

ICRA 2024 ThAT33.03

Safe Receding Horizon Motion Planning with Infinitesimal Update Interval

Inkyu Jang, Sunwoo Hwang, Jeonghyun Byun, and H. Jin Kim*

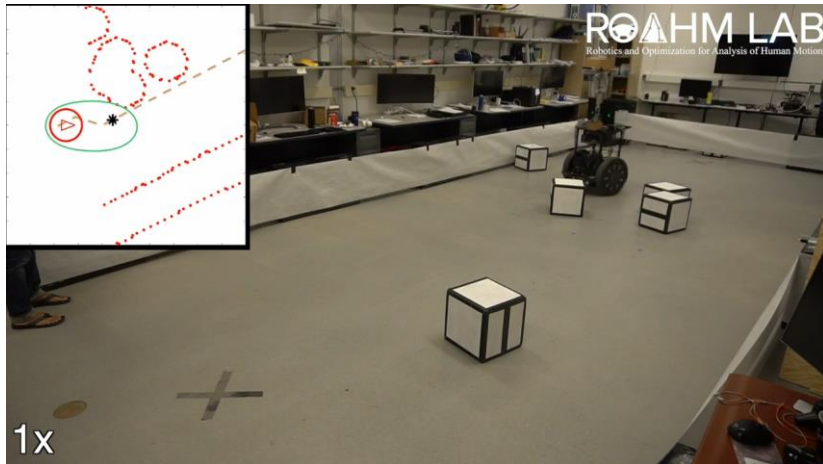
Laboratory for Autonomous Robotics Research, Seoul National University, Seoul, Korea



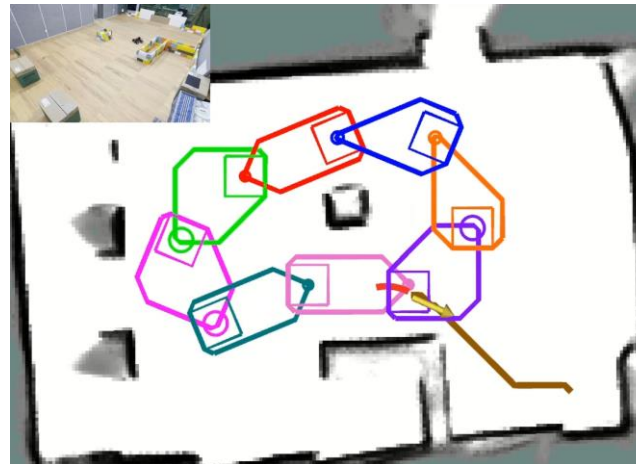
ICRA2024
YOKOHAMA | JAPAN



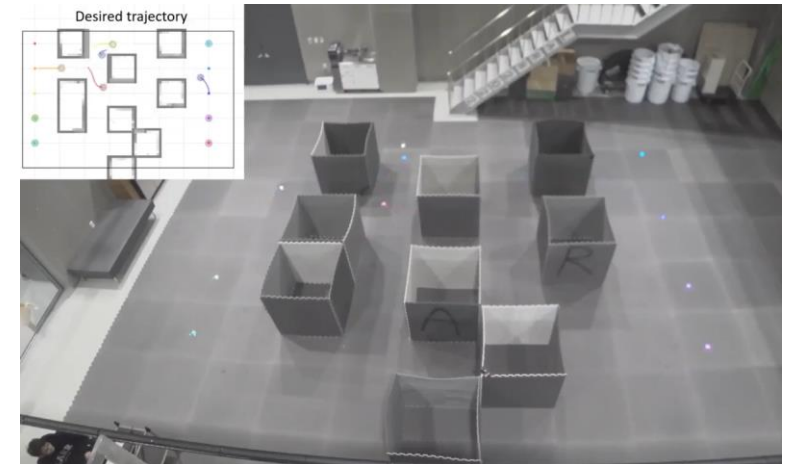
Receding Horizon Motion Planning



Kousik, et al., 2020 [1]



Jang, et al., 2021 [2]



Park, et al., 2023 [3]

- [1] Kousik, Shreyas, et al. "Bridging the gap between safety and real-time performance in receding-horizon trajectory design for mobile robots." *The International Journal of Robotics Research* 39.12 (2020): 1419-1469.
- [2] Jang, Inkyu, et al. "Robust and recursively feasible real-time trajectory planning in unknown environments." *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2021.
- [3] Park, Jungwon, et al. "DLSC: Distributed multi-agent trajectory planning in maze-like dynamic environments using linear safe corridor." *IEEE Transactions on Robotics* 39.5 (2023): 3739-3758.

