WEP Warwick Evans Publishing

International Journal of Computer Science and Information Technology

ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 8, Number 3, Year 2026

DOI: https://doi.org/10.62051/ijcsit.v8n3.13

Journal homepage: https://wepub.org/index.php/IJCSIT/index

Unmanned Farm Path Optimization Strategy Based On Improved A* Algorithm

Haifei Zhang

School of Mechanical Engineering, Xihua University, Chengdu, China

ABSTRACT

The objective of this study is to solve the problems of low search efficiency, many redundant nodes and lack of terrain consideration in the path planning of unmanned farms with the traditional A* algorithm. An improved A* algorithm was proposed to improve the efficiency of path planning, reduce the energy consumption of agricultural machinery and enhance the adaptability of actual scenarios. Firstly, in order to balance the actual cost and the heuristic estimation cost, the dynamic dynamic weight coefficient is added on the basis of the traditional A* algorithm, so that the heuristic function can achieve an adaptive effect, increasing the importance of the heuristic function when it is far away from the target point, and decreasing the importance of the heuristic function when it is close to the target point. Secondly, the refinement of the raster map and the smoothing of the path are proposed, and the terrain influence factor and Bezier curve smoothing are introduced, so that the mobile robot can avoid the high-cost area as much as possible and obtain a continuous and smooth path. Finally, the simulation laboratory was carried out by PyCharm to build a raster map of the farm, and the performance of the traditional A* algorithm and the improved A* algorithm was compared. Compared with the traditional A* algorithm, the path length of the improved A* algorithm is only about 1.12% longer than that of the original algorithm, while the search time is reduced by about 98.56%, and the search node is increased by 93.40%.The improved A* algorithm is far better than the traditional A* algorithm in terms of search efficiency, search node and path smoothness.

KEYWORDS

Improved A* algorithm; Path planning; Unmanned farms

1. INTRODUCTION

With the growth of the global population and the decline of agricultural labor force, agricultural production is facing unprecedented challenges. Traditional agriculture relies on manual labor for farming, sowing, fertilizing, and harvesting, which is inefficient and constrained by factors such as weather and labor costs. Modern agriculture is developing towards mechanization and intelligence to increase production efficiency, reduce labor costs, and optimize the utilization of agricultural resources. The promotion of agricultural mechanization has made large-scale and precision agricultural production possible, covering equipment such as tractors, seeders, harvesters, and drones. However, current agricultural machinery still mainly relies on manual operation and lacks autonomous decision-making capabilities, especially in complex environments such as large-field operations, orchard management, and greenhouse production. How to optimize the operation path of agricultural machinery becomes an urgent problem to be solved. The unmanned farm, as the development direction of intelligent agriculture, realizes the full automation of agricultural production through drones, autonomous agricultural machinery, and intelligent sensing technology. One of the core aspects is efficient and reasonable path planning, and the path planning of agricultural machinery plays an important role in improving operation efficiency, reducing fuel consumption, and

Content from this work may be used under the terms of CC BY-NC 4.0 licence (https://creativecommons.org/licenses/by-nc/4.0/). Published by Warwick Evans Publishing.

lowering soil compaction. Reasonable path planning not only shortens the operation time but also optimizes the driving trajectory of agricultural machinery, reduces repetitive operations and ineffective driving, improves the overall intelligence level of agricultural production, and ensures the efficiency, energy saving, and safety of the operation.

Path planning algorithms are the key to autonomous path planning of mobile robots, and the performance of the algorithm determines the quality of path planning. It is a research hotspot in the field of mobile robots at present [1]. To achieve path planning on the map, path planning algorithms are indispensable. There are many algorithms for global path planning, including Dijkstra [2], A* algorithm [3], ant colony algorithm [4], and genetic algorithm [5]. The most widely used is the A* algorithm, but the traditional A* algorithm performs relatively poorly in large-scale environments and is highly dependent on heuristic functions. Moreover, the paths generated by the traditional A* algorithm are insufficiently smooth. In the research of many scholars in the past, some optimization methods have been proposed to address these issues. He Yubo et al. improved the distance-based variable weight evaluation function based on the traditional A* algorithm, improving the efficiency of path search and reducing the required storage [6]. Jiang Chengjie et al. calculated the environmental obstacle rate to change the weight coefficient of the heuristic function in different environments, thereby optimizing the A* algorithm and effectively improving the time and turning number of path planning [7]. Gao Jiusu and Xu Weifeng improved the heuristic function, reducing the risk of the algorithm falling into local optimum, thereby reducing the search nodes and search time [8].

