Path Planning Algorithm Analysis of Multiple AGV

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Abstract. Intelligent logistics is an important part of intelligent manufacturing, and Automated Guided vehicle (AGV), as a part of seamless enterprise production system and storage system, is an important technical equipment to achieve intelligent logistics, and has been widely used in factories, warehousing and logistics environment such as automatic handling scenarios. Since a single AGV in the same site can no longer meet the trend of automated factory, it is important to effectively schedule and plan paths for multiple AGVs in limited space. Aiming at multi-AGV system, this paper analyzes and organizes the common path planning algorithms in the market, in order to improve the effectiveness and safety of AGVs. The A* algorithm and the ant colony algorithm's principles will be analyzed in the first part of the paper. Then describe the research status of the two respectively and summarize the advantages and defects respectively. Finally, prospect the development progress of AGV coordinated scheduling and path planning.

Keywords: Automated Guided vehicle, Intelligent logistics, Path planning, A* algorithm, Ant colony algorithm.

1. Introduction

With the development of economy and the expansion of market demand, AGV has become an important part of enterprise intelligent logistics and enterprise informatization with its wide applicability. The promotion and development of Industry 4.0 also makes us clearly realize that how to ensure safety and improve effectiveness in the operation of multi-AGV is the technical problem that should be broken through now [1]. Among the path planning algorithms of multi-AGV systems, ant colony algorithm and A* algorithm are paid special attention because of their unique advantages and wide application prospects. First, there is room for improvement of both algorithms, such as introducing time window, considering three-dimensional space, optimizing heuristic function, etc, adapt to the special needs of multi-AGV systems; Secondly, A* algorithm and ant colony algorithm have extensive research foundation and practical application cases in the field of path planning. Analysis of these two algorithms can learn from existing research results and provide theoretical and practical basis for multi-AGV path planning; Finally, the performance of these two algorithms in multi-AGV path planning can help researchers and engineers understand the advantages and limitations of different algorithms, so as to select or design more suitable algorithms for specific application scenarios.

The ant colony algorithm is a probabilistic optimization algorithm that uses heuristic pheromones, which has the advantages of strong robustness and easy integration with other algorithms, but it also has problems such as uneven path and easy to fall into local optimal solutions. Numerous researchers have proposed various optimization strategies and improvement ideas in response to the drawbacks of the conventional ant colony algorithm. In order to decrease the number of turning nodes and increase the real movement efficiency, Shuo Wang et al. suggested an enhanced ant colony algorithm based on an artificial gravity field and the triangle pruning approach [2]; W. Wang et al. Proposed an AGV that utilizes the fast-scaling Random-tree ant colony algorithm (RRT*-ACO). The combination of both the fast search mechanism of the RRT* algorithm and the positive feedback advantage of the ant colony algorithm is utilized by this method to improve robustness [3]; Z. Wang proposed a multiattribute scheduling rule for ant colony optimization simulated annealing algorithm, aiming to improve priority and applicable scenarios [4]; J. Li proposed a custom distance calculation using ant colony algorithm as an optimization algorithm for multi-objective navigation and introduced logarithmic function to avoid ant colony algorithm falling into the local optimal solution [5].

Besides of ant colony algorithm, A* algorithm is also widely discussed in AGV path planning methods, its variants provide an efficient path search framework by combining actual path cost and heuristic estimation. The different variants can be improved and optimized according to the needs of specific applications, which is highly malleable. For example, variants of Hierarchical A* improve the applicability of the algorithm in automotive applications [6]. The multi-objective path planning strategy combined with the improved A* and greedy algorithm is used in multi-point planning to improve the smoothness of the path and shorten the path length [7]. Furthermore, the integration of Adaptive A* with an advanced Dynamic Window Approach (DWA) for path planning introduces adaptive weighting into the heuristic function of A*, coupled with the trajectory point prediction capability of the DWA algorithm. This fusion significantly boosts the efficiency of path planning and dynamic obstacle avoidance ability [8].

