A high-performance motion planning method based on asymptotically optimal RRT

Tianbin Meng
School of Mechanical and Electronic Engineering, Beijing Jiaotong University
Beijing, Haidian District, China

Jiwu Wang
School of Mechanical and Electronic Engineering, Beijing Jiaotong University
Beijing, Haidian District, China
E-mail: mengtianbin888@163.com, jwwang@bjtu.edu.cn
www.bjtu.edu.cn

Abstract

The motion planning algorithm of the robot arm plays an important role in the working process of the robot arm, especially in the complex environment, an efficient algorithm is more conducive to the robot arm to complete the corresponding planning task. Aiming at the problems such as low exploration efficiency and poor planning path in the current motion planning task of robotic arm, we propose a distance constraint mechanism. Based on $RRT^*$and $Informed-RRT^*$, the algorithm uses halton sequence to generate random points and introduces the current lowest cost path length. To avoid useless nodes extension. The simulation results show that the algorithm with distance constraint mechanism can improve the exploration efficiency and planning quality to some extent.

Key words: mechanical arm, Motion planning, Distance constraint, Improved RRT^*algorithm, halton sequence

1. Introduction

The robot arm has changed from the original rough industrial production equipment to today's multi-disciplinary industrial automation equipment, entering all corners of society, showing the powerful role of the robot arm. At the same time, higher requirements are also put forward for the motion planning of the robotic arm. Therefore, the study of the motion planning of the robotic arm has important engineering value [1], [2].

At present, there are four main types of path planning methods for robotic arms: graph search-based algorithm, artificial potential field method, random sampling method and deep reinforcement learning method [3]. The algorithm based on graph search needs to be discretized in the whole planning space, so it is not suitable for the space with higher latitude. The artificial potential field method is easy to make the manipulator fall into the local minimum under the influence of the influence field, and the efficiency is greatly reduced. Methods based on deep reinforcement learning also have problems of poor process interpretability and stability [4].

The method based on random sampling is one of the most common methods for path planning of manipulators. Its core idea is to replace the complex actual planning space by the simple planning space obtained by sampling, so as to reduce the space complexity. the method based on random sampling is efficient and suitable for high-dimensional space. Lavalle [5] proposed a classical RRT algorithm, which has strong exploration ability and probability completeness, but cannot guarantee the optimal solution and a large number of unnecessary waypoint searches. Frazzoli [6] proposed RRT^* on the basis of RRT, which is an algorithm with asymptotic optimality. Compared with RRT, it adds two processes of re-selecting parent nodes and rewiring, Therefore, an optimal or suboptimal path can be found. Gammell [7] improved on the basis of RRT^* and proposed the $Informed-RRT^*$ algorithm. The principle is that after finding the first feasible solution, the subsequent sampling range is limited to a high-dimensional ellipsoid determined by the cost of the feasible solution. The convergence speed of RRT^* is improved.

To sum up, in order to solve the problem of low efficiency and too many redundant nodes in the RRT^* computing planning. In this paper, a distance constraint mechanism is introduced to improve RRT^* and $Informed-RRT^*$, which can greatly reduce the search and expansion of unnecessary waypoints and plan a high-quality path.

2. Methodology

2.1. Random tree growth distance constraint mechanism

RRT^* algorithm has asymptotic optimality, but the random number growth in the sampling process has a strong blindness, thus reducing the efficiency of the algorithm. $Informed-RRT^*$ Although the sampling points can be limited to an ellipse, the expansion of random trees within the ellipse is still blind. Therefore, this paper proposes a distance constraint mechanism, which introduces the current lowest cost path length. When the random tree is extended, the minimum actual cost to reach the new node is calculated plus the Euclidean distance from the new node to the end point. If the estimated distance is greater than the current lowest cost path length, the new node will not be extended, which increases the search efficiency of the algorithm to a certain extent. A condition that determines whether a new node can be expanded:

$$g_T(x_{new}) + \hat{h}(x_{new}) < c_{best} \quad (1)$$

Where $g_T(x)$ represents the minimum actual cost from the starting point to the new node, $\hat{h}(x)$ represents the Euclidean distance from the new node to the end point, and c_{best} is the current lowest cost path length.

