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Research on a Bidirectional RRT* Algorithm Integrating Multi-Strategy Sampling and Nonlinear Adaptive Step Size for Ship Path Planning

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Abstract. Addressing the issues of poor path quality, lengthy planning time, low efficiency, and excessively sharp turns in traditional RRT algorithms for ship path planning, this paper proposes a bidirectional Rapidly Expanding Random Tree (RRT) algorithm based on multi-strategy sampling and nonlinear adaptive stride. The algorithm replaces the single-tree expansion of traditional RRT with a dual-tree expansion and incorporates a nonlinear adaptive step size mechanism. This enables the algorithm to autonomously adjust step sizes based on the obstacle environment while mitigating the high randomness inherent in traditional RRT, resulting in more stable output. This paper employs a method that integrates multiple sampling strategies to address long planning time and planning efficiency. When sampling within the obstacle space, 10% of samples are taken directly at target points, 20% near target points, and 40% near the nearest tree node to the target. Through simulation verification on relevant experimental platforms, under identical environments, iteration counts, and consistent variables, the average of 10 experiments shows a 16.54% reduction in average planning time and a 19.69% reduction in average path length compared to the traditional RRT algorithm. Furthermore, considering the maneuverability constraints of actual ships, this paper introduces a minimum turning radius constraint and employs a chamfering method to handle sharp turning points. The improved algorithm achieves higher planning efficiency and superior path quality, and can be used as a reference for autonomous ship path planning.

Keywords: Unmanned ships; Bidirectional Rapidly Expanding Randomized Trees; Path planning; Adaptive stride.

1. Introduction

With the development of marine resources and the rapid advancement of intelligent shipping, unmanned ships have demonstrated significant application value in maritime emergency response, resource exploitation, and environmental monitoring[1]. The most critical capability of unmanned ships is autonomous path planning, which forms the foundation for their self-navigation.

Path planning, as one of the core technologies in fields such as mobile robots, unmanned ships, and autonomous driving, aims to find the optimal or near-optimal path for a mobile platform from its starting position to a target location within complex environments. To ensure unmanned ships can navigate complex and dynamic waters with high-quality routes, developing an efficient path planning algorithm that adapts to intricate aquatic environments while satisfying ship kinematic constraints is crucial.

In recent years, many scholars have made a lot of optimizations to a variety of algorithms for path planning. Among them, Li et al. [2] proposed an RRT algorithm with adjustable probability and sampling area, and an RRT algorithm based on Dijkstra optimization for the problems of low planning efficiency, high randomness, and poor path quality of the RRT algorithm. Still, the algorithm did not combine with the kinematic characteristics of the ship (such as the minimum turning radius), which makes it difficult to apply directly to unmanned ship path planning. Xia

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Haotian et al. [3] improved the path planning method based on the A* algorithm by adjusting the weights of the cost function, which improved the safety of path planning, shortened the path length, and reduced the flight cost. Liu et al. [4] carried out an in-depth study on the algorithmic efficiency of the ship's trajectory planning problem. They put forward an intelligent trajectory planning algorithm based on the adaptive step length notification RRT*. Zhai et al [5] proposed an improved sparse A* algorithm for the problems of excessive node expansion and failure to consider the current ship state and parameters that are common in traditional path planning algorithms. Wang et al. [6] proposed a fusion algorithm based on improved RRT and A* for the shortcomings of the rapidly expanding random tree (RRT) algorithm and the A* algorithm in global path planning for substation inspection robots. Zhongwan Tan et al. [7] proposed an improved RRT-Connect algorithm for the problems of low path planning efficiency, poor obstacle avoidance, and poor quality of generated paths in complex environments. Feng Zepeng et al. [8] proposed an improved A* algorithm combined with the artificial potential field method for path planning in complex environments with limited search efficiency and insufficient dynamic obstacle avoidance capability. Lin et al. [9] proposed an improved A*algorithm combining prediction strategy, redundant inflection point elimination strategy, and inflection point cost function to reduce the length of the path, the inflection points, and the turning angles. Tan et al. [10] proposed an improved RRT-Connect algorithm to reduce the length of the path, the inflection points, and the turning angles. Ganesan et al. [11] proposed a hybrid sampling-based path planning method, hybrid RRT*, to address the limited sampling nature of RRT. An et al [12] improved the A* algorithm by optimising the computation of the movement cost, which enabled the algorithm to integrate environmental data more efficiently. Yang et al. [13] proposed a method that combines the A-star search algorithm (A*) and the Artificial Potential Field method (APF) synergistically. Wang et al [14] proposed an improved path planning algorithm based on the combination of A* and DWA in response to the problem that global planning algorithms are unable to avoid unknown moving and static obstacles and that local planning algorithms are prone to fall into local optima in large-scale environments.

