

# Multi-robot material delivery in industrial parks based improved on A \* algorithm

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**Abstract.** To realize the intellectualization of the industrial park and liberate the employees from the repetitive work, the material distribution method based on muti robot needs to be studied. This paper explores and improves two multi robot path planning algorithms HCA and CBS based on A \* algorithm through the specific analysis of the environment in the industrial park, so that the robot can avoid dynamic obstacles. Furthermore, after simulation through webots, the advantages and disadvantages of the two algorithms are compared. Finally, through the demand analysis of the industrial park, a feasible scheme for multi-robot path planning in the industrial park is obtained.

**Keywords:** A \* algorithm; multi robot; path planning; dynamic obstacle avoidance.

## 1. Introduction

In today's intelligent era, in order to optimize productivity and internal work efficiency, enterprises in many fields have adopted intelligent reforms. However, the integrated intelligent management system of the industrial park has just started. There are still many problems in the park, such as waste of human resources and low efficiency of management. Therefore, further research is needed for the intelligent reform of the industrial park in all aspects [1], [2]. The material distribution in the industrial park, as a repetitive and even dangerous work, is very time-consuming and wastes human resources. To improve the logistics speed in the industrial park and improve the utilization rate of human resources, it is important to replace traditional manual material distribution method with robot distribution method. Nowadays, there are many examples of using robots to replace people, such as intelligent warehouses which use robots to manage warehouses instead of people [3], and robots that transport medical drugs or devices in hospitals to replace nurses [4]. At the same time, many scholars have also studied the robot distribution in the industrial park environment and given some feasible solutions. However, with the continuous development of industrial park intelligence, the demand for material transportation efficiency also increases, so the multi robot collaborative material distribution technology has important research value.

The distribution of various materials in industrial parks often requires different types of robots. For the transportation of some large steel products, a robot like a trolley with lifting devices is required [5]. For some light loads with a high target point, UAVs can be used for transportation [6]. For ordinary objects on land, mobile robots (AGVs) are widely used, such as cargo robots used in intelligent warehouses [7]. Moreover the types of mobile robots can also be classified as wheeled mobile robots [8] which transport small objects, forklift robots which are widely used to transport medium-sized goods in factories [9] and robots which transport large goods, similar to parking robots used to transport cars in intelligent parking lots [10]. Because of the high utilization rate of wheeled robots in land mobile robots, they are more universal, so this kind of robot is the focus of this paper.

For the problem of multi robot cooperative work, many scholars have done many research on robot path planning and obstacle avoidance navigation algorithms in various scenarios. The mainstream multi robot path planning algorithms include A \* algorithm, the most effective direct search method for finding the shortest path in the static road network, which can be used in multi robot path planning through the improvement of A \* algorithm [11]. In addition, genetic algorithm is also applied to path planning of multiple robots [12]. It is an algorithm that uses Darwin's evolutionary model under natural selection for reference, simulates the problem to be resolved into a process of biological

evolution, generates the solution of the next generation by copying, crossing, mutation and so on, and eliminates and increases the solutions with low and high fitness respectively, so that a better solution can be obtained after N generations of evolution. Moreover, the artificial potential field method is also an algorithm for multi robot path planning. The algorithm treats the target and obstacle as objects with gravitational and repulsive forces respectively, so that the robot can move along the direction of the combined force of gravitational and repulsive forces [13]. Apart from the above classical algorithms, there are also some relatively new algorithms, such as the path planning algorithm based on deep reinforcement learning [14]. It mainly uses neural network training to train some functions, so as to obtain a model which can accurately predict the next step of the robot after multiple training.

As a very classic path planning algorithm, the A\* algorithm is simple both in programming and operation. It can be used only by modifying a small amount of code for different environments, which means it has a strong adaptability to the environment. Compared with the newer algorithm, A\* algorithm is in a more timely manner, does not require frequent iterative updates, has less code, runs fast, and does not require hardware support with higher configuration [15], which is very suitable for industrial parks with less intelligence. Therefore, to solve the problem of multi robot material distribution in the industrial park, this paper improves, HCA (Hierarchical Cooperative A star) [16] and CBS (Conflict based search) [17], the two multi robot path planning algorithms based on algorithm A\*. After that, modeling and simulation are carried out in webots, and the advantages and disadvantages of the two algorithms are compared. Finally, a feasible scheme for multi robot path planning in industrial parks is obtained, which provides a basis for future optimization and improvement.

The overall structure of this paper is as follows: Chapter II mainly describes the methods proposed in this paper systematically. Chapter III mainly explains the preparatory work of the experiment and displays and analyzes the final experimental results. Chapter IV gives the corresponding conclusions according to the experimental results.

