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PATH PLANNING ALGORITHM USING INFORMED RAPIDLY EXPLORING RANDOM TREE*-CONNECT WITH LOCAL SEARCH

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Abstract

The objective of this study is to propose a path planning algorithm using the Informed RRT*-Connect algorithm and a RRT*- based local search algorithm. The Informed RRT*-Connect algorithm is a two-way version of RRT* where sampling is limited to the area that is predicted to provide a better solution. The proposed local search algorithm uses the idea of an informed RRT* where the sampling process is carried out at a certain distance from the best path obtained from the previous path planning algorithm. The performance of the proposed algorithm with the RRT*, Informed RRT*, and RRT*-Connect algorithms using several benchmark cases, namely clutter, trapping, and narrow, respectively, were compared. The test results showed that the use of the Informed RRT*-Connect algorithm with a local search algorithm can increase the convergence rate and final solution quality compared to other algorithms. The Informed RRT*-Connect algorithm can have a high convergence speed because it uses two search trees and performs searches only in a limited area. The local search algorithm can improve the quality of the final solution because it performs exploitation searches along the previous final path. So, the Informed RRT*-Connect algorithm with a local search algorithm has the potential to be used in systems that require fast and optimal path planning algorithms such as robots and autonomous vehicles.

Keywords: Informed RRT*, Informed RRT*-Connect, Local search, Path planning, RRT*-Connect.

1. Introduction

Path planning problem have various implementations such as Unmanned Aerial Vehicle, self-driving cars, computational biology, robotics, medical application, virtual prototyping, and graphics animation [1-7]. The path planning algorithm is divided into two categories, namely graph-based search methods and sampling-based methods [8]. The graph-based search methods discretizes the configuration space, then search through the states, but the performance of graph-based search methods decreases in high dimensions [9]. The sampling-based method uses random sampling to construct a path in configuration space. For applications in high dimensional state spaces, sampling-based methods have shown significant practical impacts [10]. Examples of sampling-based methods are Rapidly-exploring Random Trees (RRT) and RRT* [11]. The RRT algorithm is suboptimal, while the RRT* is asymptotic optimal [12]. This means that RRT* returns a solution if there are sufficient iterations and the solution exists. This paper focuses the discussion on developing path planning algorithms based on RRT* algorithm.

RRT* explores state space like RRT, but RRT* can be optimized by the search tree via rewiring its branches to produce a smaller cost path [13]. RRT* is still continuing to search the state space after the first solution is found to find a better path. RRT* -Connect [14-16] is a bidirectional version of RRT*. Then, RRT*-Connect can find a solution faster than RRT*, especially when there is a narrow passageway to reach the destination location. RRT*-Connect gradually grows two trees simultaneously: one is from the initial location and the other is from the destination location. Both of these trees are trying aggressively to find a connection. Similar to RRT*, RRT*-Connect also continue to search the state space after the first solution is found to find a better solution than the current one. However, the computational complexity of the RRT* and RRT*-Connect is quite heavy, because both of them examine all regions to optimize the resulting path. Gammell et al. propose a more efficient method to reduce path costs [17-19]. Gammell et al. introduced the Informed RRT* algorithm which limits the sampling space based on the cost path information of the first solution found by RRT*. However, the Informed RRT* algorithm struggles when there is a narrow passageway to reach the destination location. Some researchers have proposed two-way planning methods of Informed RRT* or presumably called Informed RRT*-Connect [10, 20]. The Informed RRT*-Connect algorithm behaves like RRT*-Connect until the first path is generated. Then, based on the cost path information from that first path, an ellipsoid area is created which limit the sampling process of the informed RRT*-Connect. This promotes the algorithm the ability to produce nearly optimal solutions, indeed, with fewer iterations. But, the performance advantages from the above algorithms are possibly having various parameters depending on the environmental conditions. Therefore, as an effort to improve the performance of the path produced by the path planner above, the authors propose the use of local search algorithms based on RRT*. The proposed local search algorithm performs the sampling process at a certain distance from the best path obtained from the previous path planning algorithm.

The paper has contributions in proposing a path planning algorithm using the Informed RRT*-Connect algorithm and a local search algorithm based on RRT*. The informed RRT*-Connect algorithm is used to produce one of the best paths that can be generated. Furthermore, the path is minimized when using the local search algorithm. Local search algorithms can minimize the distance from that path because of the exploitation search along the existing path. The performance of proposed algorithm was compared against the RRT*, Informed RRT* and RRT*-Connect algorithms using several benchmark cases. Some of the test benchmarks used are trap environment, clutter, and multiple narrow passages. The test results show that the use of informed RRT*-Connect algorithm and local search algorithm based on RRT* can produce better path planning performance. Therefore, the informed RRT*-Connect algorithm and the local search algorithm based on RRT* have the potential to be used on systems that need path planning algorithms such as robots or autonomous vehicles.