Based on the above research, reducing the path planning time and search nodes of mobile robots is an important issue. This paper mainly considers the complex working environment of the farm and optimizes the traditional A* algorithm, proposing an improved A* algorithm and conducting experimental simulation verification. The experimental results show that the optimized A* algorithm is relatively better than the traditional A* algorithm, effectively shortening the path planning time and the number of search nodes, and improving the efficiency of mobile robots.

2. ENVIRONMENTAL MAP DESCRIPTION

In path planning, environmental modeling is a crucial step, and the grid method is a commonly used map representation method. This method divides the environmental space into regular discrete grid cells, with each grid corresponding to an environmental area, and assigns different values based on whether it is accessible. For example, 0 is usually used to represent a feasible area, and 1 represents an obstacle area. Grid maps have the advantages of simple data, ease of calculation, and suitability for various path planning algorithms, and are widely used in robot navigation and autonomous driving systems. By reasonably setting the grid resolution, a balance can be achieved between computational complexity and environmental accuracy,

thus meeting the requirements of different application scenarios. This paper will use the grid method to construct a farm environment map, as shown in Figure 1. The map is divided into four areas: black area, blue road area, red muddy area, and blank ordinary area. The black areas surrounding and evenly distributed simulate the field positions, the randomly distributed ones in the middle of the map are obstacles, the blue long-shaped areas are high-quality roads, the red long-shaped areas are muddy sections, and the blank areas are ordinary sections. Agricultural machinery can freely move on the ordinary sections, high-quality sections, and muddy sections.

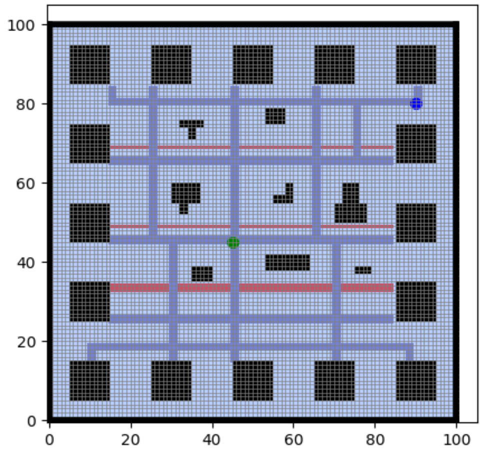

Figure 1. Schematic diagram of the farm grid map

3. TRADITIONAL A* ALGORITHM

The A* algorithm is a heuristic search algorithm, commonly used in path planning and graph searching. This algorithm is based on graph searching and heuristic estimation, and can find the optimal path in the shortest time. Moreover, it is more efficient than traditional search algorithms such as breadth-first search or Dijkstra algorithm. The goal of the A* algorithm is to find the path with the lowest total cost from the starting point to the destination in a weighted graph. During the search process, the algorithm selects the expanded nodes based on an estimation function. The working principle of the A* algorithm can be regarded as a combination of Dijkstra algorithm and heuristic search. Dijkstra algorithm solely relies on the actual cost that has been traversed, while A* predicts the remaining cost from the current node to the destination through a heuristic estimation function, reducing unnecessary node searches and improving search efficiency.

The core idea of the A* algorithm is the cost estimation function, which calculates the total cost of each node. It can be expressed by the formula as:

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

$\mathrm{g}(n)$: The actual cost from the starting point to the current node n.

$\mathrm{h}(n)$: The heuristic estimated cost from the current node n to the target node.

And each time, the algorithm will prioritize expanding the node with the smallest value of $f(n)$.

Different cost values and heuristic function sizes both affect the nodes explored during path search. When $g(n) > \mathrm{h(n)}$ the A* algorithm places greater emphasis on the known actual cost, making it more similar to Dijkstra's algorithm, which only considers the shortest path cost from the start node to the current node and ignores heuristic estimates. On the other hand, when $h(n) > g(n)$, A* tends to explore nodes that appear closer to the goal, making its behavior more akin to a greedy algorithm, which only cares about the heuristic estimate from the current node to the target node while ignoring the actual path cost.