Receding Horizon Motion Planning

Common Procedure

1. Initialize $x(0)$ as the robot's initial state.
2. Whenever time t becomes a multiple of τ_{plan} , try to find the next trajectory.
 - 2-1. If the search succeeds, switch to the next trajectory.
 - 2-2. If it fails, stay on the current trajectory.
3. Repeat until the task is accomplished.

Optimal Safe Receding Horizon Motion Planning

For a control-affine dynamical system

$$\dot{x} = f(x) + g(x) \cdot u$$

with safety constraints

$$d(x) \geq 0,$$

Problem 1

min.	$\mathcal{J}[x, u]$	
	x, u	
s.t.	$x(0) = x(t)$	(initial condition)
	$\partial_{\tau}x(\tau) = f(x(\tau)) + g(x(\tau)) \cdot u(\tau)$	(dynamic feasibility)
	$d(x(\tau)) \geq 0$	(safety)
	$\partial_{\tau}x(T) = 0$	(final stop)
	$u(\tau) \in U$	(input feasibility)

x, u : receding horizon state and input trajectories
 U : set of all feasible inputs

Optimal Safe Receding Horizon Motion Planning

Problem 1

$$\min_{x, u} \quad \mathcal{J}[x, u]$$

$$\text{s.t.} \quad x(0) = x(t)$$

$$\partial_{\tau} x(\tau) = f(x(\tau)) + g(x(\tau)) \cdot u(\tau)$$

$$d(x(\tau)) \geq 0$$

$$\partial_{\tau} x(T) = 0$$

$$u(\tau) \in U$$

Strengths

1. High expressivity and optimality
2. Recursive feasibility (due to final stop cond.)

Limitations

1. Infinite-dimensional, direct optimization intractable
2. Extremely heavy computation

Parametrized Trajectory Optimization

Problem 1

$$\min_{x, u} \quad \mathcal{J}[x, u]$$

$$\text{s.t.} \quad x(0) = x(t)$$

$$d(x(\tau)) \geq 0$$

$$\partial_{\tau} x(T) = 0$$

$$u(\tau) \in U$$

Problem 2

$$\min_k \quad J(t, k) \quad (\text{trajectory cost})$$

$$\text{s.t.} \quad x(k, 0) = x(t) \quad (\text{initial condition})$$

$$w(k) \geq 0 \quad (\text{safety})$$

$$k \in K \Leftrightarrow \rho(k) \geq 0 \quad (\text{parameter feasibility})$$

k : Trajectory parameter
 $x(k, \tau)$: Dynamically feasible trajectory with final stop condition
 J : Trajectory cost
 $w(\cdot)$: Possibly multi-dimensional safety indicator for trajectory
 K : Set of all feasible trajectory parameters

Parametrized Trajectory Optimization

Problem 2

$$\begin{array}{ll} \min. & J(t, k) \\ \text{s.t.} & x(k, 0) = x(t) \\ & w(k) \geq 0 \\ & \rho(k) \geq 0 \end{array}$$

Strengths

1. Online computation doable
2. Safety guaranteed through $w(\cdot)$

Limitations

1. Still heavy computation for high-frequency updates
2. Recursive feasibility not guaranteed, due to the initial condition

Note on the Update Interval τ_{plan}

It **denotes how promptly the system can respond** to possibly changing environmental conditions

→ It is favorable to keep τ_{plan} as short as possible

It **serves as a time budget** to complete searching for the next trajectory

→ τ_{plan} cannot be shortened beyond the computation power

What happens when we consider infinitesimal update interval (i.e., $\tau_{\text{plan}} \searrow 0$)?

Parametrized Trajectory Optimization in a Recursively Feasible Form

Problem 2

$$\begin{aligned} \min. \quad & J(t, k) \\ \text{s.t.} \quad & x(k, 0) = x(t) \\ & w(k) \geq 0 \\ & \rho(k) \geq 0 \end{aligned}$$