## 2. Methodology

### 2.1. Scenario demand analysis of industrial park

The industrial park is a delimited region through administrative means, conducting scientific integration within a certain space, improving the intensity of industrialization, highlighting industrial characteristics, and optimizing the functional layout, which makes it be a modern industrial division and cooperation production area that can adapt to industrial upgrading and market competition. Generally, the types of industries entering the industrial park are relatively developed in the early stage, such as food manufacturing, textile industry, garment industry, wool manufacturing, furniture industry, paper industry, petrochemical industry, transportation industry, chemical manufacturing, warehousing industry, etc. These industries all have a great demand for the transportation of materials, and the transportation speed of materials can directly affect the processing efficiency of factories. In addition to the use of robots to transport materials, there are often some fixed route transportation methods such as mine cars in the industrial park. As shown in Fig. 1.



**Figure 1.** The mine cars in the industrial park.

Although the movement path of these mine cars is generally regular and it is good for a single robot to avoid, for multiple robots, robots need to avoid mine cars and other robots at the same time, which greatly limits the movement of robots. Therefore, it is necessary to improve the general multi robot path planning algorithm to adapt to the actual environment in industrial parks.

**2.2. Application of A \* algorithm in robot navigation**

A \* algorithm is a single robot path search algorithm suitable for grid environment. It combines Dijkstra algorithm and BFS algorithm, so it has the advantages of these two algorithms, that is, it cannot only search for the shortest path, but also use heuristic functions to find the best path. When it is used, A \* algorithm will calculate the comprehensive priority for each node, as shown in equation (1).

$$F(n) = G(n) + H(n) \tag{1}$$

Where,  $F(n)$  is the comprehensive priority of the node,  $G(n)$  is the cost from the starting point to the current point,  $H(n)$  is the estimated cost from the current point to the target point, that is, the heuristic function of A \* algorithm.

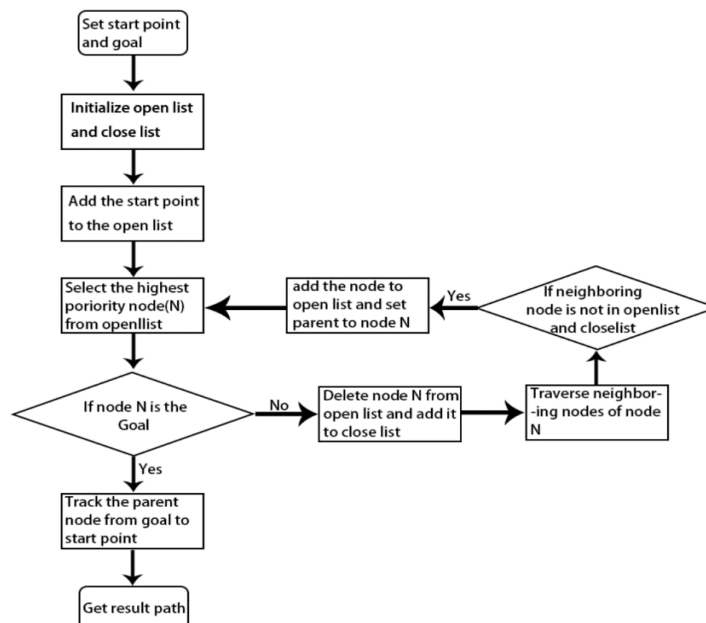
The calculation of cost will vary according to the Manhattan distance or Euclid distance. Take  $H(n)$  as an example, such as equation (2) and (3).

$$H(n) = D * (abs(x - goal.x) + abs(y - goal.y)) \tag{2}$$

$$H(n) = D * \sqrt{(x - goal.x)^2 + (y - goal.y)^2} \tag{3}$$

Where,  $D$  is the distance of a grid;  $y$  and  $x$  are the vertical and horizontal coordinates of the current point respectively;  $goal.y$  and  $goal.x$  are the vertical and horizontal coordinates of the target point respectively.

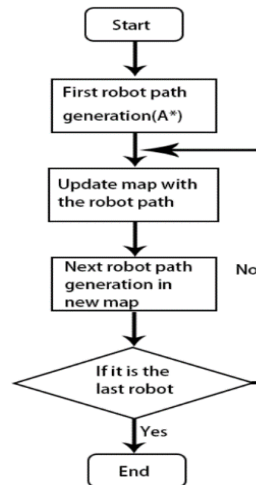
To keep the algorithm simple, Manhattan distance is used to reduce the computational complexity. The process of the A \* algorithm is shown in Fig. 2. At the beginning, an open list and a close list will be created. Firstly, put the starting point into the open list, and then filter the node with the highest comprehensive priority in the open list. After a node is selected, it will be deleted from the open list and added to the close list. Then the points near the selected node will be placed in the open list to continue filtering the next node. However, if the points already in the close list will not be selected again, the above process will be cycled until the target point is selected, and then a best path can be obtained by backtracking.



