WEP Warwick Evans Publishing

International Journal of Computer Science and Information Technology

ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 4, Number 3, Year 2024
DOI: https://doi.org/10.62051/ijcsit.v4n3.29
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research on Obstacle Avoidance Path Planning of Intelligent Transfer Device Based on Improved RRT Algorithm

Li Xia [1, 2], Yuming Qi [1, 2]

[1] Institute of Robotics and Intelligent Equipment, School of Mechanical Engineering, Tianjin University of Technology and Education, Tianjin 300222, China

[2] Tianjin Key Laboratory of Intelligent Robot Technology and Application, Tianjin 300222, China

ABSTRACT

As an important assistive device for people with lower limb dysfunction, the intelligent transfer device (IDS) has high requirements for path planning safety and movement efficiency during autonomous navigation. In obstacle spatial path planning, the rapidly exploring random trees (RRT) algorithm has the problems of environment exploration blindness and slow convergence speed. Therefore, a path planning method that improves the RRT algorithm is proposed. Firstly, a sampling strategy combining restricted region search and probabilistic goal bias is used to improve the orientation of path planning. Then, a dynamic variable step size expansion strategy is adopted to solve the poor convergence speed of the random tree. Finally, the path node reconnection and fitting optimization based on safe distance is proposed to solve the redundancy of nodes and the discontinuity of curvature in the initial path. The results show that the improved RRT algorithm reduces the average search time by 99.70%, 61.56%, and 60.22%, respectively, compared to the RRT, RRT*, and Informed RRT* algorithms.

KEYWORDS

Intelligent transfer device; Path Planning; Rapidly exploring random trees; Dynamic variable step size expansion strategy; Node reconnection optimization

1. INTRODUCTION

It is predicted that by 2050, individuals aged 65 years and older will represent 16% of the global population, while the percentage of individuals with disabilities may exceed 15% [1]. The issue of care for individuals with lower limb dysfunction is becoming increasingly critical, and how to improve the quality of life for these individuals is a current societal challenge that needs to be addressed. Intelligent transfer devices, as essential care equipment, facilitate the movement and transfer of the elderly or individuals with lower limb dysfunction in daily care, thereby reducing the burden on caregivers or family members. However, current intelligent transfer devices have significant shortcomings in autonomous navigation and path planning, including inaccurate localization, redundant path planning, and inefficiency, which severely limit their practical use [2].

Path planning is the core of the field of mobile robotics, which requires a mobile robot to detect the external environment based on sensors, and then plan a route on its own to satisfy the physical constraints of the robot and avoid collision [3]. Path length, safety, and efficiency are the main indicators for evaluating the performance of path planning algorithms [4, 5]. In the field of path planning, algorithms are usually divided into two categories based on the availability of map information: global path planning and local path planning. Global path planning algorithms include the A^* algorithm [6], the RRT algorithm [7], the Probabilistic Roadmap Method (PRM) [8], and

Dijkstra's algorithm [9], which can quickly find a path from start to end in a deterministic map environment. Local path planning algorithms, including the artificial potential field method, dynamic window method (DWA) [10], and Bessel curve algorithm [11], mainly solve the real-time obstacle avoidance problem of robots in uncertain or dynamically changing environments [12].

The RRT algorithm is a sampling-based path planning method, which is widely used in the field of mobile robot control due to its simple algorithmic structure and fast computation speed [13]. However, the RRT algorithm has some limitations, such as blind search, poor convergence, and redundant nodes and non-smoothness in the initial path [14]. To address these issues, researchers have proposed a number of improvements. Li et al. [15] introduced an improved RRT-Connect algorithm that improves search efficiency by incorporating a heuristic search strategy, but the algorithm exhibits a bias toward a particular search direction, which may affect the optimality of the path search.

Therefore, an improved RRT algorithm is proposed to solve the blind search, slow convergence, and redundant path nodes in the traditional algorithm. A sampling strategy combining restricted region search and probabilistic target bias and a dynamic variable step size expansion strategy for the random tree are proposed to improve the search efficiency of the algorithm. Then, path node reconnection optimization and B-spline curve fitting are applied to optimize the initial planning path, reducing redundant nodes and curvature discontinuities, thereby improving the path quality and ensuring the continuity and smoothness of the motion path of the intelligent transfer device.

