Model Predictive Control for the Benchmark Autonomous Robot Navigation (BARN) Challenge at IEEE ICRA 2024

Introduction

The BARN Challenge aims at creating a benchmark for navigation systems and pushing the boundaries of their performance in these challenging and highly constrained environments. Since 2022, the BARN Challenge has aimed to benchmark the various teams' algorithms against the classical control baselines in Robot Operating System (ROS), as well as learning-based approaches. [1], [2]

Abstract

We used Model Predictive Control (MPC), a form of optimization problem to optimize a short trajectory in the future time steps (receding horizon) with the lowest cost to achieve our objective function while satisfying the kinematics and obstacle constraints.

Problem Formulation

- MPC over horizon N as non-linear optimization

Optimization variables $[\boldsymbol{x}, \boldsymbol{u}] = [x, y, \theta, vr, vl, ar, al]$

$$\arg\min_{\boldsymbol{x},\boldsymbol{u}} \sum_{k=0}^{N-1} J_x(\boldsymbol{x}_k, \boldsymbol{u}_k)$$

$s.t.$

$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k, \boldsymbol{u}_k)$

$\boldsymbol{x}_k \in X, \boldsymbol{u}_k \in U$ (control limits)

$\boldsymbol{x}_0$= filtered odometry

$\boldsymbol{x}_k - \boldsymbol{x}_{obs_i}$ > safe distance $\forall i = 0,1 \ldots, m$ obstacles

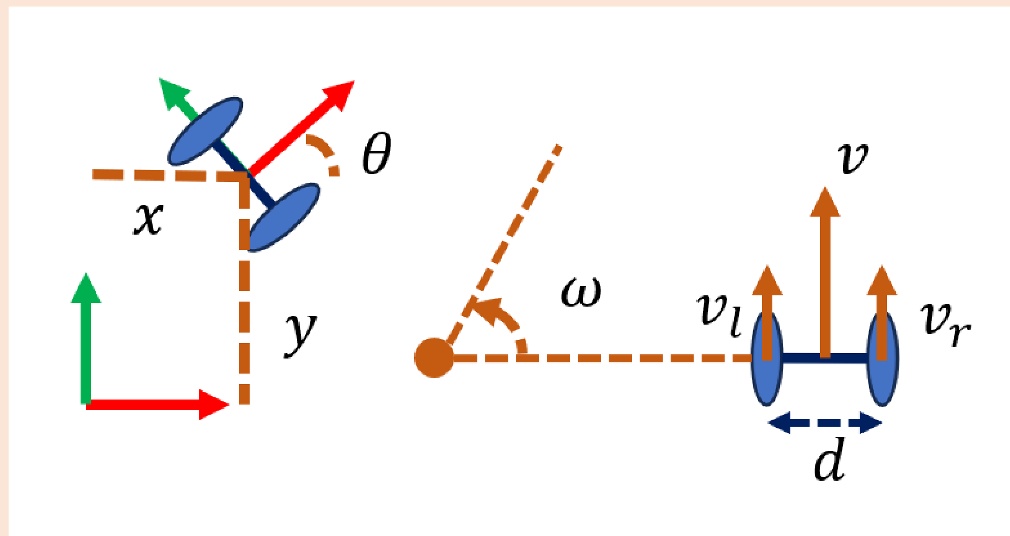
- Objective function each time step in the horizon

$$\begin{aligned} J_x = & \; w_v(|v_k| - v_{ref})^2 \\ & + w_x[(x_k - x_{ref_k})^2 + (y_k - y_{ref_k})^2] \\ & + w_a(a_k - a_{k+1})^2 \end{aligned}$$

- Matches reference velocity
- Follow the global plan reference
- Minimize acceleration

