



Path Planning for Robotics

A brief Review

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Outline

- 1 Primitives
 - 1.1 Robots Modeling
 - 1.2 Robot Planing Problems
- 2 Heuristics and Discretization
 - Bugs algorithm
 - Potentials to guide feedback control
 - Dijkstra
- 3 Sample-based Path finding
 - Probabilistic Roadmaps
 - Rapidly Exploring Random Trees
- 4 Reiforcemrnt Learning
 - Intro of RL
 - resource and simulation enviroment

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Position and Orientation Representation

- ① Pose: position and orientation
- ② Frame and coordinate transforms
- ③ Rotation Representations

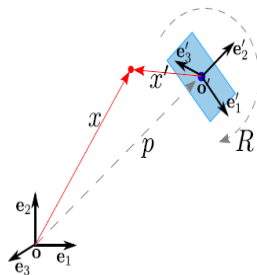
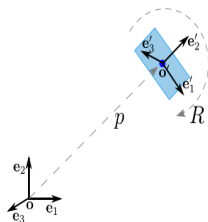
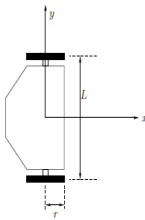


图: frame transforms

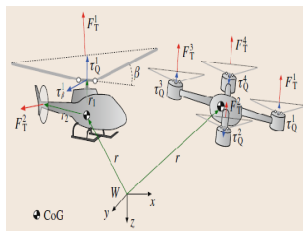
图: position and orientation

Different robots

- Wheel robots



- UAV



- **Manipulation**



Robot Manipulation Kinematics

- DH Table
- Forward Kinematics
- Inverse Kinematics
 - analytical solution
 - numerical solution

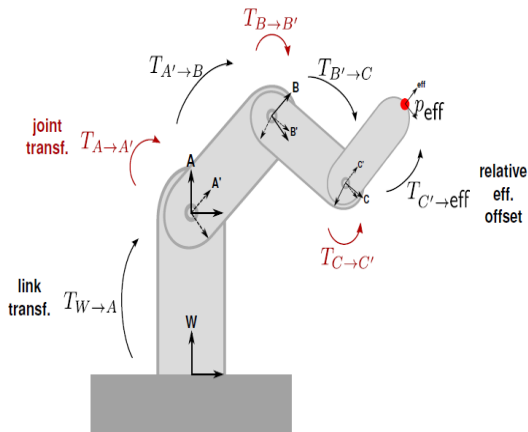


图: model of manipulation

Wheel robot Kinematics

Many mobile robots use a differential drive.

Control method

$$\dot{x} = \frac{r}{2}(u_r + u_l) \cos \theta$$

$$\dot{y} = \frac{r}{2}(u_r + u_l) \sin \theta$$

$$\dot{\theta} = \frac{r}{L}(u_r - u_l)$$

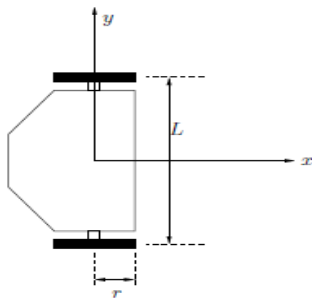


图: mobile robot model

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Path Finding Examples

• Wheel Robot

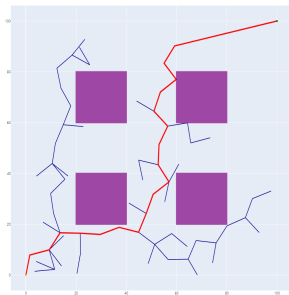


图: path finding in 2D map

• UAV

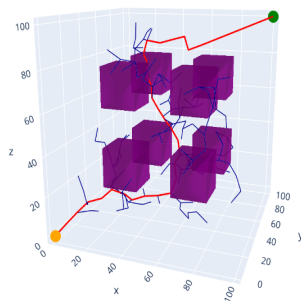


图: path finding in 3D map

Code: <https://github.com/motion-planning/rrt-algorithms>

Path Finding Examples

- Robot Manipulation planning

attention

Unlike the path finding in 2D or 3D map, for the manipulation with freedom of six or seven, **planning in a 6D or 7D 'map' is much more difficult.**

