RBE 550 Advanced Algorithms

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1 Introduction

In this assignment, I implemented D* and Informed RRT* using Python.

1.1 D*

D* is a discrete single-source incremental planning/replanning algorithm which guarantees a globally optimal solution to the shortest path problem. At a high level, D* plans an initial path, just as A* or Dijkstra does. Then, as the edge costs change (whether from the robot moving or as the obstacle states evolve), D* repairs the path while ensuring global optimality. This global optimality guarantee as well as the thoughtful analysis associated with it is what makes D* so powerful, and why it was able to motivate A. Stenz's Focussed D*, D* Lite, and Field D*.

1.2 Informed RRT*

Informed RRT* is a variant of RRT* which restricts the sampling after the goal is found to a hyperspheroid, refining the path and the homotopy classes explored. The importance of Informed RRT* is the author's careful analysis on the optimality guarantees of the resuling framework. Informed RRT* is probabalistically as good as or better than RRT* when it comes to refining the path, since Informed RRT* makes use of the c_min heuristic to parameterize a subset of the volume to sample from.

2 Results

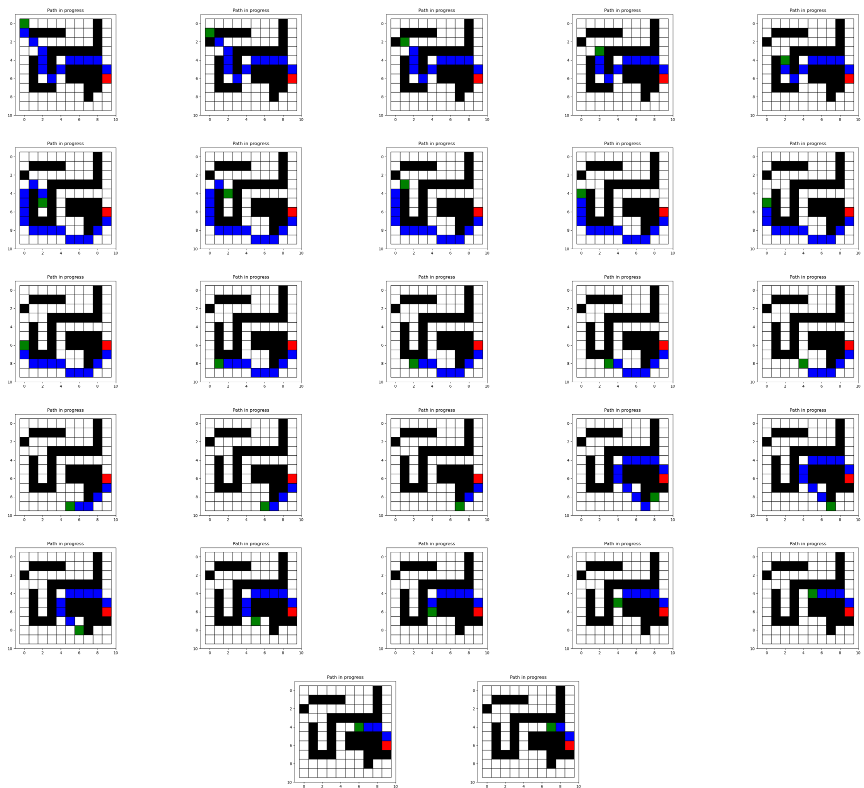
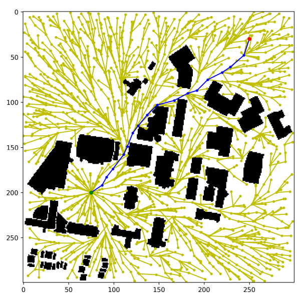
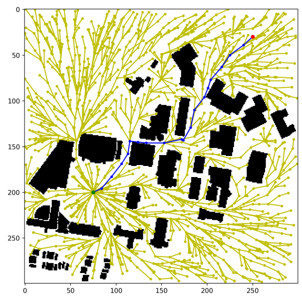


