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A Probabilistic Time-Constrained Based Heuristic Path Planning Algorithm in Warehouse Multi-AGV Systems ⋆

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Abstract: This paper mainly focuses on the path planning algorithm of multi-AGV system in the warehouse environment. We first analyze and model the path network of multiple AGVs based on dynamic stochastic network theory. Then, a probabilistic time constraint is added in the process of the well-known A* heuristic algorithm, and the solution of the time cost is proposed based on probability theory. Furthermore, a multi-AGV conflict avoidance strategy suitable for heuristic planning algorithms is achieved in combination with queuing mechanism. Finally, numerical simulation experiments of the warehouse multi-AGV system are realized and demonstrate the effectiveness of the proposed algorithm.

Keywords: Path planning, multi-AGV, heuristic search, industrial warehouse, A* algorithm.

1. INTRODUCTION

The introduction of automated warehouses has facilitated more industrial factories because of their flexible solutions (Sabattini, et al., 2013). More and more automated guided vehicles (AGVs) are being used in warehouses to meet the growing transportation and cargo sorting tasks, and the number of AGVs usually reaches hundreds of vehicles. Compared with single-AGV products, multi-AGV systems are gaining popularity due to the advantages of wide coverage, versatility, flexibility as well as powerful task-solving complexity and efficiency (Kitts, et al., 2008).

However, the complex control and scheduling of multi-AGV systems has become a new challenging issue. Multiple AGVs in a warehouse environment perform movements between different workstations through certain fixed routes. Path planning and obstacle avoidance strategies will directly affect the efficiency and flexibility of the warehouse. Therefore, it is important to deal with the collision problems and improve the utilization of limited path resources in a multi-AGV work scenario.

In recent years, researchers have proposed a number of methods for robot planning and collision avoidance (Dias, et al., 2004; Dogar, et al., 2015; Hofbaur, et al., 2007; Blackmore, et al., 2011). Heuristic algorithms among path planning and search algorithms are widely used in research and practice because of the favourable directivity and low computational cost. Typical algorithms such as sampling based methods (Bekris, et al., 2012), computation tree logic (Saha, et al., 2014), potential field methods (Pamosoaji, et al., 2013), collision-avoidance based methods (Alonso-Mora, et al., 2012), optimization programming (Morgan, et al., 2014) and so on. It is confirmed that each algorithm is applicable to different application scenarios, and the heuristic algorithm for path planning and collision avoidance of multiple AGVs has become a key to improve the security and efficiency of the warehouse multi-AGV system.

Generally speaking, heuristic planning algorithms could effectively reduce the computational cost of path planning. In terms of warehouse efficiency, not only the shortest path but also the possible congestion and conflicts among multiple AGVs should be considered, that is, there need to be constrained at the time level. Taking the safety of machines and personnel while working with multiple AGVs into account, the failure of one AGV should not affect the normal operation of the entire system. The main purpose of this paper is to optimize the path planning and conflict avoidance method of the multi-AGV system in warehouse scenarios, and propose a heuristic algorithm based on dynamic random networks. The dynamic random variable of time consumption is added. The probability theory is used to model the AGV motion path network, and then the utilization rate of the fixed path resources in multi-AGV system has been improved according to the proposed heuristic function.

The rest of this paper is organized as follows. In Section 2, the state-of-the-art research is introduced. In Section 3, the heuristic path planning algorithm is dicussed in detail, which contains dynamic stochastic path network modeling, probabilistic time-constrained planning process, and secu-

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rity strategy. In Section 4, the simulation experiments are analyzed, and the effectiveness of the proposed method is demonstrated. Section 5 concludes this work.

2. RELATED WORK

Oboth et al. (1999) early proposed a dynamic path planning algorithm, which first solves the time shortest path of the AGV to the end point, and then selects the path according to the state of each AGV in the system. The method is computationally intensive and could not guarantee the optimal path. A Petri net decomposition method was proposed by Nishi et al. (2010) to calculate the shortest feasible path, which ensures the shortest path of each AGV. However, the conflict avoidance relationship among multiple AGVs could lead to deadlock (Zhou, et al., 2017). By transforming the static path planning problem into the optimal sequence problem of the time-based Petri net, Nishi et al. (2012) solved the conflict and deadlock among the AGVs, while the method is suitable for path planning of a small amount of AGVs.

