# Motion Planning Part 1

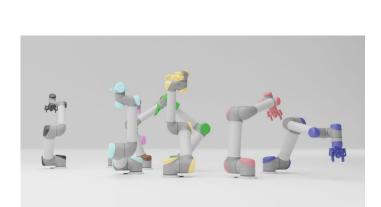
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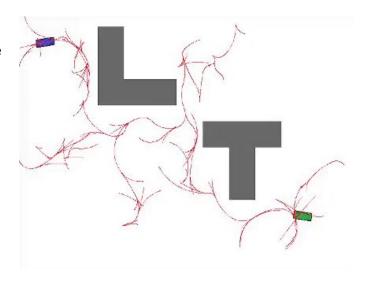
# What is Motion Planning?

- Given a **start** and **goal**, compute a sequence of movements while **avoiding obstacles** and satisfying constraints.

#### - Examples:

- Robot arm from start  $\rightarrow$  goal, with obstacle in between.
- Or a car navigating from point A to B on a map.



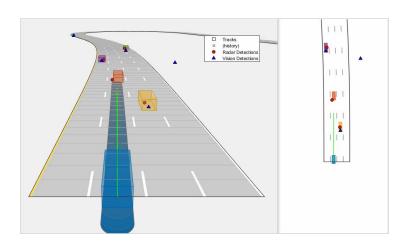


# Why is Motion Planning Important?

- Enable autonomous decision-making for:
  - **Navigating** environments
  - **Manipulating** objects
  - Coordinated multi-robot tasks
- Human-like behavior: **plan before act**

#### Some key terms:

Concept	Meaning
Path	Geometric route in space (no time)
Motion	Feasible movement considering robot dynamics
Trajectory	Time-parameterized path



# What are the challenges here?

- Motion planning is robotics is hard because it poses unique challenges (some of which are partially solved and some are still being researched)
- 1. High-dimensional configuration spaces
- 2. Obstacles in complex environments: dynamic and static obstacles
- 3. Robot constraints: joint limits, dynamics, uneven terrain etc
- 4. Real-time requirements

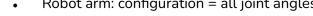
### **Basics of Motion Planning: C-space**

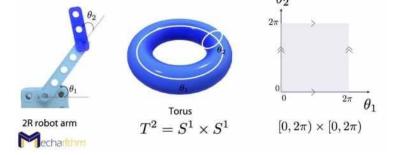
The **configuration** of a robot is a complete specification of its position.

C-space = space of all possible robot configurations.

#### **Examples:**

- Point robot in 2D:  $(x,y) \to \mathbb{R}^2$
- Rigid body in 2D:  $(x, y, \theta) \rightarrow SE(2)$
- Rigid body in 3D:  $(x, y, z, \alpha, \beta, \gamma) \rightarrow SE(3)$
- Robot arm: configuration = all joint angles



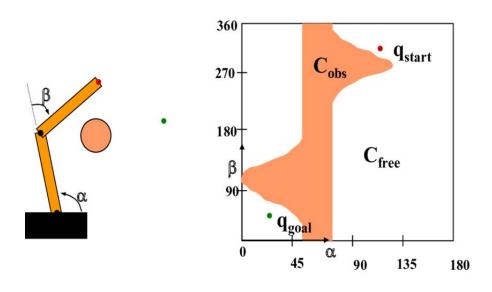


Why is C-space useful?

Converts the planning problem into a geometric problem and sampling, search, and optimization algorithms can easily operate in C-space.

### **Basics of Motion Planning: Obstacles in C-space**

- Obstacles in workspace get mapped to regions in **C-space**
- A configuration is **invalid** if the robot at that configuration collides with an obstacle



**C-obstacle** = set of configurations where robot collides with an obstacle

Free space  $C_{free}^-$  = valid configurations

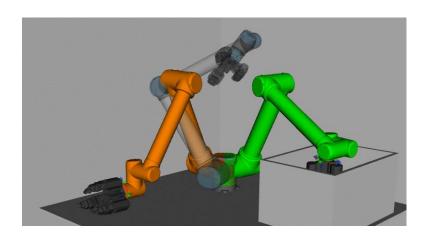
 $\mathbf{q}_{\mathsf{start}}$ : Starting configuration

 $\mathbf{q}_{goal}$ : Goal configuration

## **Motion Planning Problem Setup**

Given,  $q_{\mathrm{start}}, q_{\mathrm{goal}} \in C_{\mathrm{free}}$  and the obstacle map

Goal: Find a continuous path  $\tau:[0,1]\to C_{\mathrm{free}}$  st  $\tau(0)=q_{\mathrm{start}}$  and  $\tau(1)=q_{\mathrm{goal}}$ 