Choosing an appropriate heuristic function is crucial for the performance of the A* algorithm. There are various ways to calculate the distance, and common heuristic functions include: Chebyshev distance, Manhattan distance, and Chebyshev distance.

Euclidean distance (applicable to two-dimensional space):

$$h(n)=\sqrt{(x1-x2)^2+(y1-y2)^2} \tag{2}$$

Manhattan distance (used for grid maps, allowing only horizontal or vertical movement):

$$\mathrm{h}(n)=|x1-x2|+|y1-y2| \tag{3}$$

Chebyshev distance (allowing diagonal movement):

$$h(n)=\max(|x1-x2,|y2-y1||) \tag{4}$$

4. IMPROVE THE A* ALGORITHM

4.1. Dynamic Heuristic Function Optimization

The total cost obtained by the traditional A* algorithm during the search process is the sum of the actual cost and the heuristic cost estimation. The proportion between the actual cost and the estimated cost is closely related. In this paper, the A* algorithm is improved. Considering the actual operating conditions, the path search algorithm should quickly move to any position at the beginning of the search; while at the end of the search, it is most important to move to the target point. Therefore, a weightw ($w\geq1$), is designed in the heuristic function. When approaching the target point, the weight is reduced, thereby reducing the importance of the heuristic function, and at the same time increasing the relative importance of the actual cost of the path. This paper dynamically adjusts the weight w through the complexity of the map, the size of the map, the density of obstacles, and the terrain influence system, as shown in the following formula:

$$\mathrm{f}(n)=g(n)+w(n)*h(n) \tag{5}$$

$$\mathrm{w}(n)=1+(w_{\max}-1)*(h(\mathrm{n})/h_{start})+k*d_o(n)*c_t(n) \tag{6}$$

$$\mathrm{h}_{start}=w*h(n) \tag{7}$$

$$\mathrm{w}_{\max}=base*\frac{\sqrt{(x_{\max}-x_{\min})^2+(y_{\max}-y_{\min})^2}}{D_{std}}*\left(1+k*\frac{\sum obmap}{x_{\mathrm{width}}*y_{\mathrm{width}}}\right) \tag{8}$$

In the formula: $g(n)$ the distance value from the initial node to the current node; $h(n)$ the distance value from the current node to the target node; $w(n)$ representative dynamic weight value; $\mathrm{h}_{\mathrm{start}}$ represent the initial value of the heuristic function; $w_{\max}$ representing the maximum value of dynamic weight; base representative path weight base; $\mathrm{d}_o(n)$ representing the density of obstacles; $\mathrm{c}_t(n)$ representative terrain influence coefficient; D_{std} representative path complexity benchmark value; k representative coefficient of obstacle density influence; obmap representative of the initial obstacle; $\mathrm{x}_{\mathrm{width}}\mathrm{y}_{\mathrm{width}}$ the width representing the horizontal and vertical directions of the map.

4.2. Multi-factor Path Cost Calculation

The traditional A* algorithm does not take the working environment into account in ordinary grid maps and is not affected by conditional factors. This paper proposes a terrain cost hierarchical model based on the characteristics of unmanned farm environments. Ordinary grid maps are insufficient to reflect the issues that need to be considered in practice and the resulting path impacts. In this paper, in addition to the basic obstacles (black), multiple factors such as roads (blue), wet areas (red), and normal operation areas (green) are introduced into the cost map. The paths of the traditional A* algorithm and the improved A* algorithm with the same obstacles and with the introduction of cost terrain are compared as shown in Figure 2. Compared with the single obstacle judgment in the traditional A* algorithm, in this paper, high-cost areas of wetlands and low-cost areas of field roads are established, and the terrain coefficient factor is introduced in the calculation of dynamic weights. $c_t(n)=10.0$, $c_t(n)=0.1$, Since it is considered that there are some inaccessible areas in the farm environment, such as muddy roads and gravel roads, when adjusting the terrain coefficient factor to deal with the red area, the maximum force is applied to make the agricultural vehicle avoid such roads and choose the more smooth paths instead. Even if some of the optimal paths are lost, this is more in line with the actual working scenario requirements. The coefficient factor is implemented to parameterize the terrain through the cost_map matrix, and then it is introduced into the heuristic function, as shown in the formula:

