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Research on Path Planning Based on Bidirectional A* Algorithm

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ABSTRACT A refined bidirectional A* algorithm proposes to address the issue of imprecise path planning for unmanned mining vehicles navigating through complex open-pit mining terrains. To ensure the smooth traversal of these vehicles, a gradient factor incorporates into the cost function to circumvent obstacles along the pathway. Additionally, a weighted coefficient introduces into the heuristic function to fine-tune the combination of Euclidean and Manhattan distances, enhancing the accuracy of path distance measurement and ultimately leading to an optimal path. The enhanced algorithm adeptly simultaneously explores from both the starting and end points, significantly reducing search time and improving path planning efficiency. Utilizing the established map of the mining environment, an experiment for unmanned mining vehicle path planning devises, and a simulation test of the global path planning algorithm conducts using the MATLAB platform. The experimental results demonstrate that the refined bidirectional A* algorithm exhibits accelerated search speed and superior path planning effectiveness.

INDEX TERMS A* Algorithm, Open-Pit Mining Area, Path Planning, Synchronous Bidirectional Search, Unmanned Mining Truck

Ⅰ. INTRODUCTION

As autonomous driving technology continues to advance, unmanned mining trucks have become prevalent in mining operations. Compared to traditional mining trucks, unmanned counterparts offer heightened safety, reduced labor costs, and enhanced transportation efficiency, thereby enriching socioeconomic benefits [1]. However, in open-pit minin g areas, rugged and winding roads with steep slopes present considerable challenges to the speed and trajectory of unmanned mining trucks. Consequently, ensuring the safe operation of unmanned mining trucks in complex terrain has emerged as an imperative undertaking.

Presently, conventional path planning predominantly revolves around traditional search algorithms and intelligent algorithms, including the A* algorithm [2], Dijkstra's algorithm [3], ant colony algorithm [4], grey wolf algorithm [5], and genetic algorithm [6]. Scholars worldwide have proposed diverse solutions to the conundrum of path planning for unmanned mining trucks. For instance, Xing B et la. [7] an enhancement of deep learning techniques through the refinement of reward functions and action selection mechanisms, which consequently enables subaqueous vehicles to operate with increased safety in the challenging environs of the deep sea. Xie Y et al. [8] incorporate a cellular genetic algorithm to address the intricacies of loading and unloading tasks, taking into account factors such as road elevation, gradient, quality, and the velocity of the trucks. By integrating the mechanism of clandestine migration within the genetic algorithm, they have successfully actualized a comprehensive transportation route for mining vehicles. Lei T et al. [9] construct a stratified framework employing deep learning methodologies to actualize the CCPP trajectory for bicycling. Furthermore, they harness nature-inspired algorithms for vehicular obstacle avoidance, culminating in the realisation of autonomous vehicle navigation. Lei Z et al. [10] have presented a sophisticated approach to autonomous mining vehicle path tracking based on the Model Predictive Control (MPC) algorithm. They have empirically demonstrated that the implementation of the MPC algorithm contributes to a reduction in the vehicle's deviation angle, thereby enhancing the precision of its trajectory. Wang M et al. [11] elucidate the current research landscape of unmanned driving technologies within the mining sector. They offer a detailed exposition on the positioning and path-planning aspects of unmanned driving systems, underscoring the enhancement of enterprise efficiency afforded by these technological advancements. Xin P et al. [12] have proposed a model predictive control strategy, which, through the formulation of an optimization function and the incorporation of a terminal equation, ensures that the model predictive controller exhibits superior tracking performance during the unmanned mining vehicle's trajectory followin g