2. Method

In Fig. 1, we present the proposed algorithm of Informed RRT*-Connect. In order for this algorithm to have optimal asymptotic solutions, the ChooseParent and Rewire processes have been included in lines 15, 17, 27 and 29. Through the ChooseParent process, a parent node is selected which minimizes the length of the path from the new node to the initial node. As for the Rewire process, a new parent node is searched, which can minimize the length of the path to the initial node. This ChooseParent and Rewire process guarantees an optimal solution if enough iterations are provided [11].

Algorithm 1 : $X_{soln} \leftarrow Informed\ RRT^{*} - Connect\ (q_{init}, q_{goal})$

1. $T_A \leftarrow InitializeTree()$
2. $T_B \leftarrow InitializeTree()$
3. $T_A \leftarrow InsertNode(\emptyset, q_{init}, T_A)$
4. $T_B \leftarrow InsertNode(\emptyset, q_{goal}, T_B)$
5. $X_{soln} \leftarrow \emptyset$
6. $c_{best} \leftarrow \infty$
7. **for** $k \leftarrow 1$ **to** N **do**
8. $c_{best} \leftarrow CalculateShirtestPathLength(X_{soln})$
9. $q_{rand} \leftarrow InfomedSample(q_{init}, q_{goal}, c_{best})$
10. $Q_{\boldsymbol{near}} \leftarrow Near(T_A, q_{rand})$
11. $q_{nearest} \leftarrow NearestNeighbor(q_{rand}, Q_{near}, T_A)$
12. $q_{new} \leftarrow Steer\ (q_{nearest}, q_{rand}, \Delta q)$
13. **if** $Obstaclefree(q_{nearest}, q_{new})$ **then**
14. $Q_{\boldsymbol{near}} \leftarrow Near(T_A, q_{new})$
15. $q_{min} \leftarrow ChooseParent(q_{new}, Q_{near}, q_{nearest})$
16. $T_A \leftarrow InsertNode(q_{min,} q_{new}, T_A)$
17. $T_A \leftarrow Rewire(T, Q_{near}, q_{min})$
18. **if** $CanConnected(q_{new}, T_B)$ **then**
19. $X_{soln} \leftarrow UpdateBestPath(T_A, T_B)$
20. **end if**
21. **end if**
22. $Q_{\boldsymbol{near}} \leftarrow Near(T_A, q_{rand})$
23. $q_{nearest} \leftarrow NearestNeighbor(q_{rand}, Q_{near}, T_A)$
24. $q_{new} \leftarrow Steer\ (q_{nearest}, q_{rand}, \Delta q)$
25. **if** $Obstaclefree(q_{nearest}, q_{new})$ **then**
26. $Q_{\boldsymbol{near}} \leftarrow Near(T_B, q_{new})$
27. $q_{min} \leftarrow ChooseParent(q_{new}, Q_{near}, q_{nearest})$
28. $T_B \leftarrow InsertNode(q_{min,} q_{new}, T_B)$
29. $T_B \leftarrow Rewire(T, Q_{near}, q_{min})$
30. **if** $CanConnected(q_{new}, T_A)$ **then**
31. $X_{soln} \leftarrow UpdateBestPath(T_A, T_B)$
32. **end if**
33. **end if**
34. **end**

Fig. 1. Informed RRT*-Connect algorithm.

To minimize the time required, two trees explore the environment in the proposed algorithm. One tree starts searching from the starting node (lines 10-21 in Fig. 1). The second tree starts searching from the destination node (lines 22-33 in Fig. 1). To increase the convergence rate and the final solution quality, the sampling process is focused on an ellipsoid subset of the state space which is thought to provide a better solution than the existing solutions. In the proposed algorithm, the sampling process in the ellipsoid subset is carried out on lines 8-9 in Fig. 1. The detailed sampling process is shown in Fig. 2.

In the proposed local search algorithm, the path creation process mimics the process in the Informed RRT* algorithm. The difference is that the sampling process is only carried out at a certain distance from the current best pathway. The detailed process of the local search algorithm is shown in Fig. 3. The sampling process around the best path that has been found is carried out in line 4 in Fig. 3.

Algorithm 2: $q_{rand} \leftarrow InfomedSample(q_{init}, q_{goal}, c_{best})$
if $c_{best} < \infty$ **then**
    $c_{min} \leftarrow \|q_{init} - q_{goal}\|_2$
    $x_{center} \leftarrow (q_{init} + q_{goal})/2$
    $\boldsymbol{C} \leftarrow RotationToWorldFrame(q_{init}, q_{goal})$
    $r_1 \leftarrow c_{best}/2$
    $\{r_i\}_{i=2,\dots,n} \leftarrow \left(\sqrt{{c_{best}}^2 - {c_{min}}^2}\right)/2$
    $\boldsymbol{L} \leftarrow diag\{r_1, r_2, \dots, r_n\}$
    $x_{ball} \leftarrow SampleUnitBall$
    $q_{rand} \leftarrow (\boldsymbol{CL}x_{ball}) \cap X$
else
    $q_{rand} \leftarrow RandomSample(X)$
end if
return q_{rand}

Fig. 2. Informed sample operations on informed RRT*-Connect algorithm.

