Homework 3: Sample-based Path Finding

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1. Matlab Part

The path search result of RRT is showed in Figure 1. The expanding length increases, path cost increase.

The path search result of RRT* with 800 iterations is showed in Figure 2. The final path has a cost of 950.09, which is a shorter path compared with RRT.

2. ROS Part

Use ompl (The Open Motion Planning Library) to achive RRT* path search function. Follows the tutorial of ompl under this link: https://ompl.kavrakilab.org/optimalPlanningTutorial.html. Include these two head files:
#include <ompl/geometric/planners/rrt/RRTstar.h>
#include <ompl/geometric/planners/rrt/InformedRRTstar.h>

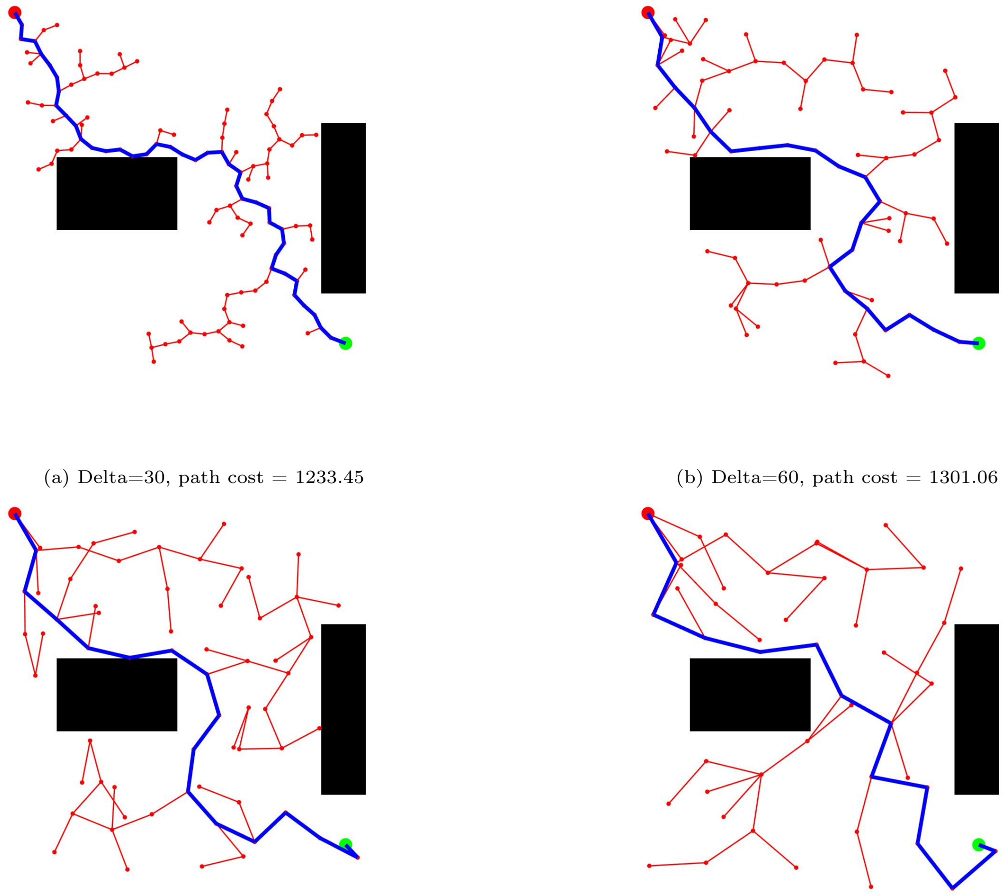
Use these two lines code to invoke RRT* or informed RRT* package:
ob::PlannerPtr optimizingPlanner(new og::RRTstar(si))
ob::PlannerPtr optimizingPlanner(new og::InformedRRTstar(si))

The RRT* path finding result and informed RRT* path finding result are showed in Figure 3 and Figure 4.

3. Main Takeaways

Sample-based planner do not attempt to explicitly construct the C-space and its boundaries.

