

A Study of Heuristic-based Path Planning in Complex Maze Using the A* Algorithm with Cost Optimization and Visualization

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Abstract. Route planning is crucial in areas such as robotics, autonomous driving, and drone navigation. Especially in earthquake and other disaster scenarios, route planning in emergency rescue is more difficult. In this paper, A route planning method combining the A star algorithm and multi-cost optimization is proposed to consider road deterioration, risk areas, and different crossing costs in the complex post-earthquake environment. By simulating a 20×20 post-disaster maze, the crossing costs are randomly assigned. Algorithm A is used to determine the cheapest path from the starting point to the destination point. The results show that the optimized A* algorithm has excellent performance in terms of path length, search efficiency, and computational overload, especially in a complex disaster environment. Dynamic visualization technology shows the process of finding nodes and the final path, which helps to improve the decision-making efficiency of emergency response and provides strong technical support for disaster relief.

Keywords: A* algorithm, Path planning, Heuristic search, Cost optimization, Maze solving.

1. Introduction

Path planning is a key challenge for robotics, autonomous navigation, drone rescue missions, and disaster emergency response. In these applications, finding the optimal path between the starting point and the target, while avoiding obstacles, is the key to efficient system operation [1]. This becomes even more important after natural disasters such as earthquakes, as building collapses and road damage complicate planning safe and efficient roads [2]. The classic Dijkstra algorithm ensures the shortest path by exploring all possible paths, but its computational cost is high, and it is not suitable for large and complex post-disaster environments [3]. To address this problem, Hart et al. [4] introduced the A* algorithm, which combines a heuristic function to evaluate the potential cost of reaching the goal, optimizes the Dijkstra method by focusing on the most promising paths, and significantly improves search efficiency.

However, the traditional A* algorithm has a limitation, that is, it assumes that the terrain traversal price is uniform, that is, all traversable units are regarded as having the same moving cost, which is unrealistic in post-earthquake scenarios [5]. Due to terrain damage, aftershock risk, and other factors, crossing costs may vary from region to region. For example, heavily damaged roads may be unsafe or take more time to cross [3]. This requires a path planning algorithm that not only takes into account path length but also optimizes real-world traversal costs. In Pearl's research on heuristic search strategies, emphasized how well-designed heuristics can greatly improve the efficiency of A*, especially in complex environments such as post-disaster terrain [6].

In addition, post-disaster environments are dynamic and complex, and static cost assumptions often fail to reflect evolving challenges. Some paths, though shorter, may require more energy or time to cross due to dangerous terrain or infrastructure damage [2]. The D* lite algorithm of Koenig and Likhachev provides an effective solution for dynamic environments, which can adjust path planning in real-time according to changes in the environment, thus reducing the computational overhead [7]. This approach is critical to dealing with the challenge of real-time wayfinding in a disaster environment where terrain and roads are constantly changing.

This paper presents an improved A* algorithm, which introduces a multi-cost optimization strategy. By introducing a cost matrix, this paper assigns different traversal costs to different regions

in the post-earthquake environment, minimizing the total traversal cost instead of just considering the path length [5]. In A study by Kang et al., algorithm A was modified to address challenges in modular factory land transportation, including the optimization of modular structures and complex terrain [8].

In addition, a dynamic visualization component is introduced that tracks the progress of the algorithm in real time, showing the nodes visited and the paths being explored. This allows rescuers to clearly understand how the algorithm makes decisions in high-risk areas, selecting the optimal path based on a combination of terrain and crossing costs [6]. Fuchs and Simon proved that re-optimization of the A* algorithm in a dynamic environment can further improve efficiency, which is consistent with the multi-cost optimization method proposed in this paper [9]. In environmental reference, this paper refers to how to apply the improved A* algorithm to the safe path planning model in an earthquake environment [10].

Experiments are carried out in MATLAB to simulate a 20×20 cell post-disaster maze, in which the passing price of each cell is randomly assigned from 1 to 5, and the obstacle value is assigned as infinite cost. The results show that the improved A* algorithm can effectively find the path with the least cost even in the environment of terrain cost change. This study solves the limitations of the uniform cost assumption of the traditional A* algorithm and provides a practical solution for dynamic emergency routing in complex environments [7-8].