Factors to be considered in multi-AGV systems include path length, collision avoidance, task priority and execution time. Due to the complexity of path planning for multi-AGV systems, efficient algorithms are needed to ensure their stability and response speed. This article delves into the examination and evaluation of both the A* algorithm and the ant colony algorithm, engaging in a comparative analysis of their respective merits and limitations. Following this, it outlines potential avenues for future optimization, grounded in addressing the identified shortcomings. Although these two algorithms are analyzed in detail in this paper, it is still necessary to explore how to use heuristic algorithms, deep learning and other technologies to better realize dynamic path planning of multi-AGV systems in order to cope with more complex environment changes and unpredictable situations. It is hoped that the research of this paper can provide the theoretical support of more intelligent and efficient AGV path planning management scheme for the industry, and provide a useful reference for the automation level and the overall benefit of the production line.

2. Optimization analysis of ant colony algorithm

2.1. Traditional ant colony algorithm

The ant colony algorithm was introduced by Italian scientist M. Dorigo in 1992 as a quasi-heuristic algorithm. The primary objective is to replicate the behavior of ants during foraging. The path transition probability of ant colony algorithm is as follows:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{a_{ij}(t)}{\sum_{k\in N_i^k} a_{il}(t)}, if\ j\in N_i^k \\ 0 \qquad\qquad\quad , if\ j\notin N_i^k\end{cases} \tag{1}$$

In the formula (1), $p_{ij}^{k}(t)$ is the probability that the *k* ant selects point *j* from point *i* at time *t*, N_i^k $=\{0,1,2,\dots,m-1\}$ is the set of optional waypoints for the *k* ant as the node i.

The pheromone updating mechanism of k ant between waypoints i and j can be calculated as follows:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{2}$$

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{3}$$

In the formula (2), ρ as pheromone volatilization coefficient, $\Delta\tau_{ij}(t)$ for the first moment t path (i,j) after addition of pheromones, and $\Delta\tau_{ij}(t)$=0. As $\Delta\tau_{ij}^{k}(t)$ represent when the moment t ant k through path (i,j) residual information prime value when the moment is t. The formula is as follows:

$$\Delta\tau_{ij}^{k}(t,t+1)=\begin{cases}\frac{Q}{L_k}, & \text{The } k \text{ ant accesses } j \text{ from } i\\ 0, & \text{Else}\end{cases} \tag{4}$$

In the formula (4), Q is the constant of pheromone intensity, L_k is the AGV movement path of ants in the current iteration.

2.2. Hybrid ant colony algorithm based on artificial potential field

Based on traditional ant colony algorithm, in order to speed up algorithm convergence, assist ants in finding the best path more quickly, and prevent issues like locally optimum solutions and inaccessible targets, the potential field force is implemented. The combination of ant colony algorithm and artificial potential field can make AGVs applicable not only to global search, but also to local search, so that it has better extensibility and obstacle avoidance performance.

In hybrid ant colony algorithm, the improvement of heuristic information is very important. As a heuristic function, heuristic information directly affects the decision probability of ants in route selection, and then affects the convergence speed of the algorithm and the quality of the final result. In traditional ant colony algorithm, heuristic information is only related to the Euclidean distance between the nodes i and j. When the Euclidean distance value is small, the heuristic information value is larger, so that the ant colony algorithm often ignores the influence of obstacles on the path planning, so that the planning result falls into the local optimal value. Therefore, the guidance of potential field force to heuristic information is added on the basis of the original heuristic information, which is expressed by ϑ_s. Here is the formula:

