深蓝学院
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Sample-based path finding

Lecture 3

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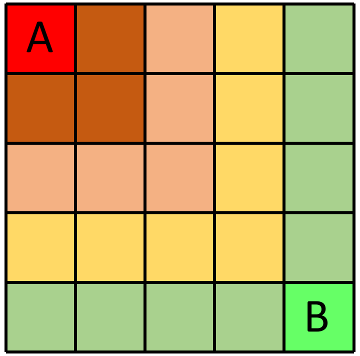
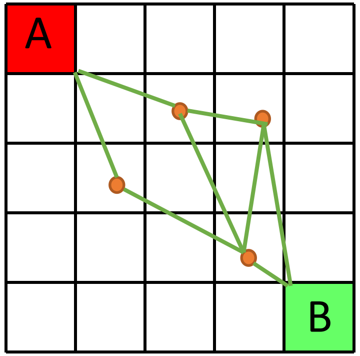
Preliminaries

Sampling Based-Planners

- Do not attempt to explicitly construct the C-Space and its boundaries
- Simply need to know if a single robot configuration is in collision
- Exploits simple tests for collision with full knowledge of the space
- Collision detection is a separate module- can be tailored to the application
- As collision detection improves, so do these algorithms
- Different approaches for single-query and multi-query requests





Preliminaries

Notion of Completeness in Planning

- Complete Planner: always answers a path planning query correctly in bounded time
- Probabilistic Complete Planner: if a solution exists, planner will eventually find it, using random sampling (e.g. Monte Carlo sampling)
- Resolution Complete Planner: same as above but based on a deterministic sampling (e.g sampling on a fixed grid).

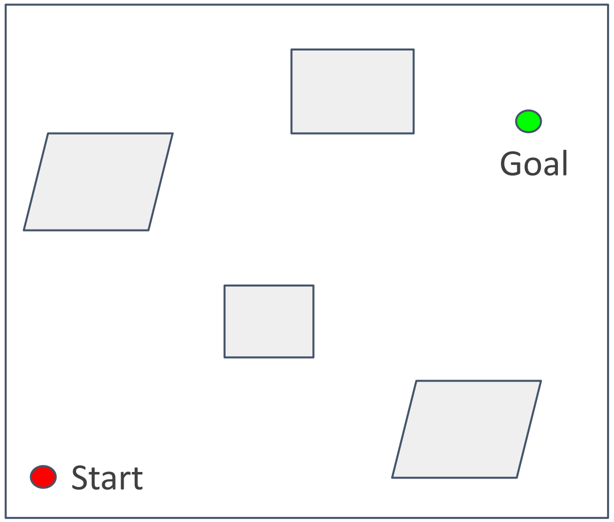
Content

Probabilistic Road Map

Probabilistic Road Map

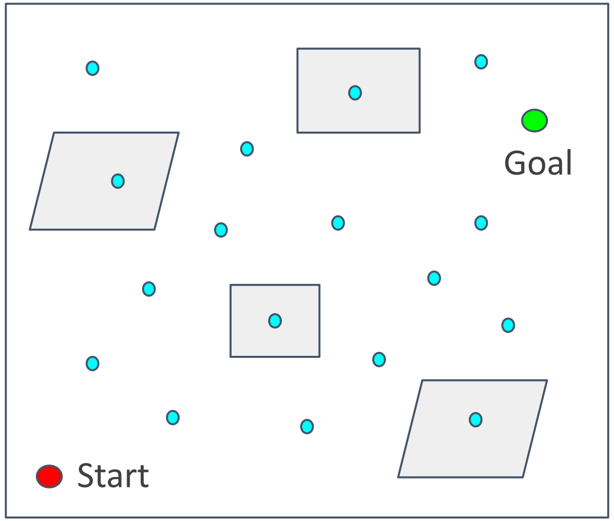
What is PRM?

- A graph structure
- Divide planning into two phases:
  - Learning phase:
  - Query phase:
- Checking sampled configurations and connections between samples for collision can be done efficiently.
- A relatively small number of milestones and local paths are sufficient to capture the connectivity of the free space



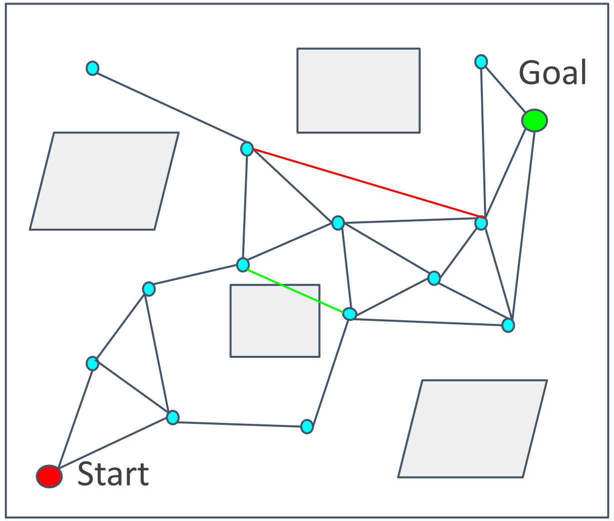
Probabilistic Road Map

- Learning phase:
  - Sample N points in C-space
  - Delete points that are not collision-free
- Detect the c-space with random points



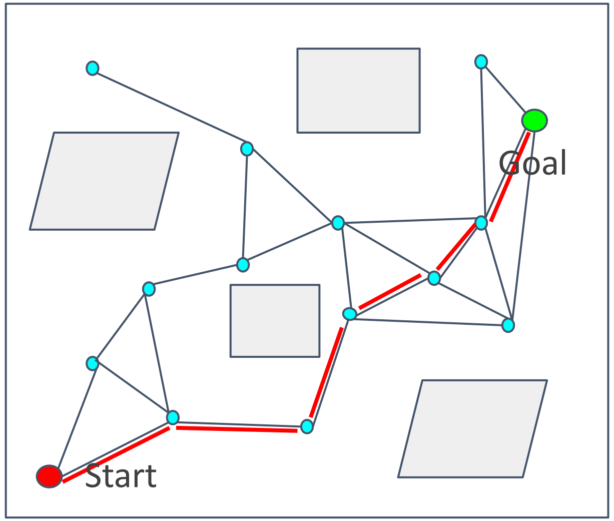
Probabilistic Road Map

- Learning phase:
  - Connect to nearest points and get collision-free segments.
  - Delete segments that are not collision free.



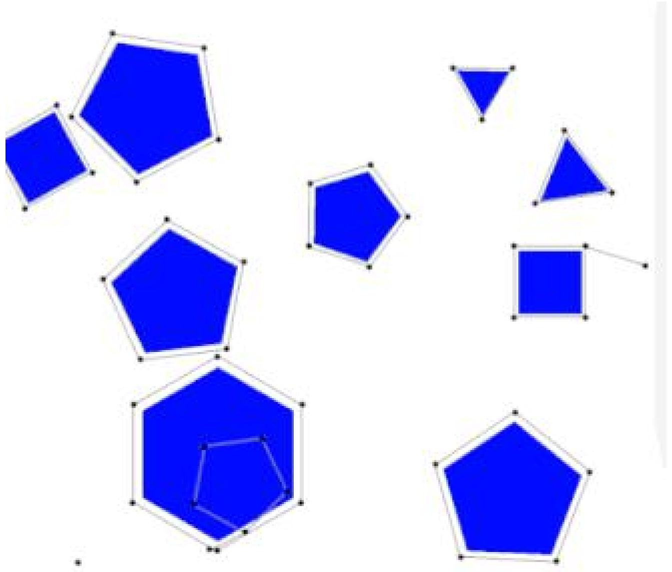
Probabilistic Road Map

- Query phase:
  - Search on the road map to find a path from the start to the goal (using Dijkstra’s algorithm or the A* algorithm).
  - Road map is now similar with the grid map (or a simplified grid map)

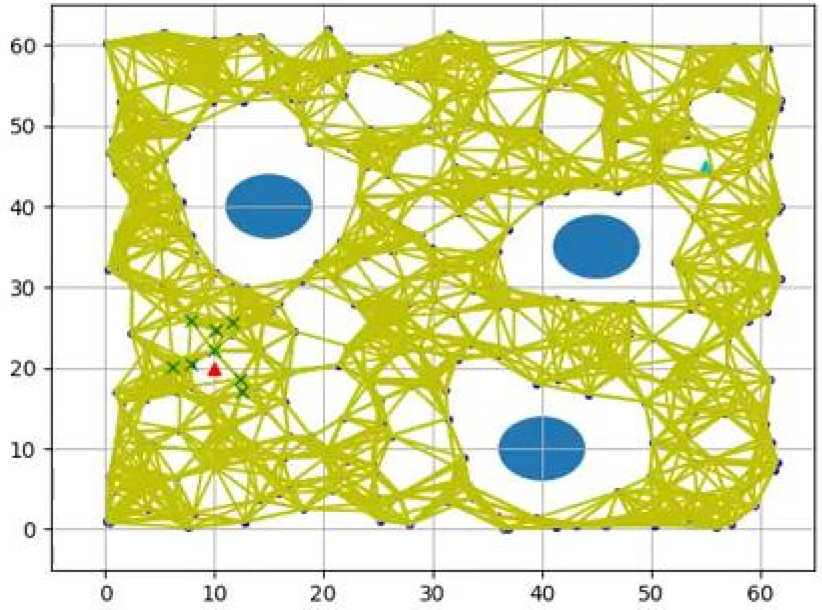


Probabilistic Road Map

Learning phase[1]



Query phase[2]

