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Standard Search Algorithms

Q1) For PRM, what are the advantages and disadvantages of the four sampling methods in comparison to each other?

<u>A1.</u>

Uniform Sampling	Random Sampling	Gaussian Sampling	Bridge Sampling
Uniform sample across C-space Will get more nodes to find the path throughout the entire free C-space	Random Sample Across C-space Has mixed result depending on the sampling	Samples only along the edge Will not cover the free space very well	Samples only along narrow paths Will not cover free space very well
Simple to implement	Simple to Implement	Must place checking conditions throughout the C-Space	Must place checking conditions throughout the C-Space
Usually fails to go through narrow paths	Has mixed results depending on sampling	Can define the obstacles avoidance strategies	Can find paths through narrow passages
Used when more free space is there	Used to test results	Used with less free space	Used with very less free space

Q2) For RRT, what is the main difference between RRT and RRT*? What change does it make in terms of the efficiency of the algorithms and optimality of the search result?

A2.

RRT* is an optimized version of the RRT algorithm. When the number of nodes approach infinity the RRT* algorithm will give out the shortest possible path to reach the goal. The overall algorithm is the same as RRT however it employs three changes:

- a) Recording distance relative from parent node
- b) Figuring out the neighbors of the current node
- c) Rewiring Rearranging the family based on costs (cheapest neighbor)

However, all this comes at a price of computational efficiency. The time to find a path with RRT* could be eight times more as compared to RRT. This is because a lot of memory is consumed in examining, rewiring and collision checking.

The search path for RRT* as much more optimal as compared to RRT which would break as soon as a path is found. RRT* keeps running until it runs out of sampling points, meanwhile optimizes it path at every iteration for every new sample which could be found for reducing the overall cost of traversal.

Q3) Comparing between PRM and RRT, what are the advantages and disadvantages?

A2.

PRM's are multi-query planners. This means that we sample the C-space once and then make connections between the start and the goal by connecting them to the roadmap. These roadmaps can be re-used to find paths for different configurations of the start and goal positions.

RRT is a single-query algorithm. This means that every time we need to find a path between start and goal, we would construct it online. These trees are re-executed to generate paths for a new set of start and goal position.

RRT terminates as soon as the goal is found. This mean that the runtime is shorter as compared to other algorithms. However, the path found may not be the optimal one. This could also be used in dynamic environment as a new path can be constructed as soon as any change is noticed.

The PRM may take time initially to construct the node map. It then uses a graph-search method like A* or Dijkstra to traverse though the roadmap. However, there could be issue when you

need to plan in real time with dynamic obstacles, as new search from the current to the goal position would be needed again. PRM could also sample points inside closed or narrow spaces if nodes located inside the obstacles are not discarded. PRM consider the idea that the environment won't change over time.

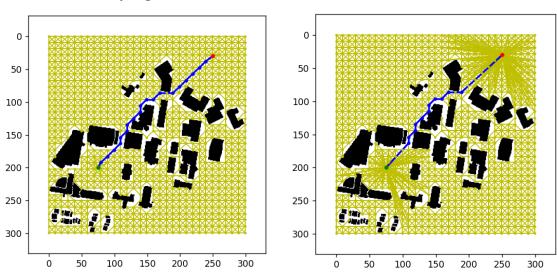
PRM retains the graph structure and reuses it every time whereas RRT can find path in dynamic environment but with the expense of optimality.

Algorithm Results and Explanation

PRM.

We get the following results for PRM for different sampling methods:

Uniform Sampling:

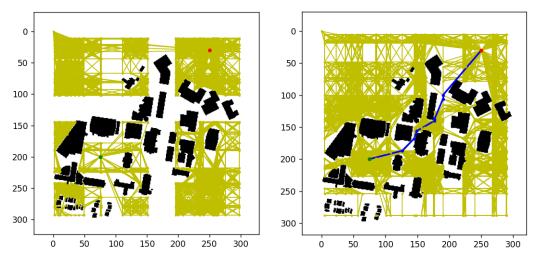


In the first figure we see that for uniform sampling we do not require large radii for the KDtree. A larger radius causes unwanted connection in free space.

Since this map has a much more free space as compared to narrow regions, a uniform sampling based method is easy to implement and a path can also be easily found out. The cell size is almost same to that of the narrow gaps.

Method: The entire space is equally distributed into equally spaces nodes for sampling

Random Sampling:

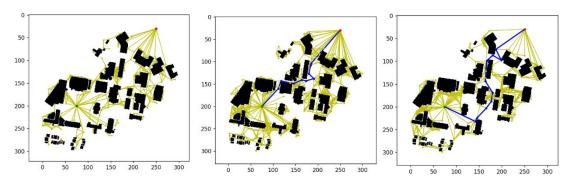


In these two images we see that random sampling fails in the first case whereas it is successful for the second case. This entirely depends on how the nodes are sampled on the map. If we are lucky then we might get a feasible path.