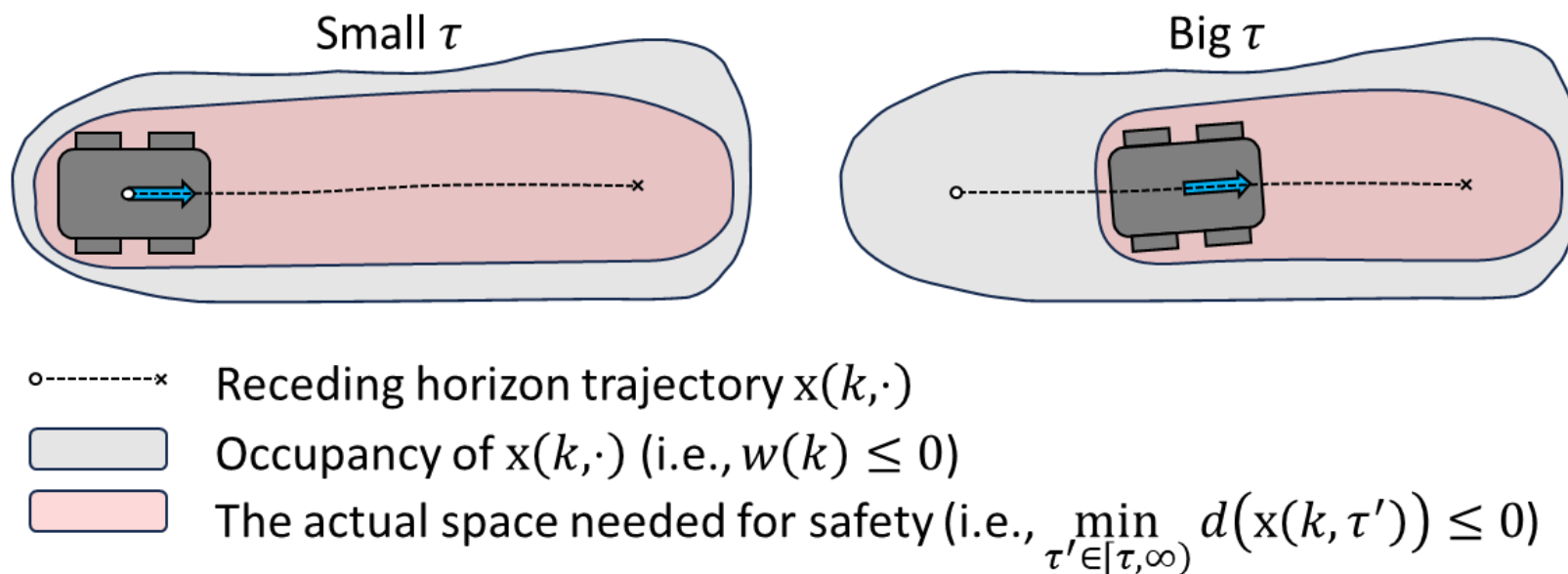
Problem 3

$$\begin{aligned} \min. \quad & J(t, k) + \lambda \tau && \text{(augmented cost)} \\ \text{s.t.} \quad & x(k, \tau) = x(t) && \text{(initial condition)} \\ & w(k) \geq 0 && \text{(safety)} \\ & \rho(k) \geq 0 && \text{(parameter feasibility)} \\ & \tau \geq 0 && \text{(starting time feasibility)} \end{aligned}$$

λ : A positive constant
 τ : The indicator at which time point on the parametrized trajectory the robot will start

Parametrized Trajectory Optimization in a Recursively Feasible Form

Why add auxiliary term $\lambda\tau$?



➔ We want to keep τ small to avoid excessive conservatism (waste of space)

Parametrized Trajectory Optimization in a Recursively Feasible Form

Problem 3

$$\min_{k, \tau} \quad J(t, k) + \lambda \tau$$

$$\text{s.t.} \quad x(k, \tau) = x(t)$$

$$w(k) \geq 0$$

$$\rho(k) \geq 0$$

$$\tau \geq 0$$

Strength

Recursively feasible

Limitation

Still heavy computation for high-frequency updates

Taking the Limit $\tau_{\text{plan}} \searrow 0$

With infinitesimal τ_{plan} , the trajectory parameters k and τ are controlled through \dot{k} and $\dot{\tau}$.