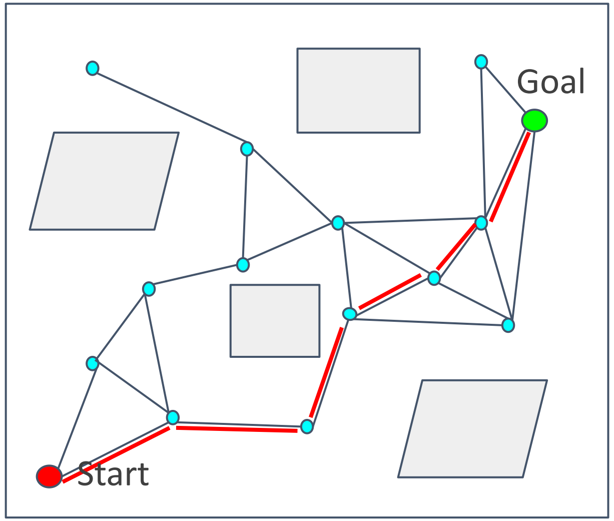


[1] https://en.wikipedia.org/wiki/Probabilistic_roadmap
[2] https://www.youtube.com/watch?v=8Dln3sS_p4Q

Probabilistic Road Map

Pros and Cons

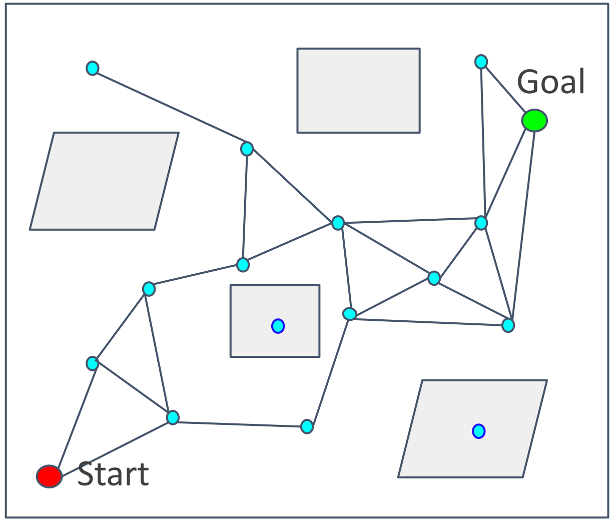
- Pros
  - Probabilistically complete
- Cons
  - Required to solve 2 point boundary value problem
  - Build graph over state space but no particular focus on generating a path
  - Not efficient



Probabilistic Road Map

Note: towards improving efficiency

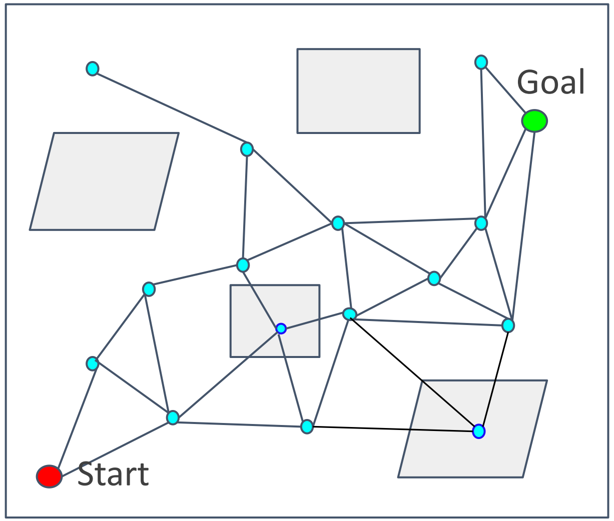
- Lazy collision-checking
  - Collision-checking process is time-consuming, especially in complex or high-dimensional environments.
  - Sample points and generate segments without considering the collision (Lazy).



Probabilistic Road Map

Lazy collision-checking

Sample points and generate segments without considering the collision (Lazy).

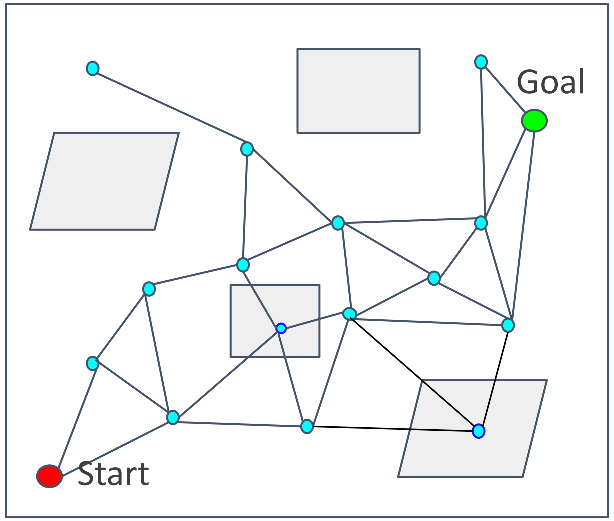


Probabilistic Road Map

Lazy collision-checking

Collision-checking if necessary:

Find a path on the road map generated without collision-checking

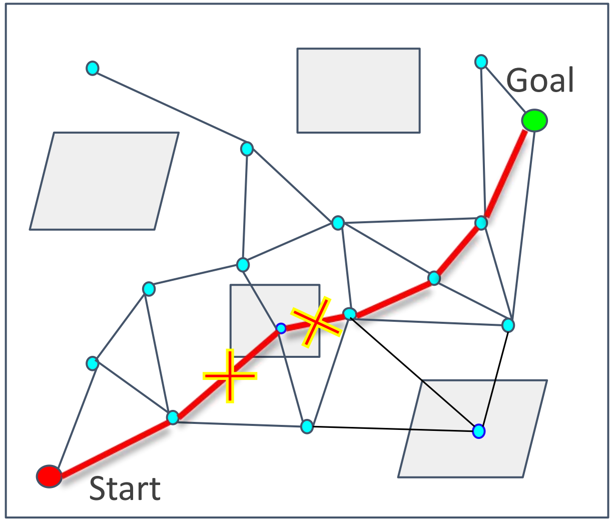


Probabilistic Road Map

Lazy collision-checking

Collision-checking if necessary:

Delete the corresponding edges and nodes if the path is not collision free.

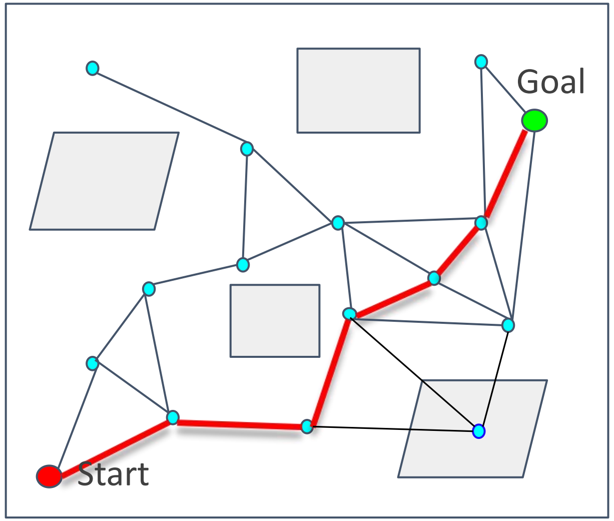


Probabilistic Road Map

Lazy collision-checking

Collision-checking if necessary:

- Delete the corresponding edges and nodes if the path is not collision free.
- Restart path finding.



Probabilistic Road Map

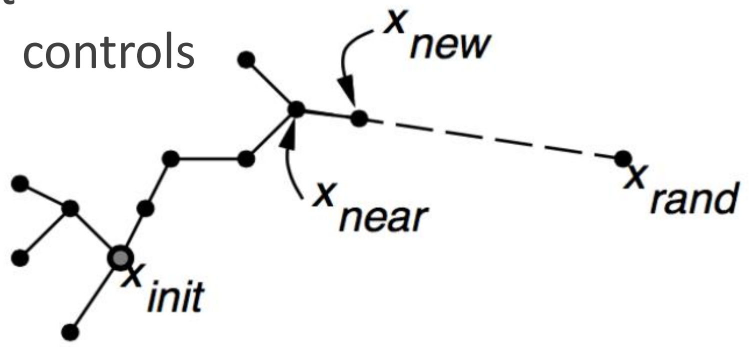
Note:

- Learning phase
- Query phase
- Lazy collision-checking

Rapidly-exploring Random Tree

Rapidly-exploring Random Trees

- Build up a tree through generating “next states” in the tree by executing random controls



Rapidly-exploring Random Trees

Algorithm 1: RRT Algorithm

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    if $CollisionFree(\mathcal{M}, E_i)$ then
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    if $x_{new} = x_{goal}$ then
        Success();
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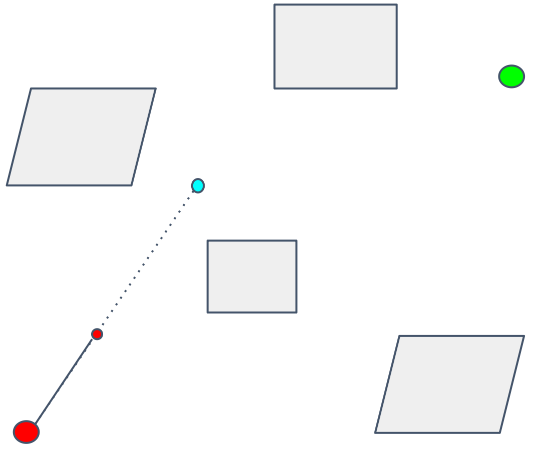

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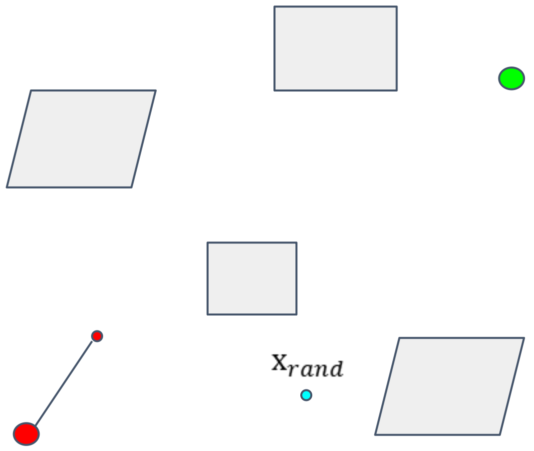