Also notice to get a feasible path we either increase the number of samples on the map or increase the radii of the KDTree.

Method: The entire space is randomly distributed for sampling

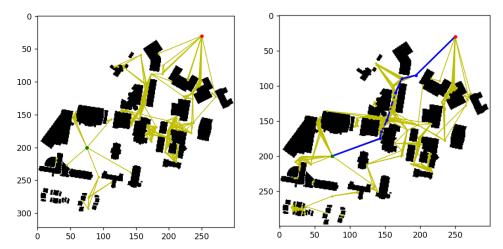
Gaussian Sampling:



Here we see three images for Gaussian based sampling. In the first one we fail to find a path. This happens as the points are sampled near the edges of the obstacles. This leaves us with very few ways to make connections. We either increase the sampling size as seen in the second image or increase the radii of the KDtree as seen in the third image.

<u>Method:</u> Here first we take random samples across the space. Then we pick another point from a Gaussian distribution centered at our sampled point. If both the points are collision free or inside obstacle, they are discarded. Otherwise, the one which is free is kept and the other discarded.

Bridge Sampling:



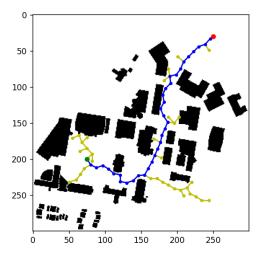
Like gaussian sampling in case of bridge sampling we sample points only across narrow passage. This is good for confided space but for spaces with of lot for free space, it becomes problematic sic ewe run out of samples to joins. In large free space we can only make connections by using larger radii for KDTree.

<u>Method:</u> Here first we take random samples across the space. Then we pick a point which is inside an obstacle. Then we pick another point from a Gaussian distribution centered at our sampled point. If both the points are inside obstacle, we will pick another point, i.e., the midpoint of these two points. If the midpoint is in free space, we will use it for sampling.

RRT.

We implemented two RRT based method:

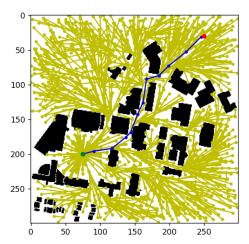
Standard RRT:



We see in the above image an implementation of standard RRT algorithm. This tree expands randomly in any direction until it reaches the goal. The path found is not optimal.

<u>Method:</u> Initiate a new random node and find its nearest node. Then explore in that direction if no collision is there. Keep expanding throughout the tree until the goal is achieved.

RRT*:



In the above image we can see an implementation of the RRT* algorithm. This algorithm works in a similar fashion like standard RRT but keeps optimizing the path even when the goal is found. If there are infinite sampling points RRT* will find the shortest path. We can see a more optimal path for RRT* as compared to RRT.

<u>Method:</u> Initiate the same way you would for RRT. However, when adding new nodes to the graph make sure that you rewire the costs for the cheapest way. Correspondingly also reduce the costs for the neighbors if possible.

Code:

PRM:

```
# Standard Algorithm Implementation
# Sampling-based Algorithms PRM

import matplotlib.pyplot as plt
import numpy as np
import networkx as nx
from scipy import spatial

# Class for PRM
class PRM:
    # Constructor
    def __init__(self, map_array):
        self.map_array = map_array  # map array, 1->free, 0-
>obstacle
    self.size_row = map_array.shape[0] # map size
```

```
def dis(self, point1, point2):
        return zip (row idx, col idx)
```

```
def uniform sample(self, n pts):
def random_sample(self, n_pts):
def gaussian sample(self, n pts):
```

```
self.samples.append([f x, f y])
                self.samples.append(g)
    if self.map array[g[0]][g[1]] == 0:
                if self.map array[mid x, mid y] == 1:
                     self.samples.append([mid x, mid y])
ax.imshow(img)
```

```
def sample(self, n_pts=1000, sampling method="uniform"):
        self.gaussian sample(n pts)
        self.bridge sample(n pts)
```

```
kdtree = spatial.KDTree(np.array(self.samples))
self.graph.add nodes from(node list)
```

```
goal_pairs.append(('goal', self.samples.index(node),
self.draw map()
```

RRT:

```
# Standard Algorithm Implementation
# Sampling-based Algorithms RRT and RRT*
```

```
import matplotlib.pyplot as plt
import numpy as np
          self.size_row = map_array.shape[0]  # map size
self.size_col = map_array.shape[1]  # map size
          self.vertices.append(self.start)
```

```
if self.map array[x][y] == 0:
def get_new_point(self, goal bias):
def get nearest node(self, point):
            minimum = self.dis(node, point)
```

```
fig, ax = plt.subplots(1)
   near node = self.get nearest node(curr node)
```

```
new node = Node(new row, new col)
    self.vertices.append(new node)
```

```
self.vertices.append(self.goal)
```