Problem 3

$$\begin{aligned} \min_{k, \tau} \quad & J(t, k) + \lambda \tau \\ \text{s.t.} \quad & x(k, \tau) = x(t) \\ & w(k) \geq 0 \\ & \rho(k) \geq 0 \\ & \tau \geq 0 \end{aligned}$$

Problem 4

$$\begin{aligned} \min_{u, \dot{k}, \dot{\tau}} \quad & \partial_k J(t, k) \cdot \dot{k} + \lambda \dot{\tau} + \frac{1}{2} \mu_k \|\dot{k}\|^2 + \frac{1}{2} \mu_\tau \dot{\tau}^2 \\ \text{s.t.} \quad & \partial_k x(k, \tau) \cdot \dot{k} + \partial_\tau x(k, \tau) = f(x(t)) + g(x(t)) \cdot u \\ & \partial_k w(k) \cdot \dot{k} + \alpha(w(k)) \geq 0 \\ & \partial_k \rho(k) \cdot \dot{k} + \gamma(\rho(k)) \geq 0 \\ & \dot{\tau} + \sigma(\tau) \geq 0 \\ & u \in U \end{aligned}$$

Taking the Limit $\tau_{\text{plan}} \searrow 0$

The cost term

$$\boxed{\min_{k, \tau} J(t, k) + \lambda \tau} \quad \Rightarrow \quad \boxed{\min_{u, \dot{k}, \dot{\tau}} \partial_k J(t, k) \cdot \dot{k} + \lambda \dot{\tau} + \frac{1}{2} \mu_k \|\dot{k}\|^2 + \frac{1}{2} \mu_\tau \dot{\tau}^2}$$

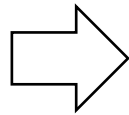
$$\frac{d}{dt} J(t, k) = \partial_t J(t, k) + \partial_k J(t, k) \cdot \dot{k} \quad : \quad \partial_t J \text{ term is omitted, because it does not depend on } u, \dot{k}, \dot{\tau}$$

$$\frac{1}{2} \mu_k \|\dot{k}\|^2 + \frac{1}{2} \mu_\tau \dot{\tau}^2 \quad : \quad \text{The quadratic regularization term is added for numerical stability}$$

Taking the Limit $\tau_{\text{plan}} \searrow 0$

Equality Constraint

$$\mathbf{x}(k, \tau) = x(t)$$



$$\partial_k \mathbf{x}(k, \tau) \cdot \dot{k} + \partial_\tau \mathbf{x}(k, \tau) = f(x(t)) + g(x(t)) \cdot u$$

Take the time derivative on both sides, and the equality is satisfied *indirectly*.

Note: The input u shows up here!

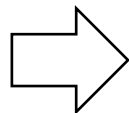
Taking the Limit $\tau_{\text{plan}} \searrow 0$

Inequality Constraint

$$w(k) \geq 0$$

$$\rho(k) \geq 0$$

$$\tau \geq 0$$



$$\partial_k w(k) \cdot \dot{k} + \alpha(w(k)) \geq 0$$

$$\partial_k \rho(k) \cdot \dot{k} + \gamma(\rho(k)) \geq 0$$

$$\dot{\tau} + \sigma(\tau) \geq 0$$

The nonnegativity constraints are replaced by *CBF-QP-style* constraints [1].

The functions α , γ , and σ are class K functions.

[1] Ames, Aaron D., et al. "Control barrier functions: Theory and applications." *2019 18th European control conference (ECC)*. IEEE, 2019.

The safety filter

Problem 4

$\min_{u, \dot{k}, \dot{t}}$	$\partial_k J(t, k) \cdot \dot{k} + \lambda \dot{t} + \frac{1}{2} \mu_k \ \dot{k}\ ^2 + \frac{1}{2} \mu_\tau \dot{t}^2$	(trajectory cost)
s.t.	$\partial_k x(k, \tau) \cdot \dot{k} + \partial_\tau x(k, \tau) = f(x(t)) + g(x(t)) \cdot u$	(initial condition)
	$\partial_k w(k) \cdot \dot{k} + \alpha(w(k)) \geq 0$	(safety)
	$\partial_k \rho(k) \cdot \dot{k} + \gamma(\rho(k)) \geq 0$	(parameter feasibility)
	$\dot{t} + \sigma(\tau) \geq 0$	(starting time feasibility)
	$u \in U$	(input feasibility)

Hardware Experiment

Dynamics (Turtlebot 3 [1])

$x \in X = SE(2) \times \mathbb{R}^2$
(Second-order unicycle dynamics)

$$\dot{x} = \begin{bmatrix} \dot{p}_x \\ \dot{p}_y \\ \dot{\theta} \\ \dot{v} \\ \dot{\omega} \end{bmatrix} = \begin{bmatrix} v \cos \theta \\ v \sin \theta \\ \omega \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ \alpha \end{bmatrix}$$

