

Sampling-Based Methods for Path Planning: Part II

With so many slides and ideas from so many people:
Howie Choset, Nancy Amato, David Hsu, Sonia Chernova,
Steve LaValle, James Kuffner, Greg Hager

Mobile Robots vs Robot Manipulators

So far, we've seen two kinds of robots in this class:

Mobile robots:

- Treat the robot as a single rigid object that moves in the plane.
- Can describe position and orientation using $SE(2)$
 - ***If we know the values for $(x, y, \theta) \in SE(2)$, we know everything there is to know about the robot.***

Robot arms:

- A series of links connected by single-dof joints
- Describe the robot using a vector of joint variables
- Describe the position and orientation of the tool (end effector) using $SE(2)$
- The mapping between the joint variables and tool position/orientation can be tricky, but the key idea is this:
 - ***If we know the values for the joint variables, we know everything there is to know about the manipulator.***

For both robots, given the values of some set of variables, we know everything there is to know about the robot (w.r.t. its geometry).

Configuration Space

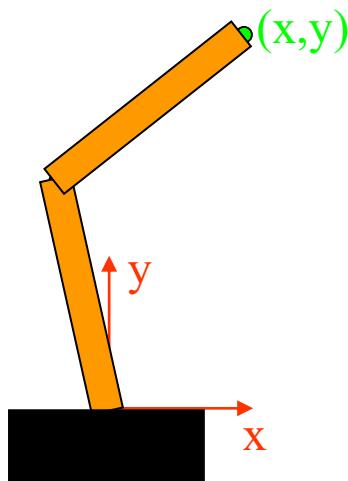
C-space formalism:
Lozano-Perez 1979

A key concept for motion planning is a **configuration**:

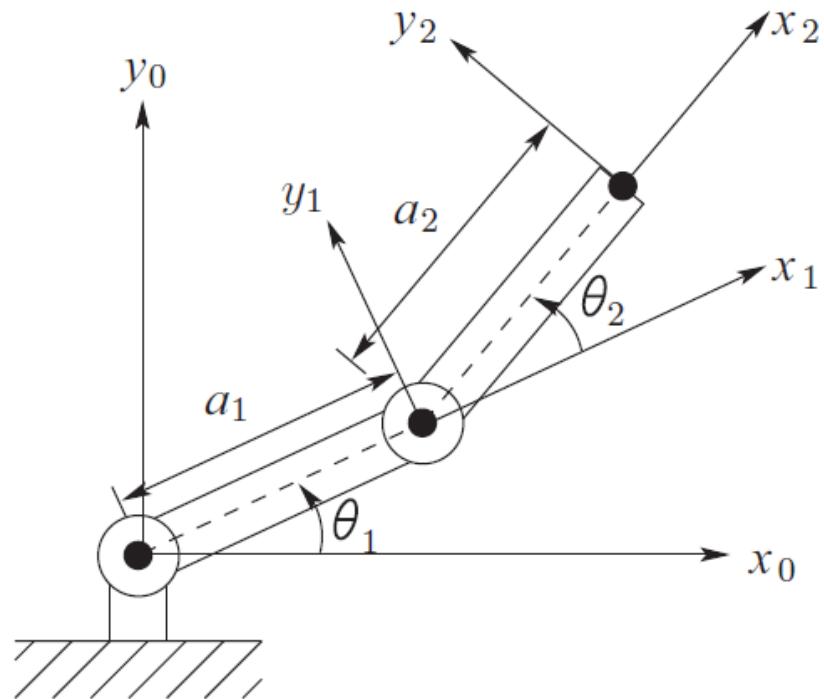
- A *configuration* of a system is a complete specification of the position of every point in the system
- The space of all configurations is the *configuration space* or *C-space*.

Forward Kinematics

Compute position of some point on the robot, given the values of joint variables



Find (x, y) in terms
of joint angles



$$x = a_1 \cos \theta_1 + a_2 \cos (\theta_1 + \theta_2)$$
$$y = a_1 \sin \theta_1 + a_2 \sin (\theta_1 + \theta_2)$$

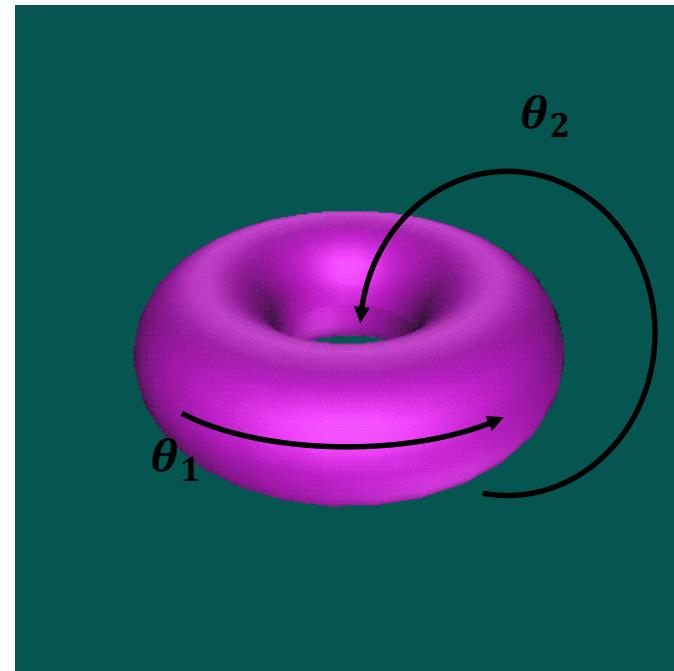
Configuration Space: two-link arm

For the End Effector:

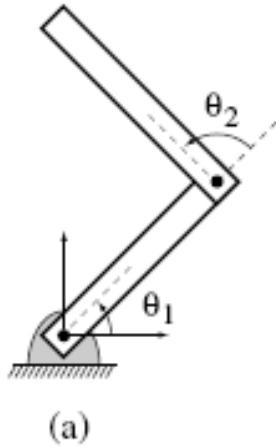
$$x = a_1 \cos \theta_1 + a_2 \cos (\theta_1 + \theta_2)$$
$$y = a_1 \sin \theta_1 + a_2 \sin (\theta_1 + \theta_2)$$

For any point (x, y) on the two-link robot, we can derive a similar set of equations:

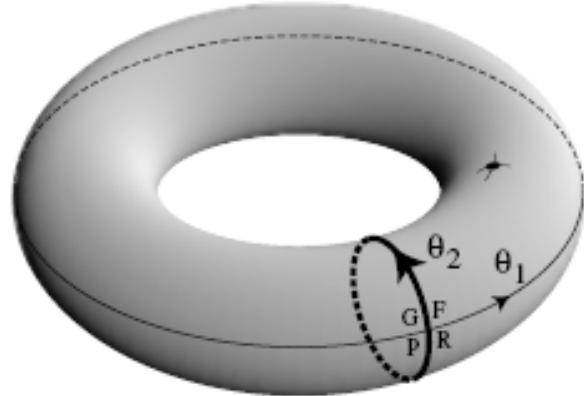
- The angles θ_1, θ_2 completely define the configuration of this robot!
- The Configuration Space for this robot is a torus!
- θ_1 is the angle *around the donut*
- θ_2 is the angle *through the hole*



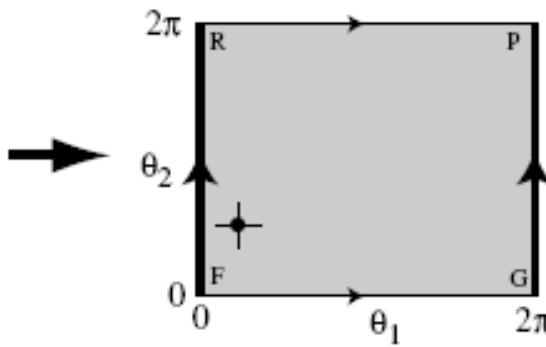
Representing the configuration space



Represent the torus as a
'square' with 'edges identified'



(b)



(c)

Obstacles in C-Space

- Let q denote a point in a configuration space \mathcal{Q}
- The path planning problem is to find a mapping $\gamma: [0,1] \rightarrow \mathcal{Q}$ s.t. no configuration along the path intersects an obstacle.
- Denote the i -th workspace obstacle by \mathcal{O}_i , and by $R(q)$ the volume occupied by the robot at configuration q .
- A configuration space obstacle $\mathcal{Q}\mathcal{O}_i$ is the set of configurations q at which the robot intersects \mathcal{O}_i

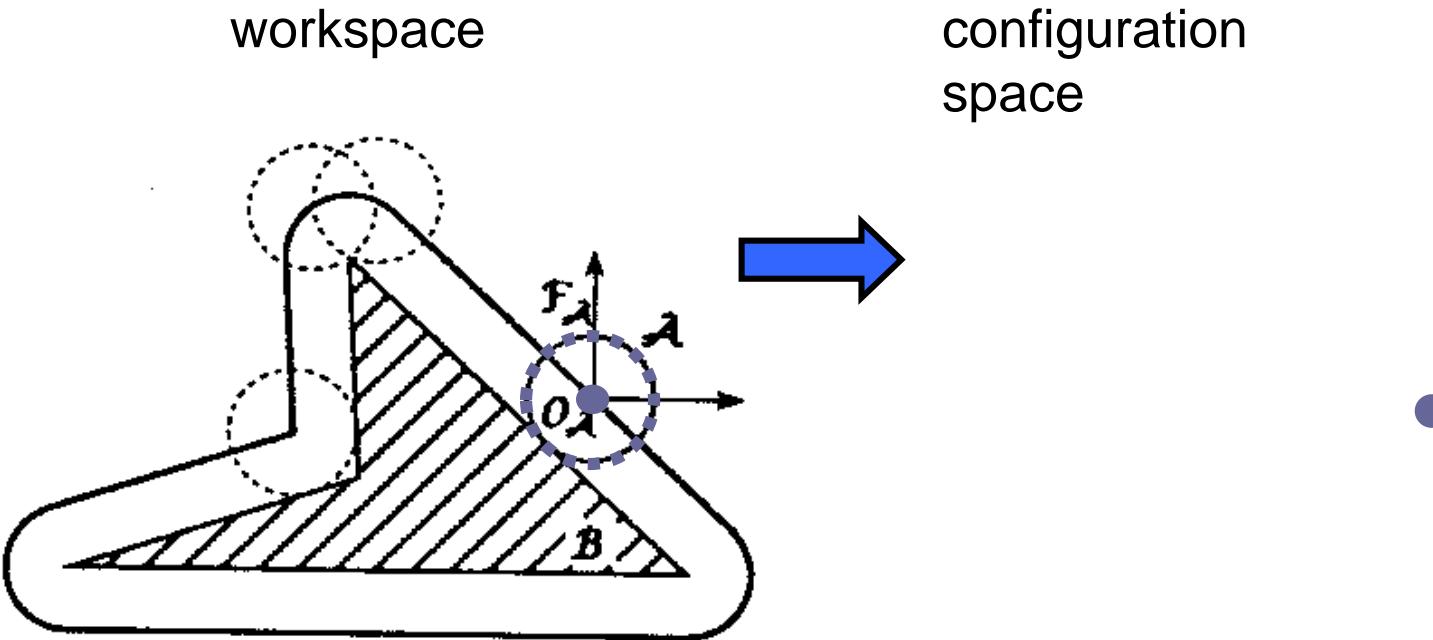
$$\mathcal{Q}\mathcal{O}_i = \{ q \in \mathcal{Q} \mid R(q) \cap \mathcal{O}_i \neq \emptyset \}$$

- The free configuration space (or just free space) \mathcal{Q}_{free} is

$$\mathcal{Q}_{free} = \mathcal{Q} - \cup_i \mathcal{Q}\mathcal{O}_i$$

- The free space is generally an open set.
- A free path is a mapping $\gamma: [0,1] \rightarrow \mathcal{Q}_{free}$.
- A semi-free path is a mapping $\gamma: [0,1] \rightarrow cl(\mathcal{Q}_{free})$.

Disc in 2-D workspace

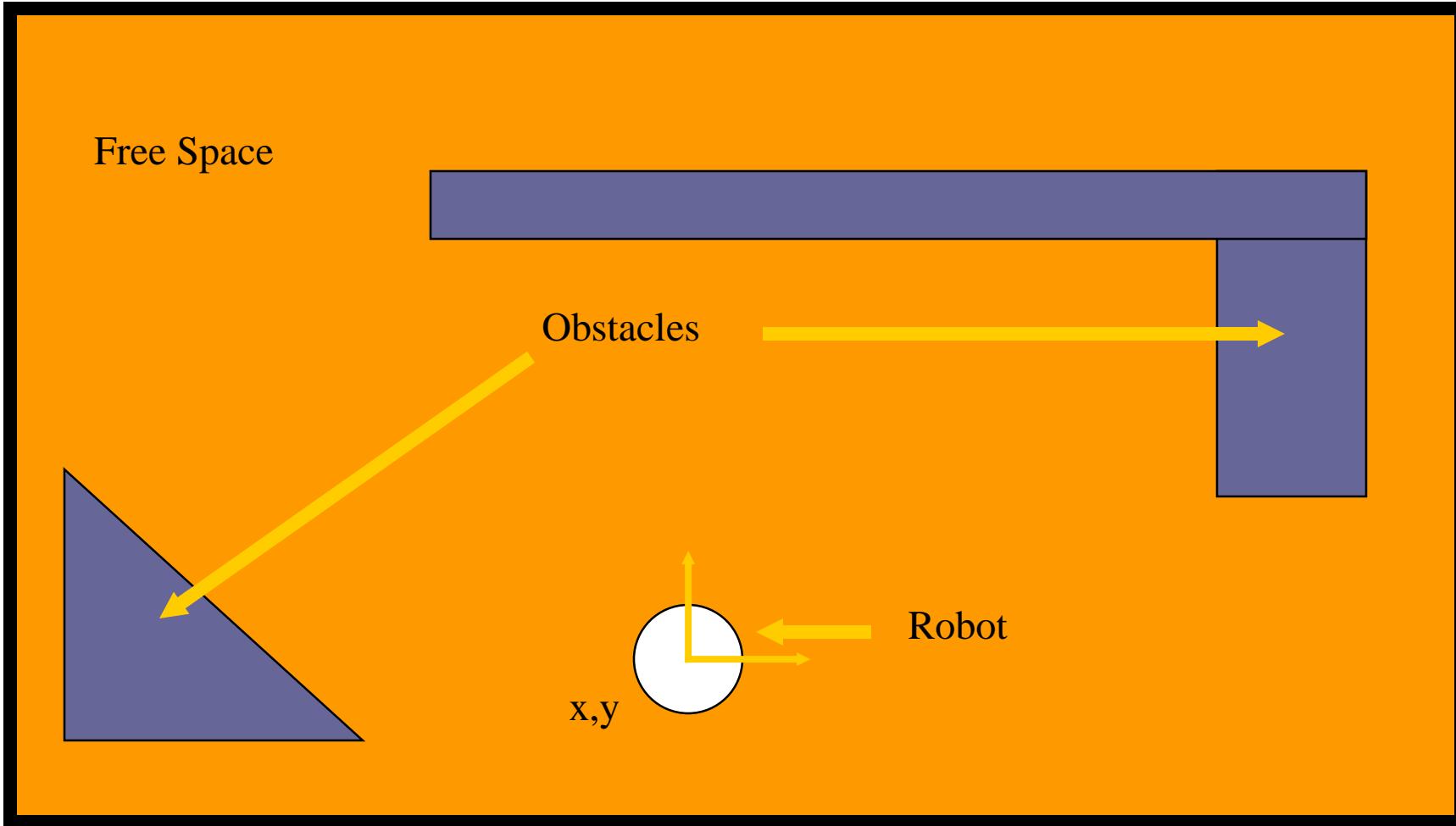


For our application

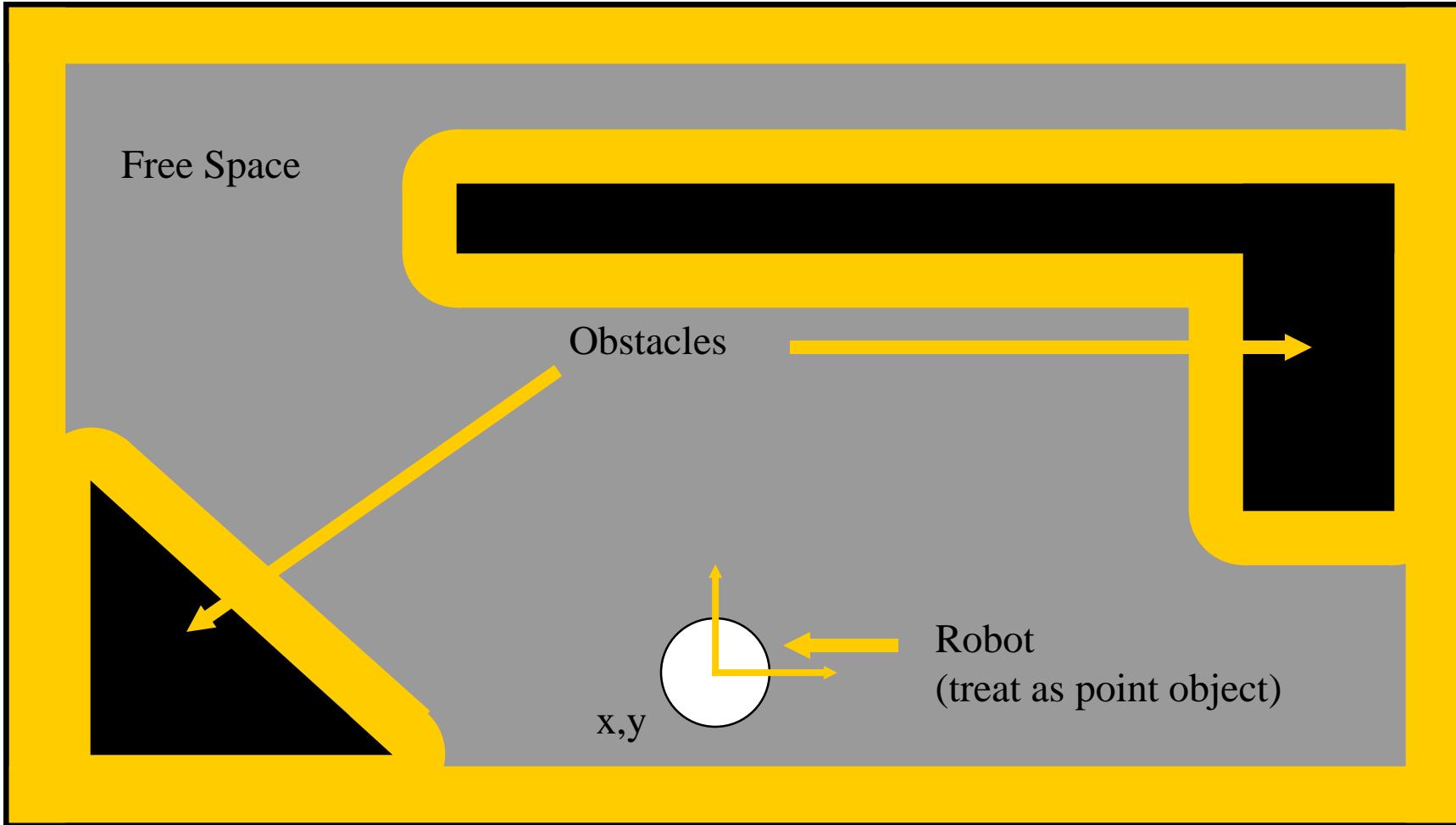
- Our mobile robot is close enough to being circular that it is fine to model it as a circle with a fixed radius.



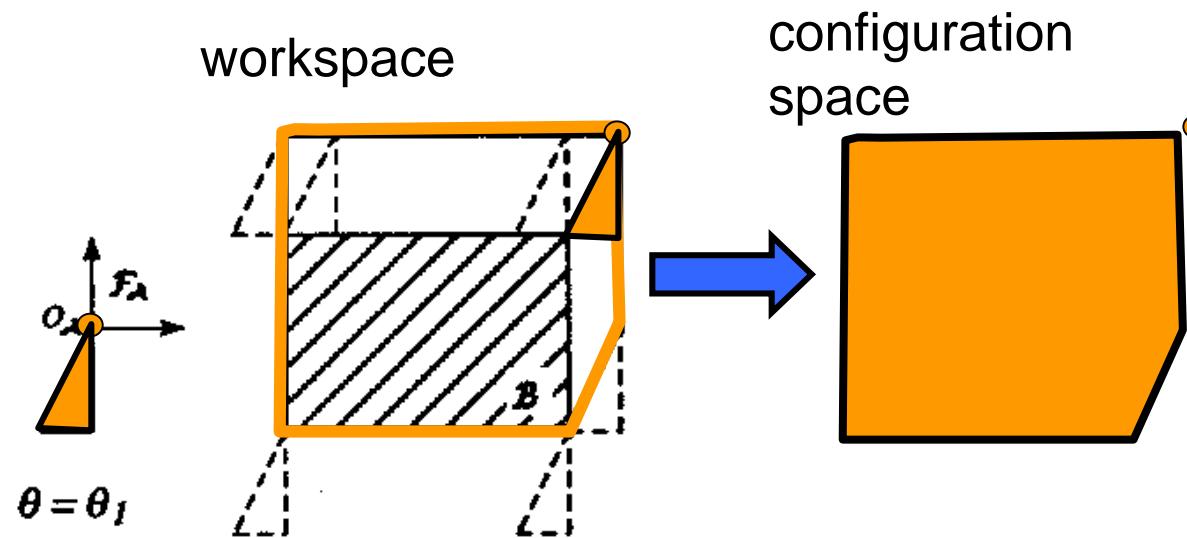
Example of a World (and Robot)



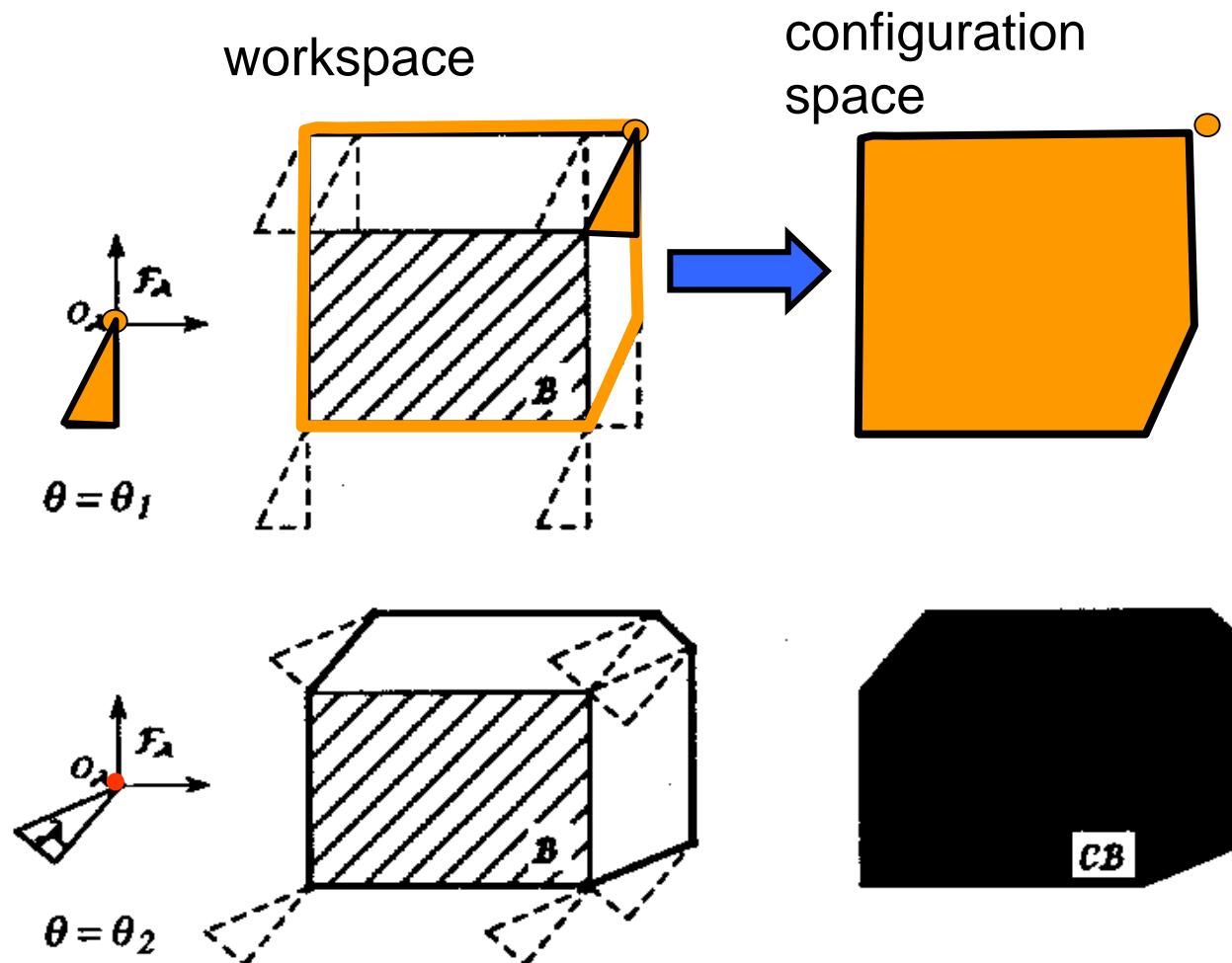
Configuration Space: Accommodate Robot Size



