CS686: RRT

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Course URL:
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Class Objectives

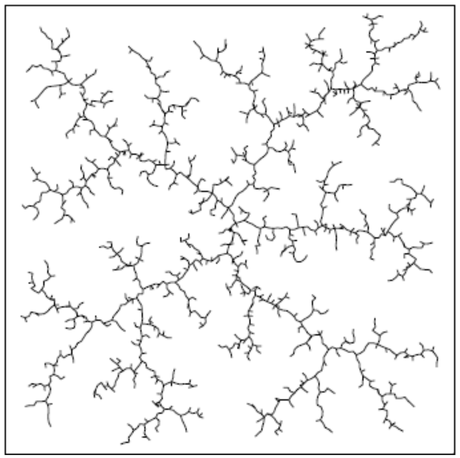
- **Understand the RRT technique and its recent advancements**
  - **RRT***
  - **Kinodynamic planning**
- **Last time**
  - **Probabilistic roadmap techniques**
  - **Sampling and re-sampling techniques**

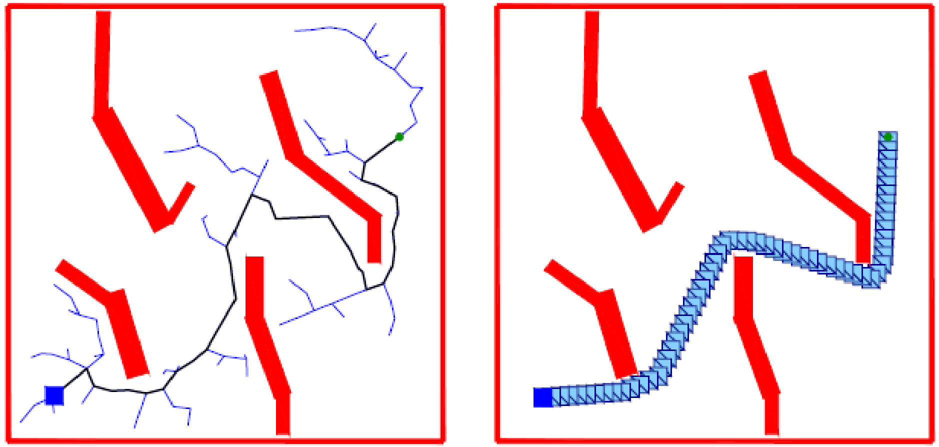
Question

- **PRM assumes that we know the global map, but how can we handle the case where we have only a partial map due to the limited sensor range?**
  - **지난시간에 배운 PRM 기법들은 글로벌 맵을 알고 있어야 문제 해결이 가능한데, 전체 맵의 일부분(센서 탐지거리 제약 등으로)만을 알고 있는 상황에서 PRM알고리즘을 적용하려면 어떤 방식으로 해야 하는지요?**

Rapidly-exploring Random Trees (RRT) [LaValle 98]

- **Present an efficient randomized path planning algorithm for single-query problems**
  - **Converges quickly**
  - **Probabilistically complete**
  - **Works well in high-dimensional C-space**



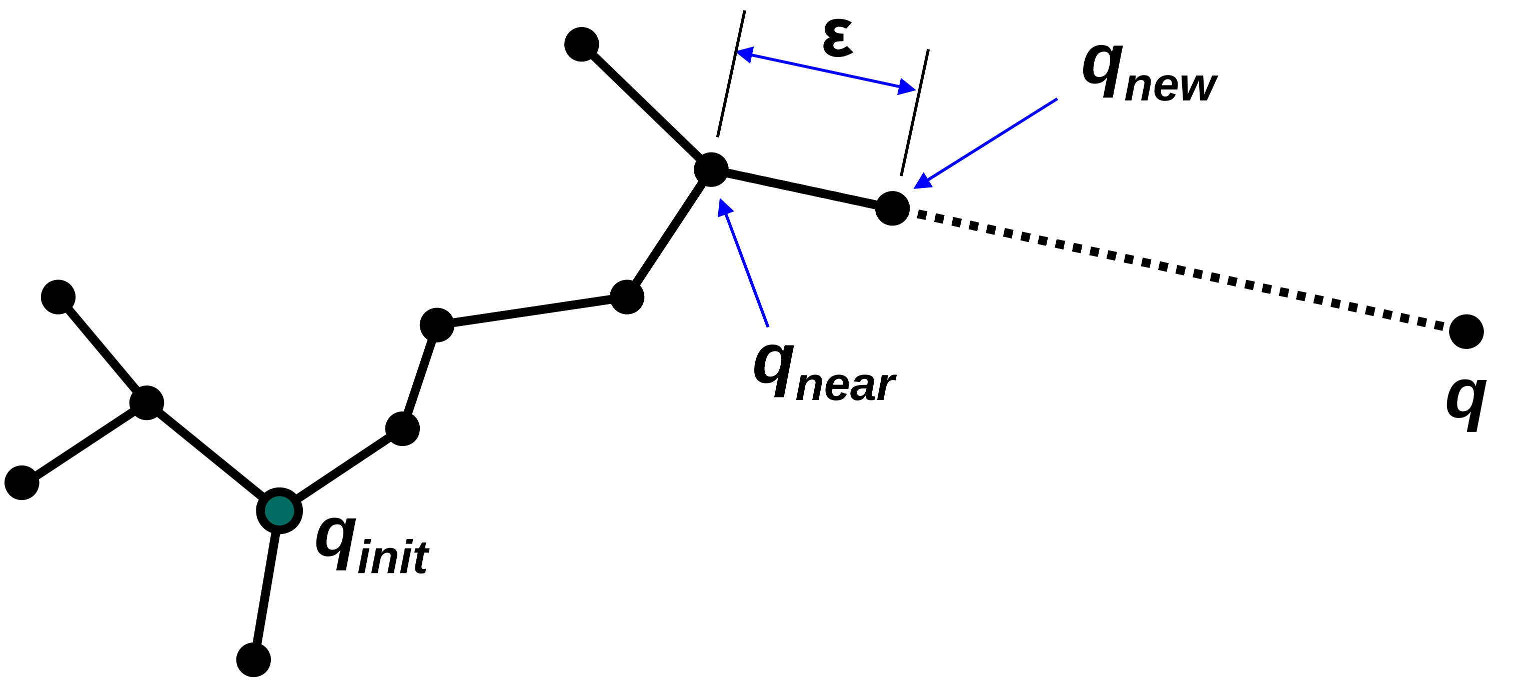


Rapidly-Exploring Random Tree

- **A growing tree from an initial state**

RRT Construction Algorithm

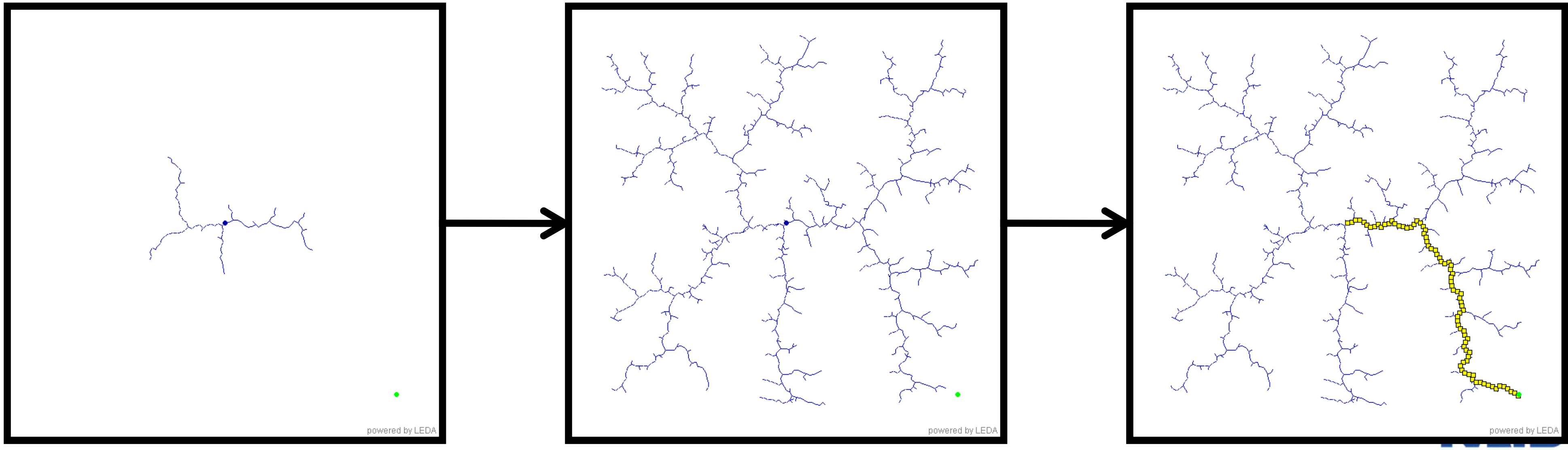
- **Extend a new vertex in each iteration**
  - **Alternatively, one can simply connect**



Overview – Planning with RRT

- **Extend RRT until a nearest vertex is close enough to the goal state**
  - **Can handle nonholonomic constraints and high degrees of freedom**

- **Probabilistically complete, but does not converge to the optimal one**



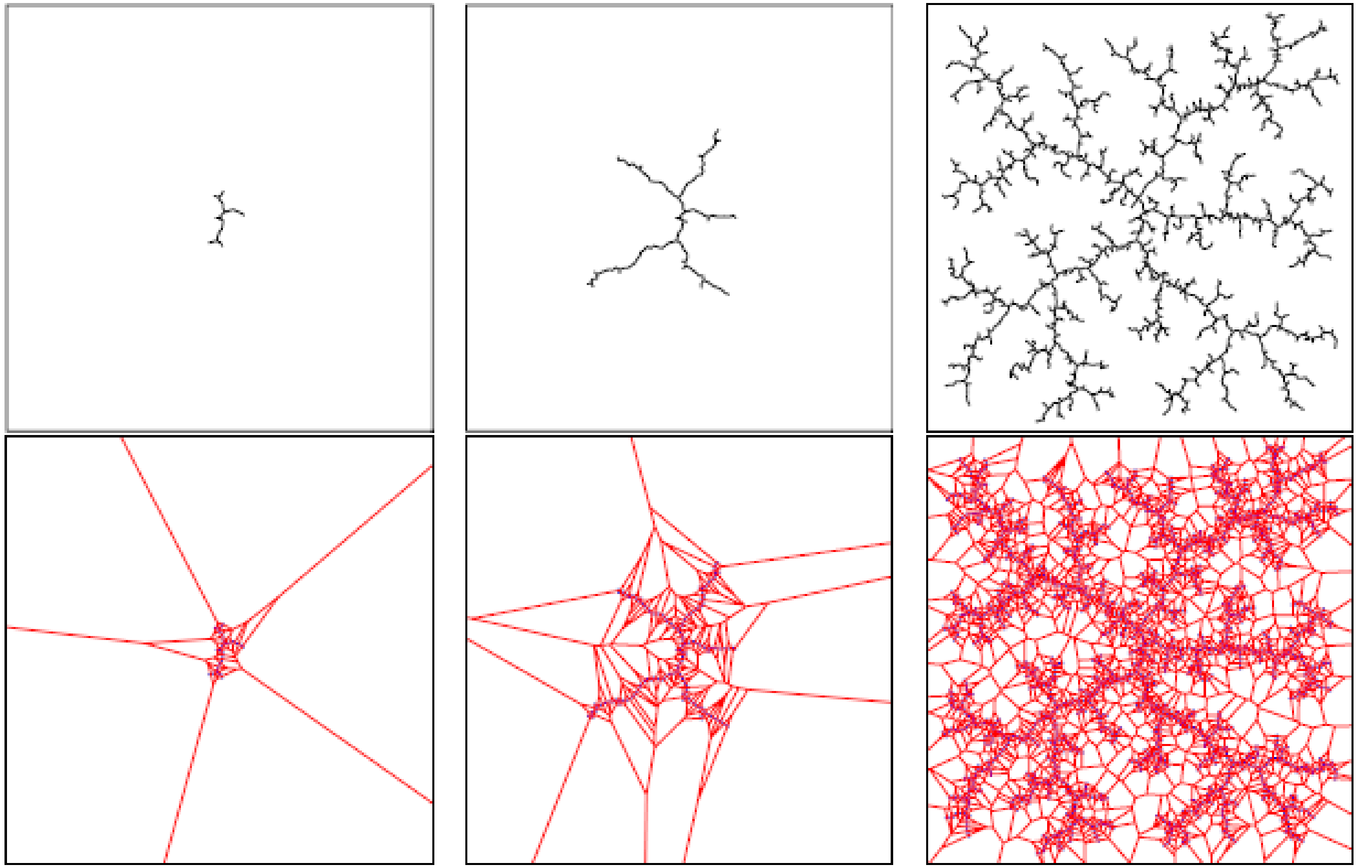
RRT Construction Algorithm

BUILD_RRT(q_{init})
$\mathcal{T}$.init(q_{init});
for $k = 1$ **to** K **do**
  $q_{rand} \leftarrow$ RANDOM_CONFIG();
  EXTEND($\mathcal{T}, q_{rand}$);
Return $\mathcal{T}$

EXTEND($\mathcal{T}, q$)
$q_{near} \leftarrow$ NEAREST_NEIGHBOR($q, \mathcal{T}$);
if NEW_CONFIG(q, q_{near}, q_{new}) **then**
  $\mathcal{T}$.add_vertex(q_{new});
  $\mathcal{T}$.add_edge(q_{near}, q_{new});
  if $q_{new} = q$ **then**
    Return *Reached*;
  else
    Return *Advanced*;
Return *Trapped*;