$$u = [a, \alpha]^T, \quad |a| \leq a_{\max}, |\alpha| \leq \alpha_{\max}$$

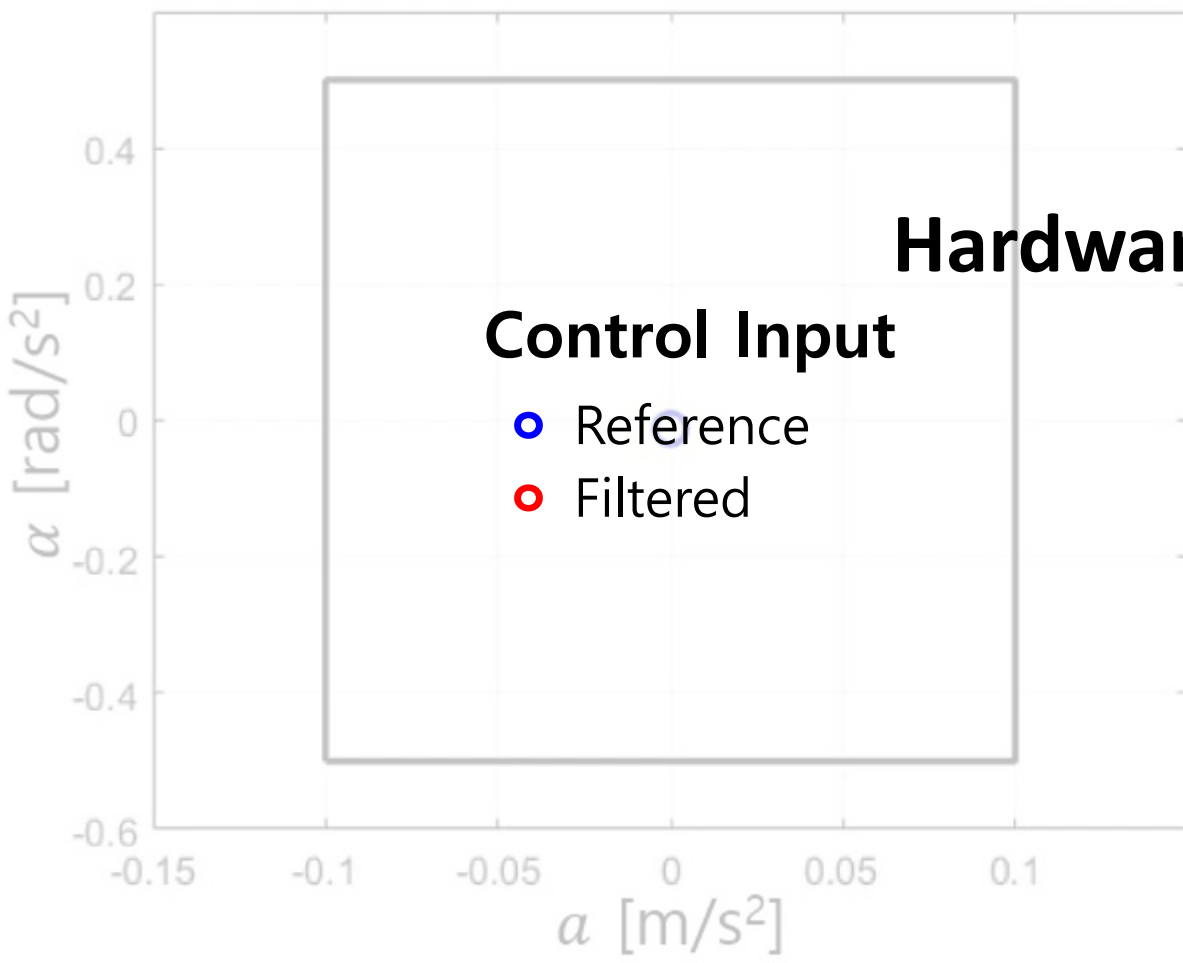
[1] Turtlebot 3,
<https://emanual.robotis.com/docs/en/platform/turtlebot3/overview/>

Safety Requirements

1. Collision avoidance w.r.t. LiDAR data points
2. Linear speed limit $|v| \leq v_{\max}$
3. Angular speed limit $|\omega| \leq \omega_{\max}$

