# **Research on AGV Path Planning in Hybrid Flow Workshop**

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## Abstract

The mixed flow workshop has a higher production capacity, in which AGV, as a key transportation equipment, replaces manual line-side material handling, which can ensure the flexibility and timeliness of the production system, so the AGV path planning problem of the mixed flow workshop is studied, so that the AGV can operate efficiently with the production system and improve the production efficiency of the workshop, which has important theoretical reference and engineering application value. In this paper, the AGV path planning problem of the mixed assembly plant is studied, and the A\* algorithm is designed and improved to carry out the global path planning of the AGV for the AGV in the mixed assembly workshop. Simulation results show that the improved A\* algorithm is better than the A\* algorithm, ant colony algorithm and Dijkstra algorithm in terms of solution time and results.

# **Keywords**

Hybrid Flow Workshop; Multi AGV Path Planning; A\* Algorithm; Global Path Planning.

# 1. Introduction

With the comprehensive promotion of Made in China 2025, enterprises have begun to layout smart chemical plants and replace traditional manual operations with intelligent equipment. Firstly, it is necessary to introduce relevant intelligent equipment, among which the Automated Guided Vehicle (AGV) used for material transportation is a key equipment that can ensure the flexibility and timeliness of the production system. For multi AGV systems, the main task is to plan the route of AGVs, which is the AGV path planning problem.

Scholars at home and abroad have conducted extensive research on solving global path planning problems. Wang Yunrui et al. <sup>[1]</sup> described a mixed flow workshop assembly line scene containing AGVs as a VRPTW problem with a known coordinate material distribution center and 10 transport vehicles delivering between it and 10 workstations. They used an improved ant colony algorithm to solve the distribution path of the AGV. Ma Xiaolu and Mei Hong <sup>[2]</sup> improved the basic potential field ant colony algorithm to solve the AGV global path planning problem. This algorithm has higher convergence efficiency and shorter optimization paths. Yu Jiaqiao and Li Yan <sup>[3]</sup> improved the basic genetic algorithm to obtain the material transportation path of intelligent workshop AGV. Zhang Zhongwei et al. <sup>[4]</sup> conducted path planning with the goal of minimizing transportation distance and energy consumption in the manufacturing workshop. They used particle swarm optimization algorithm to solve the model, and finally verified the effectiveness of the model and algorithm using an aviation precision parts manufacturing workshop AGV and proposed an improved A\* algorithm to solve the problem of multiple search nodes and long running time in the basic A\* algorithm. Specifically, it restricts AGV from expanding only to the quadrant where the target node is located

during the search process, And add turning costs in the valuation function. Zhang Y et al. <sup>[6]</sup> designed an improved ant colony algorithm that incorporates the execution task priority calculated by the charged amount of the AGV to obtain the driving path of the AGV. This article uses a design improvement A\* algorithm to perform global path planning for AGVs.

# 2. Multi AGV Path Planning for Mixed Flow Workshop

At the strategic level of manufacturing systems, transportation planning is an important means of achieving economic benefits. Designing the optimal AGV transportation route for the workshop can reduce material transportation time and improve workshop production efficiency, which is a key issue in system optimization scheduling. In the production process of the mixed flow workshop, the output of the previous process is transmitted to the next process as input, and the multi AGV system is used to complete these edge material transportation tasks. The transportation network in the workshop can be divided into several non overlapping areas, and at the same time, there cannot be more than one AGV in one area, And during the driving process, one AGV cannot occupy more than two areas simultaneously. Therefore, the transportation system can be considered as a discrete event system, and research on it can be transformed into optimization of a discrete event system, that is, an AGV system with multiple concurrent tasks. When there is a conflict of road network resources, how should AGVs cooperate and choose the optimal path to complete all tasks.

## 3. Model

The mixed flow workshop studied in this article contains many areas that are impassable by AGVs, which cannot be clearly expressed in the topology map. Therefore, this article uses the grid method to establish an environmental map of the workshop. Scholar Howden first proposed the grid method <sup>[7]</sup>, which first establishes a two-dimensional map of the actual scene, and then divides it into several equally sized pixels (also known as unit grids) from both the row and column directions. Each grid can be indexed using a two-dimensional array, and the attributes of each pixel can be expressed in binary form, making the entire map easy to maintain and modify. The AGV impassable areas are represented by 1, and the AGV passable areas are represented by 0.

The determination of unit grid size: The efficiency and path planning results of the grid method for searching maps are directly affected by the size of the unit grid. The smaller the unit grid size, the more accurate the established environmental model will be, but the higher the cost of maintaining map information; On the contrary, if the unit grid size is too large, the accuracy of environmental modeling is poor, which is not conducive to subsequent path planning. Therefore, the determination of grid size and shape needs to meet two principles. Firstly, it is necessary to ensure that the entire environment, obstacles, and important targets are fully covered by an integer number of grid regions. Secondly, in order to speed up the search for solutions, the grid size should not be too small. The model assumes the following conditions:

1) The grid adopts four-way search, which means that AGVs can only travel in four directions: up, down, left, right.