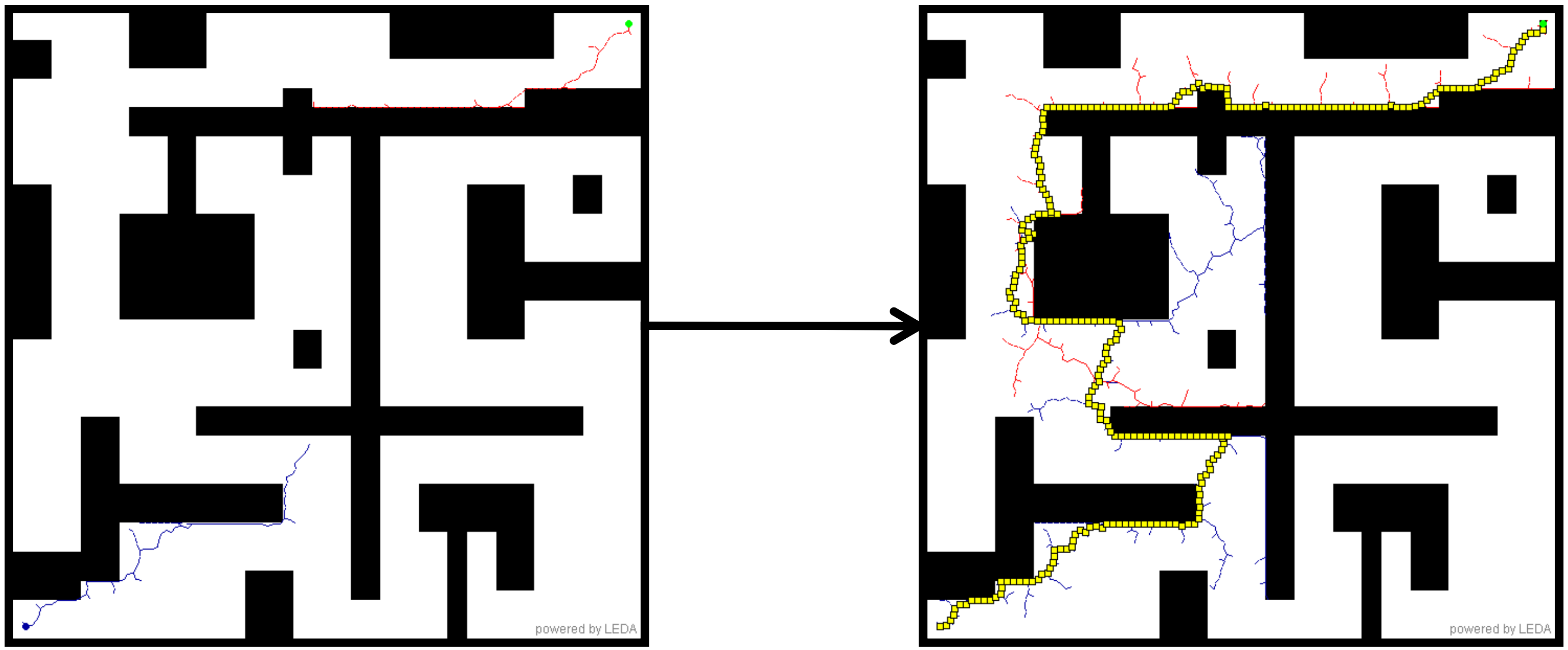
Voronoi Region

- **An RRT is biased by large Voronoi regions to rapidly explore, before uniformly covering the space**



Overview – With Dual RRT

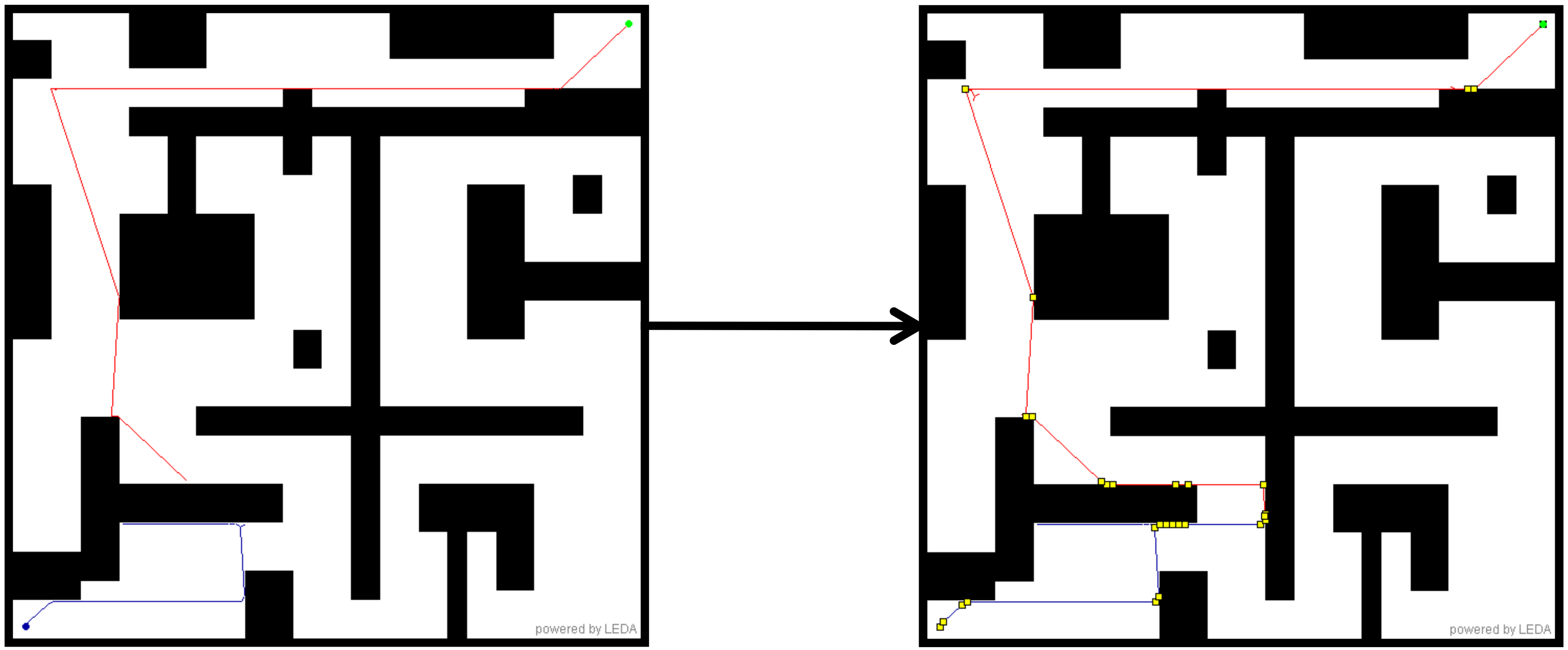
- Extend RRTs from both initial and goal states
- Find path much more quickly



737 nodes are used

Overview – With RRT-Connect

- **Aggressively connect the dual trees using a greedy heuristic**
- **Extend & connect trees alternatively**

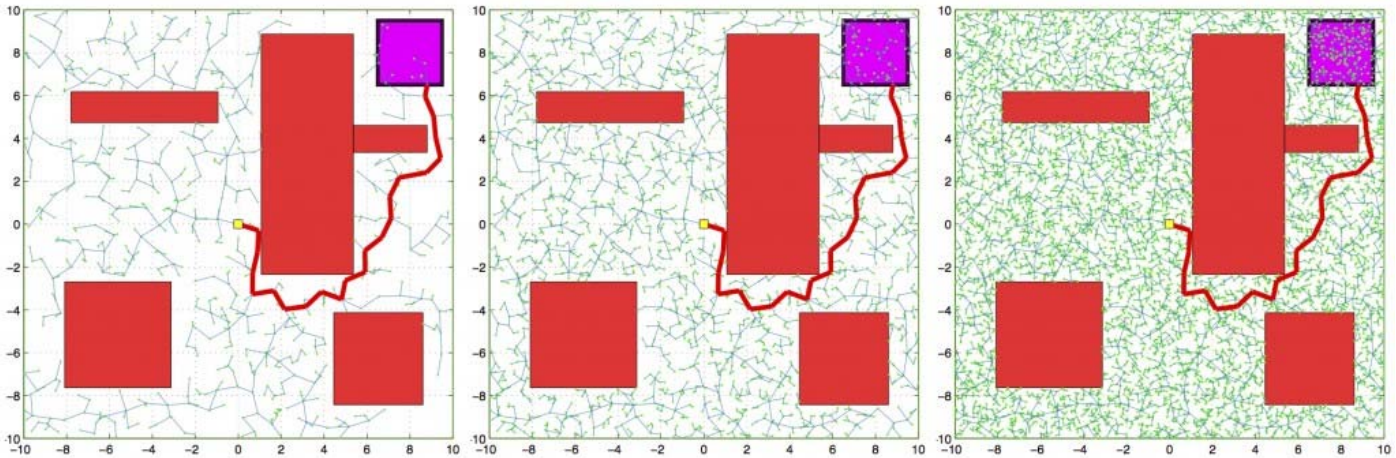


42 nodes are used

RRT*

- **RRT does not converge to the optimal solution**

RRT



(a) RRT in iteration 1,000 (b) RRT in iteration 3,000 (c) RRT in iteration 10,000

RRT*

From Sertac's homepage

RRT*

- **Asymptotically optimal without a substantial computational overhead**

Theorem [Karaman & Frazzoli, IJRR 2011]

(i) The RRT* algorithm is asymptotically optimal

$$\mathbb{P}\left(\left\{ \lim_{n\to\infty} Y_n^{\mathrm{RRT}^*} = c^* \right\}\right) = 1$$

(ii) RRT* algorithm has no substantial computational overhead when compared to the RRT:

$$\lim_{n\to\infty} \mathbb{E}\left[\frac{M_n^{\mathrm{RRT}^*}}{M_n^{\mathrm{RRT}}}\right] = \text{constant}$$

- **Y_n^{RRT*} : cost of the best path in the RRT***
- **c^* : cost of an optimal solution**
- **M_n^{RRT} : # of steps executed by RRT at iteration n**
- **M_n^{RRT*}: # of steps executed by RRT* at iteration n**

From DH's homepage

Key Operation of RRT*

- RRT
  - Just connect a new node to its nearest neighbor node
- RRT*: refine the connection with re-wiring operation
  - Given a ball, identify neighbor nodes to the new node
  - Refine the connection to have a lower cost