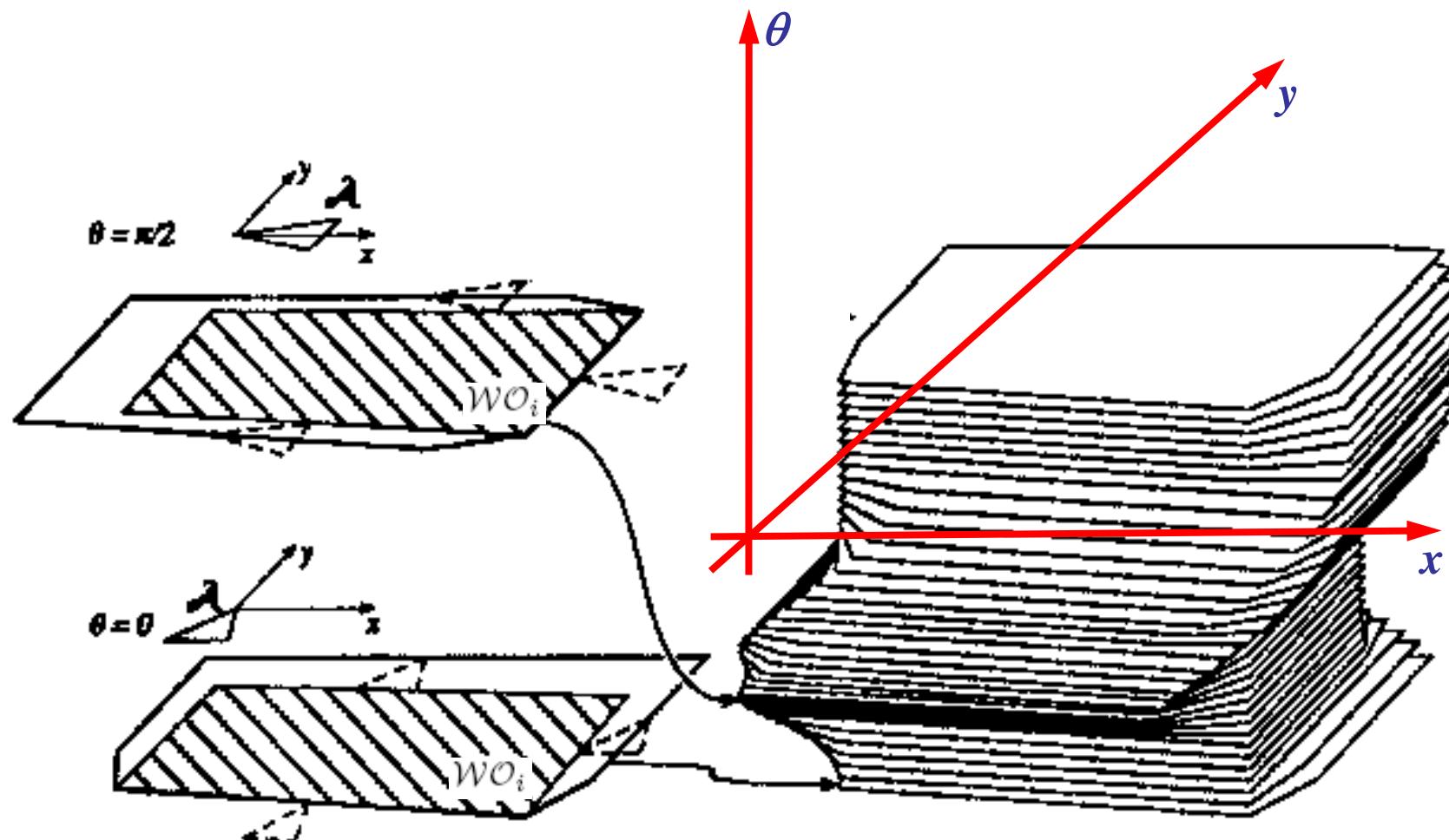
Polygonal robot translating in 2-D workspace



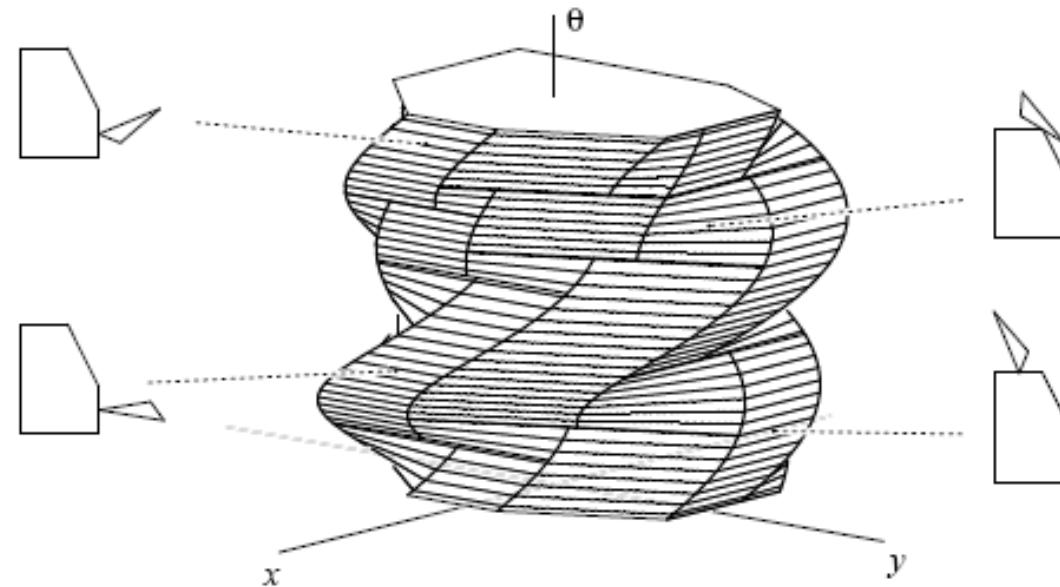
Polygonal robot translating in 2-D workspace



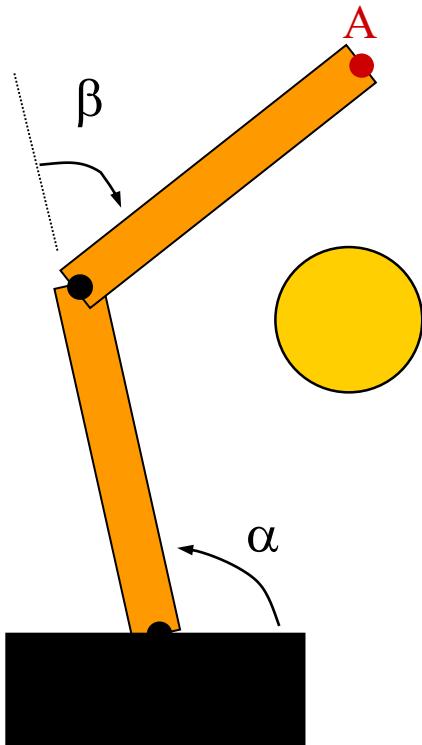
Polygonal robot translating & rotating in 2-D workspace



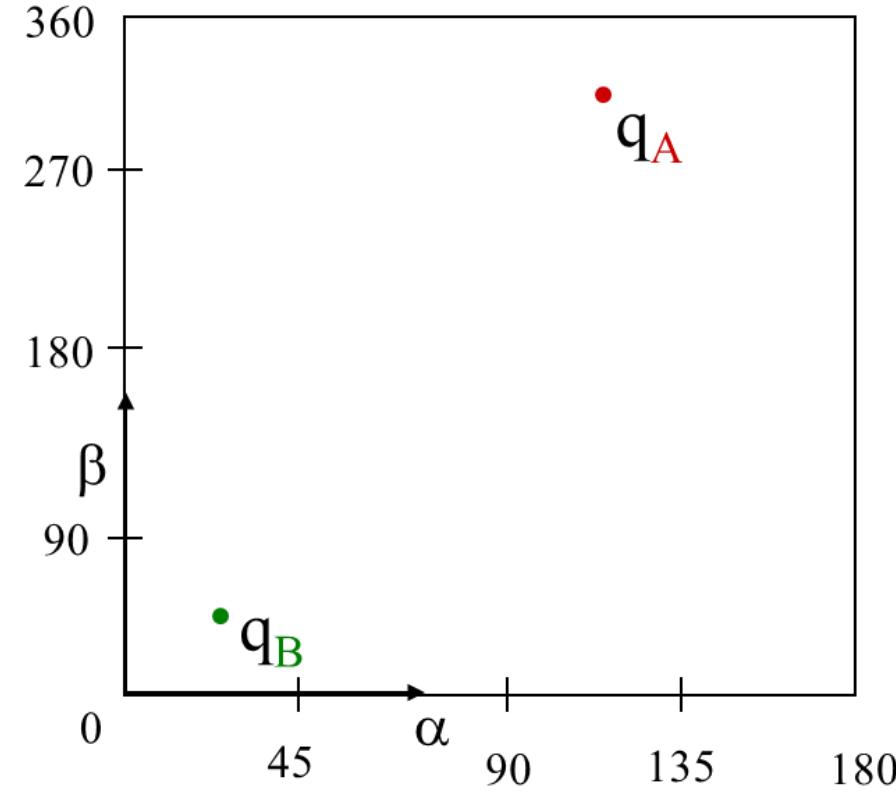
$SE(2)$



Configuration Space

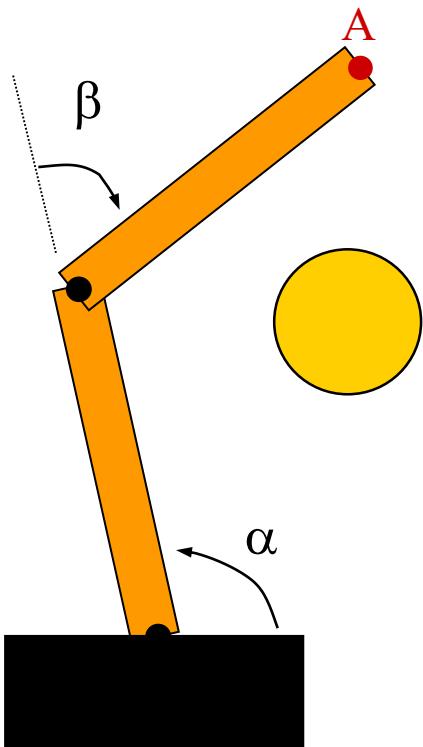


Where do we put ?

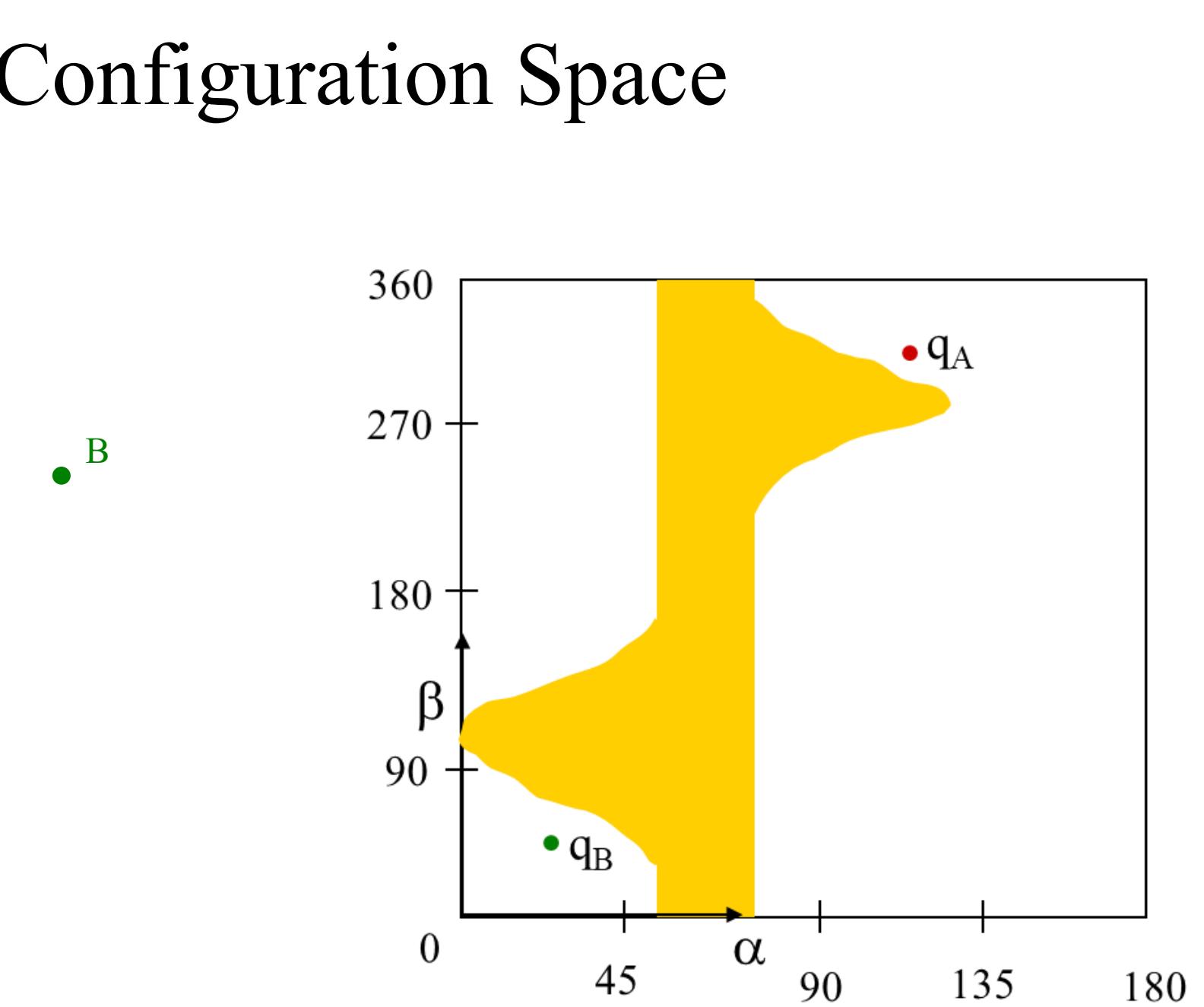


Torus
(wraps horizontally and vertically)

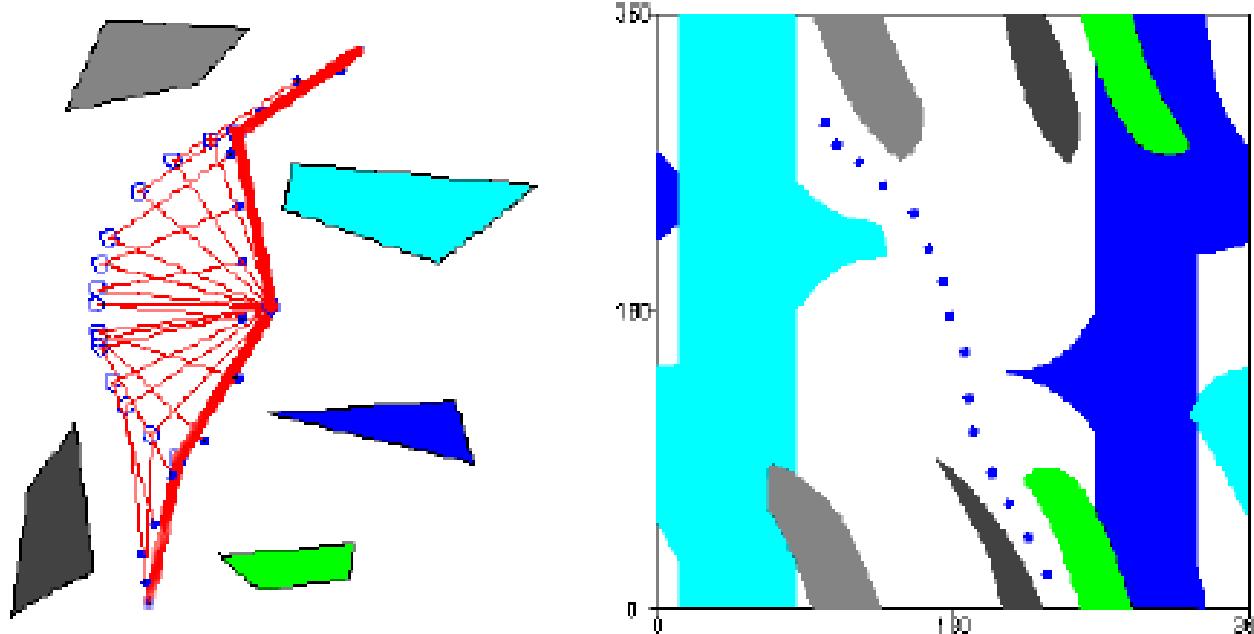
Configuration Space



B

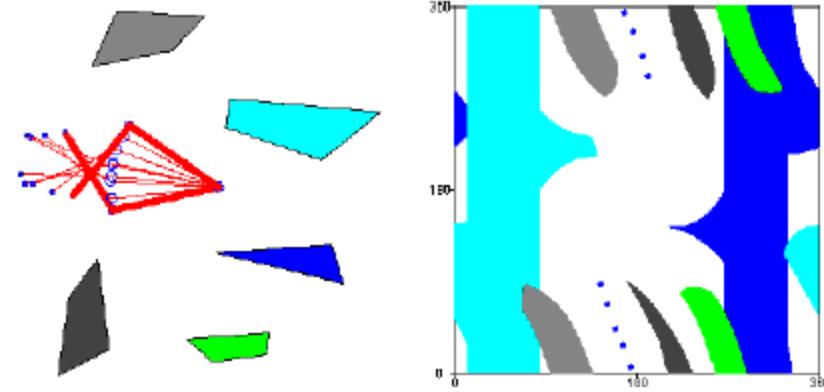
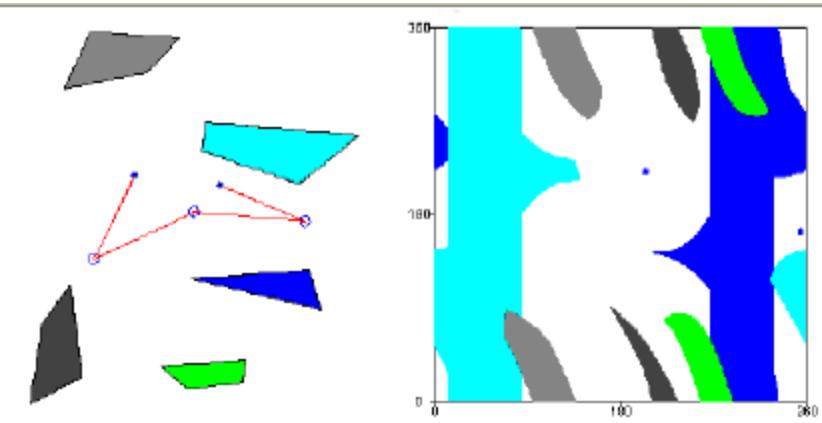


Two Link Path



Thanks to Ken Goldberg

Two Link Path



How can we automatically plan these paths?

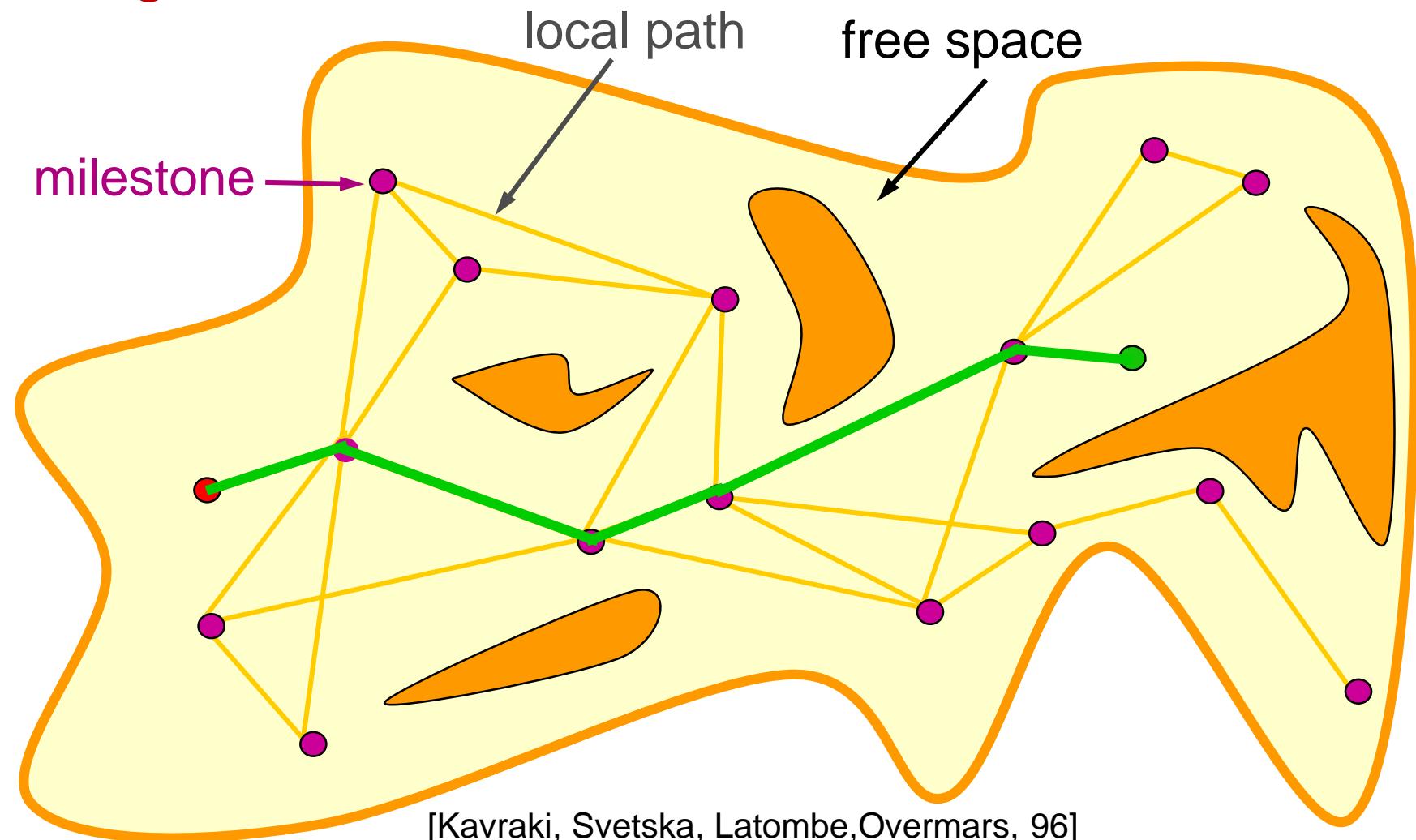
In fact, we already know how to do this:

Sampling-Based Planning!

When we first saw PRM, it was for planning paths of simple mobile robots moving in the plane.