Totally, scholars have made numerous improvements to path planning algorithms for ships. However, few scholars optimise the path quality and planning time while considering the practical application of ships. The current path planning algorithms for ships must consider their practical ship availability. Therefore, this paper proposes a two-way fast expanding random tree algorithm with the addition of the minimum turning radius restriction to consider these problems. After the relevant experimental platform simulation verification, the algorithm not only optimises the path quality and planning time, but also meets the requirement of the minimum turning radius, and the handling of sharp turning points shows a good effect. Compared with the traditional RRT algorithm and some previous scholars' optimised algorithms, the innovative algorithm proposed in this paper has a better optimisation effect on path quality.

2. Improvement of RRT(Rapidly Exploring Random Tree) Algorithm

2.1 Two-Way Asymptotically Optimal Strategy

The traditional Rapidly-Exploring Random Tree algorithm ends the generation of the random tree after finding a path due to its random nature. In order to solve this problem, this paper introduces the RRTstar algorithm, which allows the random tree to continue generating after a path is found, and iterates until it reaches the upper limit of the number of iterations or the iteration time, to find a more optimal path. However, the introduction of the RRT* algorithm also brings a problem: due to the increase in the number of iterations, the time has increased a lot accordingly. To address the issue of excessive time consumption, this paper adopts the method of Bidirectional Expanding Random Trees to reduce the duration of path planning. The traditional RRT algorithm generates a random tree from the starting point and then continuously expands it to the end point. However, we consider the end point the starting point and generate a random tree for expansion, so

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the two random trees are expanded simultaneously to reduce the time of path planning greatly. The principle of the bidirectional extended random tree is shown in Fig 2.1.

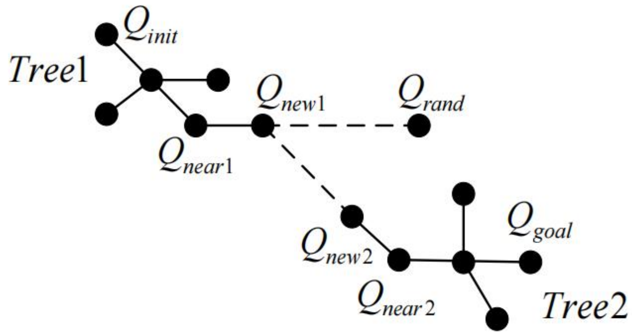

Fig2. 1 Schematic diagram of bi-directional fast expanding random tree connection

First, extend Tree1 starting from the starting point Q_{init} and generate a random sampling point Q_{rand} in the state space. Then select the nearest extended node Q_{near1} to the root node. Find an extendable collision-free node Qnew1 on the line connecting Q_{near1} and Q_{rand} according to a fixed step size. Then start extending Tree2 with Q_{goal} as the root node, and take Q_{new1} as a temporary goal point, find the nearest node Q_{near2} to Q_{new1}, and then find an extendable collision-free node Q_{new2} on the connecting line between the two according to a fixed step size. In the iterative process, the two trees expand to each other similarly, and finally, the bidirectional random trees meet.

According to Fig. 2.2-Fig 2.4 and Table 2.1, the current two-way RRT* algorithms have improved significantly in terms of time and path quality.

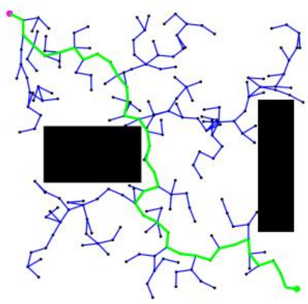

Fig2. 2 RRT

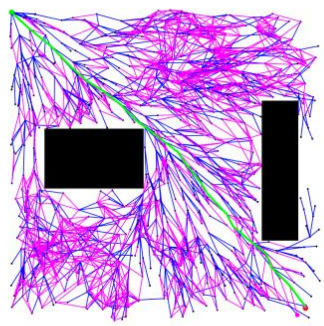

Fig2. 3 RRT*

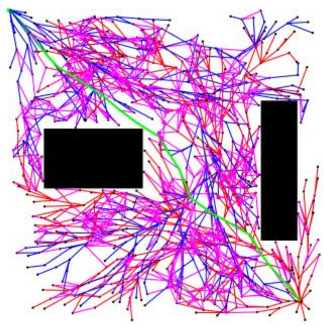

Fig2. 4 Bidirectional RRT*

Table2. 1 Comparison of algorithms

Numble	times	Number of nodes	route cost
RRT	10.28s	35	1347.86
RRT*	14.16s	21	1102.02
BIRRT*	8.58s	20	1082.45