**Figure 2.** A \* Algorithm Flow Chart.

### 2.3. Improvement of HCA

HCA is the abbreviation of Hierarchical Cooperative A star algorithm. It is actually an extension of the A\* algorithm and the basic principle of path planning is the same as that of the A\* algorithm. However, this method adds the concept of time axis, that is, the map is updated with time, and the robot needs to select nodes at different times to finally complete path planning. When using HCA, you can first rank the importance of each robot. The most important robot should plan its path first. The later robot needs to take the points of the previous robot's path nodes as static obstacles and plan its path. Then loop this process until the last robot finished planning its path. The specific flow chart is shown in Fig. 3.

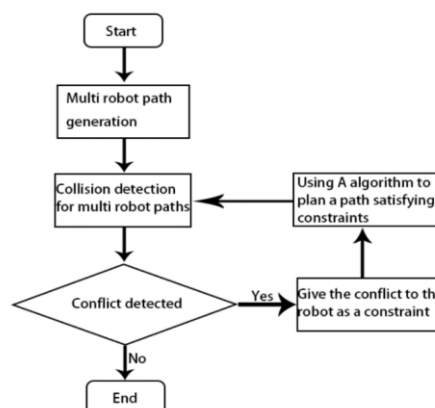


**Figure 3.** HCA Algorithm Flow Chart.

According to the principle of HCA, this algorithm can achieve no collision between robots because all robots behind the first robot will ensure that they will not reach the path nodes of the previous robots at a certain time during path planning. Now, in order to enable all robots to avoid dynamic obstacles, the path of dynamic obstacles can be treated as the first robot path, so that multiple robots can avoid dynamic obstacles.

### 2.4. Improvement of CBS

The full name of CBS algorithm is Conflict based search algorithm. It is a collision-based path planning algorithm. It is divided into two levels of search. The low-level search is responsible for planning an effective path for each robot. In this paper, A\* algorithm is used as the low-level search algorithm of CBS. The high-level algorithm is responsible for checking path conflicts. When there are conflicts, it will select the branch with the lowest cost to replan until all paths are free of conflicts. As the planned path of CBS allows the robot to wait in place, it is still necessary to add the concept of time axis as HCA does. The specific flow chart is shown in Fig. 4.



**Figure 4.** CBS Algorithm Flow Chart.

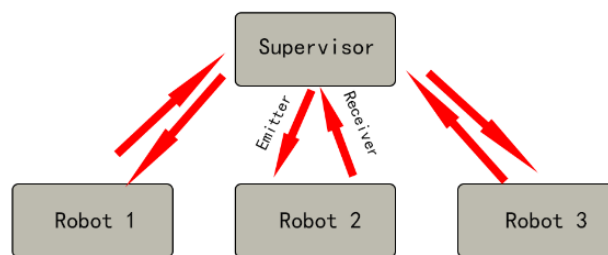
The improvement of CBS is more complicated than that of HCA, because CBS will decide to replan the path of the robot according to the cost after detecting the collision. However, if the path of a dynamic obstacle conflicts with the path of the robot, then the path of a dynamic obstacle cannot be replanned. Therefore, the improvement of CBS cannot simply add a path of a dynamic obstacle as the improvement of HCA. To solve this problem, it is necessary to judge if it is a dynamic obstacle when deciding to let which robot replan its path. By judging the dynamic and static obstacles, the robot's autonomous path planning and obstacle avoidance ability can be improved.

### 3. Results & Discussion

#### 3.1. Environment introduction

To compare the benefits and drawbacks of the two multi robot path planning algorithms and get a better scheme, it is necessary to carry out simulation tests for the two algorithms. This paper uses webots as the simulation software, because its modeling is simple, and when programming the robot controller, it can support the choice of a variety of computer languages.

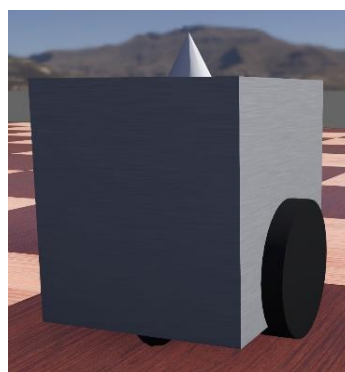
According to the understanding of the algorithm, these two algorithms are based on the omniscient perspective, so a supervisor robot is required to give instructions to all robots, and then the robots can move according to the given path instructions. The communication between robots and supervisor robot can be completed through emitters and receivers in webots. The specific principle is shown in Fig. 5.



