



MECHENG 599 Final Project Presentation

Robot Motion Planning Using Model Predictive Control and Control Barrier Function

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Methodology (CBF)

- Control Barrier Function (CBF)
- Define safe set \mathcal{C} using the control barrier function $h(x)$.
- Link control input to safety constraints by using the Lie derivatives.
- Works for control affine systems.

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

where α is an extended class K infinity function.

$$\sup_{u \in U} [L_f h(x) + L_g h(x)u] \geq -\alpha(h(x)).$$

For safety-critical control, we consider a set \mathcal{C} defined as the superlevel set of a continuously differentiable function $h : \mathcal{X} \subset \mathbb{R}^n \rightarrow \mathbb{R}$:

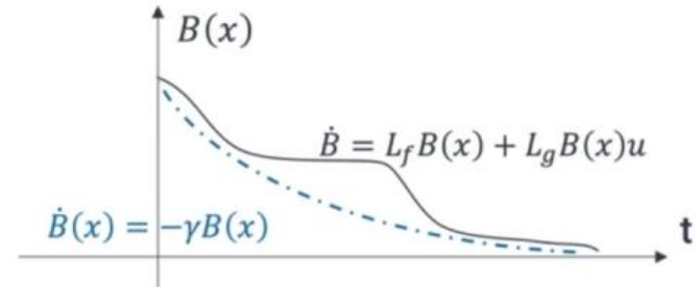
$$\mathcal{C} = \{x \in \mathcal{X} \subset \mathbb{R}^n : h(x) \geq 0\}. \quad (4)$$

Throughout this paper, we refer to \mathcal{C} as a safe set. The function h is a control barrier function (CBF) [1] if $\frac{\partial h}{\partial x} \neq 0$ for all $x \in \partial \mathcal{C}$ and there exists an extended class \mathcal{K}_∞ function γ such that for the control system (1), h satisfies

$$\exists u \text{ s.t. } \dot{h}(x, u) \geq -\gamma(h(x)), \gamma \in \mathcal{K}_\infty. \quad (5)$$

This condition can be extended to the discrete-time domain which is shown as follows

$$\Delta h(x_k, u_k) \geq -\gamma h(x_k), 0 < \gamma \leq 1, \quad (6)$$



Problem Formulation

Dynamics and Cost Function

- Nonlinear dynamics

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v \cos \theta \\ v \sin \theta \\ \omega \end{bmatrix} = \begin{bmatrix} \cos \theta & 0 \\ \sin \theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}$$

- Quadratic stage cost

$$J^*(x_k) = \min \sum_{t=k}^{k+N-1} [(x_{t|k} - x_{goal})^T Q (x_{t|k} - x_{goal}) + u_{t|k}^T R u_{t|k}] + (x_{k+N|k} - x_{goal})^T P (x_{k+N|k} - x_{goal})$$

Constraints

- Nonlinear state constraint must be satisfied

$$\sqrt{(x_{t|k}[0] - x_{obs})^2 + (x_{t|k}[1] - x_{obs})^2} - r_{obs} - r_{rob} \geq 0$$

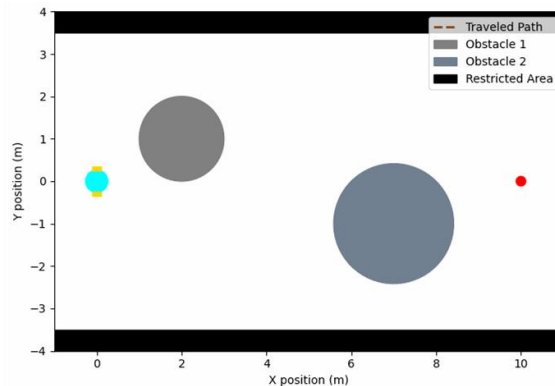
- Adjustable tolerance of error achieved by MPC-CBF

$$h(x_{t|k}) = \sqrt{(x_{t|k}[0] - x_{obs})^2 + (x_{t|k}[1] - x_{obs})^2} - r_{obs} - r_{rob}$$

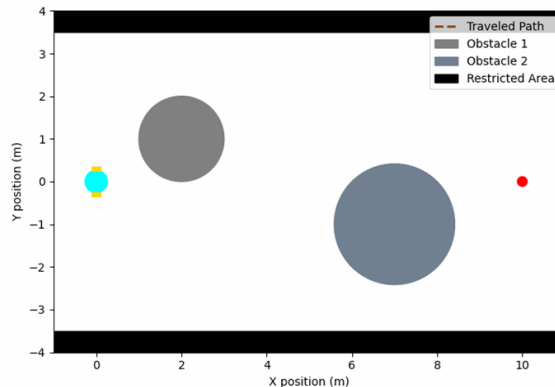
$$\Delta h(x_{t|k}) \geq -\gamma h(x_{t|k})$$

Implementation for Two Obstacles

- Validation of Both Algorithms
 - In a feedback control loop manner.
 - Based on shooting methods (ipopt). (N = 25, dt = 0.02sec, $\gamma = 0.8$)
 - Same Euclidean distance function (control barrier function) and safe distance are used for MPC-CBF.
- Implementation Details
 - Two static obstacles, $x_0 = [0,0,0]$, $x_goal = [10,0,0]$.
 - Implemented in Python 3.10, use CasADi as optimization solver. Tested on Ubuntu OS.
 - Code is available at github ([motion-planning-mpc](https://github.com/motion-planning-mpc)).