2. METHODS

2.1. Principle of RRT Algorithm

Suppose the state space of the intelligent transfer device is X, and the start and end points are X_{start} and X_{goal}, respectively. The random tree is initialized and the X_{start} is used as the root node. In each iteration, the sampling point X_{rand} was randomly selected from the state space, then all nodes in the current random tree were sequentially traversed to find the node closest to X_{rand}, denoted X_{near}, and then the line from X_{near} to X_{rand} was extended by a fixed step to obtain a new node X_{new}. If there is no obstacle in the line between X_{near} and X_{new}, then X_{new} is added to the random tree, otherwise this point is discarded and randomly resampled until the random tree expands to the end point X_{goal}. Finally, the complete path is generated by backtracking from X_{goal} to the parent node X_{start} using a tree-based introduction to backtracking.

2.2. Improved RRT Algorithm

2.2.1. Sampling Strategy Combining Restricted Region Search and Probabilistic Target Bias

This paper proposes a sampling strategy that restricts the region search and probabilistic target bias to constrain and guide the expansion direction of the sampling region and random tree. Firstly, an ellipse is constructed on the global map and X_{start} and X_{goal} are defined as the start and end points of the ellipse. The initial long axis C_{best} and short axis $C_{\min}$ of the ellipse can be solved based on the Euclidean distance.

$$C_{\text{best}} = (1+ka)\sqrt{X_{\text{goal}} - X_{\text{start}}} \qquad 0 \le ka < 1 \tag{1}$$

$$C_{\min} = C_{\text{best}}/2 \tag{2}$$

Where ka is the condition coefficient.

Then, it is determined whether the sampled point is inside the ellipse based on the fact that the sum of the distances between the point outside the ellipse and the focus is greater than the sum of the distances between the point inside the ellipse and the focus. Equation (3) serves as the standard for judgment. If $f(x,y)>1$, $\omega=0$, the sample point is outside the ellipse and refuses to be added to X_{rand}; conversely, $\omega=1$ and it is added to X_{start}. In addition, if the initial path is not discovered after the specified number of iterations, the value of *ka* is increased. If *ka* reaches the maximum value and still no path is found, path planning fails; otherwise, path planning is considered complete.

$$f(x,y)=\frac{\left((x-x_0)\cdot\cos(\theta)+(y-y_0)\cdot\sin(\theta)\right)^2}{\left(C_{best}/2\right)^2}+\frac{\left((x_0-x)\cdot\sin(\theta)+(y-y_0)\cdot\cos(\theta)\right)^2}{\left(C_{min}/2\right)^2} \tag{3}$$

$$\omega=\begin{cases}1 & f(x,y)\le 1\\ 0 & f(x,y)>1\end{cases} \tag{4}$$

Where, (x,y) are the coordinates of the sample point $Sample(M)$. $f(x,y)$ is the probability that the sample point is inside the ellipse. (x_0,y_0) are the coordinates of the center of the line between X_{start} and X_{goal}, and θ is the angle between the line connecting X_{start} and X_{goal} and the horizontal projection.

Finally, a target weighting factor β (0< β <1) is set and a sampling point X_{rand} is generated by comparing βrand with a random number β_{rand} (0< β_{rand} <1). Then,

$$X_{rand}=\begin{cases}X_{goal}, & \beta_{rand}<\beta\\ X_{rand}, & \beta_{rand}\ge\beta\end{cases} \tag{5}$$

2.2.2. Dynamically variable step size expansion strategies

The step size of the traditional RRT algorithm is a fixed value, which can't adapt to different paths. To solve this problem, a dynamic variable step size expansion method is introduced. The minimum step size is S_{min}, and the angle between X_{near} and the line connecting X_{rand} and X_{goal} is α. If α > 90°, the random tree is expanded in the direction away from the target point with a smaller step size; otherwise, a larger step size is used, and the random tree is expanded rapidly toward the target point X_{goal}. Determine the expansion strategy for dynamic variable step size based on Eq. (6).

$$S=\begin{cases}\omega S_{min}\cdot(1+2\cos(\alpha)), & \alpha\le 90^\circ\\ \omega S_{min} \quad\quad\quad\quad\quad , & \alpha>90^\circ\end{cases} \tag{6}$$