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process. This methodology enhances the controller's ability to adhere to the intended path with increased precision.Vasilis Androulakis [13] has pioneered the integration of automated shuttle vehicles, thereby substantiating the operational feasibility of auto-batching transport vehicles within the subterranean coal mining production cycle. Empirical validation has been achieved through demonstration of the preliminary results pertaining to the autonomous navigation capabilities of the prototype shuttle vehicle. Zhao et al.[14] have introduced an articulated vehicle path-following strategy predicated on feedback linearization algorithms. The path tracking controller, grounded in feedback linearization, is capable of accurately adhering to the prescribed trajectory. Y. Li et al. [7] adjusted the weights of different areas, optimized redundant points, and smoothed turning points of the path to shorten it and enhance safety. Y. Chen et al. [8] advocated a fusion of the A* algorithm and sparrow search algorithm to eliminate redundant points and generate the optimal path using Bézier curves. Liu Hui et al. [9] refined the ant colony algorithm by integrating obstacle avoidance factors and selecting paths with gentle slopes to enhance the efficiency of ant colony search and achieve the optimal path for the mining truck. Meanwhile, Zhang Hui et al. [10] introduced an enhanced A* algorithm with extended key node search and one-way search for obstacle avoidance to augment the safety of the A* algorithm. Furthermore, Zhang Zhiyao et al. [11] proposed a method to address the obstacle avoidance issue of unmanned vehicles in complex environments using data fusion Dempster-Shafer in unknown environments, culminating in rapid optimization of local paths. Despite considering terrain and environmental factors for path planning in mining environments, these studies still exhibit certain limitations in swiftly planning the global path for mining trucks and achieving safe and expedient planning for rugged mining paths. In this paper, we present an enhanced path planning algorithm based on bidirectional search using the A* algorithm, built upon the traditional A* path optimization algorithm. The algorithm constructs a mining model through mesh and expansion functions and integrates a slope factor into the cost function to better align with the mining environment. Confronting the challenge of the traditional bidirectional search A* algorithm's incapacity to swiftly and accurately plan the optimal path in the uncertain environment of a mining area, we introduce the concepts of bidirectional midpoint and virtual target point in the algorithm to steer the bidirectional search algorithm towards convergence at the opposite point. Additionally, we introduce a weight factor in the heuristic function to adjust the relationship between Euclidean distance and Manhattan distance, thereby curtailing search time and ensuring the safety, real-time performance, and accessibility of the planned path for unmanned mining trucks.

II. Traditional A* Algorithm

The A* algorithm is a heuristic-based pathfinding method, inheriting the concept of Dijkstra's algorithm. It integrates a heuristic estimation function when computing the cost function, enabling rapid optimal path search from the starting point to the endpoint within a grid map. In 3D path planning issues, the conventional A* algorithm essentially uses a heuristic function to estimate the distance from the start to the end, subsequently determining the direction of the next search. The conventional A* algorithm is presented as follows:

$$F(n)=G(n)+H(n) \tag{1}$$

For a node coordinate n in the problem solution space, $F(n)$ is an evaluation function used to estimate the minimum total cost from the starting point to the target node. $G(n)$ represents the current cost function, which signifies the cost incurred by the current node solution. $H(n)$ is the heuristic estimation function, typically employing either the Euclidean distance $O(n)$ or the Manhattan distance $M(n)$ to represent the estimated cost.

The operation process of the A* algorithm in a three-dimensional space is similar to that in a two-dimensional plane, but it requires consideration of changes in height. Therefore, in a three-dimensional space, the A* algorithm formula adopts the Euclidean distance representation, as shown in the following formula (2).

$$h(n)=\sqrt{((x_n-x_t)\times l_x)^2+((y_n-y_t)\times l_y)^2+((z_n-z_t))^2} \tag{2}$$

In formula (2), and represent the length and width of the unit grid, is the coordinate of the current node, and is the coordinate of the target point.

When implementing the A* algorithm, two main lists are primarily involved: an open list for tracking nodes yet to be evaluated, and a closed list for recording nodes that have been inspected. Initially, the algorithm places the starting point on the open list and starts the loop, selecting the node with the smallest f(x) value (least cost to the destination) from the open list to be the current node, and moving it to the closed list indicating it has been processed. Subsequently, the algorithm explores the adjacent nodes, skipping those already in the closed list, and adds new nodes not in the open list to it based on calculated g(x), h(x) values, and parent node information. This process is repeated until the end point is added to the closed list, indicating a path has been found, or the open list is exhausted, indicating the destination is unreachable. After path discovery, path reconstruction may be undertaken for path smoothing optimization, creating a more practical route.

A* algorithm in three-dimensional terrain:

(1) Initialize the map and determine the positions of the start and end points.

(2) Create an open list and a closed list, and add the starting node to the open list. During each iteration, select the node with the smallest f value from the open list and move it to the closed list.

(3) For all neighboring nodes of the current node, calculate their g value (the actual distance from the starting point to the neighbor node) and h value (the estimated distance from the neighbor node to the target node), then calculate the f value.

(4) If the neighboring node is not in the open list or its f value is smaller than before, add it to the open list and set the current node as the parent node of the neighboring node.

(5) At the end of each iteration, check if the target node has been reached. If it has, return the path; otherwise, continue looping until a path cannot be found.

The flowchart for the traditional A* algorithm is shown in Figure 1.

