Randomized Sampling-based Motion Planning Methods

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Lecture 05

B4M36UIR – Artificial Intelligence in Robotics

Overview of the Lecture

- Part 1 – Randomized Sampling-based Motion Planning Methods
  - Sampling-Based Methods
  - Probabilistic Road Map (PRM)
  - Characteristics
  - Rapidly Exploring Random Tree (RRT)

Part I

Part 1 – Roadmap-based Planning Methods

Outline

- Sampling-Based Methods
- Probabilistic Road Map (PRM)
- Characteristics
- Rapidly Exploring Random Tree (RRT)

Sampling-based Motion Planning

- Avoids explicit representation of the obstacles in $\mathcal{C}$*-space*
  - A "black-box" function is used to evaluate a configuration q is a collision free

    (E.g., based on geometrical models and testing collisions of the models)
- It creates a discrete representation of $\mathcal{C}_{free}$
- Configurations in $\mathcal{C}_{free}$ are sampled randomly and connected to a roadmap (**probabilistic roadmap**)
- Rather than full completeness they provides **probabilistic completeness** or resolution completeness

  Probabilistic complete algorithms: with increasing number of samples an admissible solution would be found (if exists)

Probabilistic Roadmaps

A discrete representation of the continuous $\mathcal{C}$-space generated by randomly sampled configurations in $\mathcal{C}_{free}$ that are connected into a graph.

- **Nodes** of the graph represent admissible configuration of the robot.
- **Edges** represent a feasible path (trajectory) between the particular configurations.

Probabilistic complete algorithms: with increasing number of samples an admissible solution would be found (if exists)

Having the graph, the final path (trajectory) is found by a graph search technique.

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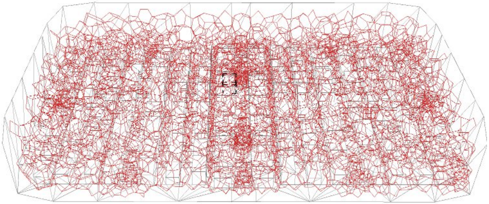

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Outline

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- Probabilistic Road Map (PRM)
- Characteristics
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Probabilistic Roadmap Strategies

Multi-Query

- Generate a single roadmap that is then used for planning queries several times.
- An representative technique is **Probabilistic RoadMap (PRM)**

Probabilistic Roadmaps for Path Planning in High Dimensional Configuration Spaces
Lydia E. Kavraki and Petr Svestka and Jean-Claude Latombe and Mark H. Overmars,
IEEE Transactions on Robotics and Automation, 12(4):566–580, 1996.

Single-Query

- For each planning problem constructs a new roadmap to characterize the subspace of $\mathcal{C}$-space that is relevant to the problem.
  - Rapidly-exploring Random Tree – RRT *LaValle, 1998*
  - Expansive-Space Tree – EST *Hsu et al., 1997*
  - Sampling-based Roadmap of Trees – SRT

    (combination of multiple–query and single–query approaches)
    Plaku et al., 2005

Multi-Query Strategy

Build a roadmap (graph) representing the environment

1. Learning phase
   1.1 Sample *n* points in $\mathcal{C}_{free}$
   1.2 Connect the random configurations using a local planner
2. Query phase
   2.1 Connect start and goal configurations with the PRM