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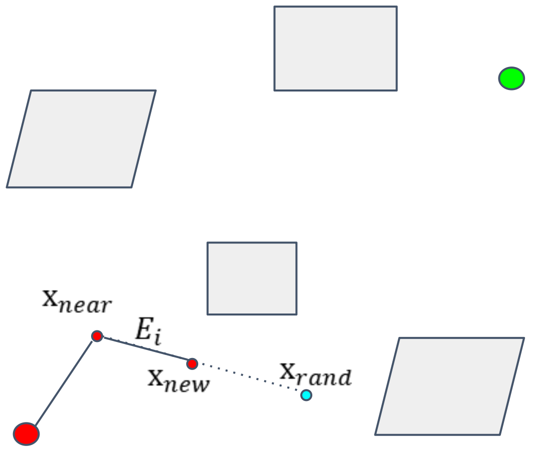

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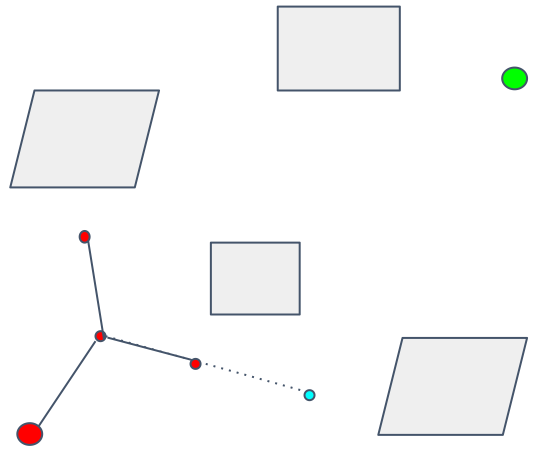

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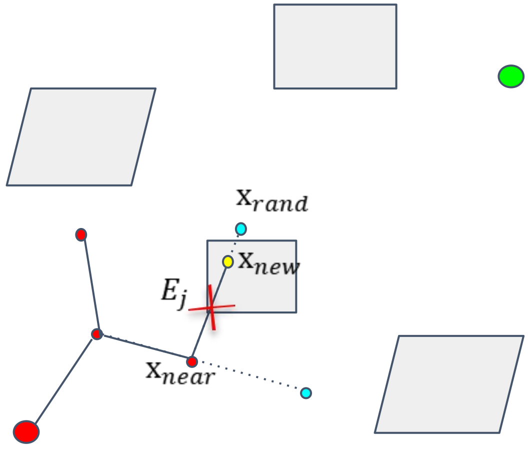

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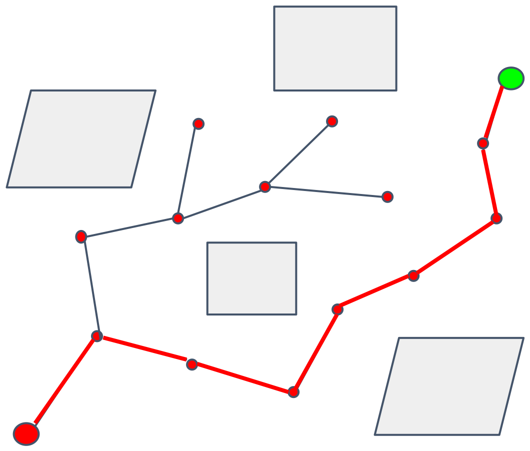


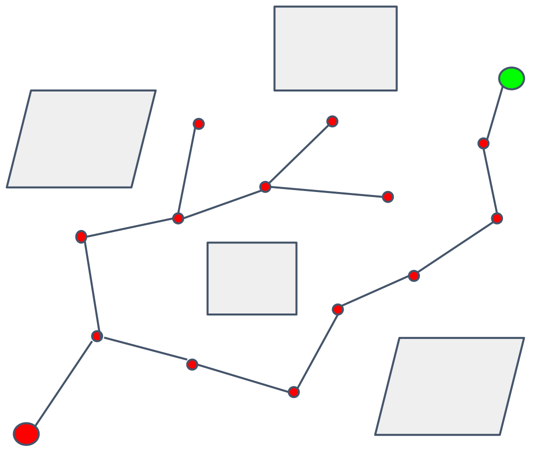
Rapidly-exploring Random Trees

Demonstration of RRT[1]

[1] https://www.youtube.com/watch?v=pOFtvZ_qVsA

Rapidly-exploring Random Trees

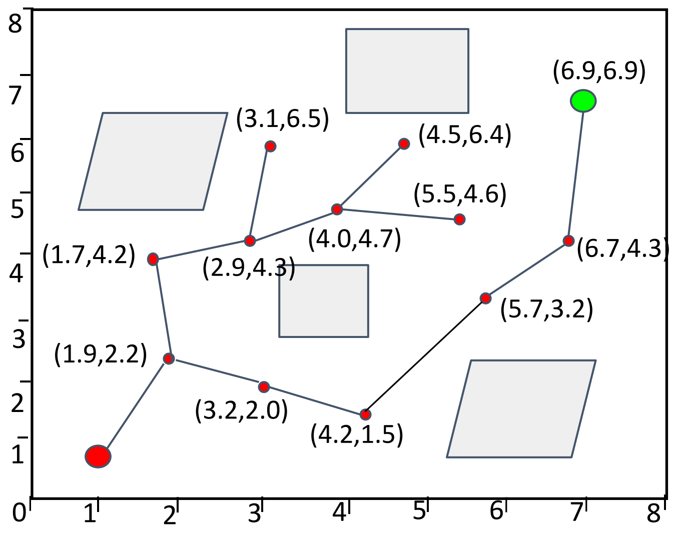
- Pros:
  - Aims to find a path from the start to the goal
  - More target-oriented than PRM
- Cons:
  - Not optimal solution
  - Not efficient(leave room for improvement)
  - Sample in the whole space

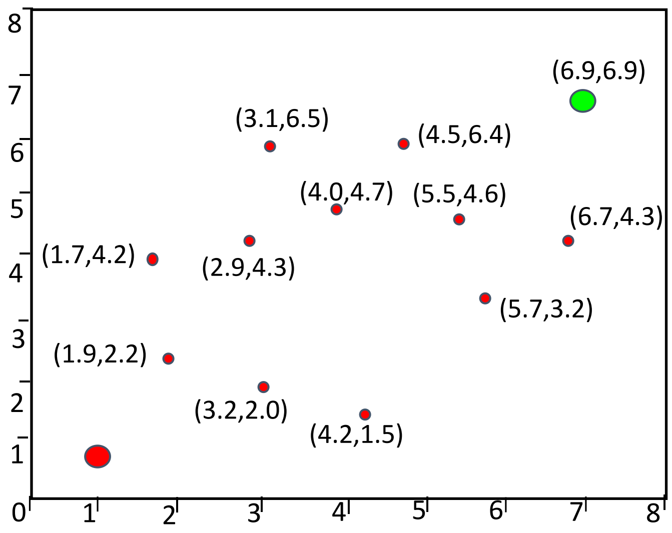


Rapidly-exploring Random Trees

Note: towards improving efficiency

Kd-tree

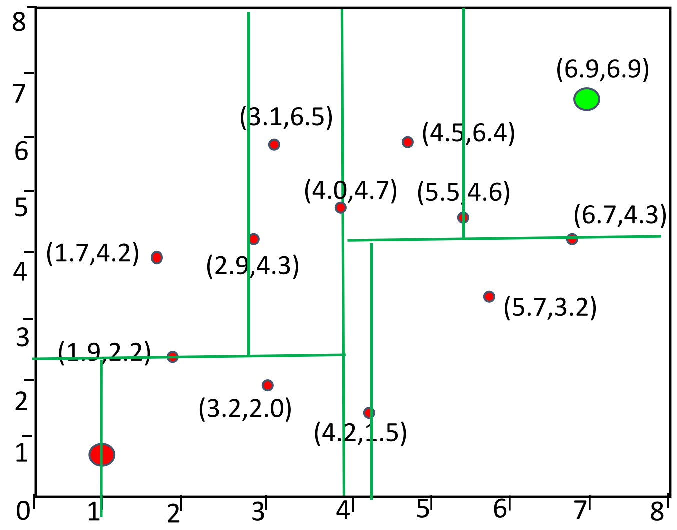


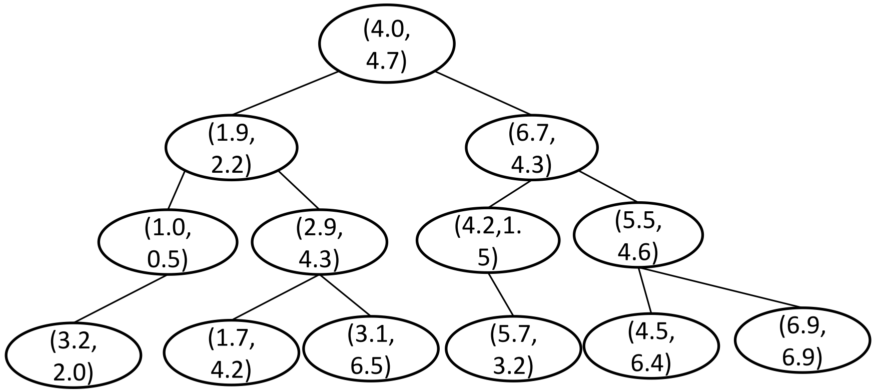


Rapidly-exploring Random Trees

Note: towards path planning efficiency

- Kd-tree



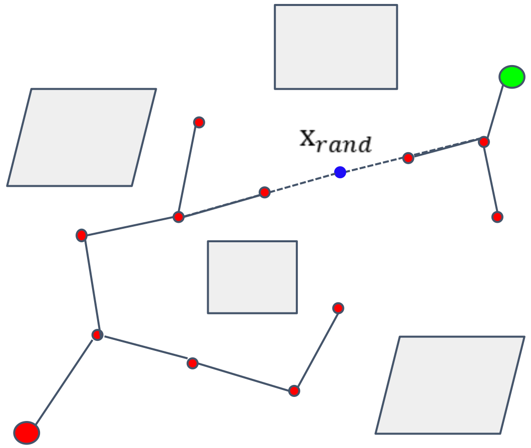


- Other variants: Spatial grid, hill climbing,etc
- 参考：https://blog.csdn.net/junshen1314/article/details/51121582