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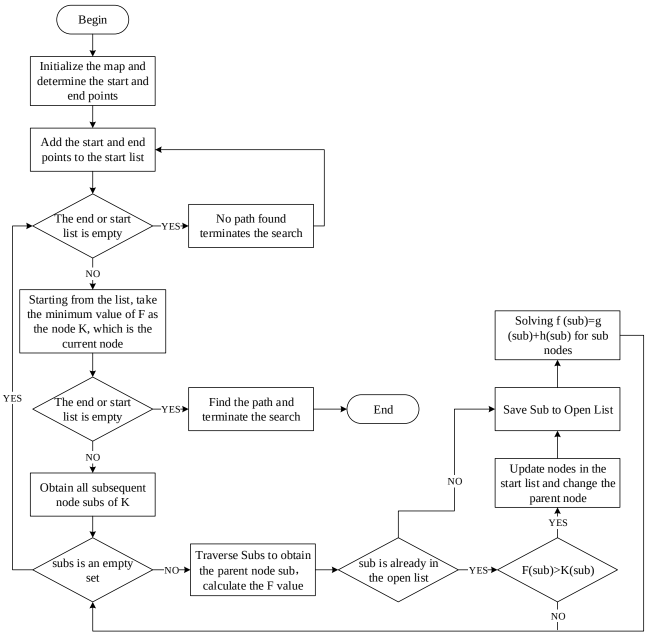

Figure 1. Conventional A* algorithm

The traditional A* algorithm traverses too many nodes during the search process, which takes a long time and results in poor search efficiency. Therefore, its application in complex mines is not ideal.

III. Improving the Bidirectional A* Search Algorithm

A. Improvement Idea

Bidirectional A* search is a heuristic search algorithm which simultaneously begins to search from the start and end points until the two searches meet. This algorithm employs the cost function of the A* algorithm to estimate the cost of each node, speeding up the discovery of the shortest path from start to end. While literature [20] proposes a bidirectional search algorithm based on A*, some issues remain, such as only being able to search for the optimal path on flat roads, and the effect of choosing the forward path as the final path is not noticeable when the paths do not intersect. Given the uneven terrain of the mine, the path planning for the dump truck facing different slopes needs to be considered. To improve this algorithm, we integrated a slope factor into the cost function, and according to the literature, set the maximum slope for the safe operation of the dump truck in the mining area at 15%. At the same time, we introduced a weight factor into the estimation function to adjust the relationship between the Euclidean and Manhattan distances, thus enabling the improved bidirectional A* search algorithm to more effectively reach the optimal solution during the path search process.

The improved process of the bidirectional A* algorithm is as follows:

(1) Initialize the parameters of the map, perform forward and backward searches from the starting point and the end point, and add them to the corresponding open and closed lists.

(2) Select the node N1 with the minimum F value from the open lists of the forward and backward searches. If N1 and N2 are both in the closed list of the other side, it means that a path is found and the search can be terminated. Otherwise, continue to the next step.

(3) For node N1, traverse all its neighboring nodes, adding the slope factor and avoiding paths with a slope greater than 15%. Calculate its F value, and select the node with the minimum F value in the open list of the forward search to add to the closed list. If the node is already in the closed list, update its existing node.

(4) For node N2, traverse all its neighboring nodes, adding the slope factor and avoiding paths with a slope greater than 15%. Calculate its F value, and select the node with the minimum F value in the open list of the backward search to add to the closed list. If the node is already in the closed list, update its existing node.

(5) Add a weight coefficient to h to adjust the Euclidean and Manhattan distances.

(6) If the neighboring node is not in the open list or its F value is smaller than before, add it to the open list and set the current node as the parent node of the neighboring node.

(7) At the end of each cycle, check if the target node has been reached. If so, return the path; otherwise, continue the loop until no path can be found.

The flowchart of the A* algorithm has been enhanced as depicted in Figure 2.