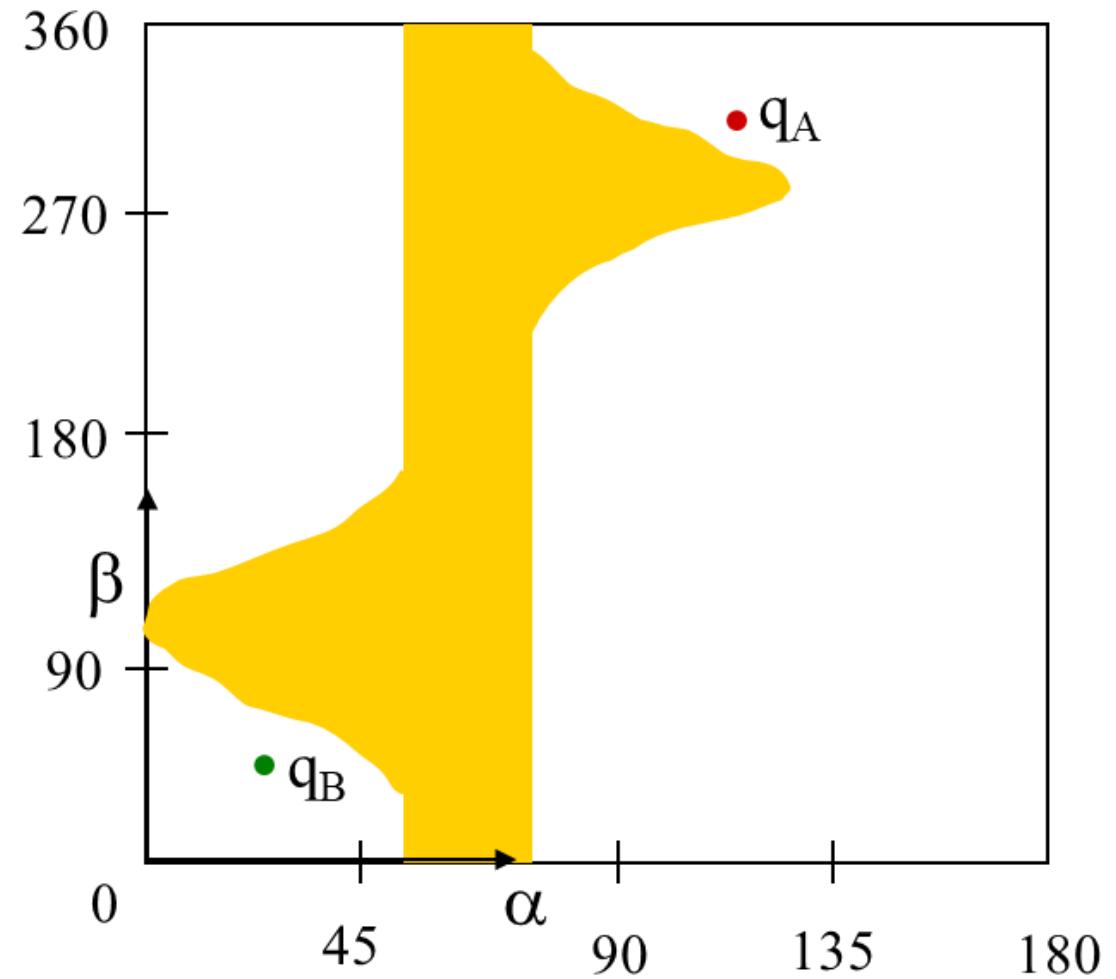
With the concept of C-Space, We can easily generalize the method.

The only changes needed are in the local path planner and collision-checking routines.



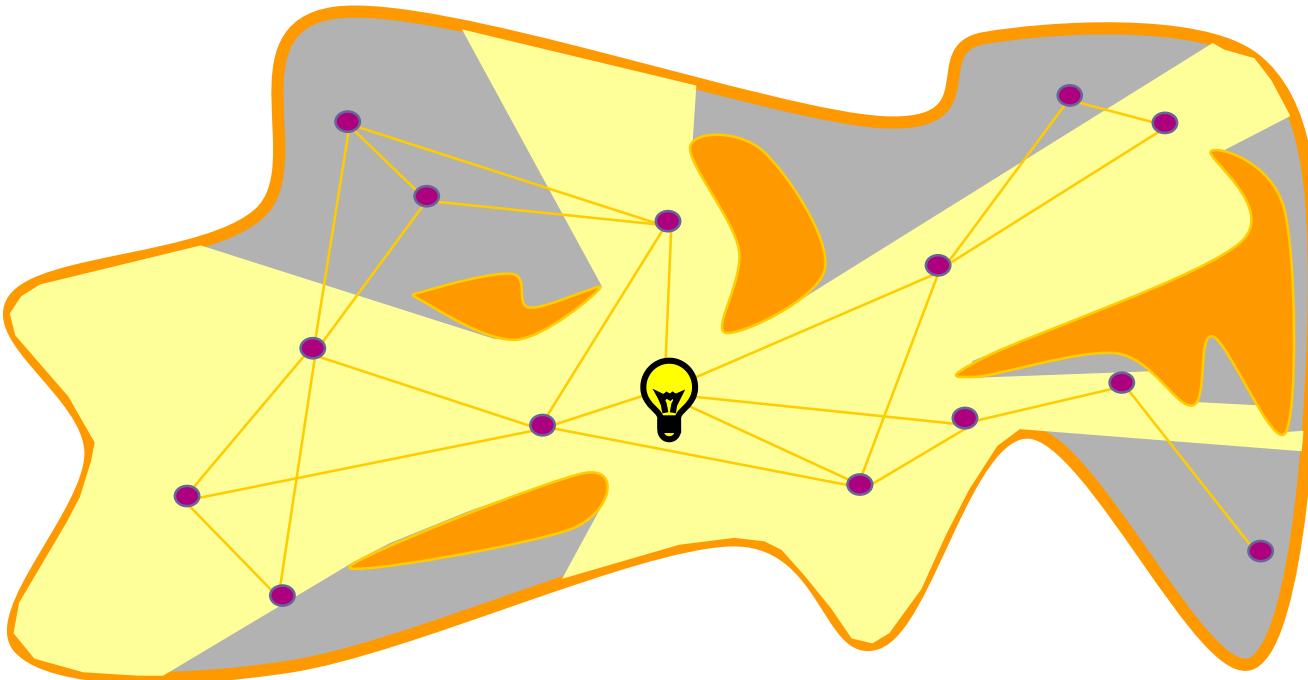
Why is Path Planning Difficult?

- The hard part for path planning is explicitly constructing a representation of the configuration space obstacle region (or the free configuration space).
 - For the example here, we used a grid, and merely evaluated each grid point to see if it was collision free.
 - This works for simple 2D cases, but if we discretize each axis into N intervals, the number of grid cells becomes N^d for a d -dimensional configuration space:
 - ***This approach does not scale!***
 - With sampling-based planning, we need to answer the question:
 - ***Does the straight-line path between two samples cause a collision?***
- This is not such a difficult query – fast collision checking algorithms exist.



Why does it work? Intuition

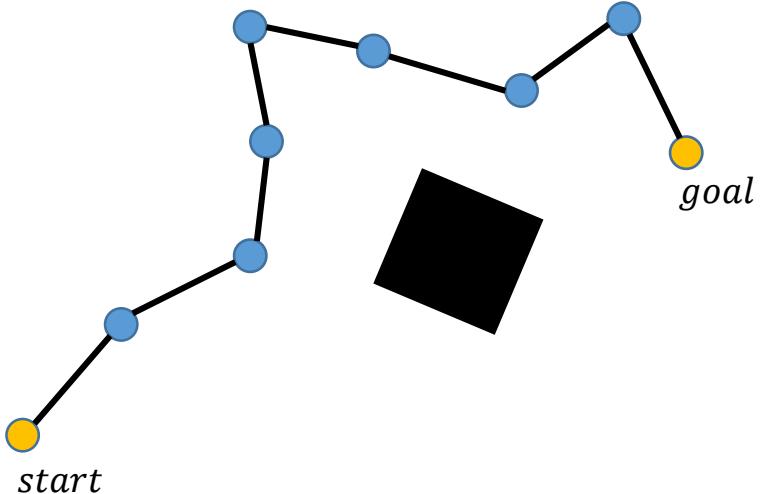
- A small number of milestones **almost** “cover” the **entire** configuration space.



- Rigorous definitions and exist (of course!)

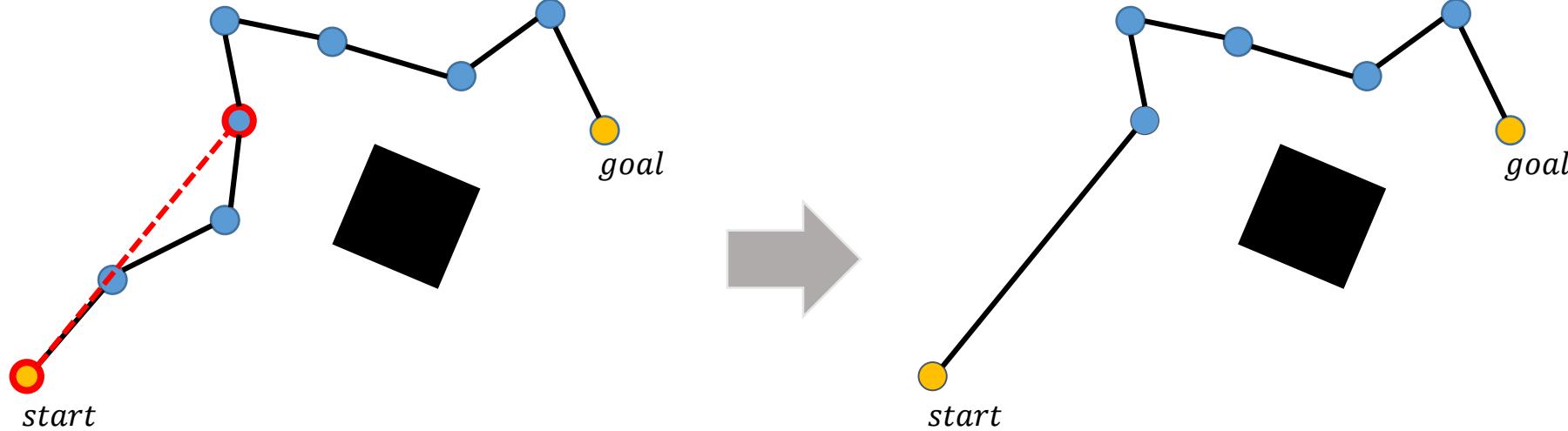
Optimizing the path

- Milestone-based paths are far from optimal and require additional refinement before they are usable
- A typical solution can look like this:



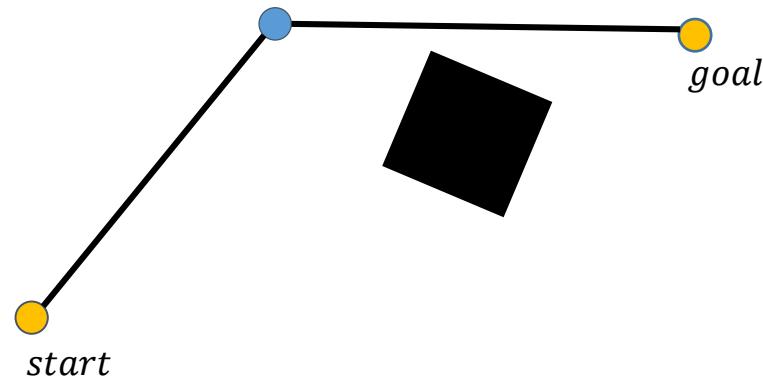
Optimizing the path

- A simple way to improve the path, is to repeatedly pick two nodes at random, and check whether they can be connected by a straight line without collision. If so, use the line to shorten the path.



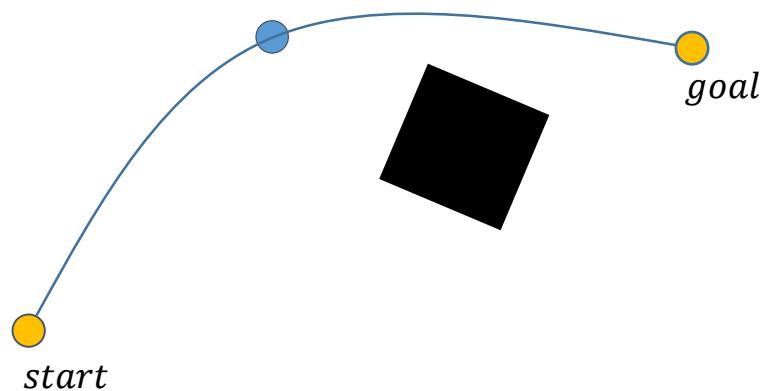
Optimizing the path

- Repeat for N iterations, or until no further improvements are being made
- The result is not an optimal path, but shorter and more efficient than the original

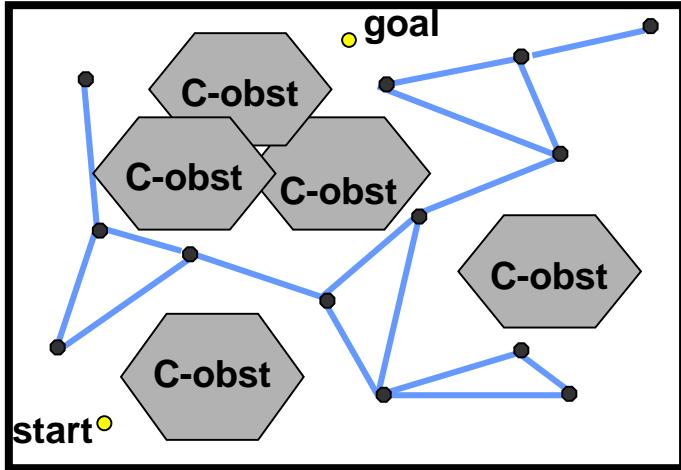


Smoothing the path

- Optionally, the shortened path can then be smoothed to allow for continuous robot motion



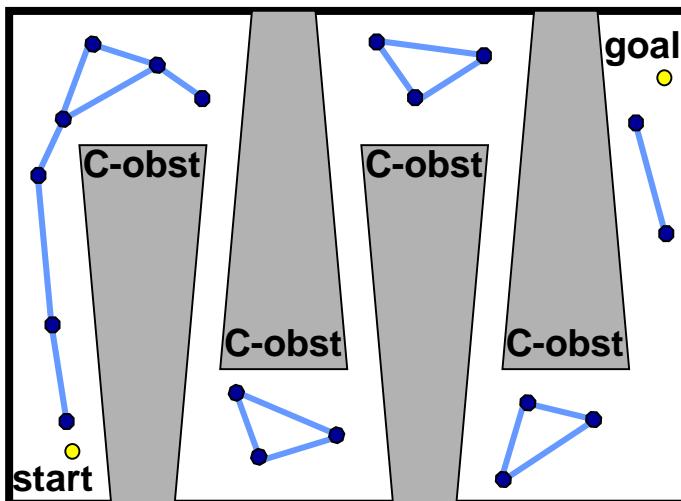
Good news, but bad news too



Sample-based: The Good News

1. *probabilistically complete*
2. Do not construct the C-space
3. apply easily to high-dimensional C-space
4. support fast queries w/ enough preprocessing

Many success stories where PRMs solve previously unsolved problems



Sample-Based: The Bad News

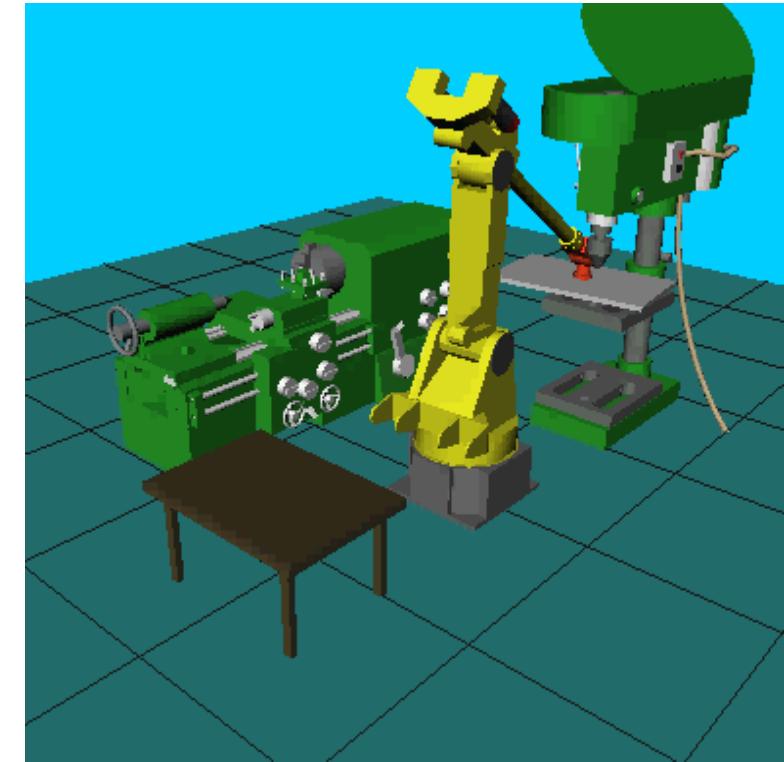
1. don't work as well for some problems:
 - unlikely to sample nodes in *narrow passages*
 - hard to sample/connect nodes on constraint surfaces
2. No optimality or completeness

PRM variants

- There are (very) many...
- Lazy PRM:
 - Create a dense PRM without ANY collision checking
 - When you have q_{init} and q_{goal} :
 - Find $q_{init} \rightarrow s_1 \rightarrow s_2 \rightarrow q_{goal}$
 - Check only the edges in the returned path for collisions, remove any edges with collisions.

Assumptions

- Static obstacles
- Many queries to be processed in the same environment
- Examples
 - Navigation in static virtual environments
 - Robot manipulator arm in a workcell
- Advantages:
 - Amortize the cost of planning over many problems
 - Probabilistically complete



General Types of approaches that use sampling

Sampling-based methods typically fall into two categories:

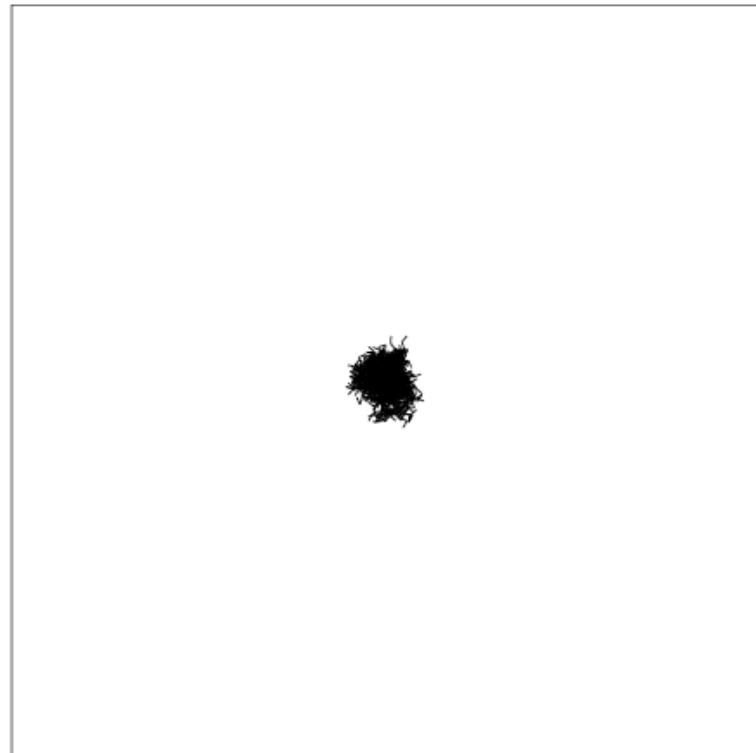
| | Multi-query | Single-query |
|-------------------|--|---|
| Phases | 1. Roadmap construction 2. Searching | Roadmap construction and searching online |
| Typical algorithm | Probabilistic Roadmap (PRM) | Rapidly Exploring Random Tree (RRT) |
| Pros | Fast searching | No preprocessing |
| Cons | Inability to deal with environment changes | No memory |

Rapidly-Exploring Random Tree (RRT)

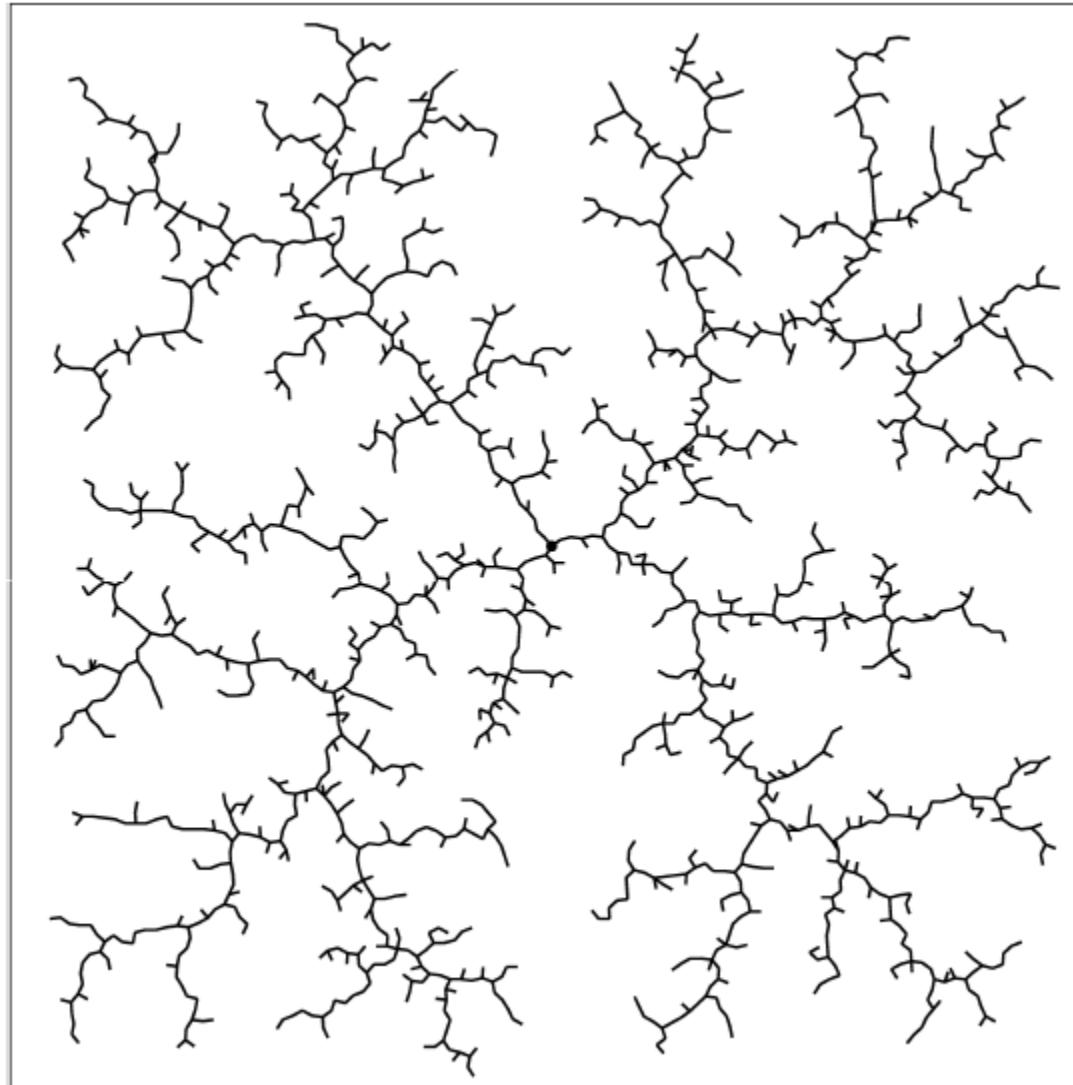
- Searches for a path from the initial configuration to the goal configuration by expanding a search tree
- For each step,
 - The algorithm samples a target configuration and expands the tree towards it.
 - The sample can either be a random configuration or the goal configuration itself, depends on the probability value defined by the user.

Naïve random tree

- Pick a vertex at random
- Move in a random direction to generate a new vertex
- Repeat...