Algorithm 3 : $X_{sol} \leftarrow LocalSearch(X_{sol})$
1. $T \leftarrow InitializeTree()$
2. $T \leftarrow InsertNode(\emptyset, q_{init}, T)$
3. **for** $k \leftarrow 1$ **to** N **do**
4. $q_{rand} \leftarrow SamplingNearBestPath(X_{sol}, d)$
5. $Q_{\boldsymbol{near}} \leftarrow Near(T, q_{rand})$
6. $q_{nearest} \leftarrow NearestNeighbor(q_{rand}, Q_{near}, T)$
7. $q_{new} \leftarrow Steer\ (q_{nearest}, q_{rand}, \Delta q)$
8.   **if** $Obstaclefree(q_{nearest}, q_{new})$ **then**
9. $Q_{\boldsymbol{near}} \leftarrow Near(T, q_{new})$
10. $q_{min} \leftarrow ChooseParent(q_{new}, Q_{near}, q_{nearest})$
11. $T \leftarrow InsertNode(q_{min,} q_{new}, T)$
12. $T \leftarrow Rewire(T, Q_{near}, q_{min})$
13.   **end if**
14. **end**

Fig. 3. Local search algorithm based on RRT*.

3. Results and Discussion

This study compares the performance of the RRT*-Connect informed algorithm with the performance of the RRT*, Informed RRT* and RRT*-Connect algorithms. Some of the test benchmarks used are multiple narrow passages, clutter and trap environment [10]. For this experiment, a simulation program has been created using labVIEW. The performance parameters compared are the convergence rate and final solution quality. Three types of testing are carried out on multiple narrow passages, clutter and trap environment. Imitating the test scheme carried out by Karaman and Frazzoli [11], all algorithms run for 20,000 iterations in 100 times and the cost of the best path in the trees was calculated to get mean value for each iteration. The results are shown in Figs. 4 to 6. In Figs. 4 and 5 (multiple narrow passages and clutter environments), it appears that the Informed RRT*-Connect algorithm has the best convergence rate and final solution quality compared to Informed RRT*, RRT*, and RRT*-Connect.

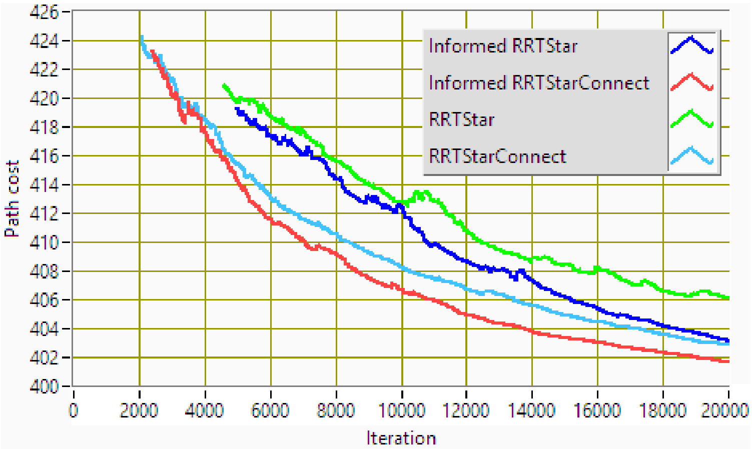


Fig. 4. The cost of the best paths of the four algorithms plotted against iterations averaged over 100 trials in multiple narrow scenarios.

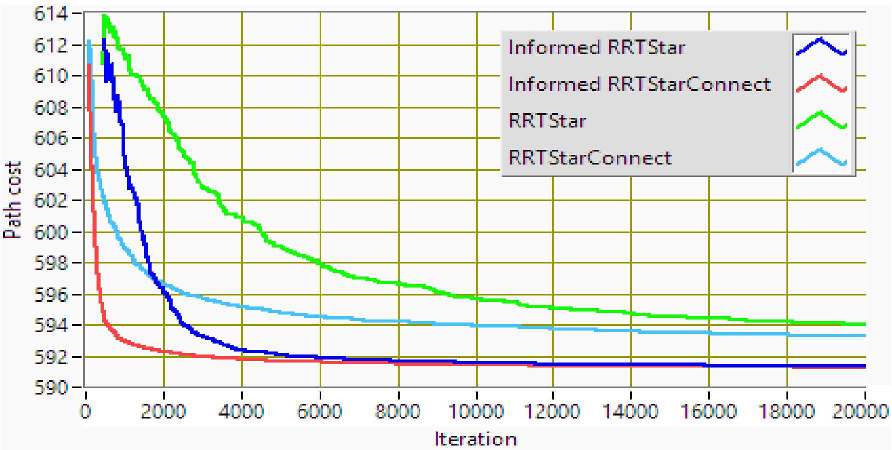


Fig. 5. The cost of the best paths of the four algorithms plotted against iterations averaged over 100 trials in clutter environment.

