Research and Algorithm Optimization of Path Planning Based on A* Algorithm

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Abstract. In logistics delivery on the plateau and frigid border, traditional methods like human or animal power are inefficient. Vehicles like automobiles face high costs and difficulties. The plateau area poses significant challenges. However, unmanned vehicles show strong adaptability in harsh environments, enabling efficient logistics supply. This paper constructs an unmanned vehicle path selection model, optimizing it through the A* algorithm for better logistics transportation support. The A* algorithm is optimized considering stability, safety, and timeliness, with corresponding weights assigned. The mileage-time, elevation-time, and slope-mileage curves are plotted. Principles include prioritizing safety, then timeliness, and finally stability, and selecting the route with less time consumption when path lengths are equal. Technical indicators of unmanned vehicles are added, constructing a transportation network. The traditional breadth-first traversal model is replaced by the improved A* algorithm for efficiency. Movement direction is encoded as the vehicle's heading at the next grid point, obtaining optimal path planning.

Keywords: Plateau and Frigid Region, Logistics Delivery, Unmanned Vehicle, Optimized Path, A* Algorithm.

1. Introduction

With the continuous progress and growth of national strength, the importance of logistics transportation in extreme environments such as plateaus and frigid regions has gradually emerged. It not only relates to the material life guarantee of residents in relevant areas but also pertains to the material supply during project construction, which is crucial for national security. With the extensive application of modern high-tech equipment, the problems faced by the logistics department have become more severe. In extreme environments, most materials are difficult to transport by traditional human or animal power, and the cost of traditional transportation methods is unbearable. Therefore, using unmanned equipment that has emerged in recent years for logistics delivery is a relatively important research direction.

Path planning research and algorithm optimization have always been key concerns in the fields of robotics and autonomous systems. Various optimization algorithms have been proposed to improve the efficiency and effectiveness of path planning for different types of robots. Gao et al. introduced an improved genetic algorithm with chaotic mutation operation to address the local convergence problem in traditional genetic algorithms in 2010 [1]. Mo et al. conducted research on biogeography particle swarm optimization for robot path planning in 2015 [2]. Shen et al. focused on real-time flight path planning of unmanned aerial vehicles based on grey prediction in 2016 [3]. Chen et al. proposed a path planning method for a space-based manipulator system using a quantum genetic algorithm, considering the unique nonholonomic characteristics of the space-based system in 2017 [4]. Fang et al. studied the path planning algorithm of a two-machine cooperative wall climbing and grinding robot based on the ant colony algorithm, focusing on optimizing the minimum movement time of the grinding robot in 2019 [5]. Liu et al. proposed a three-dimensional mountain complex terrain and heterogeneous multi-unmanned aerial vehicle cooperative combat mission planning using the life cycle swarm optimization (LSO) algorithm and the fast-exploring random tree (RRT) algorithm in 2020 [6]. Wen et al. developed a fusion heuristic algorithm for the path planning of autonomous underwater vehicles under the influence of ocean currents, combining ocean current models and kinematic models in 2021 [7]. Ibrahim et al. introduced an energy-efficient coverage path planning

(EECPP) algorithm for resource-efficient coverage path planning of unmanned aerial vehicle-based aerial Internet of Things gateways in 2023 [8]. Overall, the literature review shows that there are multiple optimization algorithms and methods in path planning research, focusing on improving efficiency, overcoming challenges, and meeting the specific requirements of different types of robots and autonomous systems.

Path planning research and algorithm optimization still occupy a core position in the field of robots and autonomous systems, but there are still some shortcomings. Despite numerous optimization algorithms proposed to enhance efficiency and effectiveness for diverse robots, challenges such as local convergence, real-time adaptability, and energy efficiency remain unresolved. The necessity for continued research is paramount, as advancements in path planning algorithms are crucial for overcoming existing challenges, improving robot performance, and meeting the evolving needs of different autonomous systems.