Rapidly-Exploring Random Tree

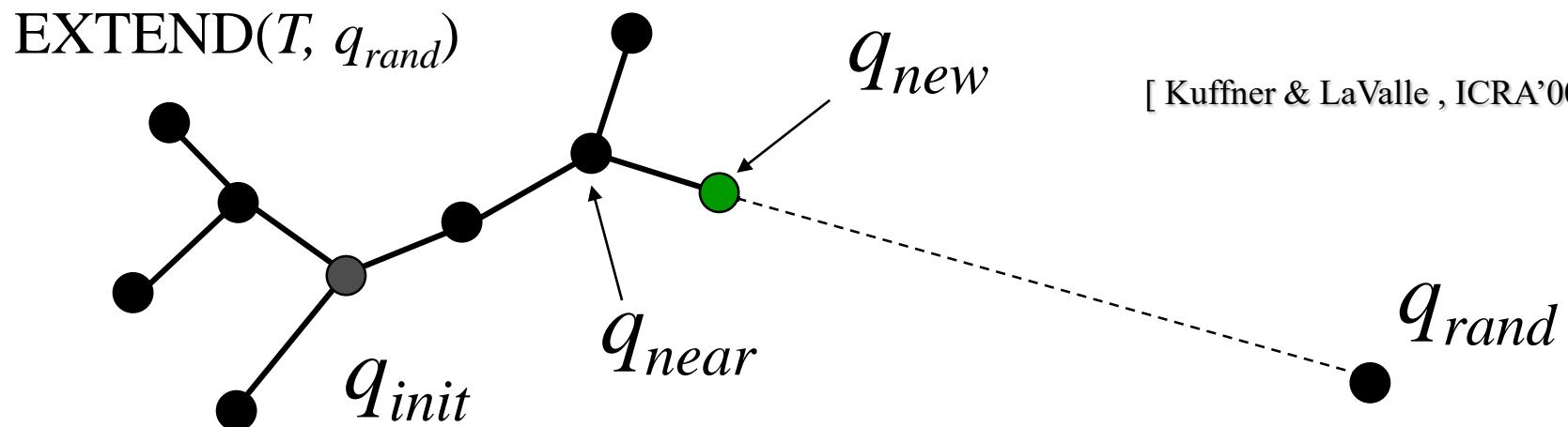


The Basic Idea: Iteratively expand the tree

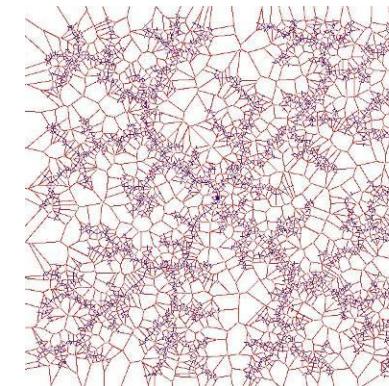
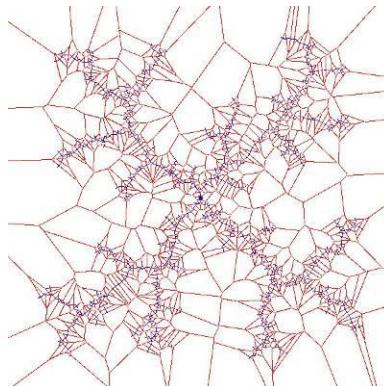
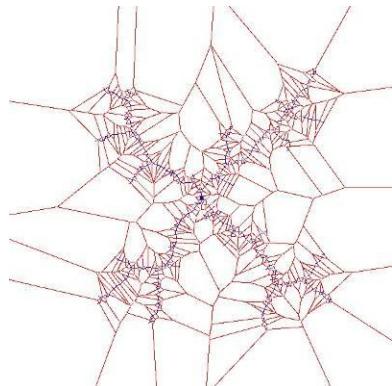
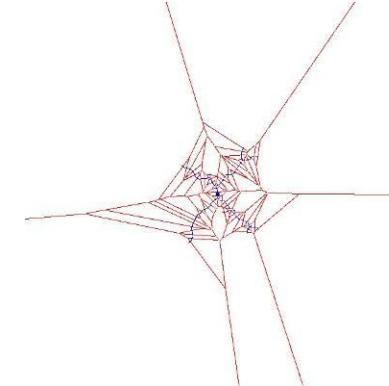
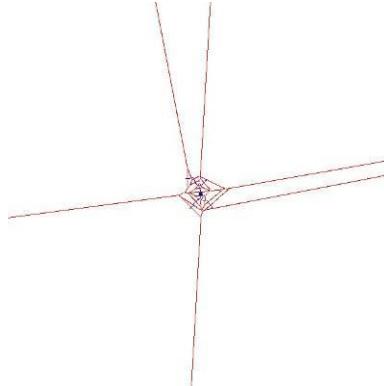
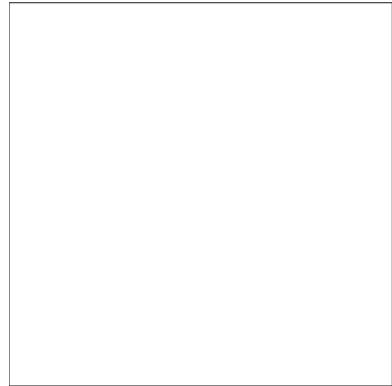
- Denote by T_k the tree at iteration k
- Randomly choose a configuration q_{rand}
- Choose $q_{near} = \arg \min_{q \in T_k} d(q, q_{rand})$
 - q_{near} is the nearest existing node in the tree to q_{rand}
- Create a new node, q_{new} by taking a small step from q_{near} toward q_{rand}

Path Planning with RRTs

```
BUILD_RRT ( $q_{init}$ ) {  
     $T.init(q_{init})$ ;  
    for  $k = 1$  to  $K$  do  
         $q_{rand} = \text{RANDOM\_CONFIG}()$ ;  
        EXTEND( $T$ ,  $q_{rand}$ )  
    }  
}
```

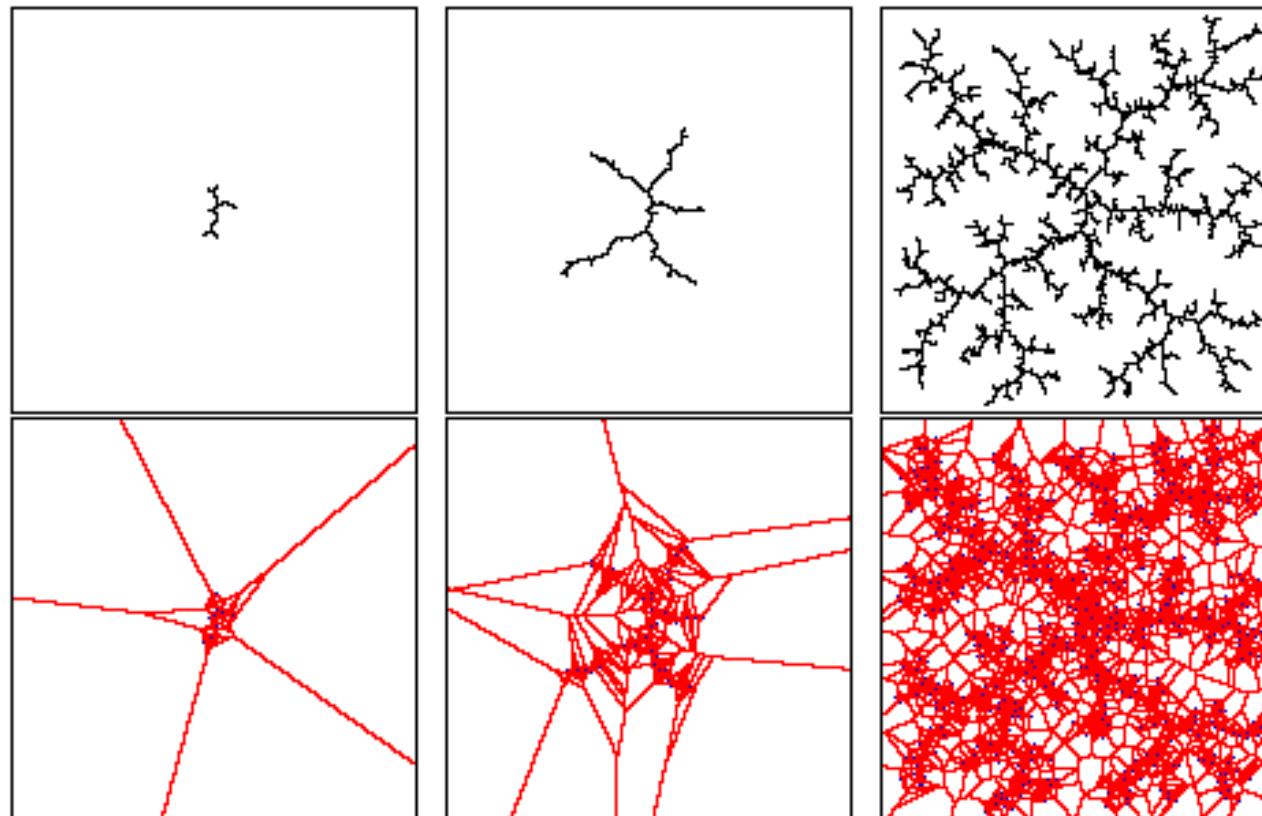


RRTs and Bias toward large Voronoi regions



<http://msl.cs.uiuc.edu/rrt/gallery.html>

Why are RRT's rapidly exploring?



The probability of a node being selected for expansion (i.e. being a nearest neighbor to a new randomly picked point) is proportional to the area of its Voronoi region.

Biases

- Bias toward larger spaces
- Bias toward goal
 - When generating a random sample, with some probability pick the goal instead of a random node when expanding
 - This introduces another parameter
 - James' experience is that 5-10% is the right choice
 - If you do this 100%, then this is a RPP

RRT in Action...

RRT

Requires the following functions:

RRT

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`p = RandomSample()`

Uniform random sampling of free configuration space

RRT

Requires the following functions:

$p = \text{RandomSample}()$

Uniform random sampling of free configuration space

$v = \text{Nearest}(p)$

Given point in Cspace, find vertex on tree that is closest to that point

RRT

Requires the following functions:

$p = \text{RandomSample}()$

Uniform random sampling of free configuration space

$v = \text{Nearest}(p)$

Given point in Cspace, find vertex on tree that is closest to that point

$p' = \text{Steer}(p, \text{goal})$

For a point p and a goal point, find p' that is closer to the goal than p

RRT

Requires the following functions:

$p = \text{RandomSample}()$

Uniform random sampling of free configuration space

$v = \text{Nearest}(p)$

Given point in Cspace, find vertex on tree that is closest to that point

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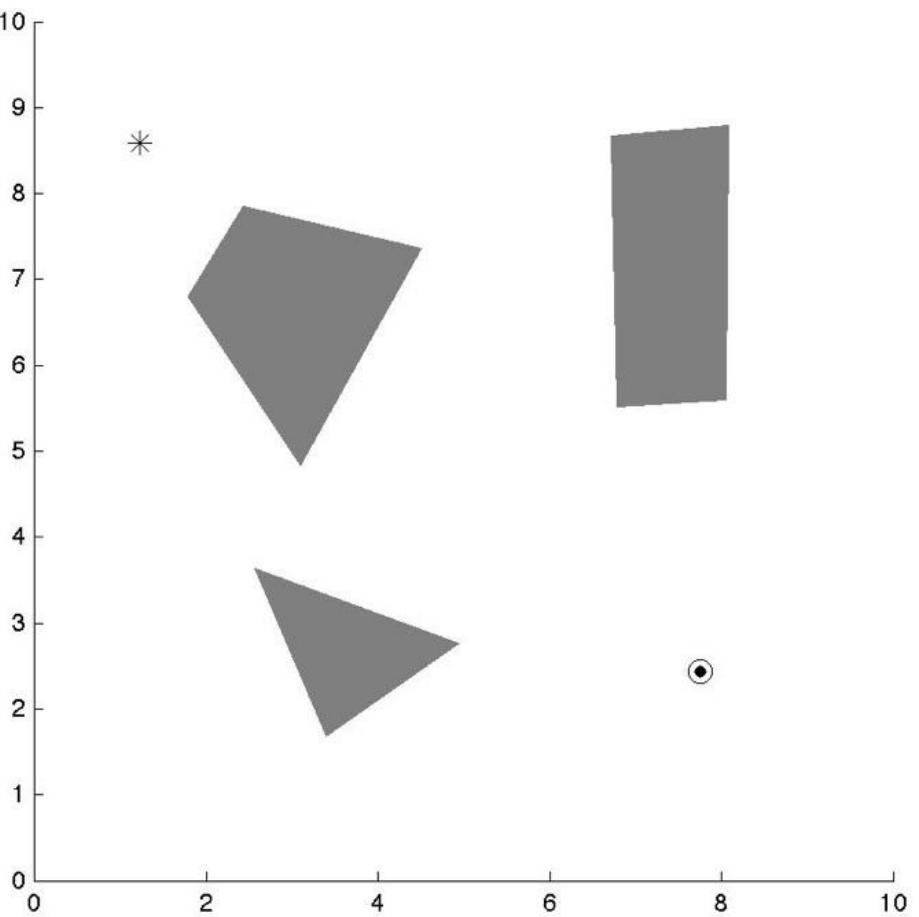
For a point p and a goal point, find p' that is closer to the goal than p

$\text{ObstacleFree}(p)$

Check if a given Cspace point is in the free space

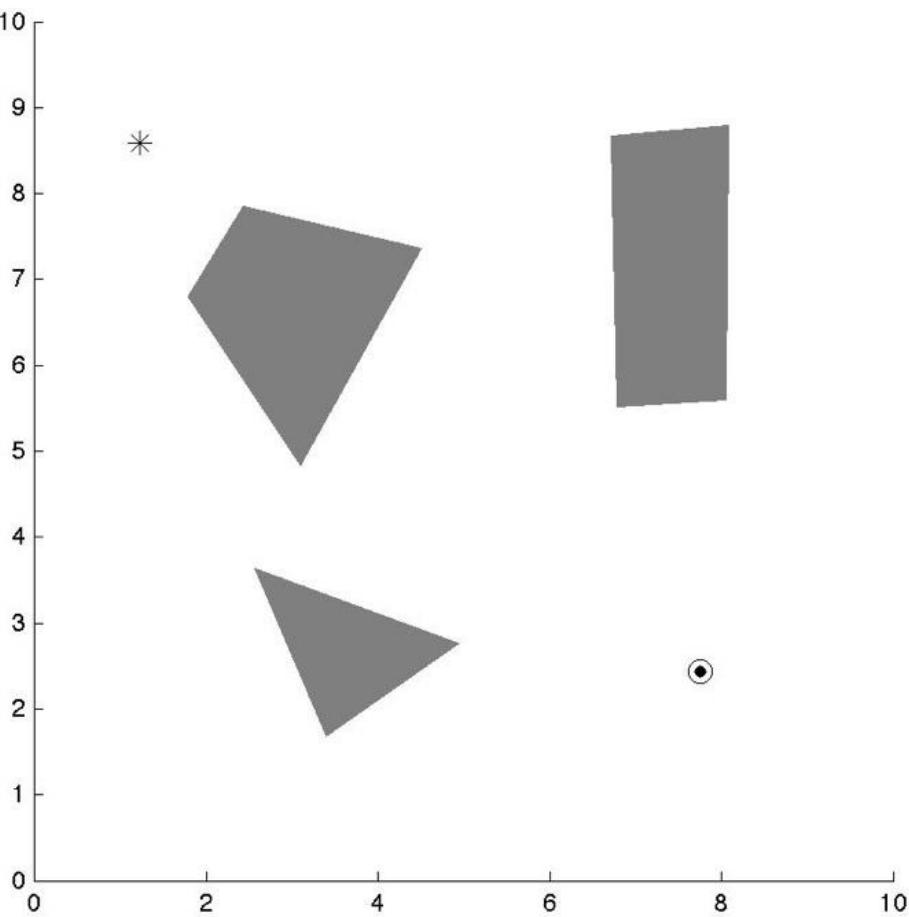
RRT

```
 $V \leftarrow \{x_{init}\}; E \leftarrow \emptyset$ 
for  $i = 1$  to  $N$ 
     $G \leftarrow (V, E)$ 
     $x_{rand} \leftarrow RandomSample()$ 
     $x_{nearest} \leftarrow Nearest(G, x_{rand})$ 
     $x_{new} \leftarrow Steer(x_{nearest}, x_{rand})$ 
    if  $ObstacleFree(x_{nearest}, x_{new})$ 
         $V \leftarrow V \cup \{x_{new}\}$ 
         $E \leftarrow E \cup \{(x_{nearest}, x_{new})\}$ 
```