   E.g., using a local planner

   2.2 Use the graph search to find the path

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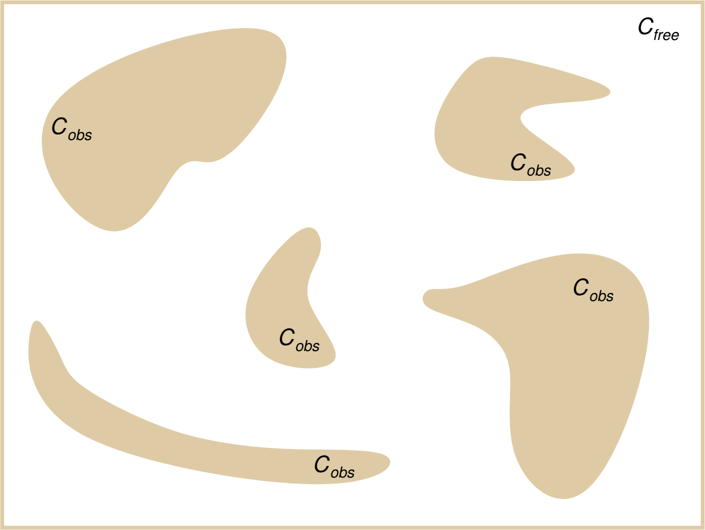
First planner that demonstrates ability to solve general planning problems in more than 4-5 dimensions.