2.3. Path Planning for the Intelligent Transfer Device

2.3.1. Path Node Reconnection Strategy Based on Safe Distance

The improved RRT algorithm, based on the above strategy, can plan a path quickly. However, the path contains redundant nodes, resulting in a significant number of turns. To solve this problem, a path node reconnection strategy based on a safe distance is proposed. The path connected by the dashed line in Fig. 1 is the path planned by the RRT algorithm without introducing the path node reconnection strategy. This path includes nodes from the initial node set Q_n = {Q_1, Q_2, Q_3, Q_4, Q_5, Q_6, Q_7, Q_8, Q_9} that are connected in sequence, with Q_1 and Q_9 as the start and end points, respectively. After introducing the path node reconnection strategy, the goal point Q_9 is designated as the root node of the random tree. Then, each node in the initial node set is connected sequentially based on Q_9 while collision detection is performed. The collision detection shows that the line segments Q_9Q_4, Q_9Q_3,

Q_9Q_2, and Q_9Q_1 all intersect with obstacles, except for the line segment Q_9Q_5, so node Q_5 is included in the optimized node set. Then, using node Q5 as the new starting point of the optimized node path, each node in the initial path node set is connected in turn, followed by a new round of collision detection. The result shows that there is no collision in the line segment Q_5Q_1, so the node Q_1 is added to the node optimization set. With the addition of the starting point Q1 to the optimized node set, the path node reconnection process is complete. Finally, the optimized node set {Q1, Q5, Q9} is connected sequentially to obtain the optimized path, as shown by the solid line in Fig. 1.

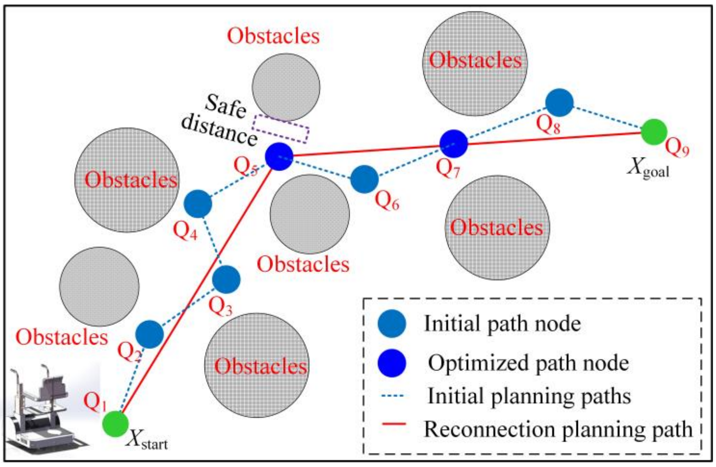


Figure 1. Schematic diagram of path node reconnection

2.3.2. Curve Optimization

The path consists of multiple line segments after node reconnection, with abrupt changes in course angle at the nodes. This does not meet the practical application requirements of the intelligent transfer device. Therefore, to make the curvature of the optimized paths continuous while retaining some of the straight paths, a cubic B-spline curve is used to fit the paths.

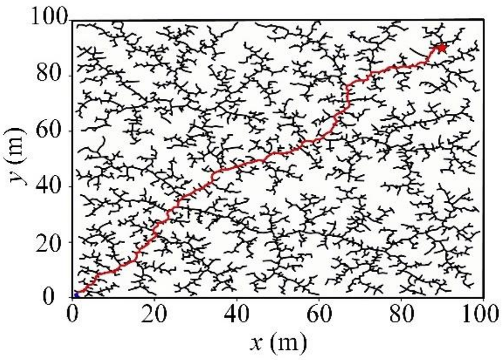
2.4. Flow of the Improved RRT Algorithm

The path planning algorithm for the intelligent transfer device based on the improved RRT algorithm consists of three parts: a sampling strategy that combines restricted region search and probabilistic target bias; a dynamic variable step size expansion strategy for the random tree; and a path node reconnection optimization and cubic B-spline curve fitting method based on the safe distance to obtain a smooth and collision-free path.