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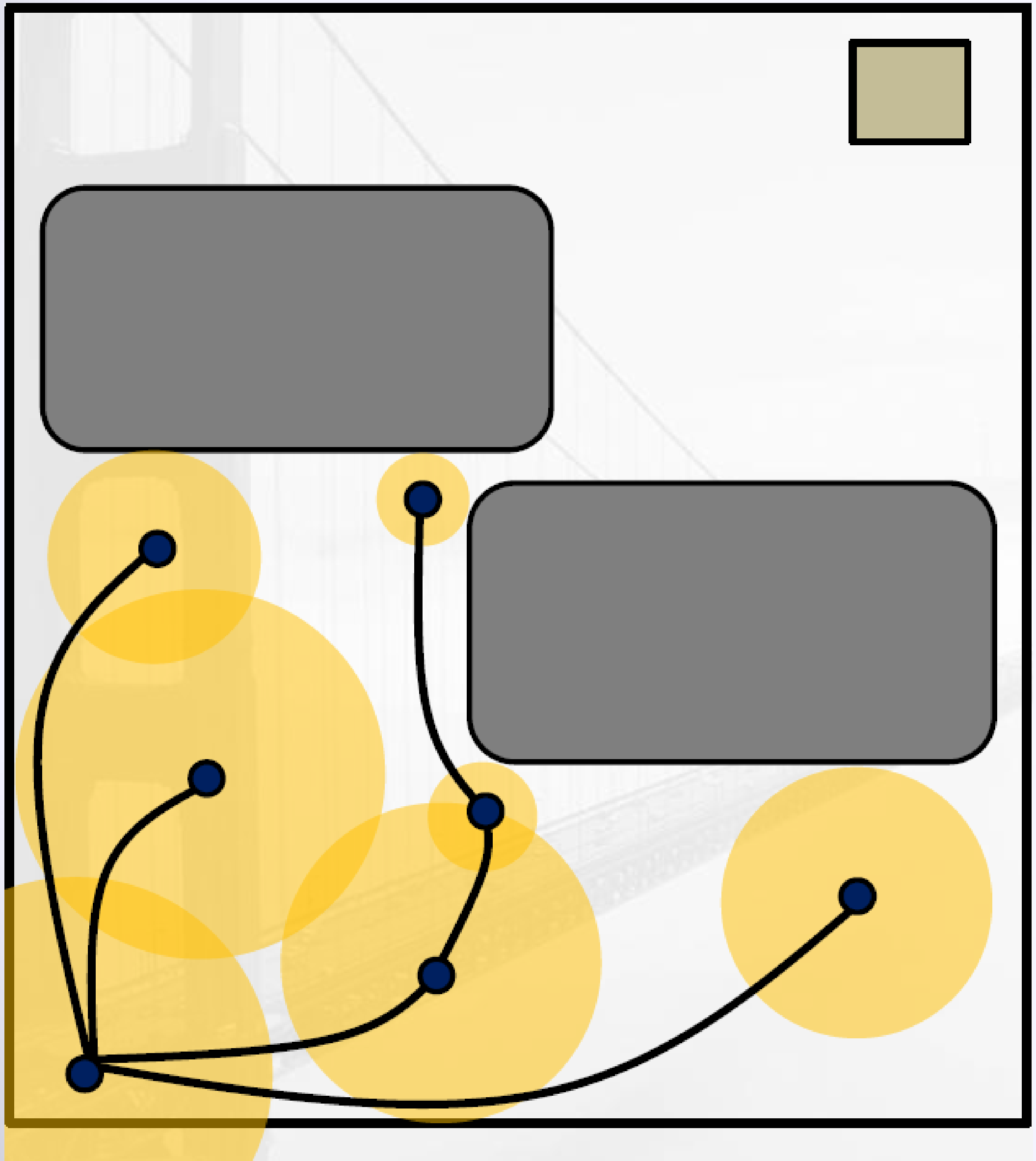
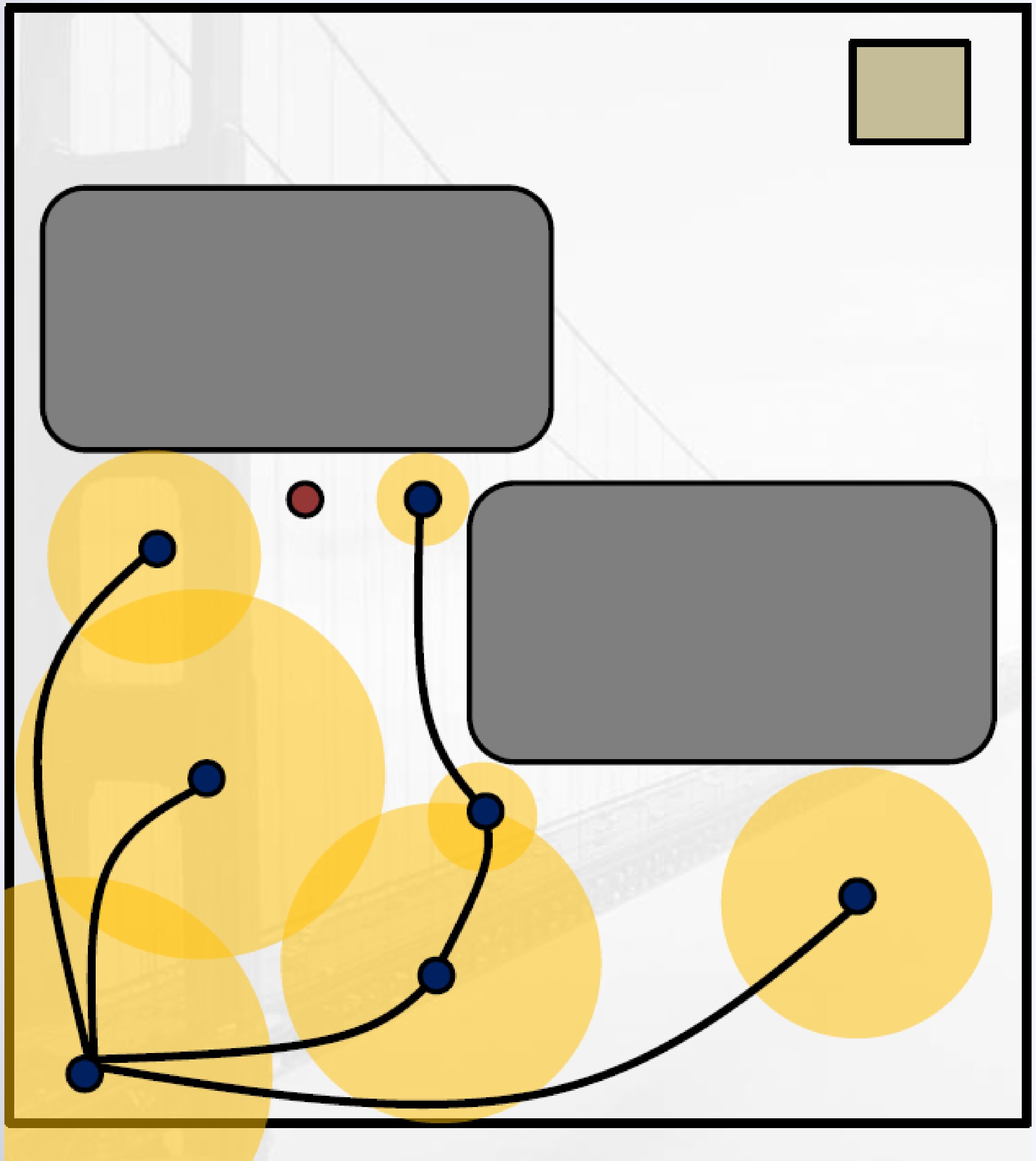
Example: Re-Wiring Operation