Similarly, the current lowest cost path length is also introduced in the process of rewiring in random trees. When a new node is selected as the parent node at a certain point in the neighborhood, if the minimum actual cost to reach the point plus the Euclidean distance from the point to the end point is greater than the current lowest cost path length, the parent node of the node will not be replaced. A condition that determines whether a node in the neighborhood can replace the parent node:

$$g_T(x_{new}) + ||x_{new} - x_{near}|| + \hat{h}(x_{near}) < c_{best} \quad (2)$$

Where $||x_{new} - x_{near}||$ indicates the Euclidean distance between x_{new} and x_{near}.

2.2. Random sampling point optimization strategy

RRT^* and $Informed - RRT^*$ algorithms have the problem of poor uniformity in the random sampling of points in space, so the space cannot be explored more fully. A random point sampling method based on halton sequence is proposed for reference to halton sequence. Random sampling method (Fig.1) and halton sequence-based sampling method (Fig.2) are shown in the figure below.

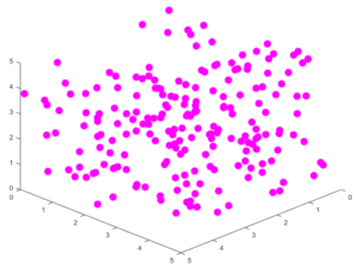


Fig.1 Random sampling method

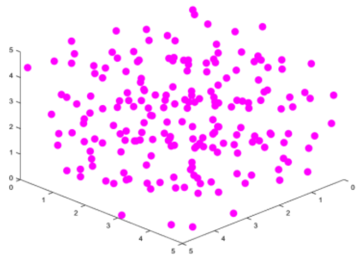


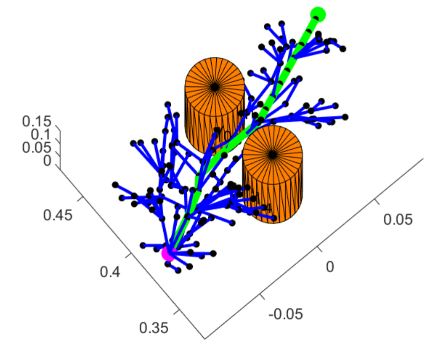
Fig.2 Sampling method based on halton sequence

It can be observed that the sampling points in the upper left part of Fig. 1 are sparse, while the middle part is dense. In Fig. 2, the distribution of sampling points is more uniform, thus improving the ability to explore the space.

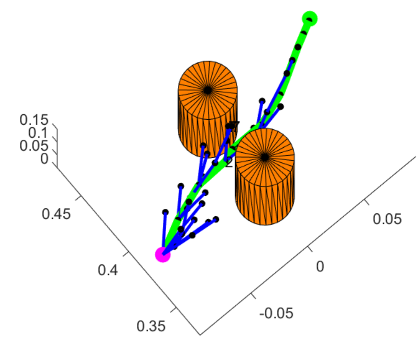
3. Algorithm simulation analysis

In order to verify the validity of the distance constraint mechanism, the RRT^*, $Informed - RRT^*$ and the improved $DC - RRT^*$ and $DC - Informed - RRT^*$ are simulated and analyzed experimentally in a three-dimensional environment.

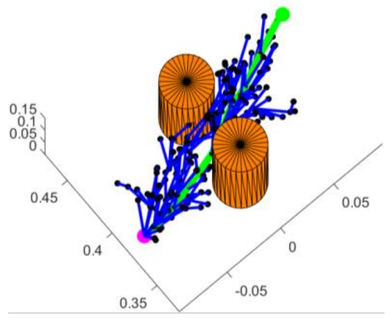
In MATLAB, simulation experiments in simple and complex obstacle avoidance environments are set respectively. The simulation environment was set to the three-dimensional space of $[0.2 \times 0.12 \times 0.2]$, the search starting point was $[-0.09\ 0.37\ 0.1]$, the target point was $[0.09\ 0.43\ 0.1]$, the exploration step was 0.01, and the number of iterations was set to 100 to reduce the randomness of the algorithm. The experimental results are shown in the figure and table below.



