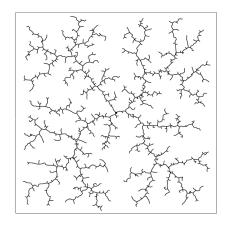
COMS W4733: Computational Aspects of Robotics

Lecture 19: Probabilistic Planning

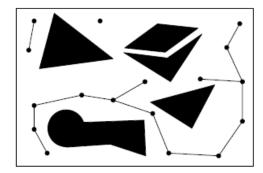


Instructor: Tony Dear

Sampling-Based Methods

- Planning in high-dimensional spaces is hard
- Constructing high-dimensional C-spaces is hard as well
- Do we always need a complete and accurate C-space representation?
- Idea: If we can find a sampling of valid (collision-free) configurations that can be connected, that may be enough to build a roadmap

Sacrifice some optimality, completeness



Sampling-Based Methods

- Collision checking: Need to do this efficiently as part of sampling process
- Probabilistic completeness: If a solution exists, the planner will eventually find it, e.g. by increasing the density of sampling
- Resolution completeness: As with cell decomposition, solutions may exist if resolution is higher than some threshold but not lower

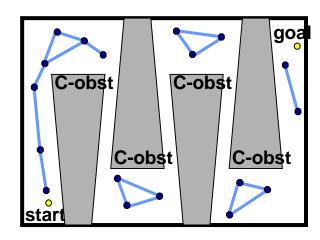
In practical settings, sampling methods often work better than exact roadmap methods!

Probabilistic Roadmaps

- Idea: Randomly check different robot configurations q_{rand}
 - E.g., positions of a mobile robot in space, joint configurations of a manipulator
- If $q_{\rm rand}$ is a collision-free configuration according to robot kinematics and collision checker, then add it as a node to our roadmap
- Attempt to connect $q_{\rm rand}$ to "nearby" nodes already in the graph using local paths generated by a *local planner*
- Collision-free local paths are added as edges to the roadmap

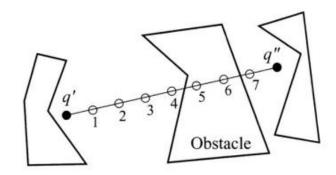
Probabilistic Roadmaps

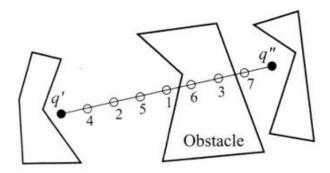
- How to sample configurations? Uniform sampling is usually easiest
 - May not be sufficient in low-volume areas or narrow passageways
- How to check collisions? Often easier to check in the workspace
- What about the *local planner*?
- Try to find local paths to k nearest neighbors
- Try straight paths and then check for collisions

