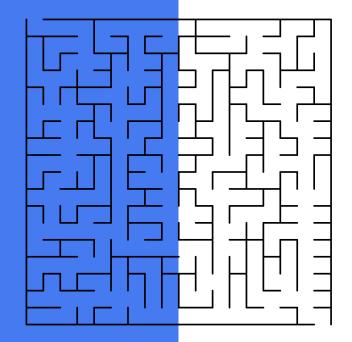
16-745 Optimal Control and Reinforcement Learning

Trajectory Planning with obstacle avoidance

Team: Into the Unknown

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01. Introduction

Motivation and Problem Statement

02. Overview

Environment Setup and Approaches overview

03. Current Status

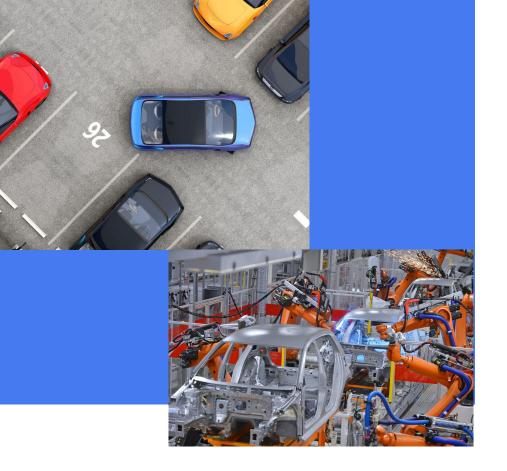
Theory, Implementation, and Result: RRT, A*

04. To be completed

R* and Proposed Extension

05. Conclusion Limitation and Future Work

Content



Motivation

Robots operating in real world will always have plan and replan around the obstacles.

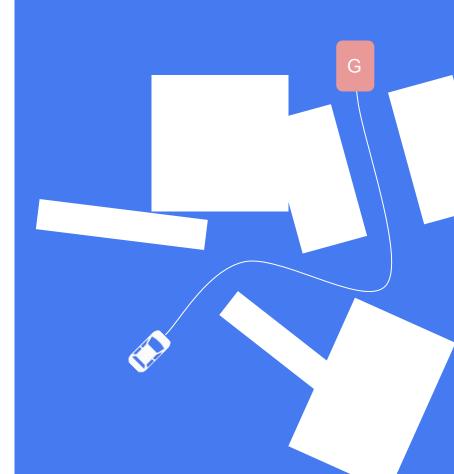
- Parking a Car
- Manufacturing using manipulator arm

Problem Statement

Traverse an Ackermann Vehicle from starting position to goal position in presence of obstacles

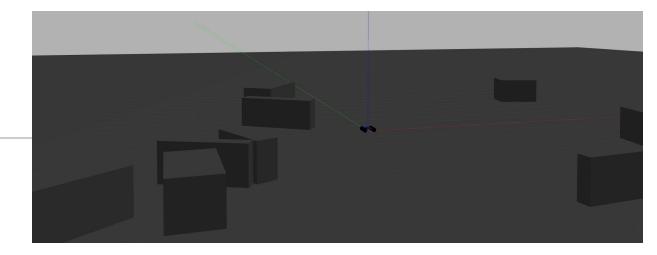
Goal:

Implement and compare classic approaches and propose an extension



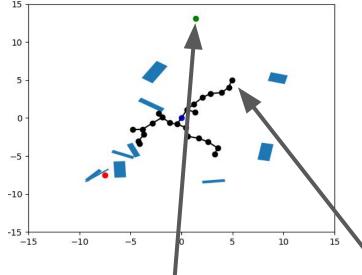
Overview of the project

Gazebo-ROS Environment



Script to generate a gazebo world with random obstacles



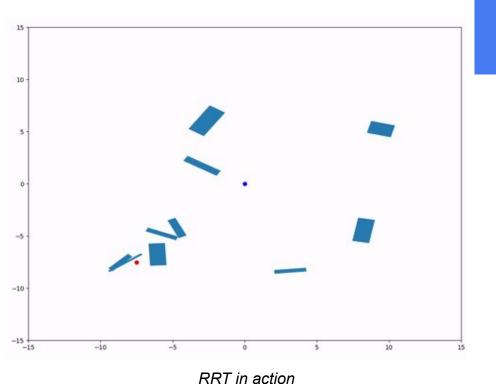


RRT Rapidly Exploring Random Tree

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Growing a tree:

