

# H0E76A: Model Predictive Control

## — Homework assignments —

Matties Roofthooft

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The assignments below are homework assignments related to the exercise sessions that are organized throughout the semester. The assignments count for 7/20 of the total marks on this course, and are graded based on the following deliverables

### Deliverables

- A report containing the answers to the questions and any numerical values or plots that are asked in the assignments. You can write your solutions directly in this `tex`-file. Make sure to fill in your name above.
- A single zip-archive containing all the code to generate the plots included in your report. Make sure to add a `readme` file describing which script(s) to run (and the working directory from which to do so) to reproduce your results. It is recommended that you have at least one separate script per session.

Most of the assignments build upon the solutions obtained from the sessions. Solutions for the exercise sessions will be made available on Toledo shortly after each session. Before submitting your final report, make sure that you verify your solutions from the sessions if you reuse them here.

## SESSION 1 LQR AND DYNAMIC PROGRAMMING

### Assignment 1.1

Compare the finite horizon controllers  $K_N$  you computed during the session with the infinite horizon LQR controller.

- Implement the infinite horizon LQR controller  $u = K_\infty x$  (with initial state  $x_0 = (10, 10)$ ).<sup>a</sup> Write the obtained value for  $K_\infty$ . **Remark.** Report your answers with at least four decimal places.
- Plot the simulated closed-loop trajectory of this controller with the trajectories of the finite-horizon controller. What happens as you increase  $N$ ?
- Explain this observation based on the recursion relation used earlier and the discrete-time algebraic Riccati equation (DARE).

<sup>a</sup>Use `solve_discrete_are` from `scipy.linalg`.

$$K_\infty = \begin{bmatrix} 1.28645067 & 2.31256493 \end{bmatrix} \quad (1)$$

Figure 1 shows that increasing the prediction horizon  $N$ , makes the trajectory converge towards the infinite horizon trajectory (drawn in black).

At each time step in MPC  $K_N$  is used to calculate the input, the sequence  $K_N$  converges towards  $K_\infty$  so therefore it logically the closed-loop trajectories will converge as well.

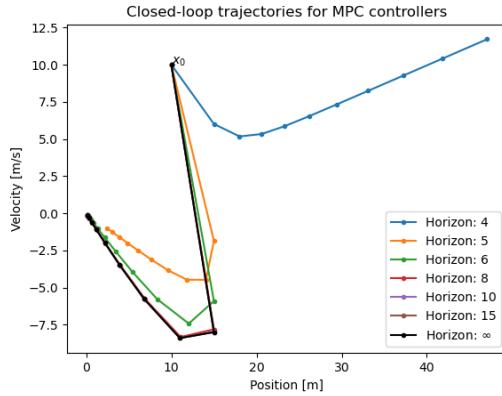


Figure 1: Closed loop trajectories of MPC controllers

### Assignment 1.2

Numerically compare the quality of the finite-horizon LQR controller to the infinite horizon controller. For the same fixed  $x_0$  as before and for  $N$  ranging from 1 to  $10^{\text{a}}$ :

- Plot  $V_N = x_0^\top P_N x_0$  versus  $N$
- Plot  $V_\infty = x_0^\top P_\infty x_0$  on the same axis (this is just a horizontal line).
- Approximate the infinite horizon cost for the finite-horizon controller using a long state and input trajectory:

$$\hat{V}_N = \sum_{k=0}^{\infty} (x_k^\top Q x_k + x_k^\top K^\top R K x_k) \approx \sum_{k=0}^{100} (x_k^\top Q x_k + x_k^\top K^\top R K x_k).$$

and add a plot of  $\hat{V}_N$  vs.  $N$  on the same figure.

- Describe what you observe: Do you observe convergence? Which quantities converge to which and in what direction? Briefly explain these observations.

<sup>a</sup>**Hint:** manually set the  $y$ -limit of the plot to  $[0, 2000]$ . Otherwise, the costs of unstable controllers will dominate the figure.

Figure 2 shows that the approximation of the sum bounds from above while the other estimation bounds from below. Both quantities converge towards the infinite horizon cost which is  $V_\infty = 1006.40329$ .