$$\vartheta_s=\alpha^{F_{tol}\cdot cos\theta} \tag{5}$$

In the formula (5), α is the constant greater than 1, and F_{tol} is the combination of gravitational and repulsive forces in the potential field. θ is the angle between the AGV advancing path and the resultant force F_{tol}. According to the principle of the hybrid ant colony algorithm, in the early stage of iteration, since pheromones and heuristic information have little effect on the transition probability, artificial potential field heuristic information should be added to strengthen the guiding role of AGV path planning, so that the search is goal-oriented; In the late iteration period, when pheromone concentration is at a relatively high level and there is a significant gap in the heuristic information among paths, the guidance function of the heuristic information can be cancelled. Therefore, the artificial potential field's influence coefficient λ is used to control its range. The improved heuristic information formula is as follows:

$$\eta_{ij}(t)\begin{cases}\frac{\alpha^{F_{tol}\cdot cos\theta}}{d^2(i,j)}*\frac{N_{max}-\lambda*N_{cur}}{N_{max}}, & \lambda*N_{cur}\le N_{max}\\ \frac{\alpha^{F_{tol}\cdot cos\theta}}{d^2(i,j)}, & \lambda*N_{cur}>N_{max}\end{cases} \tag{6}$$

In the formula (6), N_{cur} is the current number of iterations, and N_{max} is the maximum number of iterations. The initial heuristic information is modified to the quadratic times of the original, which can enhance the guidance of the path length to the algorithm [9]. The specific implementation steps of the improved ant colony AGV path planning algorithm are shown in the Fig. 1.

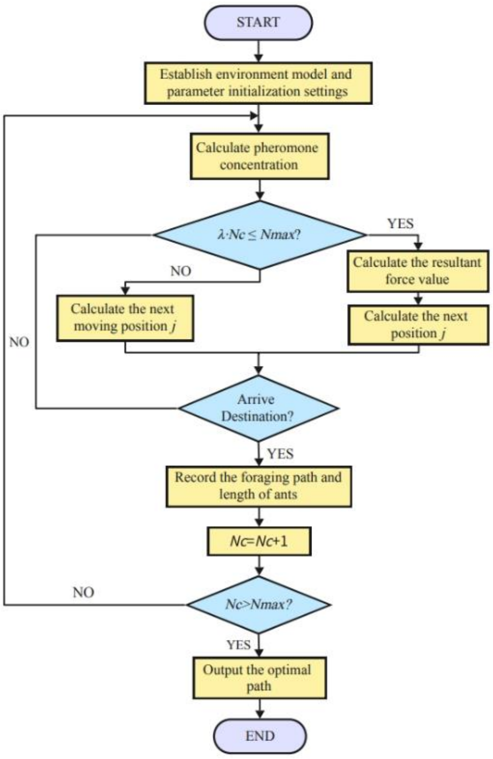

Figure 1. Flowchart of Hybrid Ant Colony Static Path Planning Algorithm [9]

2.3. Merge Ant colony algorithm and Genetic algorithm

Combining two types of optimization algorithms—genetic and ant colony, aims to maximize each one's benefits and increase search efficiency [10]. To overcome the limitations of conventional genetic algorithms in path planning. The problem of poor initial path quality is solved by combining the improved genetic algorithm with the ant colony algorithm, premature convergence, long turn times, and angles, easy deadlock, extreme regions, and too many redundant path nodes. The improved algorithm has been shown to be more effective than the traditional ant colony algorithm through simulation experiments. It has the potential to enhance its ability to avoid falling into local optimal solutions, converge faster, and generate paths of higher quality and shorter length [11]. This combination can be achieved through the following steps, it is shown in Fig. 2.