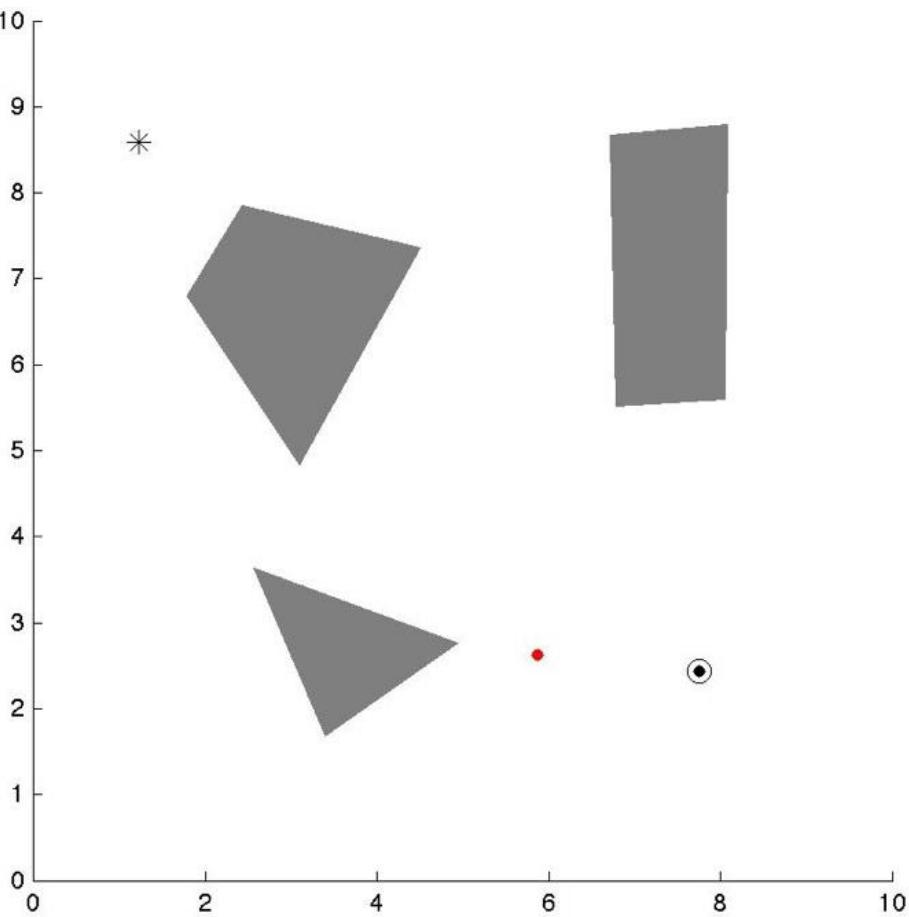
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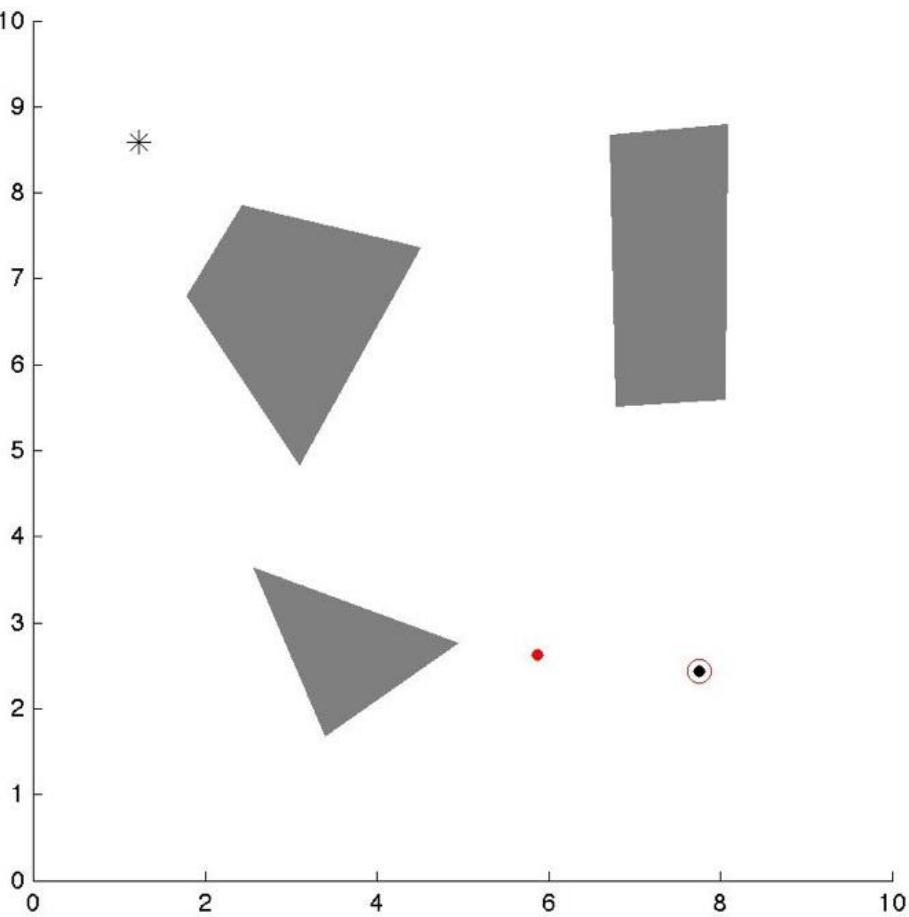
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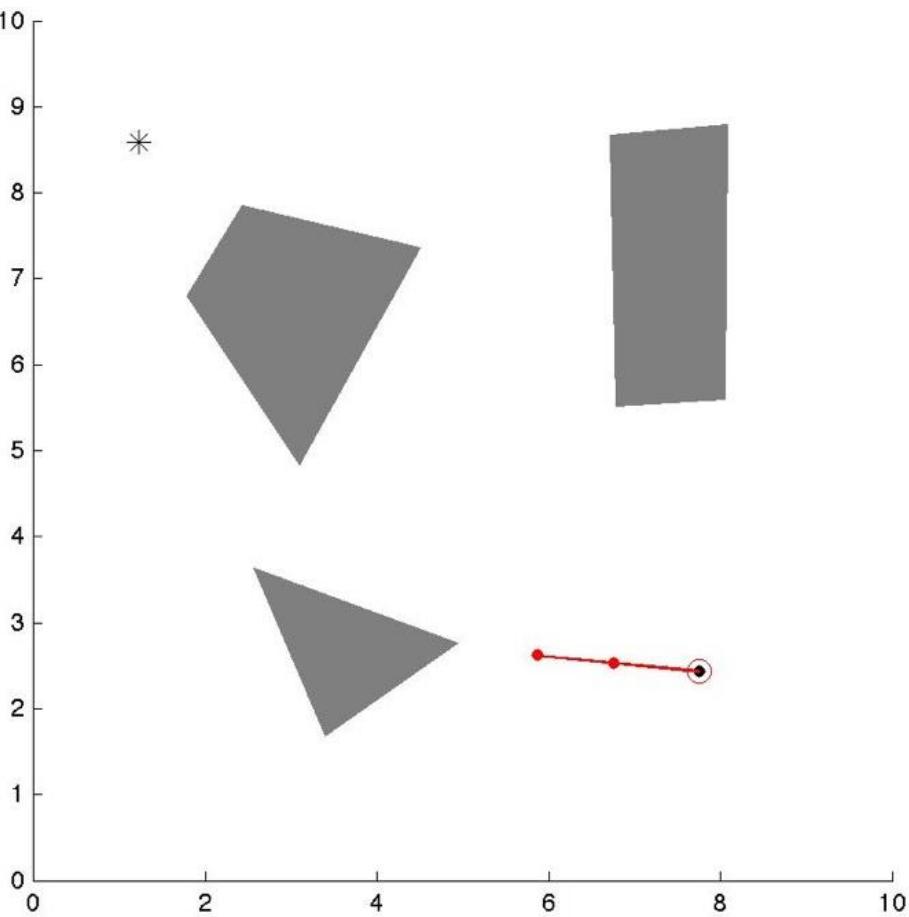
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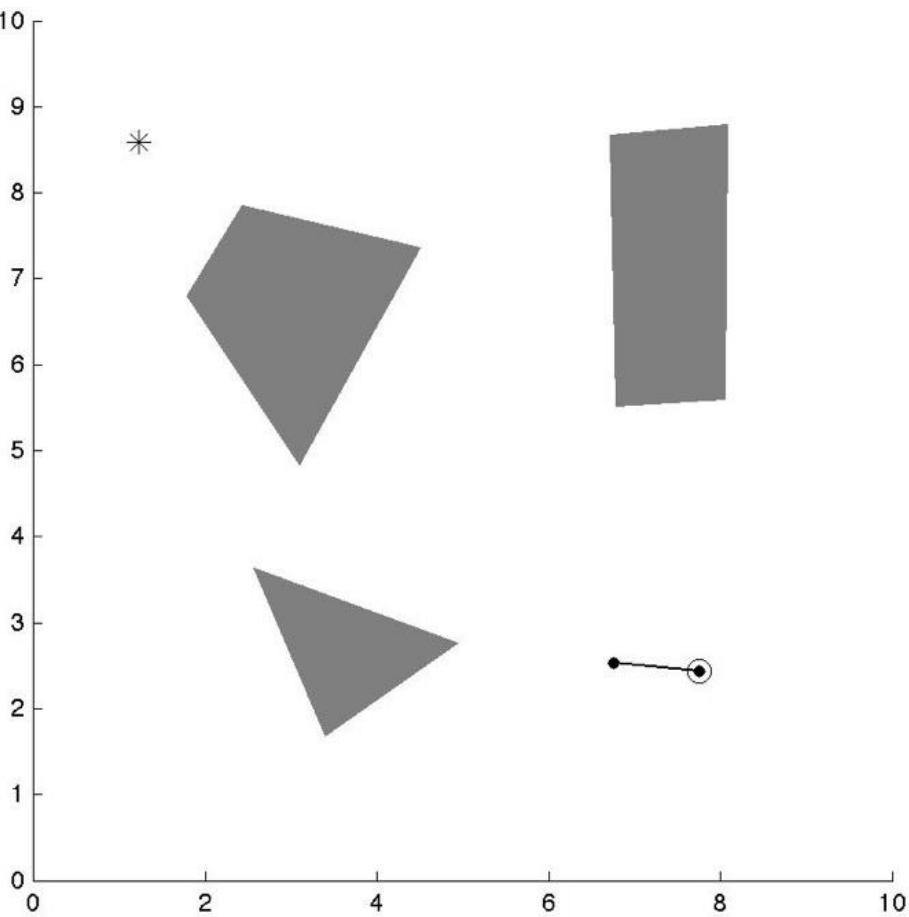
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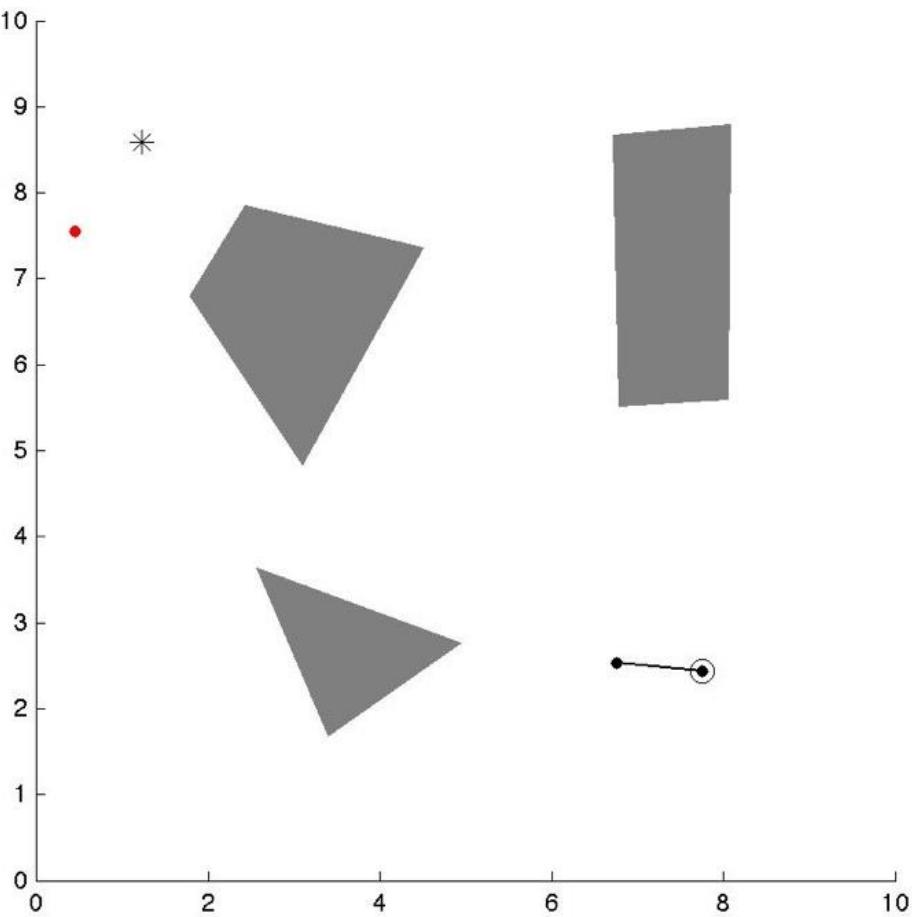
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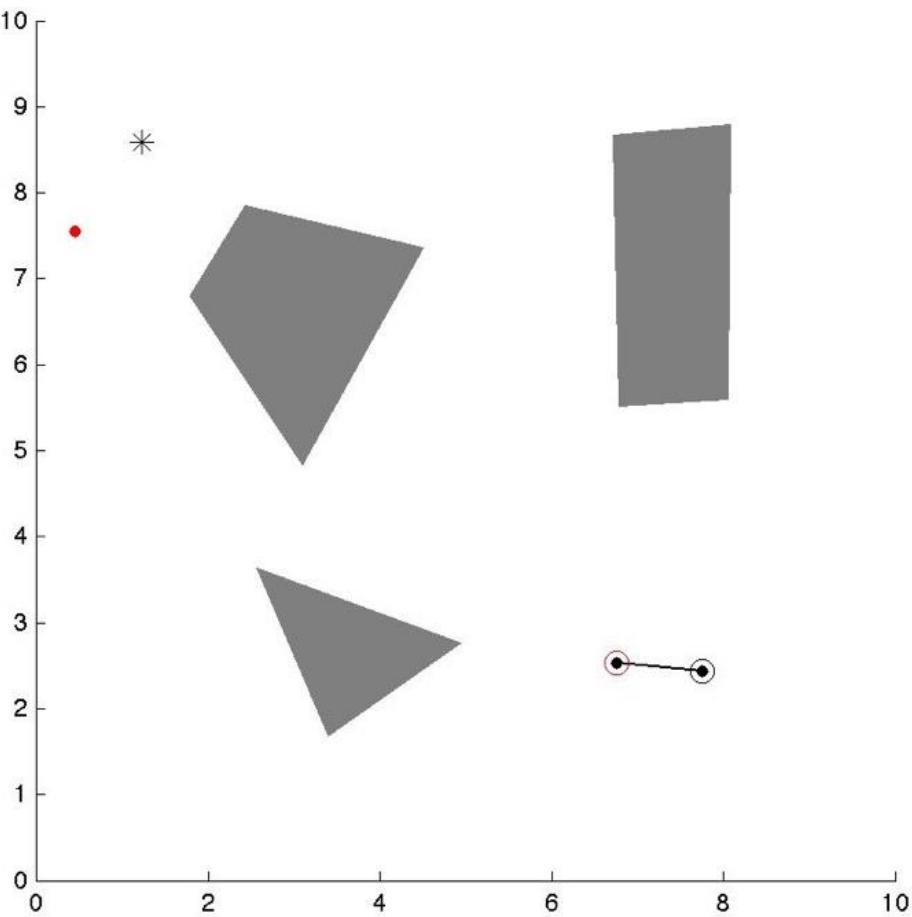
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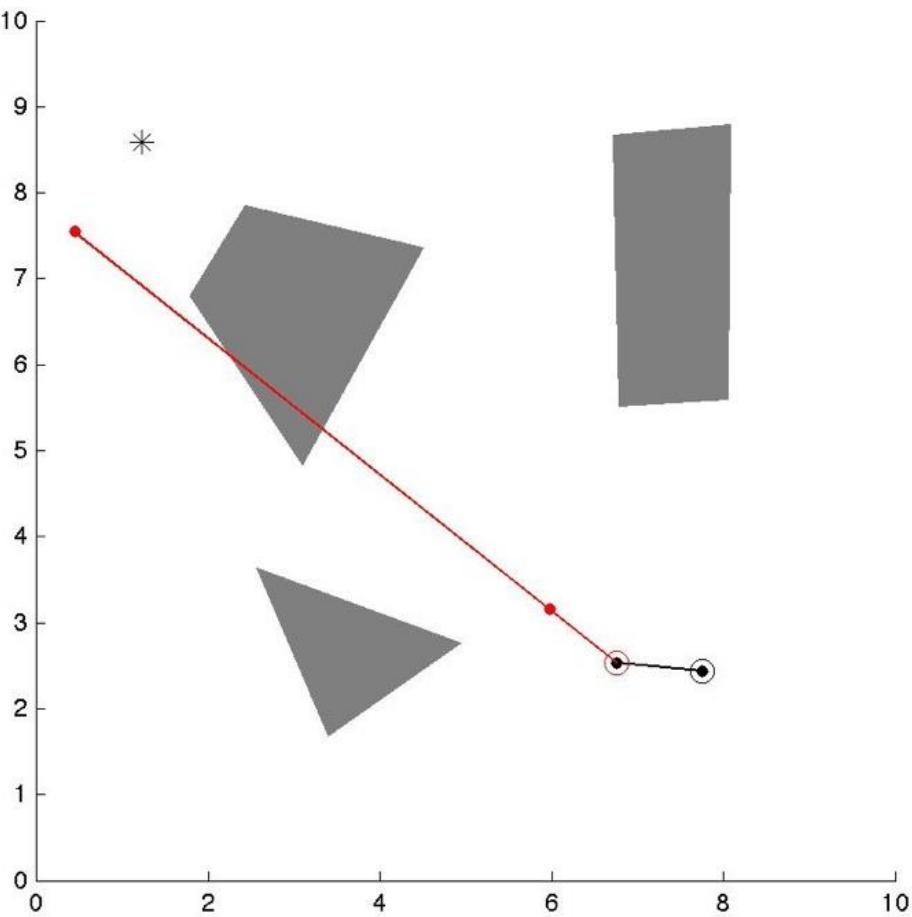
RRT

```
 $V \leftarrow \{x_{init}\}; E \leftarrow \emptyset$ 
for  $i = 1$  to  $N$ 
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         $V \leftarrow V \cup \{x_{new}\}$ 
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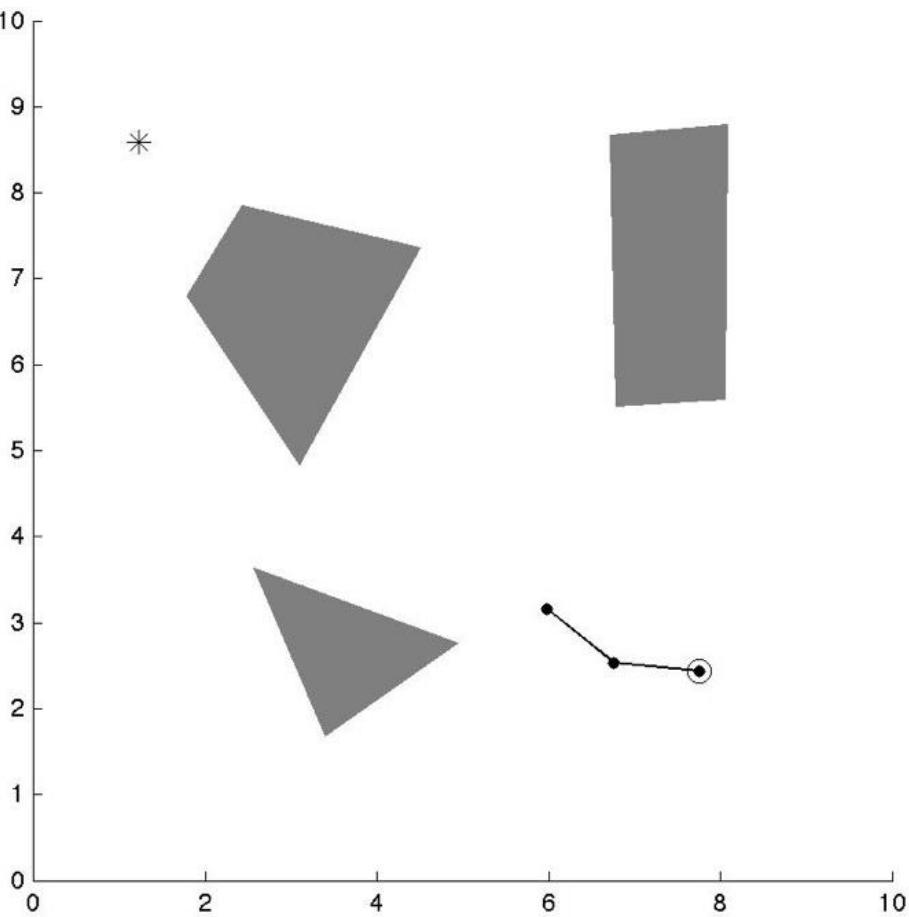
RRT

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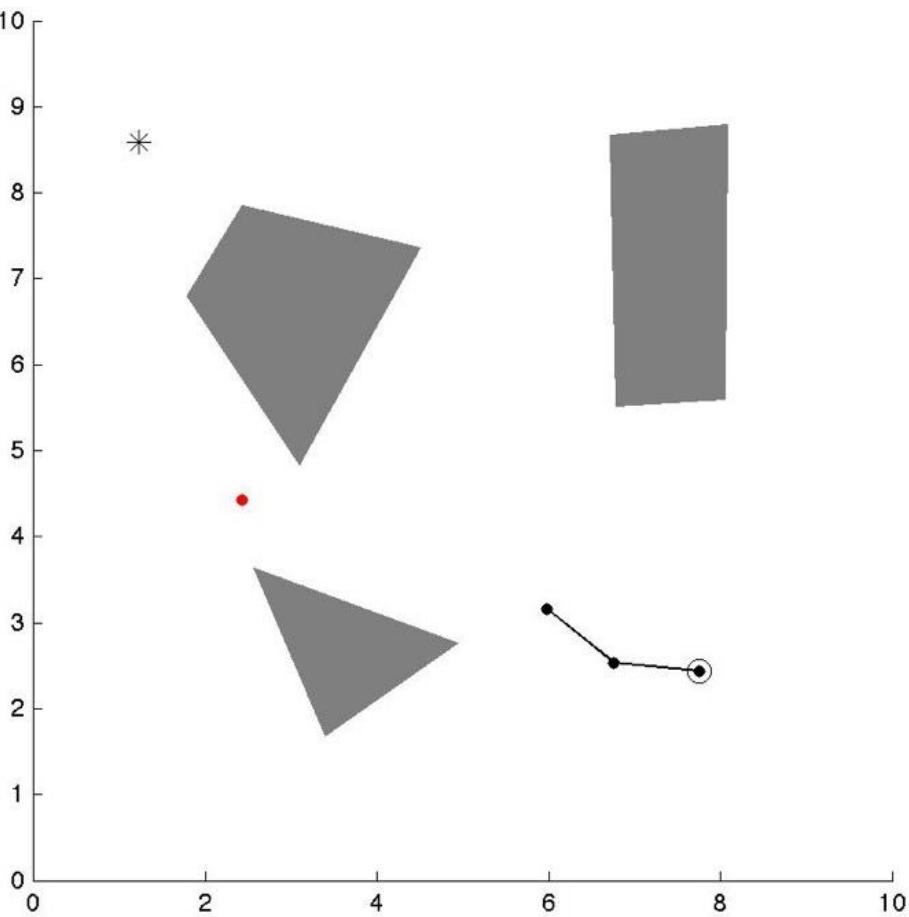
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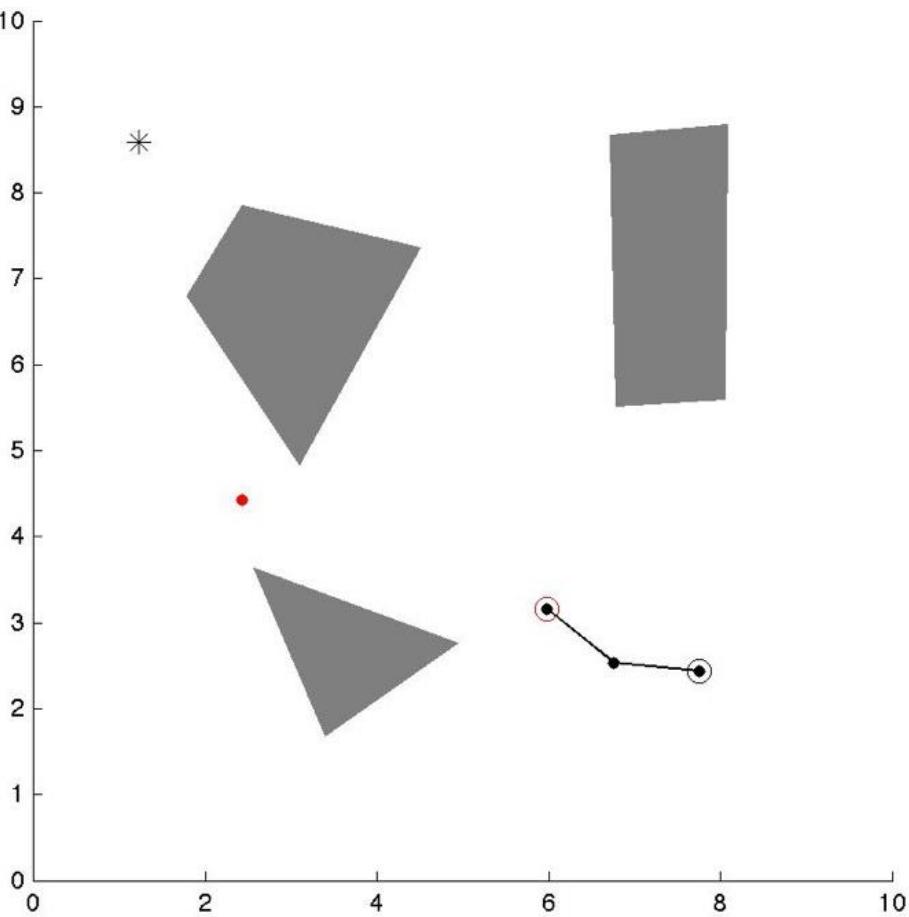
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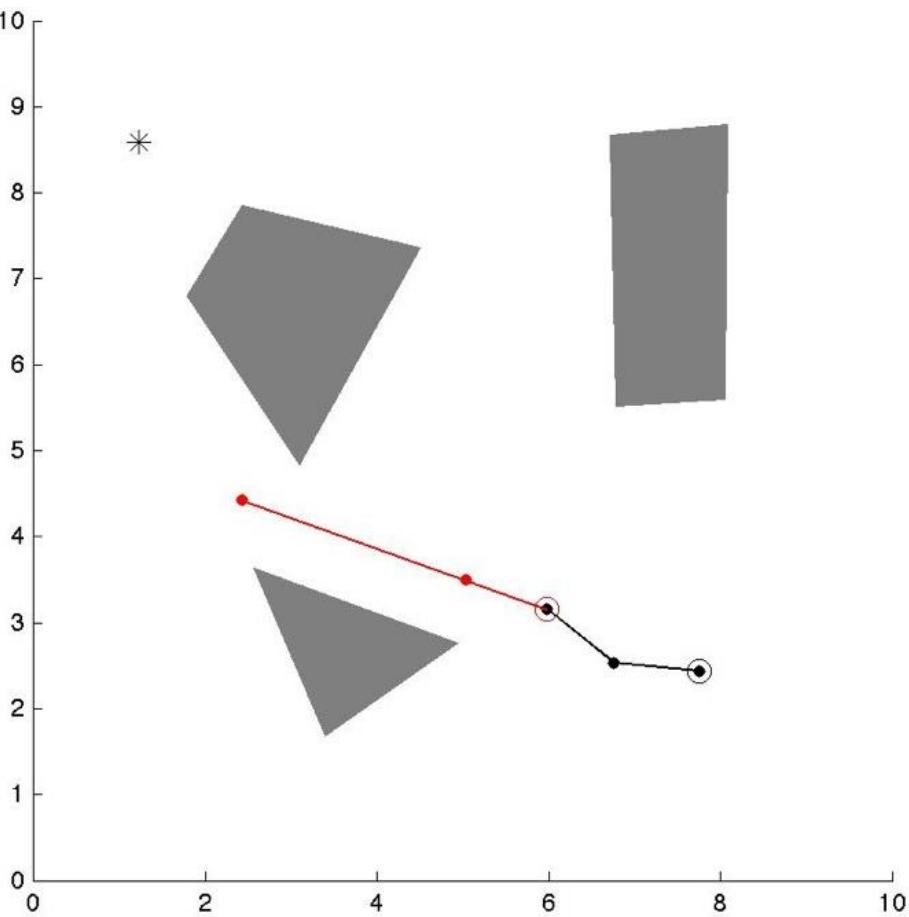
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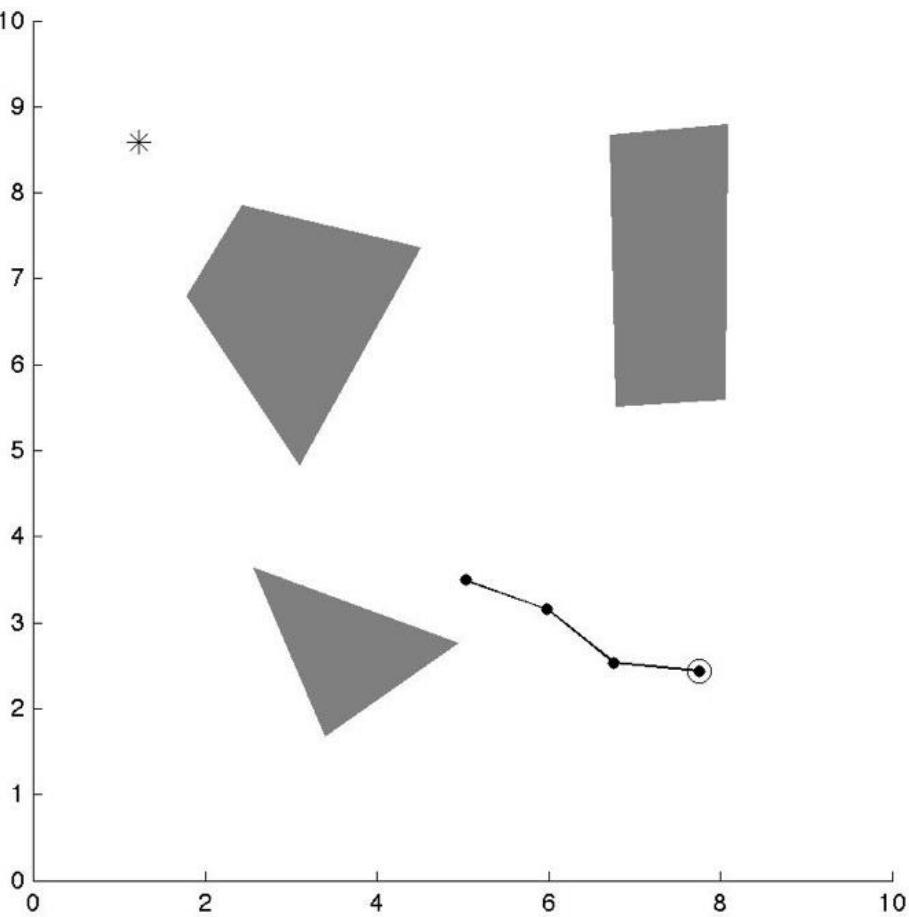
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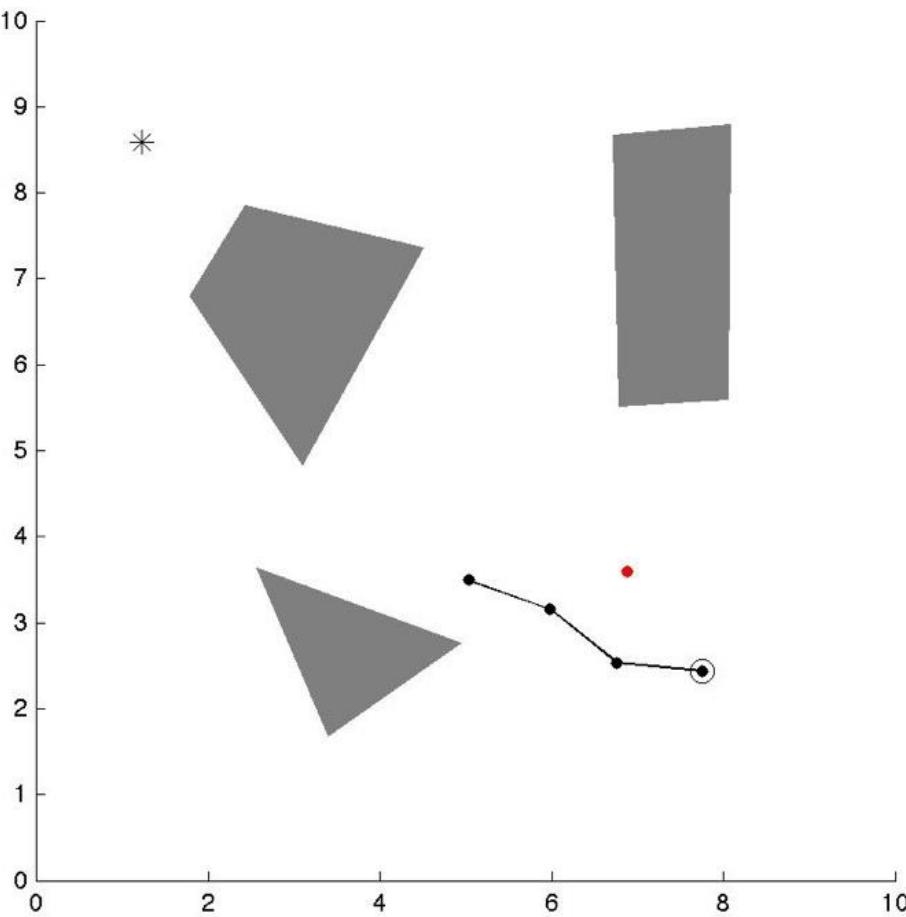
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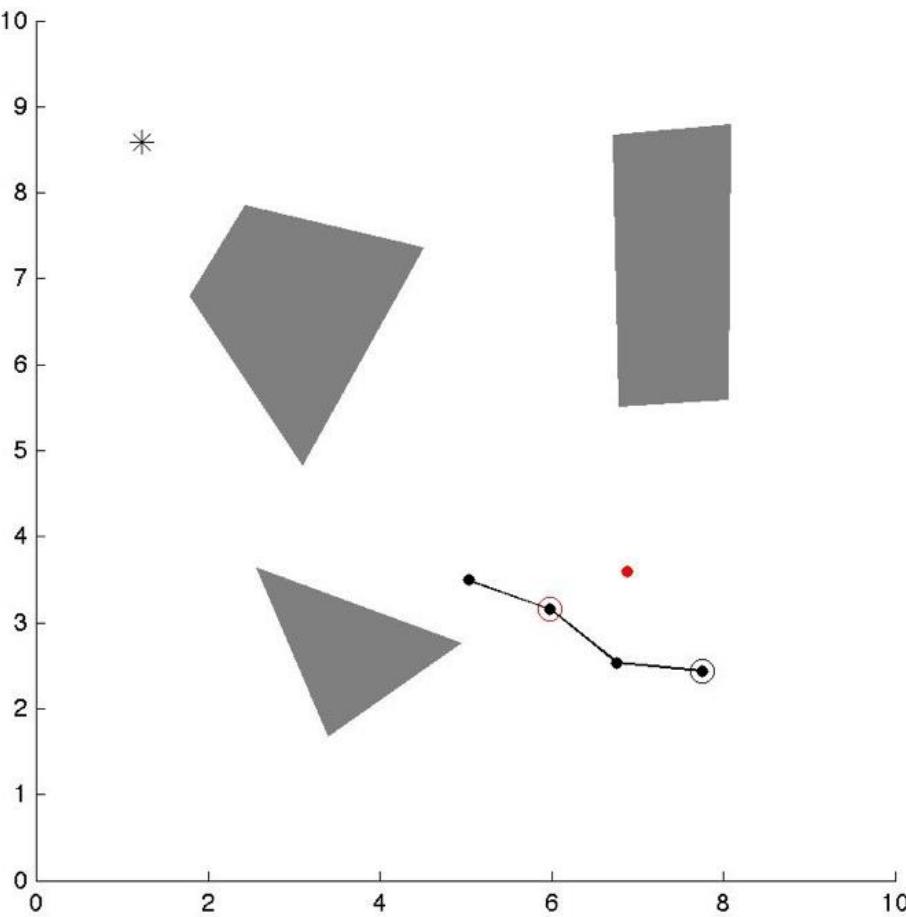
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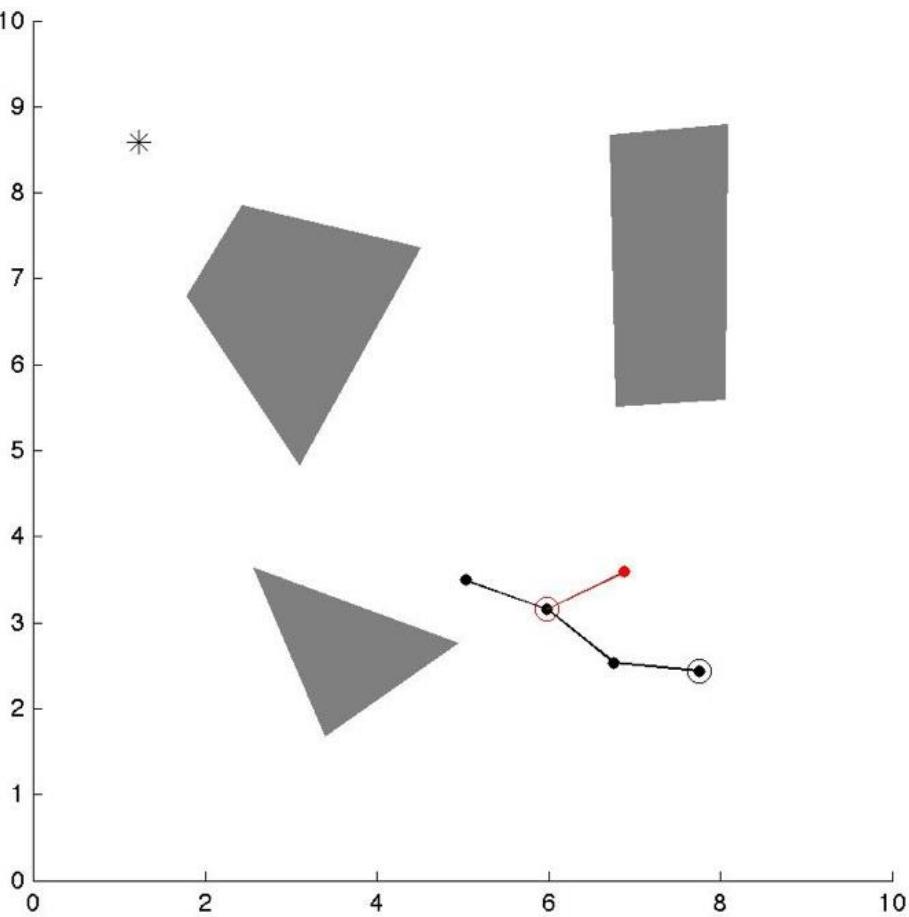
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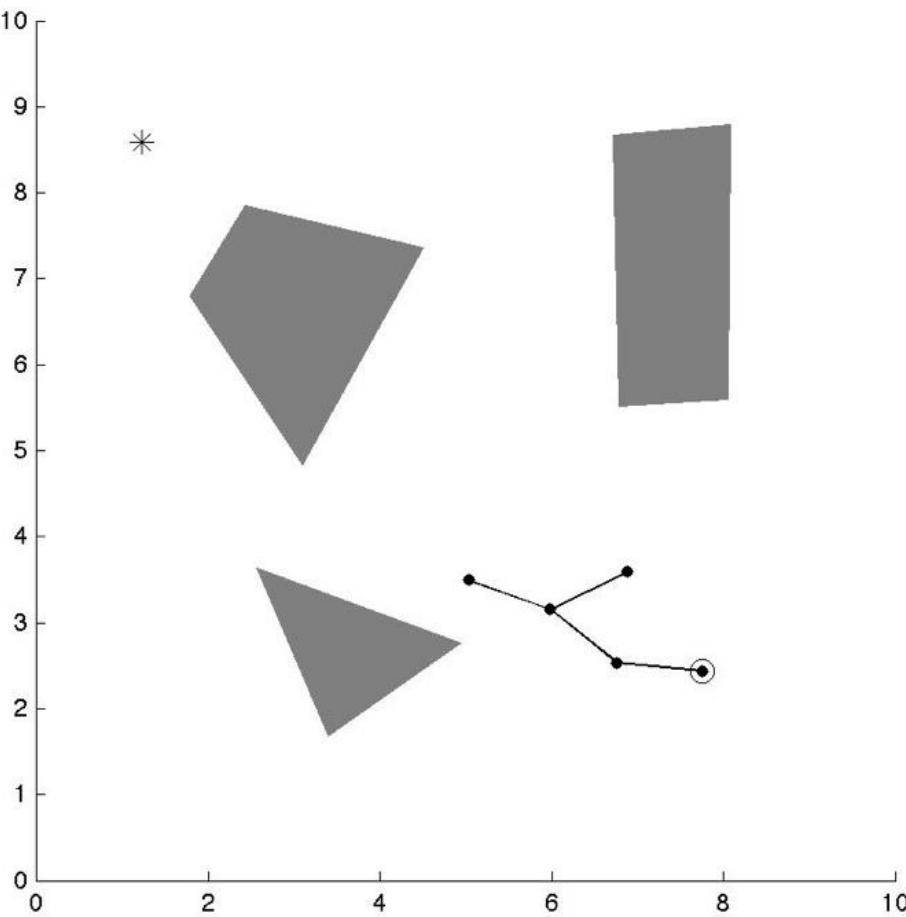
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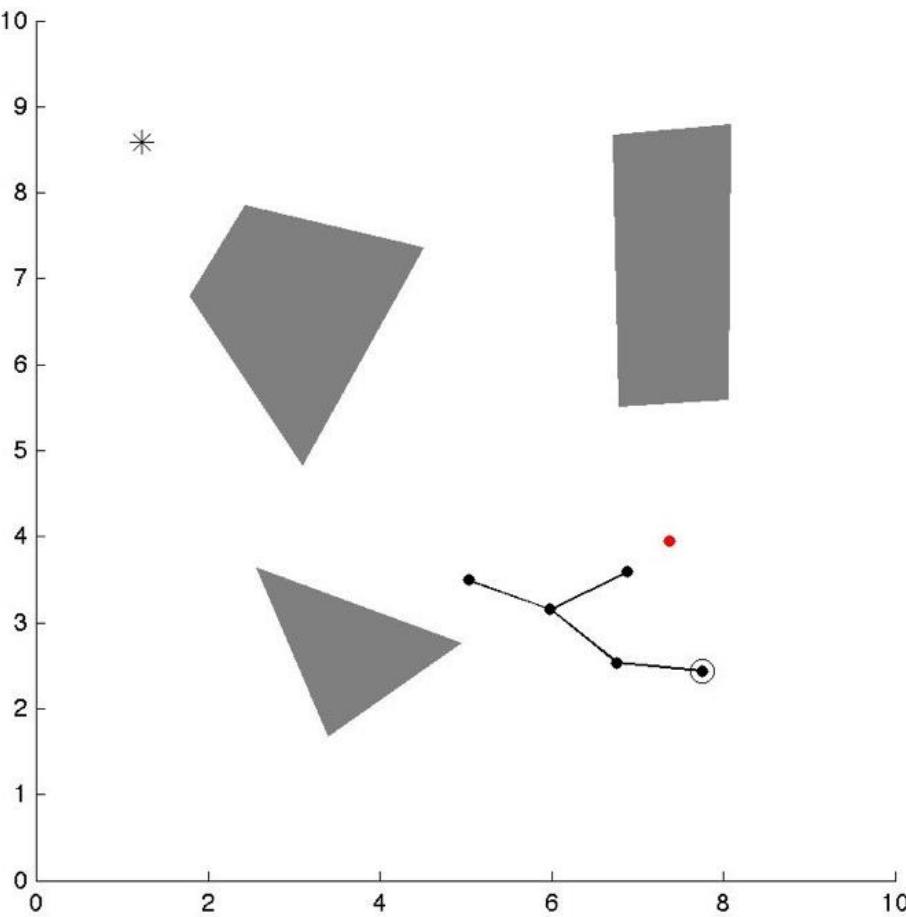