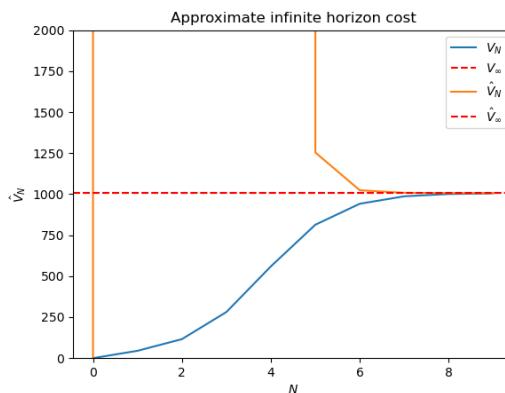


Figure 2: Approximation of infinite horizon cost

## SESSION 2 LINEAR MPC AND CONVEX OPTIMIZATION

**See the session 2 sheet for the set-up.**

The goal of this assignment is to look more closely at what goes wrong in the final exercise of the session, and to gain some intuition about ways to fix it. In essence, the problem that occurs is a symptom of the myopic nature of MPC, that is, it can only take into account what happens in the very near future. To rectify this, we have to provide it with information about the long-term behavior of the system under the applied controls.

**Remark.** The assignments in this session should be performed in discrete time.

### Assignment 2.1

Consider the vehicle at a fixed position and velocity  $(p_0, v_0)$ . Suppose we apply the maximum brake, i.e.,  $u_t = u_{\min}$  for  $t = 0, \dots, T$ . Write an expression of  $T$  as a function of  $v_0$ , such the vehicle can come to standstill in  $T$  steps.

Since the change in velocity each timestep is  $T_s u_{\min}$  the minimal timestep to stationarity is:

$$T = \left\lceil \frac{-v_0}{T_s u_{\min}} \right\rceil \quad (2)$$

### Assignment 2.2

For a given  $T$ , compute the total braking distance, i.e., the distance travelled during the deceleration:  $p_T - p_0$ .

$$p_{k+1} = p_k + T_s v_k \quad (3)$$

$$\Delta p_{k+1} = T_s v_k \quad (4)$$

We calculate distance travelled as  $d = p_T - p_0$  as the sum of the position increments during the timesteps until a stationary velocity is reached:

$$d = \sum_{k=0}^T \Delta p_{k+1} = \sum_{k=0}^T T_s v_k = T_s \sum_{k=0}^T (v_0 + k T_s u_{\min}), \quad (5)$$

$$d = T_s v_0 T + T_s^2 u_{\min} \sum_{k=0}^T k = T v_0 T_s + u_{\min} T_s^2 \left( \frac{T+1}{2} \right). \quad (6)$$

### Assignment 2.3

Use the result of the previous exercises to formulate a constraint on a state  $x = (p, v)$  that will guarantee that there will always exist a control input that will keep future states in the set  $S = \{x \mid p \leq p_{\max}\}$ .

The breaking distance given initial velocity  $v_0$  should be lower than the distance to the wall to prevent a crash.

$$d(v_0) \leq p_{\max} - p_0 \quad (7)$$

### Assignment 2.4

Write a function that takes the horizon  $N$  as an input and that for all initial states  $[-10, 0] \leq x_0 \leq [1, 25]$  (sampled in a grid), checks whether your MPC controller is feasible at this initial state. Set  $u_{\min} = -5$ . Leave the other settings at the same values as the ones in the session.

For all  $N \in \{2, 5, 10\}$ , make a plot showing the set of states that are feasible (this can be a simple scatter plot), and draw the boundary of the constraint you derived in Assignment 3.

**Remark.** You only have to check the initial feasibility of the MPC problem, not recursive feasibility.

## SESSION 3 MPC THEORY: TERMINAL INGREDIENTS

During the sessions, we have computed polyhedral invariant sets to use for the terminal ingredients in our MPC controller. Alternatively, we can use ellipsoidal sets. The goal of this assignment is to compute such sets in a few different ways and compare them with the invariant sets we've computed during the session.

### Assignment 3.1

Let  $K, P$  denote the optimal, infinite-horizon LQR gain and the solution of the discrete-time Riccati equation, respectively. As shown in the lectures, any level set

$$\text{lev}_\alpha V_\infty = \{x \mid V_\infty(x) = x^\top Px \leq \alpha\}$$

is a positive invariant set for the system under the policy  $u = Kx$ . However, not all states  $x \in \text{lev}_\alpha V_\infty$  necessarily satisfy the state and input constraints.