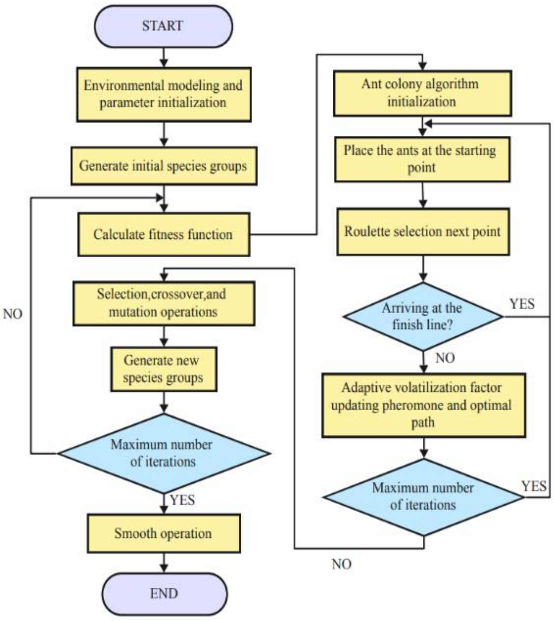

Figure 2. Fusion algorithm flowchart [10]

2.4. Advantages and defect

The above analysis of ant colony algorithm is aimed at solving the problems such as slow convergence speed and local extreme point when traditional ant colony algorithm is used for global path planning of AGV. The hybrid ant colony algorithm and fusion algorithm can improve the convergence speed and help AGV find the optimal shortest path faster. But there are still some uncertain factors such as applying only two-dimensional path planning and not considering the actual constraints of the workshop moving environment.

The analysis of all the improved ant colony algorithms in this paper basically satisfies the conditions of AGV planning with uncomplicated environment. However, most of the papers lack the application of the algorithm in the three-dimensional level and the applicability of the larger AGV, in order to solve these problems, it is still considering the model update mode and path conflict. In the future, it is essential to further research the multi-AGV path planning and task assignment algorithms, focusing on expanding the algorithm to the three-dimensional field, reducing the difficulty of the algorithm and the uncertainty of the workshop to meet the above challenges.

3. Optimization Analysis of A* Algorithm

3.1. Classical A* Heuristic Search Approach

The A* algorithm stands as a seminal heuristic search methodology, renowned for its prowess in unraveling the shortest path amidst intricate networks, a feat that has earned it widespread acclaim in the realm of path planning. At its essence, this algorithm meticulously prioritizes nodes through a meticulous evaluation function, a process that encapsulates the very heart of its operation.:

$$f(n) = g(n) + h(n) \tag{7}$$

This criterion encompasses the node's total precedence, integrates two distinct facets: the tangible cost incurred from the inception to the current node, and the heuristically conjectured cost extending from that node towards the ultimate destination—a concept colloquially referred to as the heuristic function [11]. Fig. 3 presents a flowchart that meticulously charts the implementation of the A* algorithm.

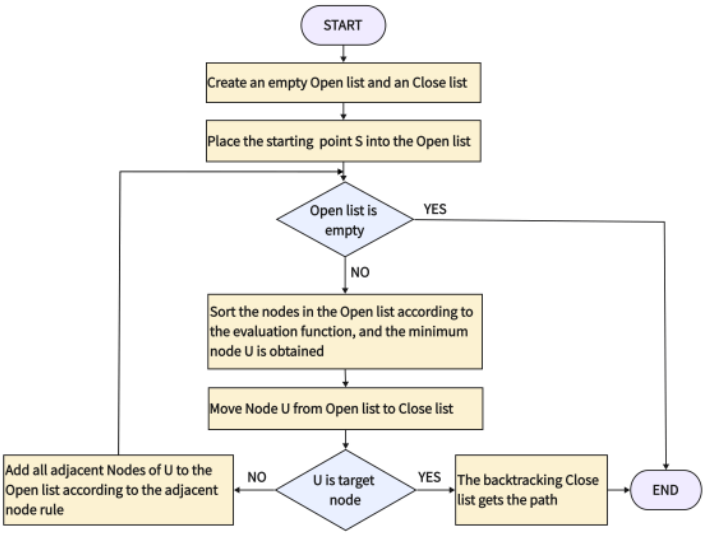

Figure 3. Illustrative Flowchart Depicting the Execution of the A* Algorithm

Provided that the heuristic estimation remains feasible, adhering to a ceiling below the actual traversal cost, the A* algorithm efficiently converges towards the shortest path in a time-sensitive manner. Given its straightforward conceptual framework and straightforward execution, it has garnered widespread adoption in the domain of Automated Guided Vehicle (AGV) path planning. Nevertheless, when confronted with expansive or intricately connected graphs, the proliferation of nodes evaluated by the algorithm translates into a surge in computational overhead, potentially jeopardizing both efficiency and the certainty of locating the optimal path. Thus, the effectiveness of the A* algorithm hinges crucially on the aptness of the heuristic function. Meanwhile, in a dynamically changing environment, the path needs to be recalculated constantly, which affects the real-time performance.