1. Definition: complete planner, probabilistic complete planner, resolution complete planner.
2. PRM (probabilistic road map)
   - Learning phase build map
   - Query phase find path (e.g. with A*)
   - Cons: 2 steps, not efficient
   - Improvement: lazy collision check
3. RRT (rapidly-exploring random tree)



(a) Delta=30, path cost = 1233.45

(b) Delta=60, path cost = 1301.06

(c) Delta=90, path cost = 1387.07

(d) Delta=120, path cost = 1477.52

Figure 1: RRT path search result with different expanding length (Delta)

- Pros: find a path, target oriented
- Cons: not optimal
- Improvement: Kd-tree, bidirectional RRT

4. Optimal sampling-based planner with rewire function: RRT*, kinodynamic-RRT*

5. Advaced methods: only sample within certain region, e.g.informed RRT*, cross-entropy motion planning.

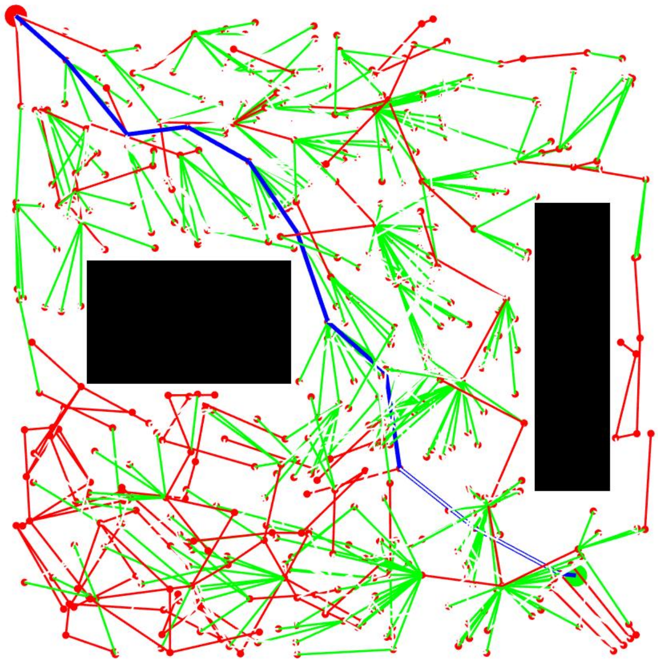


Figure 2: RRT* path search result, path cost is 950.09.