Tai et al. (2017) added time constraints to planning process and proposed a dynamic path planning algorithm based on time window model. The time window is arranged through calculating the time between each path node in AGV motion. Then the A* algorithm is used to plan paths. An improved A* path planning algorithm considering safety distance was proposed by Singh et al. (2018). Under the condition of safe distance constraint, the mobile robot is guaranteed to find the shortest path in a conflict-free environment. This method could achieve collision avoidance among multiple AGVs, but it sacrifices the utilization efficiency of the path and occupies more computing resources. Song et al. (2019) proposed an improved A* algorithm, in which three steps of smoothing process effectively enhance the smoothness of the planned path and reduce the length of the path. Wang et al. (2018a) added path risk value assessment based on A* algorithm that ensures better obstacle avoidance effect in the global map. However, there is no uniform standard for path length cost and risk weight. Therefore, the estimated path is different from the actual value and could not be guaranteed to be optimal. Wang et al. (2018b) proposed an improved potential field ant colony algorithm, which combines artificial potential field method with improved information update mechanism to ensure the optimal path search of the robot in static grid. The algorithm has better global search ability and convergence speed.

3. HEURISTIC PATH PLANNING ALGORITHM

3.1 Traditional A Algorithm*

A* algorithm (Hart, et al., 1968) is one of the most useful path planning algorithms on account of its heuristic function, which searches for the shortest path while greatly reducing the computational cost. The heuristic function can be described as:

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

where n is the number of steps during the movement, $g(n)$ represents the distance (usually Manhattan distance) between the current position and the starting position while $h(n)$ represents the estimated distance between the current position and the ending position. The choice of the optimal path depends on the value of $f(n)$.

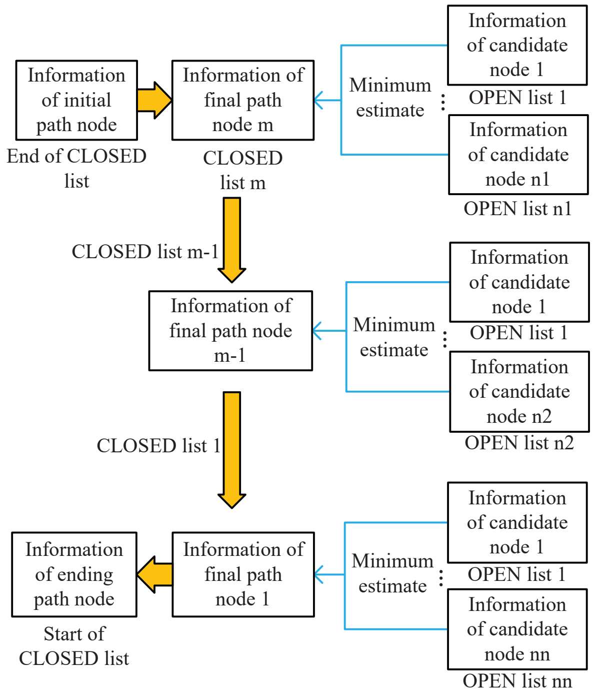

Fig. 1. Flow diagram of traditional A* algorithm

The algorithm has two lists named OPEN list and CLOSE list, respectively. During the looping searching process, the OPEN list is established to store the candidate nodes that will be detected later while the CLOSED list is to store the selected nodes of the final path. The detailed steps of A* algorithm is shown in Fig. 1. While searching the optimal path, the nodes adjacent to the current node are added to the OPEN list in sequence. According to the evaluation index of the heuristic function, the algorithm selects the adjacent node with the optimal evaluation value of the target node and adds it to the CLOSED list. After a complete search process, the nodes contained in the CLOSED list will become the optimal path. In the scenario of AGV optimal path planning, when an AGV moves from the starting position, the algorithm continuously searches for the minimum distance $h(n)_{min}$ of all possible paths from the current position to the ending position, and selects the next target position accordingly. The algorithm effectively guarantees the shortest distance $f(n)_{min}$ from the starting to the ending position. In addition, the path planning effects are different due to the types of evaluation indicators of the algorithm. If the time consumption is considered as the evaluation index, that is, the time cost of the AGV through each path is a certain value, the improved A* algorithm selects the optimal path by searching for the minimum time cost. The constant time consumption in this condition is similar to constant distance, so the path network is still static and can not effectively reflect the real-time situation of the occupied path. (Carley, 2003).