$$w(n)=1+(w_{\max}-1)*(h(n)/h_{start})+k*d_o(n)*c_t(n) \quad (9)$$

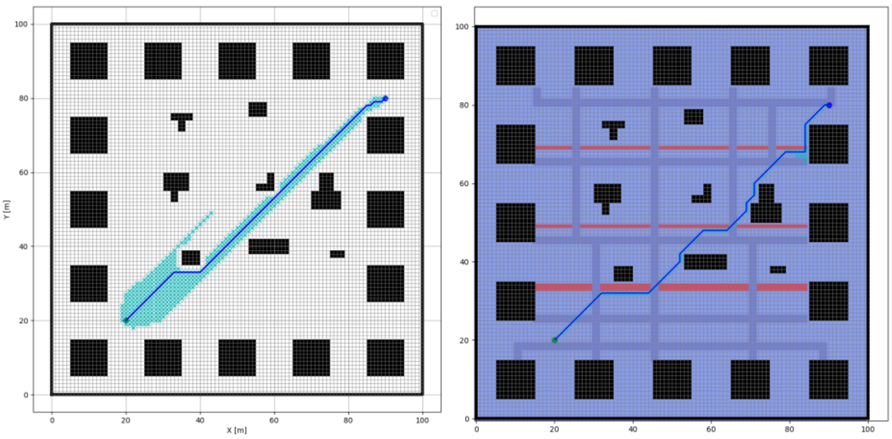

Figure 2. Cost Terrain Improvement

4.3. Path Smoothing Optimization

In the paths generated by the traditional A* algorithm, due to its search process being based on a grid map, the final path often presents a jagged zigzag line with numerous discontinuous corners. This is not conducive to the smooth driving of the vehicle in practical agricultural machinery path planning applications, and is prone to causing control difficulties, increased energy consumption, and mechanical wear and tear.

To solve these problems, this paper introduces Bezier curves to smooth the original A* path, generating a more continuous and smooth path suitable for agricultural machinery operation. Bezier curves are a curve interpolation method commonly used in computer graphics and path planning, which can construct a curve trajectory with good continuity through a small number of control points.

The path points generated by the A* algorithm are extracted as the control points of the Bezier curve, and the custom evaluate_bezier function is called to perform interpolation calculation on the path. This function is based on the n-order Bezier curve formula, and generates intermediate path points through piecewise interpolation, thereby eliminating sharp turns in the path while retaining its original shape, making the overall path more smooth.

The processed smooth path not only has a more coherent shape but also meets the kinematic constraints of agricultural machinery, helping to improve the feasibility and practical application effect of the path. Figure 3 shows the optimized smooth path. Based on the farm working environment and considering the terrain cost issue, the Bezier curve smoothens the zigzag part, and the uncontrollable contact with high-cost areas is acceptable. Considering that the continuous sharp turns have a significant impact on actual work for agricultural machinery vehicles, some muddy sections can be tolerated without affecting the path planning, and still obtained a better path.