Rapidly-exploring Random Trees

Note: towards improving efficiency

Bidirectional RRT / RRT Connect

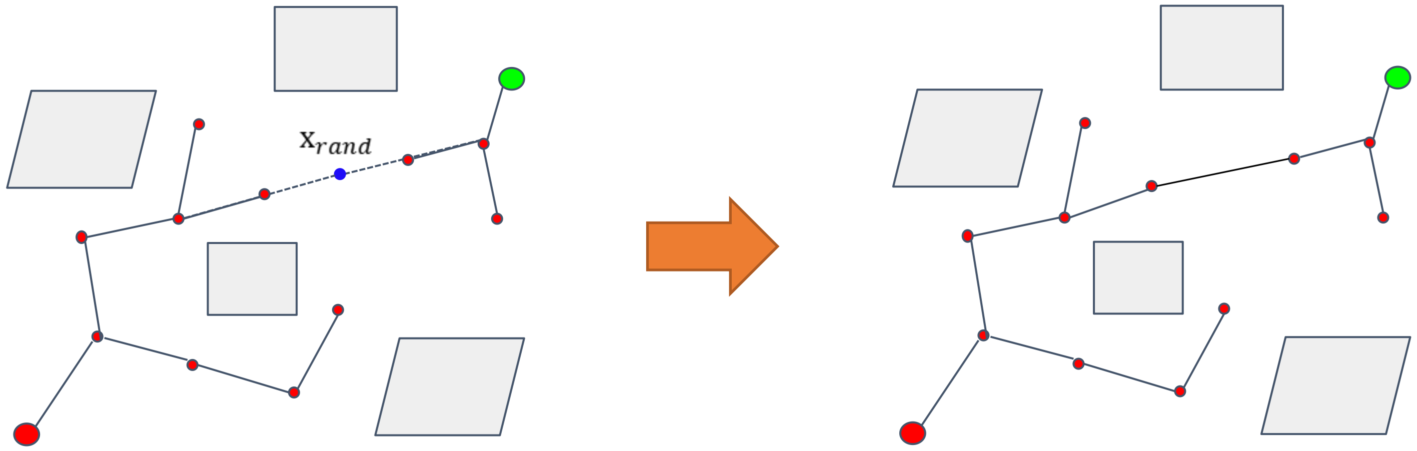


- Grow a tree from both the start point and the goal point
- Path finding when two trees are connected

Rapidly-exploring Random Trees

Note: towards improving efficiency

Bidirectional RRT / RRT Connect



Rapidly-exploring Random Trees

Note: towards path planning efficiency

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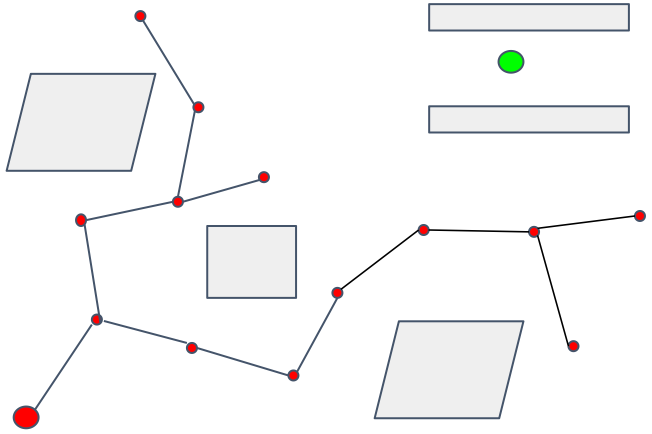

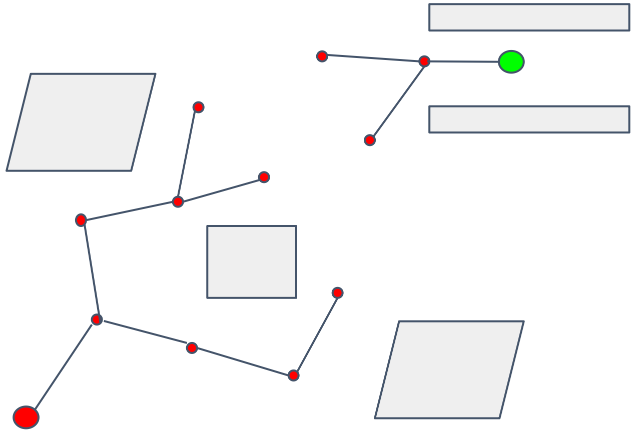

Rapidly-exploring Random Trees

- Incrementally build
- Rapidly searching
- Key functions: Sampling, Nearest, Collision-checking

Optimal sampling-based path planning methods

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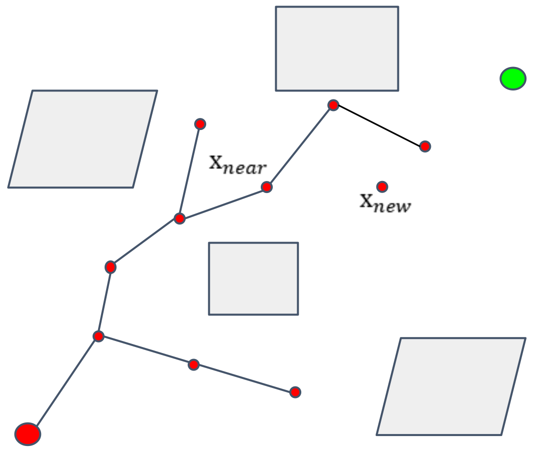
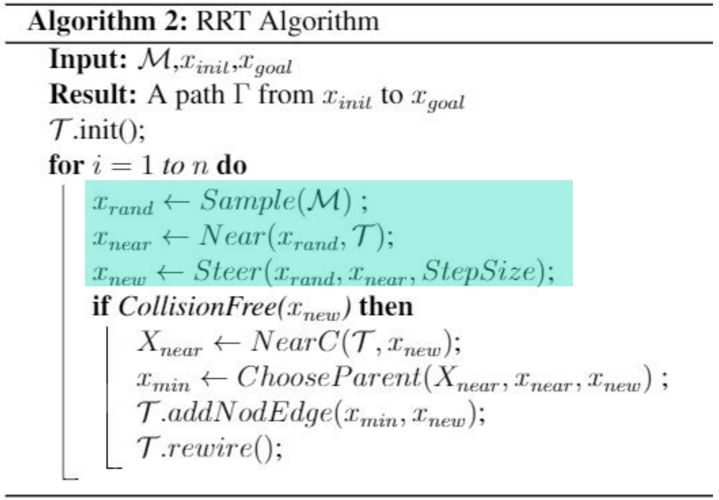
Rapidly-exploring Random Tree*





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        $\mathcal{T}.addNodEdge(x_{min}, x_{new})$;
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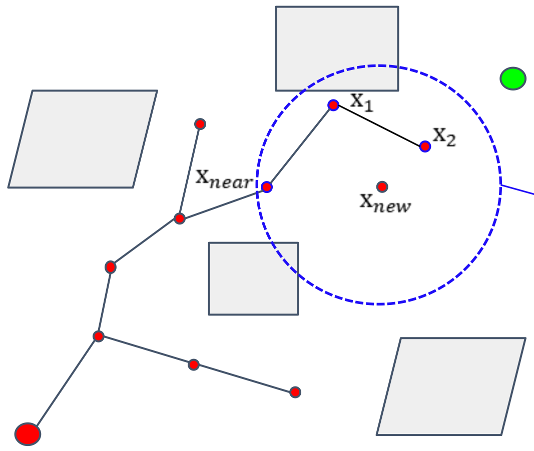
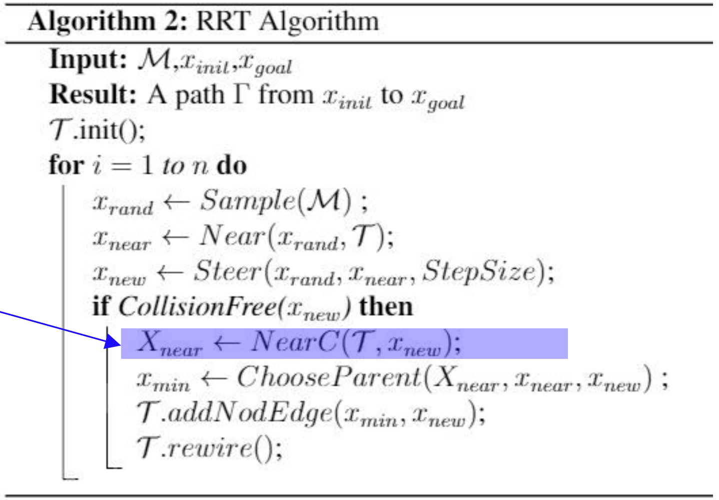
Optimal sampling-based path planning methods