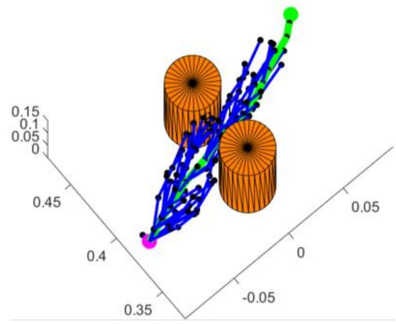
a. RRT^* algorithm tracing



b. $DC - RRT^*$ algorithm tracing



c. $Informed - RRT^*$ algorithm tracing



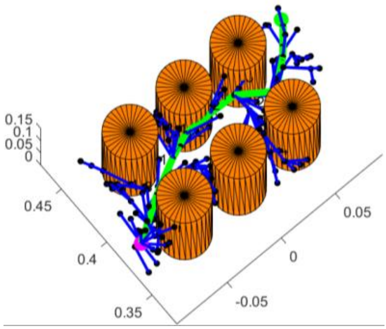
d. $DC - Informed - RRT^*$ algorithm tracing

Fig.3 Algorithm tracing in 3D simple scenes

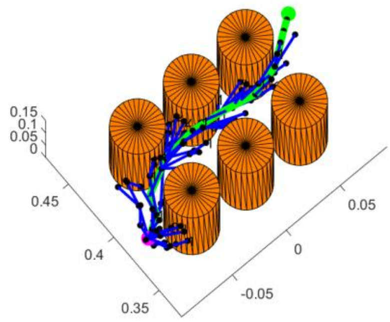
Table 1. Performance comparison of algorithms in 3D simple scenes.

algorithm	average path length /m	average running time /s	Node usage /%
RRT^*	0.2042	6.67	6.62%
$DC - RRT^*$	0.1934	5.41	10.96%
$Informed - RRT^*$	0.1930	8.42	6.38%
$DC - Informed - RRT^*$	0.1906	5.72	12.31%

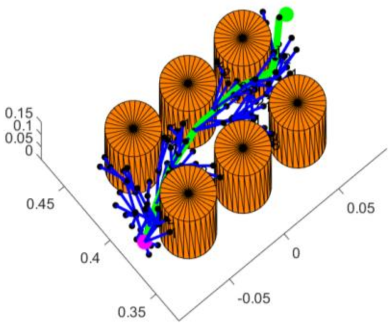
As shown in Fig. 3, The blue line represents the extended branch, and the green line represents the final path. RRT^* produces many useless branches. $Informed - RRT^*$ also has some useless branches, but fewer than RRT^*. The final path of the two is tortuous and the path length is long. After the introduction of distance constraint mechanism, the useless branches of $DC - RRT^*$ and $DC - Informed - RRT^*$ are significantly reduced, the final path is smoother and the path length is shorter. Combined with the data in Table 1, the average path of $DC - RRT^*$ is reduced by 5.29% from 0.2042m to 0.1934m compared with RRT^*. The average running time decreased by 18.90% from 6.67s to 5.41s; The node utilization rate is increased from 6.62% to 10.96%, and the average path of $DC - Informed - RRT^*$ and $Informed - RRT^*$ is reduced from 0.1930m to 0.1906m by 1.24%. The average running time decreased by 32.07% from 8.42s to 5.72s; Node usage increased from 6.38% to 12.31%.



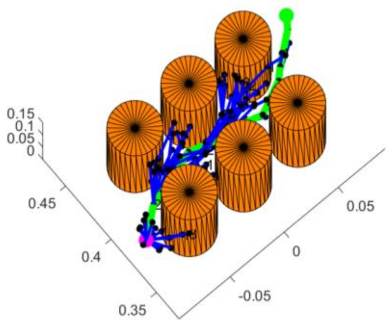
a. RRT^* algorithm tracing



b. $DC-RRT^*$ algorithm tracing



c. $Informed-RRT^*$ algorithm tracing



d. $DC-Informed-RRT^*$ algorithm tracing

Fig.4 Algorithm tracing in 3D complex scenes

Table 2. Performance comparison of algorithms in 3D complex scenes.