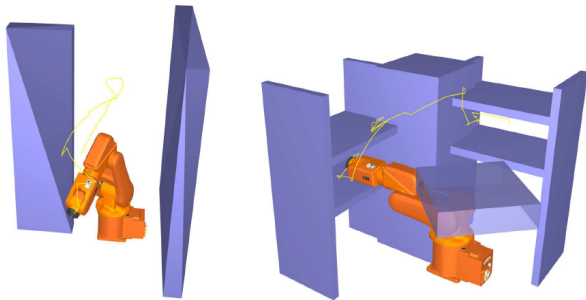


图: path finding in 3D map

motion planning Primitives

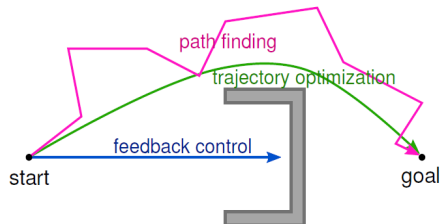


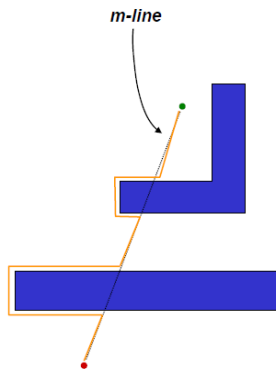
图: Feedback control, path finding, trajectory optim.

- feedback control: E.g., $q_{t+1} = q_t + J^\#(y^* - \phi(q_t))$
- Path Finding Find some $q_{0:T}$ with only valid configurations
- Trajectory Optimization: $\arg \min_{q_{0:T}} f(q_{0:T})$

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"Bugs 2" Algorithm



- head toward goal on the m-line
- if an obstacle is in the way, follow it until you encounter the m-line again.
- Leave the obstacle and continue toward the goal

图: bug2 v1.0

"Bugs 2" Algorithm

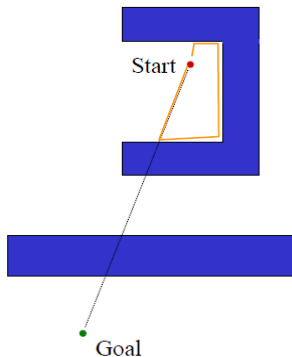


图: bug2 v1.0

BUG!!!

- head toward goal on the m-line
- if an obstacle is in the way, follow it until you encounter the m-line again.
- Leave the obstacle and continue toward the goal

"Bugs 2" Algorithm

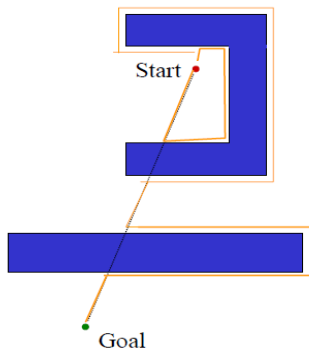


图: bug2 v2.0

- head toward goal on the m-line
- if an obstacle is in the way, follow it until you encounter the m-line again **closer to the goal**.
- Leave the obstacle and continue toward the goal

"Bugs 2" Algorithm

- **Conclusion**

- Other variants: TangentBug, VisBug, RoverBug, WedgeBug, . . .
- only 2D! (TangentBug has extension to 3D)
- Guaranteed convergence
- Still active research:
K. Taylor and S.M. LaValle: I-Bug: An Intensity-Based Bug Algorithm

Tips

Useful for minimalistic, robust 2D goal reaching
not useful for finding paths in joint space