2.2 ForwardNearestRRT Sampling Strategy

At present, the existing improved RRT algorithms adopt the method of scattering random sampling points across the entire map when searching for the optimal path. However, it is obvious that areas far from the path do not require point scattering. Therefore, this paper considers scattering points only where necessary to enable the random tree to be generated purposefully—specifically, to make the random tree grow toward our target point. In the context of the bidirectional extended random tree in this paper, each endpoint is the target point of the other. Therefore, this paper introduces the strategy of F (forward) N (nearest neighbour) RRT multiple sampling combinations. In this paper, the combination of multiple sampling strategies of FNRRT is used instead of the pure random sampling of traditional RRT. In this study, multiple different parameters are set for

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comparison to find the optimal parameter tuning combination. As shown in the Table2.2, this study selects three groups of parameters for a control experiment and conducts the experiment ten times to take the average value. From the data in Table 2.2, it can be seen that this group of parameters has a short planning time and a low path cost. Therefore, 10% probability is set to sample the target point directly, 20% probability is sampled near the target point, 40% probability is sampled near the node closest to the target, and the remaining 30% is still taken as traditional uniform random sampling.

Table2. 2 Comparison of Various Data

Numble	Planning time	Path length
10%，10%，20%	18.11	878.19
10%，20%，40%	6.51	865.73
10%，15%，30%	12.25	872.37

2.3 Adaptive Step Size

Since the expansion step size of the random tree is fixed, the random tree is expanded with a constant step size even in some areas far from obstacles. Therefore, if the step size can be reduced when approaching obstacles to ensure safety, while increased when far from obstacles to improve efficiency, this would be beneficial. For this reason, this paper introduces an adaptive step size mechanism.

In a previous experimental study, this paper did two sets of function algorithms for adaptive step-size mechanisms, one linear and the other nonlinear, due to the uncertainty of how the algorithm path planning will work within the limitations of the two functions. Therefore, in this paper, two kinds of functions are introduced. The three weight factors of both are set to 20%, 30%, and 50%, and other related variables are also kept consistent. Five experiments were conducted respectively with the help of relevant simulation experiment platforms. The experimental results are shown in Fig2.5. It can be clearly observed that the stability of the planning time and path length of the nonlinear adaptive step is better, and the path length of the nonlinear adaptive step is optimised by 2.2% compared with that of the linear adaptive step. Although it is slightly inferior in terms of planning duration, the stability of "generally consistent results" is a key prerequisite for real-ship applications. If the planning results vary greatly each time, crew members or control systems will be unable to predict the ship's navigation trajectory and time consumption, which will lead to operational risks. Therefore, this paper adopts a nonlinear adaptive step size mechanism based on power functions.

Because the weighting factor is not easy to determine, this paper uses three sets of data, each comprising ten tests, and their average value as a control to select the most appropriate weighting factor.

Table2. 3 Comparison of Various Data

Numble	Planning time	Path length
30%，30%，40%	10.35	911.29
20%，20%，60%	9.39	900.22
20%，30%，50%	9.42	906.68

From the data in the figure, the best results are obtained when the goal_factor goal orientation factor is 0.2, the start_factor starting point influence factor is 0.2, and the obstacle_factor obstacle safety factor is 0.6.

$$F\_goal = \min\left(1, (d\_goal/R\_goal)^\wedge p_{goal}\right) \quad (2\text{-}1)$$

$$F\_start = \max\left(0.1, 1-(d\_start/R\_start)^\wedge p\_start\right) \quad (2\text{-}2)$$

$$F\_obs = \min\left(1, (d\_goal/R\_obs)^\wedge p\_obs\right) \quad (2\text{-}3)$$

$$F\_adaptive = w\_goal \times F\_goal + w\_goal \times F\_start + w\_obs \times F\_obs \quad (2\text{-}4)$$

$$\delta = \delta\_min + F\_adaptive \times (\delta\_max - \delta\_min) \quad (2\text{-}5)$$