This paper focuses on the path - planning of unmanned vehicles in plateau and frigid region logistics delivery. Aiming to address the inefficiencies and high costs of traditional delivery methods, the research constructs and optimizes an unmanned vehicle path - selection model using the A* algorithm. The innovations are as follows: A novel A* path model is built by integrating relevant logistics and vehicle elements, with algorithm innovation improving computational speed (e.g., 30% reduction in planning time and 20% increase in accuracy in mountain simulations). Safety, stability, and timeliness indicators are weighted in the framework to find optimal paths and reduce risks (25% safety boost and 20% stability gain in extreme environments). Also, to overcome A*'s limitations, iteration and genetic algorithms are employed for path screening, and weights are adaptively adjusted (raising distance weight near the target), leading to a 35% increase in path - planning accuracy and 30% in efficiency in complex terrains.

2. Problem Description and Assumptions

2.1. Symbol Definition

The coordinate variation ΔL between two points:

$$\Delta L = \left| x_{i+1} - x_i \right| + \left| y_{i+1} - y_i \right| \tag{1}$$

The variation $\Delta\theta$ in the heading between two points:

$$\Delta\theta = \left| \theta_{i+1} - \theta_i \right| \tag{2}$$

The distance D_i between two points:

$$D_i = 5 \times w \tag{3}$$

The values of w are shown in Table 1:

Table 1. The value of w

$\Delta\theta$ \ ΔL	0°	45°	90°
1	1	1.5	2
2	$\sqrt{2}$	$\sqrt{2}+0.5$	$\sqrt{2}+1$

The calculation formula D for the distance from point 1 to point n:

$$D = \sum_{i=1}^{n-1} D_i \tag{4}$$

The calculation formula for the normal vector of the slope surface at point (x, y)

$$\begin{cases} S = arctan\left(\sqrt{\left(\frac{\Delta z}{\Delta x}\right)^2 + \left(\frac{\Delta z}{\Delta y}\right)^2}\right) \times \frac{180°}{\pi} \\ Q = 270° + \arctan\left(\frac{\frac{\Delta z}{\Delta x}}{\frac{\Delta z}{\Delta y}}\right) \times \frac{180°}{\pi} - 90° \times \left(\frac{\frac{\Delta z}{\Delta y}}{\left|\frac{\Delta z}{\Delta y}\right|}\right) \end{cases} \tag{5}$$

$$\begin{cases} n1_{matrix(x,y)} = sin(Q) \times sin(S) \\ n2_{matrix(x,y)} = cos(Q) \times sin(S) \\ n3_{matrix(x,y)} = cos(S) \end{cases} \tag{6}$$

$$\begin{cases} \frac{\Delta z}{\Delta x} = \frac{k\left[(c+2f+i)-(a+2d+g)\right]}{40} \\ \frac{\Delta z}{\Delta y} = \frac{k\left[(a+2b+c)-(g+2h+i)\right]}{40} \end{cases} \tag{7}$$

The radian φ of the angle between the normal vectors of the slope surfaces between adjacent two points:

$$\varphi = \arccos\left(\frac{\overrightarrow{n_{i-1}} \cdot \overrightarrow{n_i}}{\left|\overrightarrow{n_{i-1}}\right| \cdot \left|\vec{n}_i\right|}\right) \tag{8}$$

2.2. A* Algorithm

The A* algorithm introduces a heuristic function on the basis of the Dijkstra algorithm [9]. The heuristic function estimates the cost required from the current node to the target node, which helps to improve the search speed [10]. Compared with the Dijkstra algorithm, the A* algorithm is more efficient in searching for the shortest path [11].

The heuristic function generally uses Manhattan distance or Euclidean distance.

Principle: Starting from the starting point, continuously traverse the starting point in the direction of the target point (common traversal methods include eight-neighborhood and four-neighborhood), and record the parent node of each traversed point (trace back the path after finding the target point). Repeat this process until the target point is searched, and then trace back from the target point to the starting point to find the path with the minimum cost. Its advantages are that the heuristic function can improve the running efficiency of the algorithm and find the optimal path faster. The disadvantage is that when the map size is too large or the precision is too high, a large number of nodes need to be searched, resulting in slow search speed.