3.2. Analysis of Optimization of A* Algorithms

The optimization analysis of A* algorithms is discussed in this paper through the following three categories, each citing newer optimizations for specific analysis.

3.2.1 Heuristic function optimization

Building upon the existing evaluation framework, we incorporate an enhanced approach that leverages the introduction of a line connecting the initial and target nodes, integrating angle and scale factors for refinement. Additionally, we adopt a bidirectional strategy aimed at diminishing the search node count, thereby enhancing the efficiency of pathfinding. Furthermore, we implement a triple-pass uniform B-spline curve smoothing technique, which not only eliminates redundant nodes but also ensures a smoother path, ultimately refining the AGV's movement trajectory [12].

Geometric A* algorithms optimize paths through grid modeling combined with specific filtering functions $p(x,y)$ and $w(x,y)$ filtering out some nodes. Grid modeling actually involves dividing the searched space into a regular grid form, with each grid cell representing one of the nodes respectively, which helps to simplify the problem and improve the algorithm's tractability. However, the specific filtering used in the geometric A* algorithm in the paper is not exactly equivalent to filtering techniques in the traditional sense, such as Kalman filter or Gauss filter. Its filtering mechanism is closer to an optimization strategy in path planning, which reduces computation and improves search efficiency by selectively ignoring certain nodes. This strategy can be regarded as a heuristic path optimization technique, only emphasizing the reduction of redundant nodes through function filtering [13].

3.2.2 A variant of the traditional A* algorithm for optimization

The refined BSGA* (Bidirectional Search Gaussian-A*) algorithm addresses challenges in global path planning by introducing enhancements. Firstly, it achieves dynamic heuristic function weighting through the integration of the Gaussian function, effectively reducing computational overhead. Secondly, it employs a bidirectional search architecture to mitigate the issue of redundant node exploration, particularly in scenarios with substantial obstacles between the start and goal points. Lastly, a multi-tiered turning point filtering mechanism is implemented to further refine and smoothen the path. The authors compared with other global planning algorithms through experiments in a simulated environment, and this algorithm is significantly better than the currently existing algorithms such as AEO, GA, PSO, etc [14].

The EBHSA* methodology is employed to enhance both the efficacy and robustness of route planning processes, thereby optimizing their performance. It is in fact a pseudo-code implemented through MATLAB. In the paper to validate the results of the EBHSA* algorithm was tested the traditional A* as well as four layers of superimposed references for comparison, respectively, the addition of EA* with extended distances, then the introduction of the two-way strategy EBA*, followed by EBHA* with heuristic functions and finally the smoothing EBHSA*. Through simulations and field tests, it is verified that the operation of the EBHSA* algorithm not only leads to a great reduction in time, but also reduces the number of critical nodes in right-angle turns and close to obstacles guaranteeing smoothness and robustness of the path. These improvements make the EBHSA* algorithm has a good potential for application in the direction of path planning [15].

3.2.3 Algorithmic combinations for situation-specific fulfillment

Based on the A* algorithm, the Floyd algorithm is added for path smoothing optimization and then combined with the greedy algorithm is applied to the multi-objective point planning strategy.

