i of goods used in high frequency, medium frequency and low frequency are assigned as 1, 2 and 3, respectively.

Variable J_i means whether robot r_i is carrying goods at the current moment, yes means robot r_i is in the shipment stage at this time, assign a value of 1, and no means robot r_i is in the delivery stage at this time, Assign a value of 2. Variable $h_{(n)_i}$ represents the heuristic time of the current position of robot r_i to reach the target point.

In the warehouse model in this paper, the priority of selecting weights is as follows: Firstly, the more frequent the material demand is, the more priority the corresponding robot will pass, which is the dominant factor. Secondly, if the robots in conflict are transported of the same kind of goods, the robot in the shipping state has higher priority than the robot in the receiving state. Thirdly, in the case of conflict between robots of the same material class and the same receiving/shipping state, the shorter the remaining heuristic time, the higher the priority to pass.

When multiple robots encounter conflict at the intersection, the central controller calls the dynamic weighting table. By comparing the dynamic weight W_i of the robots in the conflict situation, the sequence of passing is determined and the reservation table of corresponding robots is updated. The reservation table of the robot that passes first keeps 0 in the intersection grid, that is, the idle state remains unchanged. The reservation table of the waiting robot is updated to 1 in the intersection grid, which closes the intersection until the robot is allowed to pass through.

3 The Simulation Results

In order to verify the effectiveness of the algorithm, A* algorithm based on reservation table is compared with the optimization algorithm using dynamic weighted table (the optimization algorithm for short) designed in this paper in the warehouse raster map model established in this paper. The simulation experiment was carried out by MATLAB and the simulation experiment is as follows:

In the raster map established in this paper, 8 robots are arranged. The operation efficiency of A* algorithm and the optimization algorithm is compared by simulating 40 material transportation tasks in each group. In order to simulate the transportation characteristics of flood control material warehouse, this paper judged the efficiency of the algorithm by comparing the efficiency of high-frequency material shipment, high-frequency material pickup efficiency, medium-frequency material pickup efficiency and the time of the algorithm.

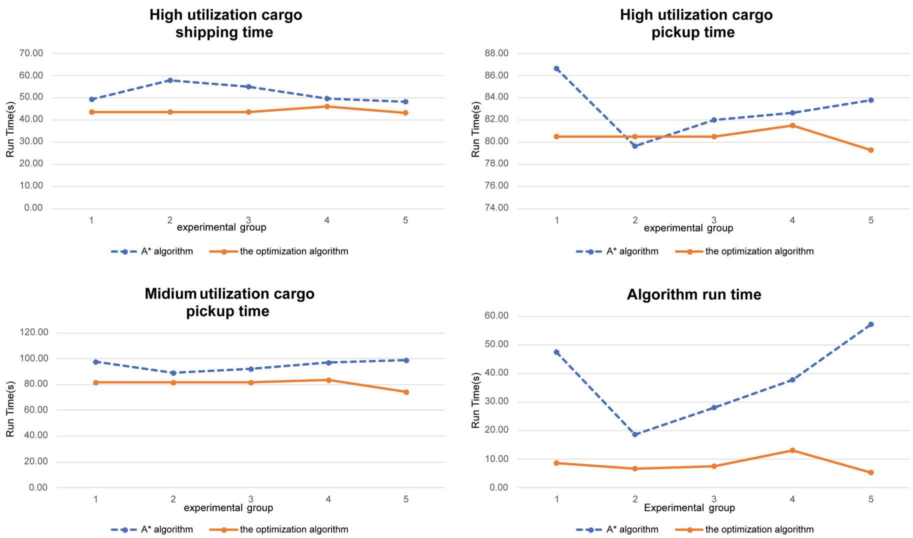

Fig. 7. Comparison of simulation experimental results between A* algorithm and optimization algorithm.

The simulation results are shown in Fig. 7. Figure 7 shows the comparison of the completion time of each index of the two algorithms in the five groups of transport tasks. Compared with A* algorithm, the four experimental indicators of The optimization algorithm have been improved to different degrees. Compared with A* algorithm, the optimization algorithm improves the average shipment efficiency by 14.89%, the average high-frequency pickup efficiency by 2.89%, and the average medium-frequency pickup efficiency by 15.1%. The addition of dynamic weighting table in the optimization algorithm does not have negative effect on intermediate frequency goods because it improves the priority of high frequency goods. In addition, due to the addition of the dynamic weighting table, the robot can make quick decisions when it encounters conflicts and avoid unnecessary path planning. As a result, the running efficiency of the optimization algorithm is improved by 75.05% compared with A* algorithm.

4 Conclusion

In this paper, based on the characteristics of flood control material warehouse, an improved A* algorithm under the reservation table and dynamic weighted table is proposed. The following experiments are completed: building the grid map of the warehouse and dividing the storage areas of goods with different frequency of use; joining the reservation table to prevent the robot from path conflict. This paper innovatively adds dynamic weighting table, which gives priority to high priority goods, and improves the operation efficiency of the warehouse under flood control. The feasibility and efficiency of the proposed method are verified by simulation experiments.

Acknowledgment. This work is supported by the Shandong Provincial Natural Science Foundation ZR2020KF027 and Shandong Key R&D Program under Grant 2019JZZY021005.

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