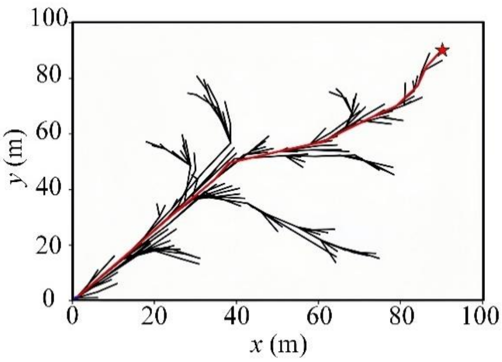
3. SIMULATION EXPERIMENTS AND ANALYSIS

3.1. Analyzing the Performance of Different Algorithms

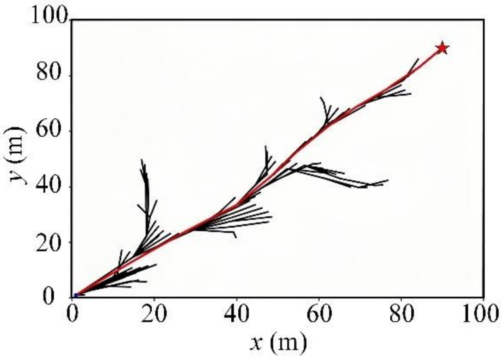
The traditional RRT algorithm, the RRT* algorithm, the informed RRT* algorithm, and the improved RRT algorithm in this paper are compared and analyzed in unobstructed, simple, and complex environments, respectively. Each algorithm performs 10 sets of experiments, and each set of experiments includes 50 times of path planning. The starting point of the path is set to (1, 1), the goal point is set to (90, 90), the initial step size and the safe distance D_{obs} are set to 1 m, respectively. The results of the path planning are shown in Fig. 2, Fig. 3, and Fig. 4.



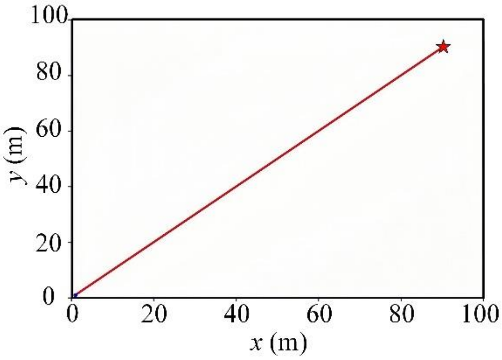
(a) Traditional RRT algorithm



(b) RRT* algorithm

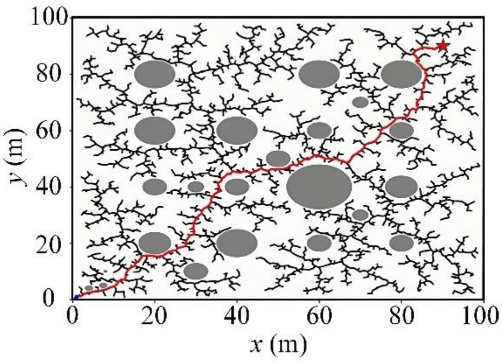


(c) Informed RRT* algorithm

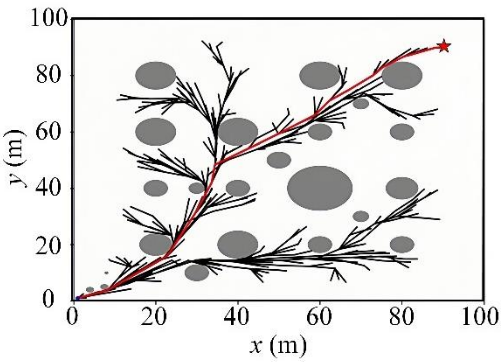


(d) Improved RRT algorithm

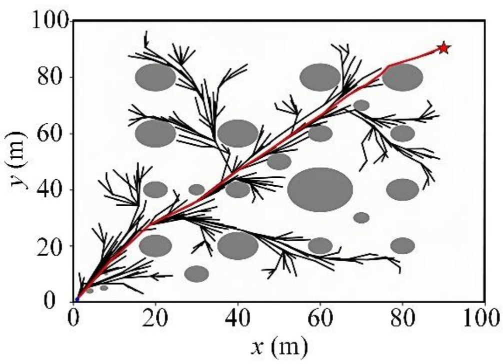
Figure 2. Path planning in unobstructed environment (red line)