Rapidly-exploring Random Tree*





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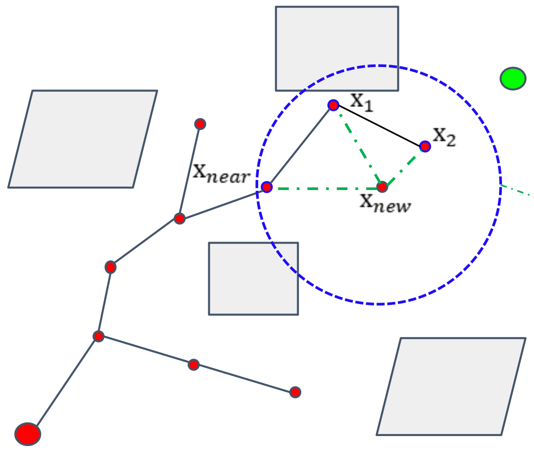
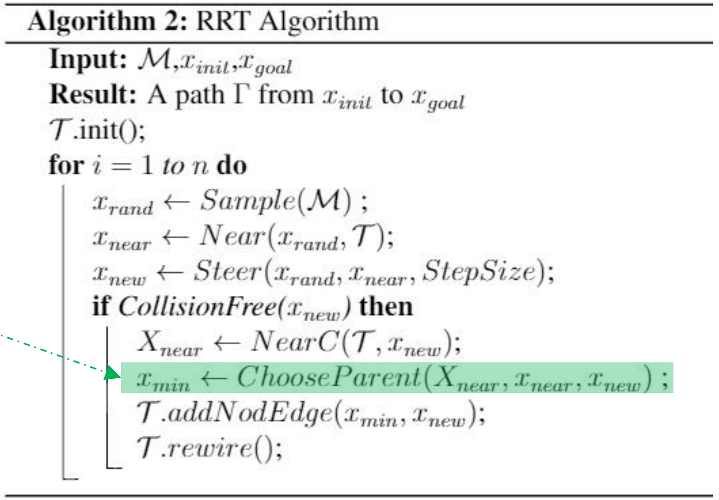
Optimal sampling-based path planning methods

Rapidly-exploring Random Tree*





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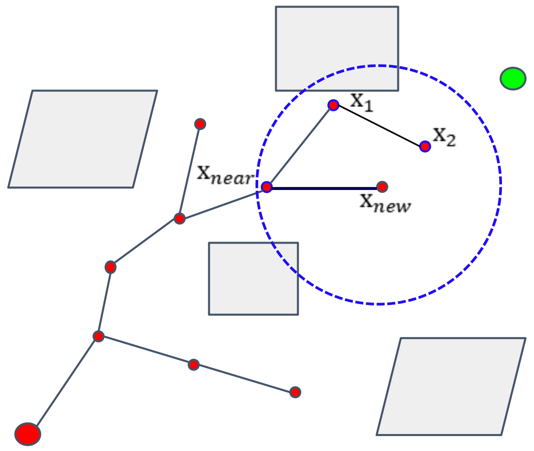
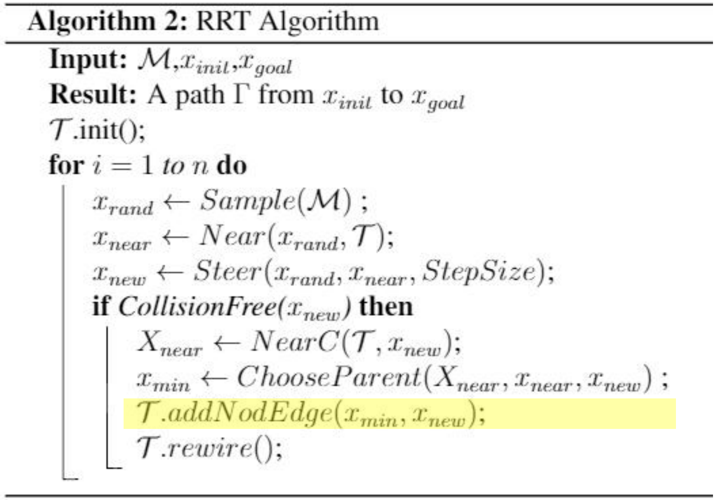
Optimal sampling-based path planning methods

Rapidly-exploring Random Tree*





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Optimal sampling-based path planning methods

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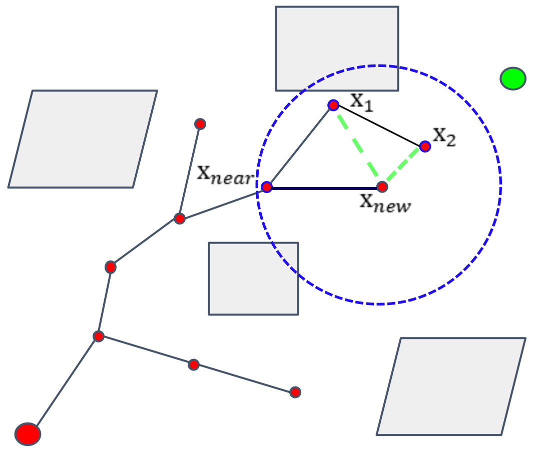

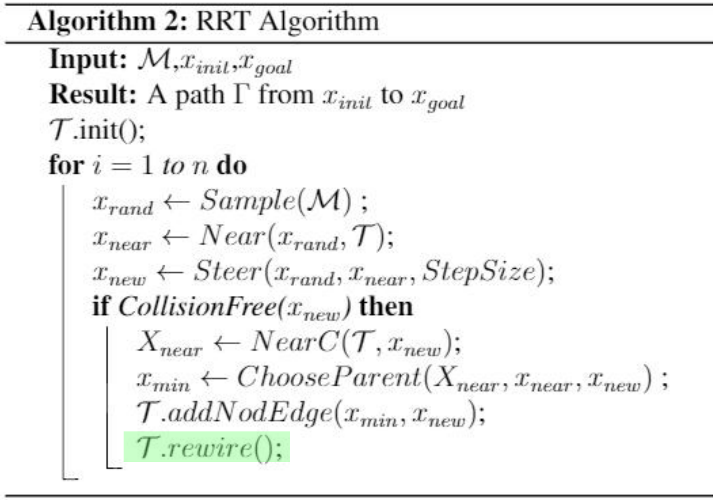

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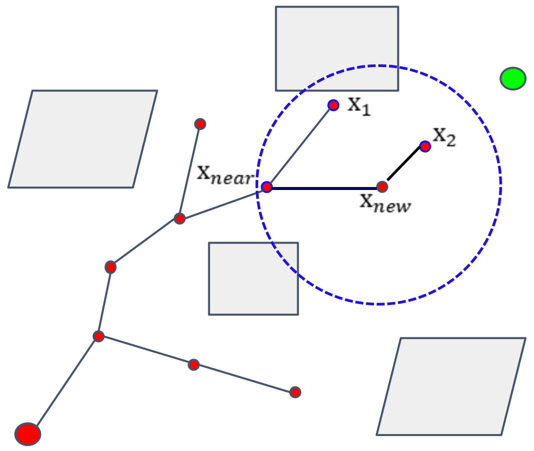
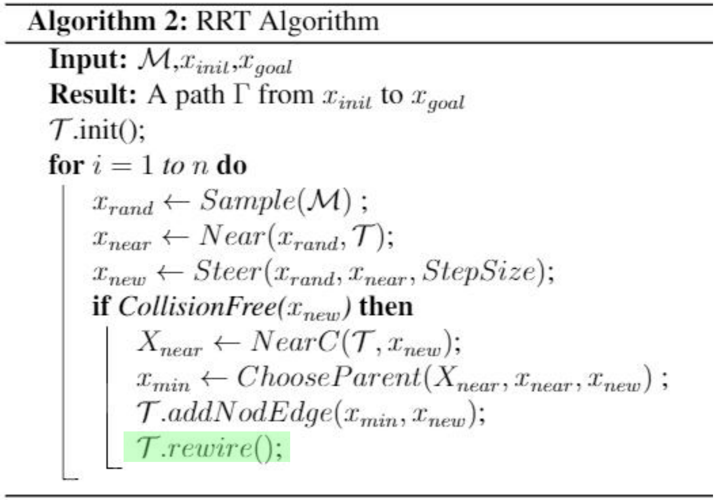
```

Optimal sampling-based path planning methods

Rapidly-exploring Random Tree*



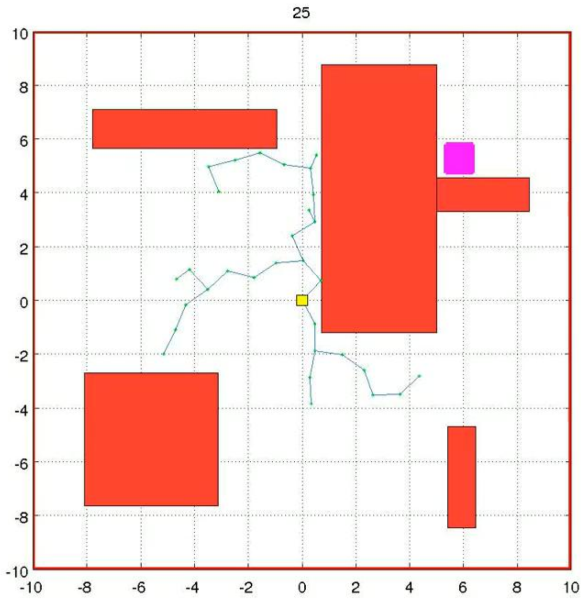


Algorithm 2: RRT Algorithm