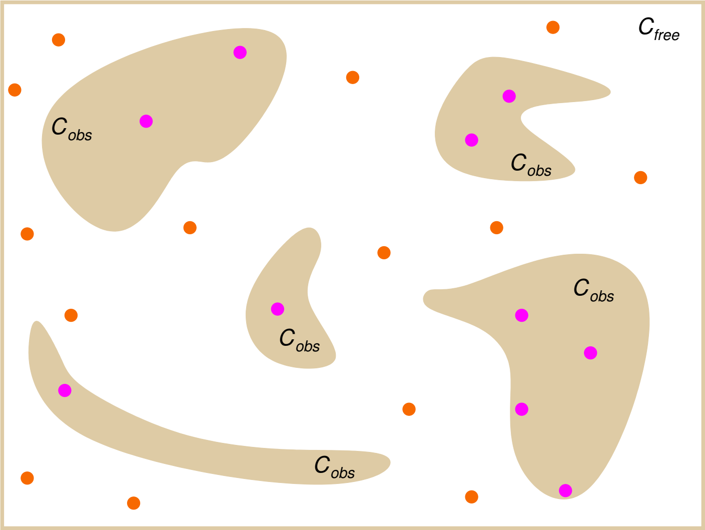
PRM Construction

Given problem domain



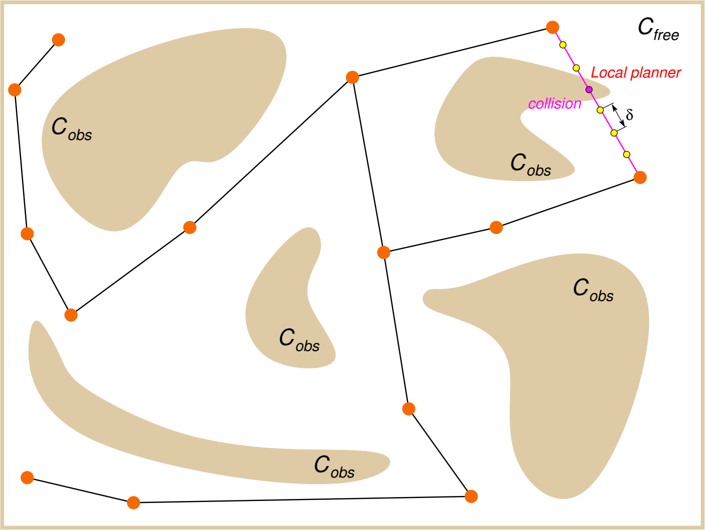
PRM Construction

Random configuration



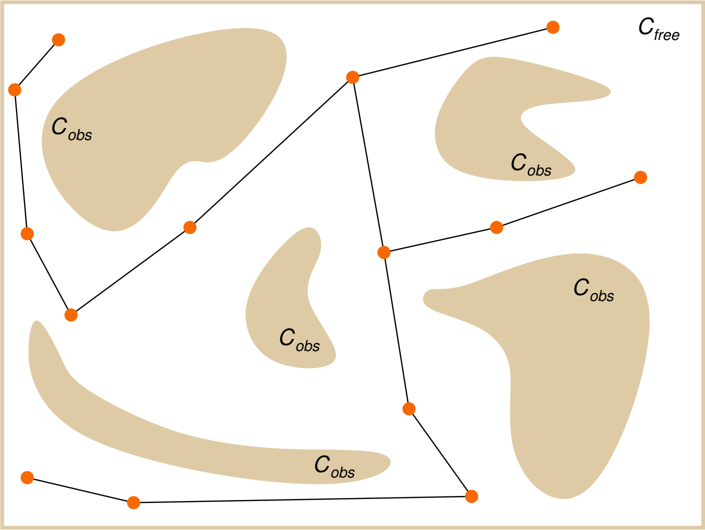
PRM Construction

Connecting random samples



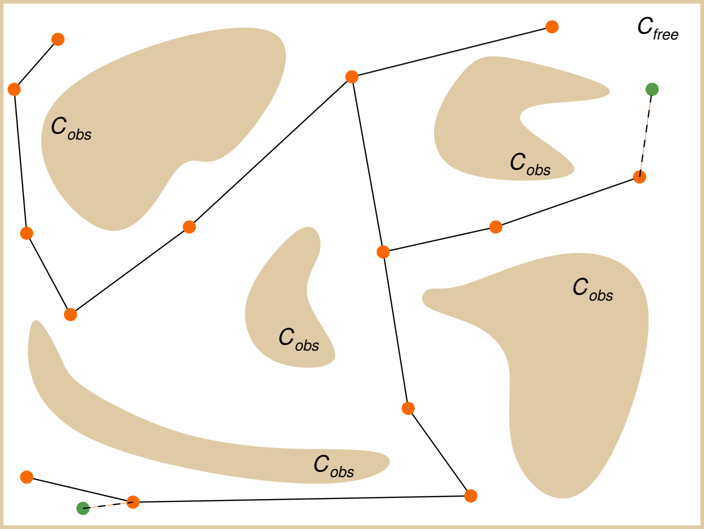
PRM Construction

Connected roadmap



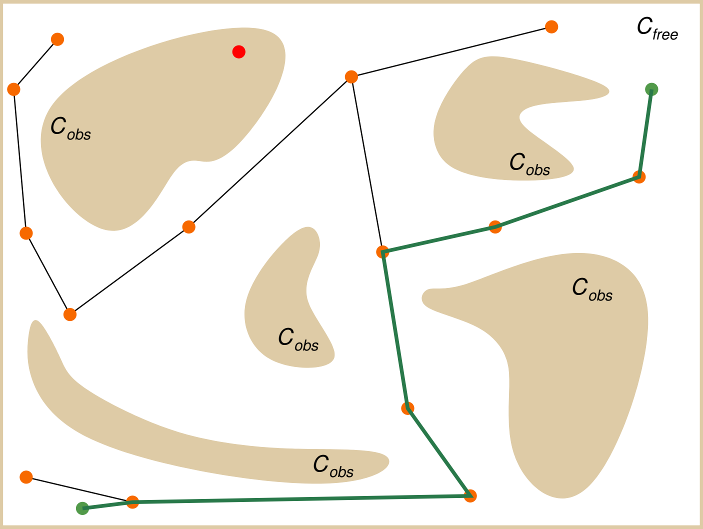
PRM Construction

Query configurations



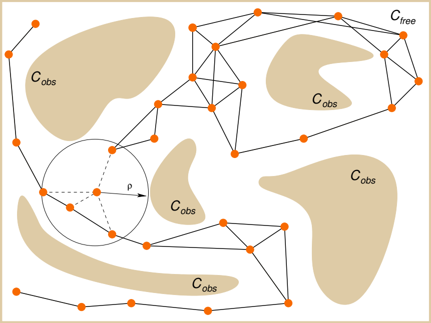
PRM Construction

Final found path



Practical PRM

- Incremental construction
- Connect nodes in a radius ρ
- Local planner tests collisions up to selected resolution δ
- Path can be found by Dijkstra's algorithm



What are the properties of the PRM algorithm?

We need a couple of more formalism.