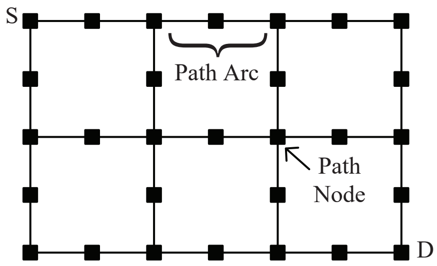

Fig. 2. Schematic diagram of multi-AGV path network

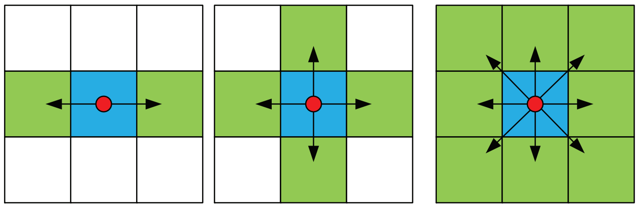

Fig. 3. Schematic diagram of 2-direction, 4-direction and 8-direction motion in path network

3.2 Dynamic Stochastic Path Network Model

We are devoted to combine the characteristics of the AGV operating environment in industrial warehouses and build a specific model of the multi-AGV moving path network that is similar to the grid-shaped network. Based on the structural characteristics of path network, we define the set of path node V, path arc E, and path cost W. The details are shown as follows:

$$\begin{cases} V^{1\times n} = \{1, 2, \cdots, n\}, \\ E \in \mathbb{R}^2 = \{(i,j)|i,j \in V\}, \\ W(t) = \{w_{ij}(t)|(i,j) \in E, t \in [t_0, t_m]\}. \end{cases} \tag{2}$$

As shown in Fig. 2, the path network consists of a set of path arcs (line segment) and path nodes (black square). The AGV has a directional movement within the path network (e.g. from the starting node S to the target node D) according to the task. In warehouse environment, the path space of the AGV motion is usually limited, and the number of motion directions would affect the efficiency of the path resources. In the grid-shaped network shown in Fig. 3, the AGV has a maximum movement direction of 8 at each node. To save path resources of the network in a multi-AGV warehouse system, we specify the motion direction to be 4 at the turn node, while 2 at the node on the path arc. Specifically, the AGV has only two directions of forward and backward for the path arc node, and two turning directions of left and right have been added to the intersection node (only left or right turning direction is increased at the T-junction).

In order to establish and control the time consumption of the system, we make use of the theory of dynamic random network to define the AGV path network.

The path cost from node i to node j is defined as $w_{ij}(t)$, where t is the start time of AGV movement. We assume that the cost of an arc is time-dependent and independent of each other on the time closed interval $[t_0, t_m]$, where t_0 and t_m represent the start and stop time in the current movement, respectively, so the cost $w_{ij}(t)$ could be a time continuous random variable with the distribution function of $F(w_{ij}, t)$. In addition, we define the partial path set between node i and node j as $X = \{x_{ij}|(i,j) \in E, x_{ij} \in \{0,1\}\}$. The entire cost of the final path consists of every path and can be expressed as $C(t_0) = \sum_{(i,j)\in E} w_{ij}(t)x_{ij}$.

According to probability distribution theory, $C(t_0)$ is a random variable that depends on continuous time. In the warehouse multi-AGV system, numerous uncertainties in the time-consuming links such as AGV straight-forward, turning, and collision avoidance would result in the uncertainty of the cost of each path arc. Assume that $R(s,d)$ represents the set of partial path from the starting node to the target node, and $C(R_{s,d})$ represents for the consumption of the entire path. Therefore, the key issue is to find the distribution of the minimum cost $C_{\min} = \min\{C(R_{s,d})\}$ on the basis of the distribution characteristics and statistical data of the path network, and then plan the optimal path with lowest cost.

Due to probability theory (Sheng, 2001), it is necessary to obtain the probability distribution function (or probability density function) of the path to judge the probability optimal path, and calculate the statistical data of the path consumption. However, the probability distribution of each path arc is different and varies with time. The path network in the warehouse environment has a large scale together with a number of path arcs and nodes. It requires a large amount of computing resources whether inferring the probability distribution of each independent path or directly estimating the entire path distribution. In one word, the process is inefficient and complicated (Pynadath, et al., 1995). To simplify the calculation process, we take advantages of the theorem (Sheng, 2001) as follows.

