## Sampling-Based Motion Planning

CMPT 882
Mar. 6

## Outline

- Configuration space
- Probabilistic road maps (PRM)
- PRM*
- Rapidly-exploring random trees (RRT)
- RRT*
- Robust real-time planning (FaSTrack)


## Configuration Space (C-Space)

- Similar to state space, but considers reachability
- Usually state space does not consider the set of states that a system can reach
- Configuration space is the subset of the state space reachable by the system
- Example: mechanical joints
- Rigid bodies in 2D:
- 2D position and one rotation angle
- Rigid bodies in 3D:
- 3D position and three rotation angles
- Connected rigid bodies
- Concatenate positions and angles (but not every position and angle is reachable)


## Planning in C-Space

- Reduce objects to a point, and augment obstacles
- Example: Sliding rectangular block to goal



## Planning in C-Space

- Reduce objects to a point, and augment obstacles
- Example: Sliding and rotating rectangular block to goal



## Probabilistic Road Map

- Draw N samples
- Keep points outside of obstacles
- Choose a disk radius
- For each kept point, draw edge between it and all other points within the disk
- Keep edges that are collision free (expensive)
- Use graph search algorithm (e.g. A*, Dijkstras) on the resulting graph to find a path


## Probabilistic Road Map



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## Tuning Parameters

- Sampling distribution
- Deterministic samples are possible
- Collision checker - determines type of obstacles that can be considered


## Rapidly-Exploring Random Tree

- Draw a sample
- Connect to nearest neighbour
- Continue until path is found


## Rapidly-Exploring Random Tree



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## Rapidly-Exploring Random Tree

- Draw a sample
- Connect to nearest neighbour
- Continue until path is found

RRT*

- Draw a sample
- Connect to nearest neighbour
- Rewire paths in a cheaper way
- Look within some radius
- Can we get to the sample in a cheaper way?
- Is there a cheaper way to get to the samples within the radius?
- Continue until path is found

RRT*


RRT*


RRT*


RRT*


RRT*


RRT*


RRT*


## Tuning Parameters

- Sampling distribution
- Deterministic samples are possible

- Nearest sample vs. nearest point covered by the tree


## Tuning Parameters

- Sampling distribution
- Deterministic samples are possible

- Nearest sample vs. nearest point covered by the tree
- Collision checker - determines type of obstacles that can be considered
- Number of trees
- Having more than one tree may decrease time needed to find a feasible path


## Comments

- PRM
- Could be slow
- May need many samples
- RRT
- Incrementally draw samples $\rightarrow$ has potentially fewer samples
- Quality of solution may be very poor $\rightarrow$ RRT*
- Inherently, complexity is still exponential
- Hope: obtain feasible (potentially bad) solution quickly


## A Difficult Case

- Narrow gaps



## Analysis

- Potential computational bottlenecks
- Collision checking
- Nearest-neighbour finding
- Optimality
- Asymptotic, as number of samples goes to infinity
- Convergence rate: suboptimality bound is $O\left(n^{-\frac{1}{d}}\right)$
- $n$ - number of samples
- $d$ - number of dimensions


## System Dynamics

- RRT and PRM, as presented, is a geometric planner
- Cannot account for system dynamics
- Incorporating system dynamics
- Make sure edges between nodes are dynamically feasible
- Difficult in general, but has been done for special cases
- Backward and forward reachability concepts are useful
- Some references
- LaValle, Kuffner. "Randomized Kinodynamic Planning," 2001.
- Webb, Van Den Berg. "Kinodynamic RRT*: Asymptotically optimal motion planning for robots with linear dynamics," 2013.
- Schmerling, Janson, Pavone. "Optimal Sampling-Based Motion Planning under Differential Constraints:the Drift Case with Linear Affine Dynamics," 2015.


## Robustness

## Slow and Accurate Planning:



- Optimal control
- Guarantees on safety and goals
- Handles external disturbances (e.g. wind)
- Slow to compute

FaSTrack:
Goal


- Precompute a tracking error bound based on relative state between the true system and the planned path
- Make it modular \& easy to incorporate in all sorts of real-time path/trajectory planners


## Fast (but less accurate) Planning:

Goal


- Very fast with simple dynamics
- May not capture all system behavior
- Not necessarily robust to disturbances


## Precomputed Tracking Bound

Rufus Isaacs

Homicidal Chauffeur Problem (1951)


$$
\begin{array}{cc}
{\left[\begin{array}{c}
\dot{\dot{y}} \\
\dot{y} \\
\dot{\theta}
\end{array}\right]=\begin{array}{c}
v \cos \theta \\
v \sin \theta \\
\omega
\end{array}} & {\left[\begin{array}{c}
\dot{x} \\
\dot{y}
\end{array}\right]=\begin{array}{l}
u_{p x} \\
u_{p y}
\end{array}} \\
u_{s}=\omega & u_{p}=\left[u_{p x}, u_{p y}\right]
\end{array}
$$



## Precomputed Tracking Bound

- Tracking system (car) pursues planning system (runner)
- Planning system tries to evade tracking system
- What will be the maximum relative distance over time?

Note:
Maximum relative distance over time
$\equiv$ Worst possible tracking error over time
$\equiv$ Tracking error bound

## Precomputed Tracking Bound

Goal: Map initial relative state to worst possible tracking error over time


## Relative System

$$
\dot{r}=\left[\begin{array}{c}
\dot{x_{r}} \\
\dot{y_{r}} \\
\dot{\theta}
\end{array}\right]=\begin{gathered}
v \cos \theta-u_{p x} \\
v \sin \theta-u_{p y} \\
\omega
\end{gathered}
$$

## Precomputed Tracking Bound

Goal: Map initial relative state to worst possible tracking error over time


Planning system tries to maximize error

Tracking system tries to minimize error
Keep track of maximum cost over time

$$
V(t, x(t))=\max _{\Gamma[u](\cdot)} \min _{u(\cdot)} \max _{s \in[t, 0]} l(x(s))
$$

- Take $t \rightarrow-\infty$ for infinite time horizon case


## Example: 10D Tracking 3D Single Integrator using RRT

10D near-hover quadrotor model

$$
\left[\begin{array}{c}
\dot{x} \\
\dot{v}_{x} \\
\dot{\theta}_{x} \\
\dot{\omega}_{x} \\
\dot{y} \\
\dot{v}_{y} \\
\dot{\theta}_{y} \\
\dot{\omega}_{y} \\
\dot{z} \\
\dot{v}_{z}
\end{array}\right]=\left[\begin{array}{c}
v_{x} \\
g \tan \theta_{x} \\
-d_{1} \theta_{x}+\omega_{x} \\
-d_{0} \theta_{x}+n_{0} u_{x} \\
v_{y} \\
g \tan \theta_{y} \\
-d_{1} \theta_{y}+\omega_{y} \\
-d_{0} \theta_{y}+n_{0} u_{y} \\
v_{z} \\
k_{T} u_{z}-g
\end{array}\right]
$$

3D single integrator

$$
\left[\begin{array}{c}
\dot{x} \\
\dot{y} \\
\dot{z}
\end{array}\right]=\left[\begin{array}{l}
v_{x} \\
v_{y} \\
v_{z}
\end{array}\right]
$$