From ball tree paper

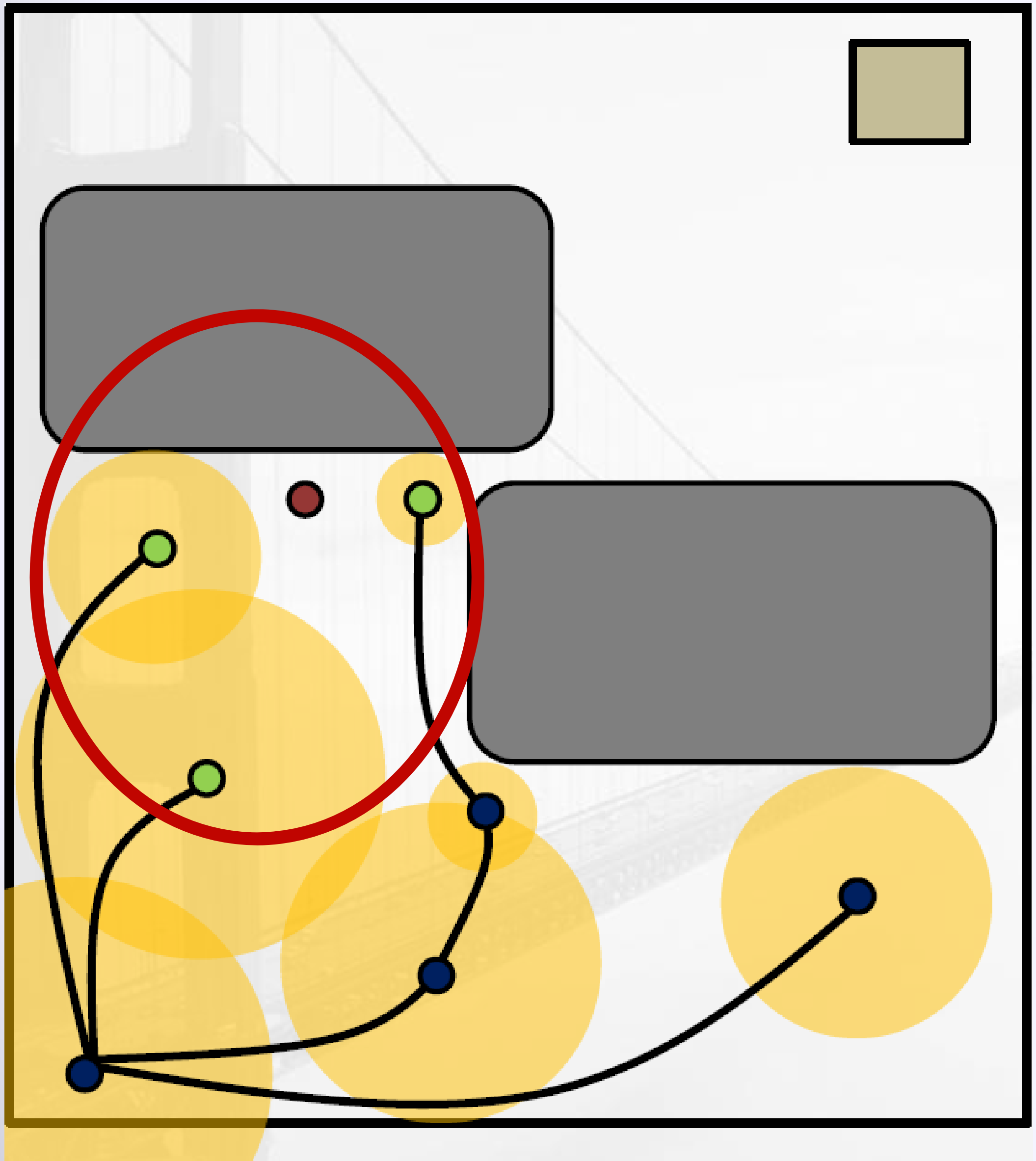
Example: Re-Wiring Operation



Generate a new sample

From ball tree paper

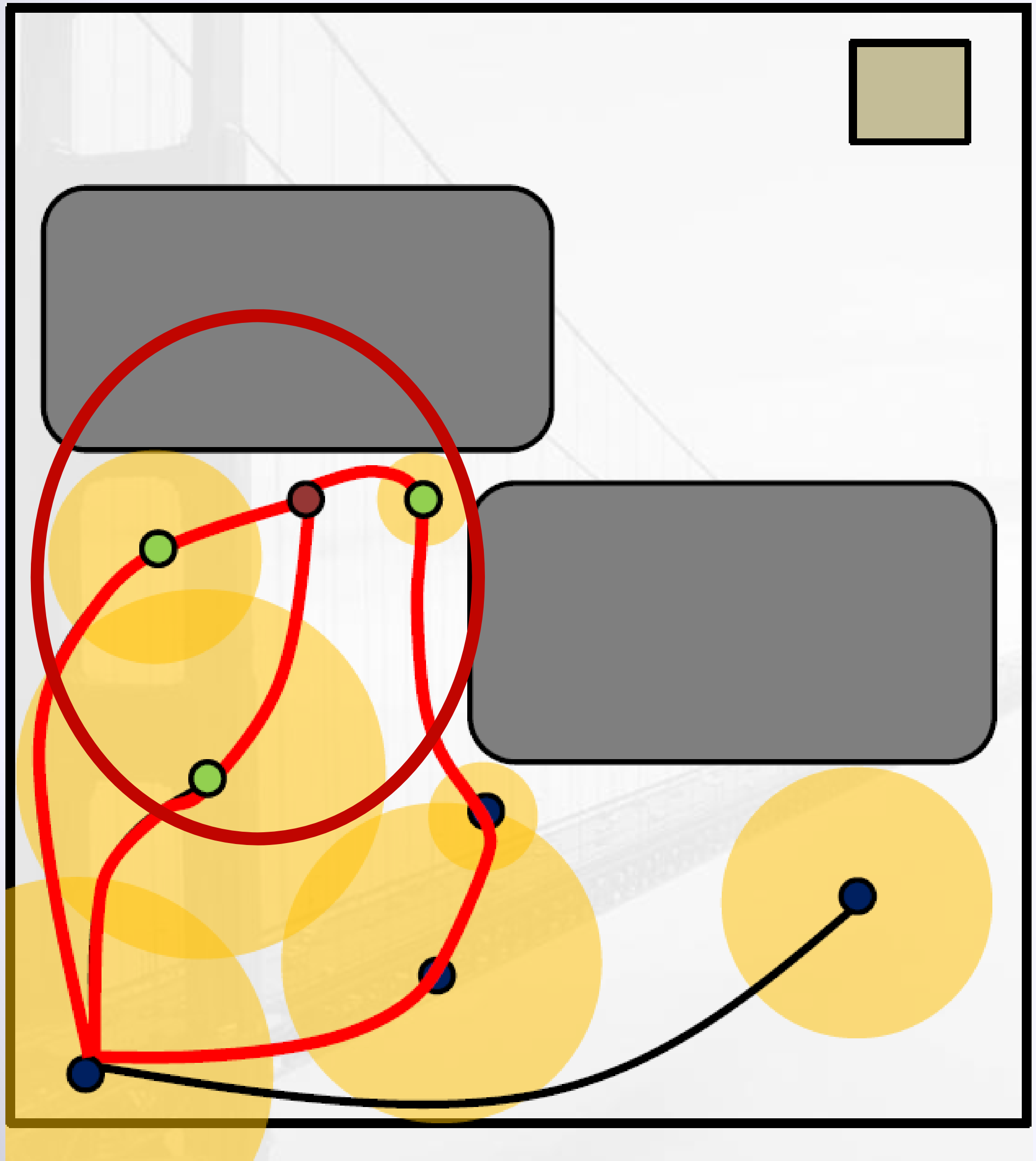
Example: Re-Wiring Operation



Identify nodes in a ball

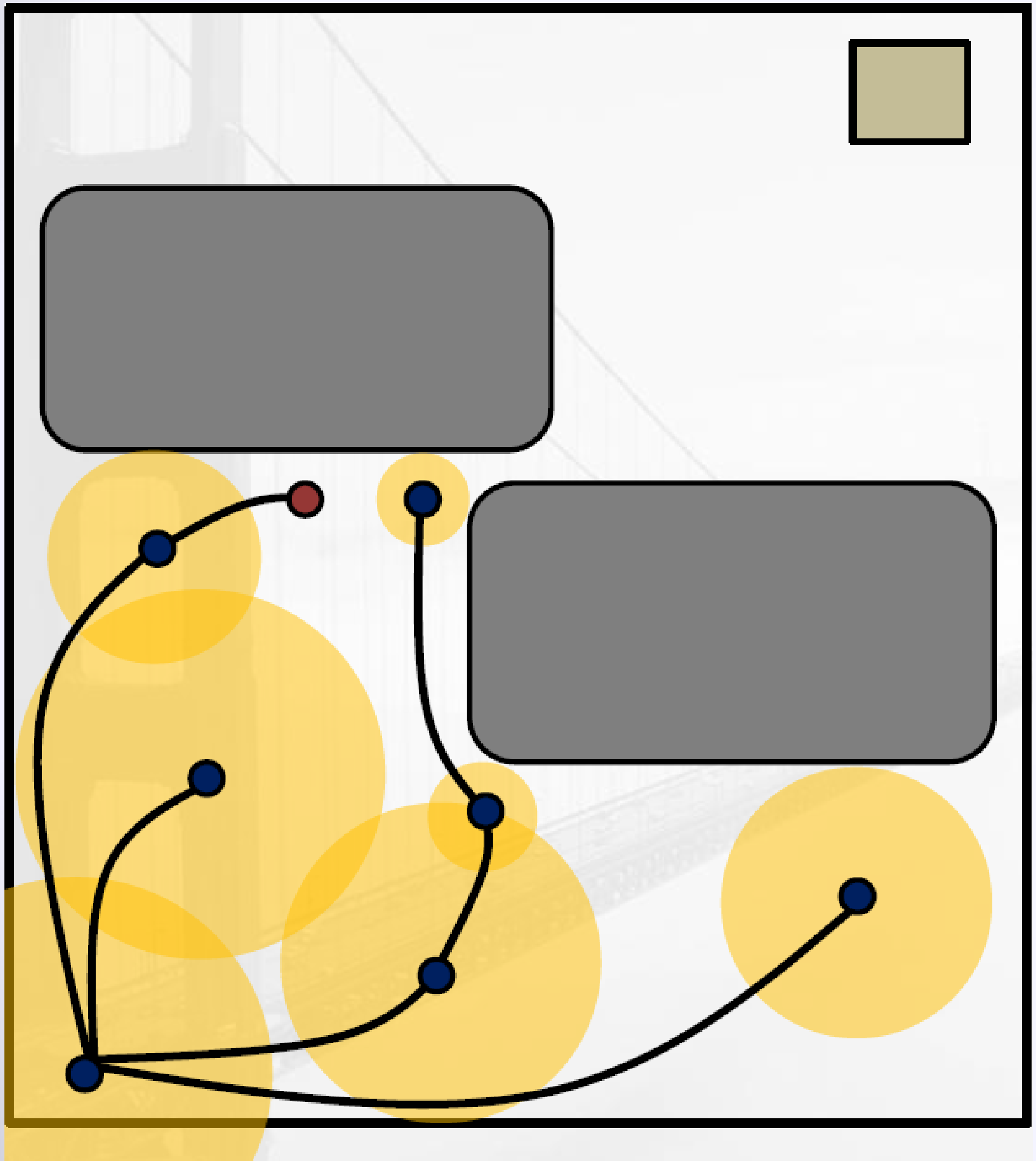
From ball tree paper

Example: Re-Wiring Operation



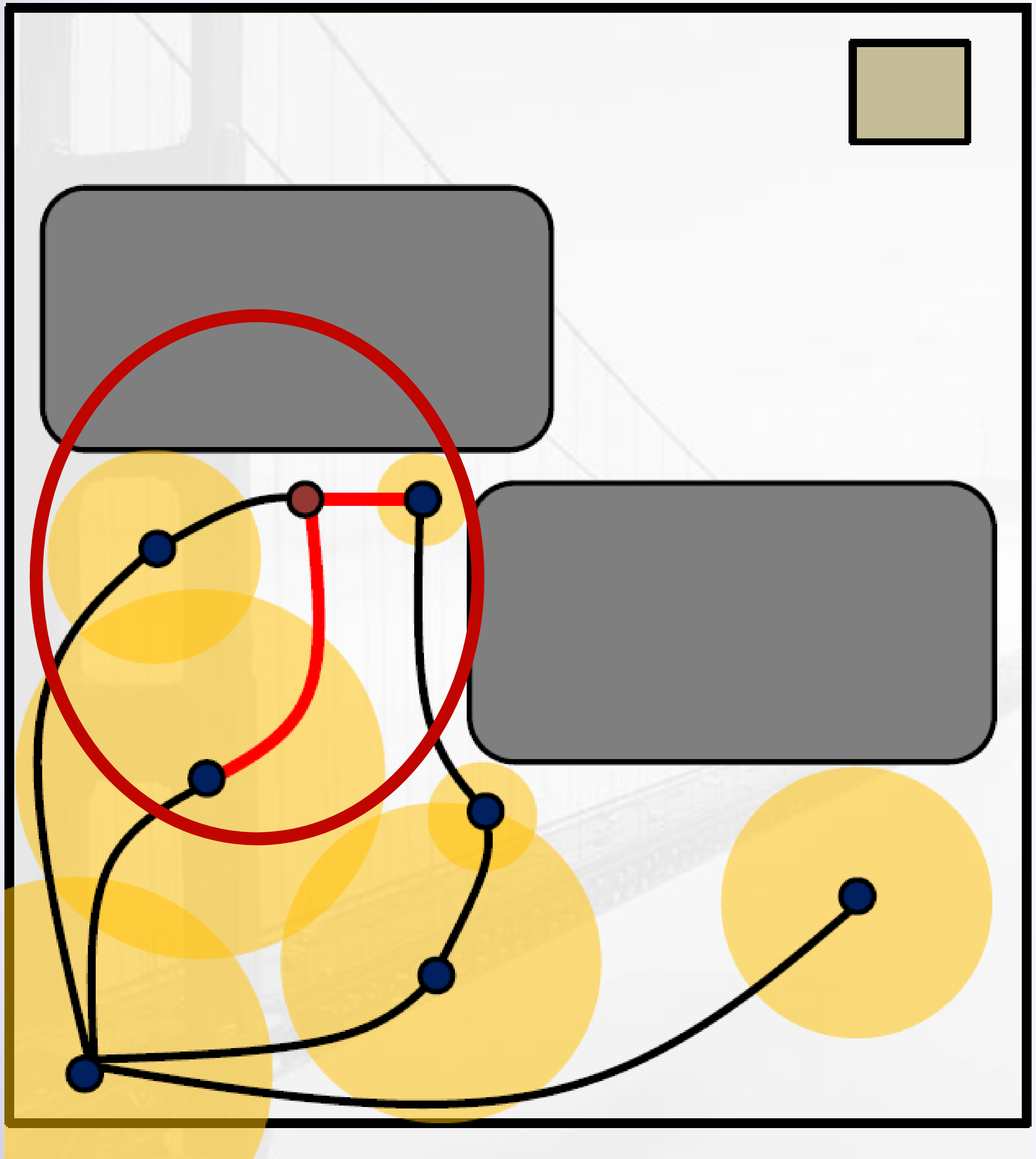
Identify which parent gives the lowest cost

Example: Re-Wiring Operation



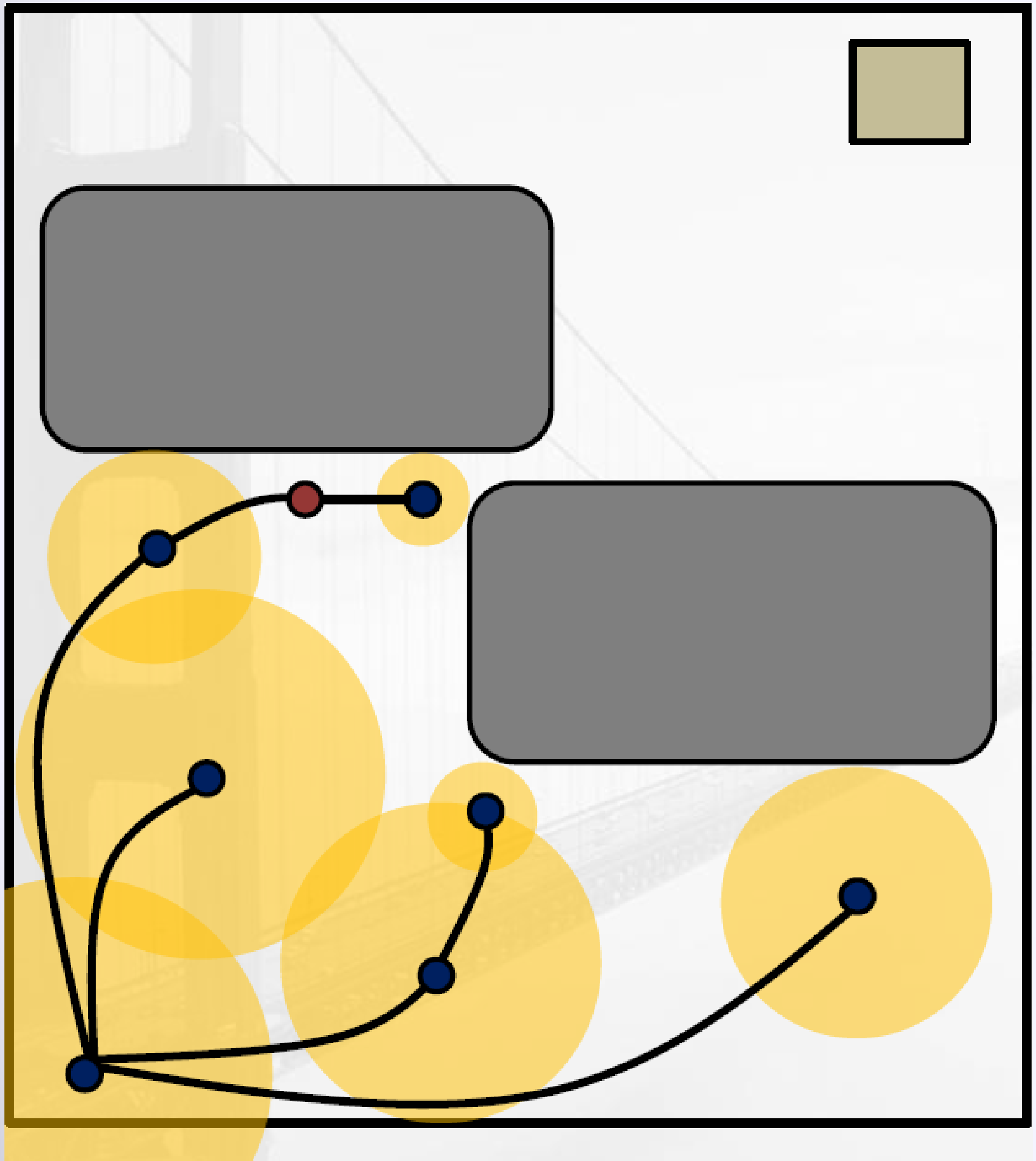
From ball tree paper

Example: Re-Wiring Operation



Identify which child gives the lowest cost

Example: Re-Wiring Operation



Video showing benefits with real robot

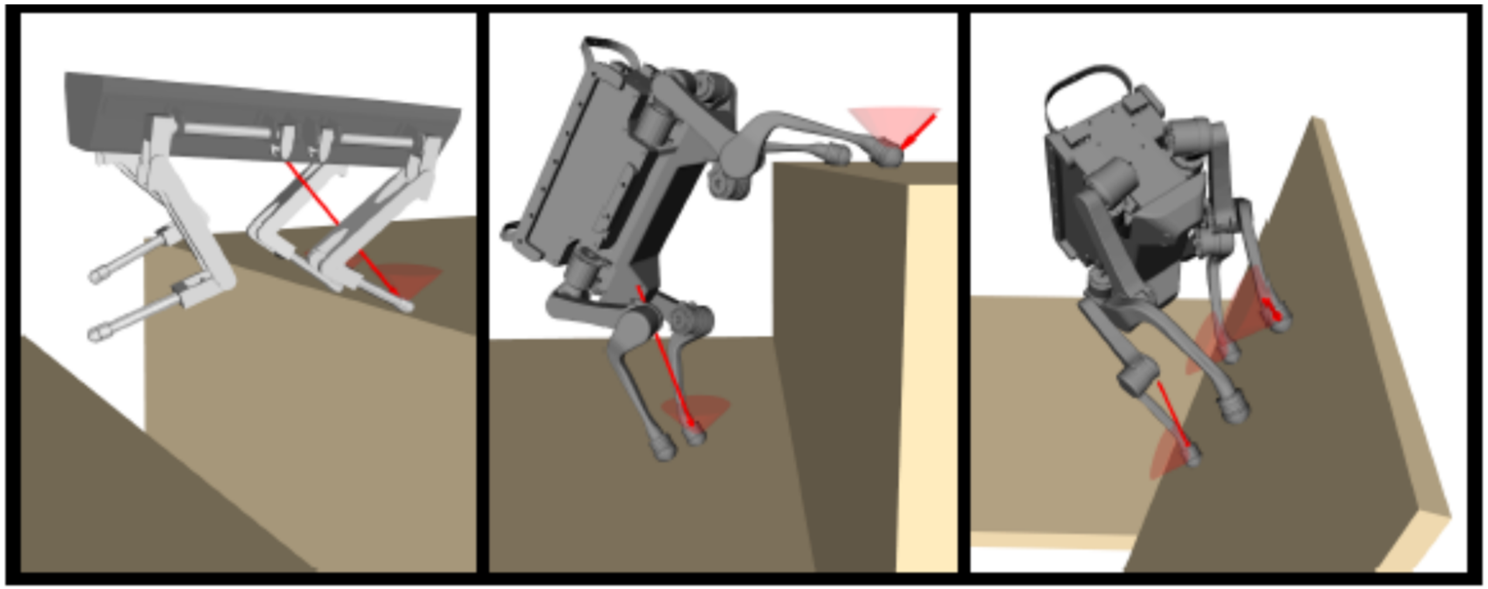
From ball tree paper

Kinodynamic Path Planning

$$\text{ALSO GIVEN:} \quad h_i(q,\dot{q},\ddot{q}) \leq 0,\ h_i(q,\dot{q},\ddot{q}) = 0,\ \ldots$$

$$\text{FIND:} \quad \tau \text{ that satisfies } f_i(q),\ g_i(q,\dot{q}),\ h_i(q,\dot{q},\ddot{q})$$

- **Consider kinematic + dynamic constraints**



Gait and Trajectory Optimization for Legged Systems through Phase-based End-Effector Parameterization