Write down the expression for the largest value of  $\alpha$  such that

$$\begin{cases} x \in X \\ Kx \in U \end{cases} \quad \forall x \in \text{lev}_\alpha V_\infty,$$

where  $X = \{x \in \mathbb{R}^n \mid H_x x \leq h_x\}$  and  $U = \{u \in \mathbb{R}^m \mid H_u u \leq h_u\}$  are the (polyhedral) sets of feasible states and inputs, respectively.

**Hint.** The notion of a support function might be of use.

The section of both sets remains a polyhedral set.

$$X_K = \{x \in \mathbb{R}^n \mid H_x x \leq h_x; \quad H_u Kx \leq h_u\} \quad (8)$$

$$X_K = \{x \in \mathbb{R}^n \mid Hx \leq h\} \quad (9)$$

With  $H = \begin{bmatrix} H_x \\ H_u Kx \end{bmatrix}$  and  $g = \begin{bmatrix} h_x \\ h_u \end{bmatrix}$ . The problem is a set inclusion problem by utilizing the support function for ellipsoids  $\sigma_{\epsilon(\alpha)}(v)$  we can derive an expression.

$$\alpha^* = \min \left\{ \frac{g_i^2}{h_i^\top P^{-1} h_i} \mid i = 1, \dots, d \right\}. \quad (10)$$

With  $h_i$  every row in linear matrix  $H$  and  $g_i$  values in  $g$  of the combined set  $X_K$ .

### Assignment 3.2

Plot the ellipsoidal set (You can use the given `Ellipsoid` class we provide, together with the function `visualization.plot_ellipsoid` for this) together with the polyhedral set  $\{x \in \mathbb{R}^n \mid x \in X, Kx \in U\}$ . Is the obtained ellipsoidal set a valid terminal set for the MPC problem?

No the obtained ellipsoidal isn't a valid terminal set yet since it doesn't consider recursive feasibility but only one step.

Alternatively, we can more directly encode the requirements for the invariant set and solve a convex optimization problem to find it.

Let  $E = \{x \in \mathbb{R}^n \mid x^\top Px \leq 1\}$  denote our candidate set, where now  $P$  is the positive definite shape matrix. Let  $K \in \mathbb{R}^{m \times n}$  furthermore be a candidate state feedback gain. Our goal is to determine  $P$  and  $K$  to obtain the "largest" possible positive invariant set for  $x_{t+1} = Ax_t + Bu_t$  under the policy  $u_t = Kx_t$ .

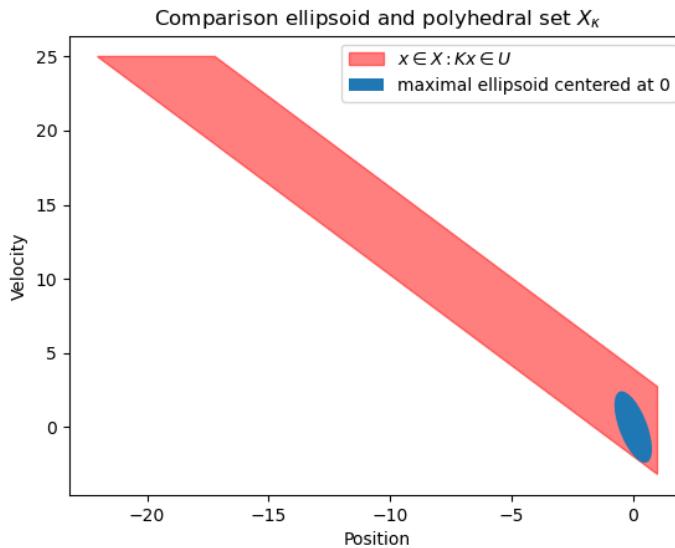


Figure 3: Ellipsoid set assignment 2

### Assignment 3.3

Formulate a constraint on  $P$  and  $K$  that guarantees that

$$x^T P x \leq 1 \implies x^T (A + BK)^T P (A + BK) x \leq 1 \quad \forall x \in \mathbb{R}$$

We can write this implication in terms of a matrix inequality since it holds  $\forall x \in \mathbb{R}^\times$

$$(A + BK)^T P (A + BK) \leq P \tag{11}$$

And thus:

$$P - (A + BK)^T P (A + BK) \geq 0 \quad (\text{PSD}) \tag{12}$$

### Assignment 3.4

Show that the previous constraint can be written as the linear matrix inequality (LMI)

$$\begin{bmatrix} S & (AS + BF)^T \\ AS + BF & S \end{bmatrix} \geq 0$$

**Hint.** Doing this involves the following steps.

1. multiply the inequality you obtained from the left and the right by  $P^{-1}$
2. Introduce the change of variables
  - $S = P^{-1}$
  - $F = KS$
3. Apply the [Schur complement lemma](#).