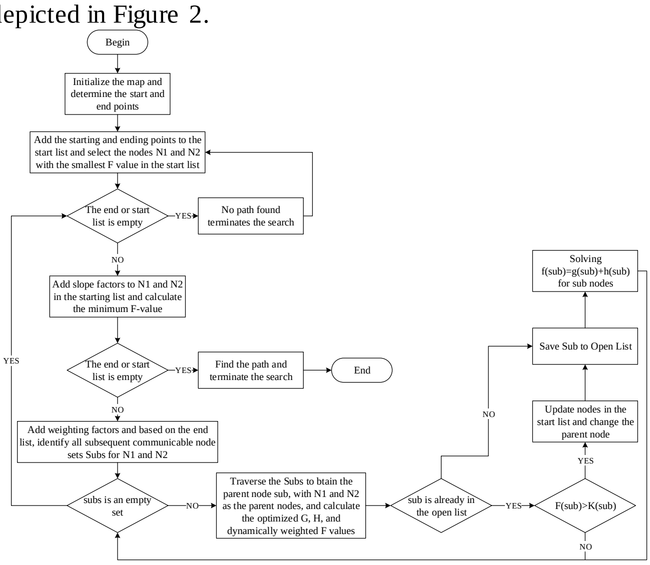

Figure 2. Enhanced A* algorithm

B. Optimizing the cost function

Due to the variable terrain of the mining area, it is necessary to consider the path planning of the mining vehicle when facing different slopes [21]. Therefore, a slope factor is added to the cost function to ensure safer travel of the mining vehicle within the mining area. According to reference [21], the maximum slope for safe travel of the mining vehicle in the mining area is set at 15%. The formula for calculating the slope is shown in equation (3):

$$i = \frac{\Delta h}{\Delta L} \times 100\% \tag{3}$$

In the formula, h represents the height difference between two adjacent nodes, L denotes the horizontal distance between the two nodes, and i signifies the slope between the two adjacent nodes. Considering that different slopes require different speeds for the dump truck, the relationship between the mine slope, the power and transmission ratio of the dump truck, the total mass of the dump truck, and the driving speed is given according to the literature, as shown in Equation (4):

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$$v_i = \begin{cases} \dfrac{3600\eta P}{mg(f+i)} & ,0 \le i \le 15\% \\ \dfrac{3600\eta P}{mgh} & ,-15\% \le i < 0 \end{cases} \quad (4)$$

v_i represents the driving speed of the dump truck on a path with a slope of i, η denotes the total transmission efficiency, f is the coefficient of friction, P signifies the total output power, m represents the total mass of the dump truck when fully loaded, and g stands for the acceleration due to gravity. When the dump truck is traveling on a horizontal surface, the speed is v_0. The relationship between v_0 and the formula (4.4) can be derived as follows:

$$\frac{v_0}{v_i} = \begin{cases} 1+\dfrac{i}{f} & ,0 \le i \le 15\% \\ 1 & ,-15\% \le i < 0 \end{cases} \quad (5)$$

Therefore, based on the slope and speed, Equation (5) is utilized as the current cost function, serving as the movement cost in the enhanced A* algorithm, as depicted in Equation (6).

$$g(n) = \begin{cases} g(n-1) + (1+\dfrac{i}{f})O(n) & ,0 \le i \le 15\% \\ g(n-1) + O(n) & ,-15\% \le i < 0 \end{cases} \quad (6)$$

C. Improving the Heuristic Function

Shortest path search is a common problem in computer science, and different distance measurement methods can be used to calculate the distance between nodes [22]. Among them, Euclidean distance [23] and Manhattan distance [24] are two common distance measurement methods, and they have different applicable scenarios. Euclidean distance is suitable for the shortest path search in unobstructed and open areas. Manhattan distance is suitable for the shortest path search in areas with many obstacles, closed, and even circular areas. In actual three-dimensional scenarios, there are both unobstructed, open flat areas and areas with many obstacles. Selecting either Euclidean or Manhattan distance monotonically as the heuristic function throughout the entire search process cannot take into account both types of terrain, and therefore, cannot achieve an optimal pathfinding strategy. Therefore, introducing bidirectional midpoints and virtual target points to guide bidirectional convergence towards each other and setting a heuristic function that can dynamically change the distance function in the algorithm. The heuristic function is improved by adding a weighting coefficient, denoted as w, to control the combination of Euclidean distance and Manhattan distance. This is shown in formula (7).

$$h(n) = (1-\alpha)O(n) + \alpha M(n) \quad (7)$$

During the path search, the space with the smallest $f(n)$ is selected from the open list each time. If there are obstacles within the four-grid range of the current space to be visited, the A value needs to be increased when calculating $h(n)$; if there are no obstacles, the α value should be reduced. The increase or decrease of the α value depends on the specific three-dimensional map situation, and by default in this paper, α is increased to 1 and reduced to 0. The use of a dynamically adjusted heuristic function can take into account the characteristics of both distances, obtaining better pathfinding results than traditional heuristic functions.