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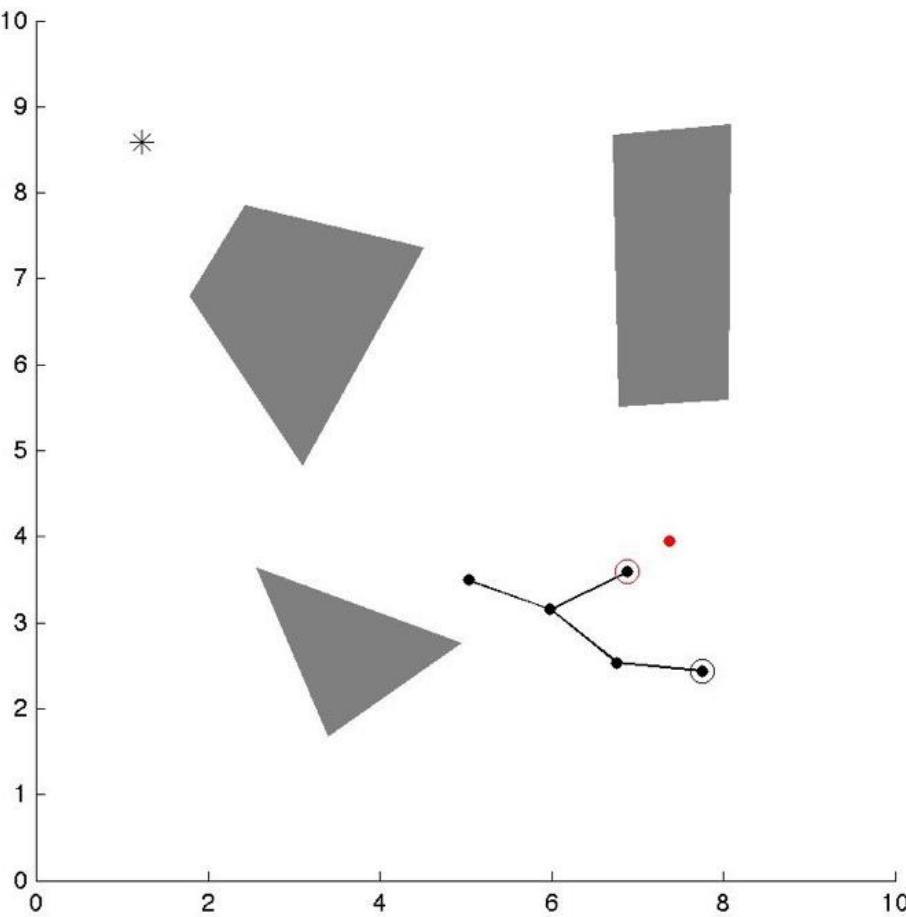
RRT

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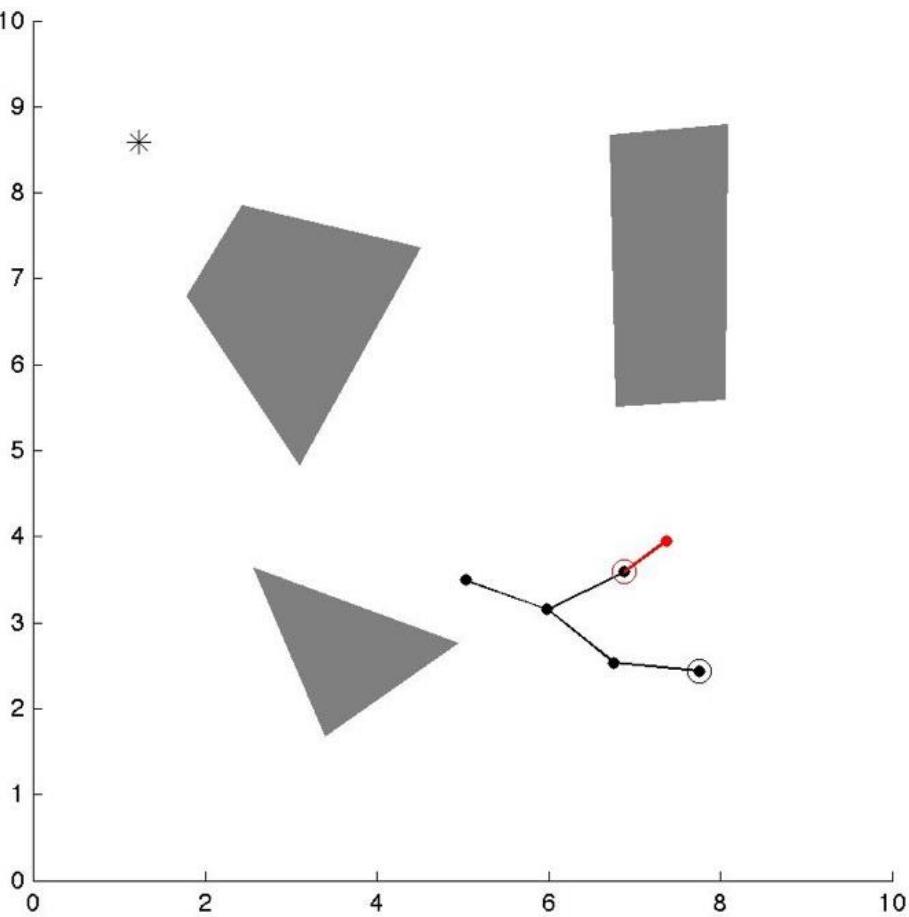
RRT

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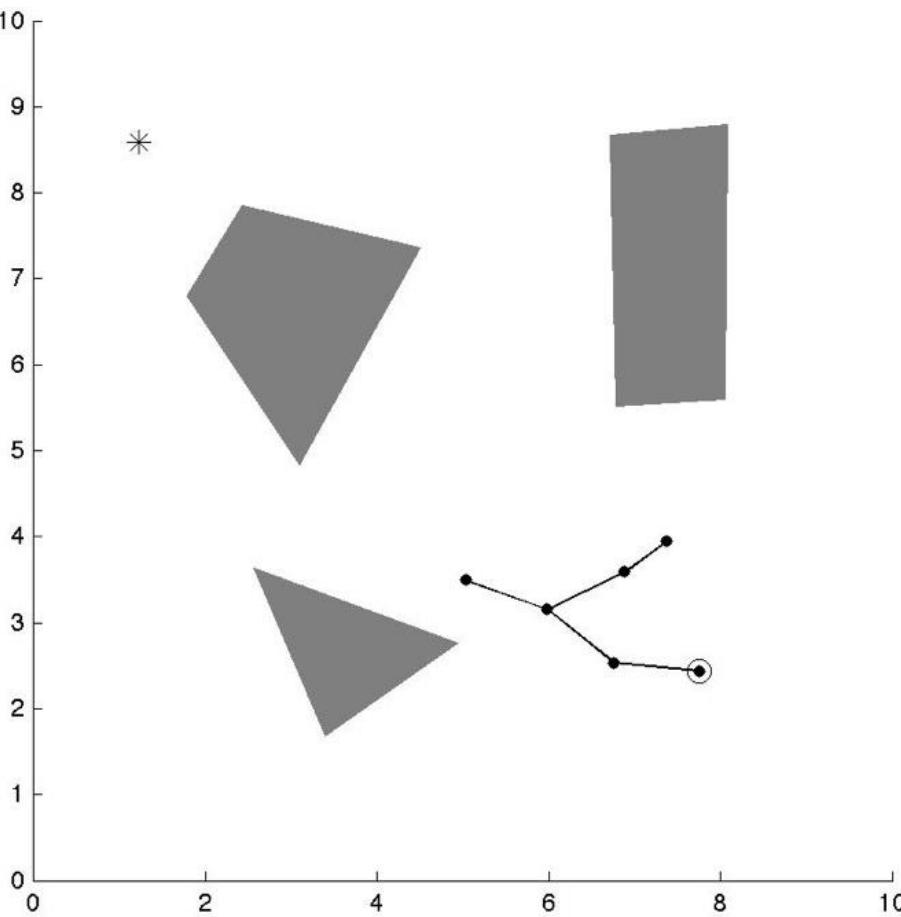
RRT

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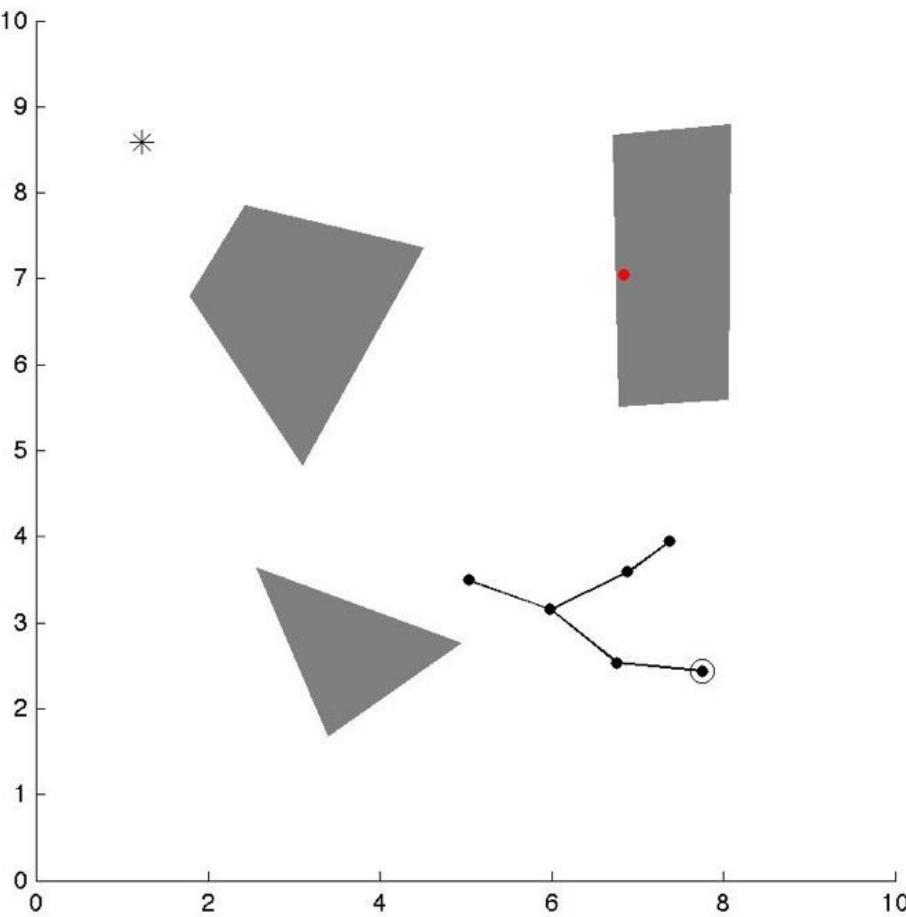
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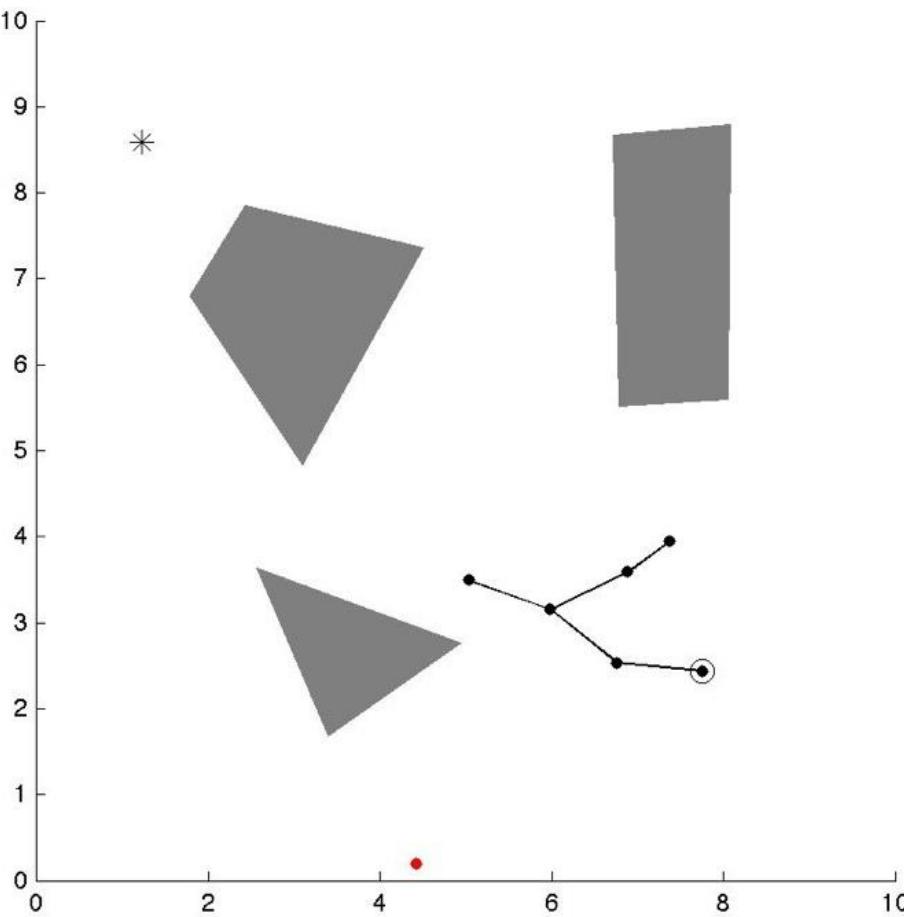
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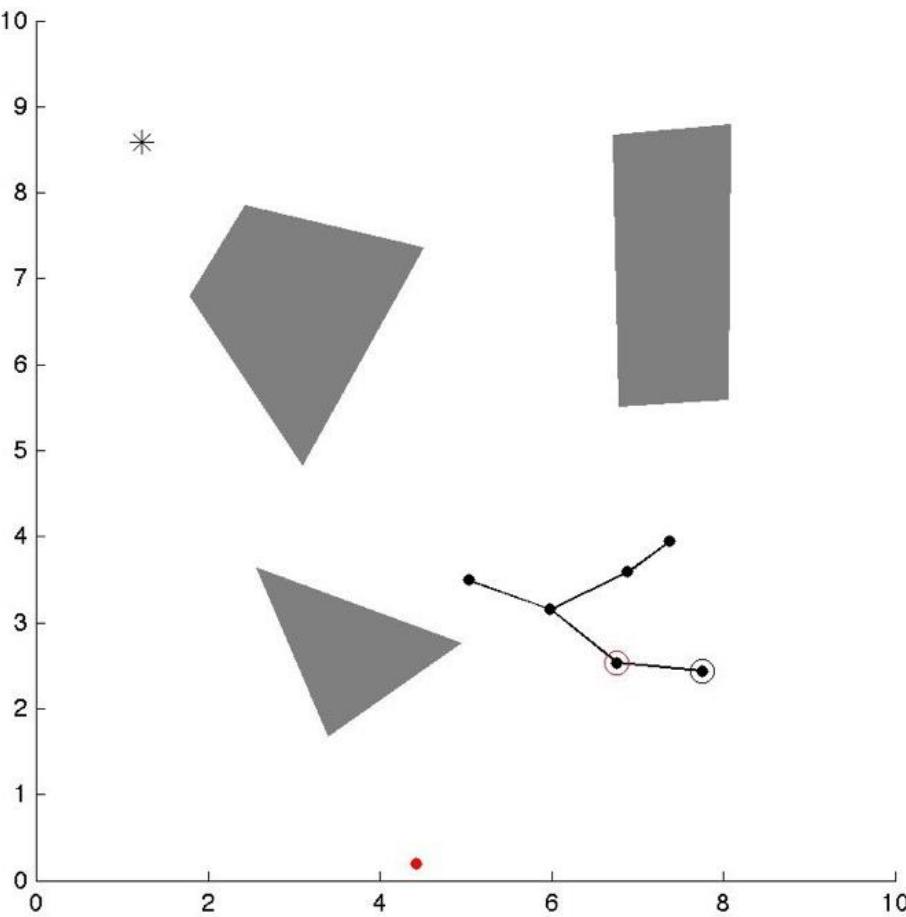
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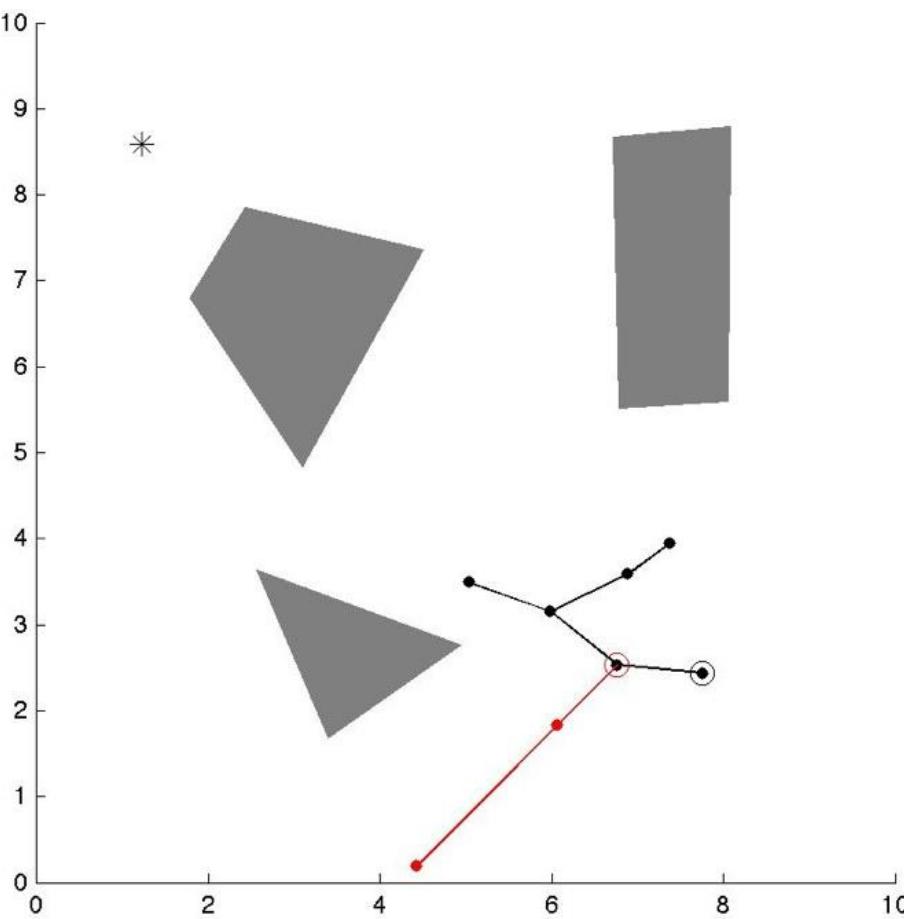
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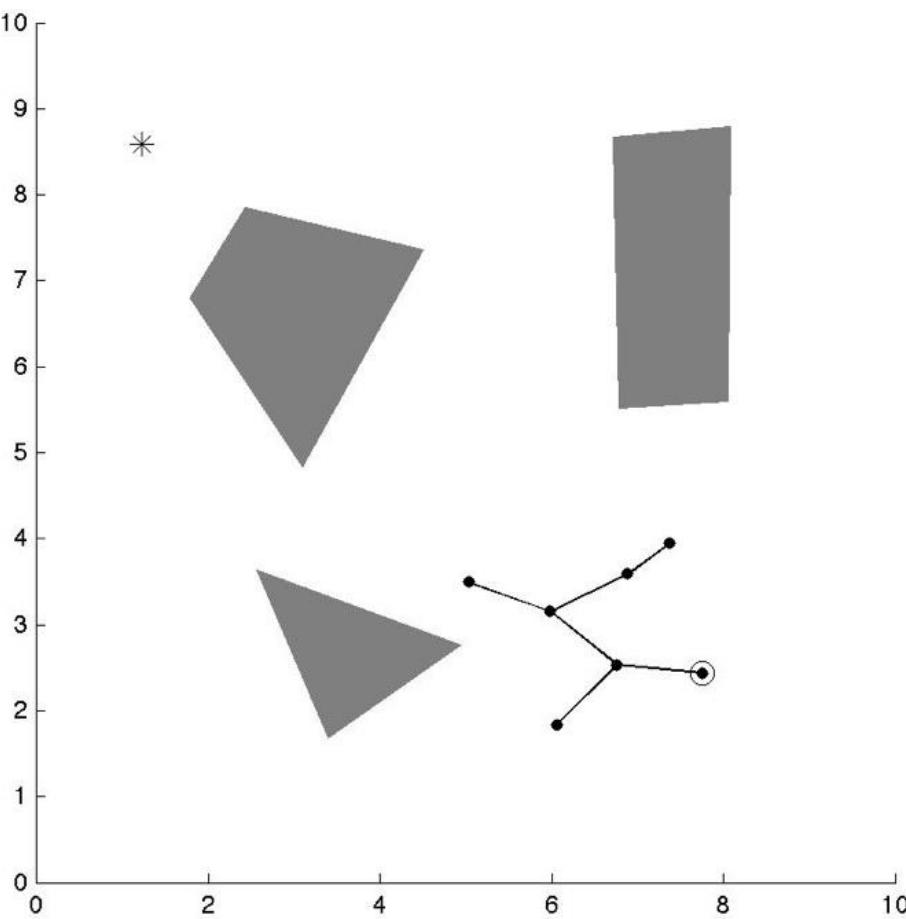
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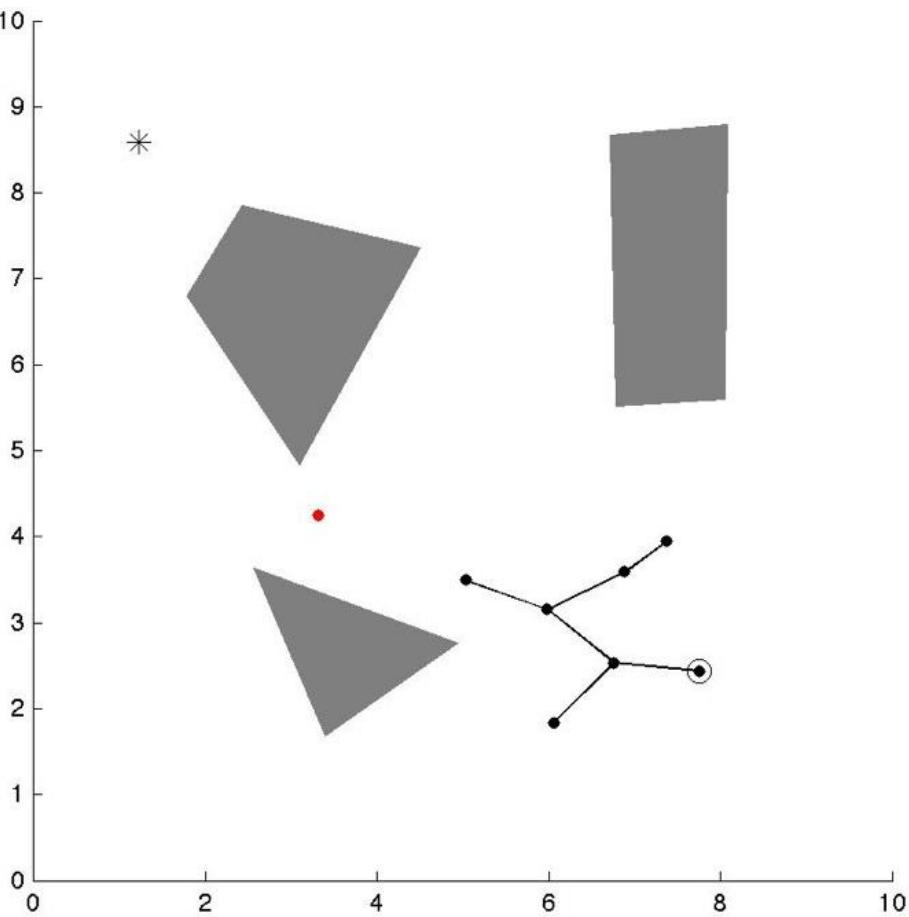
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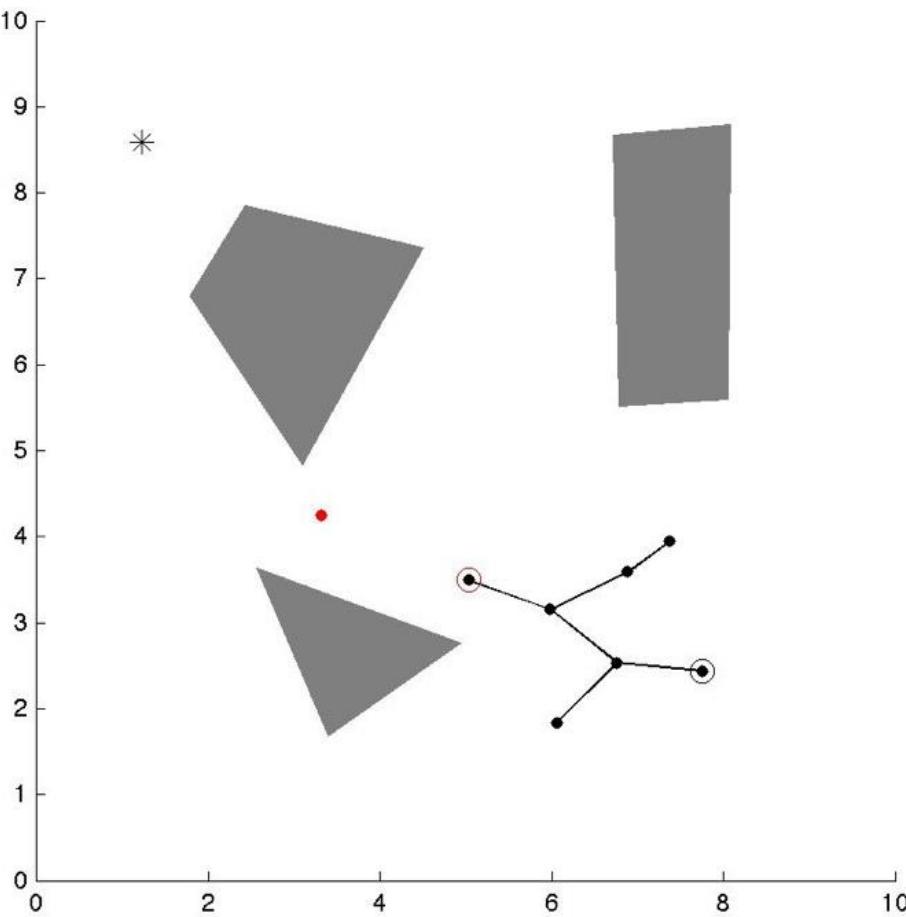
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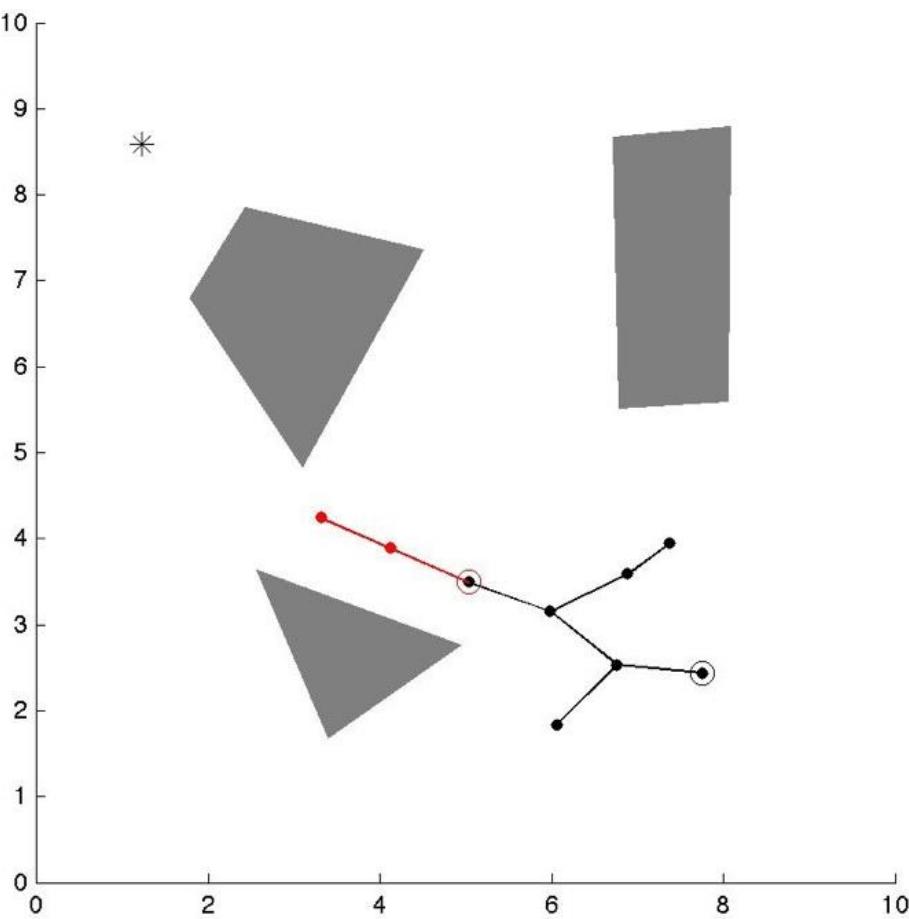
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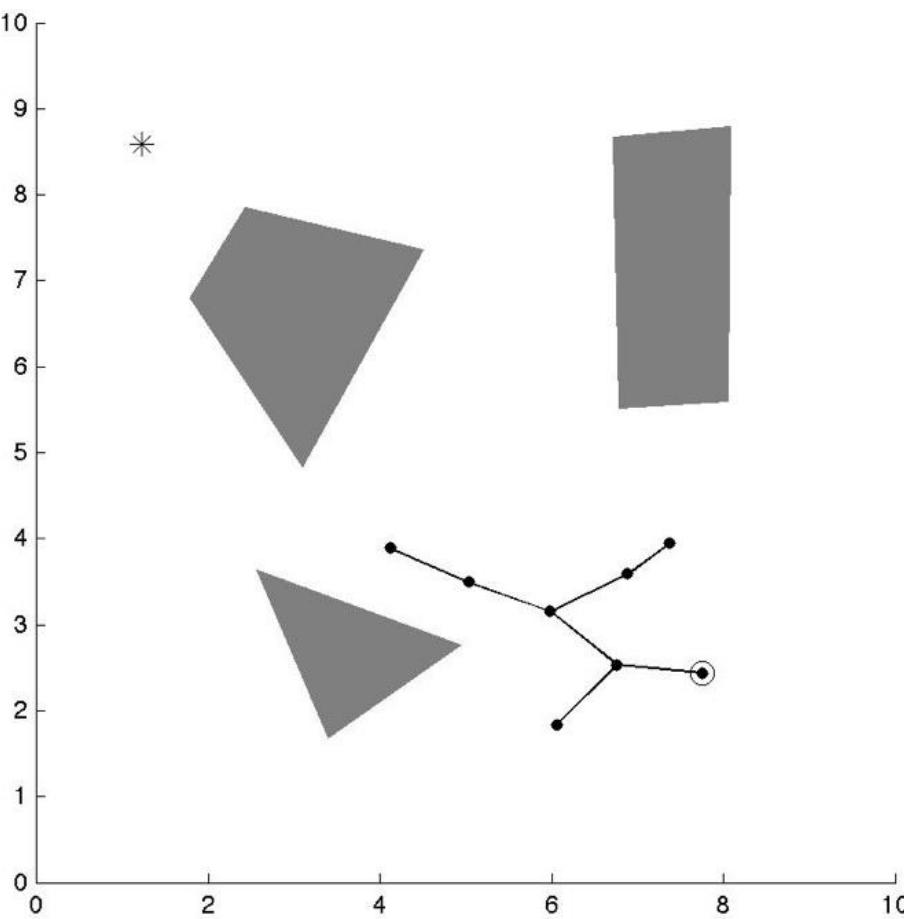
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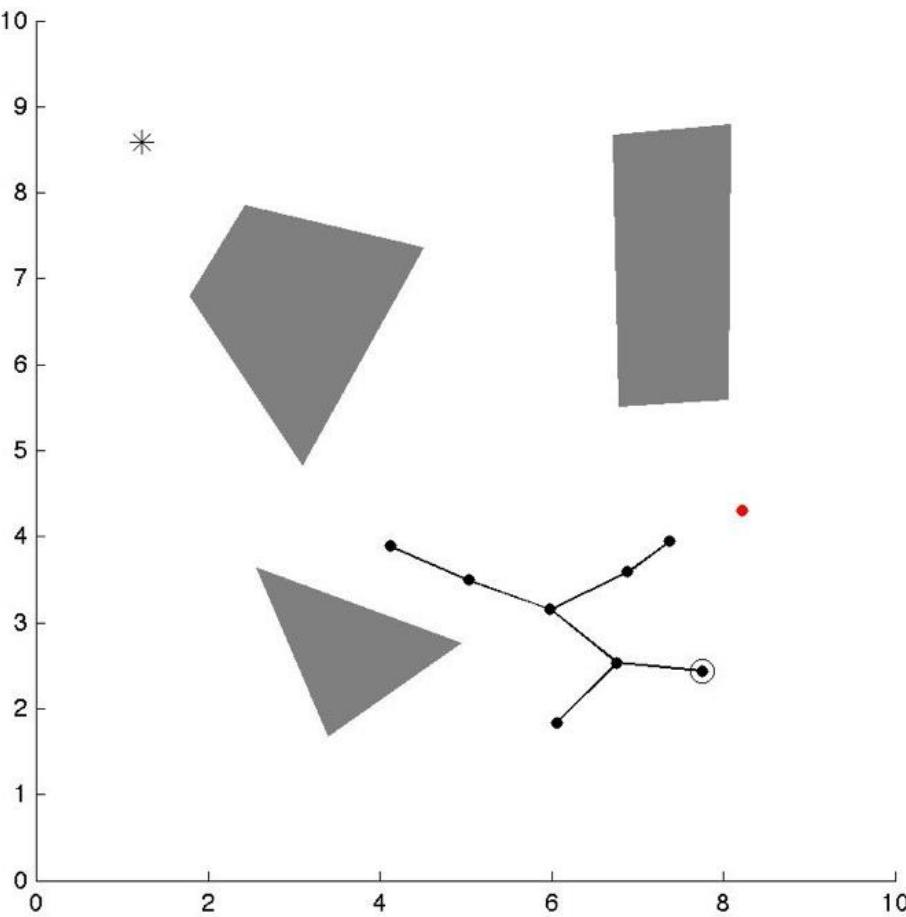
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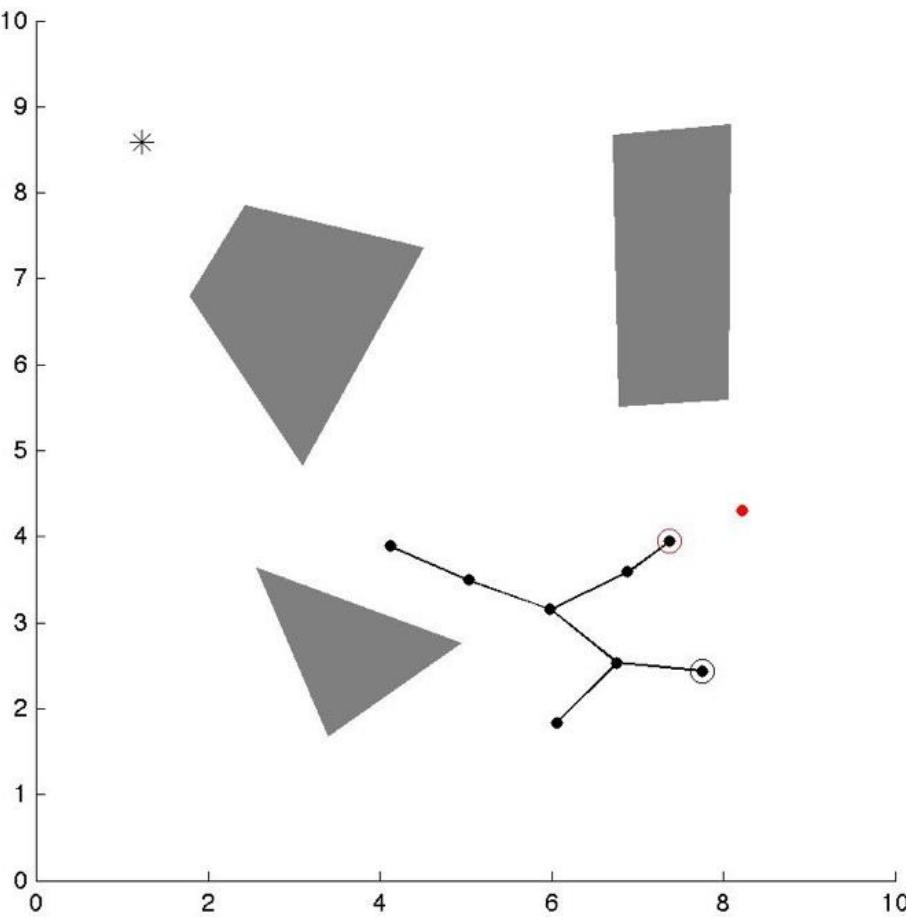
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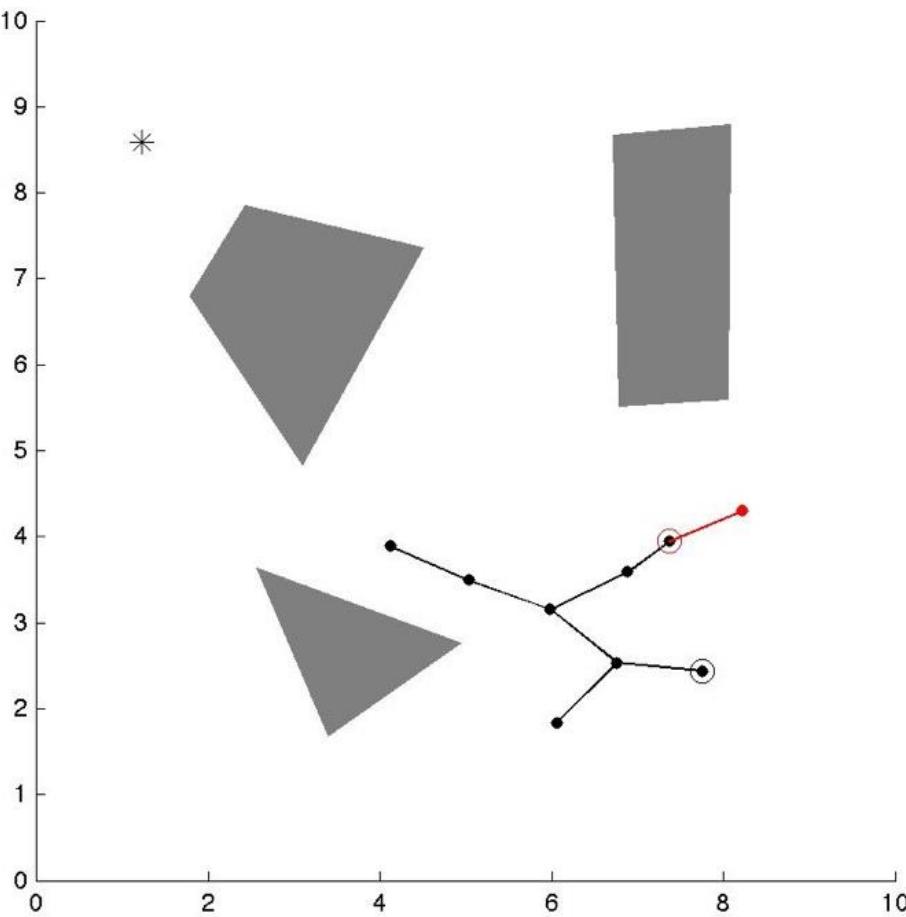
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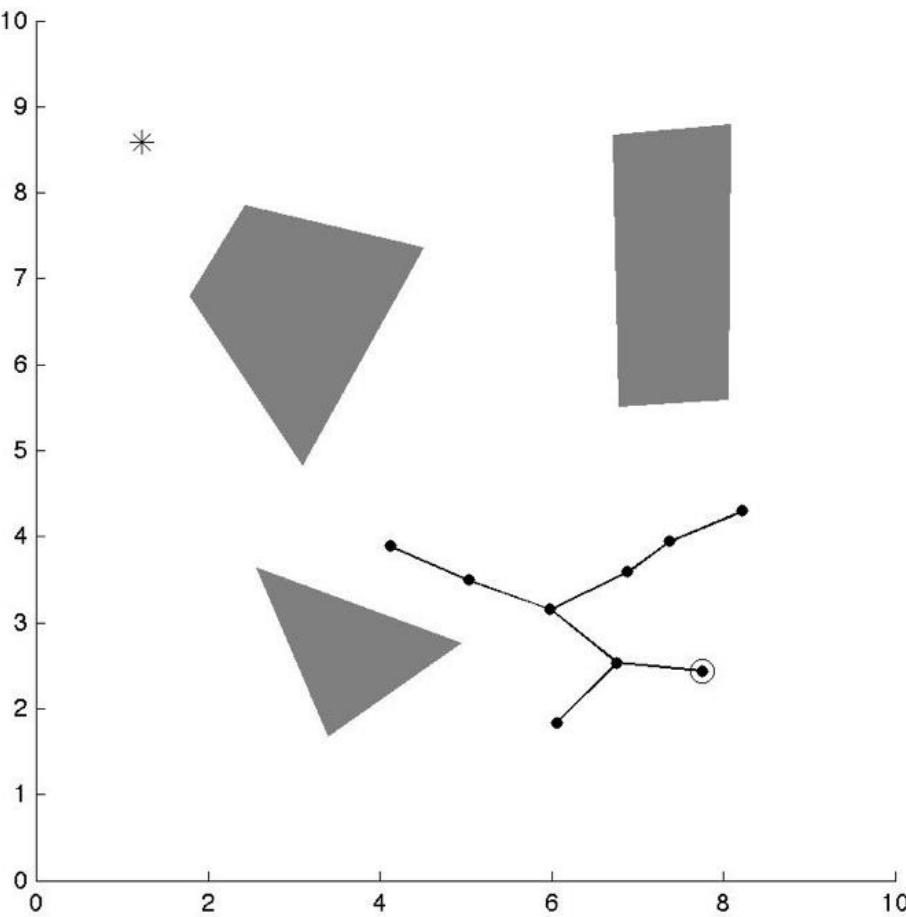
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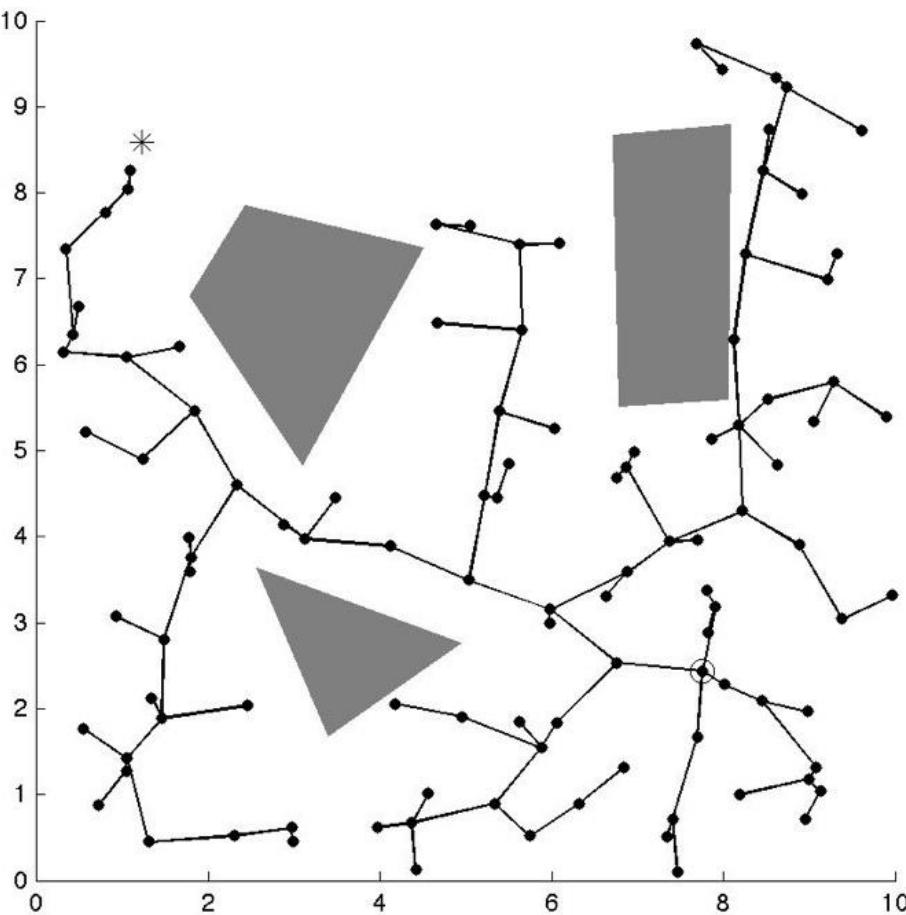
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RRT

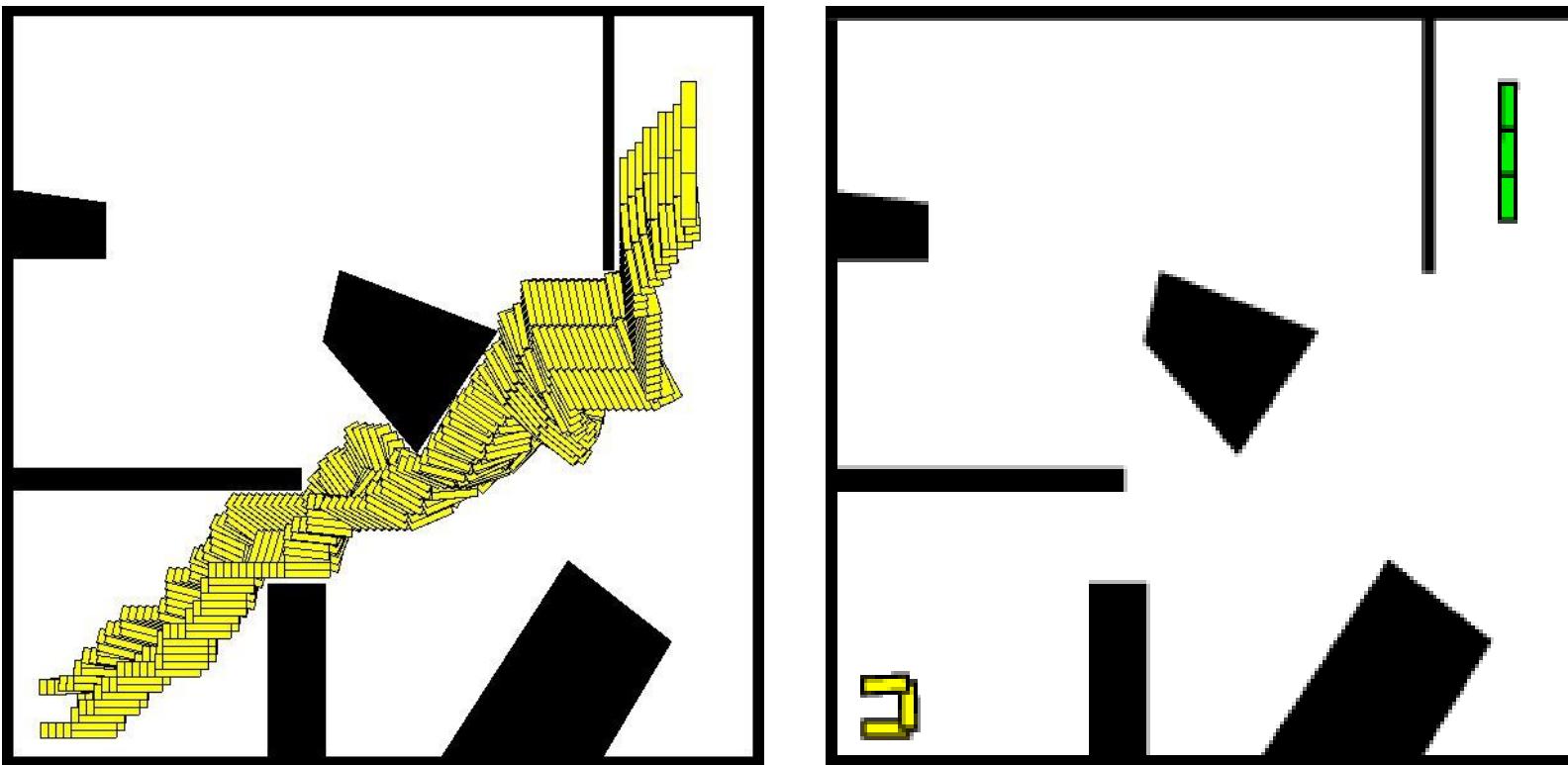
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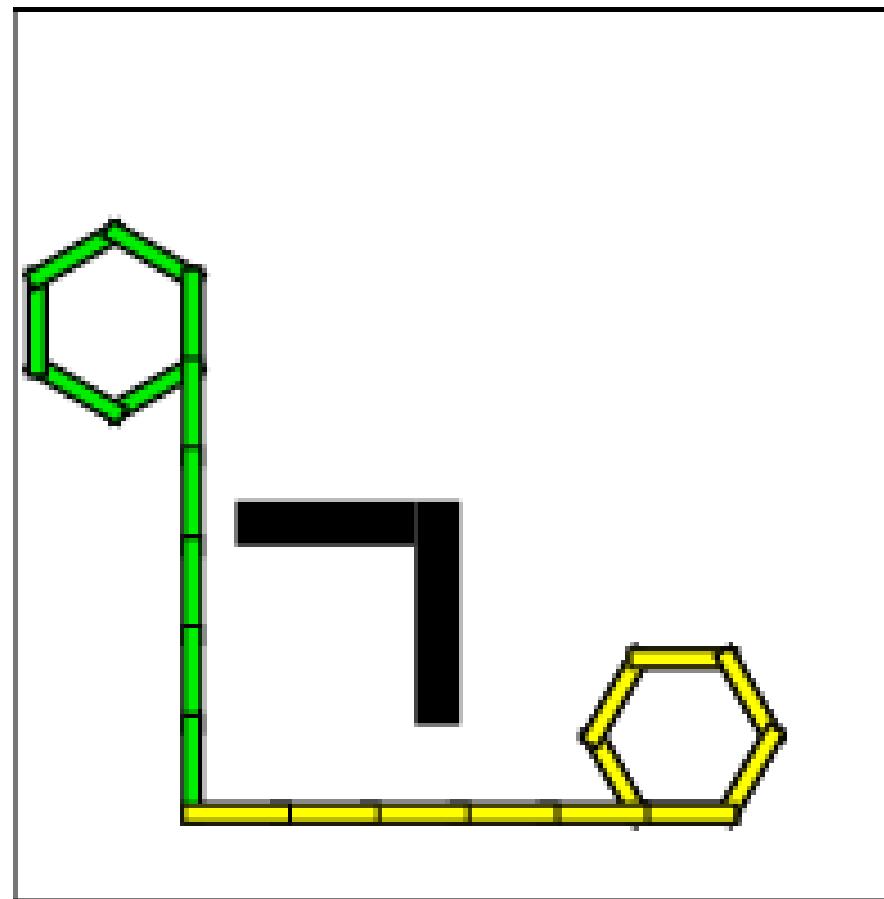
RRT - Bias to Goal