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Artificial Potential Field

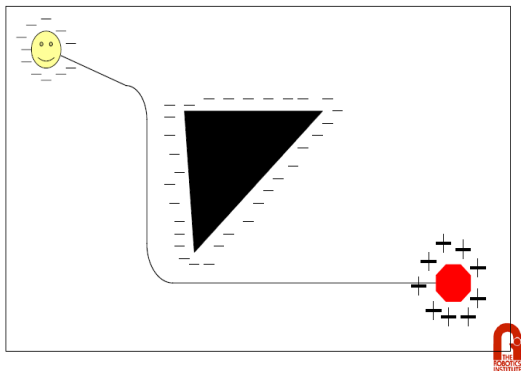


图: Start-Goal Algorithm: Potential Functions

Artificial Potential Field

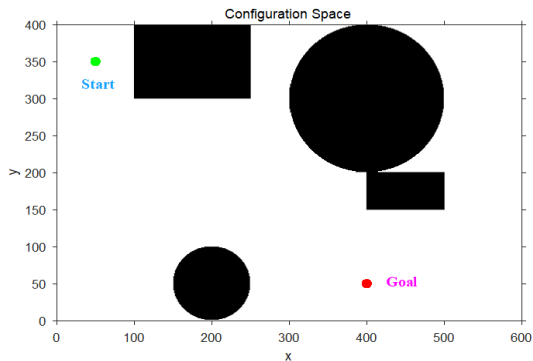


图: A sample

Artificial Potential Field

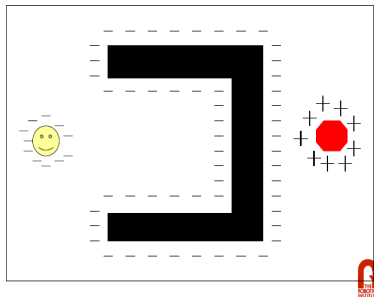


图: Local minimum

Conclusion

- Very simple, therefore popular
- Does not solve **locality** problem of feedback control.

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The Wavefront Action



图: start search

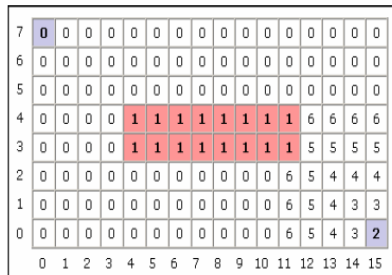


图: and again and again

Starting with the goal, set all adjacent cells with "0" to the current cell +1. We'll use 8-Point Connectivity in our example

The Wavefront Action Done

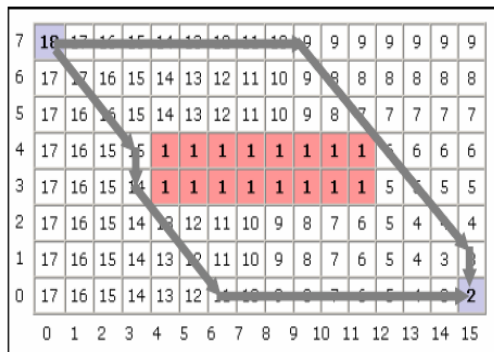


图: path found

To find the shortest path, according to your metric, simply always move toward a cell with a lower number

Dijkstra

- **conclusion**

- Is efficient in discrete domains
- Produces optimal (shortest) paths
- Applying this to continuous domains requires discretization
 - Grid-like discretization in high-dimensions is daunting! (curse of dimensionality)
 - What are other ways to “discretize” space more efficiently?

A^* , a method like Dijkstra, learn about it by yourself if needed!

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Probabilistic Road Maps

Step1: Probabilistic Road Maps –generation

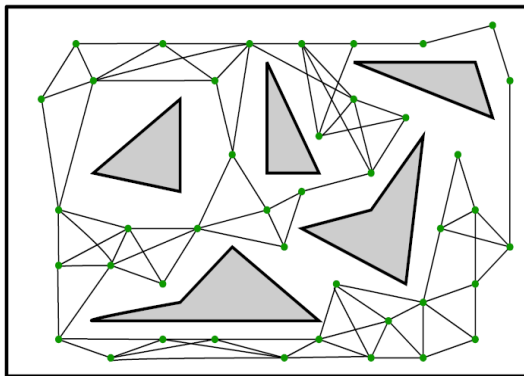


图: generates a graph $G = (V; E)$ of configurations

Probabilistic Road Maps

Step2: Given the graph, use (e.g.) Dijkstra to find path from q_{start} to q_{goal}