Multiplying inequality from left and right by  $P^{-1}$

$$P^{-1} - P^{-1}(A + BK)^T P (A + BK) P^{-1} \geq 0 \tag{13}$$

Introduce the change of variables:

$$S - S(A + BK)^T P (A + BK) S \geq 0 \tag{14}$$

$$S - S(A + BK)^\top P(AS + BF) \geq 0 \quad (15)$$

$$S - ((A + BK)S^\top)^\top P(AS + BF) \geq 0 \quad (16)$$

Since  $S = S^\top$

$$S - (AS + BF)^\top P(AS + BF) \geq 0 \quad (17)$$

Applying Schur complement lemma, we arrive at the LMI:

$$M = \begin{bmatrix} S & (AS + BF)^\top \\ AS + BF & S \end{bmatrix} \geq 0 \quad (18)$$

### Assignment 3.5

Recall from the lectures that

$$E \subseteq \{x \in \mathbb{R}^n \mid Hx \leq g\} \iff \sigma_E(H_i) \leq g_i, \forall i = 1, \dots, p,$$

where  $\sigma_E$  denotes the support function of the ellipsoid  $E$  and  $H_i$  the  $i$ th row of  $H$ . Use this fact to show that all states in our candidate invariant set  $E$  satisfy the state constraints if and only if

$$H_{x,i}^\top SH_{x,i} \leq h_{x,i}^2, \quad i = 1, \dots, m_x,$$

with  $H_{x,i}$  the  $i$ th row of  $H_x$  and  $h_{x,i}$  the  $i$ th coordinate of  $h_x$  (see Assignment 1) and  $S = P^{-1}$  as before.

**Hint.** An expression for the support function of an Ellipsoid is given in the slides. (It's also a useful exercise to derive it yourself from the definition, but this is not part of the assignment)

*Proof.* Let the candidate invariant set be the ellipsoid

$$E = \{x \in \mathbb{R}^n \mid x^\top Px \leq 1\}, \quad P > 0,$$

and denote  $S = P^{-1}$ . The state constraint set is the polyhedron

$$X = \{x \in \mathbb{R}^n \mid H_x x \leq h_x\},$$

where  $H_{x,i}$  is the  $i$ th row of  $H_x$  and  $h_{x,i}$  the  $i$ th component of  $h_x$ . From the lecture result, we have

$$E \subseteq X \iff \sigma_E(H_{x,i}) \leq h_{x,i}, \quad i = 1, \dots, m_x,$$

where  $\sigma_E$  denotes the support function of  $E$ .

The support function of the ellipsoid  $E = \{x \mid x^\top Px \leq 1\}$  is

$$\sigma_E(v) = \|P^{-1/2}v\|_2 = \sqrt{v^\top P^{-1}v} = \sqrt{v^\top Sv}.$$

Applying this with  $v = H_{x,i}^\top$  gives

$$\sigma_E(H_{x,i}) = \sqrt{H_{x,i}^\top SH_{x,i}}.$$

Thus the inclusion condition becomes

$$\sqrt{H_{x,i}^\top SH_{x,i}} \leq h_{x,i}, \quad i = 1, \dots, m_x.$$

Since both sides are nonnegative, squaring yields an equivalent constraint:

$$H_{x,i}^\top SH_{x,i} \leq h_{x,i}^2, \quad i = 1, \dots, m_x.$$

This proves the required equivalence.  $\square$

### Assignment 3.6

Similarly, show that  $u = Kx$  satisfies the input constraints for all  $x \in E$ , if and only if

$$h_{u,i}^2 - H_{u,i}^\top FPF^\top H_{u,i} \geq 0, \quad \forall i = 1, \dots, m_u.$$

Use the Schur complement lemma to write this constraint as an LMI in  $F$  and  $S$ .