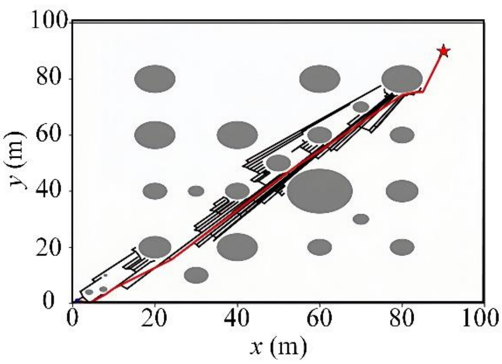
(a) Traditional RRT algorithm



(b) RRT* algorithm

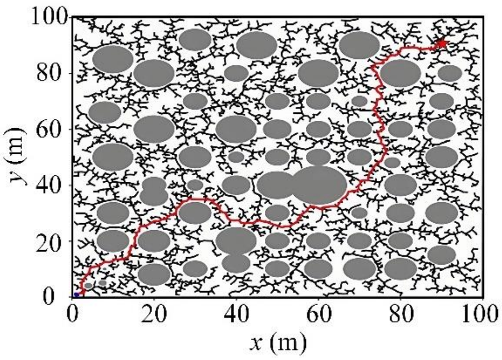


(c) Informed RRT* algorithm

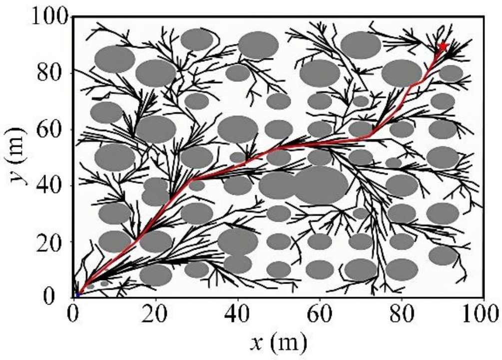


(d) Improved RRT algorithm

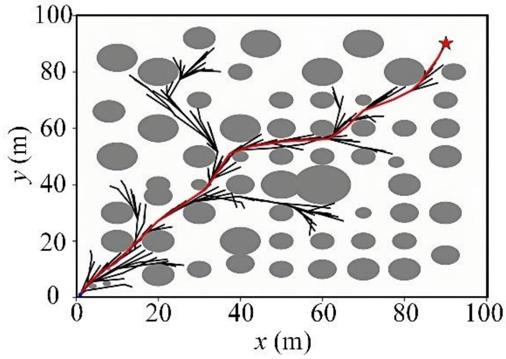
Figure 3. Path planning in simple environment (red line)



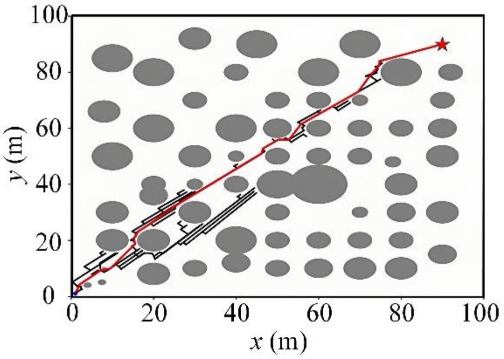
(a) Traditional RRT algorithm



(b) RRT* algorithm



(c) Informed RRT* algorithm



(d) Improved RRT algorithm

Figure 4. Path planning in complex environment (red line)

The proposed improved RRT algorithm is oriented, the number of path nodes is reduced, and the obstacle avoidance ability of the random tree expansion is improved compared to the traditional RRT algorithm, the RRT* algorithm, and the informed RRT* algorithm.

The analysis of the path search time for 500 * 3 experiments shows that the proposed algorithm can well reduce the path search time and improve the path planning efficiency, as shown in Table 1. In the three environments, the path search time of the Improved RRT algorithm is reduced by 99.96%, 99.16%, and 98.99% compared to the RRT algorithm; by 50%, 59.37%, and 75.31% compared to the RRT* algorithm; and by 50%, 56.66%, and 74% compared to the informed RRT* algorithm, respectively.

Table 1. Comparison of path search time in different environments

Environment type	Path search time /s			
	RRT	RRT*	Informed RRT*	Improved RRT
Unobstructed	32.12	0.02	0.02	0.01
Simple	31.1	0.64	0.6	0.26
Complex	38.91	1.58	1.5	0.39

The analysis of the number of iterations for the 500 * 3 experiments shows that the improved RRT algorithm reduces the number of iterations and improves the efficiency of path planning, as shown in Table 2. In the three environments, the number of iterations of the improved RRT algorithm is reduced by 97.48%, 93.06%, and 92.28% compared to the RRT algorithm; by 50.25%, 20.09%, and 5.43% compared to the RRT* algorithm; and by 50%, 6.04%, and 3.76% compared to the informed RRT* algorithm, respectively.