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Eq. 2-1 is the formula to control the influence of the node distance from the target point, and its purpose is to approach quickly with a large step size when far away from the target, and to control accurately with a small step size when close to the target. Eq. 2-2 controls the influence of the node's distance from the starting point, to ensure a smooth start with a small step size when approaching the starting point, and to gradually increase the step size when moving away from the starting point. Eq. 2-3 controls the effect of the node's distance from the nearest obstacle, to advance cautiously with small step lengths when approaching the obstacle, and move quickly with considerable step lengths when moving away from the obstacle. Eq. 2-4 combines adaptive factors, and Eq. 2-5 is the formula for the final step size.

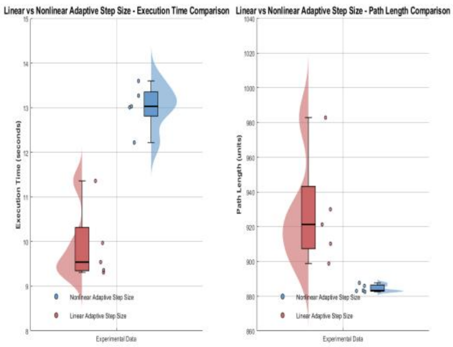

Fig2. 5 Data cloud and rain charts

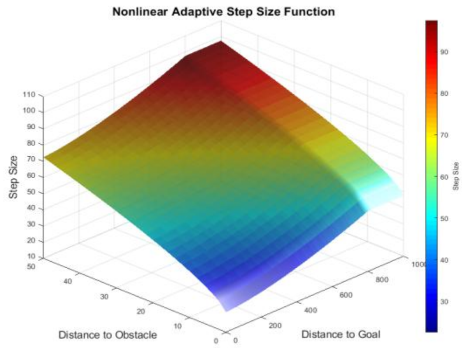

Fig2. 6 3D schematic of the final step size

Here is the pseudo-code involving multi-strategy sampling with adaptive step size.

1: r ← random(0,1)
2: if r < 0.1 then x_rand ← goal
3: else if r < 0.35 then x_rand ← goal + randomOffset()
4: else if r < 0.6 then x_rand ← nearestToGoal(T) + offset
5: else x_rand ← randomPoint(mapBounds)
6: x_near ← findNearest(T, x_rand)
8: dist_goal ← distance(x_near, goal); dist_obs ← nearestObstacle(x_near, MAP)
9: factor ← w_1×(dist_goal/$range_1$)^p_1 + w_2×(dist_obs/$range_2$)^p_2
10: delta ← minStep + factor×(maxStep - minStep)
11: x_new ← x_near + delta × normalize(x_rand - x_near)

2.4 Minimum Turning Radius Limit and Path Smoothing

Considering the practical application of unmanned ships, it is difficult for unmanned ships to execute large turns, so this paper restricts the minimum turning radius. In addition, the paths planned by existing algorithms all have sharp corners for turns. Therefore, we need to smooth the corner sections to enhance the practicality of this paper's proposed method. In this paper, two path smoothing methods are used. The first method starts from the starting point, checks each path point one by one, and for each point, searches backward for the farthest point that can be directly connected—while ensuring that the reconnected path meets the requirements of collision detection and turning radius constraints. The second method is arc chamfering smoothing. First, it detects the sharp corners in the path, and then replaces the sharp linear corners with arcs.

3. Simulation analysis

3.1 Path Planning In Complex Environments

This paper takes the path planning approach in a real nautical chart to verify the possibility of applying the improved RRT algorithm in a real environment. The map construction problem is the

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basis for the study of path planning, and its core lies in transforming the actual map model into an abstract model in digital space. Standard map construction methods include raster and geometric methods.

This paper uses the raster method for map construction. Its core technical points:

(1) Colour space conversion: RGB to HSV, easy to distinguish between different waterway elements

(2) HSV-based land recognition: using hue (H), saturation (S), brightness (V) thresholds to extract land

(3) Morphological optimisation: expansion, filling, erosion operations to eliminate noise and smooth the boundary

(4)Raster representation: binary map (land=1, water=0) to provide input for path planning algorithms

Since the superiority of this algorithm has been initially verified in a simple rectangular obstacle map in the early stage, a certain area of Tianjin Port is selected as the current path planning obstacle environment for this chart, with large obstacles manually added. In order to further verify the advantages of the improved RRT algorithms in this paper, 20 experiments were conducted in each of the narrow and complex map environments using the RRT* algorithm and BIRRT* algorithm, as well as the improved RRT algorithm incorporating the FN sampling strategy and the adaptive step size, respectively, while keeping the relevant variables consistent. The schematic diagrams of the operation results of each algorithm are shown in Fig3.1–3.3. In Fig3.3, the area with dense random tree expansion has been enlarged. This is because the FN sampling strategy has a 20% probability of sampling near the target point, which enables the random tree to expand extensively around the target point. Consequently, the path can be found more quickly, reducing the planning duration.