State Space Formulation

- **Kinodynamic planning → 2n-dimensional state space**

C denote the C-space

X denote the state space

$$x = (q, \dot{q}), \text{ for } q \in C, x \in X$$

$$x = [q_1 \;\; q_2 \;\; \dots \;\; q_n \;\; \frac{dq_1}{dt} \;\; \frac{dq_2}{dt} \;\; \dots \;\; \frac{dq_n}{dt}]$$

Constraints in State Space

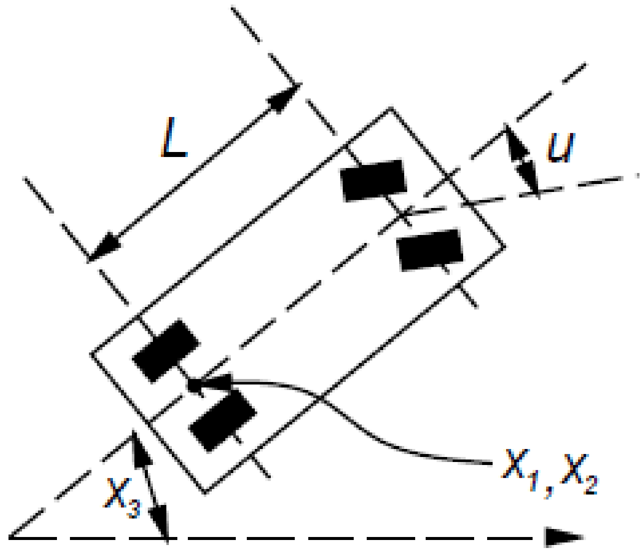
$$h_i(q, \dot{q}, \ddot{q}) = 0 \text{ becomes } G_i(x, \dot{x}) = 0,$$

$$\text{for } i = 1, \ldots, m \text{ and } m < 2n$$

- **Constraints can be written in:**

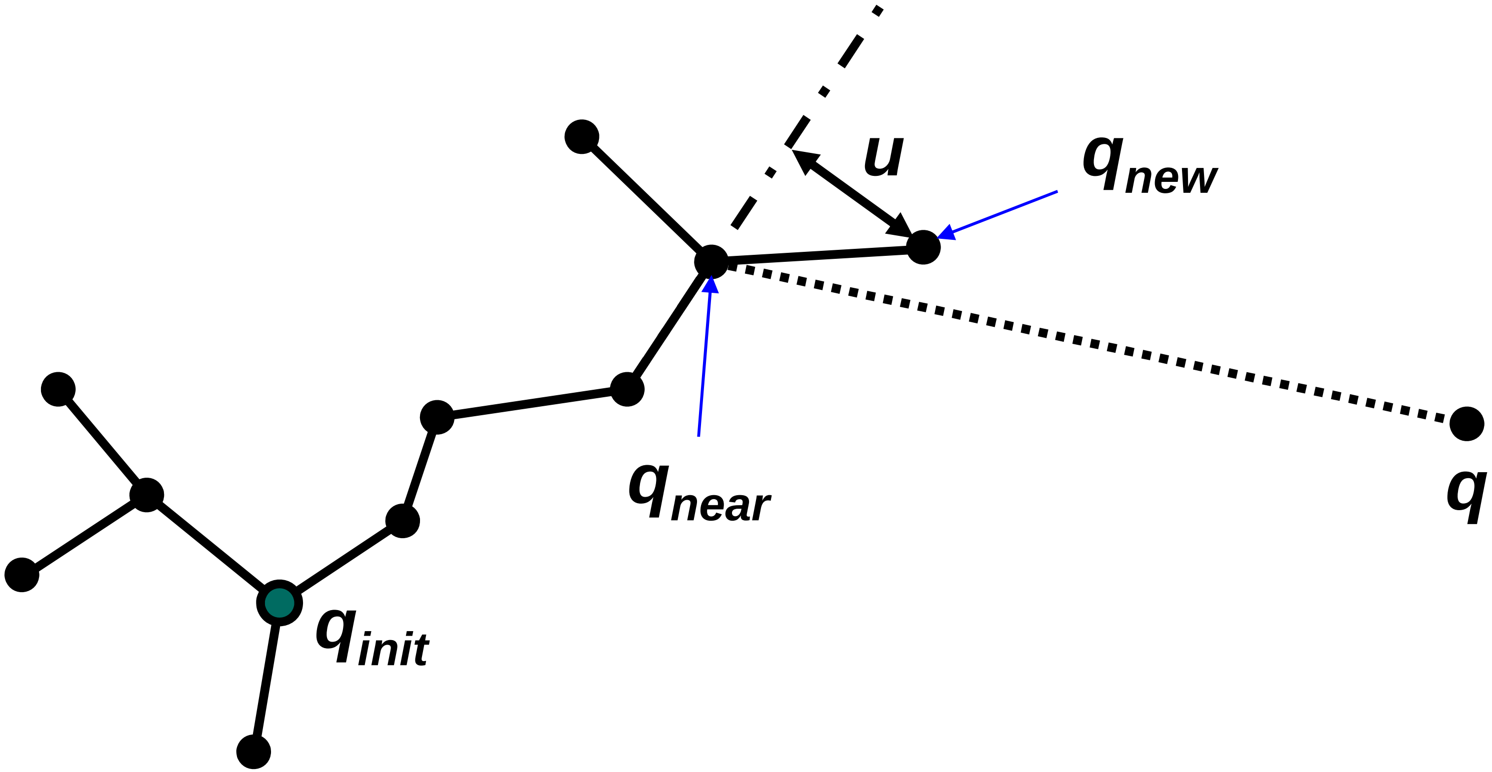
$$\dot{x} = f(x, u)$$

$$u \in U, \quad U: \text{Set of allowable controls or inputs}$$

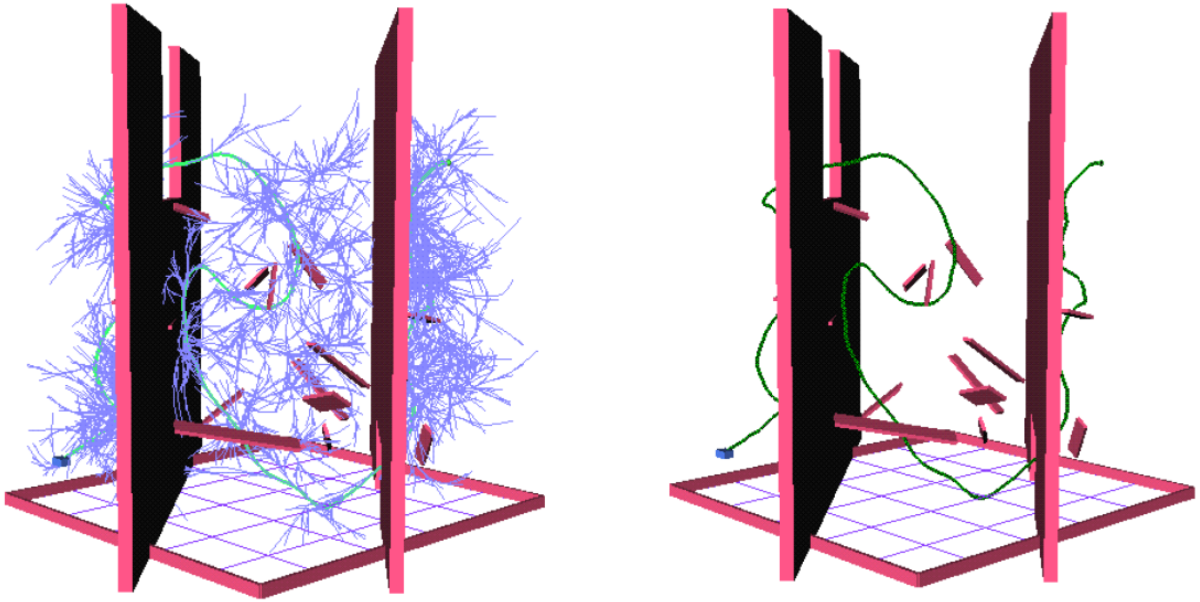


Rapidly-Exploring Random Tree

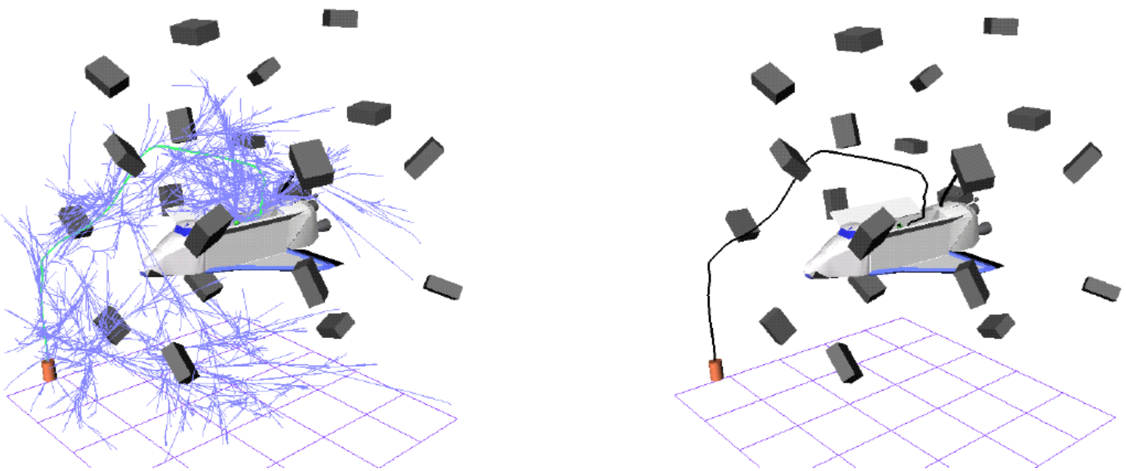
- **Extend a new vertex in each iteration**



Results – 200MHz, 128MB

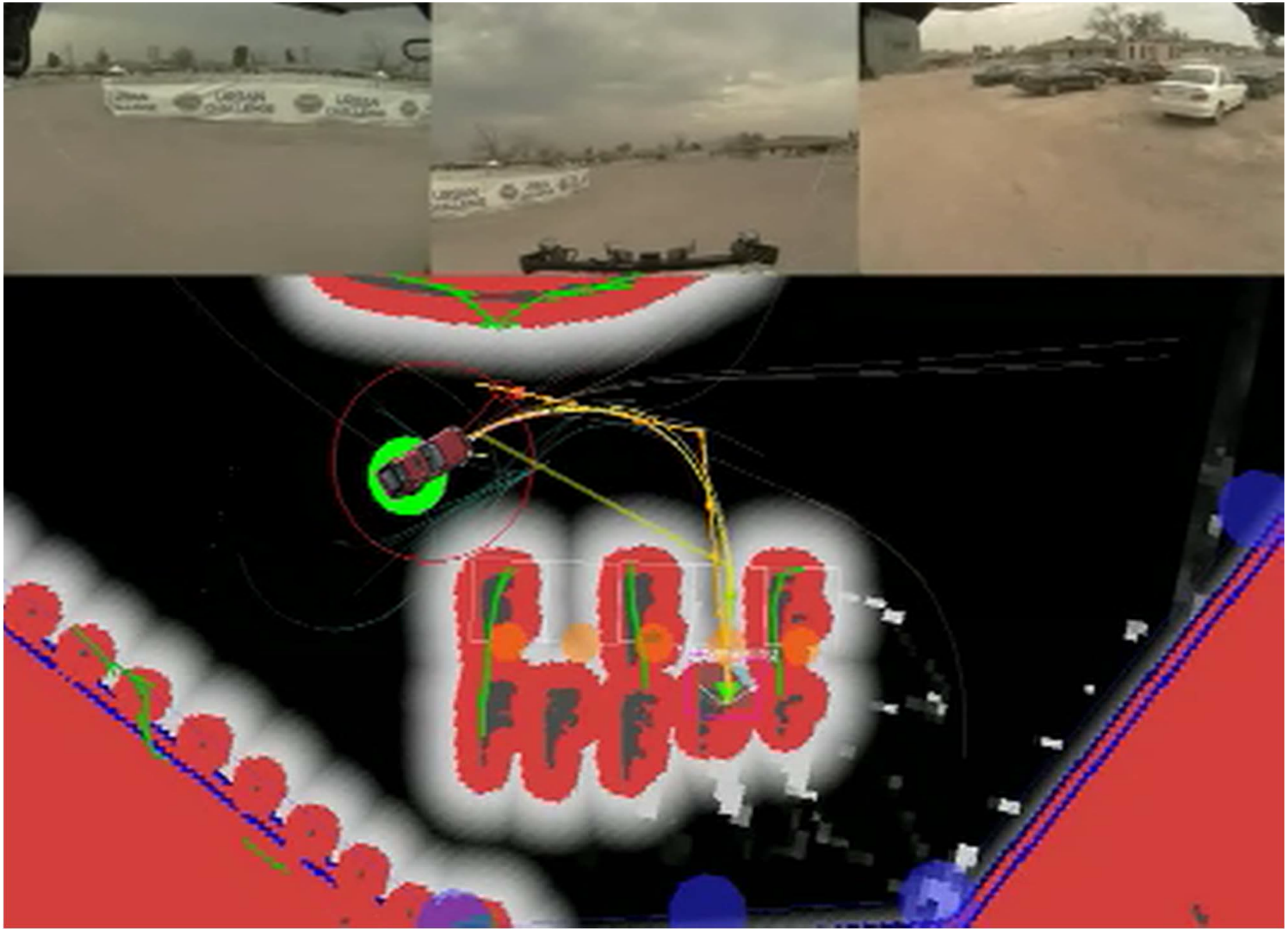


- 3D translating
- X=6 DOF
- 16,300 nodes
- 4.1min



- 3D TR+RO
- X=12 DOF
- 23,800 nodes
- 8.4min

RRT at work: Successful Parking Maneuver



Some Works of Our Group

- Narrow passages
  - Identify narrow passage with a simple one-dimensional line test, and selectively explore such regions
  - Selective retraction-based RRT planner for various environments, Lee et al., T-RO 14
  - http://sglab.kaist.ac.kr/SRRRT/T-RO.html