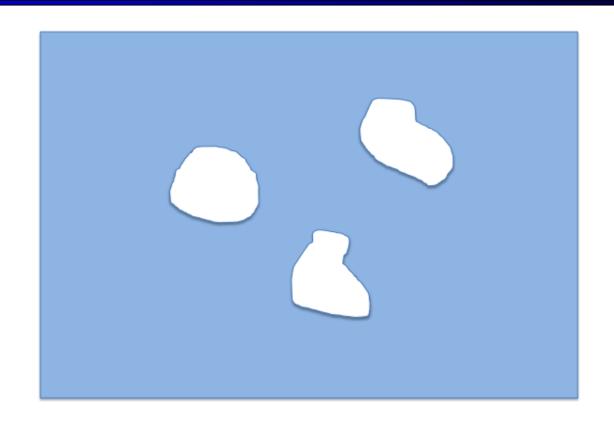


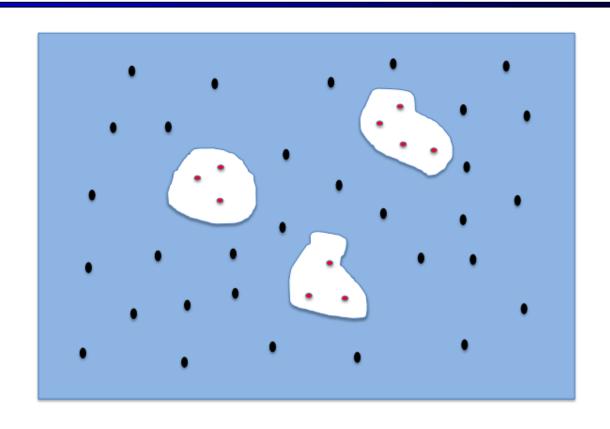
Collision Detection

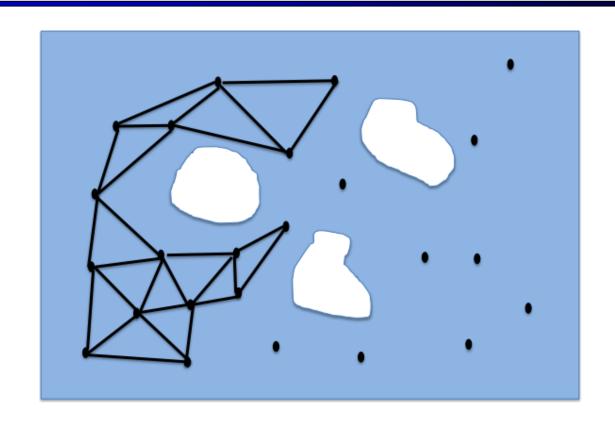
- Many different ways of checking for collisions efficiently
- Ex: Detecting collisions between straight lines and polygons
- Naïve approach: Subsample discrete points along the line
- Check whether midpoint collides with any polygons, then recursively subdivide and check segment midpoints for collisions

