CSM-RRT*: an improved RRT* algorithm based on constrained sampling mechanism

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Abstract

The Rapidly Exploring Random Tree Star (RRT*) is recognized as a better path planning algorithm, but its path quality and path planning speed still have room for improvement. In this paper, an improved RRT* algorithm(CSM-RRT*) based on constrained sampling mechanism is proposed .The entire planning process is divided into two steps: fast exploration and optimization of the initial path. Subsequently, a dynamic sampling region consists of removed redundant nodes and collision nodes is formed around initial path By prioritizing exploration within this dynamic region, computational resources can be saved and the asymptotic optimal path can be quickly converged from the initial path. Eventually, simulation results presented in various obstacle environments confirm the efficiency of CSM-RRT*.

Keywords: Path planning, RRT*, Constrained sampling mechanism, Dynamic sampling region

1. Introduction

Rapidly-exploring Random Tree(RRT) is a sampling- based algorithm. Many scholars have conducted research on it. To further improve the speed of the RRT, a double-tree algorithm RRT-Connect [1] makes the target tree and the start tree grow alternately. To improve the path quality, RRT* [2] conducts the process of parent node selection and Rewire for the samples. As the number of nodes increases, the path gradually optimizes, but this process will consume a lot of time.In order to plan the best possible path within the same time, Informed RRT* [3] adopts an elliptical heuristic domain sampling method and continuously shrinks the elliptical region.In order to reach an optimum or near optimum solution at a much faster rate, Smart-RRT* [4] accelerate the rate of convergence. In addition, P-RRT* [5] incorporates the artificial potential field in RRT* to provide transcendental information for the path.Quick-RRT* [6] enlarges the set of possible parent vertices, which generates a better initial solution and converges to the optimal faster than RRT*.PQ-RRT* [7] combines the P-RRT* with the Quick-RRT* to generate better initial solutions.

Further research on path quality and planning speed of the RRT* has specific significance for solving the problem in complex constraints. Based on constrained sampling mechanism ,this paper proposes an improved RRT*algorithm, CSM-RRT*.By comparing with other algorithms, effectiveness of the proposed algorithm is verified.

2. CSM-RRT*

This section introduces the strategies of the CSM-RRT*, including the following aspects: ChooseParent, Rewire and constrained sampling mechanism.

2.1. *Constrained sampling mechanism*

2.1.1. Node saved strategy

The regional exclusion mechanism(Fig.1) was proposed, in which random sampling points were eliminated in a circular area of the node to ensure the sparsity of the entire tree and improves the exploration efficiency.

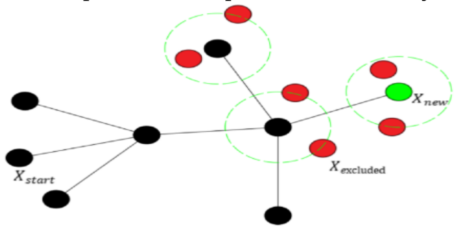
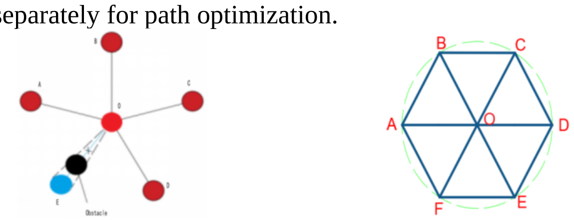


Fig.1 regional exclusion mechanism.

X_{start} represents the initial node, X_{goal} represents the target, $X_{excluded}$ represents the nodes abandoned by the regional exclusion mechanism, and the circular dashed line represents the size of the exclusion region.

However, the x_{rand} was eliminated rather than x_{new} .Additionally, this method only focuses on the sparsity of the entire tree, without considering the sparsity of individual node. To address this issue,regional exclusion mechanism and node saved strategy are combined and applied to the path planning of the manipulator, ensuring the sparsity of both the entire tree and individual sub-node. The results proved to have good effect.

As shown in Fig.2, after adopting the region exclusion mechanism, the parent node O can extend 6 nodes if the exclusion radius r is equal to step size, and the distance between each node is equal to the step size. However, in general, the distance of each node is greater than the step size, when a parent node extends 4 nodes. For a node, we can record the number of expansions and collisions. And the constraint condition is set to 5 times. When the sum of the number of extensions and collisions reaches 5 times, it means that the node has been expanded, or there are a lot of obstacles around it, and it is difficult to continue to expand. In this case, we can save itself to ensure that the next sampling node will not appear in the vicinity again. At the same time, the redundant nodes of the regional exclusion mechanism will also be saved separately for path optimization.