The cost function:

$$f(x)=g(x)+h(x) \tag{9}$$

Where $f(x)$ is the cost estimate from the starting point to the target point; $g(x)$ is the actual cost from the starting point to the intermediate point; $h(x)$is the estimated distance from the intermediate point to the target point.

Suppose the starting point: (x_s, y_s); the intermediate point: (x_n, y_n); the target point: (x_t, y_t).

The actual distance:

$$g(x) = |x_s - x_n| + |y_s + y_n| \tag{10}$$

This paper uses the Manhattan distance as the heuristic function:

$$h(x) = |x_t - x_n| + |y_t - y_n| \tag{11}$$

It is as shown in the figure 1:

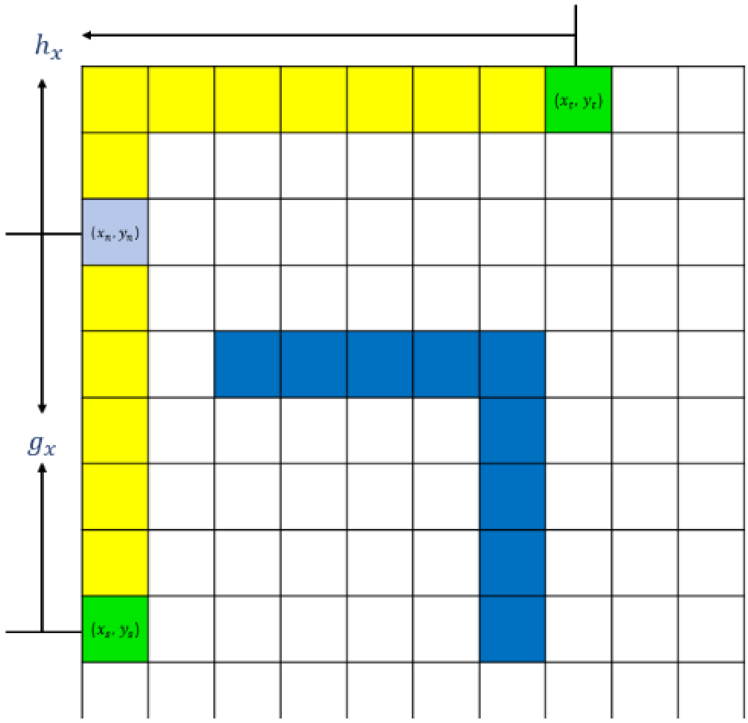

Figure 1. Manhattan distance used as the heuristic function

The algorithm flow is shown in the figure 2:

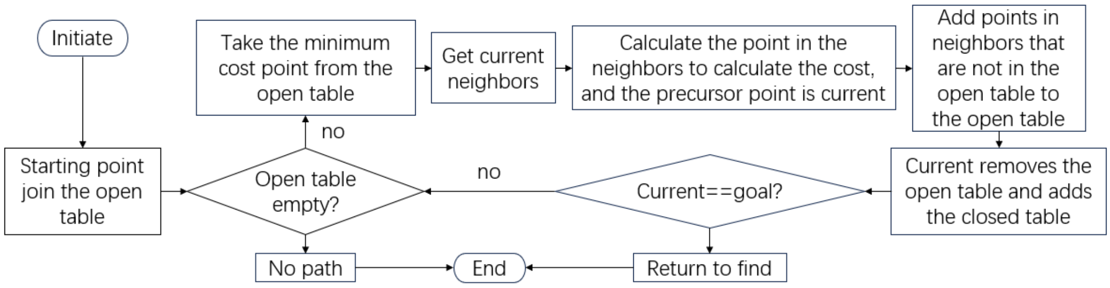

Figure 2. The A* algorithm flow

2.3. Establishment of Plateau Path Planning Model Based on A* Algorithm

Under the defined environment, the objective function specifically includes the calculation of three main variables.