```
 $V \leftarrow \{x_{init}\}; E \leftarrow \emptyset$ 
for  $i = 1$  to  $N$ 
     $G \leftarrow (V, E)$ 
    with probability  $p$ 
         $x_{rand} \leftarrow RandomSample()$ 
    otherwise
         $x_{rand} \leftarrow x_{goal}$ 
         $x_{nearest} \leftarrow Nearest(G, x_{rand})$ 
         $x_{new} \leftarrow Steer(x_{nearest}, x_{rand})$ 
        if  $ObstacleFree(x_{nearest}, x_{new})$ 
             $V \leftarrow V \cup \{x_{new}\}$ 
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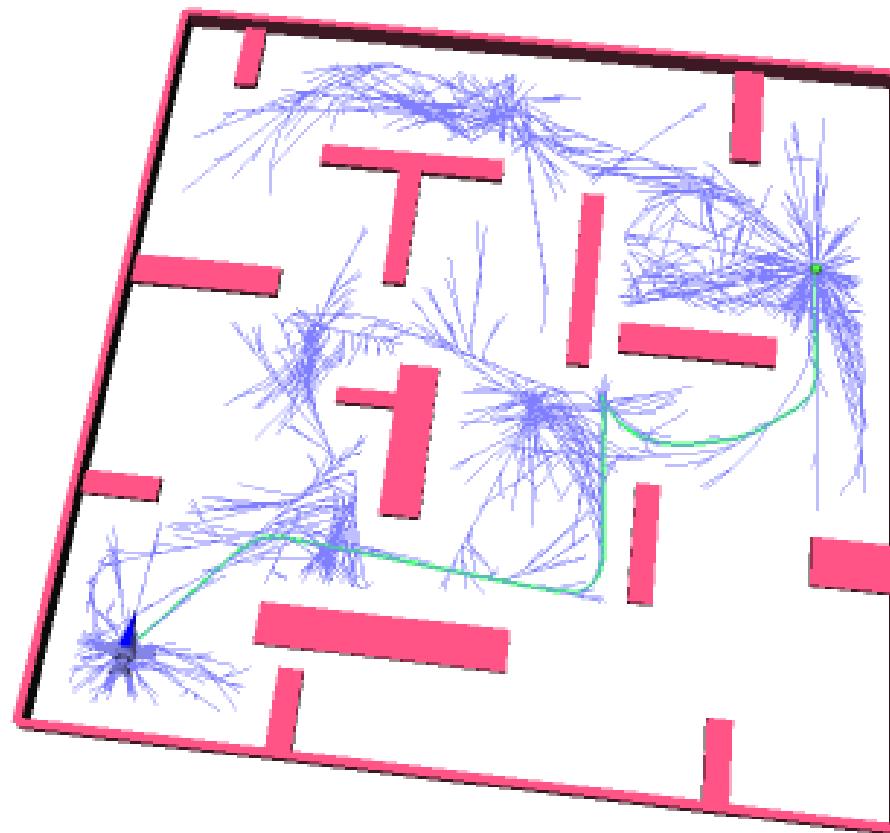
Articulated Robot