By amalgamating the refined cost function and heuristic function, the formula for the heuristic function is depicted in formula (8).

$$f(n) = \begin{cases} g(n-1) + (2+\dfrac{i}{f}-\alpha)O(n) + \alpha M(n) & ,0 \le i \le 15\% \\ g(n-1) + (2-\alpha)O(n) + \alpha M(n) & ,-15\% \le i < 0 \end{cases} \quad (8)$$

IV. Comparison of experimental results of the improved two-way A* algorithm

This paper uses an IntelI CoreI i5-7300HQ CPU @ 2.50GHz, 8GB of RAM laptop and MATLAB R2020b as the experimental hardware and software. The experiment compares the algorithm running time, path length, and number of traversed path nodes for the A* algorithm in reference [2], the bidirectional A* algorithm in reference [20], and the improved bidirectional A* algorithm proposed in this paper. The simulation experiments are compared with the improved A* algorithm in reference [2] and the bidirectional A* algorithm in reference [21], using time, path length, and path nodes as the comparison indicators to observe the experimental results.

A. Mine Environment Modeling

The mine environment is complex, with rugged roads, varying slopes, and obstacles. Therefore, for mine car path planning, it is necessary to first establish a working environment model for the mine car. In this paper, based on the actual mine environment, the mine is virtualized, and a grid method [20] is used in MATLAB to construct the mine model using the mesh function, placing it in a three-dimensional coordinate system. Initially, through data collection and preprocessing, the data import and cleaning capabilities of MATLAB are utilized to ensure data quality. Subsequently, interpolation techniques and mesh generation tools, such as griddata and delaunayTriangulation, are employed to construct the spatial framework of the mine area. During the geological model construction phase, surface fitting and geostatistical methods, including fit and kriging, are applied to meticulously depict the structure of the ore body. In the three-dimensional visualization segment, MATLAB rich plotting functions, such as scatter3, surf, and slice, bring the model to life in vivid display. In the analysis and optimization phase, MA TLAB's analytical tools are used to predict mining risks and optimize the model.Points are uniformly sampled on the surface of the mountain model, and these points are connected in a certain order. A triangle subdivision algorithm is used to generate the mesh. The resulting mesh accurately describes the shape of the mountain surface, as shown in Figure 3.

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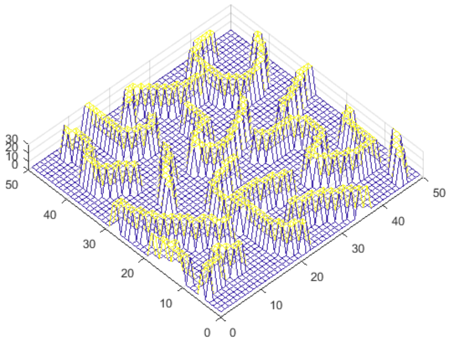
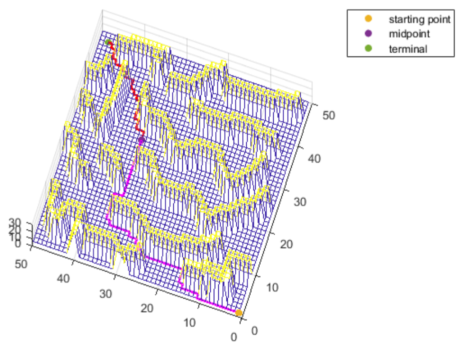


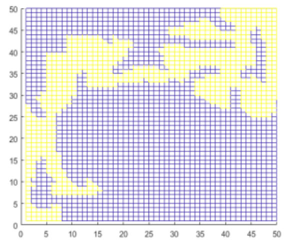
Figure 3. Simulated Mine Model

B. Mine Environment Map Simulation Experiment

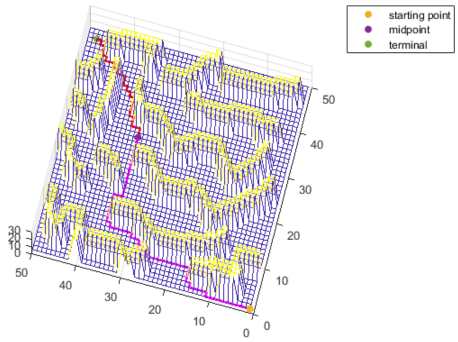
Initially, path simulation is performed based on the mine environment map, with randomly positioned start and target points within the map. The path planning outcomes utilizing the enhanced A* algorithm, when the weight α of the heuristic function $h(n)$ assumes various values, are illustrated in the figure. Here, the yellow point denotes the starting point, the green point signifies the target point, and the purple points represent the intermediate points.