Retration-based RRT [Zhang & Manocha 08]

- **Retraction-based RRT technique handling narrow passages**

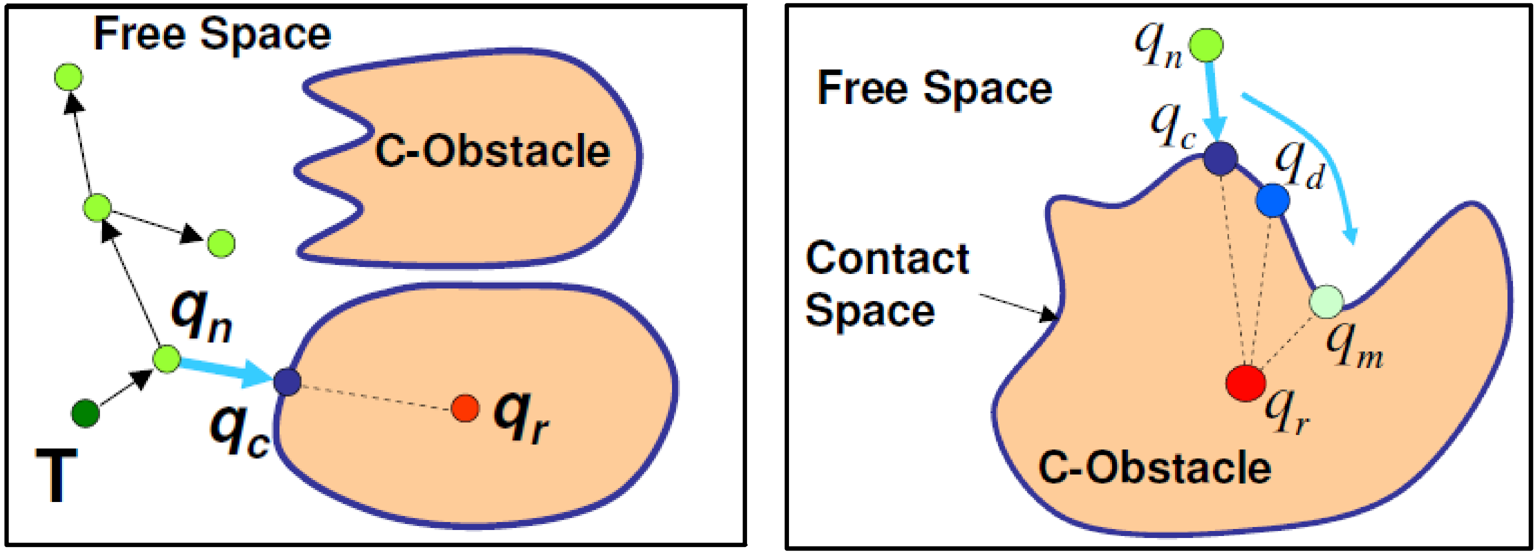
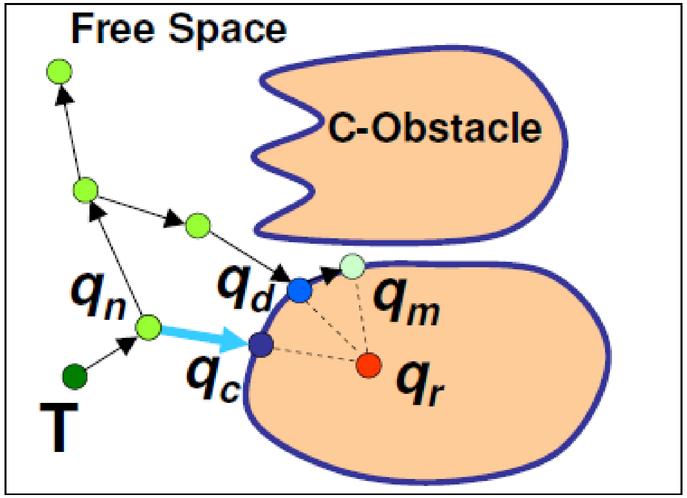


image from [Zhang & Manocha 08]

- **General characteristic:**
  Generates more samples near the boundary of obstacles

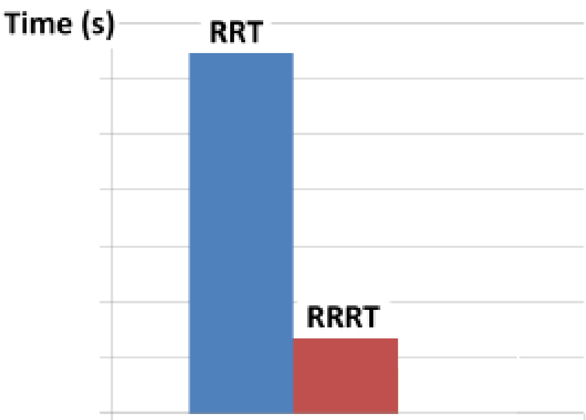
RRRT: Pros and Cons



with narrow passages

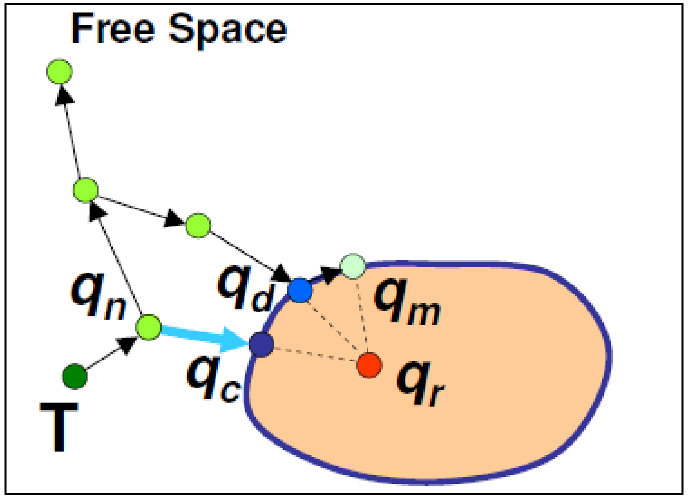
without narrow passages

images from [Zhang & Manocha 08]



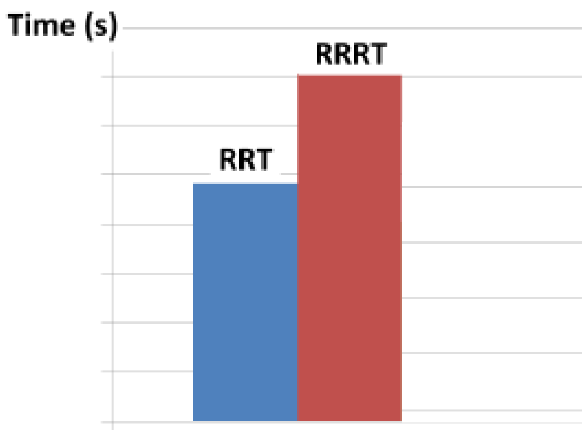
RRRT: Pros and Cons

with narrow passages



without narrow passages

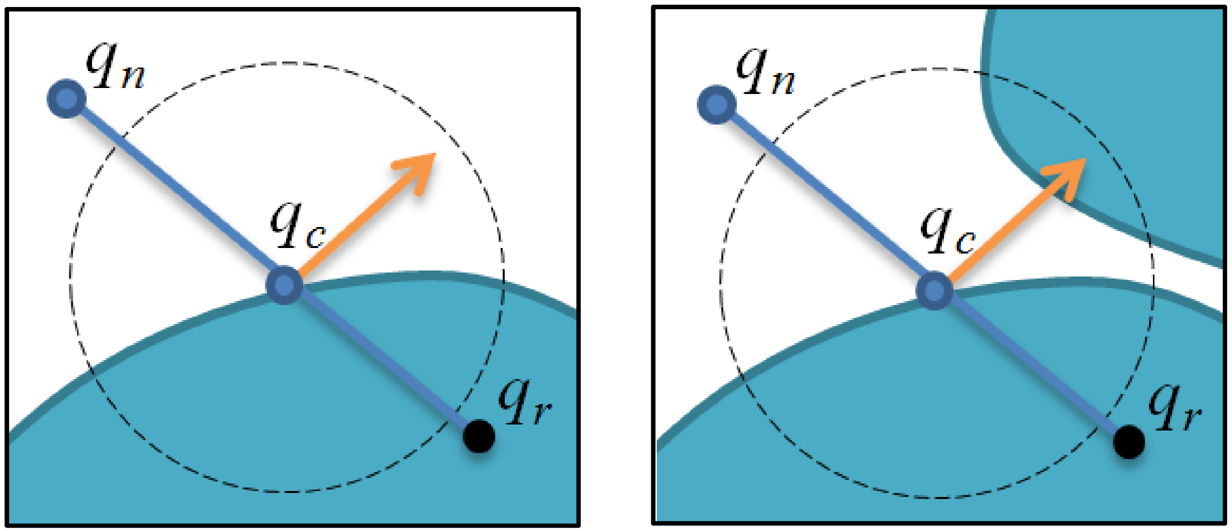
images from [Zhang & Manocha 08]



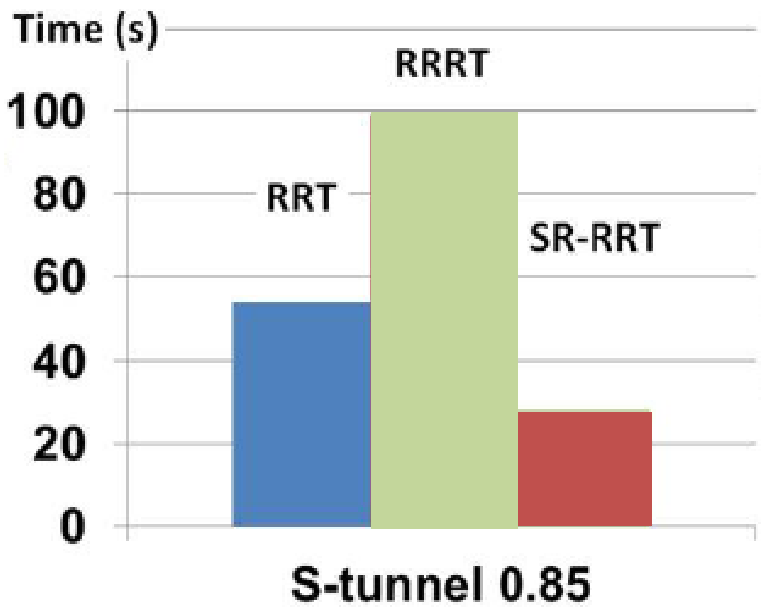
Bridge line-test [Lee et al., T-RO 14]

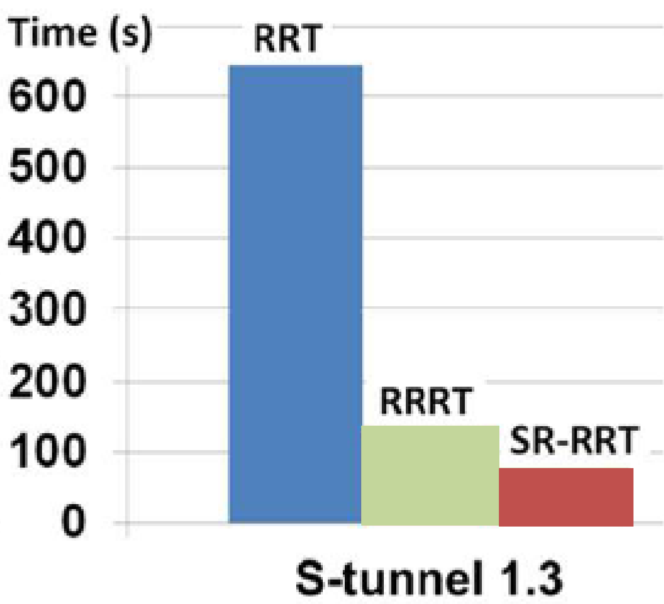
- To identify narrow passage regions

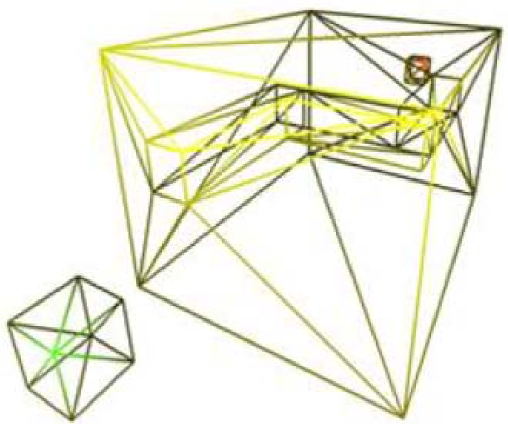
- Bridge line-test
  1. Generate a random line
  2. Check whether the line meets any obstacle



