

# Motion Planning

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## collision detections

- using triangle faces
- model the mesh with spherical meshes
- Convex Decomposition
- use signed distance function (SDF)

## Probabilistic Roadmap Method (PRM)

### algorithm

1. Map construction phase:

- Randomly sample states in  $C_{free}$ 
  - $C = [\theta_{1_{min}}, \theta_{1_{max}}] \times [\theta_{2_{min}}, \theta_{2_{max}}] \times \dots \times [\theta_{n_{min}}, \theta_{n_{max}}]$
  - How to sample states in  $C_{free}$  : Rejection Sampling
    - sample uniformly over  $C$
    - Reject the sample not in the  $C_{free}$ , that is, collide with environment or obstacles.
- Connect every sampled state to its neighbors
  - choose  $k$  closest neighbors to each sampled state
  - check if the line between the two states intersects with any obstacles or environment
    - linearly interpolate between the two states to find if any collision exists

2. Query phase:

- Run path finding algorithms like Dijkstra to find a path from start state to target state
- if start state and target state are not in the graph, first find the nearest state to start state and the nearest state to target state and find a path between these two states, then connect this path the start and target.

## Limitations: Narrow Passages

- issue: sampling in narrow passages are sparse and highly possible to be discarded after collision detection
- solution:
  - i. Guasson sampling:
    - Generate one sample  $q_1$  uniformly in  $C$
    - Generate another sample  $q_2$  from a guasson distribution centered at  $q_1$  with variance  $\sigma$
    - if  $q_1 \in C_{free} \wedge q_2 \notin C_{free}$ , add  $q_1$  to the vertex set.  
attribute: samples are near the boundary, but samples in the narrow passage are still too sparse.
  - ii. Bridge Sampling:
    - Generate one sample  $q_1$  uniformly in  $C$
    - Generate another sample  $q_2$  from a guasson distribution centered at  $q_1$  with variance  $\sigma$
    - $q_3 = (q_1 + q_2)/2$
    - if  $q_1 \notin C_{free} \wedge q_2 \notin C_{free} \wedge q_3 \in C_{free}$ , add  $q_3$  to the vertex set.  
attribute: samples are dense in the narrow passage, but sparse in other areas.
  - iii. Hybrid Sampling:
    - use Bridge Sampling to sample  $N_1$  verts and Uniform Sampling to sample  $N_2$  verts. Then find path among these  $N_1 + N_2$  verts.

## suitable application case

- static scenes: if scene is dynamically changing, PRM needs to construct a new map every time
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# Rapidly-Exploring Random Tree (RRT)

## algorithm

1. start with  $q_{start}$
2. decide a destination state for this step.
  - strategy 1: random exploration: randomly sample a state in  $C_{free}$
  - strategy 2: greedy exploitation: go along  $q_{now}$  and  $q_{goal}$
  - set hyperparameter  $\beta$  to control the exploration/exploitation trade-off
3. find the nearest neighbor to the destination state on the current tree, denote it as  $q_{now}$
4. connect  $q_{now}$  to  $q_{dest}$  with a straight line path, and go along this line with a step size  $\alpha$  to  $q_{new}$
5. check if the path collides with any obstacles or environment and if  $q_{new} \in C_{free}$  and if  $q_{new}$  has already been visited

## refinement

1. RRT-Connect: Grow two trees from  $q_{start}$  and  $q_{goal}$
2. Shortcutting: refine jerky, unnatural paths
  - Sample two points along the path and check if the line connecting them intersects with any obstacles or environment
  - If the line does not intersect, connect the two points with a straight line path and delete the original path between these two points.
3. Shortcutting with Random Restarts: do RRT multiply times, and apply shortcutting accordingly. Pick the path with the smallest cost.

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# Control System

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In the following part, we have  $\theta_e(t) = \theta_{dest} - \theta_{now}$

1. Proportional Control
  - $u = K_p(\theta_{dest} - \theta_{now})$
  - if control signal changes derivative of state, we have

$$\dot{\theta}_{now} = K_p(\theta_{dest} - \theta_{now})$$

consider that  $\theta_e = \theta_{dest} - \theta_{now}$ , then we have

$$\dot{\theta}_{dest} - \dot{\theta}_e = K_p\theta_e(t)$$

Assume  $\dot{\theta}_{dest} = c$ , the solution to this ODE is

$$\theta_e(t) = \frac{c}{K_p} + (\theta_e(0) - \frac{c}{K_p})e^{-K_p t}$$

- if control signal changes the second derivative of the state, we have

$$\ddot{\theta}_e(t) + K_p\theta_e(t) = 0$$

which is a Simple Harmonic Motion

- For the first case, where control signal changes the first derivative of the state, the final state will have a steady-state error as long as  $\dot{\theta}_{dest} \neq 0$ ; and in the second case, the final state will never stop oscillating.

2. Integral Control

- $u = K_i \int_0^t (\theta_e t) dt$
- if control signal changes the first derivative of the state, we have

$$\ddot{\theta}_e(t) + \theta_e(t) = 0$$

which is a Simple Harmonic Motion

- useful when the system has a steady-state error and we want to minimize it.

3. Derivative Control

- $u = K_d \dot{\theta}_e(t)$
- Accounts for "future behavior" or "trend"
- Attempts to reduce overshooting

4. PI Control

- $u = K_p \theta_e(t) + K_i \int_0^t (\theta_e t) dt$
- if the control signal changes the first derivative of the state, we have

$$K_p \ddot{\theta}_e(t) + K_i \dot{\theta}_e(t) + \theta_e(t) = 0$$

which will have three kind of solutions:

- over damped: there exist a overshooting
- under damped: the state converge slowly to the destination
- critically damped: there is no overshooting, and the state converge fast to the destination

#### 5. PD control

- $u = K_p \theta_e(t) + K_d \dot{\theta}_e(t)$
- if the control signal changes the second derivative of the state, we have

$$\ddot{\theta}_e(t) + K_d \dot{\theta}_e(t) + K_p \theta_e(t) = 0$$

which will also have three kind of solutions like PI control.

#### 6. PID control

- $u = K_p \theta_e(t) + K_i \int_0^t (\theta_e(t)) dt + K_d \dot{\theta}_e(t)$
- if the control signal changes the first derivative of the state, or the state itself, we will have three solutions like PI control.

## compare between different control systems

### Effects of *increasing* a parameter independently

Parameter	Rise time	Overshoot	Settling time	Steady-state error	Stability
$K_p$	Decrease	Increase	Small change	Decrease	Degrade
$K_i$	Decrease	Increase	Increase	Eliminate	Degrade
$K_d$	Minor change	Decrease	Decrease	No effect in theory	Improve if $K_d$ small