**Figure 5.** Communication principle between robots.

After the above analysis, this paper found that the environment needs to establish four modules: robots, supervisor robot, mobile obstacle and static obstacles.

The first is the establishment of the robot. To reduce the error caused by the geometric shape of the robot in the algorithm simulation process, the robot is simply modeled in this paper. The robot is also equipped with a receiver to receive the supervisor's path information and action instructions. At the same time, with GPS and IMU sensors, the robots can always know its distance and direction from the target point. The specific modeling is shown in Fig. 6.



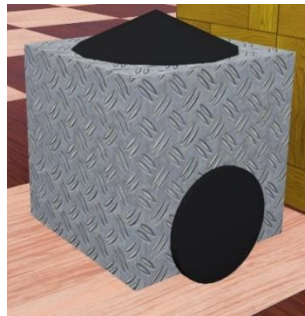
**Figure 6.** Robot modeling.

Since the main function of the supervisor robot is to send information and instructions, it does not need to move, so it does not need to conduct entity modeling, just add the corresponding emitter and receiver. The nodes to be added are shown in Fig. 7.

- ▼ ■ children
  - > ● Receiver "receiver"
  - > ● Emitter "emitter"
  - > ● Emitter "emitter\_1"
  - > ● Emitter "emitter\_2"
  - > ● Emitter "emitter\_3"

**Figure 7.** Nodes of the supervisor robot.

The mine car with a repetitive motion in reality is set as a robot traveling along the specified route in this experiment, and then used as a dynamic obstacle to test the reliability of the algorithm. Although it is not accused by the supervisor, it still needs to send its own path information to the supervisor so that other robots can avoid it. Therefore, it still has a receiver and emitter on it. The specific modeling is shown in Fig. 8.



**Figure 8.** Modeling of dynamic obstacles.

Finally, there are static obstacles. Static obstacles are mainly to simulate some containers or small buildings in the industrial park that need robots to avoid. The specific modeling is shown in Fig. 9.



**Figure 9.** Modeling of static obstacles.

Since both algorithms are based on A \* algorithm, and A \* algorithm is applicable to grid environment, in order to make the robot's moving path clearer, grid settings are adopted for the floor design. The specific construction environment is shown in Fig. 10.



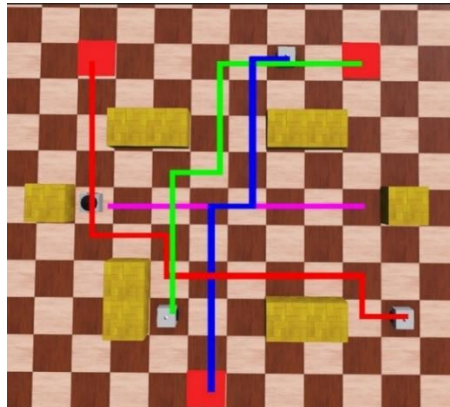
**Figure 10.** Overall environment modeling.

The red position in the Fig. 10 represents the target point of the robot, the number next to it represents the target point belongs to the robot labeled with this number, and the number next to the

robot represents the label of this robot is this number. Dynamic obstacles move back and forth between the two obstacles at the leftmost and rightmost ends. The current state is set as the zero time state in this simulation.

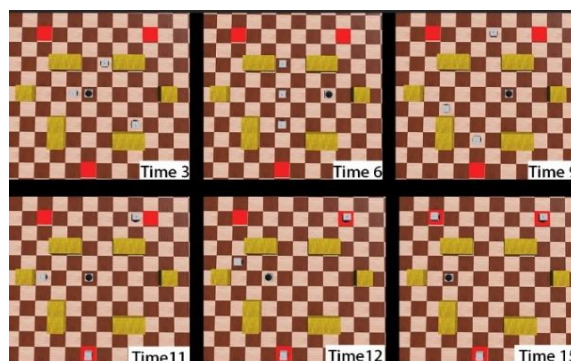
### 3.2. Experimental effect and comparative analysis

After the environment is built, start the simulation comparison. The first is the simulation of HCA. The simulation result of three robot paths after the specific code runs are shown in Fig. 11.