Results







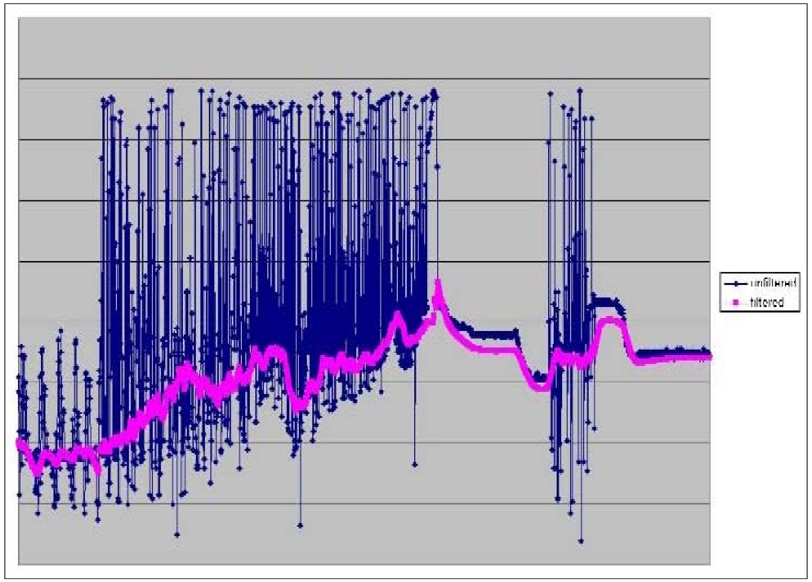
Video

Related Works of Our Group

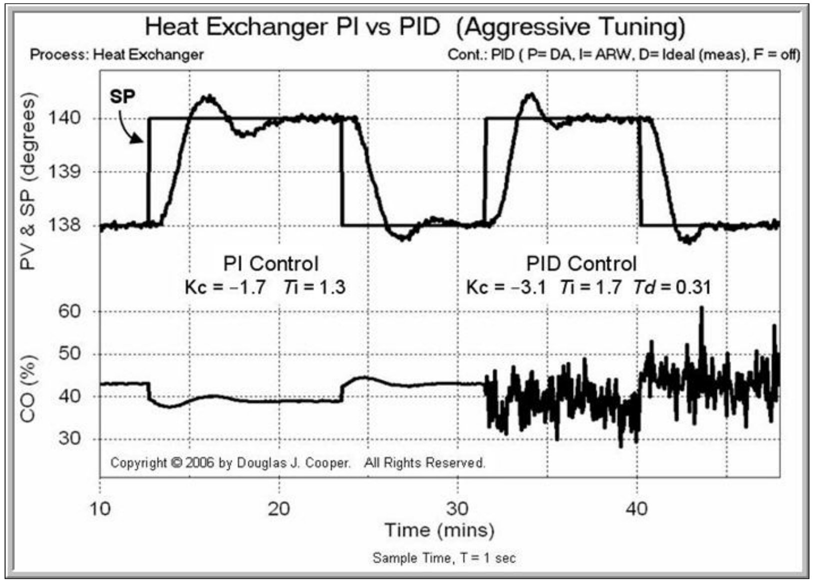
- **Handling narrow passages**
- **Handling uncertainty and dynamic objects**
  - **Anytime RRBT for handling uncertainty and dynamic objects, IROS 16**

Handling Sensor Errors

- **Uncertainty caused by:**
  - **Various sensors**
  - **Low-level controllers**



Sensor noise

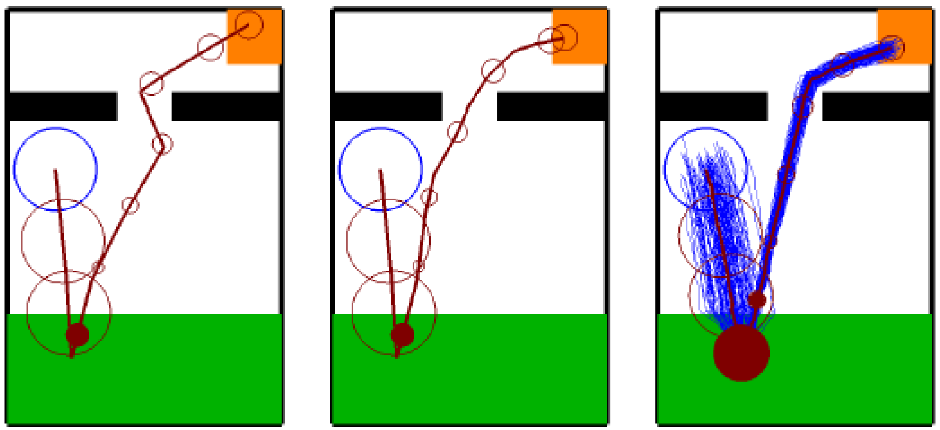


Controller noise

Rapidly-exploring Random Belief Tree
[Bry et al., ICRA 11]

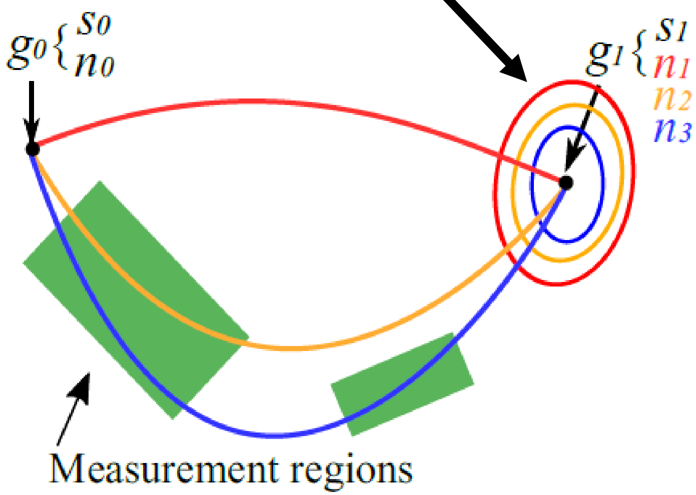
- Use Kalman filter to propagate Gaussian states
- Improve solutions toward optimal

Multiple belief nodes in the same vertex



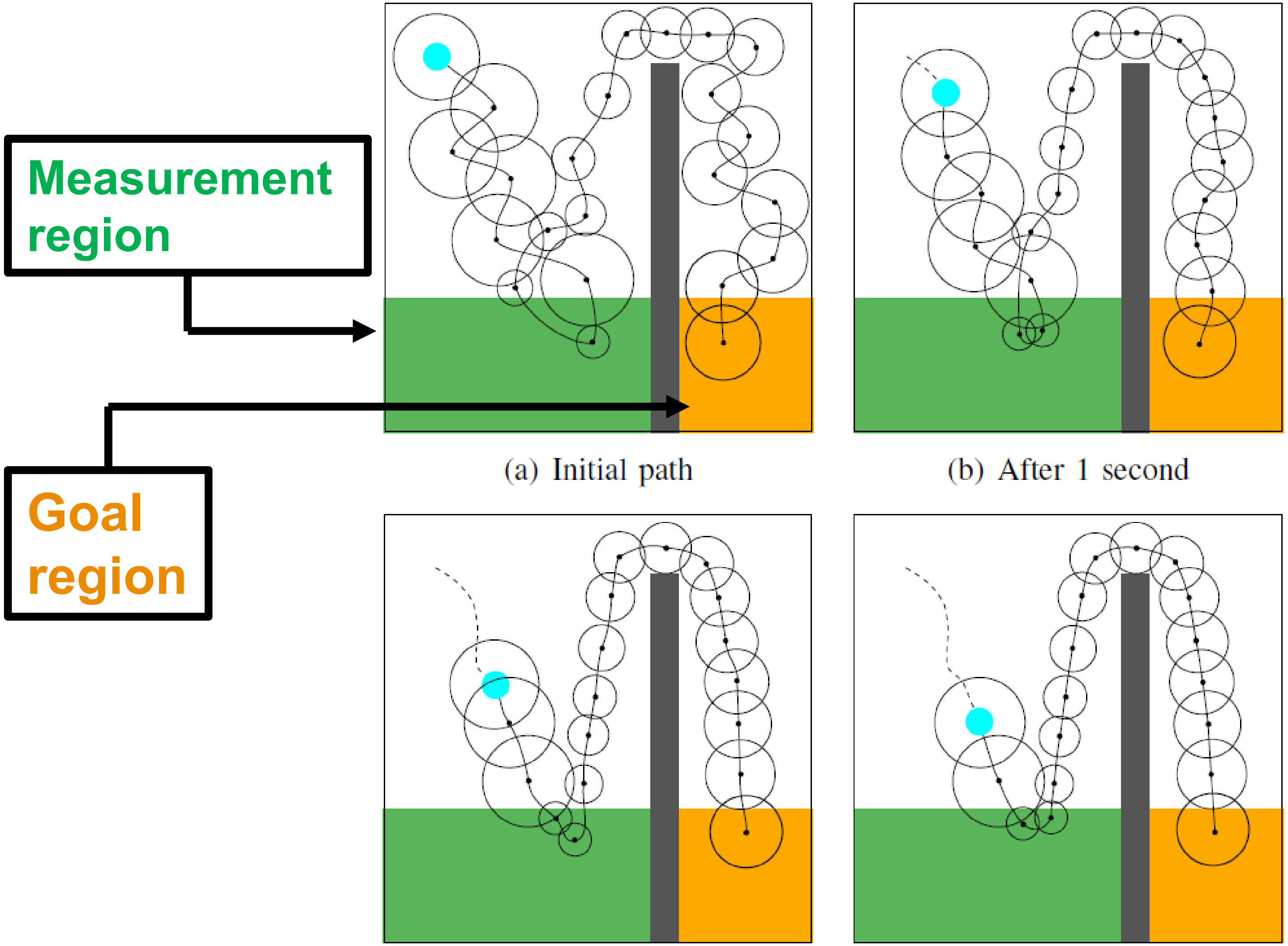
500 1000 1500

Number of iteration



Preserve optimal path

Main Contribution: Anytime Extension [Yang et al.,IROS 16]



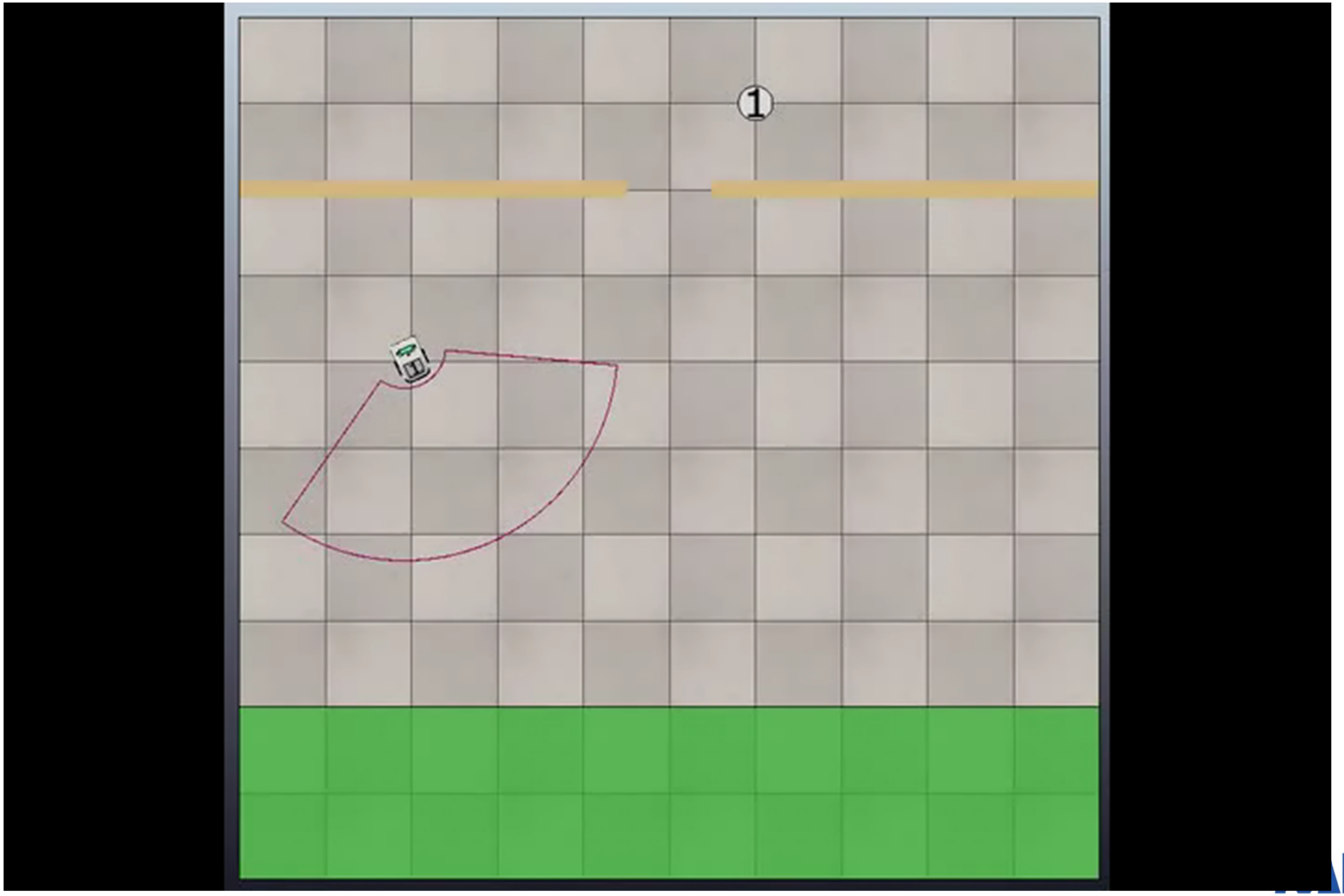
(a) Initial path (b) After 1 second

(c) After 3 seconds (d) After 5 seconds

Bigger circle means higher uncertainty

The robot computes better path while executing the path

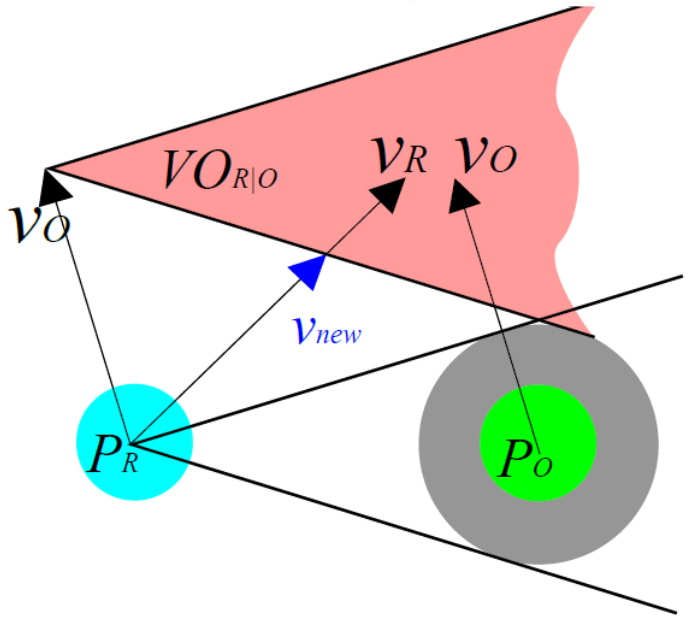
Main Contribution: Anytime Extension



Velocity Obstacle: Local Geometric Analysis

- **Used for collision avoidance among multiple robots**
- **When v for Robot is in the VO, we will have collision**