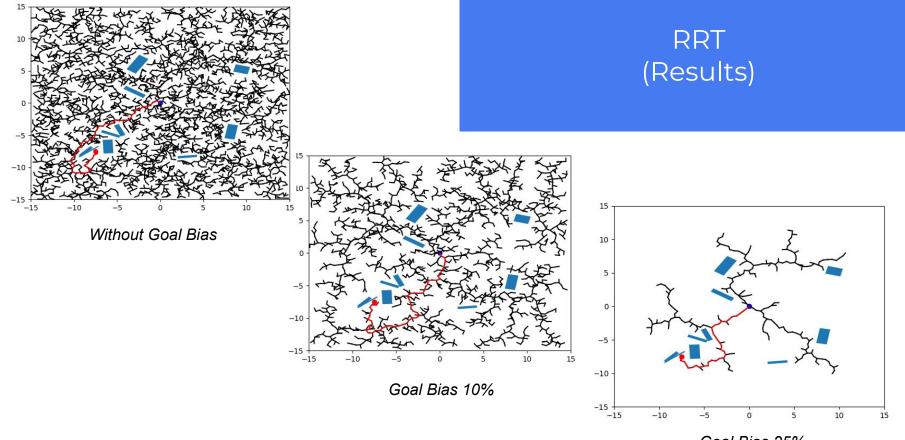
- Sample a *random point* in the space
- From the existing tree structure find the <u>closest point</u>
- Consider the <u>new edge</u> from closest point in the direction of the sampled point
- If edge's intersection with obstacle is null, add the <u>edge</u> and corresponding <u>node</u> in the tree



RRT (Implementation)

Key Details:

- Implemented from scratch
- A sampled node is sampled near goal region with some probability (Let's call it goal bias)
- Step length is also randomly sampled each time
- Kd-Tree for efficiently finding the closest node to sampled node
- Occupancy grid for validating new nodes and edge

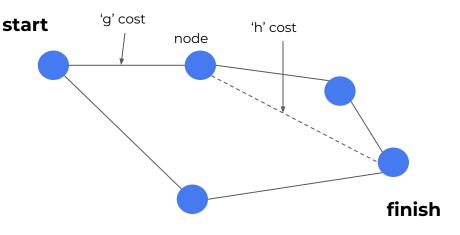


Goal Bias 25%

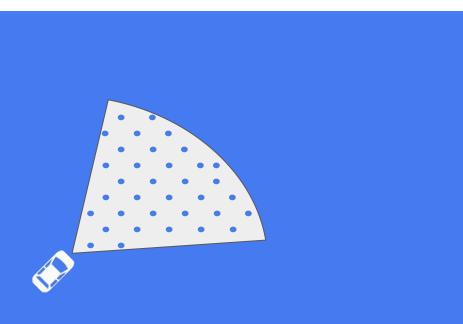
Creating a trajectory with A*:

- Maintain two lists of nodes
 - Nodes that have not been explored (open list)
 - Nodes that have been explored (closed list)
- Each node consists of its (x,y) coordinate values and direction theta.
- Each node has two associated costs:
 - From the start node to the current node ('g' cost)
 - Estimated cost (heuristic) to the goal ('h' cost)
- Chose the node from the open list with lowest total cost (g+h) to explore
- Generate a list of successors to this node based on system constraints (e.g. steering angle and obstacles)
- Evaluate the cost functions for these new nodes and add each node to the open list.
- If one of these nodes already exists in the open list and the stored 'g' cost is greater, update this node in the open list, as a cheaper path to this node has been discovered
- Iterate until the goal has been reached