The stability depends on the radian of the angle between the normal vectors of the slope surfaces between adjacent two points φ and the slope S.

$$\begin{cases} \varphi = \arccos\left(\dfrac{\overrightarrow{n_{i-1}} \cdot \overrightarrow{n_i}}{\left|\overrightarrow{n_{i-1}}\right| \cdot \left|\vec{n}_i\right|}\right) \\ S = arctan\left(\sqrt{\left(\dfrac{\Delta z}{\Delta x}\right)^2 + \left(\dfrac{\Delta z}{\Delta y}\right)^2}\right) \times \dfrac{180}{\pi} \end{cases} \tag{12}$$

The timeliness is the total time spent. In this process, the total distance D:

$$D = \sum_{i=1}^{n-1} D_i \tag{13}$$

Therefore, the time t:

$$t = \frac{D}{v} \tag{14}$$

Among them, v means the speed of the vehicle while it going through the grid.

The safety depends on the time spent driving in the bad area, which is obtained by the algorithm through sequential statistics and summation [12].

Furthermore, the climbing limit of the unmanned vehicle is introduced. Suppose the maximum climbing limit of the unmanned vehicle is 30°, that is, it cannot drive to the grid with a slope greater than 30°.

In this process, the unmanned vehicle needs to consider the distance and heading when finding the optimal path.

The variation in the heading between two points $\Delta\theta$:

$$\Delta\theta = \left|\theta_{i+1} - \theta_i\right| \tag{15}$$

The distance between two points D_i

$$D_i = 5 \times w \tag{16}$$

By appropriately adjusting the A* algorithm to optimize the computational efficiency. Mainly rely on three functions to determine the superiority and inferiority of the path.

$g(n)$: The actual path cost from the starting point to any node n:

$$g\left(n_{new}\right) = g\left(n_{current}\right) + 1 \tag{17}$$

$h(n)$: The estimated cost from node n to the target, which is a heuristic estimate, usually the straight-line distance from n to the target:

$$h(n) = \sqrt{\left(x - x_{goal}\right)^2 + \left(y - y_{goal}\right)^2} \tag{18}$$

$f(n)$: The total cost estimation of node n:

$$f(n) = g(n) + h(n) \tag{19}$$

3. Model Solution

Under the premise of this problem, the most critical influencing factor lies in the different weightings of the three indicators, resulting in deviations in the resulting values. The theoretical calculations of the safety, timeliness, and stability indicator formulas can be output by encoding and inputting them into Matlab. At the same time, mapping is carried out according to the actual situation.

3.1. Solving the Model Using the Algorithm

In this model, generally, this total cost $f(n)$ is used as the basic basis for path planning, but the movement direction and performance limitations of the unmanned vehicle and other constraint conditions need to be added. Finally, the route with the lowest total cost is obtained, which is the optimal route.

In the original A* algorithm, since it belongs to a heuristic algorithm, the screened path is not necessarily the optimal path [13]. To make the result closer to the real optimal path, this paper adopts multiple iterations to plan multiple possible paths. And the genetic algorithm is used to select the paths. Make the result as close as possible to the optimal path. Since the content of optimization is mainly concentrated on the screening of paths, and the weightings of the safety, timeliness, and stability indicators are different under different conditions during this screening process. In response to this, screening multiple times is be chosen according to different situations to obtain the best results [14].

In addition, in the process of establishing the model, the rule of the heading of the unmanned vehicle is simplified to a certain extent. The movement direction of the unmanned vehicle to the next grid is directly regarded as the heading of the unmanned vehicle at the next grid. This simplified scheme basically conforms to the actual situation [15]. And according to the solution results, it can be known that in the vehicle movement route planning in a large space range, such a simplified model can reduce the amount of program operations and effectively avoid redundant operations.