```
Input: $\mathcal{M}$, $x_{init}$, $x_{goal}$
Result: A path $\Gamma$ from $x_{init}$ to $x_{goal}$
$\mathcal{T}$.init();
for $i = 1$ to $n$ do
    $x_{rand} \leftarrow Sample(\mathcal{M})$ ;
    $x_{near} \leftarrow Near(x_{rand}, \mathcal{T})$;
    $x_{new} \leftarrow Steer(x_{rand}, x_{near}, StepSize)$;
    if CollisionFree($x_{new}$) then
        $X_{near} \leftarrow NearC(\mathcal{T}, x_{new})$;
        $x_{min} \leftarrow ChooseParent(X_{near}, x_{near}, x_{new})$ ;
        $\mathcal{T}.addNodEdge(x_{min}, x_{new})$;
        $\mathcal{T}.rewire()$;
```

Optimal sampling-based path planning methods

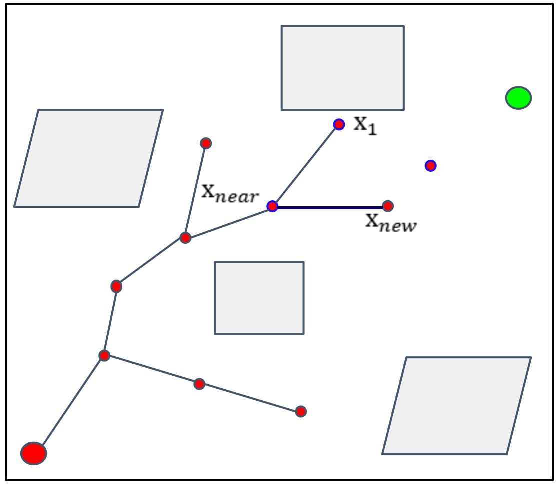
Rapidly-exploring Random Tree*

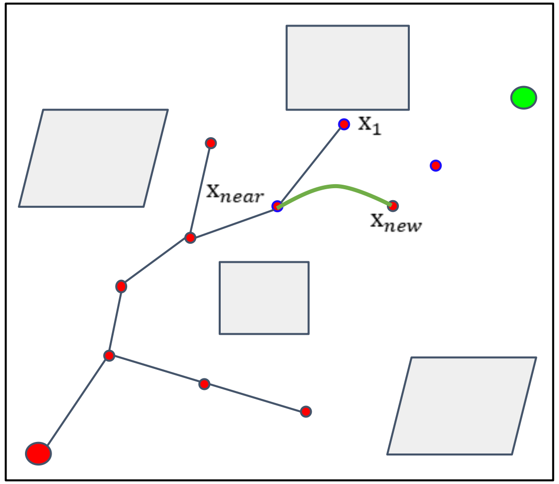


https://www.youtube.com/watch?v=YKiQTJpPFkA

Optimal sampling-based path planning methods

Kinodynamic-RRT*



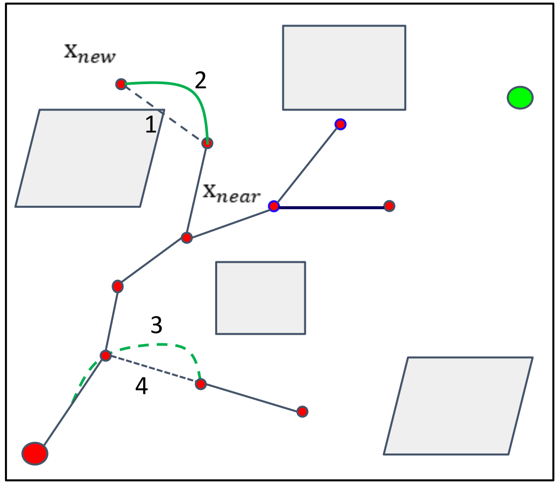


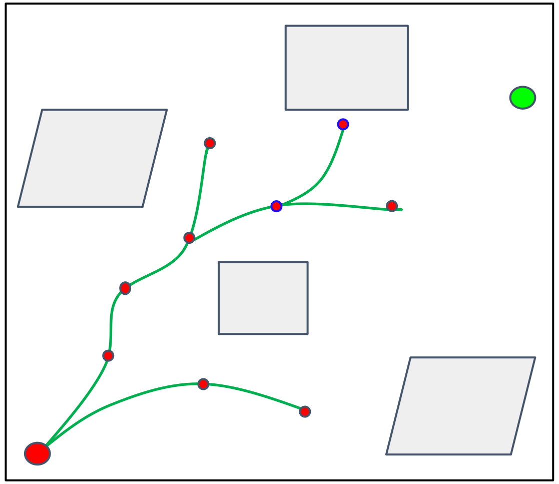
Change Steer() function to fit with motion or other constraints in robot navigation.

[Kinodynamic RRT*: Optimal Motion Planning for Systems with Linear Differential Constraints]

Optimal sampling-based path planning methods

Kinodynamic-RRT*

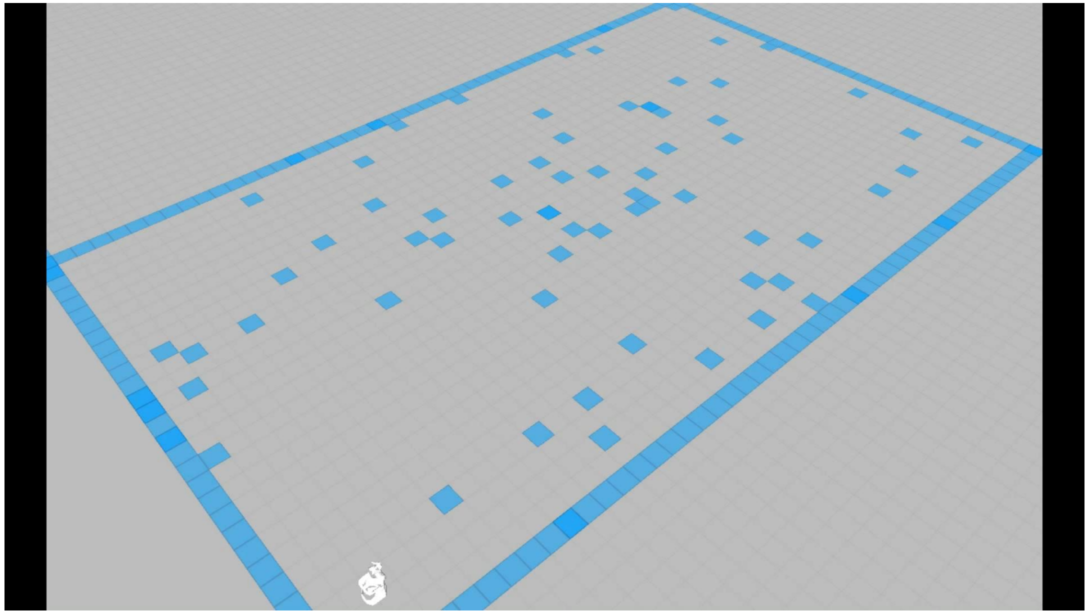




Change **Steer()** function to fit with motion or other constraints in robot navigation.

Optimal sampling-based path planning methods

Kinodynamic-RRT*

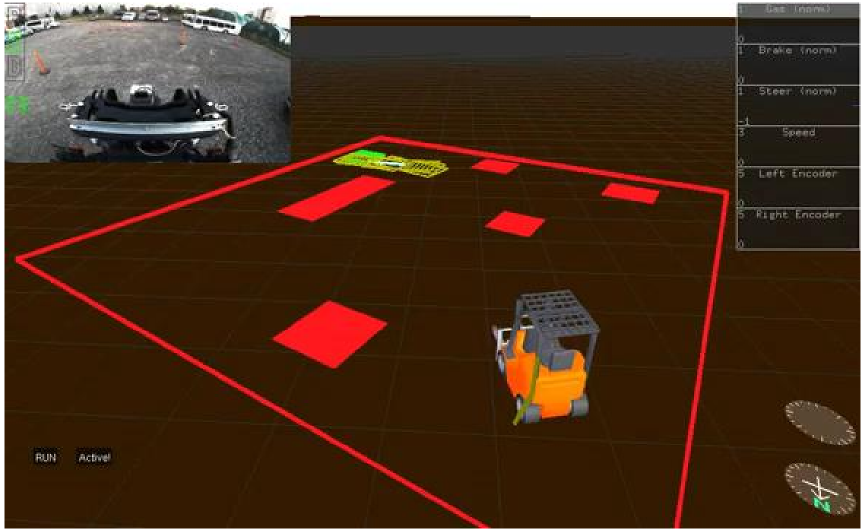


Change Steer() function to fit with motion or other constraints in robot navigation.

[1] https://www.youtube.com/watch?v=RB3g_GP0-dU

Optimal sampling-based path planning methods

Anytime-RRT*



Keep optimizing the leaf RRT tree when the robot executes the current trajectory Anytime Fashion

Anytime Motion Planning using the RRT*