Practical PRM

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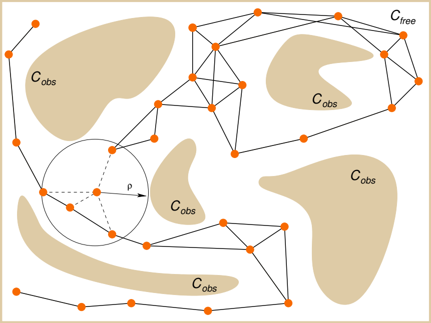

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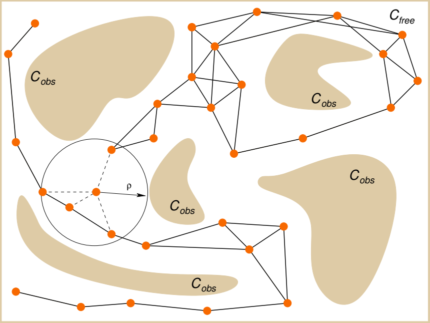

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Path Planning Problem Formulation

- Path planning problem is defined by a triplet
$$\mathcal{P} = (\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal}),$$
    - $\mathcal{C}_{free} = \mathrm{cl}(\mathcal{C} \setminus \mathcal{C}_{obs})$, $\mathcal{C} = (0,1)^d$, for $d \in \mathbb{N}$, $d \geq 2$
    - $q_{init} \in \mathcal{C}_{free}$ is the initial configuration (condition)
    - $\mathcal{G}_{goal}$ is the goal region defined as an open subspace of $\mathcal{C}_{free}$
- Function $\pi : [0,1] \to \mathbb{R}^d$ of *bounded variation* is called :
    - **path** if it is continuous;
    - **collision-free path** if it is path and $\pi(\tau) \in \mathcal{C}_{free}$ for $\tau \in [0,1]$;
    - **feasible** if it is collision-free path, and $\pi(0) = q_{init}$ and $\pi(1) \in \mathrm{cl}(\mathcal{Q}_{goal})$.

- A function π with the total variation $\mathrm{TV}(\pi) < \infty$ is said to have bounded variation, where $\mathrm{TV}(\pi)$ is the total variation
$$\mathrm{TV}(\pi) = \sup_{\{n \in \mathbb{N}, 0=\tau_0<\tau_1<\ldots<\tau_n=s\}} \sum_{i=1}^{n} |\pi(\tau_i) - \pi(\tau_{i-1})|$$
- The total variation $\mathrm{TV}(\pi)$ is de facto a path length.

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Path Planning Problem

- **Feasible path planning**:

  For a path planning problem $(\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$

  - Find a feasible path $\pi : [0,1] \to \mathcal{C}_{free}$ such that $\pi(0) = q_{init}$ and $\pi(1) \in \text{cl}(\mathcal{Q}_{goal})$, if such path exists.
  - Report failure if no such path exists.

- **Optimal path planning**:

  The optimality problem ask for a feasible path with the minimum cost.

  For $(\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$ and a cost function $c : \Sigma \to \mathbb{R}_{\geq 0}$

  - Find a feasible path π^* such that $c(\pi^*) = \min\{c(\pi) : \pi \text{ is feasible}\}$.
  - Report failure if no such path exists.

  The cost function is assumed to be monotonic and bounded, i.e., there exists k_c such that $c(\pi) \leq k_c \, \text{TV}(\pi)$.

Path Planning Problem

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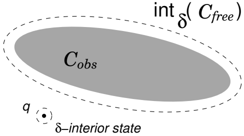
Probabilistic Completeness 1/2

First, we need **robustly feasible path planning problem** $(\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$.



- $q \in \mathcal{C}_{free}$ is *δ-interior state* **of** *$\mathcal{C}_{free}$* if the closed ball of radius δ centered at q lies entirely inside $\mathcal{C}_{free}$.
- *δ-interior* of $\mathcal{C}_{free}$ is $\text{int}_{\delta}(\mathcal{C}_{free}) = \{q \in \mathcal{C}_{free} | \mathcal{B}_{/,\delta} \subseteq \mathcal{C}_{free}\}$.