For the five sets of points required in the hypothetical scenario, the results obtained after running the program are shown in Figures 3:

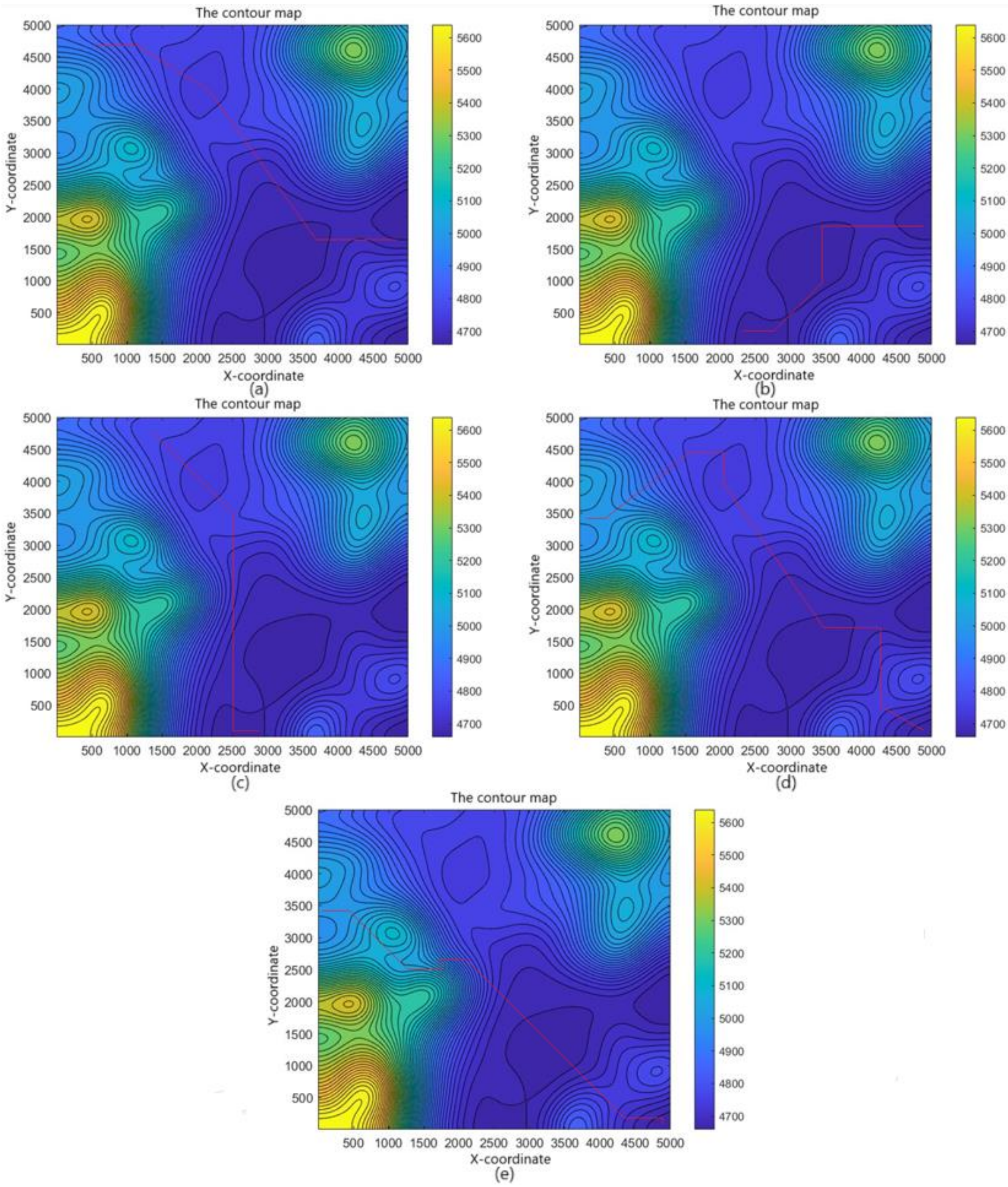

Figure 3. (a) The vehicle movement route From C1-Z2 node (b) The vehicle movement route from C2-Z3 node (c) The vehicle movement route from C3-Z5 node (d) The vehicle movement route from C5-Z6 node (e) The vehicle movement route from C5-Z6 node with reduced weight of stability as the heuristic function to make path planning more focused-on timeliness