Theorem 1. For the two random variables X and Y, the expected value $E(X)$ of X is less than the expected value $E(Y)$ of Y is equivalent to $P(X \leq Y) \geq 0.5$, that is, $E(X) \leq E(Y) \Leftrightarrow P(X \leq Y) \geq 0.5$.

Theorem 1 provides a new solution that we could transform the calculation of probabilistic shortest path into the comparison of the expected value between two path costs. Therefore, we only need to compare the expected time consumption of two paths when adding a probabilistic time constraint to a heuristic algorithm.

3.3 Probabilistic Time-Constrained Heuristic Algorithm

Combined with the previous perspective, we define an improved A* algorithm heuristic function with probability time conditions as equation (3).

$$f(j, t_s) = g(j, t_s) + h(j, t_s). \tag{3}$$

Similar to the heuristic function of A* algorithm, $g(j, t_s)$ and $h(j, t_s)$ represent the value of completed cost and estimated cost, respectively. t_s is the start time from the starting node, and j is the current node. For the paths that AGVs have already passed, we consider the actual path length and AGV speed, especially adding the time cost T of turning at the intersection. Assume that the average speed of AGV is v_e, then the actual cost $g(j, t_s)$ can be expressed as

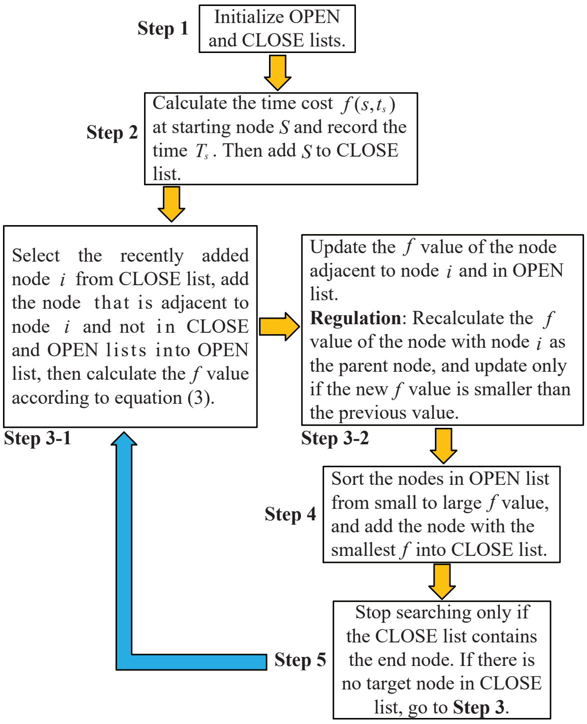

Fig. 4. Flow diagram of improved heuristic algorithm

$$g(j,t_s) = \begin{cases} L_p/v_e + T_o + \sum_{1}^{n} T, n \leq num(node), \\ L_p/v_e + T_o, \end{cases} \quad (4)$$

where L_p is the whole length of the path, T_o is the time cost of AGV parking, and n is the maximum number of turning nodes. L_p is calculated by Manhattan distance, i.e. the distance between node $A(x_A, y_A)$ and $B(x_B, y_B)$ could be $L_{AB} = |x_A - x_B| + |y_A - y_B|$. In addition, equation (4) presents two conditions of turning or not.

For the estimated cost $h(j,t_s)$ of the path, we need to evaluate according to the obtained expected value of time as shown in equation (5).

$$h(j,t_s) = \sum_{1}^{m} E(\omega_{ij}(t)), m \leq num(arc), \quad (5)$$

where $E(w_{ij}(t))$ is the expected value of time cost and m is the maximum number of path arcs. To explain clearly, Fig. 4 shows a flow chart of the improved algorithm process.

3.4 Path Network Security Strategy

Multiple AGVs in the warehouse move in a limited space, and there may exist accidental parking or joint use of path resources. Avoiding collision conflicts caused by power failures, mechanical faults, etc., ensuring the safety of internal and human-machine interaction processes in multi-AGV system is fundamental to efficient planning.

There are usually four types of conflicts in a fixed path network. As shown in Fig. 5, they are chasing conflict, anti-directional conflict, intersection conflict, and fault parking conflict. In order to avoid possible conflicts in multi-AGV system, we propose an available conflict avoidance method based on queuing mechanism. Fig. 6 shows the possible conflicts of AGVs in the path network proposed in this paper. The detailed conflict avoidance strategy process is shown in Fig. 7, which consists of four main steps.