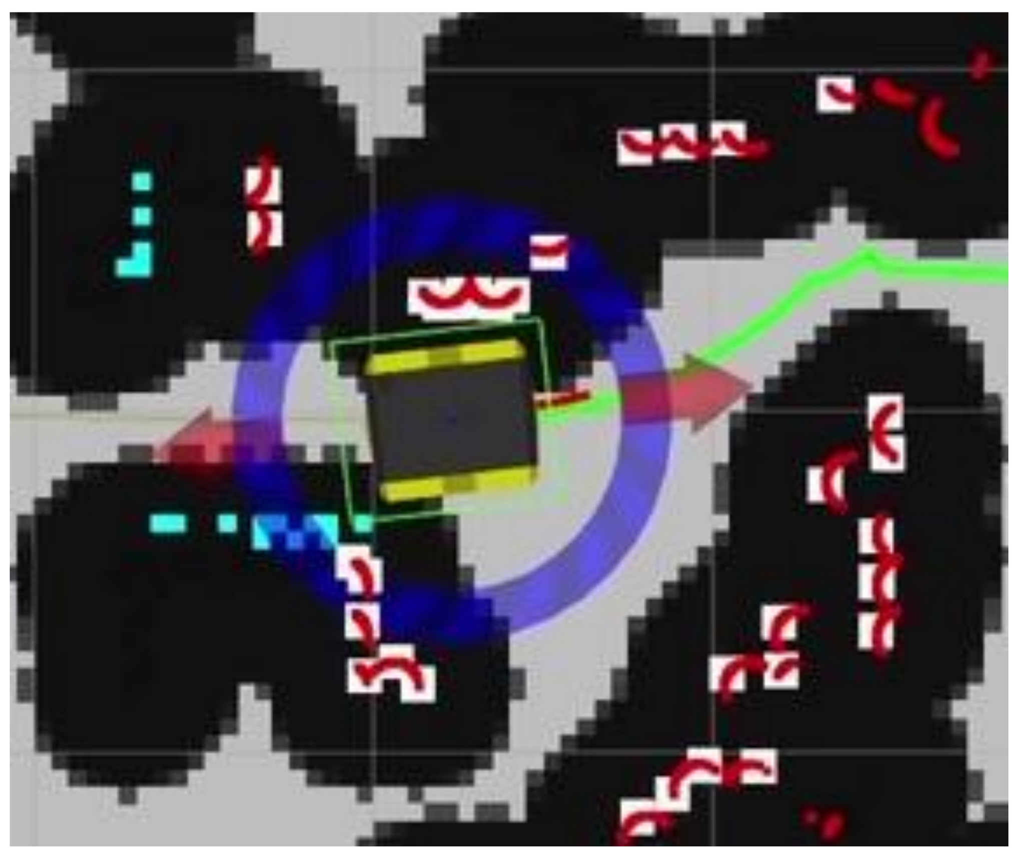
- Kinematic model $f(\boldsymbol{x}_k, \boldsymbol{u}_k)$ of differential wheel robot

$$\begin{aligned} v_r &= v - \omega \cdot \tfrac{d}{2} \; ; \; v_l = v + \omega \cdot \tfrac{d}{2} \\ x_{k+1} &= x_k + \cos\theta \cdot v_k \cdot \Delta t \\ y_{k+1} &= y_k + \sin\theta \cdot v_k \cdot \Delta t \\ \theta_{k+1} &= \theta_t + \omega \cdot \Delta t \\ v_{k+1} &= v_k + a \cdot \Delta t \end{aligned}$$



Implementation

- The optimizer used for the MPC Non-linear solver **CasADi** [3] is used to solve the MPC
- To increase the computational time, the number of obstacles used in the MPC calculation is obtained by **sampling the raw** Lidar scan at 15 datapoints spacing.
- *move_base* navigation package from ROS for our global planner. From the Lidar scan, **global** and **local costmap** are continuously updated.
- The robot forward Lidar scan has the field-of-view of $[-135°, 135°]$. To cover the blind spot of the lidar, **obstacles at the rear** are detected using **local costmap**. Only the outer cells of an occupied block in the occupancy map are used.
- By detecting the **distance to the nearest obstacle** to switch the mode between "safe", "obstacle nearby", "careful" modes
- Different modes have **different MPC parameters** such as the control limit space U, the weights of the objective terms w_v, w_x, w_a. The parameters will also be fine-tuned in the physical runs



Visualization of the collision objects:

- Globally planned trajectory: green line
- MPC horizon: red line from the robot
- Raw Lidar scan: red dots
- Obstacles from sampled Lidar: white
- Obstacles in the blind spot: cyan
- Local costmap: black patches

Future works

We aim to explore the various extensions of MPC to tackle moving obstacles as proposed by the organizers in the upcoming BARN 2025. Sampling-based Model Predictive Path Integral (MPPI) control and the use of Reinforcement Learning with differentiable MPC will be explored. [4],[5]

MLDA@EEE Team Github Code

BARN Challenge 2024 Information

[1] X. Xiao *et al.*, 'Autonomous Ground Navigation in Highly Constrained Spaces: Lessons learned from The BARN Challenge at ICRA 2022'

[2] X. Xiao *et al.*, 'Autonomous Ground Navigation in Highly Constrained Spaces: Lessons learned from The 2nd BARN Challenge at ICRA 2023'

[3] J. A. E. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and M. Diehl, 'CasADi: a software framework for nonlinear optimization and optimal control'

[4] G. Williams, A. Aldrich, and E. Theodorou, 'Model Predictive Path Integral Control using Covariance Variable Importance Sampling'

[5] A. Romero, Y. Song, and D. Scaramuzza, 'Actor-Critic Model Predictive Control'