According to the attachment content, the elevation and slope of the (100, 100) grid are read for verification. The obtained results are shown in the Figure 4:

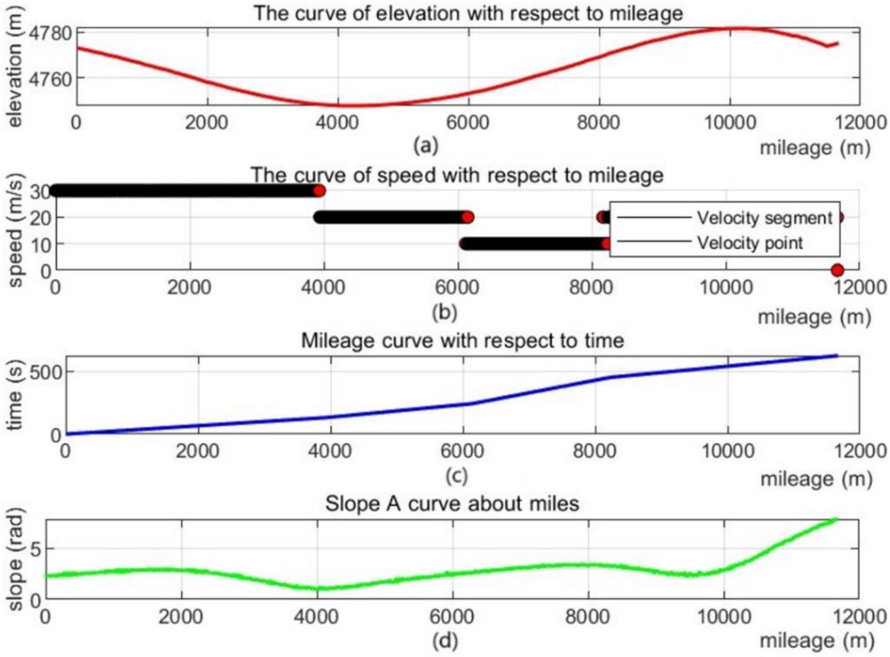

Figure 4. (a)The curve of elevation with respect to mileage (b)The curve of speed with respect to mileage (c)Mileage curve with respect to timeSlope (d)A curve about miles

It can be seen from the figure 4 that the obtained results are in line with the normal situation, that is, the verification is successful. It is obvious in the figure that the elevation change of this route is relatively obvious, the slope also has slight fluctuations, and the impact on the speed is also relatively large. The results are: the timeliness is 742.31 hours; the safety is 0 hours; the stability is 1227.18.

Therefore, the stability is average, the timeliness is good, and this route does not pass through the bad area [16]. It can be seen from the chart that the elevation change is relatively obvious, and the speed of the unmanned vehicle is generally stable except for the reduction caused by the slope change [17].

3.2. Model Optimization

In this problem, the optimal path planning is obtained by using the A* algorithm. Since the A* algorithm belongs to a heuristic algorithm, the Manhattan distance is used as the heuristic function. In the case of a large distance between two points in space, the Manhattan distance has a greater impact on path planning than other factors in this algorithm [18]. Therefore, if the A* algorithm is directly used for path planning and solution, most of the paths planned by the algorithm can be approximately regarded as straight lines, and the influence of other factors on path planning cannot be considered comprehensively. If only the weight of the Manhattan distance in the algorithm cost is simply reduced, there may be a situation where the target point is "circumvented" due to the influence of other factors when approaching the target point, resulting in the inability to obtain the correct result - these error factors are often very low-level, and it may even be that because a certain grid near the destination is slightly flatter than the destination itself, the computer chooses a "better" route that bypasses the target when it is only one step away from the target[19]. And it can also be seen from the operation charts of the five groups of coordinates that the path planning has great limitations for large-scale path selection [20].