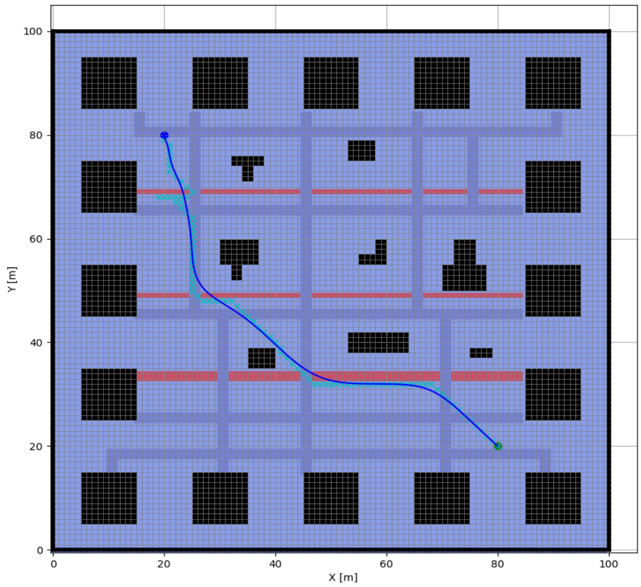

Figure 3. Smoothly processed path

5. SIMULATION RESULTS COMPARISON

In order to verify the effectiveness of the improved A* algorithm in path planning on a two-dimensional grid map, a simulation experiment was conducted using the PyCharm Community Edition 2024.1.1 software. A farm grid map environment was established, and under the premise of ensuring that all experimental conditions were the same, the improved A* algorithm and the traditional A* algorithm were compared and analyzed based on the parameters used to measure the path superiority. The simulation results shown in Figures 4 and 5 were obtained. Tables 1 and 2 present the experimental results of the improved A* algorithm and the traditional A* algorithm in maps with the same number of obstacles, including the time consumed for searching the path, the number of search nodes, and the path length.

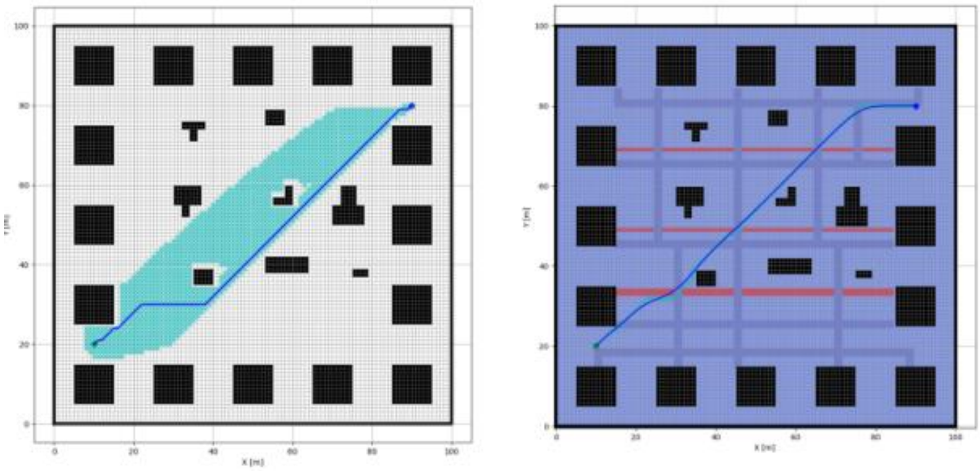

Figure 4. Experiment 1 (100x100)

Table 1. Experimental Comparison Results

Comparison indicators	Traditional A* algorithm	Improve the A* algorithm
Search time	9.171479s	0.14s
Search node	1392	82
Path length	104.85m	106.02m

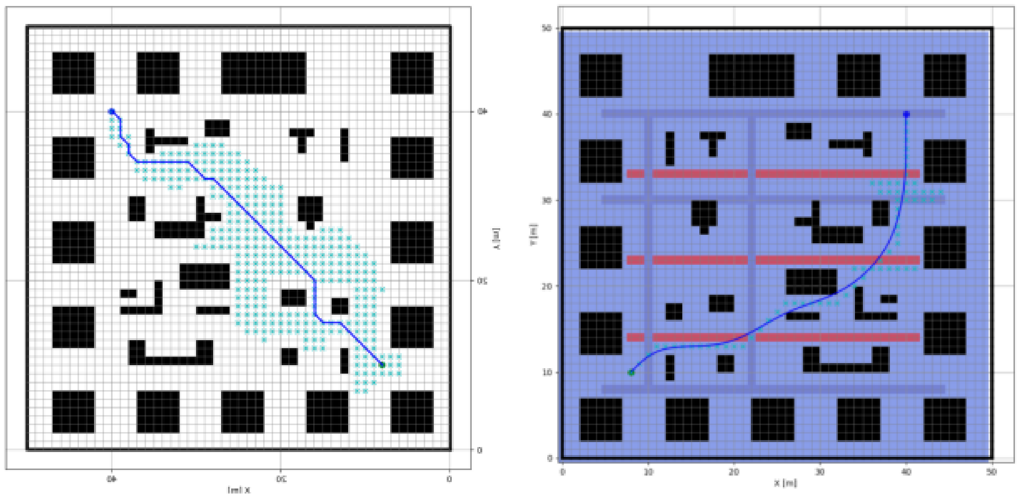

Figure 5. Experiment Two (50x50)

Table 2. Experimental Comparison Results

Comparison indicators	Traditional A* algorithm	Improve the A* algorithm
Search time	1.245790s	0.14s
Search node	1392	82
Path length	104.85m	106.02m

From the comparison of the above experimental results, it can be seen that the improved A* algorithm, compared with the traditional A* algorithm, in large-scale scenarios with normal obstacle quantities and small-scale scenarios with excessive obstacle quantities, the path length is only approximately

1.12% longer than the original algorithm, while the search time has been reduced by approximately 98.56%, and the number of search nodes has increased by 93.40%.