(a)Node extension range (b) collision detection failed node

Fig.2 Node saved strategy

2.1.2 Dynamic sampling region

As shown in Fig.3, after the initial path planning is completed, each node in the path has an exclusion region, which contains a large number of redundant nodes and collision points. For path optimization, the main goal of path optimization is to obtain an optimal or asymptotic optimal path.In general, an optimal path can only be obtained when the path is close enough to the obstacle.Therefore, redundant and collision nodes close to the initial path should be employed to concentrate on meaningful areas, while discarding nodes with higher path costs.Starting from the node closest to the endpoint, the nodes with the lowest path cost in the dynamic sampling domain are selected to continuously improve path quality. The initial path quickly converges to the optimal path through cyclic iteration.

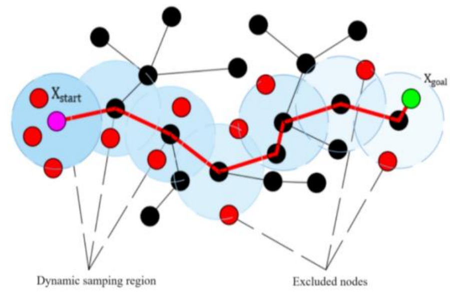
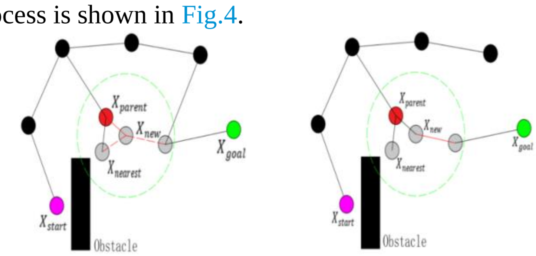


Fig.3 Dynamic sampling region

With further optimization of the path, dynamic region will change and contain many nodes. Nodes in dynamic regions can be included multiple times, resulting in increased runtime. To accelerate exploration, hash table is used. In other words, even if a node is included in the exclusion region many times, its distance to the starting point only needs to be detected once, and the result is saved and used directly later to avoid repeated distance detection.

2.2. *ChooseParent and Rewire*

RRT* sets X_{near} within a certain radius range of the new node and as candidate parent nodes and candidate child nodes during ChooseParent and Rewire.The process is shown in Fig.4.

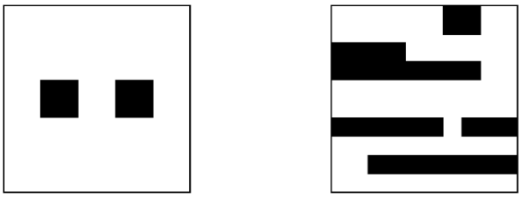


(a)chooseParent (b)Rewire

Fig.4 Process of ChooseParent and Rewire.

3. Simulation results and Analysis

In order to ensure the reasonability of the statistical results, 50 sets of valid data are gotten for each algorithm when comparing each indicator. The experimental environment is shown in Fig.5.



(a) (b)

Fig.5 Simulation environment (a)Simple environment (b)Cluttered environment. The entities are obstacles

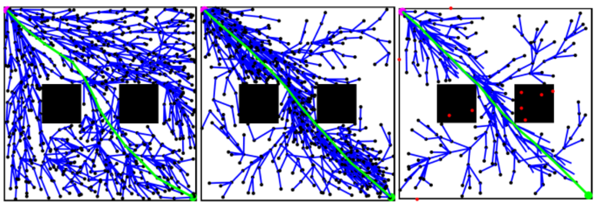
The results are compared in four directions: initial path planning time T_{init}, the suboptimal path planning time $T_{5\%}$, the initial path cost C_{init} and the suboptimal path cost C_{cost}.

3.1. *Compare of algorithm convergence speeds*

The convergence speed of the algorithm is compared by $T_{init}$and $T_{5\%}$.

3.1.1 Simple environment

Fig.6 shows the path planning results of the three algorithms in the simple environment, and Table 1 shows the average value of T_{init} and $T_{5\%}$.