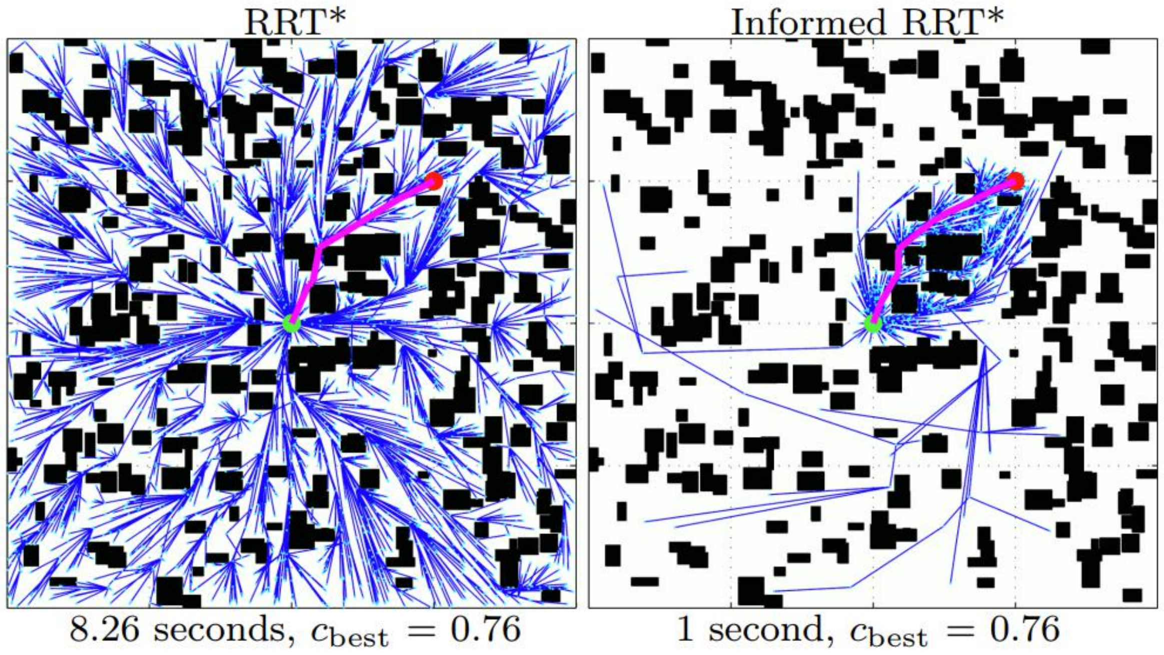
Optimal sampling-based path planning methods

- Rewire function
- RRT*
- Kino-dynamic RRT*
- Anytime RRT*

Advanced Sampling-based Methods

Advanced Sampling-based Methods

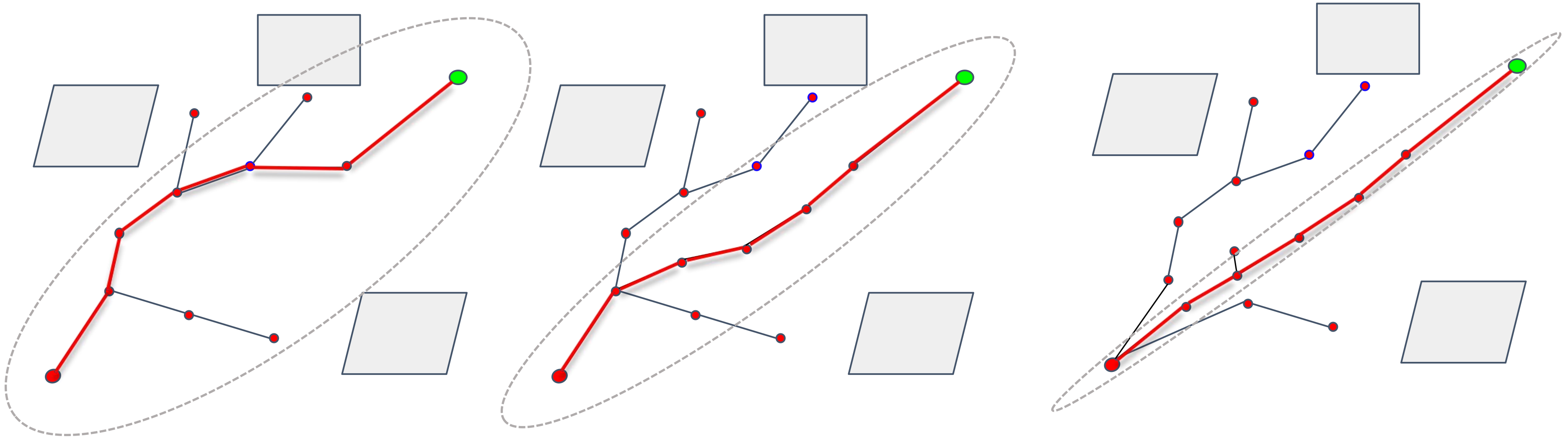
Informed RRT*



[Informed RRT*: Optimal sampling-based path planning focused via direct sampling of an admissible ellipsoidal heuristic]

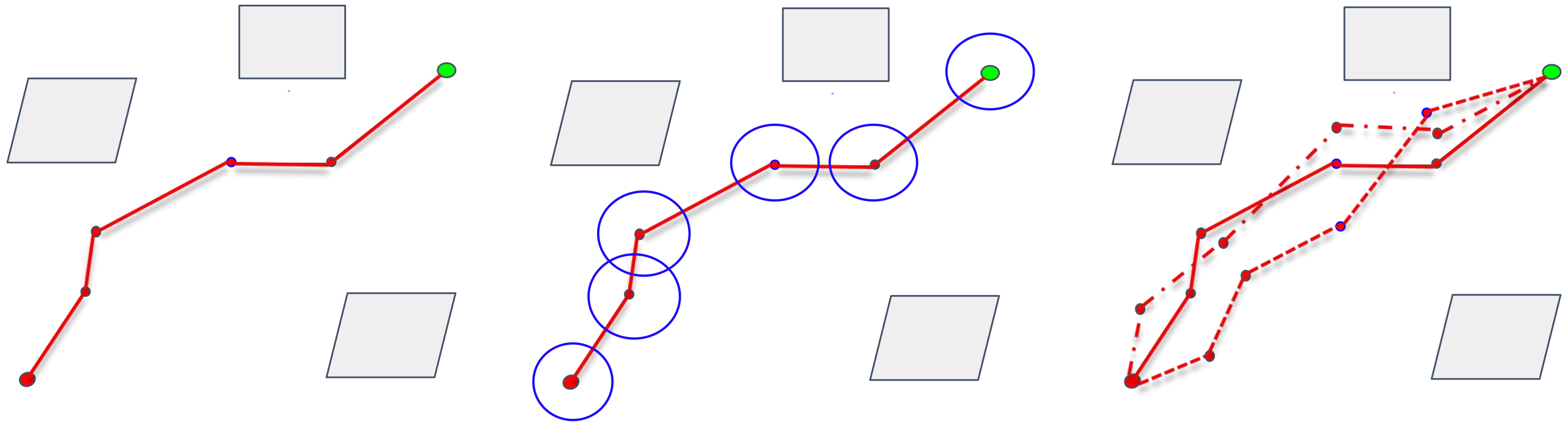
Advanced Sampling-based Methods

Informed RRT*



Advanced Sampling-based Methods

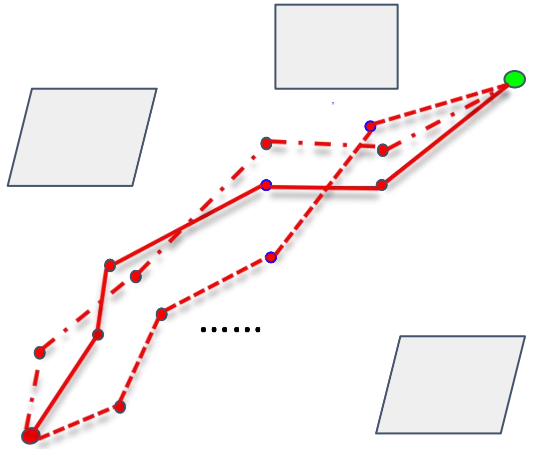
Cross-entropy motion planning



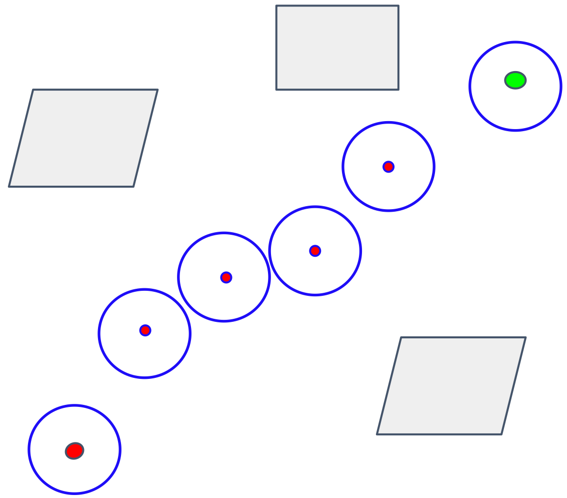
Cross-entropy motion planning

Advanced Sampling-based Methods

Cross-entropy motion planning



Select elite paths

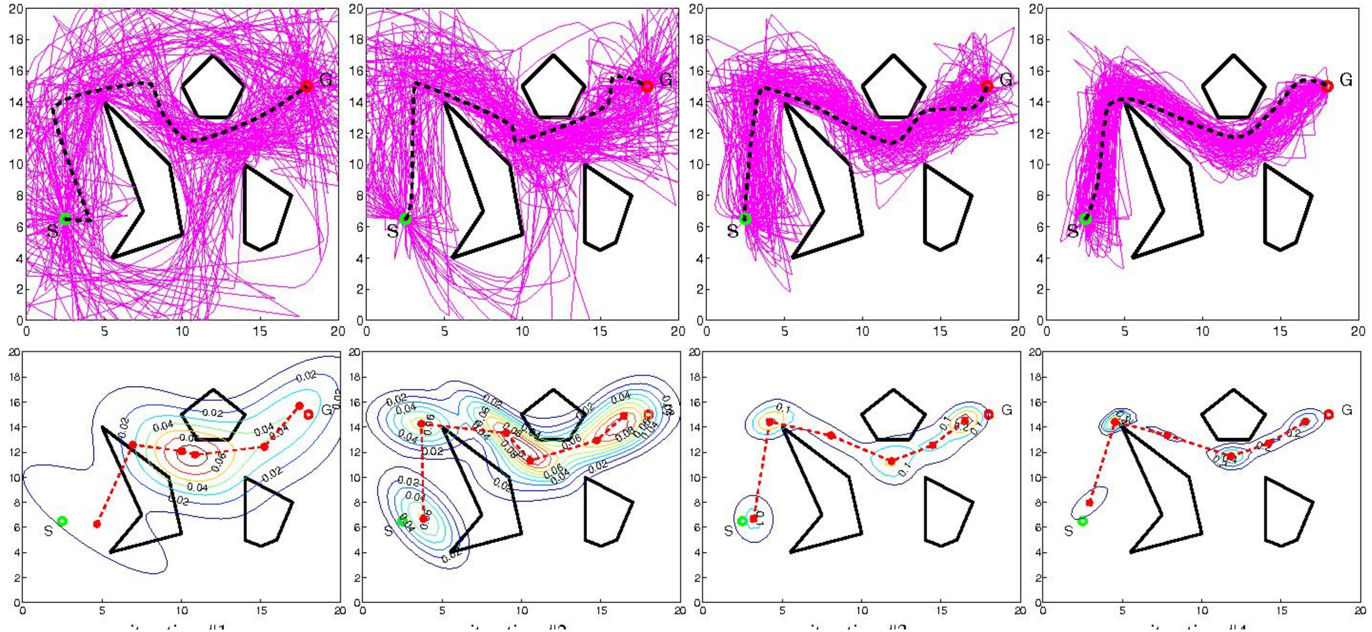


Update sample region

Next sample round

Advanced Sampling-based Methods

Cross-entropy motion planning



Link of implementation on github:

Advanced Sampling-based Methods

Other variants

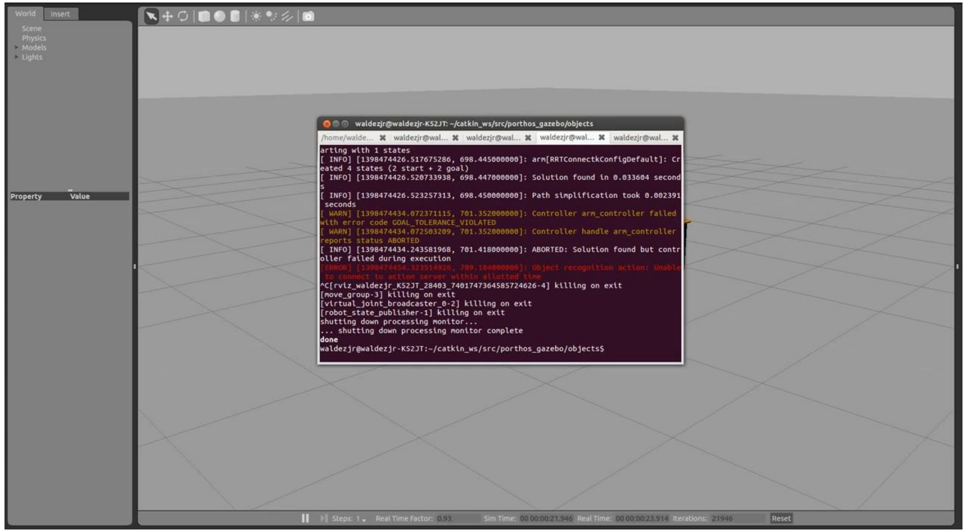
- Lower Bound Tree RRT (LBTRRT)[a]
- Sparse Stable RRT[b]
- Transition-based RRT (T-RRT)[c]
- Vector Field RRT[d]
- Parallel RRT (pRRT)[e]
- Etc.[f]

[1] An Overview of the Class of Rapidly-Exploring Random Trees
[2] http://msl.cs.uiuc.edu/rrt/
[a] https://arxiv.org/pdf/1308.0189.pdf
[b] http://pracsyslab.org/sst_software
[c] http://homepages.laas.fr/jcortes/Papers/jaillet_aaaiWS08.pdf
[d] https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6606360
[e] https://robotics.cs.unc.edu/publications/Ichnowski2012_IROS.pdf
[f] https://github.com/zychaoqun

Implementation

Implementation

- Open Motion Planning Library [1]
- Moveit with ROS [2]
- Tutorials[3]

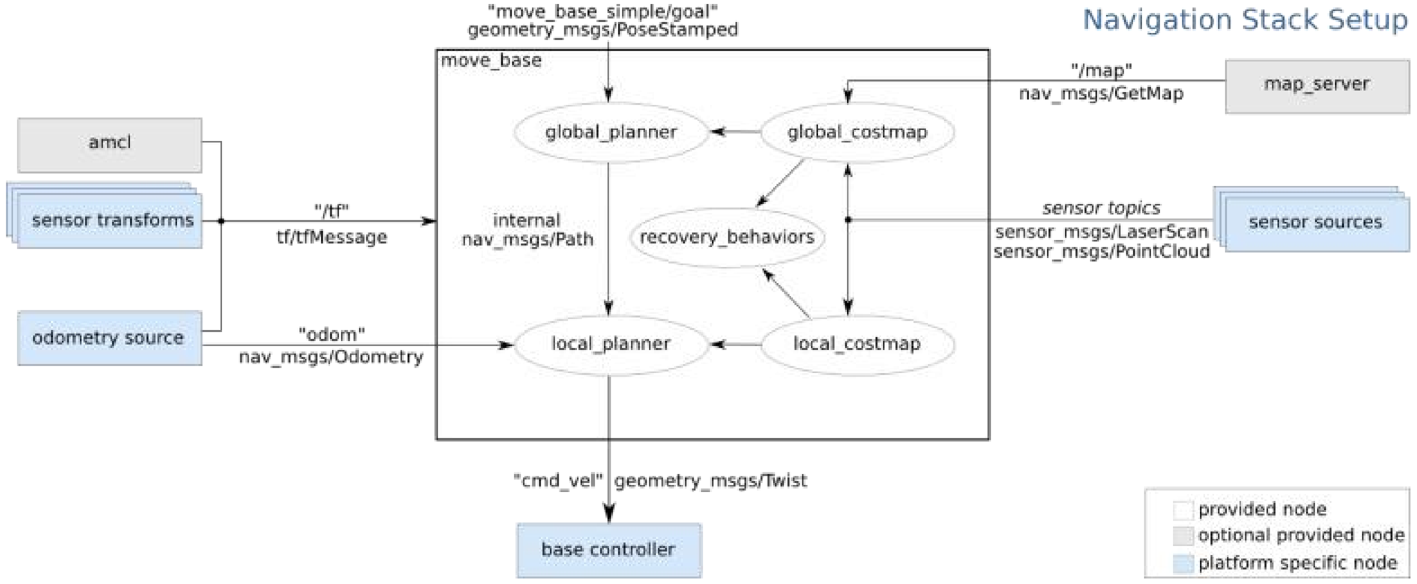