Table 2. Comparison of the number of iterations in different environments

Environment type	Number of iterations / times			
	RRT	RRT*	Informed RRT*	Improved RRT
Unobstructed	3968	201	200	100
Simple	4931	428	364	342
Complex	5635	460	452	435

4. CONCLUSION

In this paper, the improved RRT algorithm is used to achieve safe, accurate, and efficient path planning for an intelligent transfer device. Simulation experiments show that the proposed algorithm reduces the average search time by 99.70%, 61.56%, and 60.22%, and the average path length by 20.91%, 2.85%, and 2.17%, respectively, compared to the RRT, RRT*, and Informed RRT* algorithms.

ACKNOWLEDGMENTS

This work was supported in part by the Natural Science Key Project of Tianjin Municipal Education Commission Scientific Research Program (2022ZD026, 2022ZD032, 23YFYSHZ00280)

REFERENCES

[1] Cheng, Y.; Fang, Y.; Zheng, J.; Guan, S.; Wang, M.; Hong, W., The burden of depression, anxiety and schizophrenia among the older population in ageing and aged countries: an analysis of the Global Burden of Disease Study 2019. General Psychiatry 2024, 37, (1).

[2] Tan, C. S.; Mohd-Mokhtar, R.; Arshad, M. R., A Comprehensive Review of Coverage Path Planning in Robotics Using Classical and Heuristic Algorithms. Ieee Access 2021, 9, 119310-119342.

[3] Hakeem, A.; Gehani, N.; Ding, X. N.; Curtmola, R.; Borcea, C., Multi-Destination Vehicular Route Planning with Parking and Traffic Constraints. In Proceedings of the 16th Eai International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (Mobiquitous'19), 2019; pp 298-307.

[4] Kim, Y. N.; Ko, D. W.; Suh, I. H., Confidence random tree-based algorithm for mobile robot path planning considering the path length and safety. International Journal of Advanced Robotic Systems 2019, 16, (2).

[5] Chu, L.; Wang, Y.; Li, S.; Guo, Z.; Du, W.; Li, J.; Jiang, Z., Intelligent Vehicle Path Planning Based on Optimized A* Algorithm. Sensors 2024, 24, (10).

[6] Zheng, T.; Xu, Y.; Zheng, D., AGV Path Planning based on Improved A-star Algorithm. In 2019 IEEE 3rd Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), IEEE: Chongqing, China, 2019; pp 1534-1538.

[7] Wang, Y.; Jiang, W. S.; Luo, Z.; Yang, L.; Wang, Y. Q., Path planning of a 6-DOF measuring robot with a direction guidance RRT method. Expert Systems with Applications 2024, 238.

[8] Huang, Y. Z.; Wang, H.; Han, L.; Xu, Y. Q., Robot path planning in narrow passages based on improved PRM method. Intel Serv Robot 2024, 17, (3), 609-620.

[9] Li, H. L.; Qian, L. X.; Hong, M.; Huang, H. P.; Zhang, Y. X.; Yan, Q. L., Effective anti-submarine decision support system based on heuristic rank-based Dijkstra and adaptive threshold partitioning mechanism. Appl Soft Comput 2024, 161.

[10] Molinos, E. J.; Llamazares, A.; Ocaña, M., Dynamic window based approaches for avoiding obstacles in moving. Robot Auton Syst 2019, 118, 112-130.

[11] Elhoseny, M.; Tharwat, A.; Hassanien, A. E., Bezier Curve Based Path Planning in a Dynamic Field using Modified Genetic Algorithm. Journal of Computational Science 2018, 25, 339-350.

[12] Szczepanski, R.; Tarczewski, T.; Erwinski, K., Energy Efficient Local Path Planning Algorithm Based on Predictive Artificial Potential Field. Ieee Access 2022, 10, 39729-39742.

[13] Wang, J.; Li, J.; Song, Y.; Tuo, Y.; Liu, C., FC-RRT*: A modified RRT* with rapid convergence in complex environments. Journal of Computational Science 2024, 77.

[14] Hong, L.; Song, C.; Yang, P.; Cui, W., Two-Layer Path Planner for AUVs Based on the Improved AAF-RRT Algorithm. Journal of Marine Science and Application 2022, 21, (1), 102-115.

[15] Li, J.; Huang, C.; Pan, M., Path-planning algorithms for self-driving vehicles based on improved RRT-Connect. Transportation Safety and Environment 2023, 5, (3).