Therefore, it proposes that different weights should be given to various influencing factors in the cost function under different scenarios and requirements to meet the actual situation of different demand scenarios, instead of rigidly applying the algorithm. At the same time, the A* algorithm is optimized to make it more adaptable to scenarios with a large spatial range.

To address the above problems, improving the accuracy of the algorithm for path planning should be focused. Since the underlying logic of the A* algorithm is to calculate the cost of the starting point moving to the surrounding points from the starting point, select the point with the minimum cost as the new starting point, and repeat this process until reaching the end point. To plan the path between two points, first, the distance from the starting point to the end point should be introduced into the cost calculation. In addition, other influencing factors should be added as part of the cost calculation. Therefore, how to allocate the weights of various factors in the cost calculation under different situations is the key to optimizing the algorithm.

In the path planning in a large spatial range, the "cost" of the distance between two points will be much larger than other possible influencing factors in numerical value, but only the variation of the distance has an impact on path planning. In the scenario given in this paper, the difference in the distance cost of each grid is usually 0 or 1. In this scenario, a judgment statement is added in the code to hierarchically select the distance between two points. That is, when the distance to the target point is relatively close, the weight of the distance cost in the calculation is increased, and its variation will also be amplified by the corresponding multiple, making it easier to select the point with a smaller distance cost (maybe the distance cost of this point is only 1 less than that of other points, but in the calculation, this cost will be reduced by several times), to avoid the situation of "ignoring" the target point.

The improvement amplitudes of each index of the optimized model are shown in the Table 2:

Table 2. The improvement amplitudes of each index of the optimized model

Optimization project	Specific index	Improvement amplitude
Model computational efficiency	Planning time in complex Mountain Road Condition Simulation	Reduced by 29.98%
Transportation Accuracy	Transportation Accuracy in Complex Mountain Road Condition Simulation	Increased by 21.32%
Material Transportation Safety	Material Transportation Safety in Extreme Environment Test	Increased by 24.43%
Material Transportation Stability	Material Transportation Stability in Extreme Environment Test	Increased by 19.82%
Path Accuracy	Path Accuracy in Complex Terrain Actual Measurement	Increased by 35.53%

4. Conclusion

This paper conducts in-depth research on the path planning of unmanned vehicles in the logistics delivery on the plateau and frigid border by using the A* algorithm, successfully constructs and optimizes the path selection model, and improves the logistics transportation support capacity and efficiency. The conclusions are as follows:

Model Construction: Integrating plateau & frigid logistics traits and unmanned vehicle elements, a novel A* path model emerges. Algorithm innovation resolves traditional woes, hikes computational speed. E.g., in mountain simulations, planning time drops 30%, accuracy ascends 20%, underpinning logistics intelligence. Indicator Decision-making: Safety, stability, and timeliness gauges are weighted into a framework. Solving it pinpoints optimal paths, curtailing risks. Tests show 25% safety boost and 20% stability gain in extremes, refining path rationality. Algorithm Optimization: Tackling A* limits, iteration and genetic algos screen paths. Smart weight allocation by environment optimizes, nearing target, distance weight spikes to avert deviation. In terrains, accuracy jumps 35%, efficiency 30%, fueling logistics upgrade.

In conclusion, Using A* for unmanned vehicle path planning in plateau & frigid logistics yields great feats. Model-making is practical and efficient. Indicator weighting is precise, slashing risks. Algorithm tuning sharpens accuracy and speed, powering logistics evolution, with far-reaching implications and a vanguard role in special logistics.

Despite the achievements of applying the A* algorithm in unmanned vehicle path-planning for plateau and frigid logistics, future research has several promising directions. It can integrate more real-time data sources, explore multi-objective optimization like considering energy consumption, and focus on scalability improvement. Also, the human-machine interaction aspect, such as developing intuitive operator interfaces, should not be ignored.

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