*Proof.* Consider the control law

$$u = Kx, \quad x \in E = \{x \in \mathbb{R}^n \mid x^\top P x \leq 1\}, \quad P > 0,$$

and let  $S = P^{-1}$  and  $F = KS$ . The input constraint set is

$$U = \{u \in \mathbb{R}^{n_u} \mid H_u u \leq h_u\}, \quad H_{u,i} \text{ is the } i\text{th row of } H_u, \quad h_{u,i} \text{ its } i\text{th entry.}$$

We require that all inputs satisfy the constraints:

$$H_{u,i} u = H_{u,i} Kx \leq h_{u,i}, \quad \forall x \in E.$$

The maximum value along each direction  $H_{u,i}$  is given by the support function of the ellipsoid:

$$\max_{x \in E} H_{u,i} Kx = \sqrt{(H_{u,i} KS)P(H_{u,i} KS)^\top} \leq h_{u,i}.$$

Squaring both sides and transposing scalar gives the equivalent quadratic inequality:

$$H_{u,i}^\top FPF^\top H_{u,i} \leq h_{u,i}^2, \quad i = 1, \dots, m_u.$$

To express this as an LMI in  $F$  and  $S$ , we apply the Schur complement lemma. For a scalar  $h_{u,i}^2$  and symmetric positive definite  $S$ , the inequality

$$h_{u,i}^2 - H_{u,i}^\top FPF^\top H_{u,i} \geq 0$$

is equivalent to

$$\begin{bmatrix} h_{u,i}^2 & H_{u,i}^\top F \\ F^\top H_{u,i} & S \end{bmatrix} \succeq 0.$$

Thus, the input constraints for all  $x \in E$  can be enforced by the following LMI for all  $i = 1, \dots, m_u$ :

$$\begin{bmatrix} h_{u,i}^2 & H_{u,i}^\top F \\ F^\top H_{u,i} & S \end{bmatrix} \succeq 0, \quad S > 0,$$

with decision variables  $F$  and  $S$ . □

### Assignment 3.7

Since the volume of the ellipsoid is proportional to  $\log \det P^{-1}$ , we can now compute the largest (in terms of volume) invariant set by maximizing  $\log \det S$  subject to the constraints in Assignments 4 to 6.

Implement this problem using cvxpy and plot the resulting ellipsoid (using the given utility code as before) together with the new polyhedral set  $\{x \in \mathbb{R}^n \mid x \in X, FS^{-1}x \in U\}$ .

## SESSION 4 NONLINEAR MPC

We revisit the autonomous parking task but in a slightly more challenging situation. Suppose that there is a vehicle in the adjacent parking spot.



Figure 4: Autonomous parking task with obstacle

Naturally, the vehicle can in no circumstance be allowed to collide with the stationary obstacle. The goal of this assignment is to modify the MPC formulation from the exercise session to include collision avoidance constraints.

One way of formulating the collision avoidance constraint is to cover each vehicle with a single row of circles as illustrated in fig. 5. Here,  $d$  denotes the horizontal distance between the center of each circle and its intersection with the rectangle,  $r$  denotes the radius of the circles,  $l$  is the length of the vehicle and  $w$  is the width of the vehicle.

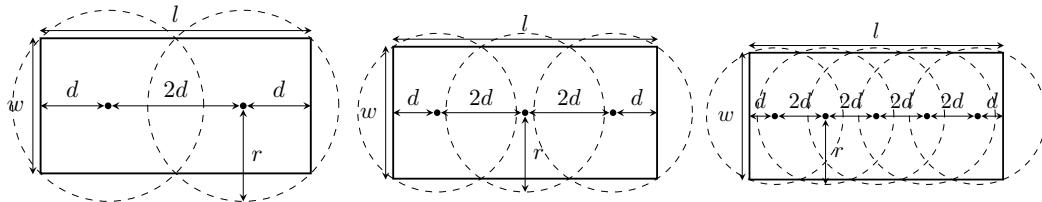


Figure 5: Vehicle covering with 2, 3 and 5 circles respectively.

### Assignment 4.1

Let  $n_c$  denote the number of circles used to cover the vehicle. Based on the figure, derive an expression for the **centers**  $c_i \in \mathbb{R}^2$ ,  $i = 0, \dots, n_c - 1$  and the radius  $r \in \mathbb{R}_+$  of the circles as a function of  $l$ ,  $w$  and  $n_c$ . Assume that the origin lies in the center of the vehicle (i.e., the rectangle).

Consider a vehicle of  $l = 4$  and  $w = 2$ , and take  $n_c = 3$ . To verify your results, use `Circle` and `Rectangle` from `matplotlib.patches` to plot it for this example.