It is shown in Fig. 6 that the convergence rate and final solution quality of Informed RRT*-Connect are not the best. The performance of Informed RRT*-Connect can vary depending on the environmental conditions used. Therefore, to improve the performance of the path produced Informed RRT*-Connect, the authors use the local search algorithms based on RRT*. The average length of the final path produced by Informed RRT*-Connect is 761.16, while the average length of the final path produced by RRT*-Connect is 757.3. However, if the local search algorithm is implemented, then the average length of the final path only reached 751.67. It means that the use of an Informed RRT*-Connect algorithm and a local search algorithm based on RRT* can produce better final solution quality. Example of the solution paths and search tree by the local search is presented in Fig. 7.

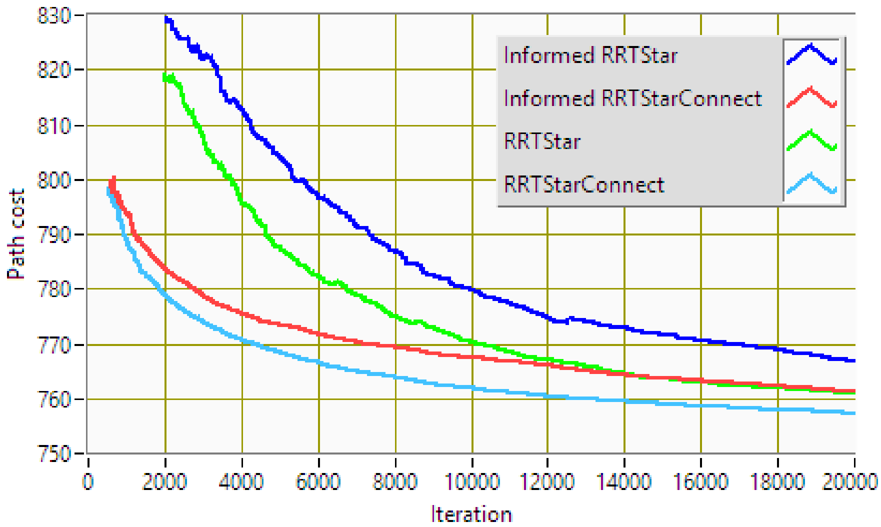
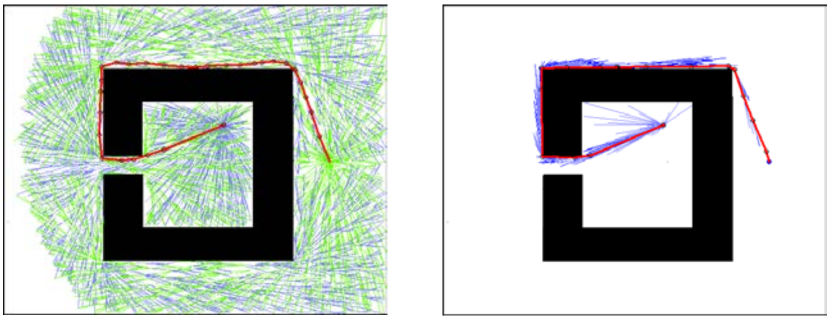


Fig. 6. The cost of the best paths of the four algorithms plotted against iterations averaged over 100 trials in trap environment.



(a) cost path : 761.68 (b) cost path : 750.96

Fig. 7. Solution paths and search trees example obtained by (a) Informed RRT*-Connect algorithm, and (b) after using the local search algorithm.

4. Conclusion

This paper has demonstrated a path planning algorithm using the Informed RRT*-Connect algorithm and a local search algorithm based on RRT*. Using the local search algorithm based on RRT*, the path generated by the informed RRT*-Connect algorithm can be minimized. The performance of the proposed algorithm with the RRT*, Informed RRT*, and RRT*-Connect algorithms using several benchmark cases, namely clutter, trapping, and narrow, respectively, were compared. The test results show that the use of an informed RRT*-Connect algorithm and a local search algorithm based on RRT* can produce better path planning performance. So, the RRT*-Connect algorithm and the local search algorithm based on RRT* have the potential to be used on systems that need path planning algorithms such as robots or autonomous vehicles.

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