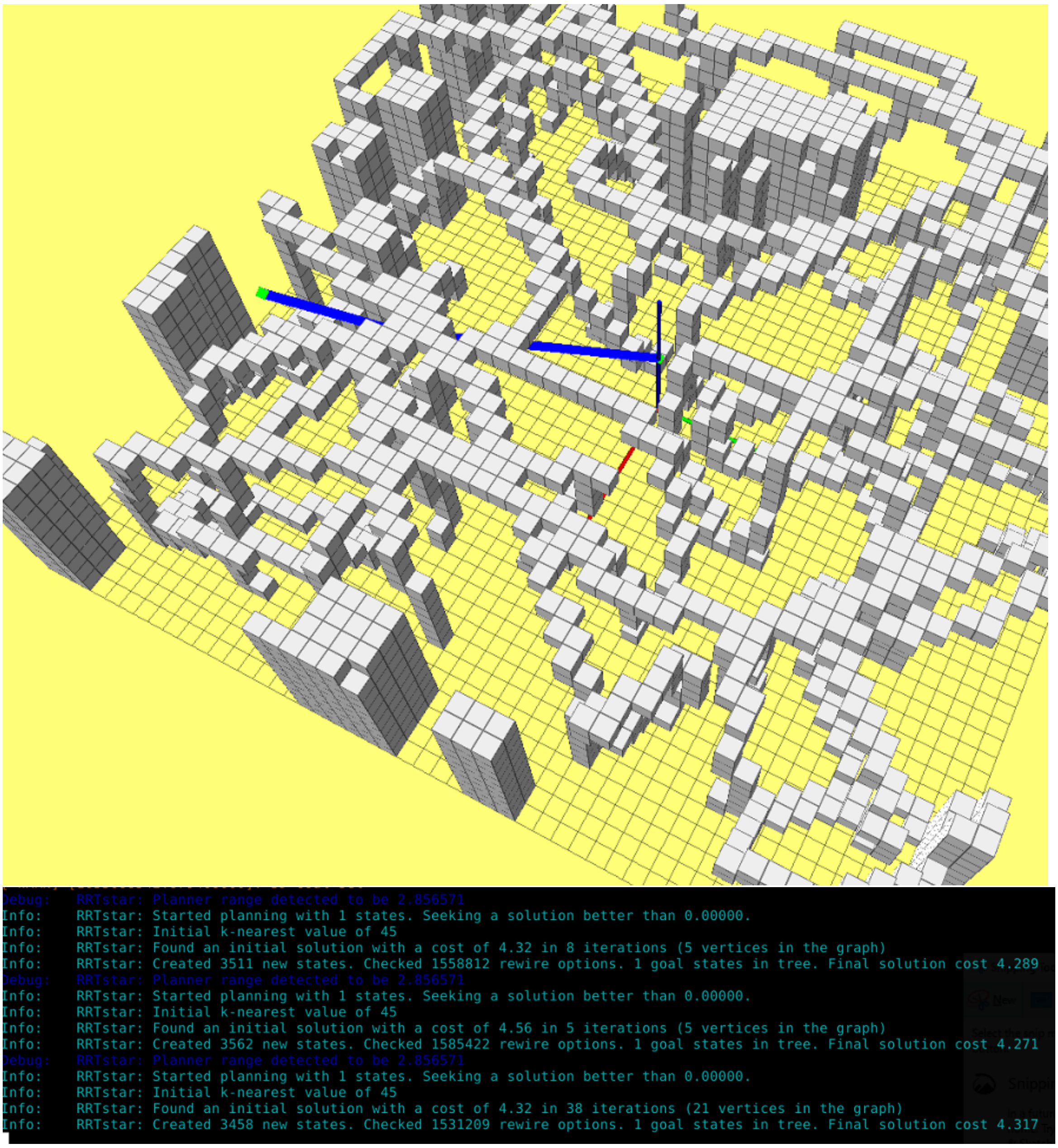


Figure 3: RRT* path finding result with ompl.