```
arting with 1 states
[ INFO] [1398474426.517675286, 698.445000000]: arm[RRTConnectkConfigDefault]: Cr
eated 4 states (2 start + 2 goal)
[ INFO] [1398474426.520733938, 698.447000000]: Solution found in 0.033604 second
s
[ INFO] [1398474426.523257313, 698.450000000]: Path simplification took 0.002391
 seconds
[ WARN] [1398474434.072371115, 701.352000000]: Controller arm_controller failed
with error code GOAL_TOLERANCE_VIOLATED
[ WARN] [1398474434.072503209, 701.352000000]: Controller handle arm_controller
reports status ABORTED
[ INFO] [1398474434.243581968, 701.418000000]: ABORTED: Solution found but contr
oller failed during execution
[ERROR] [1398474454.323514926, 709.184000000]: Object recognition action: Unable
 to connect to action server within allotted time
^C[rviz_waldezjr_K52JT_28403_7401747364585724626-4] killing on exit
[move_group-3] killing on exit
[virtual_joint_broadcaster_0-2] killing on exit
[robot_state_publisher-1] killing on exit
shutting down processing monitor...
... shutting down processing monitor complete
done
waldezjr@waldezjr-K52JT:~/catkin_ws/src/porthos_gazebo/objects$
```

[1] https://ompl.kavrakilab.org/
[2] https://moveit.ros.org/
[3] https://industrial-training-master.readthedocs.io/en/melodic/_source/session4/Motion-Planning-CPP.html

Implementation

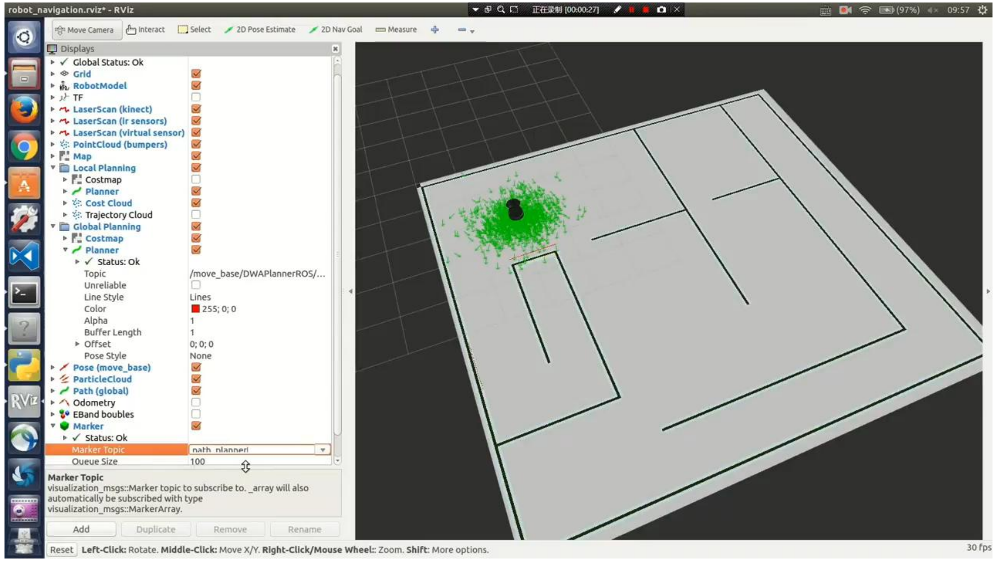
- Navigation stick - ROS



http://wiki.ros.org/move_base

Implementation

- Navigation stick - ROS
  - Global planner
    A*,D*, RRTs,etc
  - Local planner
    Dwa,eband, Teb,etc



robot_navigation.rviz* - RViz

Displays

Global Status: Ok	
Grid	☑
RobotModel	☑
TF	☐
LaserScan (kinect)	☑
LaserScan (ir sensors)	☑
LaserScan (virtual sensor)	☑
PointCloud (bumpers)	☑
Map	☑
Local Planning	☑
Costmap	☐
Planner	☑
Cost Cloud	☑
Trajectory Cloud	☐
Global Planning	☑
Costmap	☑
Planner	☑
Status: Ok	
Topic	/move_base/DWAPlannerROS/...
Unreliable	☐
Line Style	Lines
Color	🟥 255; 0; 0
Alpha	1
Buffer Length	1
Offset	0; 0; 0
Pose Style	None
Pose (move_base)	☑
ParticleCloud	☑
Path (global)	☑
Odometry	☐
EBand boubles	☐
Marker	☑
Status: Ok	
Marker Topic	path_planner|
Queue Size	100

Marker Topic
visualization_msgs::Marker topic to subscribe to. _array will also automatically be subscribed with type visualization_msgs::MarkerArray.

Left-Click: Rotate. **Middle-Click:** Move X/Y. **Right-Click/Mouse Wheel:**: Zoom. **Shift:** More options.

Video demonstration of RRT implemented on ROS [1]

[1] https://youtu.be/FsZ9b6fsQUg

Homework

- Implementation of RRT
  - You can either use MATLAB or C++
  - Hints: write RRT as a global planner in ROS
- Bonus: Implementation of Informed-RRT*

在线问答

Q&A

结语

感谢各位聆听！

Thanks for Listening