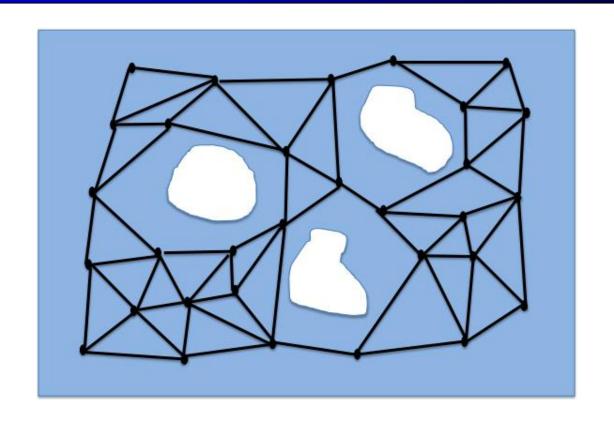


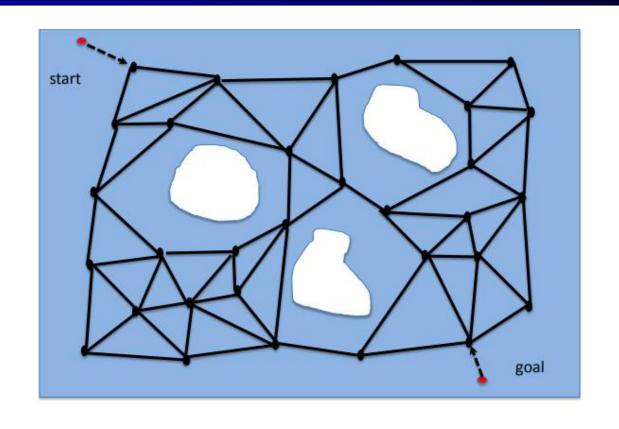


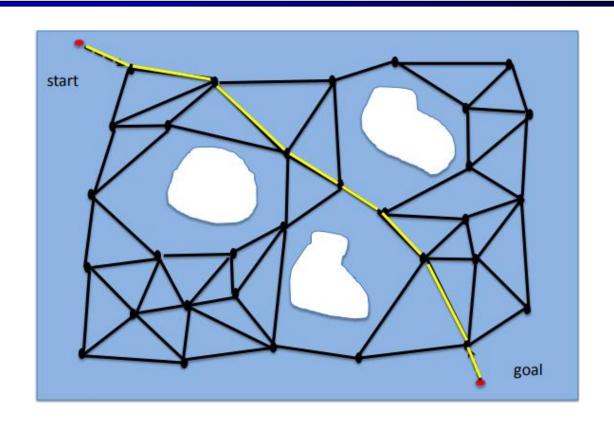


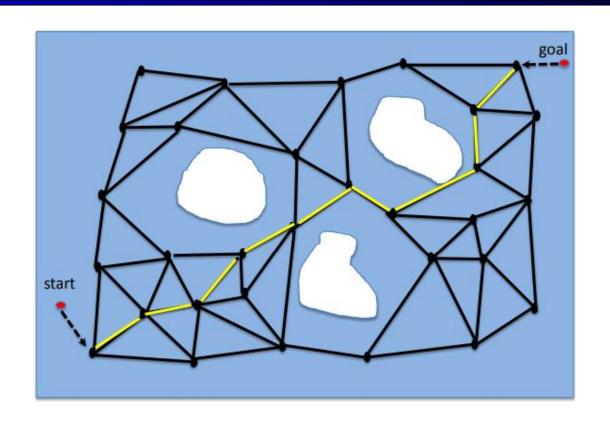












PRM Construction

```
Algorithm 6 Roadmap Construction Algorithm
    Input:
     n: number of nodes to put in the roadmap
     k: number of closest neighbors to examine for each configuration
   Output:
     A roadmap G = (V, E)

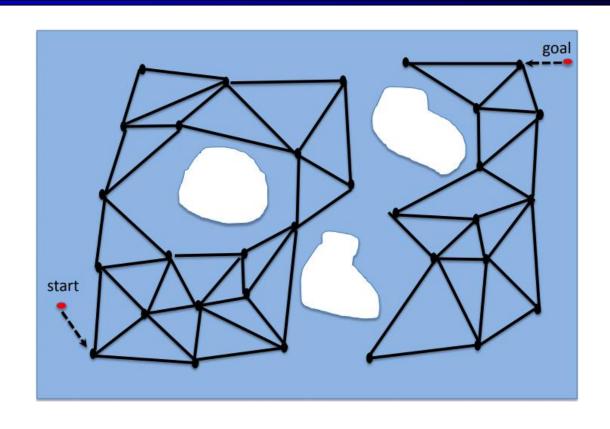
    V ← Ø

2: E ← Ø
 3: while |V| < n do
      repeat
        q \leftarrow a random configuration in Q
      until q is collision-free
      V \leftarrow V \cup \{q\}
 8: end while
9: for all q \in V do
     N_q \leftarrow the k closest neighbors of q chosen from V according to dist
      for all q' \in N_a do
       if (q, q') \notin E and \Delta(q, q') \neq NIL then
12:
       E \leftarrow E \cup \{(q, q')\}
13:
        end if
14:
      end for
16: end for
```

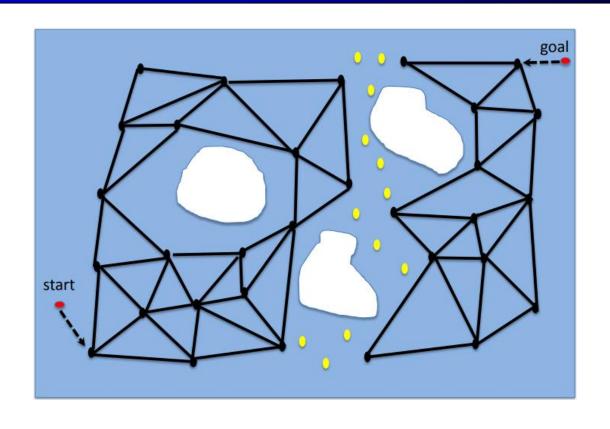
Searching for a Path

- Given start and goal configurations, we can retract them to the roadmap by connecting them to the nearest nodes with a collision-free path
- Problem: What if we can't find any valid local paths?
- Problem: What if start & goal are connected to different graph components?
- Need more samples! Try to focus on areas lacking the connections
 - Sample around start and goal if having trouble connecting them to roadmap
 - Sample in volume between connected components if components are disjoint