algorithm	average path length /m	average running time /s	Node usage /%
RRT^*	0.2191	17.16	7.63%
$DC-RRT^*$	0.2056	18.42	14.75%
$Informed-RRT^*$	0.2003	20.41	7.01%
$DC-Informed-RRT^*$	0.1965	21.95	16.66%

Fig. 4 shows the planning results of the algorithm in a complex environment. Combined with the data in Table 2, the average path of $DC-RRT^*$ decreases by 6.16% from 0.2191m to 0.2056m compared with RRT^*. The average running time is 17.16s and 18.42s respectively, the node utilization rate is increased from 7.63% to 14.75%, and the average path of $DC-Informed-RRT^*$ is reduced from 0.2003m to 0.1965m, a decrease of 1.89%. The average running time was 20.41s and 21.95s respectively, and the node utilization rate increased from 7.01% to 16.66%.

According to the analysis, since the introduction of distance constraint mechanism reduces the expansion of nodes that are useless for optimizing the path, the node utilization rate is higher, and the node distribution is more concentrated near the final path, then the node is more likely to optimize the cost of the current path. Secondly, although the introduction of distance constraint mechanism reduces the expansion of useless nodes, the nodes are more concentrated. In a simple obstacle avoidance environment, the time to reduce the expansion of useless nodes is greater than the time to increase the process of parent node re-selection and rewiring, so the average running time is reduced. In complex obstacle avoidance environments, parent node reselecting and rewiring processes increase the time more than the time to reduce the expansion of useless nodes, so the average running time increases. The distance constraint mechanism proposed in this paper enables the algorithm to select and optimize the path with higher efficiency during operation, which makes the node utilization rate increase and the final path length decrease. Especially in the simple obstacle avoidance environment, the search efficiency of the algorithm is improved to a large extent.

4. Conclusion

In this paper, a motion planning algorithm based on RRT^* and $Informed-RRT^*$ with distance constraint mechanism is proposed to improve the problems of low exploration efficiency and poor planning path in the current motion planning tasks of robotic arms under different complexity scenarios. It mainly reduces the expansion of useless nodes when the random tree grows, so that the algorithm can select and optimize the path with higher efficiency when running. Combined with halton sequence sampling method, the space exploration ability of the algorithm is improved. The simulation results show that $DC - RRT^*$ and $DC - Informed - RRT^*$ can reduce the path length, improve the node utilization rate, and improve the search efficiency of the algorithm to a large extent, especially in simple environment.

References

1. Fang H, Ong S, Nee A. Robot path planning optimiza tion for welding complex joints [J]. INTERNATIONA L JOURNAL OF ADVANC-ED MANUFACTURING TECHNOLOGY, 2017.
2. La Valle S M. Motion planning[J]. IEEE Robotics & Automation Magazine, 2011, 18 (2): 108-118.
3. Liang S. Research on off-line and on-line mo-tion pla nning methods for multi-degree of freedom manipulato r (in Chinese) [D]. Zhejiang University,2023.
4. Ying K C, Pourhejazy P, Cheng C Y, et al. Deep learning-based optimization for motion planning of dual-arm assembly robots[J]. Computers & Industrial Engineering, 2021, 160: 107603.
5. Lavalle S M. Rapidly-Exploring Random Trees: A New Tool for Path Planning[J].Research Report, 1999.
6. Karaman S, Frazzoli E. Incremental Sampling-based Algorithms for Optimal Motion Planning[C]//Robotics: Science and Systems 2010.2010.
7. Gammell J D, Srinivasa S S, Barfoot T D.In-formed RRT*: Optimal Sampling-based Path Planning Focused via Direct Sampling of an Admissible Ellipsoidal Heuristic[J].IEEE, 2014.

Authors Introduction

Mr. Tianbin Meng

He is a postgraduate in Beijing Jiaotong University. His research interests are Robot arm motion planning.

Dr. Jiwu Wang

He is an associate professor, Beijing Jiaotong University. His research interests are Intelligent Robot, Machine Vision, and Image Processing.