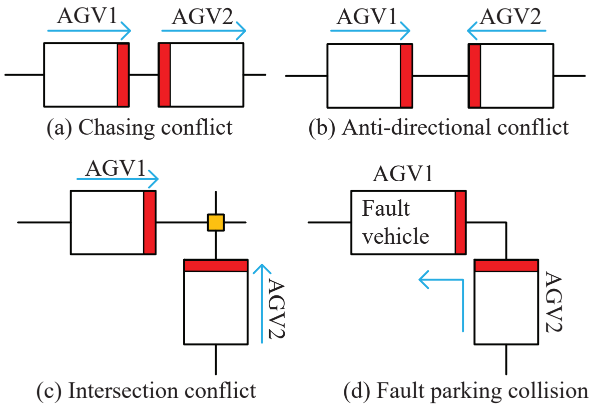

Fig. 5. Four typical types of conflicts

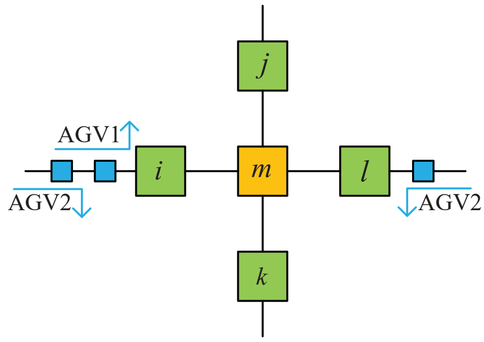

Fig. 6. Schematic diagram of AGV conflicts in path network

4. SIMULATION EXPERIMENT

In the experimental session, we developed the simulation scenario of the warehouse multi-AGV system through JAVA programming, and expanded the path network shown in Fig. 2. The path network consisted of 3510 path arcs and 1800 nodes, which could accommodate 350 AGVs simultaneously.

In order to calculate the probability time distribution in the path network, we set 35 fixed starting points and 110 fixed ending points firstly. The initial time cost of each path arc was set 900 milliseconds, and 1000 milliseconds of the turning nodes. We have used the traditional A* algorithm for planning and made statistics on the situation where free-motion AGVs occupied road network resources.

According to the experimental data, the time cost per 30 minutes of every arc almost obeys the normal distribution. Table 1 and Table 2 show the results of the normality test for randomly selecting a path arc in the 15th 30-minute period.

It is shown that the skewness and kurtosis approache 0. Besides, the significance of the KS and SW test in normality test is more than 0.05. Hence the obtained

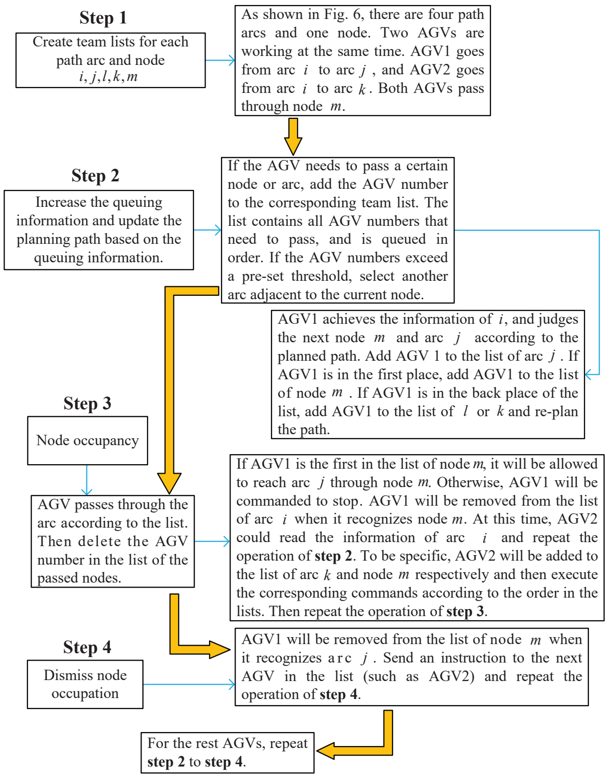

Fig. 7. Flow diagram of conflict avoidance strategy

statistical data in Table 1 and Table 2 could be considered to follow a normal distribution.