**Hint:** This task involves only basic geometry.

We first calculate the horizontal distance  $d$ .

$$l = 2n_c d \quad (19)$$

$$d = \frac{l}{2n_c} \quad (20)$$

The centers of the circles then become

$$\mathbf{c}_i = \begin{pmatrix} -l/2 + d(1 + 2i) \\ 0 \end{pmatrix} \quad \text{for } i = 0, \dots, n_c - 1 \quad (21)$$

Using pythagoren theorem we obtain:

$$r = \sqrt{\left(\frac{w}{2}\right)^2 + d^2} \quad (22)$$

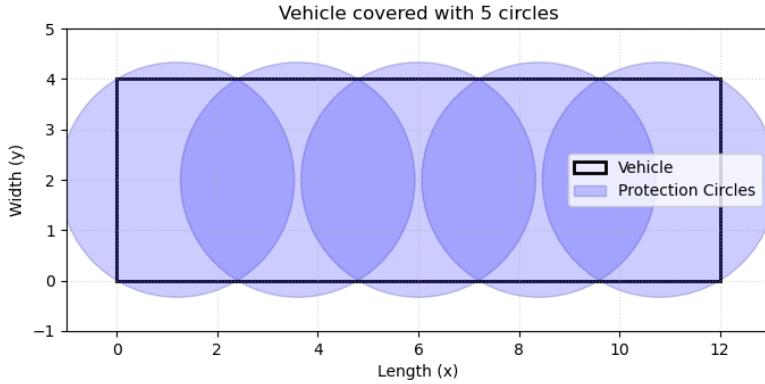


Figure 6: Vehicle covered with 5 circles.

#### Assignment 4.2

Given that the current vehicle state is  $x = (p_x, p_y, \psi, v)$ , express the center  $\bar{c}$  of a circle in global coordinates, given that its local coordinates (aligned with the vehicle, as in the previous exercise) are given by  $c$ .

For a vehicle of length  $l = 4$ , width  $w = 2$ , with its center at  $p = (2, 2)$  and heading angle  $\psi = \frac{\pi}{4}$ , use your result (combined with the previous assignment) to plot the covering circles on this vehicle for  $n_c = 3$ .

**Hint:** You can write your result in terms of the rotation matrix  $R(\psi)$  defined by the heading angle  $\psi$ . There is no need to work out everything into individual components.

The center of a circle in global coordinates,  $\bar{c}$ , is given by:

$$\bar{c} = p + R(\psi)c \quad (23)$$

where  $p = \begin{pmatrix} p_x \\ p_y \end{pmatrix}$  is the vehicle's global position, and  $R(\psi)$  is the 2D rotation matrix:

$$R(\psi) = \begin{pmatrix} \cos(\psi) & -\sin(\psi) \\ \sin(\psi) & \cos(\psi) \end{pmatrix} \quad (24)$$

#### Assignment 4.3

Given that the controlled vehicle is covered by circles with centers  $\bar{c}_i$   $i = 0, \dots, n_c - 1$  (expressed in global coordinates) and radius  $r$ , and similarly the obstacle vehicle is covered by circles with centers  $\bar{c}'_j$  and radius  $r'$ . Formulate a set of *smooth* constraints

$$g(\bar{c}_i, \bar{c}_j) \leq 0$$

on  $\bar{c}_i$  and  $\bar{c}'_j$ ,  $i, j \in 0, \dots, n_c - 1$ . which – when satisfied – guarantees that the intersection between the two vehicle rectangles is empty.

Additionally, show whether this set of constraints is convex or not.

**Hint:** Squaring can get rid of isolated points of non-smoothness.

The vehicle will not crash if none of its circles overlap with the ones of the obstacle vehicle. Mathematically we can formulate this as follows:

$$\|\bar{c}_i - \bar{c}'_j\|_2 \geq r + r' \quad i, j \in 0, \dots, n_c - 1 \quad (25)$$

Squaring gives:

$$g(\bar{c}_i, \bar{c}'_j) = (r + r')^2 - \|\bar{c}_i - \bar{c}'_j\|_2^2 \leq 0 \quad i, j \in 0, \dots, n_c - 1 \quad (26)$$