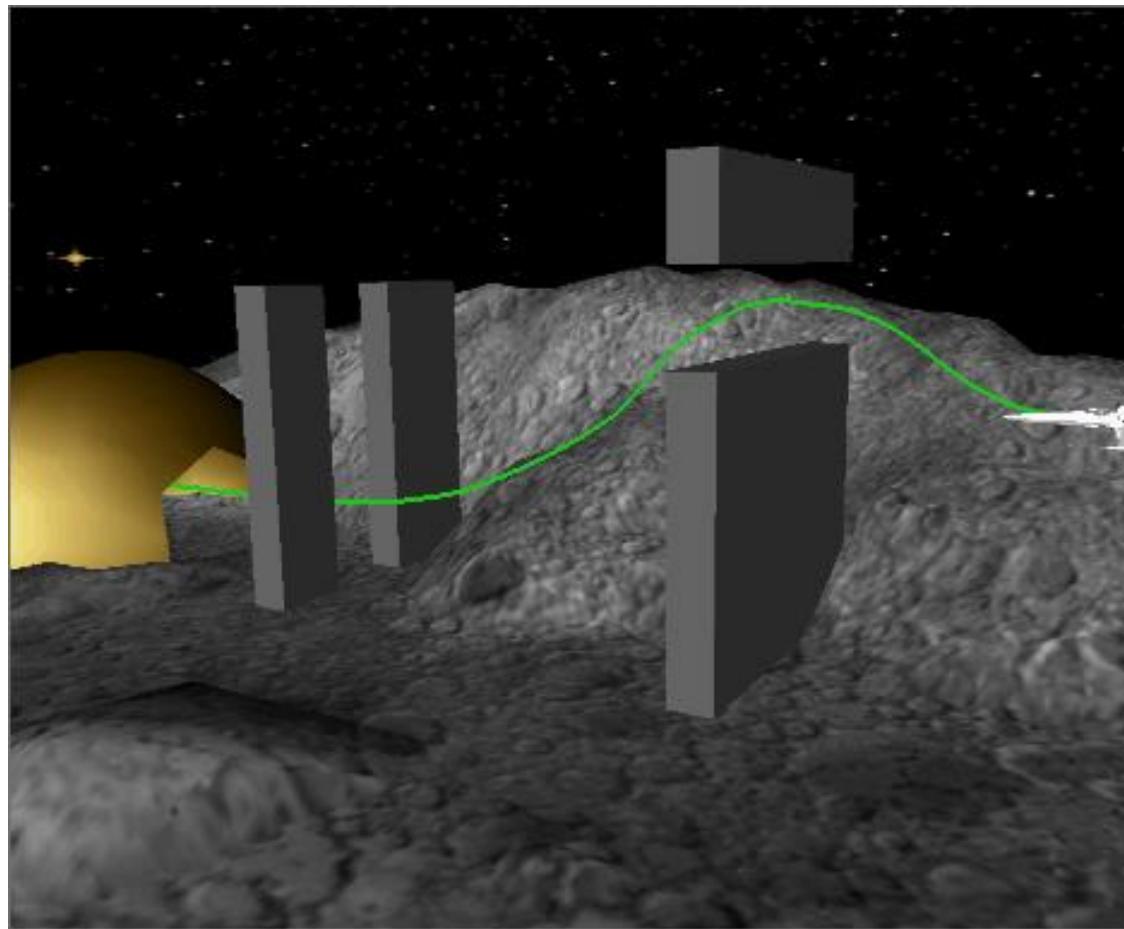
Highly Articulated Robot



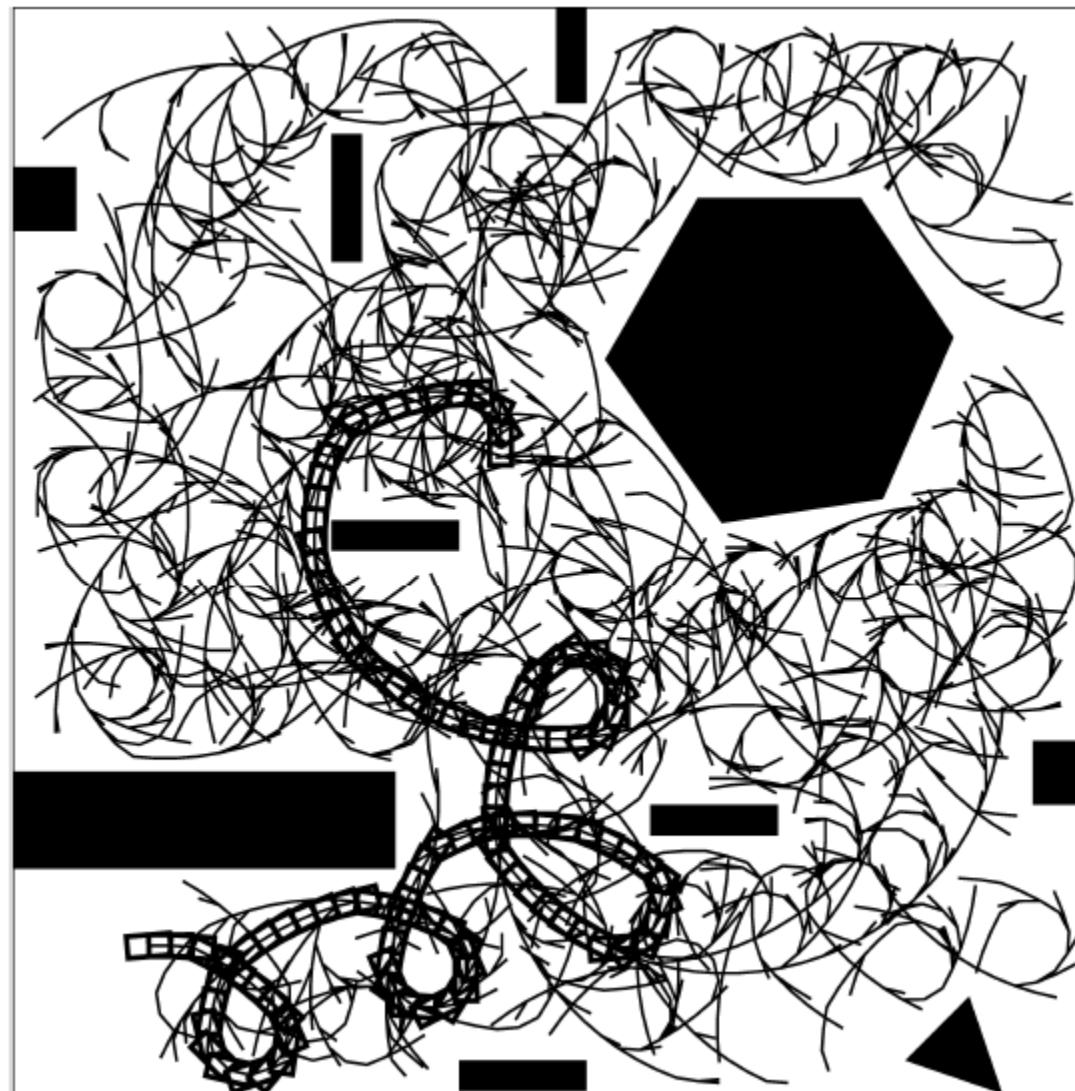
Hovercraft with 2 Thusters



Out of This World Demo



Left-turn only forward car

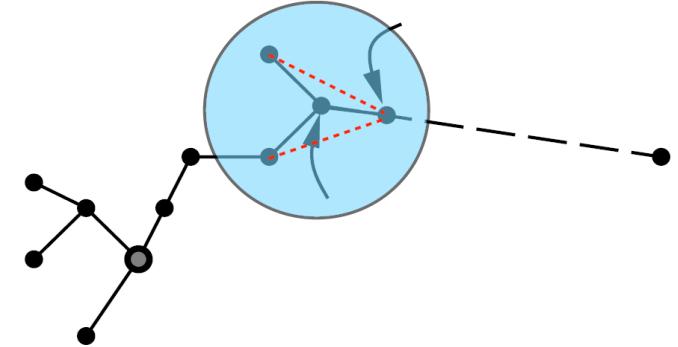


Rapidly-Exploring Random Tree (RRT)

- Advantages of RRT: very fast, works well for dynamic environments
- Disadvantages: Not optimal
 - in fact, it has been proven by Karaman & Frazzoli that the probability of RRT converging to an optimal solution is 0

Variants of RRT

- There are (very) many...
- Rapidly-exploring Random Graph (RRG):
 - Connect all vertices within neighboring region, forming a graph
- RRT*:
 - a variant of RRG that essentially “rewires” the tree as better paths are discovered.



Summary

- Both RRT and PRM are examples of **sampling based algorithms** that are **probabilistically complete**
- **Definition:** A path planner is ***probabilistically complete*** if, given a solvable problem, the probability that the planner solves the problem goes to 1 as time goes to infinity.

Links to Further Reading

- Steve LaValle's online book:
“Planning Algorithms” (*chapters 5 & 14*)
<http://planning.cs.uiuc.edu/>
- The RRT page:
<http://msl.cs.uiuc.edu/rrt/>
- Motion Planning Benchmarks
Parasol Group, Texas A&M
<http://parasol.tamu.edu/groups/amatogroup/benchmarks/mp/>