2. Traditional A* Algorithm

2.1. Map Construction

In a path planning task, the car needs to move autonomously in a complex environment, avoid obstacles, and find the optimal path from the starting point to the target. To achieve this, this paper uses a raster map to model the environment. A raster map discretizes the environment into a series of cells of equal size, where each cell represents an obstacle or represents a passable path. This method simplifies the representation of the environment, and the car can perform efficient calculations based on the state of these cells when performing path planning. A 20×20 grid map is shown in Fig. 1.

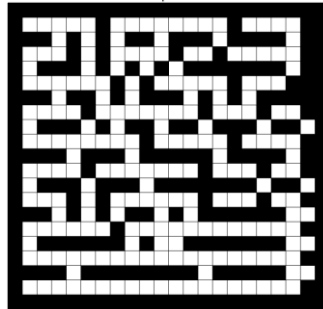


Fig 1. A 20×20 grid map modeling. (Photo/Picture credit: Original).

2.2. A* Algorithm

An algorithm is a classical heuristic search algorithm, which aims to gradually expand the optimal path by evaluating the cost function of the node, and finally find the shortest path from the starting point to the target point. Algorithm a combines Dijkstra's breadth-first search with heuristic search, and its cost function is shown in equation (1).

$$F(n) = G(n) + H(n) \quad (1)$$

Where $F(n)$ is an evaluation function, representing the total cost estimate from the starting point through node n to the target point; $G(n)$ is the actual cost from the starting point to node n ; $H(n)$ is the estimated cost from section n to the target point, also known as the heuristic function. During the execution of the A* algorithm, it maintains two lists: a list of nodes to be extended (open list) and a list of nodes to be extended (closed list). The algorithm selects the least expensive node from the open list each time to expand until the target node is added to the open list, the algorithm ends and returns

the optimal path. Therefore, the A* algorithm, with its flexible heuristic function and efficient search strategy, is widely used in robot path planning, game AI, and map navigation.

3. Improved A* algorithm

The traditional A* algorithm has certain defects. For example, under the environment of earthquakes and other conditions, different regional blocks based on different road conditions can produce different consumption when cars or robots walk on complex surfaces. Meanwhile, people cannot intuitively feel the structure through visualization. In this paper, A heuristic-based path planning and cost optimization and A* algorithm for complex labyrinths are proposed.

3.1. Cost Optimization Strategy

To solve the practical problems in path planning, this paper introduces the cost matrix to simulate the complexity of pavement conditions in different regions after earthquakes. The traffic cost of different areas is generated by a random number generator in the range of 1 to 5, representing different traffic consumption. The cost matrix reflects the energy consumption difference of the trolley on different road surfaces.

For each node, the actual cost $g(n)$ in the A* algorithm is the total cost from the starting point to the current node. In this paper, $g(n)$ includes two parts: path length and traffic cost, as shown in equation (2):

$$g(n) = g_{\text{prev}} + \text{cost}(n) \quad (2)$$

Where g_{prev} represents the cumulative cost from the starting point to the previous node, and $\text{cost}(n)$ represents the traffic cost of the current node $\text{cost}(n)$, which is determined according to the road condition of the region. Through custom rules, this paper assigns different traffic costs to different regions, ranging from 1 to 150. The higher the cost, the greater the consumption of traffic in the region and the higher the risk. The algorithm also takes into account the cost of road surface consumption and avoids inefficient, time-consuming paths.

3.2. A* Algorithm Based on Cost Optimization

The A* algorithm based on cost optimization takes the cost into account when calculating $g(n)$, and its expression is shown in Formula 3.

$$F(n) = g_{\text{prev}} + \text{cost}(n) + H(n) \quad (3)$$

Where $F(n)$ is the total evaluation cost from the starting point to the target point through node n . The A* algorithm selects the extension node based on this value. g_{prev} represents the cumulative cost from the starting point to the previous node, and $\text{cost}(n)$ represents the traffic cost of the current node $\text{cost}(n)$, which is determined according to the road condition of the region. $H(n)$: A heuristic estimate that represents the estimated residual cost from node n to the target node. In this paper, Manhattan distance is used for heuristic estimation, as shown in Equation 4:

$$H(n) = |x_{\text{goal}} - x_n| + |y_{\text{goal}} - y_n| \quad (4)$$

Where (x_n, y_n) is the coordinate of the current node n , and $(x_{\text{goal}}, y_{\text{goal}})$ is the coordinate of the target node.