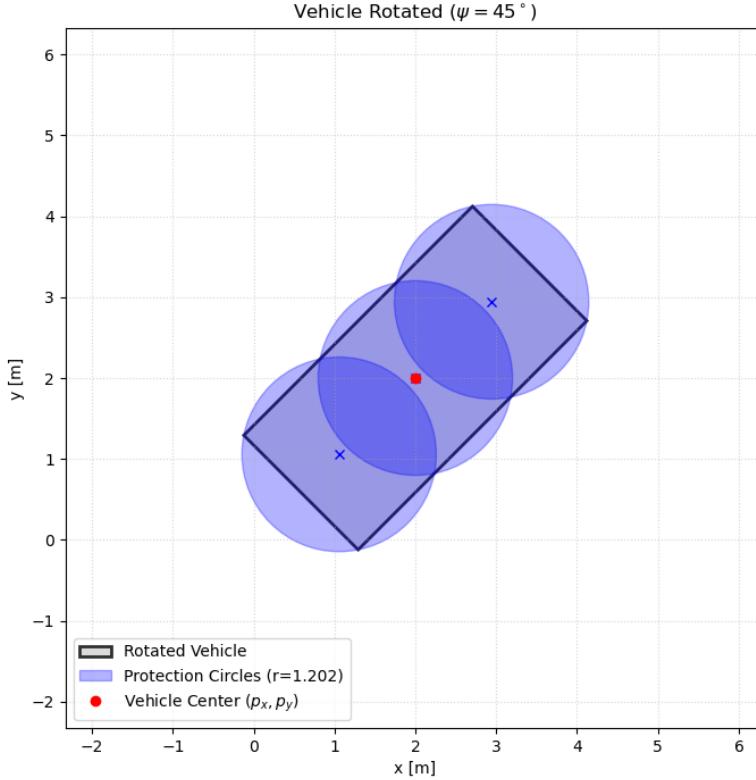


Figure 7: Rotated vehicle.

The set is defined as the exterior of a disk. The set is nonconvex, since the set is not closed under convex combination.

#### Assignment 4.4

Implement the constraint you derived into your MPC controller formulation. That is, enforce that

$$g(\bar{c}_i(x_t), \bar{c}'_j) \leq 0, \quad \forall i, j \in \{0, \dots, n_c - 1\}, \forall t \in 1, \dots, N.$$

where  $\bar{c}_i(x_t)$  is the center (in global coordinates) of the  $i$ 'th circle on the controlled vehicle expressed as a function of its state at time step  $t$ ,  $\bar{c}'_j$  is the center (in global coordinates) of the  $j$ 'th circle on the obstacle vehicle and  $g$  is the function you derived in the previous exercise. Using the following settings, Simulate your MPC controller for 100 time steps in closed loop. You can use the MPC model dynamics for the simulation (no model mismatch):

$x_0$	$(0.3, -0.1, 0, 0)$
$N$	30
$T_s$	0.08
Obstacle pos.	$(0.25, 0)$ (heading 0)

Use `plot_state_trajectory` from `given.plotting` to visualize the state trajectory, including the obstacle (simply pass the function a list with only one state, since it is stationary). Is the trajectory collision-free? Does the car converge to a point that is entirely within the parking spot <sup>a</sup>?

Optionally, you can also generate an animation using `given.animation`, but this is not a deliverable. (see the solution of the exercise session for some example code. You can use

the argument `obstacle_positions` to visualize the obstacle.)

<sup>a</sup>defined in the code as a rectangle with dimensions `PARK_DIMS=(0.25, 0.12)`

### Assignment 4.5

Play around with the tuning of  $Q$ ,  $R$ ,  $N$  or other controller parameters (perhaps even  $n_c$ , feel free to get creative) to obtain a controller which can (without collision) park the vehicle such that it is fully enclosed in the parking spot. Briefly describe your reasoning while tuning, report the final parameters that you changed from the provided defaults and illustrate the final result with a plot of the trajectory.

Without tuning the controller parameters the car wasn't able to park fully enclosed in the parking spot. The vertical positioning of the car was off. To punish this more we increased the terminal cost of the y-component. It is important to increase the terminal cost of the x-component of the controller as well. Otherwise the car decides to park before the other car instead of behind it. The tuned controller parameters are the following:

$$Q = \text{diag}(1, 3, 0.4, 0.001) \quad (27)$$

$$Q_f = 5 \cdot Q + \text{diag}(250, 3 \cdot 10^3, 100, 10) \quad (28)$$

$$R = \text{diag}(1.0, 10^{-4}) \quad (29)$$

$$N = 30 \quad n_c = 3 \quad (30)$$

The trajectory of the parking maneuver is shown in Figure 8.