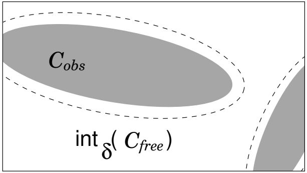
  A collection of all δ-interior states.
- A collision free path π has **strong δ-clearance**, if π lies entirely inside $\text{int}_{\delta}(\mathcal{C}_{free})$.
- $(\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$ is *robustly feasible* if a solution exists and it is a feasible path with *strong δ-clearance*, for $\delta{>}0$.

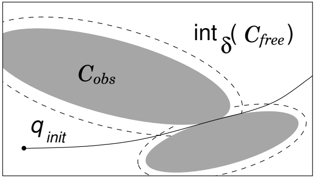
Probabilistic Completeness 2/2

An algorithm $\mathcal{ALG}$ is **probabilistically complete** if, for any *robustly feasible path planning problem* $\mathcal{P} = (\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$

$$\lim_{n \to 0} Pr(\mathcal{ALG} \text{ returns a solution to } \mathcal{P}) = 1.$$

- It is a "*relaxed*" notion of completeness
- Applicable only to problems with a **robust solution**.





We need some space, where random configurations can be sampled

Asymptotic Optimality 1/4

Asymptotic optimality relies on a notion of **weak δ-clearance**

Notice, we use strong δ-clearance for probabilistic completeness

- Function $\psi : [0, 1] \to \mathcal{C}_{free}$ is called **homotopy**, if $\psi(0) = \pi_1$ and $\psi(1) = \pi_2$ and $\psi(\tau)$ is collision-free path for all $\tau \in [0, 1]$.
- A collision-free path π_1 is **homotopic** to π_2 if there exists homotopy function ψ.

A path homotopic to π can be continuously transformed to π through $\mathcal{C}_{free}$.

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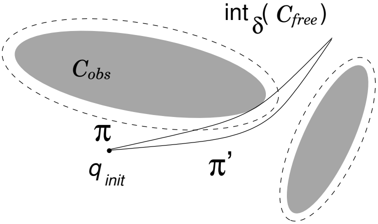
A path homotopic to π can be continuously transformed to π through $\mathcal{C}_{free}$.

Asymptotic Optimality 2/4

- A collision-free path $\pi : [0, s] \rightarrow \mathcal{C}_{free}$ has **weak δ-clearance** if there exists a path π' that has **strong δ-clearance** and homotopy ψ with $\psi(0) = \pi$, $\psi(1) = \pi'$, and for all $\alpha \in (0, 1]$ there exists $\delta_\alpha > 0$ such that $\psi(\alpha)$ has strong δ-clearance.

Weak δ-clearance does not require points along a path to be at least a distance δ away from obstacles.



- A path π with a weak δ-clearance
- π' lies in $\mathrm{int}_\delta(\mathcal{C}_{free})$ and it is the same homotopy class as π

Asymptotic Optimality 3/4

- It is applicable with a **robust optimal solution** that can be obtained as a limit of robust (non-optimal) solutions.
- A collision-free path π^* is **robustly optimal solution** if it has *weak δ-clearance* and for any sequence of collision free paths $\{\pi_n\}_{n\in\mathbb{N}}$, $\pi_n \in \mathcal{C}_{free}$ such that $\lim_{n\to\infty} \pi_n = \pi^*$,

$$\lim_{n\to\infty} c(\pi_n) = c(\pi^*).$$

There exists a path with strong δ-clearance, and π^* is homotopic to such path and π^* is of ***the lower cost****.*

- Weak δ-clearance implies robustly feasible solution problem

(thus, probabilistic completeness)

Asymptotic Optimality 4/4

An algorithm $\mathcal{ALG}$ is **asymptotically optimal** if, for any path planning problem $\mathcal{P} = (\mathcal{C}_{free}, q_{init}, \mathcal{Q}_{goal})$ and cost function c that admit a robust optimal solution with the finite cost c^*

$$Pr\left(\left\{\lim_{i\to\infty} Y_i^{\mathcal{ALG}} = c^*\right\}\right) = 1.$$

- $Y_i^{\mathcal{ALG}}$ is the extended random variable corresponding to the minimum-cost solution included in the graph returned by $\mathcal{ALG}$ at the end of iteration i.