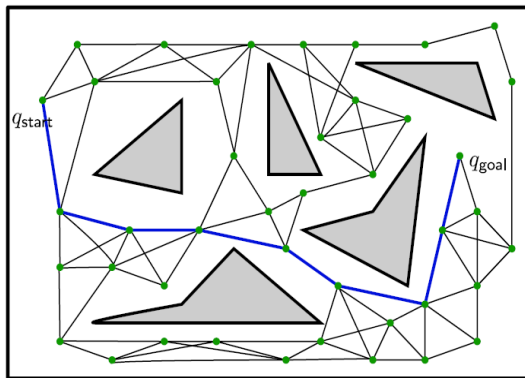


图: select a path from graph

Probabilistic Road Maps

Conclusion

- Pros
 - Algorithmically very simple
 - Highly explorative
 - Allows probabilistic performance guarantees
 - Good to answer many queries in an unchanged environment
- Cons
 - Precomputation of exhaustive roadmap takes a long time

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Motivations

- Single Query path finding: Focus computational efforts on paths for specific(q_{start} ; q_{goal})
- Use actually controllable DoFs to incrementally explore the search space: controlbased path finding.

Tips

Probabilistic Road Maps is able to solve different instances of the problem in the same environment,so it is **multi Query**,Planning time is invested in sampling and generating a roadmap

Rapidly Exploring Random Trees family

There are many varieties of RRT algorithm, ① more efficiency, ② more optimal, ③ replanning

- RRT*
- bi-RRT
- inform-RRT
- lazy-RRT
- ...

Let's see a sample

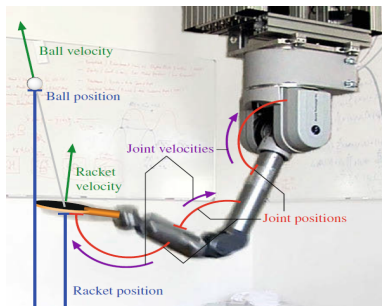
RRT VS PRM

- Pros (shared with PRMs):
 - Algorithmically very simple
 - Highly explorative
 - Allows probabilistic performance guarantees
- Pros (beyond PRMs):
 - Focus computation on single query (qstart; qgoal) problem
 - Trees from multiple queries can be merged to a roadmap
 - Can be extended to differential constraints (nonholonomicsystems)
- To keep in mind (shared with PRMs):
 - The metric (for nearest neighbor selection) is sometimes critical
 - The local planner may be non-trivial

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RL = Learning to Act in state



The agent will learn to act with that state for a max final reward. a agent will be representation by a Deep Neural Network, that is the Deep Reinforcement learning.

given a state of the robot
enviroment

Applications of RL

- Robotics
 - -Navigation, walking, juggling, helicopters, grasping, etc...
- Game
 - -Backgammon, Chess, Othello, Tetris, ...
- Control
 - -factory processes, resource control in multimedia networks, elevators,

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resource

• 研究仿真平台

- Matlab - Robotics system toolbox and RL toolbox
- Vrep - robot urdf import and OMPL
- Gazebo and ROS - a vrep in Linux(ubuntu)

• 算法

- 编程语言 python matlab
- 深度强化学习 DRL(我的研究方法)
- 进化算法 (遗传算法)EA(肇江的研究方法)
- RRT 系列 (往届师兄研究过)
- 模型预测控制算法 (感觉很有用的一种算法)

Thanks

一点建议

希望各领域师弟们尽快找到自己的研究点，并在研一上打好一些必要基础。

对硕士学位而言，时间短暂，你需要钻研一种以上的算法以拿证毕业。对于机器人智能规划的师弟，欢迎咨询我们的规划小组师兄，保持密切沟通，尽快开始你们想研究和突破的算法，有问题都可以找师兄们。