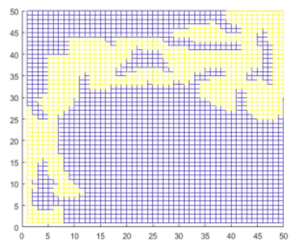
Upon experimental observation, it was found that when α is set to 0, the distance from the starting point to the destination for the minecart is 94, with 328 nodes searched for pathfinding. When α is 0.1, the distance remains 94, but the number of nodes searched decreases to 326. For α at 0.2, 0.3, and 0.5, the distance is consistently 94, with the number of nodes searched being 334, 328, and 307, respectively. When α is increased to 0.7, the distance is still 94, but the number of nodes searched significantly drops to 277. However, as α reaches 0.9 and 1, the distance increases to 97, with the number of nodes searched at 260 and 308, respectively. It is evident that when the path length is constant, a smaller number of nodes searched indicates faster minecart path planning. Therefore, α at 0.7 yields the fastest path planning. When α exceeds 0.7, the path length increases slightly, while the number of nodes searched decreases marginally. Consequently, in this study, α at 0.7 is deemed the optimal weight for the heuristic function. The path length and number of nodes searched based on the improved A* algorithm, for different values of α, are detailed in Table I.



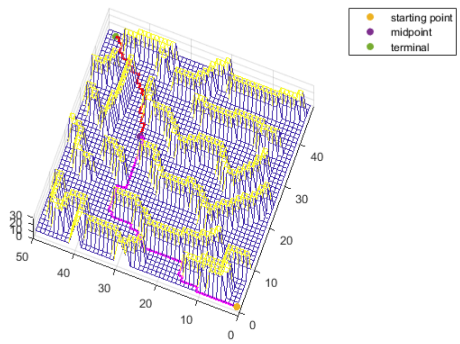


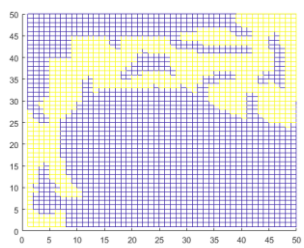
(a)α=0





(b)α=0.1





(c)α=0.2

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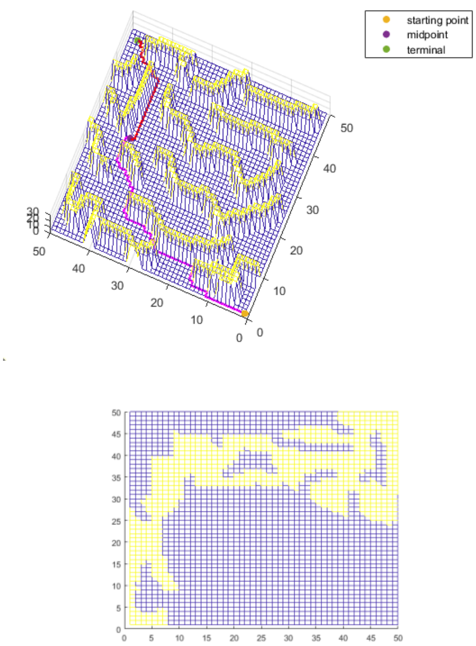
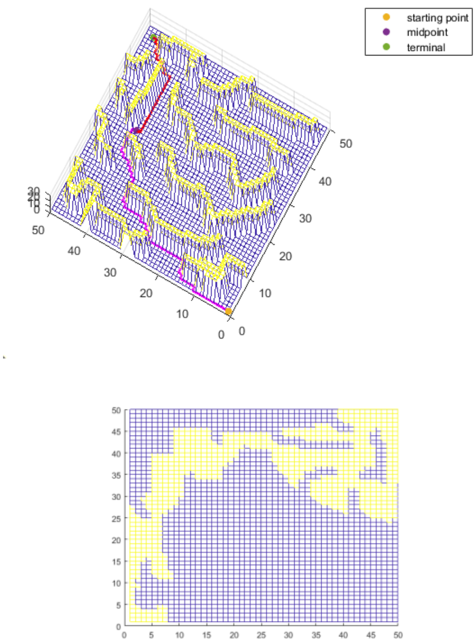
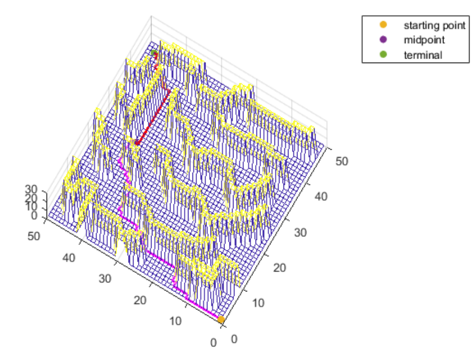
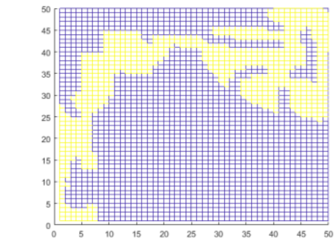