Properties of the PRM Algorithm

- Completeness for the standard PRM has not been provided when it was introduced
- A simplified version of the PRM (called sPRM) has been mostly studied
- sPRM is probabilistically complete

What are the differences between PRM and sPRM?

PRM vs simplified PRM (sPRM)

PRM

Vstup: q_{init}, number of samples n, radius ρ
Výstup: PRM – $G = (V, E)$

```
$V \leftarrow \emptyset$; $E \leftarrow \emptyset$;
for $i = 0, \ldots, n$ do
    $q_{rand} \leftarrow$ SampleFree;
    $U \leftarrow$ Near($G = (V, E), q_{rand}, \rho$);
    $V \leftarrow V \cup \{q_{rand}\}$;
    foreach $u \in U$, with increasing $||u - q_r||$ do
        if $q_{rand}$ and $u$ are not in the same connected component of $G = (V, E)$ then
            if CollisionFree($q_{rand}, u$) then
                $E \leftarrow E \cup \{(q_{rand}, u), (u, q_{rand})\}$;
return $G = (V, E)$;
```

sPRM Algorithm

Vstup: q_{init}, number of samples n, radius ρ
Výstup: PRM – $G = (V, E)$

```
$V \leftarrow \{q_{init}\} \cup \{\text{SampleFree}_i\}_{i=1,\ldots,n-1}$; $E \leftarrow \emptyset$;
foreach $v \in V$ do
    $U \leftarrow$ Near($G = (V, E), v, \rho$) $\setminus \{v\}$;
    foreach $u \in U$ do
        if CollisionFree($v, u$) then
            $E \leftarrow E \cup \{(v, u), (u, v)\}$;
return $G = (V, E)$;
```

There are several ways for the set U of vertices to connect them

- k-nearest neighbors to v
- variable connection radius ρ as a function of n

PRM – Properties

- sPRM (simplified PRM)
  - **Probabilistically complete and asymptotically optimal**
  - Processing complexity $O(n^2)$
  - Query complexity $O(n^2)$
  - Space complexity $O(n^2)$
- Heuristics practically used are usually not probabilistic complete
  - k-nearest sPRM is not probabilistically complete
  - variable radius sPRM is not probabilistically complete

Based on analysis of Karaman and Frazzoli

PRM algorithm:

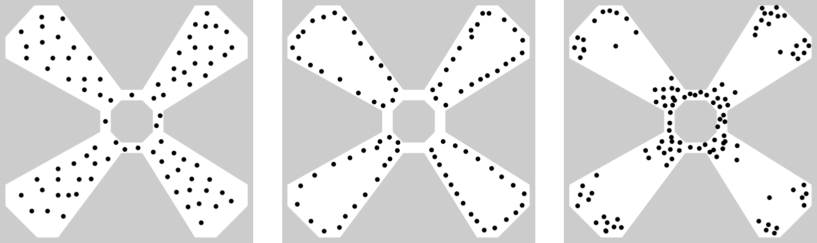
+ Has very simple implementation

+ Completeness (for sPRM)

− Differential constraints (car-like vehicles) are not straightforward

Comments about Random Sampling 1/2

- Different sampling strategies (distributions) may be applied



- Notice, one of the main issue of the randomized sampling-based approaches is the narrow passage
- Several modifications of sampling based strategies have been proposed in the last decades

Comments about Random Sampling 2/2

- A solution can be found using only a few samples.

  Do you know the Oraculum? (from Alice in Wonderland)

- Sampling strategies are important
  - Near obstacles
  - Narrow passages
  - Grid-based
  - Uniform sampling must be carefully considered.