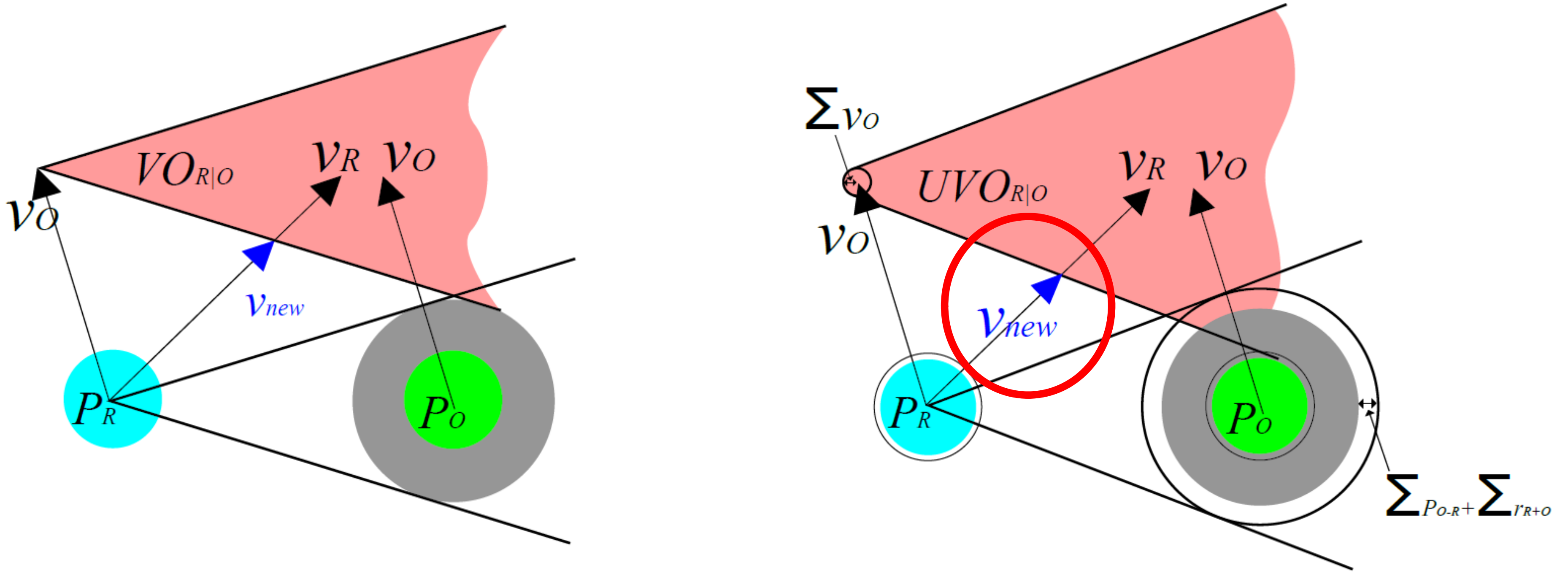
$$VO_{R|O} = \{v \mid \exists t > 0 : t(v - v_O) \in Disc(P_O - P_R, r_R + r_O)\}$$



“The hybrid reciprocal velocity obstacle” **TRO11** J Snape, J van den Berg, SJ Guy
“Reciprocal velocity obstacles for real-time multi-agent navigation” J van den Berg
“Generalized Velocity Obstacles” **IROS09**, D Wilkie, J Van den Berg

Uncertainty-aware Velocity Obstacle as Local Geometry Analysis

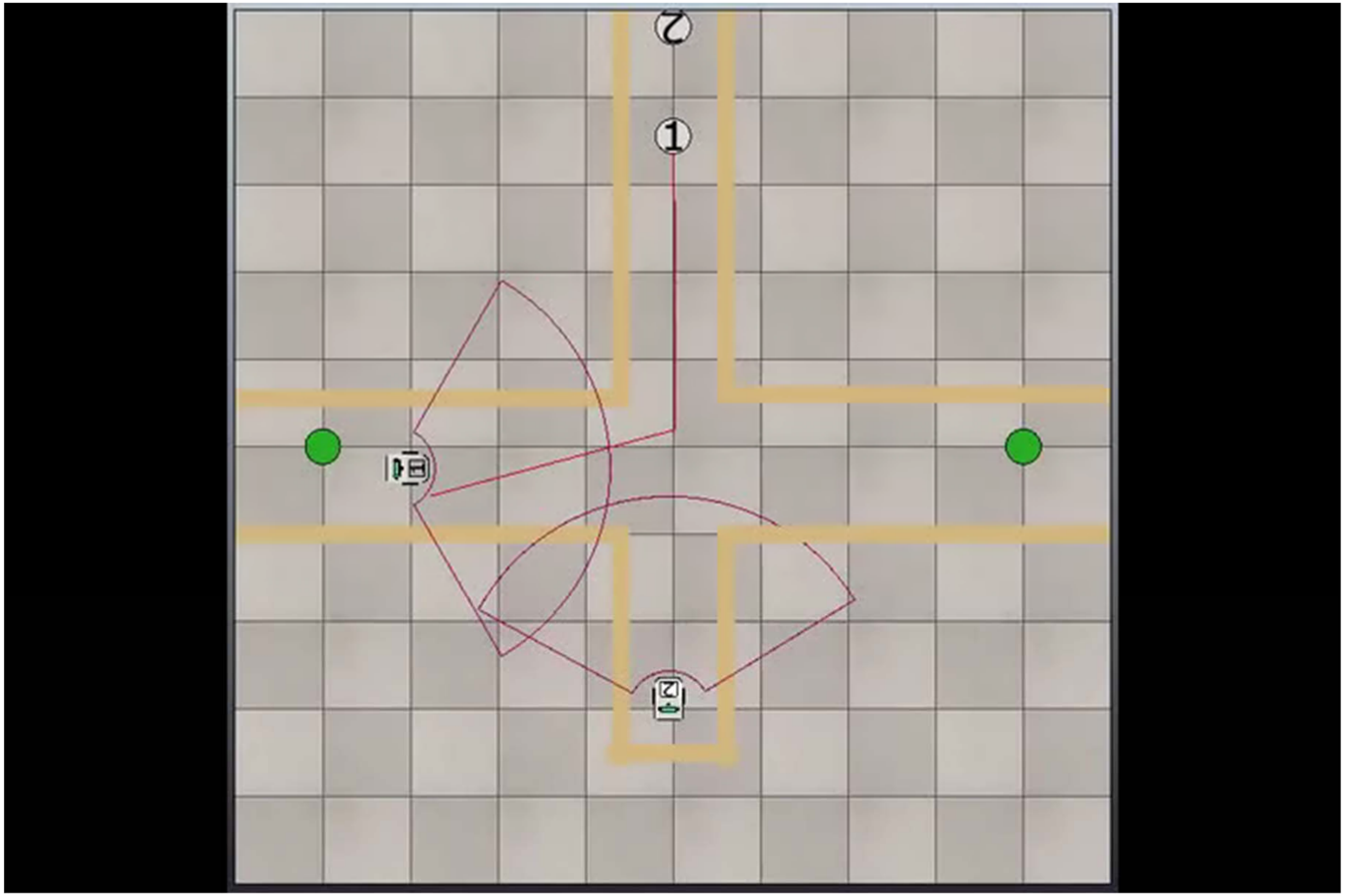
Conservative collision checking



(a) Velocity obstacle (b) Uncertainty-aware velocity obstacle

“The hybrid reciprocal velocity obstacle” **TRO11** J Snape, J van den Berg, SJ Guy
“Reciprocal velocity obstacles for real-time multi-agent navigation” J van den Berg
“Generalized Velocity Obstacles” **IROS09**, D Wilkie, J Van den Berg

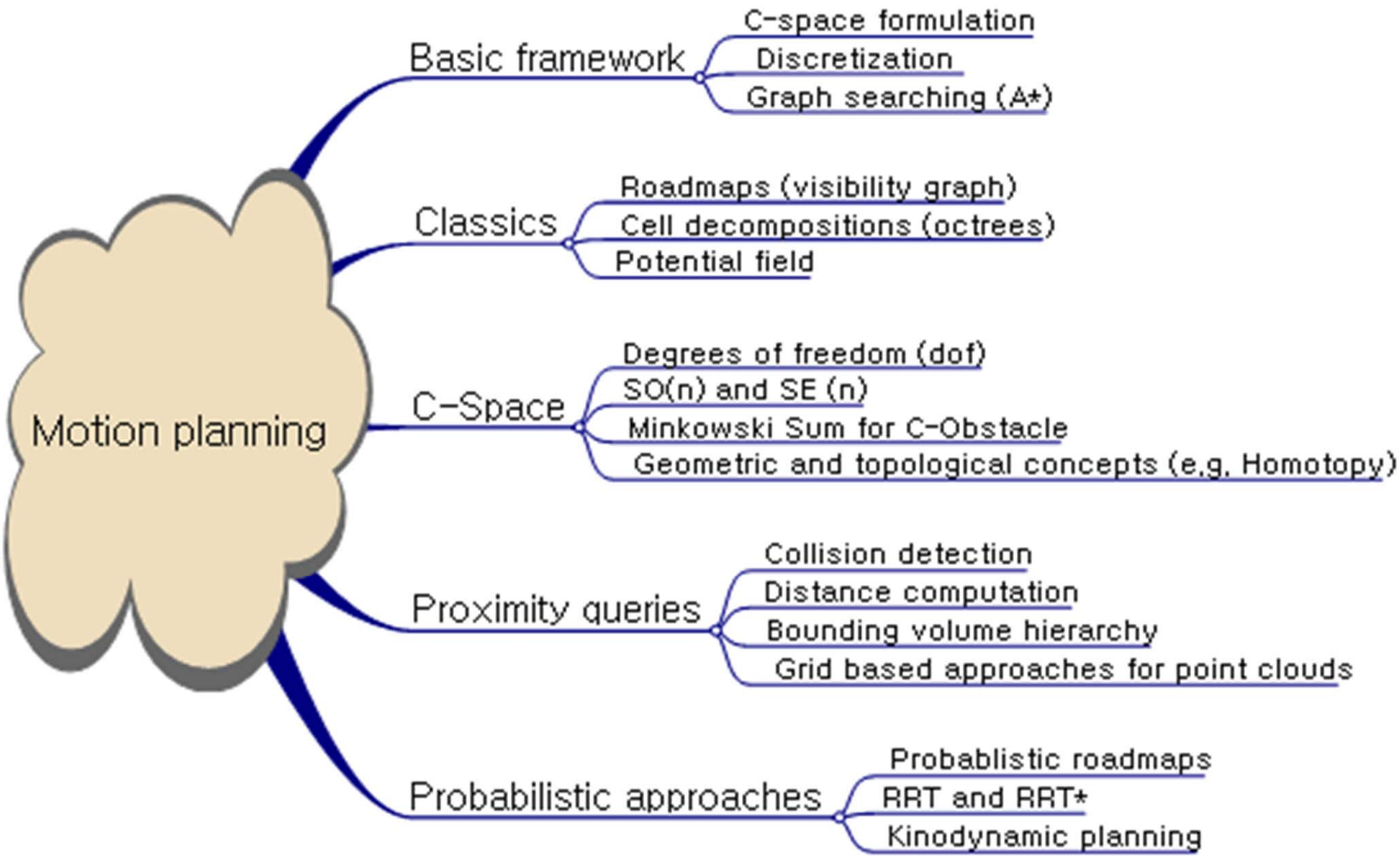
Intersection scene – with UVO



Class Objectives were:

- Understand the RRT technique and its recent advancements
  - RRT* for optimal path planning
  - Kinodynamic planning
  - Some related techniques to RRT

Summary


Motion planning
Basic framework
C-space formulation
Discretization
Graph searching (A*)
Classics
Roadmaps (visibility graph)
Cell decompositions (octrees)
Potential field
C-Space
Degrees of freedom (dof)
SO(n) and SE (n)
Minkowski Sum for C-Obstacle
Geometric and topological concepts (e.g. Homotopy)
Proximity queries
Collision detection
Distance computation
Bounding volume hierarchy
Grid based approaches for point clouds
Probabilistic approaches
Probablistic roadmaps
RRT and RRT*
Kinodynamic planning

Next Time..

- **Basic concepts of reinforcement learning**

Homework for Every Class

- **Submit summaries of 2 ICRA/IROS/RSS/CoRL/TRO/IJRR papers**
- **Go over the next lecture slides**
- **Come up with three question before the mid-term exam**