Example: Disjoint Components



Example: Disjoint Components



PRM Enhancement

- Goal: Connect as many disjoint components as possible
- One approach: Sample more nodes near narrow passages
- Focus sampling in regions around nodes with fewer neighbors
- Alternatively, try to find more sophisticated paths between components
- E.g. choose closest nodes on two components as candidates for connection
- Or maybe choose connection candidates randomly, but with bias for nodes with few neighbors (more likely near narrow passages)

PRM Enhancement

- To facilitate enhancement, we are interested in nodes in difficult regions
- Maintain a weight/heuristic for each node c as we construct the graph, e.g.
 - Number of neighbors of c within some predefined distance
 - Distance between c and nearest connected component not containing c
- Higher weights make it more likely for a node to be selected for enhancement
- We then attempt to connect the chosen candidates

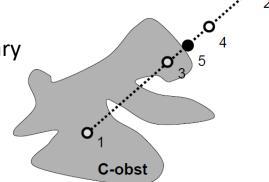
Non-Uniform Sampling: OBPRM

 Sampling uniformly in C-space is not always useful; ideally we want more samples near obstacles (narrow passages) and fewer in free space

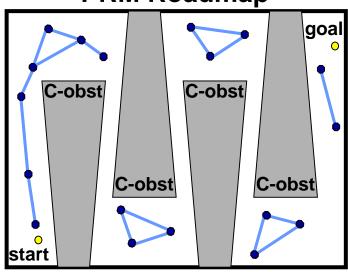
 Idea: Use invalid (colliding) samples to find a valid sample on or near the boundary of the offending obstacle

Choose a random direction and small distance away

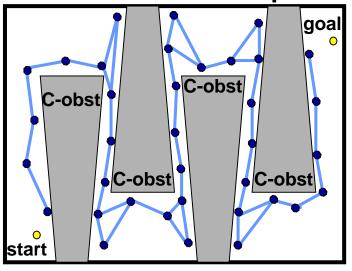
Use binary search to find corresponding point on boundary



PRM Roadmap



OBPRM Roadmap



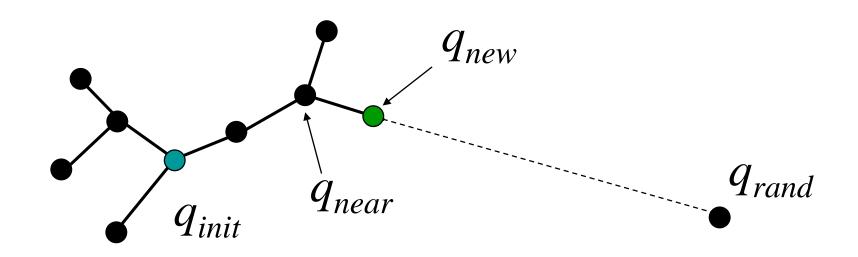
Single-Query vs Multiple-Query

- PRMs (and roadmaps in general) are good for multiple queries
- If we change the start and/or goal configurations, we can reuse the same roadmap and simply compute retractions of the new configurations
- More flexibility, but will slow down roadmap construction
- If we don't care to reuse our roadmap, we can perform sampling with a single query in mind—don't need to worry about the entire C-space
- Definite stopping point: done sampling once a path is found