    James J. Kuffner, Effective Sampling and Distance Metrics for 3D Rigid Body Path Planning, ICRA, 2004.

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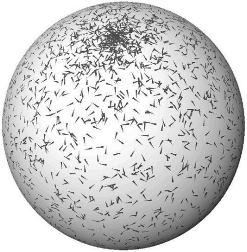
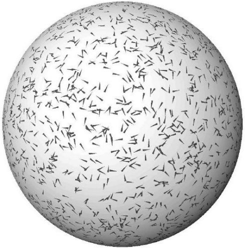


Naïve sampling



Uniform sampling of SO(3) using Euler angles

Outline

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- Characteristics
- Rapidly Exploring Random Tree (RRT)

Rapidly Exploring Random Tree (RRT)

Single–Query algorithm

- It incrementally builds a graph (tree) towards the goal area.

It does not guarantee precise path to the goal configuration.

1. Start with the initial configuration q_0, which is a root of the constructed graph (tree)
2. Generate a new random configuration q_{new} in $\mathcal{C}_{free}$
3. Find the closest node q_{near} to q_{new} in the tree

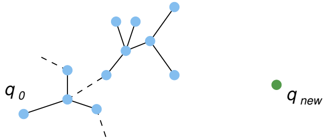
   E.g., using KD-tree implementation like ANN or FLANN libraries
4. Extend q_{near} towards q_{new}

   Extend the tree by a small step, but often a direct control $u \in \mathcal{U}$ that will move robot the position closest to q_{new} is selected (applied for δt).
5. Go to Step 2, until the tree is within a sufficient distance from the goal configuration

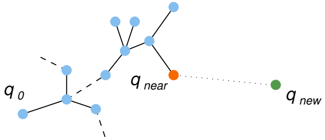
   Or terminates after dedicated running time.

RRT Construction

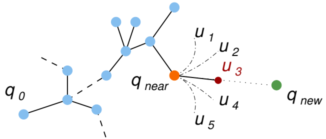
#1 new random configuration



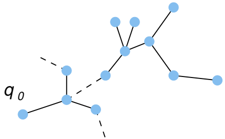
#2 the closest node



#3 possible actions from q_{near}



#4 extended tree



RRT Algorithm

- Motivation is a single query and *control-based* path finding
- It incrementally builds a graph (tree) towards the goal area.

RRT Algorithm

```
Vstup: $q_{init}$, number of samples $n$
Výstup: Roadmap $G = (V, E)$

$V \leftarrow \{q_{init}\}$; $E \leftarrow \emptyset$;
for $i = 1, \ldots, n$ do
    $q_{rand} \leftarrow$ SampleFree;
    $q_{nearest} \leftarrow$ Nearest($G = (V, E), q_{rand}$);
    $q_{new} \leftarrow$ Steer($q_{nearest}, q_{rand}$);
    if CollisionFree($q_{nearest}, q_{new}$) then
        $V \leftarrow V \cup \{x_{new}\}$; $E \leftarrow E \cup \{(x_{nearest}, x_{new})\}$;
return $G = (V, E)$;
```

Extend the tree by a small step, but often a direct control $u \in \mathcal{U}$ that will move robot to the position closest to q_{new} is selected (applied for dt).

Rapidly-exploring random trees: A new tool for path planning
S. M. LaValle,
Technical Report 98-11, Computer Science Dept., Iowa State University, 1998

Properties of RRT Algorithms

- Rapidly explores the space

  q_{new} will more likely be generated in large not yet covered parts.

- Allows considering kinodynamic/dynamic constraints (during the expansion).
- Can provide trajectory or a sequence of direct control commands for robot controllers.
- A collision detection test is usually used as a "black-box".

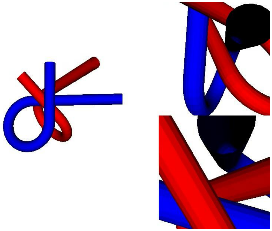
  E.g., RAPID, Bullet libraries.

- Similarly to PRM, RRT algorithms have poor performance in narrow passage problems.
- RRT algorithms provides feasible paths.