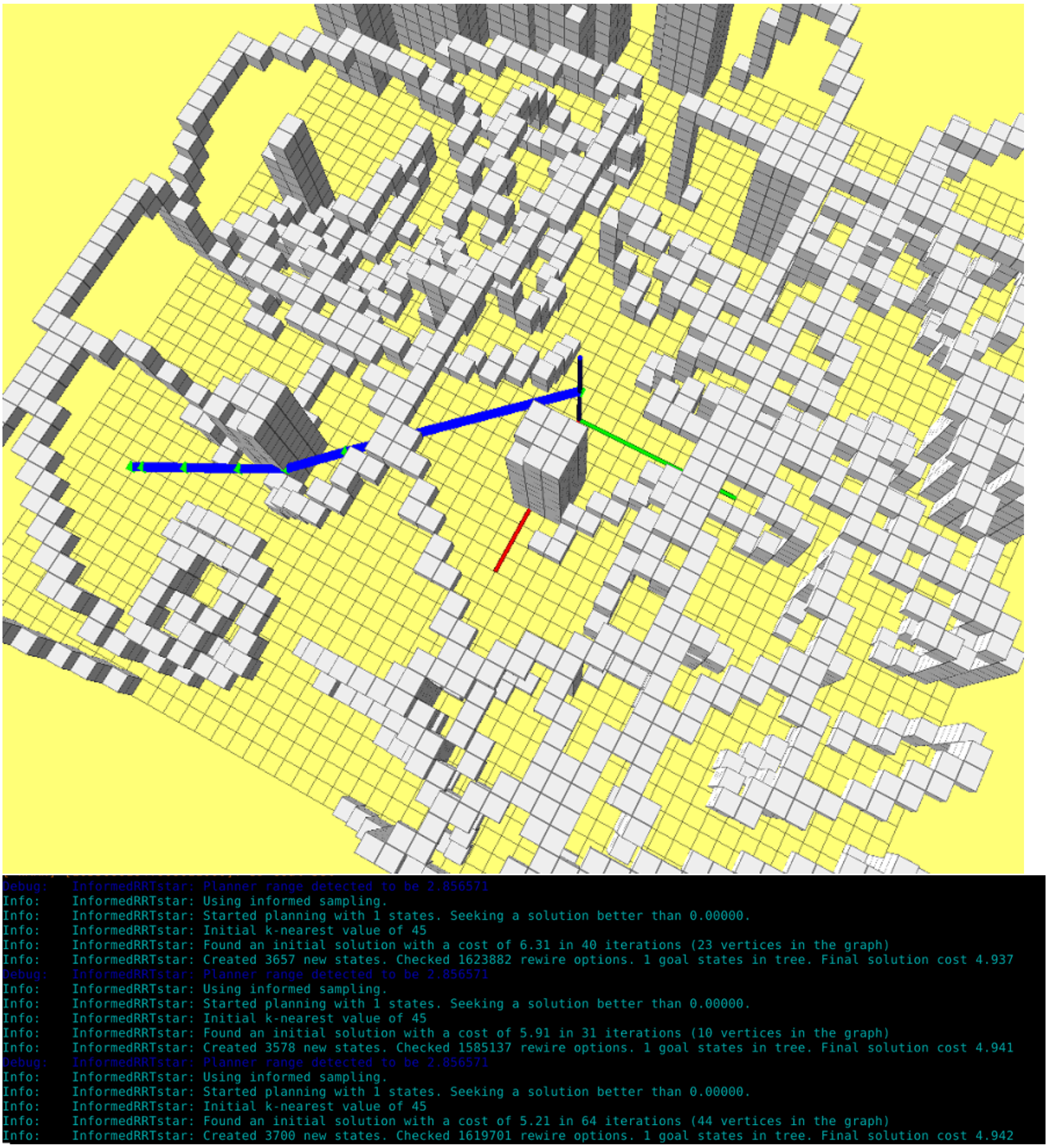


Figure 4: RRT* path finding result with ompl.

Algorithm 1: RRT Algorithm

Input: $\mathcal{M}$,x_{init},x_{goal}
Result: A path Γ from x_{init} to x_{goal}
$\mathcal{T}$.init();
for $i = 1$ *to* n **do**
    $x_{rand} \leftarrow Sample(\mathcal{M})$;
    $x_{near} \leftarrow Near(x_{rand}, \mathcal{T})$;
    $x_{new} \leftarrow Steer(x_{rand}, x_{near}, StepSize)$;
    $E_i \leftarrow Edge(x_{new}, x_{near})$;
    if *CollisionFree*($\mathcal{M}$, E_i) **then**
        $\mathcal{T}.addNode(x_{new})$;
        $\mathcal{T}.addEdge(E_i)$;
    if $x_{new} = x_{goal}$ **then**
        Success();

Algorithm 2: RRT Algorithm

Input: $\mathcal{M}$,x_{init},x_{goal}
Result: A path Γ from x_{init} to x_{goal}
$\mathcal{T}$.init();
for $i = 1$ *to* n **do**
    $x_{rand} \leftarrow Sample(\mathcal{M})$;
    $x_{near} \leftarrow Near(x_{rand}, \mathcal{T})$;
    $x_{new} \leftarrow Steer(x_{rand}, x_{near}, StepSize)$;
    if *CollisionFree*(x_{new}) **then**
        $X_{near} \leftarrow NearC(\mathcal{T}, x_{new})$;
        $x_{min} \leftarrow ChooseParent(X_{near}, x_{near}, x_{new})$;
        $\mathcal{T}.addNodEdge(x_{min}, x_{new})$;
        $\mathcal{T}.rewire()$;

Figure 5: RRT and RRT*.