Furtherly, we reset path cost of the dynamic random network according to the mean value of the statistical data and retained the start and end points as well as the number of AGVs in the path network. Assume that the completion efficiency indicates the number of times that the multi-AGV system completes tasks from the start point to the end point in every hour. Fig. 8 shows a certain motion path selected during the experiment and Fig. 9 shows the results of the comparative experiments.

Table 1. Descriptive statistics

	Statistics(ms)	Standard Error(ms)
Mean	2230.9103	110.93
95% Confidence	2003.9559 (lower bound)	/
Interval for Mean	2457.8665 (upper bound)	/
5% Trimmed Mean	2235.6650	/
Median	2200.0093	/
Standard Deviation	637.2418	/
Maximum	35004.05	/
Minimum	915.00	/
Range	2589.00	/
Interquartile Range	910.00	/
Skewness	-.101	.408
Kurtosis	-.359	.799

Table 2. Normality test

	Statistics	df	Significance
Kolmogorov-Smirnov^a	.116	33	.200*
Shapiro-Wilk	.975	33	.770

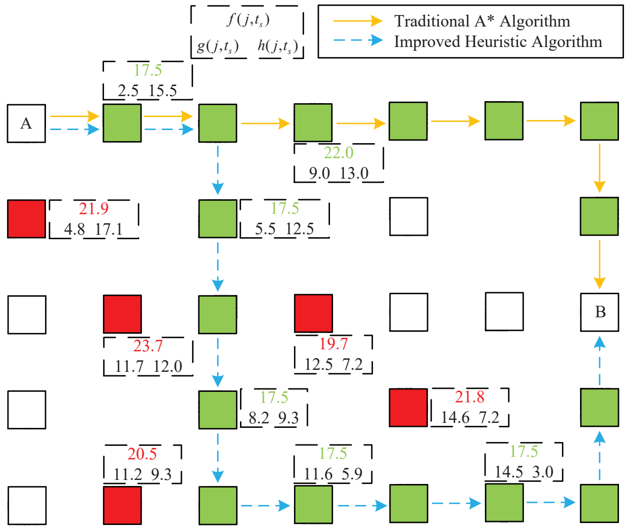

Fig. 8. Schematic diagram of planned path

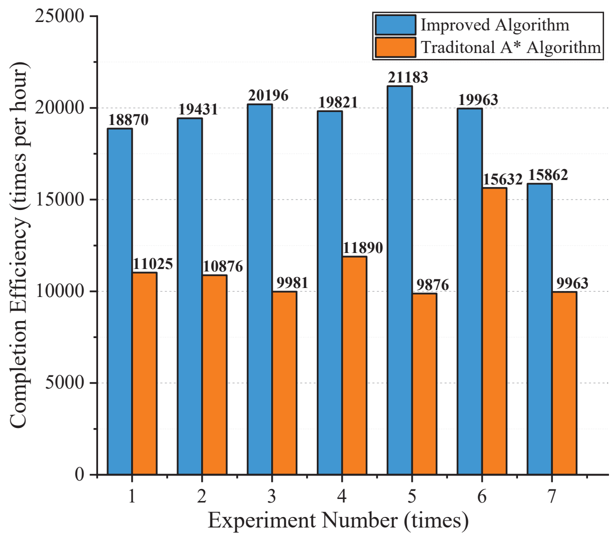

Fig. 9. Diagram of comparative experiment

In Fig. 8, A and B stand for the starting point and the ending point, respectively. The solid arrow (yellow) indicates the path planned by A* algorithm and the dotted arrow (blue) indicates the path of the improved algorithm. The dotted box expresses the time consumption. It can be seen that the path planned according to the improved algorithm of this paper is not necessarily optimal in distance on account of the added time cost.

It can be seen that the method designed in this paper has higher completion efficiency.

5. CONCLUSIONS

According to the path network characteristics of multi-AGV system in warehouse, this paper proposes a heuristic algorithm based on dynamic random network to realize multi-AGV path planning and conflict avoidance strategy. The experimental results show that compared with the shortest path search method of traditional static networks, the improved algorithm achieves multi-AGV conflict-free collaborative work and improves the efficiency of the multi-AGV system. The method of this paper provides a new idea for multi-AGV planning. The main research goal in the future is to further improve the adaptive iterative update of path arc time consumption on account of avoiding the impact caused by the change of the starting or ending point as well as the number of AGV.

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