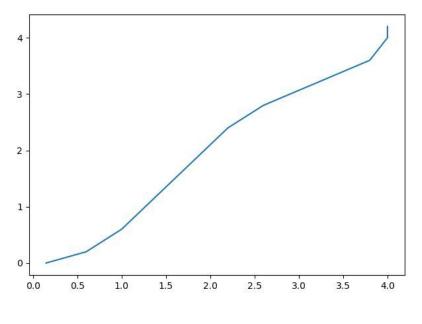






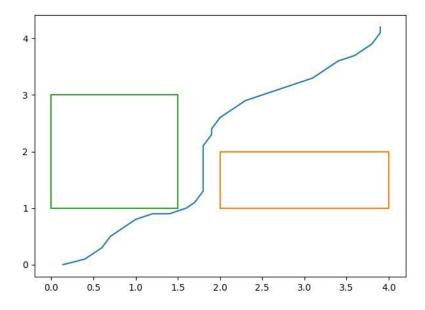
Key Implementation Details:

- Implemented from scratch
- (X,Y) grid defined in .1 meter increments
- 'g' cost is defined as euclidean distance
- 'h' cost is defined as $\sqrt{((\Delta x)^2 + (\Delta y)^2 + (\Delta \theta)^2)}$
- Allow successor nodes to be up to .5 meters away
- Each node also store its previous node, allowing for simple reconstruction of the trajectory



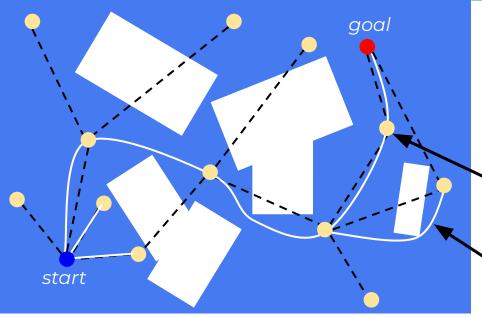
No Obstacles

A* (Results)



Multiple Obstacles

R* (Randomized A*)



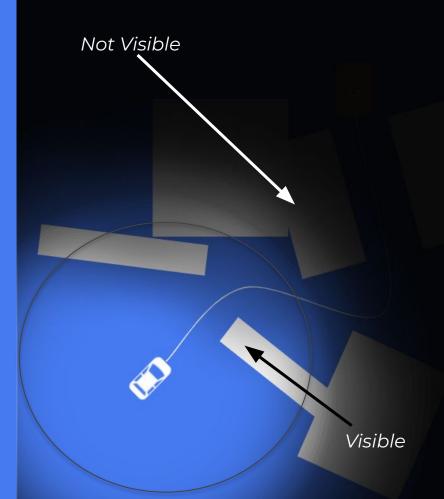
Key Idea:

- Weighted A*
 - $f = g + w^*h$ (where weight(w) > 1.0)
- Bounded suboptimal solution (*w*optimalCost*) but can convergence quite early
- Searching at 2 spatial scale level
- High level graph can quickly cover large area but feasible path between them may or may not exist.
- If certain node in the high level graph is found to be promising based on heuristic and cost, then only
 <u>Low level path</u> is attempted to be calculated using time-bound weighted A*

Proposed Extension

Real Time Trajectory Modification

- In practice, not all obstacles are known prior to driving.
- We must be able to adapt and change our desired trajectories in real time, as new information presents itself
- We aim to limit the obstacles that the vehicle can see during initial trajectory planning, and reveal these obstacles when they are within a defined distance of the vehicle.
- We are likely to use the algorithm that yields the quickest results, as computation time is crucial for this task



RRT:

- Not Optimal At All
- Not Smooth
- Convergence not consistent

A*:

- Slow(current implementation)
- Smoother than RRT, but still not Smooth
- Consumes A Lot of Memory
- Local Minima takes long
- Lack of precision(fixed grid)

R*:

- Sub Optimal

Applicable to all:

- Can not react to new obstacles introduced at runtime

Limitations

Future Work

A*:

- Optimization of code for faster runtime
- Further refine cost functions
- Explore utilizing a non-fixed grid

RRT:

- Implementing RRT* (if time permits)

R*:

- Full implementation

Proposed Extension:

- Recompute trajectories while vehicle is moving as obstacles are sensed by the vehicle

Applicable to all:

- Integrate with Pure Pursuit controller
- Add width of the vehicle into consideration
- Compare accuracy, trajectory feasibility, and compute time of each implementation