6. SUMMARY

This paper addresses the issues of low search efficiency, excessive redundant nodes, large storage volume, and how mobile robots should choose different road sections when facing complex road conditions in agricultural work environments, which are encountered in the path planning process of the traditional A* algorithm. This paper improves the A* algorithm to obtain a safe, reliable, and efficient path. Firstly, by optimizing the heuristic function and introducing dynamic weights to adjust the evaluation function to be more inclined towards the actual cost or the estimated cost in different situations, this method reduces a large number of path search nodes, saves path search time, and improves efficiency. Secondly, for the agricultural work environment, the terrain cost issue is introduced, considering that the driving efficiency of the mobile robot varies on different road sections. The grid map is refined, and three different road sections are divided, and terrain influence factors are assigned to different road sections. Through this method, the mobile robot is maximally inclined to travel on low-cost smooth road sections and avoid high-traffic muddy road sections. Finally, considering that there are many obstacles in complex working environments and the paths are mostly zigzag line-like, which is not conducive to smooth driving, Bezier curves are used to smooth the path, eliminating a large number of sharp turns, and making the robot's driving more stable. The optimized path in this paper is superior to the traditional A* algorithm in terms of search time and the number of search nodes.

REFERENCES

[1] Chen Xiaolan, Lin Lin, Luo Delin, et al. An Improved Flexible Bus Route Planning Algorithm Based onDijkstra's Method [J]. Fujian Computer, 2024, 40(12): 20-26. DOI: 10.16707/j.cnki.fjpc.2024.12.004..

[2] Jin Chao, Lin Fusheng, Song Zhifeng, et al. Research on the Application of Unmanned Aerial Vehicle Highway Inspection Based on A-Star Algorithm [J]. Jiangsu Science and Technology Information, 2022, 39(06): 32-35.

[3] Miao Yinqun, Shi Wei. Research on Path Planning for Unmanned Vehicles Based on Improved A-Star Algorithm [J]. Computer Knowledge and Technology, 2024, 20(03): 4-7. DOI: 10.14004/j.cnki.ckt.2024.0161.

[4] Yan Liang, Qiao Zhifeng, Li Mengbo. An AGV Scheduling Method for Island-Type Assembly Workshops of Automobiles Based on Hybrid Genetic Algorithm [J/OL]. Journal of Tianjin University of Technology, 1-10 [2025-03-31]. http://kns.cnki.net/kcms/detail/12.1374.N.20250317.1759.035.html.

[5] Deng Dongdong, Xu Jianmin, Meng Han, et al. Mobile Robot Path Planning Based on the Fusion of Ant Colony Algorithm and Artificial Potential Field Method [J/OL]. Journal of Instrumentation Science, 1-16 [2025-03-31]. https://doi.org/10.19650/j.cnki.cjsi.J2413095.

[6] Li Zhonglin, Luo Shaopeng, Jia Yuting. Review of Path Planning Algorithms for Mobile Robots [J]. Modern Information Technology, 2024, 8(19): 184-188. DOI: 10.19850/j.cnki.2096-4706.2024.19.034.

[7] Jiang Chengjie, Zhu Hua, Xie Yao, et al. Path Planning for Mobile Robots Based on Improved A* Algorithm [J]. Manufacturing Technology and Machine Tool, 2024, (06): 33-36 + 73. DOI: 10.19287/j.mtmt.1005-2402.2024.06.005.

[8] Gao Jiuzhou, Xu Weifeng. Autonomous Obstacle Avoidance Path Planning for Unmanned Aerial VehiclesBased on Improved A-Star Algorithm [J]. Technology and Market, 2024, 31(01): 38-43.