(a) (b) (c)

Fig.6 Path planning results in the simple environment (a) RRT*; (b)Informed-RRT*;(c) CMS-RRT*

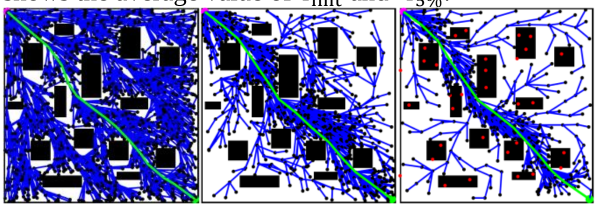
As shown in Table 1, in terms of $T_{5\%}$,the CMS-RRT * algorithm respectively saved 2.3 seconds and 1 seconds compared to RRT * and Informed-RRT*. The initial path planning speed is 2.5 times faster than the RRT* algorithm. Considering the impact of time saved by the initial path, the CSM-RRT * algorithm did not show significant performance in path optimization in simple environments.

Table1.Average of T_{init} and $T_{5\%}$ of the two algorithms in the simple environment

Algorithm	RRT*	Informed-RRT*	CSM-RRT*
Average(T_{init}/s)	2.93	1.72	0.84
Average($T_{5\%}$/s)	5.46	3.23	1.56

3.1.2 Cluttered environment

Fig.7 shows the path planning results of the three algorithms in the cluttered environment,and Table 2 shows the average value of T_{init} and $T_{5\%}$.



(a) (b) (c)

Fig.7 Path planning results in the cluttered environment (a) RRT*; (b)Informed-RRT*; (c) CSM-RRT*

As shown in Fig.7 and Table 2, it can be seen that as the map becomes more complex, the initial path search efficiency of the CSM-RRT * algorithm is not as significant as in a simple environment.However, its path optimization performance is still much better than other algorithms, with an optimization speed increased by 2~5 times.The CSM-RRT* algorithm only samples around the initial path, rather than the entire environment, avoiding path optimization in invalid areas and ensuring fast convergence to the asymptotic optimal path.

Table2.Average of $T_{init}$and $T_{5\%}$ of the two algorithms in the cluttered environment

Algorithm	RRT*	Informed-RRT*	CSM-RRT*
Average(T_{init}/s)	4.64	2.76	1.58
Average($T_{5\%}$/s)	12.93	5.02	2.58

3.2. *Compare of path quality*

The path quality of the algorithm is compared by C_{init}, C_{cost} .At the same time, in order to avoid similar simulation results, the number of algorithm iterations is set to 2000 for the convenience of viewing algorithm differences.

3.2.1 Simple environment

It can be seen from Table 3 that the path quality of CSM-RRT * is not the beset among all initial paths.This is mainly because the region exclusion mechanism and node preservation strategy in the CSM-RRT * algorithm focus more on fast exploration of the initial path.

However, the final path cost of CSM-RRT * algorithm remains minimal, proving that CSM-RRT * is superior to other algorithms.

Table3.Average of C_{init} and C_{cost} of the two algorithms in the simple environment

Algorithm	RRT*	Informed-RRT*	CSM-RRT*
Average(C_{init})	712.06	707.58	716.84
Average(C_{cost})	703.85	697.59	692.21

3.2.2 Cluttered environment

In order to verify the stability of the algorithm, 50 repeated experiments were conducted on algorithms, and the final path cost simulation results(Fig.8) of the three algorithms in cluttered environments were obtained.

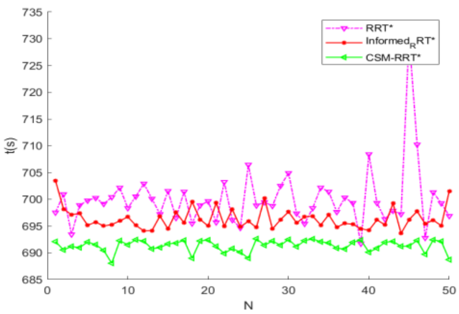


Fig.8 Path cost results in the cluttered environment

As shown in Fig. 8, the final path cost of the CSM-RRT * algorithm is much lower than those of the other algorithms, and the fluctuation between each path result is very small, indicating stable optimization ability. The performance indicates that with a limited iterations, the CSM-RRT* algorithm can quickly converge to the optimal path from initial path every time.

4. Conclusion

This paper proposes an improved RRT* algorithm, CSM-RRT*, which has some advantages in planning speed of initial path, convergence speed and path quality. The main idea of the CSM-RRT* algorithm is to remove and record the redundant nodes and collision points, control the direction of path growth and optimize paths in dynamic sampling region. Compare RRT* and Informed-RRT*,it is verified that the CSM-RRT* algorithm has good applicability to both simple and cluttered environments.

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