Rapidly-Exploring Random Trees

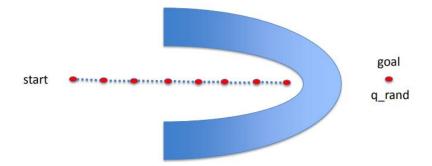
- Idea: Start a graph at the start or goal configurations and build outward
 - As opposed to arbitrarily placing samples all over the C-space
- New nodes added to the tree lie within a certain step-size δ from current tree
- Procedure: Sample random (free) configuration $q_{\rm rand}$
- Find closest tree node $q_{\rm near}$ to $q_{\rm rand}$; also find $q_{\rm new}$ a distance of step-size δ away from $q_{\rm near}$ in direction of $q_{\rm rand}$
- If path between $q_{
 m near}$ and $q_{
 m new}$ is collision-free, expand tree and connect $q_{
 m near}$ to new node $q_{
 m new}$
- q_{rand} is discarded afterward

Graph Construction



Adding Bias to RRT Construction

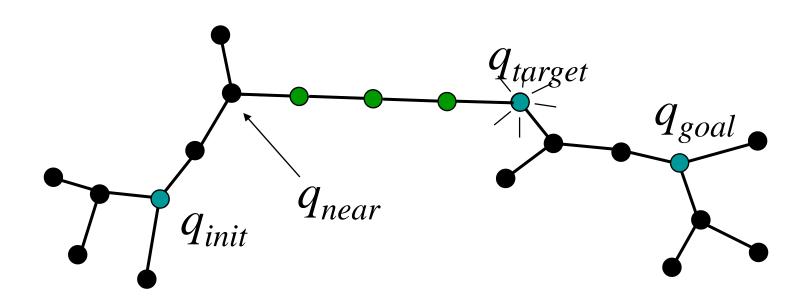
- We want to "explore" outward, but we also want to make sure that we're making progress toward the goal as we build
- Idea: Add a bias when selecting $q_{\rm rand}$ to select goal some of the time (~5%)
- Tree will expand in goal direction on occasion
- Too much bias can lead to local minima! Ex: $q_{
 m rand} = q_{
 m goal}$ all the time:



Bidirectional RRT

- We may increase efficiency even more if we grow RRTs from start and goal
- After growing for a while, we need a connection procedure
- Expand T_1 randomly and add node $q_{1,\text{new}}$
- Expand T_2 toward $q_{1,\text{new}}$; if connected, complete path is found
- If not connected but T_2 does expand and add $q_{2,\text{new}}$, swap roles and have T_1 expand toward $q_{2,\text{new}}$; iterate until finished or failure
- If not connected (collision) and no expansion, then not ready for connection

Example: Connecting RRTs



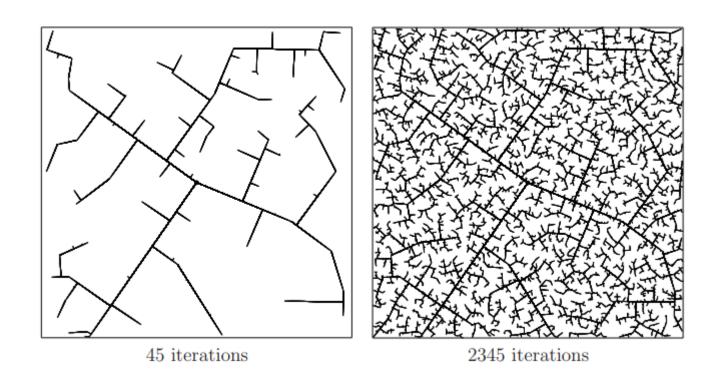
RRT Connect Algorithm

```
RRT_CONNECT (q_{init.} q_{aoal}) {
 T_a.init(q_{init}); T_b.init(q_{aoal});
 for k = 1 to K do
   q_{rand} = RANDOM\_CONFIG();
   if not (EXTEND(T_{cr}, q_{rand}) = Trapped) then
      if (EXTEND(T_{b}, q_{new}) = Reached) then
         return PATH(T_a, T_b);
   SWAP(T_a, T_b);
 return Failure;
```