2) At the same time, there cannot be more than one AGV in a cell grid, and during driving, one AGV cannot occupy two or more cell grids simultaneously.

3) When AGV receives a task, it defaults to knowing the starting and ending positions of the task.

4) All location information in the default workshop scene is known and reflected in the environmental map.

5) All AGV road networks in the workshop are bi-directional single lane, including two types: multi trajectory paths and multi loop paths.

# 4. Algorithm Design

#### 4.1 Global Static Path Planning

After applying the A\* algorithm for path planning of AGV in a mixed flow workshop, it was found that there are two main issues that need improvement:

1) Reduce turning points in task execution routes.

When AGV encounters a turn during driving, it needs to slow down and consume a certain amount of turning time. AGV takes about 5 seconds for each 90 degre turn. The A\* algorithm adds nodes in order, which is affected by factors such as machine equipment and factory design in the map that result in AGV impassable areas. This results in an S-shaped shortest path, as shown in Figure 1. When there are no obstacles, the planning result from point A to point B is the black area in the upper left part, while when there are obstacles in the system, the planning result from point B to point A is the red path.

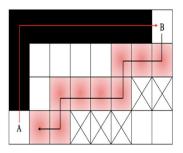


Figure 1. The A \* algorithm is affected by obstacles in the environment

Improve the basic  $A^*$  algorithm to minimize the number of turns on the route while ensuring the shortest driving distance. The core of controlling the  $A^*$  algorithm's pathfinding is the function F (n), which represents the path cost of AGV travel, where G (n) refers to the actual distance traveled between the starting point and the current position, and H (n) refers to the estimated distance traveled between the current position and the endpoint. This article uses Manhattan distance for calculation. Change the heuristic function F (n) of  $A^*$ , add a new turning cost C, sum the C value with the G value, and update it to the new G value with iteration.

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

Below is the calculation method for C value. As shown in Figure 2, following the basic A\* algorithm process, assuming starting from point A, after one round of search, it is found that point (0,1) is the point with the lowest current F value, denoted as minF Point, then point A is its parent node, denoted as minF. father Point, perform a four-way search on points (0,1), where (1,1) is the child node of the search, denoted as currentPoint.

| (0, 0)                     | (1, 0)                     | (2, 0) |
|----------------------------|----------------------------|--------|
| (0, 1)<br>minF.Po<br>int   | (1, 1)<br>current<br>Point |        |
| A<br>minF.fat<br>her.point |                            |        |

Figure 2. The calculation method of C value

The C value can be calculated by the following equation:

$$C = \begin{cases} \left\{ \begin{array}{l} \left| \begin{array}{c} currentPant.x - \min F.Point.x \right| \\ (\min F.Point.x - \min F.father.x) \\ | (currentPant.y - \min F.Point.y) - \\ (\min F.Point.y - \min F.father.y) \\ 0 \min F.PointNota startingpoint \\ \end{array} \right\} \\ \min F.PointNota startingpoint \end{cases}$$
 (2)

2) Dynamically changing the search space range of AGV during the pathfinding process.

Due to the large size of the actual workshop scene map, the search range required by the A\* algorithm also increases, resulting in a long solving time for the A\* algorithm. In order to improve the search speed of the A\* algorithm without reducing the search quality, a variable coefficient is added to the estimated distance H(n) in the heuristic function F(n). The coefficient will dynamically change with the distance from the current point to the endpoint, and the larger the distance, the smaller the coefficient. At the initial search, the distance from the endpoint is far, the coefficient is small, the estimated distance H(n) is small, and the search range for A\* is large. As AGV approaches the endpoint, the coefficient increases, the estimated distance H(n) increases, and the search range of A\* decreases.

Set the variable coefficient as  $\alpha$ , It is a function of estimating the distance H, i.e  $\alpha$ =F(H). According to the actual map of the mixed flow workshop, the distance distribution of loading and unloading between processes is between 10-28 unit grids. Therefore, the design function f (H) is considered as a piecewise function, as shown in the equation.

$$f(H) = \begin{cases} 1.5\\1\\0.5 \end{cases} \begin{array}{l} H \le 10\\10 < H < 28\\H \ge 28 \end{cases}$$
(3)

In summary, improving the A\* algorithm involves changing the heuristic function on the basis of the basic A\* algorithm to reduce path turning points and dynamically change the search range during the AGV pathfinding process, while improving thesearch speed of the A\* algorithm without compromising search quality.