(d)α=0.3

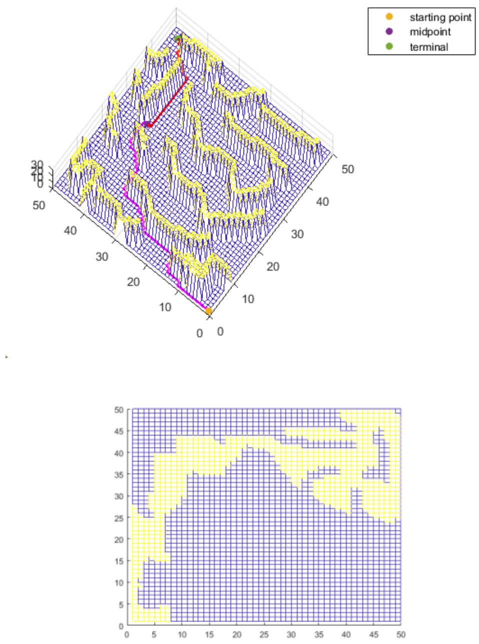


(e)α=0.5

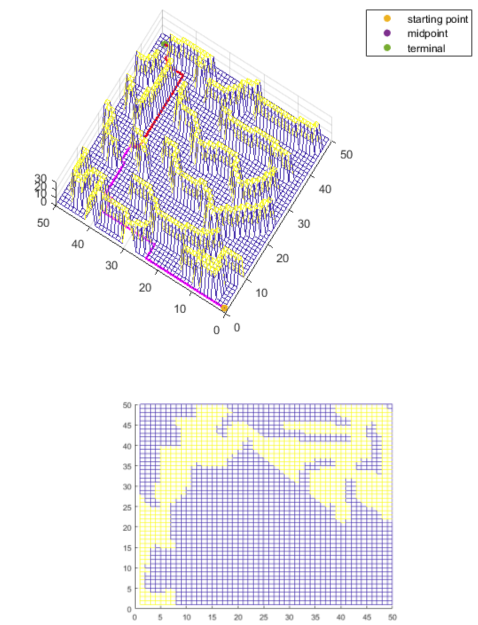




(f)α=0.7



(g)α=0.9



(h)α=1

Figure 4. Path Simulation Results Based on the Enhanced A* Algorithm

TABLE I
Number of Path Nodes for Different Values of α

Serial Number	α	Path Length	Nodes of the Path	Serial Number	α	Path Length	Nodes of the Path
1	0	94	328	5	0.5	94	307
2	0.1	94	326	6	0.7	94	277
3	0.2	94	334	7	0.9	97	260
4	0.3	94	328	8	1	97	308

In the simulation comparison experiment conducted on the simulated mine map shown in Figure 3, four sets of different start and end points were used as examples for the simulation experiment. The start and end points were [(1,1,0),(48,48,0)],[(32,1,15),(6,26,17)],[(45,16,12),(7,14,26)], and [(11,26,15),(44,48,20)], with four experiments conducted for comparison. The summary of the four experiments is shown in Table 4.2. Taking the starting point (1,1,0) and the ending point (48,48,0) as an example, simulations were performed for the algorithms in References [3], [20], and the improved bidirectional A* algorithm proposed in this paper. Figure 5 displays the path of the algorithm in Reference [3], Figure 6 shows the path of the algorithm in Reference [20], and Figure 7 illustrates the path of the improved bidirectional A* algorithm presented in this paper.