RRT Considerations

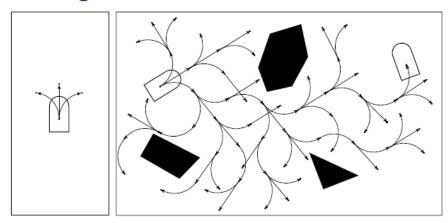
- RRT is fundamentally a balance between greedy search and exploration
- Stepsize δ may be chosen as a function of free space; with many free regions, we can choose δ to be bigger and have a more greedy construction procedure
- RRT vertex distribution converges to sampling distribution in the long term
- Probability of finding a path increases exponentially with number of iterations
- RRT is probabilistically complete but not optimal (not even asymptotically)

RRT Limiting Behavior



RRTs for Nonholonomic Robots

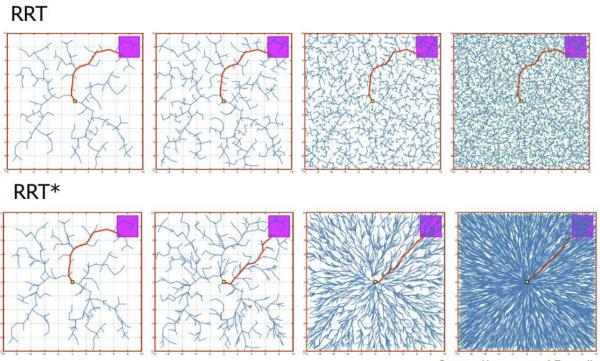
- Robots with nonholonomic constraints cannot travel in arbitrary directions
- Instead, identify admissible motion primitives, e.g. straight paths and turns with constant curvature
- When expanding RRT, only add nodes that can be reached via a motion primitive from an existing node in RRT



RRT*

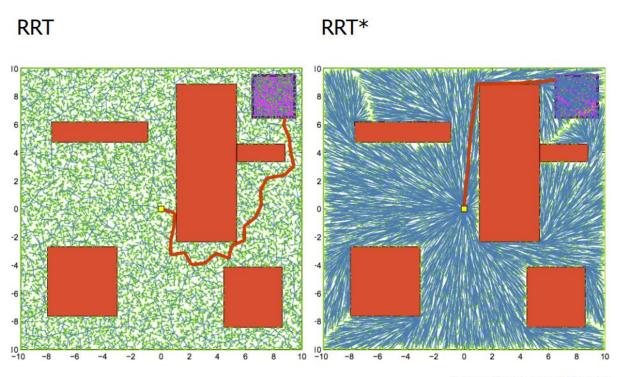
- As with PRMs, many different versions of RRTs suited for different purposes
- Rapidly-exploring random graph (RRG): New graph nodes can be connected to multiple nearby nodes in graph so far, leading to possible cycles
- Optimal RRT (RRT*): Add multiple edges to new node as in RRG, but then prune out cycles so that only those corresponding to optimal (shortest) paths from root are kept
- Existing nodes may change parents as tree grows outward!
- Trees tend to be more fan-shaped, paths tend to be smoother
- Unlike RRT, this is asymptotically optimal (but at cost of increased computation)

RRT*



Source: Karaman and Frazzoli

RRT*



Source: Karaman and Frazzoli

Summary

- Sampling-based methods are very useful when we cannot or don't need to build the entire C-space for planning
- PRM: Build an approximate roadmap through free C-space, especially regions near obstacles; supports multiple queries of different start/goal configurations
- RRT: Single-query; balance exploration and exploitation to find some coverage of C-space but simultaneously favor paths that solve given problem
- http://msl.cs.uiuc.edu/rrt/index.html
- https://en.wikipedia.org/wiki/Rapidly-exploring_random_tree
- http://demonstrations.wolfram.com/RapidlyExploringRandomTreeRRTAndRRT/