Experiment Environments





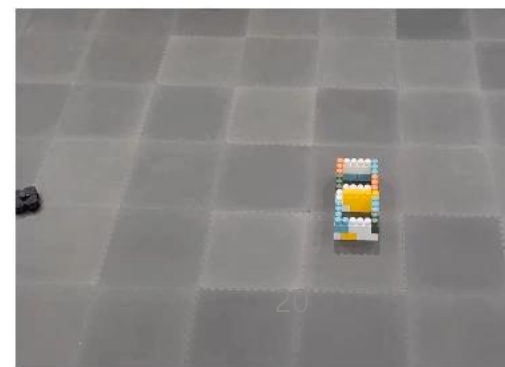
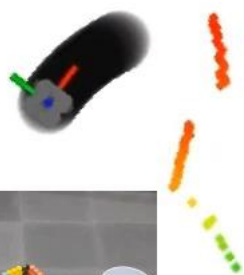
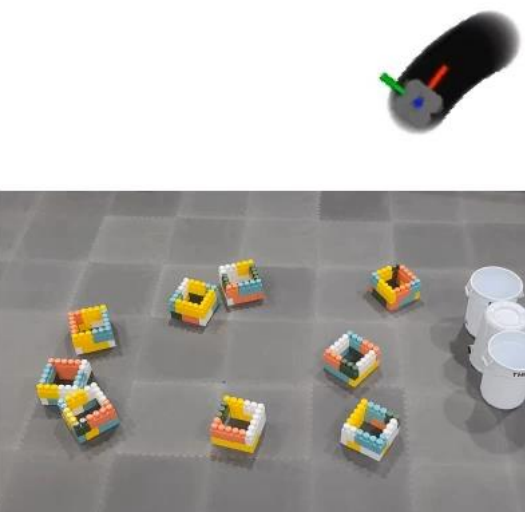
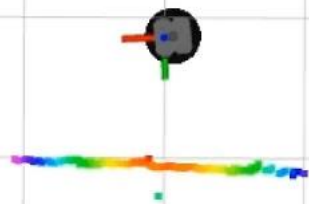
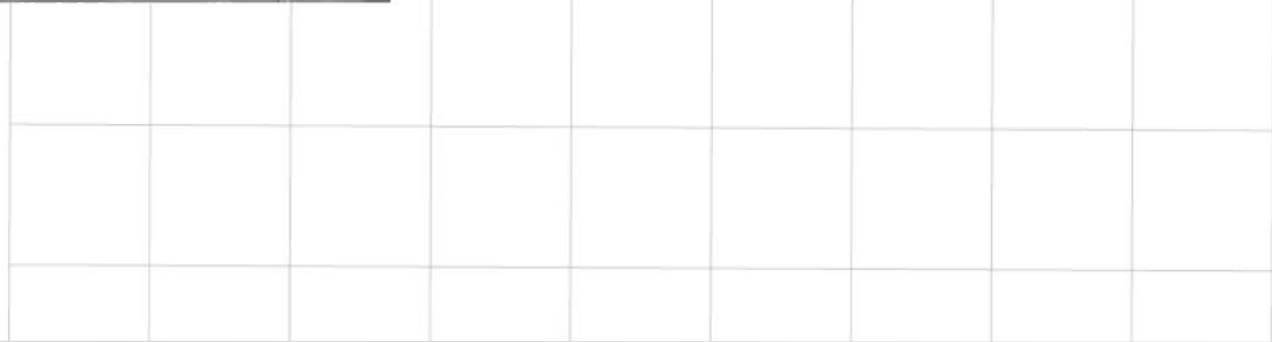
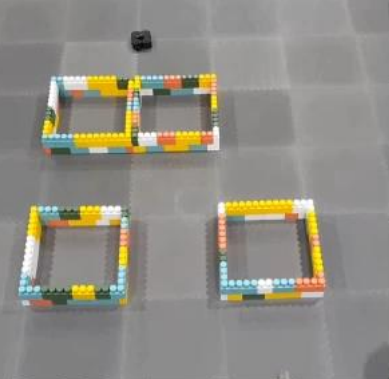
Hardware Experiment

Receding Horizon Trajectory

Colors close to red denote small w values.

Black tube denotes the currently chosen receding horizon trajectory.

Operator instructed to transmit aggressive reference inputs.



Summary

- In this work, we examined the behavior of safe receding horizon motion planning problems when the update interval becomes infinitesimal.
- With some modifications to the planning problem, infinitesimal update interval yields a safety filter based on quadratic programming (QP).
- The resulting safety filter is safe, recursively feasible, and can be solved in real-time.
- We demonstrated its performance through real-world experiments.

Thank you!



Contact

Inkyu Jang
Seoul National University, Seoul, Korea
janginkyu.larr@gmail.com

On-Site Presentation

Oral Presentation:

🕒 Thursday, May 16, 10:30 – 12:00

📍 Room 301, ThAT33.03 (Integrated Planning and Control Session)

Poster Session:

🕒 Thursday, May 16, 13:30 – 15:00