4. Experimental Simulation and Analysis

4.1. Analysis of Path Length and Cost in Different Test Runs

In the experiment of this paper, the maze size is a 20×20 grid map, obstacles and paths are represented in black and white respectively, and all obstacles are set as impassable areas. In this way, this study can turn the path planning problem of a car into a problem of finding a low-cost path from

the starting point to the target point on a raster map. The improved A* algorithm in this paper combines heuristic search and multi-cost optimization and can plan an efficient and safe route for the car according to the passing cost of each area. The experiments in this paper were conducted using MATLAB R2024a widely used software for numerical computing, simulation, and data visualization.

In Fig. 2, different color areas represent different costs to simulate the energy consumption of cars or robots in different areas after an earthquake occurs.



Fig 2. A 20x20 grid cost map. (Photo/Picture credit: Original).

Comparison experiment: In A 20×20 environment with cost optimization, A* algorithm and A* algorithm based on heuristic cost optimization are compared and verified. The comparison diagram of the path index is shown in Fig. 3.

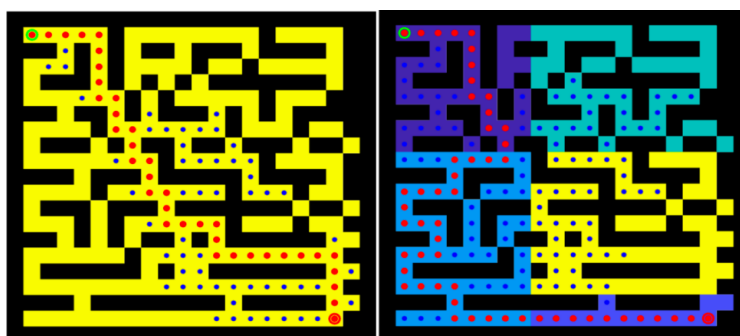


Fig 3. A 20×20 grid map simulation experiment. (Photo/Picture credit: Original).

4.2. Comparison between Distance Priority Path and Cost Optimization Path

The distance-first path mainly means that the path with a shorter distance is preferentially selected, while other factors on the path (such as path complexity, obstacles, terrain, etc.) are ignored or not considered. It is common to use something like the Manhattan distance or Euclidean distance as a heuristic function to estimate the distance from the current node to the target node.

The cost optimization path means that by assigning different costs (such as terrain difficulty, energy consumption, etc.) to each node on the path, the path with the lowest cumulative cost is preferentially selected. In general, the actual cost traveled from the starting point to the current node is considered in addition to the heuristic distance. After calculation, the data are shown in Table 1.

The distance-first path is suitable for uniform cost scenarios and is suitable for fast planning, while the cost-optimized path performs better in complex environments. In complex environments such as earthquakes, the improved A* algorithm in this paper has certain advantages.

Table 1. A* versus improved A* performance.

Comparison item	A*	improved A*
Path length	36	52
Cost consideration	3063	1633
Search time (s)	15.59	12.10
Expanded nodes	172	151
Search efficiency	0.01	0.03

5. Conclusion

This paper presents a route planning method based on heuristic algorithm a combined with a multi-cost optimization strategy. When simulating complex post-disaster environments, different regions allocate different travel costs according to road conditions. The experimental results show that compared with the traditional A* algorithm, the proposed algorithm can effectively bypass the high-cost area and significantly reduce the total schedule cost. The application of this research has important implications for disaster relief and road planning in complex environments, especially in cases where road conditions are very different, such as damaged areas or complex terrain, where algorithms provide more intelligent and practical solutions. Through the introduction of multi-cost optimization and dynamic visualization technology, rescuers can understand the basis of route selection in real-time, improving decision-making efficiency.

Future research could further optimize the algorithm, including integrating adaptive cost discounting mechanisms in dynamic environments to respond to changing terrain and road conditions. In addition, the algorithm can also be extended to 3D application scenarios such as UAV trajectory planning and multi-robot collaborative tasks. In combination with machine learning techniques, algorithms have the potential to further improve the intelligence and adaptability of route planning in a variety of complex environments by constantly learning and adjusting the cost function.

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