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#### **Grid based planning: A\***

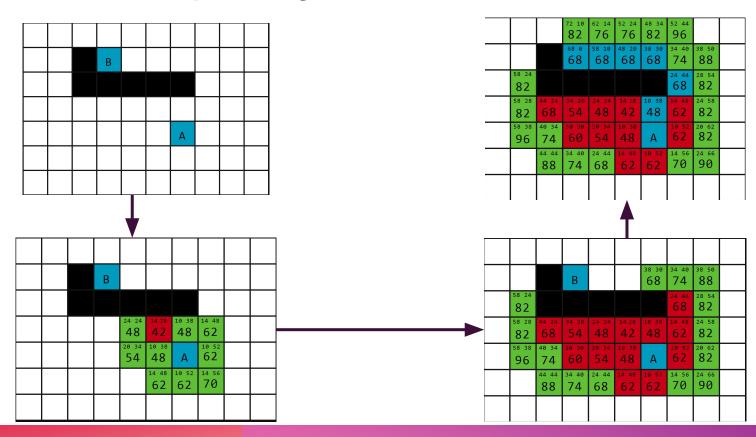
- BFS and Dijkstra's explore too many unnecessary nodes.
- We want an algorithm that: is **complete** (finds a path if one exists), is **optimal** (finds shortest path), is **efficient** (uses fewer resources)
- A\* search uses a **heuristic** to guide the search intelligently.
- A\* evaluates nodes using: f(n) = g(n) + h(n)

where, g(n): Cost from start to node n

h(n): Heuristic estimate from n to goal

and use a priority queue (min-heap) to always expand the node with the lowest f(n)

## **Grid based planning: A\***



#### **Issues Grid based planning**

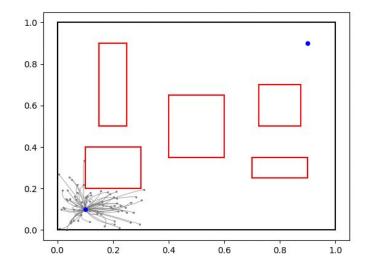
- **Resolution Dependency:** Fine grids improve accuracy but increase memory and computation time; coarse grids lose precision and may miss feasible paths.
- **Non-Smooth Paths:** Paths often consist of sharp turns and axis-aligned steps, which are not suitable for real robot motion without post-processing.
- Curse of Dimensionality: Grid size grows exponentially with the number of configuration dimensions (e.g., for arms or SE(3)), making it infeasible for high-DOF robots.

The above issues can be tackled using Sampling-based Planning.

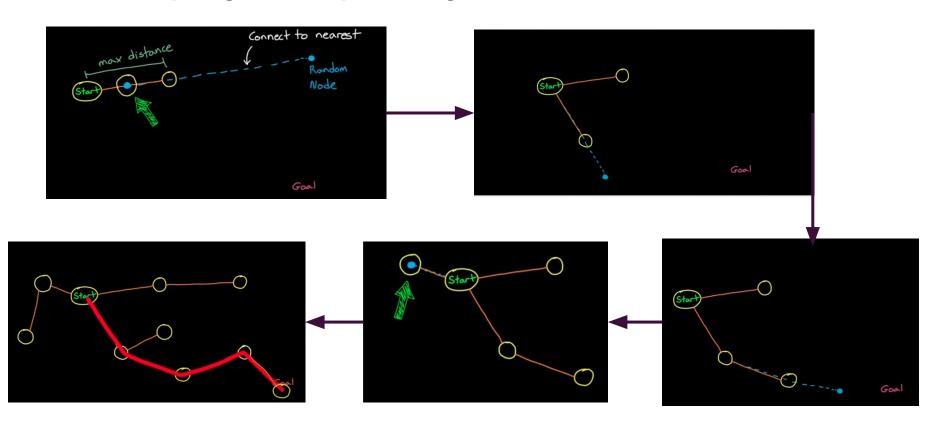
### Sampling based planning: RRT

- Grid-based methods suffer from: high memory in high-dimensional spaces, poor performance in complex C-spaces
- Sampling-based methods work directly in continuous configuration space

- Rapidly-Exploring Random Trees (RRT)
  - Builds a **tree** rooted at the start configuration
  - Randomly samples a point, grows tree **toward** it
  - Efficiently explores large, high-dimensional spaces



## Sampling based planning: RRT



## Sampling based planning: Bi-RRT

- RRT grows tree from start  $\rightarrow$  goal, but:
  - May take long to reach goal in cluttered spaces
  - Inefficient in narrow passages

#### **Idea:** Grow two trees:

- One from start
- One from goal
- Try to **connect** them