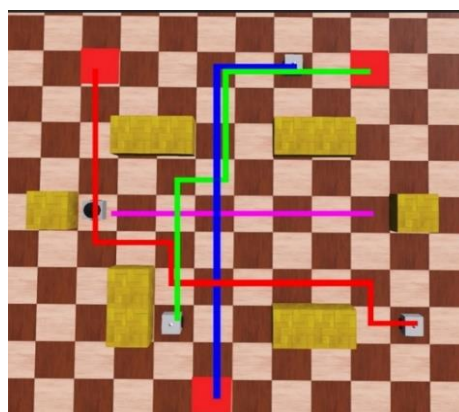
**Figure 11.** Route map of each robot under HCA algorithm.

To better observe how each robot moves, the time when the robot walks through a grid is set as a unit time. In this paper, the motion states of the three robots in different unit time point are monitored and photographed, as shown in Fig. 12.



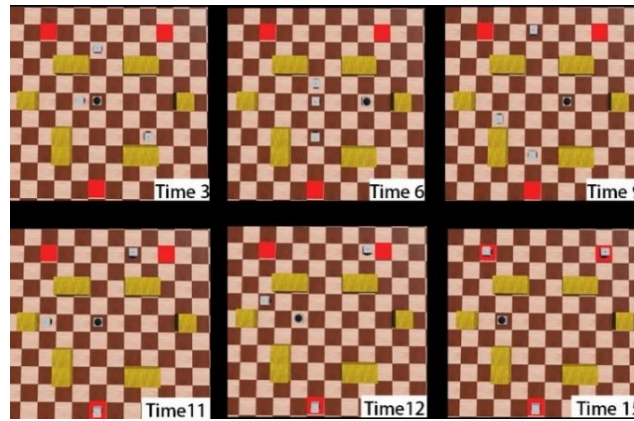
**Figure 12.** State diagram at specific time under HCA algorithm.

Then, the CBS algorithm is simulated. The specific roadmap of each robot is shown in Fig. 13.



**Figure 13.** Route map of each robot under CBS algorithm.

In the same way, the motion states are also monitored and photographed at different specific time point during the operation. And the selected specific time is the same as that of HCA simulation for comparison. Details are shown in Fig. 14.



**Figure 14.** State diagram at specific time under CBS algorithm.

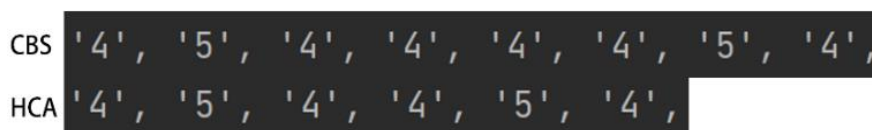
To compare the two algorithms, this paper mainly selects the total steps and total time of each robot as the comparison quantity. The time is in unit time, that is, the time taken by the robot to move a grid distance, which is about 6 seconds. The specific comparison is shown in Table 1.

**Table 1.** Comparison between HCA and CBS.

	Total steps	Total time
HCA	38	38
CBS	38	39

According to the comparison of the experimental results in the table, the total steps of the two algorithms is almost similar, while the total time of CBS is one unit more than that of HCA. According to the trajectory of the robot obtained from the previous path planning simulation, except that the path planning of No.3 robot has changed, the path planning of other robots in the two algorithms is the same. However, at the 12th unit time, No.2 robot in HCA has reached the destination, while No.2 robot in CBS is still one step away. This is why the total time of CBS is one more unit.

Finally, to explore the reasons why the above results often occur, the path points of No.2 robot are extracted, and the path points of the two paths are compared one-to-one. Although the path planning is the same, to avoid another robot under the CBS algorithm, No.2 robot stops at (4, 4) points on its path for a unit time. The specific comparison segment is shown in Fig. 15.



**Figure 15.** Comparison of robot path points under two algorithms.

According to the above analysis, CBS may be inferior in time efficiency because it allows the robot to stay still. But this kind of immobile behavior can keep the initial path obtained by A \* algorithm. CBS algorithm may perform better without considering time and quality. Later, the simulation of 5 robots is conducted, and the results are similar to the above. The specific results will not be shown considering the length of this paper.

#### 4. Conclusions

Aiming at the problem of path planning and obstacle avoidance in multi robot cooperative transportation in the industrial park environment, this paper first analyzes the specific problems in the industrial park environment and conducts simulation modeling. Then, two multi robot path planning algorithms, HCA and CBS, based on A \* algorithm are explored and improved to enable robots to avoid obstacles in industrial parks. Finally, we use webots to simulate and give a comparison for the two algorithms. The experimental results illustrate that HCA algorithm performs better in time efficiency, while CBS can reserve the initial path planned by A \* algorithm, reducing unnecessary

replanning. In industrial parks, the efficiency of transporting materials is of great Importance. Therefore, HCA is recommended as the path planning algorithm for multi robots in industrial parks.

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