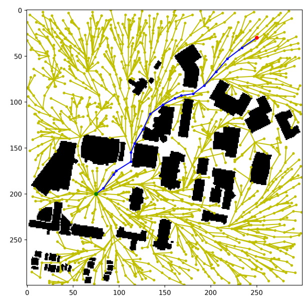
Figure 1: Sequence of D* Steps



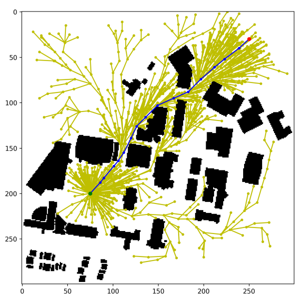
(a) RRT*: 254.3 Cost



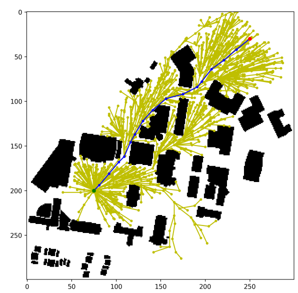
(b) RRT*: 271.5 Cost



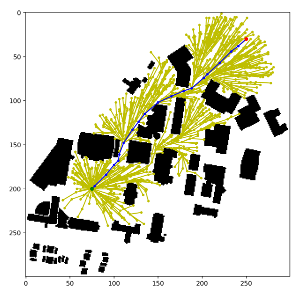
(c) RRT*: 254.6 Cost



(d) Inf. RRT*: 249.4 Cost



(e) Inf. RRT*: 250.9 Cost



(f) Inf. RRT*: 250.2 Cost

Figure 2: RRT* vs Informed RRT* with 2000 Samples

3 Discussion

D* replans a path by maintaining a one-step 'lookahead' cost which is used to keep track of whether the node's cost has changed. D* processes states differently depending on whether or not this new cost is higher, lower, or equal. The approach tends to replan faster than A* or Dijkstra's algorithm because it repairs paths rather than simply planning again from scratch. One of the powerful guarantees that D* makes is that it will return exactly the same path as you would get if you re-ran A* (assuming a permissible heuristic) or Dikstra's algorithm from scratch each time. This guarantee, as well as the finer details of the algorithm itself, are alone worth a semester of analysis—in fact, D* is so famously complex, that A. Stenz and D. Ferguson went back and re-solved the single-source incremental planning problem from scratch by introducing D* Lite, which yields the exact same results as D* but with as good or better performance and is substantially simpler to implement and analyze. To be frank, analysis and implementation of D* Lite may have been more fruitful for this assignment.

The key difference between RRT* and Informed RRT* is that the latter projects the samples into a hyperspheroid which has analytical guarantees (see [2]) to probabalistically explore all relevant homotopy classes that could potentially improve the path. Notably, these samples from Informed RRT* are far more focused on exploring the region of relevant homotopy classes than the naive RRT* sampling. This allows for far better convergence times for the same path cost. Informed RRT* also maintains RRT*'s generality to n-dimensional spaces, and doesn't add any extra parameters, keeping it nice and simple. The original authors also generously provide an optimized implementation of their approach in the Open Motion Planning Library (OMPL), which allows for straightforward validations of their results and analysis.

4 Dependencies

The code is dependent on the matplotlib, numpy, PIL, and scipy python modules, where scipy is used for the kdtree framework.

References

[1] A. Stentz, "Optimal and efficient path planning for partially-known environments," Proceedings of the 1994 IEEE International Conference on Robotics and Automation, San Diego, CA, USA, 1994, pp. 3310-3317 vol.4, doi: 10.1109/ROBOT.1994.351061.

[2] J. D. Gammell, S. S. Srinivasa and T. D. Barfoot, "Informed RRT*: Optimal sampling-based path planning focused via direct sampling of an admissible ellipsoidal heuristic," 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, Chicago, IL, USA, 2014, pp. 2997-3004, doi: 10.1109/IROS.2014.6942976.