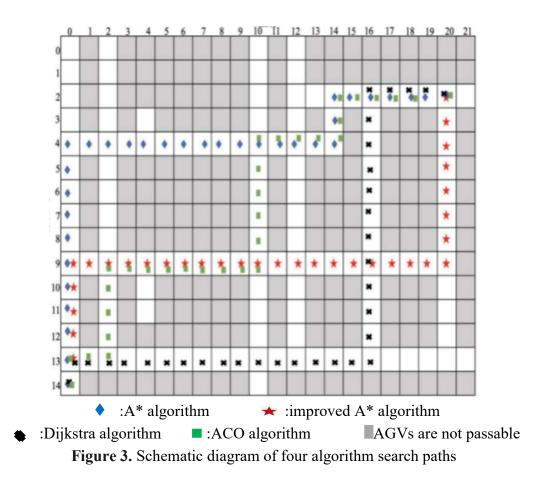
#### 5. Numerical Examples

In order to evaluate the proposed improved A\* algorithm, this section compared the solution results of A\* algorithm, improved A\* algorithm, ACO algorithm, and Dijkstra algorithm.

#### 5.1 Improvement of A\* Algorithm Effectiveness Verification

Taking the grid map of the electrode production workshop as the scene, the starting point of AGV is (0,14) and the ending point is (20,2). The routing results of the basic A\* algorithm, improved A\* algorithm, ACO algorithm, and Dijkstra algorithm are shown in Figure 9. Table 3 provides a detailed comparison of the path length (number of unit grids included in the final path), number of turns, time spent running 100 times, and probability of finding the optimal path for the four algorithms (where the first column is calculated using the environment shown in Figure 3, and the second column is calculated by randomly generating 50 different environmental grid maps). It can be seen that the four algorithms search for the same optimal path length. The improved A\* algorithm proposed in this article has the least number of turns, slightly less computational time than the basic A\* algorithm and

Dijkstra algorithm, and is significantly less likely to find the optimal path than the ACO algorithm, Dijkstra algorithm, and ACO algorithm. This indicates that the improved A\* algorithm designed in this article can effectively reduce the number of turns, while improving the search speed of the basic A\* algorithm without compromising search quality.



| algorithm                   | path<br>length | number of<br>turns | running 100 times<br>takes time(s) | The probability of finding the best path(%) |      |  |  |
|-----------------------------|----------------|--------------------|------------------------------------|---|------|--|--|
| basic A* algorithm          | 33             | 3                  | 31                                 | 100   | 100  |  |  |
| improve the A*<br>algorithm | 33             | 2                  | 29                                 | 100   | 100  |  |  |
| Dijkstra algorithm          | 33             | 3                  | 40                                 | 100   | 99.8 |  |  |
| ACO algorithm               | 33             | 7                  | 303                                | 100   | 99.0 |  |  |

 Table 1. Algorithm Comparison

Table 1 shows the calculation results of three methods. The optimal path length searched by the four algorithms is the same. The improved A\* algorithm proposed in this paper has the least number of turns, slightly less computation time than the basic A\* algorithm and Dijkstra algorithm, and significantly less probability of finding the optimal path than the ACO algorithm, Dijkstra algorithm, and ACO algorithm. This indicates that the improved A\* algorithm designed in this article can effectively reduce the number of turns, while improving the search speed of the basic A\* algorithm without compromising search quality.

## 6. Conclusion

1) Analyzed the layout of the production workshop road network and established a workshop environment map using the grid method.

2) Design and improve the A\* algorithm by adding a turning penalty function to the heuristic function, and adding a variable coefficient to estimate the distance todynamically change the search space range of AGV during the pathfinding process, inorder to obtain the global optimal path to avoid static obstacles.

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## References

- Wang Yunrui, Zhao Xuwen, Wu Zhengli, etc A Method for Material Distribution Path Planning in Assembly Workshops Based on Mixed Flow Production Mode [J]. Modern Manufacturing Engineering, 2021 (07): 109-116.
- [2] Ma Xiaolu, Mei Hong Global path planning for mobile robots based on improved potential field ant colony algorithm [J] Journal of Mechanical Engineering, 2021, 57 (01): 19-27.
- [3] Yu Jiaqiao, Li Yan Automatic Navigation Vehicle Path Planning and Scheduling Based on Improved Genetic Algorithm [J] Machine Tool and Hydraulic, 2022, 50 (05): 16-20.
- [4] Zhang Zhongwei, Li Junlan, Wu Lihui, etc Research on single AGV path planning in manufacturing workshops considering energy consumption [J] Manufacturing Technology and Machine Tool, 2021, 705 (03): 118-122.
- [5] Li Qiang, Yu Zhenzhong, Fan Qigao, et al Application of Improved A \* Algorithm in AGV Path Planning[J] Combination Machine Tool and Automation Processing Technology, 2019, 543 (05): 98-101.
- [6] Zhang Y, Wang F L, Fu F K, et al. Multi AGV path planning for indoor factory by using prioritized planning and improved ant algorithm [J] Journal of Engineering and Technical Sciences, 2018, 50 (4): 534-547.
- [7] Li Jigong, Feng Yiwei, Guo Yi Real time path planning based on grid maps in complex environments [J] Control Engineering, 2007 (14): 199-201.