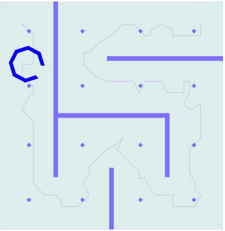
  It can be relatively far from optimal solution, e.g., according to the length of the path.

- Many variants of RRT have been proposed.

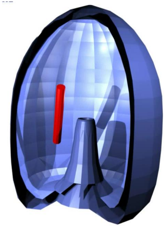
RRT – Examples 1/2



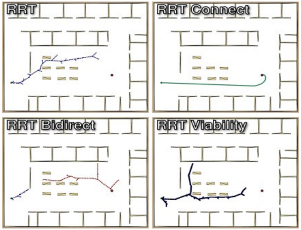
Alpha puzzle benchmark



Apply rotations to reach the goal



Bugtrap benchmark

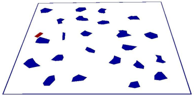


Variants of RRT algorithms

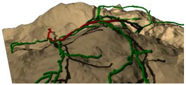
Courtesy of V. Vonásek and P. Vaněk

RRT – Examples 2/2

- Planning for a car-like robot

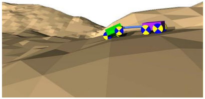


- Planning on a 3D surface



- Planning with dynamics

(friction forces)



Courtesy of V. Vonásek and P. Vaněk

Car-Like Robot

- Configuration

$$\vec{\boldsymbol{x}} = \begin{pmatrix} x \\ y \\ \phi \end{pmatrix}$$

position and orientation

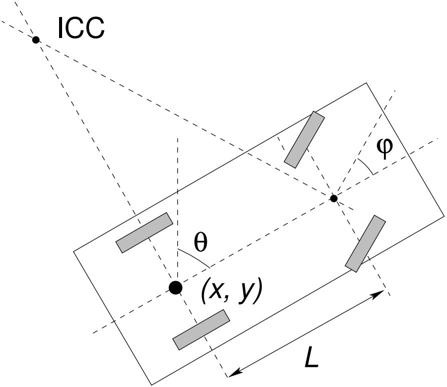
- Controls

$$\vec{\boldsymbol{u}} = \begin{pmatrix} v \\ \varphi \end{pmatrix}$$

forward velocity, steering angle

- System equation

$$\begin{aligned} \dot{x} &= v \cos\phi \\ \dot{y} &= v \sin\phi \\ \dot{\varphi} &= \frac{v}{L} \tan\varphi \end{aligned}$$



Kinematic constraints $\dim(\vec{\boldsymbol{u}}) < \dim(\vec{\boldsymbol{x}})$

Differential constraints on possible $\dot{q}$*:*

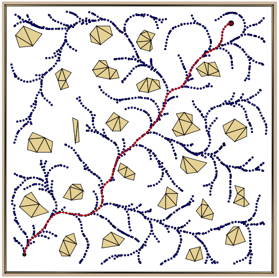
$$\dot{x}\sin(\phi) - \dot{y}\cos(\phi) = 0$$

Control-Based Sampling

- Select a configuration q from the tree T of the current configurations

- Pick a control input $\vec{\boldsymbol{u}} = (v, \varphi)$ and integrate system (motion) equation over a short period

$$\begin{pmatrix} \Delta x \\ \Delta y \\ \Delta\varphi \end{pmatrix} = \int_t^{t+\Delta t} \begin{pmatrix} v\cos\phi \\ v\sin\phi \\ \frac{v}{L}\tan\varphi \end{pmatrix} dt$$



- If the motion is collision-free, add the endpoint to the tree

E.g., considering k configurations for $k\delta t = dt$.

Summary of the Lecture

Topics Discussed

- Randomized Sampling-based Methods
- Probabilistic Road Map (PRM)
- Characteristics of path planning problems
- Random sampling
- Rapidly Exploring Random Tree (RRT)

- Next: Improved randomized sampling-based methods

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