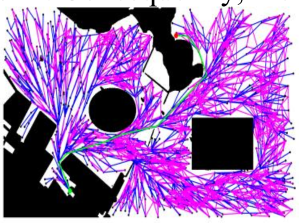
Fig3. 1 RRT*

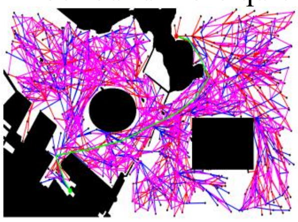
Fig3. 2 Bidirectional RRT*

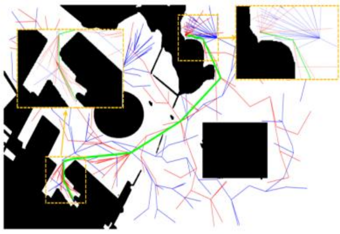
Fig3. 3 Improve RRT

Table3. 1 data comparison

arithmetic	times	route cost
RRT*	17.02s	902.58
BIRRT*	12.30s	898.36
Improvement of RRT	8.31s	877.70

From Table 3.1, the Bidirectional RRT algorithm is optimised in time by 27% compared to the Unidirectional RRT algorithm under the same constraints. Since there is only a difference between unidirectional and bidirectional, there is no significant difference regarding path cost. The improved RRT algorithm in this paper optimises by 32% in time compared to the Bidirectional RRT* algorithm. Due to the limited scope of this map, there is no significant change in the path cost. However, an optimization of 2.3% has still been achieved under these limited conditions.

3.2 Minimum Turning Radius And Corner Rounding

Since this paper is based on the improved algorithm for unmanned ships, considering the actual operation of the boat, the path shown above has a large corner, and part of the real ship can not be covered, so we need to add the minimum turning radius limit and the corner part for rounded processing. In addition, the processed corners should meet the minimum turning radius requirements. Next, the improved algorithm proposed in this paper is used to conduct experiments with turning radius constraints of 30m, 60m, and 90m respectively, so as to observe the path quality.

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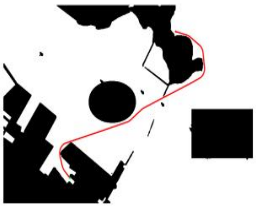

Fig3. 4 R=30m

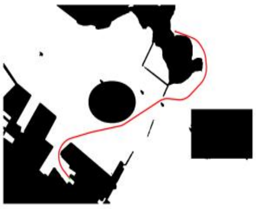

Fig3. 5 R=60m

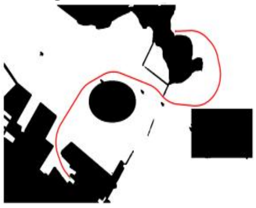

Fig3. 6 R=90m

As shown in Fig. 3.4-Fig. 3.6, the improved algorithm in this paper still has good planning ability under the constraint of minimum turning radius, which effectively solves the "kinematically infeasible" and "trajectory unsmooth" problems of the traditional RRT algorithm.

4. Summary

In this paper, an improved RRT algorithm based on unmanned ships is proposed, and the core innovations of the algorithm are embodied in four aspects: dual-tree expansion, multi-strategy sampling, nonlinear adaptive step size, and minimum turning radius constraints with circular chamfer smoothing. Simulation analysis is carried out using the relevant experimental platform. The results show that the average planning time of the improved RRT algorithm is shortened by 16.54%, 51.18% and 32.44% for the comparative RRT* and Bidirectional RRT*, respectively. The average path length is shortened by 19.69% compared with the pre-improvement period. Meanwhile, the number of nodes and turning points is significantly reduced. Meanwhile, high-quality paths can still be planned under multiple minimum turning radius restrictions.

In summary, the improved RRT algorithm proposed in this paper provides new ideas for studying the path planning problem of unmanned ships in the harbour environment and has specific practical application value.

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