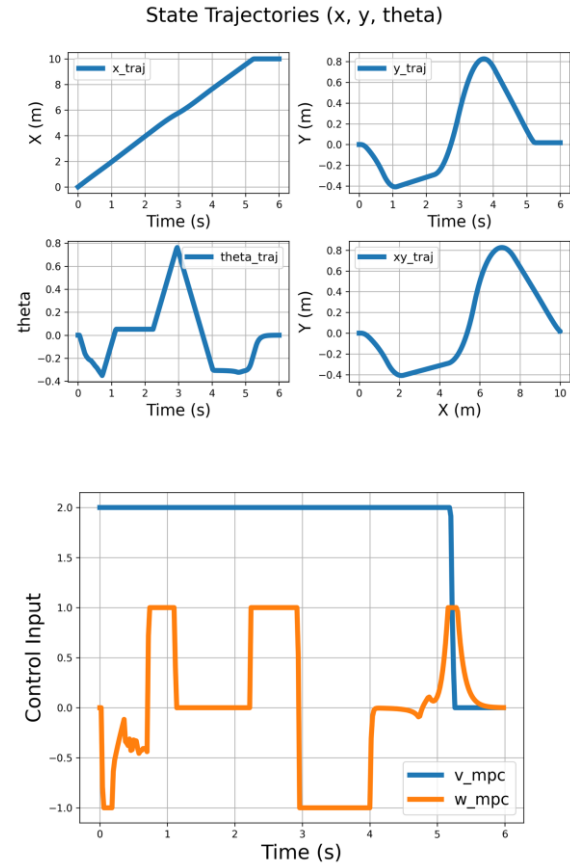
MPC - DC



MPC - CBF

Example (MPC-DC)

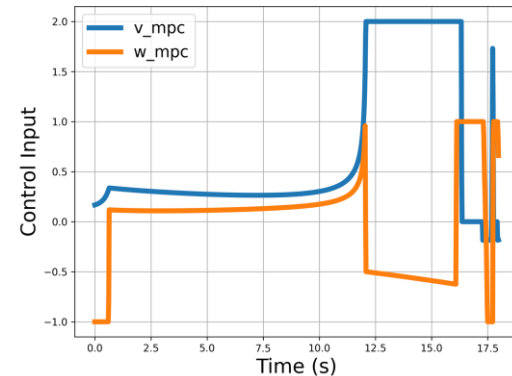
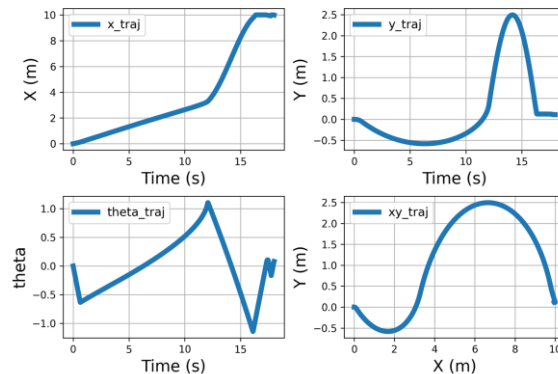
- MPC-DC
- $Q = \text{np.diag}([100,100,10])$, $R = \text{np.diag}([0.1,0.1])$, $H = 30 * Q$
- $\text{state_min} = [0, -3.5, -3.14]$, $\text{state_max} = [10, 3.5, 3.14]$
- $v_min = -2$, $v_max = 2$, $w_min = -1$, $w_max = 1$
- Euclidean distance is used to directly enforce the safety constraints.
- Take around 6 seconds to reach the goal.
- Tends to be more aggressive and resulting trajectory is relatively closer to the obstacles.



Example (MPC-CBF)

- MPC-CBF
- $Q = \text{np.diag}([100,100,10])$, $R = \text{np.diag}([0.1,0.1])$, $H = 30*Q$
- $\text{state_min} = [0, -3.5, -3.14]$, $\text{state_max} = [10,3.5,3.14]$
- $v_{\text{min}} = -2$, $v_{\text{max}} = 2$, $w_{\text{min}} = -1$, $w_{\text{max}} = 1$
- Euclidean distance is used as the control barrier function to enforce the safety constraints.
- Take around 18 seconds to reach the goal ($\gamma = 0.8$).
- Tends to be more conservative. Resulting smaller control input at the beginning and relatively further from the obstacles.

State Trajectories (x, y, theta)





Thank you!

Any questions ?