Although the discussion in the paper is for Autonomous Mobile Robots (AMRs), the multi-objective planning strategy is also applicable to the path planning of multi-AGV. This algorithm is further explained below. The path generated by the standard A* algorithm inherently comprises excess nodes, necessitating the implementation of optimization techniques to reduce redundancy. Floyd 's idea can optimize the path by retaining the key nodes and removing the redundant inflection points. This makes the improved path relatively smooth and reduces the length of the path as well as the inflection points. To address the inefficiency of the refined A* algorithm in multi-task planning scenarios, efficient multi-target point planning of the A* algorithm is achieved by combining the greedy algorithm, which ensures that the path is optimized and at the same time quickly finds a solution [16].

The integration of an adaptive A* algorithm with an enhanced DWA path planning technique introduces adaptive weight values to the conventional A* framework. Furthermore, it augments the evaluation function of the DWA algorithm by incorporating a trajectory point estimation capability. Subsequently, introduce the Douglas-Pucker algorithm and B-spline curves, which are used to reduce the unnecessary path turns, improve the motor life as well as smoothing optimization. The algorithm fusion improves the adaptability to dynamic obstacles and path smoothing, providing a more comprehensive path planning solution. However, this algorithm is mainly applicable to AGVs in factory environments because of the scale layout as well as computational resources, and may not work well in small-space home environments [7].

3.3. Advantages and defect

The above examples are only a partial analysis of improved A* optimization, however, in practical applications, there is no fixed classification method or boundaries for use, and the type and use depend on the manner and purpose of the fusion. For example, in dynamic environments where fast response and real-time obstacle avoidance are required, DWA or artificial potential field methods may be preferred, while improved A* algorithms may be more appropriate in situations where globally optimal solutions are required and where there is an accurate representation of the environment. In recent years, in order to overcome the limitations of a single method, there has been a trend to combine these methods with other algorithms to achieve better path planning results.

All the improvements to A* analysis in the paper basically focus on improving search efficiency, path smoothness, reducing computational resource consumption, and improving adaptability to dynamic environments, which are basically satisfied for multi-AGV planning conditions with uncomplicated environments. However, most of the previously reviewed articles lack in-depth testing of the algorithms in highly dynamic or unknown environments, and the computational complexity and resource consumption of the algorithms are still under-discussed. In the future, real-time performance and computational resource requirements can be tested in a wider range of application scenarios.

4. Conclusion

This paper examines the enhancements in the hybrid ant colony algorithm and the ant colony genetic algorithm, revealing that these improvements effectively leverage their respective strengths to boost efficiency, then the next generation of genetic algorithm is generated, and the last iteration is carried out by ant colony algorithm. The goal of this paper is to improve the shortcomings of traditional ant colony algorithms, but there are still some uncertainties in two-dimensional path planning, for example, some location environment constraints can not be fast and accurate responses and so on.

The A* algorithm is a Heuristic algorithm that combines the ideas of breadth-first search and greedy algorithms and guides the search process by introducing heuristics. A algorithm divides the search space into nodes, and estimates the cost from each node to the target node by heuristic function. However, the A* algorithm is obviously inefficient and inaccurate when there are too many nodes. We can improve this problem by combining the algorithm with Floyd algorithm and greedy algorithm, achieve efficiency and multiple goals. But for some unknown environment and other situations, we still need to further innovation, improvement.

After the fusion of algorithms, the limitations of traditional algorithms have been well solved. The improved ant colony algorithm and A* algorithm have achieved good results in multi-AGV coordinated management and path planning, it speeds up the convergence speed, improves the search efficiency and so on, thus saves the manpower and material resources.

In some highly dynamic or unpredictable environments, such as some sudden failures in the workshop, the two algorithms have almost no examples of in-depth testing under such unknown circumstances, if the accident happens, the path planning of AGV will be inefficient, which will result in some economic loss.

With the rapid development of computer technology, multi-AGV transportation has been used by many companies. The use of AGV technology can greatly promote economic development and liberate the labor force. We need more research, add more algorithms and traditional algorithms combined to cover more shortcomings, continue to improve efficiency and multi-target precision grasp, make the world more intelligent, more convenient, more efficient.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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