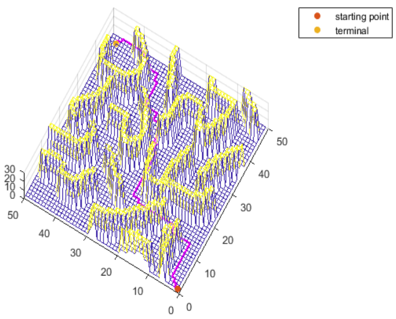


Figure 5. A* Path Planning Algorithm

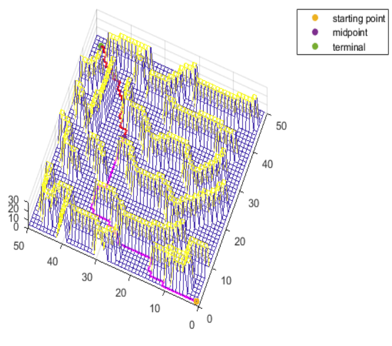


Figure 6. Bidirectional A* Path Planning Algorithm

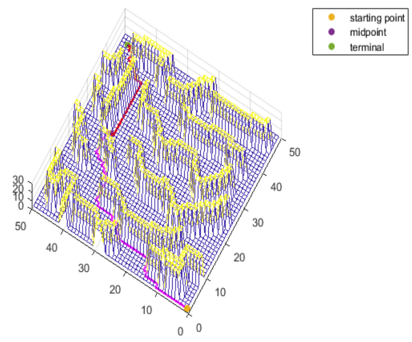


Figure 7. Enhanced A* Pathfinding Algorithm

Upon comparing Figures 5 and 7, it is evident that the A* algorithm presented in Reference [3] results in longer paths and a greater number of search nodes within three-dimensional terrains. Contrasting Figures 6 and 7 reveals that the improved A* algorithm exhibits more pronounced obstacle avoidance capabilities, effectively circumventing steep mountain paths. According to Table II, the A* algorithm proposed in this paper, when compared to the algorithm in Reference [3], has reduced the average time expenditure, achieved more concise path lengths, and decreased the number of path nodes by 66.28%, while also shortening the average search time by 44.36%. In comparison to the algorithm in Reference [20], the proposed algorithm has reduced the average search time by 14.04%, slightly decreased path lengths, and lowered the number of path nodes by 23.42%.

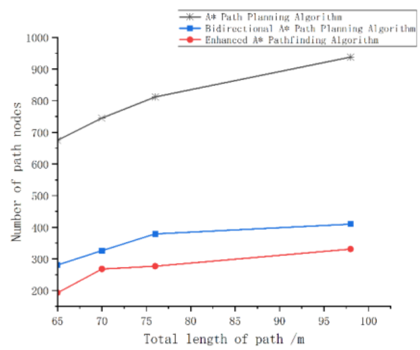


Figure 8. Presents a comparison between the improved A* algorithm and the other two algorithms.

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Based on the data in Table II, Figure 8 can be created. The comparison results in Figure 8 reveal that the number of path nodes and the total path length of the three algorithms differ depending on the specific starting and ending points. However, the improved bidirectional A* search algorithm proposed in this chapter exhibits superior characteristics to the traditional A* algorithm and the bidirectional A* search algorithm in most circumstances, as the number of path nodes and the total path length more closely approximate the optimal solution.

V. CONCLUSION

An improved bidirectional search A* algorithm is proposed for path planning of unmanned mining trucks in the complex environments of open-pit mines. Due to obstacles and steep slopes, these trucks face challenges that threaten safety. To address slope issues, a slope factor is added to the cost function, preferring paths that avoid steep inclines and choose gentler slopes for climbing. The heuristic function is optimized by integrating Manhattan and Euclidean distances, enabling faster path planning in three-dimensional mine areas and facilitating the discovery of globally optimal paths. Simulation experiments have shown that the improved algorithm can plan routes with higher safety, shorter duration, and optimal paths in complex open-pit mine environments, providing effective technical support for intelligent mining truck path planning and navigation. Unmanned mining truck research, including autonomous navigation and positioning, energy supply, and mining robotics, will evolve to include applications of 5G communication technologies, mining big data analysis, and enhancing automation, intelligence, efficiency in mining operations. These research directions aim to improve mining efficiency, reduce costs, enhance safety, and foster technological progress in the mining industry.

TABLE II
Comparison of Improved A* Algorithm with Existing Algorithm

	number	Starting point	Endpoint	The total length of the path /m	The number of nodes in the path	The duration /s
A*	1	(1,1,0)	(48,48,0)	98	938	21.53
	2	(31,1,15)	(6,26,17)	70	745	15.72
	3	(45,16,12)	(7,14,26)	76	812	17.63
	4	(11,26,15)	(44,48,20)	65	675	14.35
Bidirectional A*	1	(1,1,0)	(48,48,0)	98	410	13.44
	2	(31,1,15)	(6,26,17)	70	326	10.34
	3	(45,16,12)	(7,14,26)	76	379	11.58
	4	(11,26,15)	(44,48,20)	65	281	9.45
The enhancement of A* algorithm	1	(1,1,0)	(48,48,0)	98	331	11.72
	2	(31,1,15)	(6,26,17)	70	268	9.37
	3	(45,16,12)	(7,14,26)	76	277	9.65
	4	(11,26,15)	(44,48,20)	65	193	7.78

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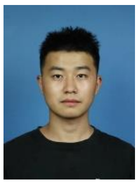

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