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Safe Receding Horizon Motion Planning with Infinitesimal Update Interval

Inkyu Jang, Sunwoo Hwang, Jeonghyun Byun, and H. Jin Kim
Department of Aerospace Engineering, Seoul National University, Seoul, Korea.

Summary

- We take **infinitesimal update interval** for a safety-aware receding horizon motion planning problem to get a **real-time safety filter**.
- The proposed algorithm is **safe**, **recursively feasible**, and runs in **real-time**.
- The proposed motion planning method was validated through **hardware experiments**.

Notes on the Replanning Interval

- It denotes **how promptly the system can respond** to possibly changing environmental conditions.
- ➙ It is favorable to keep the interval **as short as possible**.
- It serves as the **time budget to complete searching** for the next trajectory.
- ➙ It **cannot be shortened** beyond the robot's onboard computation capacity.

In this work, we consider the limit ***replanning interval* ↘ *0*.**

Trajectory parameter optimization

$$\begin{aligned} \min_{k}\quad & J(k) && \text{(trajectory cost)} \\ \text{s.t.}\quad & \mathrm{x}(k,0) = x && \text{(initial condition)} \\ & w(k) \geq 0 && \text{(safety)} \\ & \rho(k) \geq 0 && \text{(parameter feasibility)} \end{aligned}$$

- Feasibility not guaranteed, **needs an emergency brake maneuver** for safety.
- **Nonlinear, nonconvex** optimization, heavy computation.
- The update interval cannot be shortened beyond the robot's onboard computation power.

Trajectory parameter *change rate* optimization

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

- The trajectory cost is replaced with its time derivative, plus some auxiliary terms for numerical stability.
- Equality constraint satisfied indirectly using time derivatives.
- Inequality constraint satisfied using CBF-QP-style class-K functions.

✓ **Convex quadratic program** (QP), which can be solved in **real-time**.
✓ **Safety filter** that directly gives the input u.
✓ **Recursively feasible**, given the trajectories satisfy final stop conditions.

x, u	: State and input variables	$J(k)$	: Differentiable trajectory cost
k	: Trajectory parameter	$\mathrm{x}(k,\tau)$	: Parametrized trajectory with final stop condition
τ	: Indicator at which time point on the parametrized trajectory the robot will start	w, ρ	: Differentiable safety and feasibility constraints
		α, γ, σ	: Element-wise class-K functions

Experiment Result

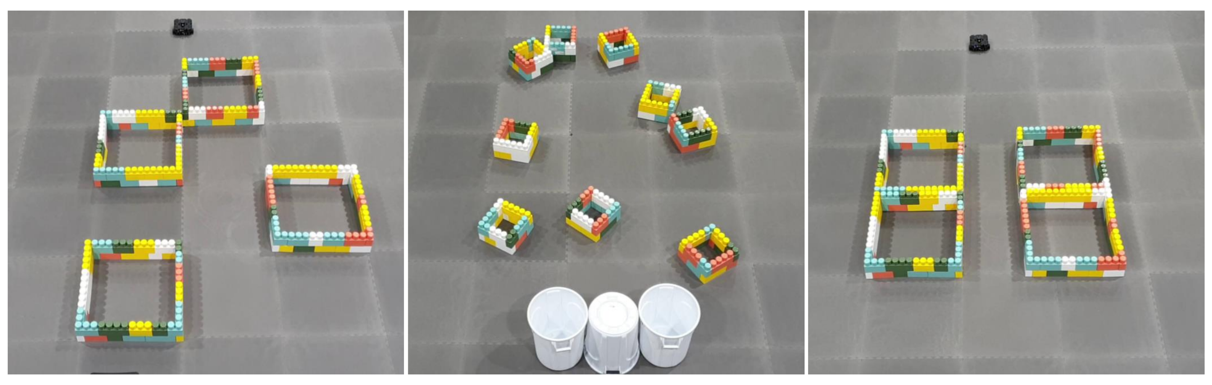
Experiment setting

- Diff-drive robot, controlled by linear / angular accelerations.
- 2D LiDAR sensor which scans obstacle distance from all directions. (up to 360 points)

Safety requirements

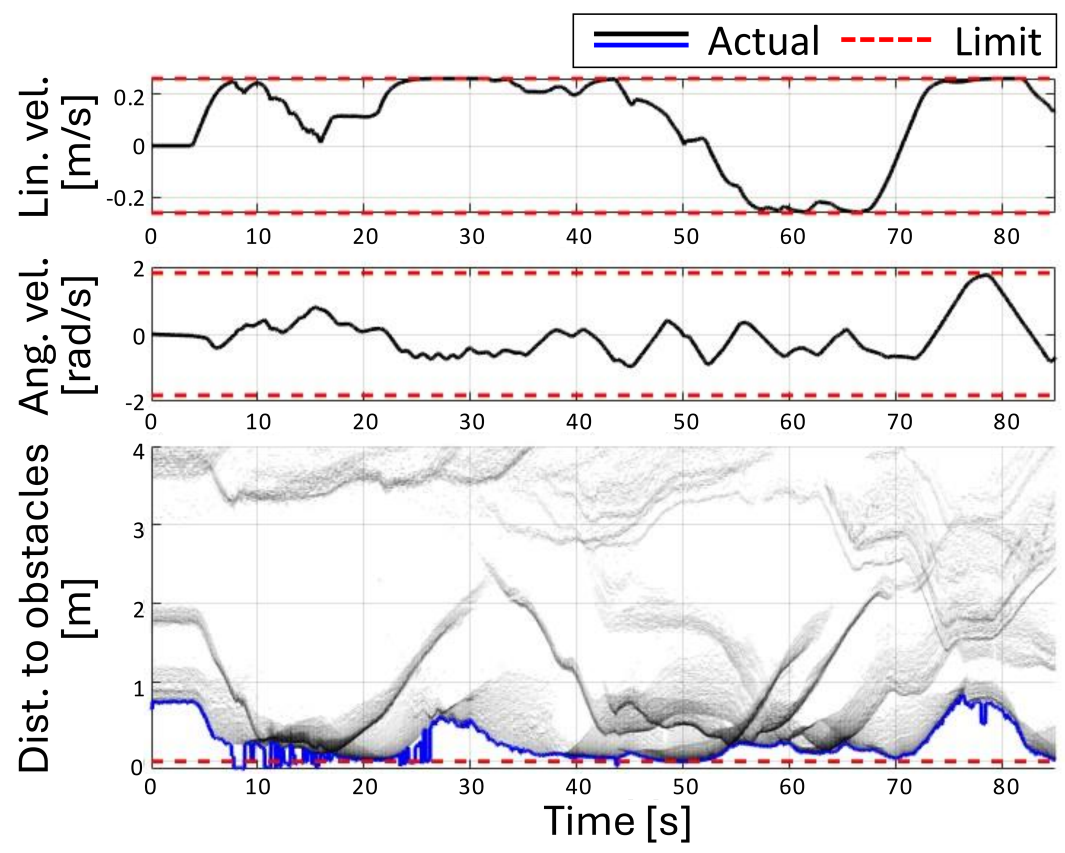
- Collision avoidance with all the LiDAR points.
- Linear / angular speed limits

Experiment environments



Exp. video @ YouTube

- The **trajectory cost was given in an aggressive way** that the robot is driven towards the obstacles.
- Even under aggressive trajectory cost, the robot was able to **avoid hundreds of LiDAR points simultaneously** using onboard computation only.



A snapshot from the experiment.