### Assignment 4.6

Measure your solver time. A quick and easy way to do this is to invoke `perf_counter` from the `time` module before and after your solver call, within the `__call__` method of your controller. In general, if a solver returns its own time, it's usually better to use this instead of measuring the time yourself, in order not to account for overhead in the modeling language. For this assignment, however, you can just use your own timing. You can log the solver time by creating a log class

```
from dataclasses import dataclass
from rcracers.simulator.core import BaseControllerLog, list_field
@dataclass
class ControllerLog(BaseControllerLog):
    solver_time: list = list_field()
```

and passing it as log to the `simulate` method:

```
from rcracers.simulator import simulate
log = ControllerLog() # Initialize an empty log
x = simulate(..., log=log) # Simulate
print(log.solver_time) # Now the solver times have been written
```

Within your solver call, you can then log it like this:

```
from time import perf_counter
def __call__(self, y, log) -> np.ndarray:
    start = perf_counter()
    solution = self.solve(y)
    stop = perf_counter()
    u = self.reshape_input(solution)
    log("solver_time", stop-start)
    return u[0]
```

Visualize the resulting solver time. Is your MPC controller real-time capable? How did you verify this? If it isn't, finetune your controller to obtain one that is real-time capable and still successfully parks into the parking area. Report your final tuning (any value that you changed from the provided defaults) and show the timings and state trajectory of the final controller.

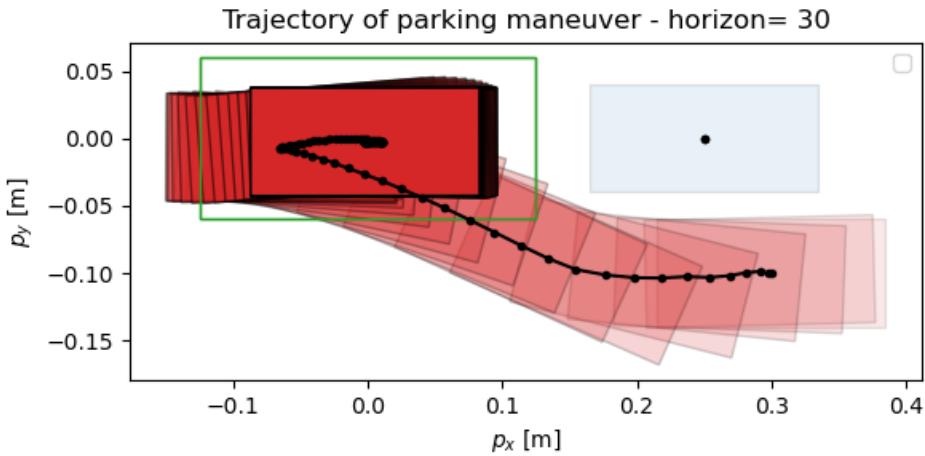


Figure 8: Trajectory of parking maneuver

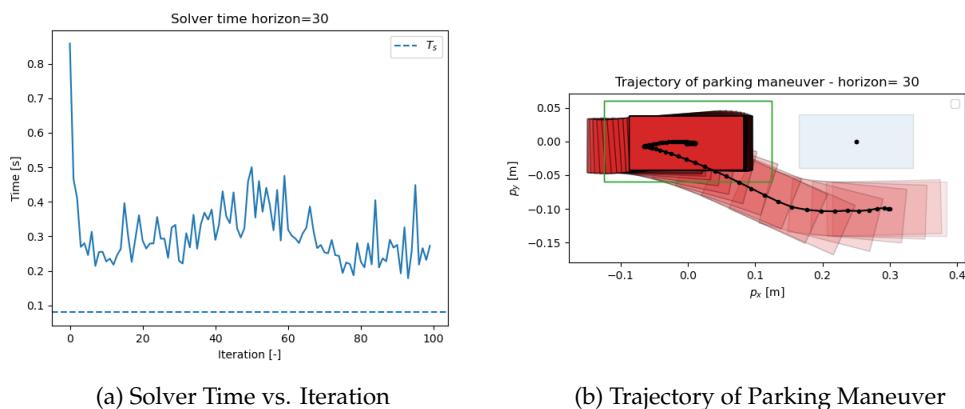
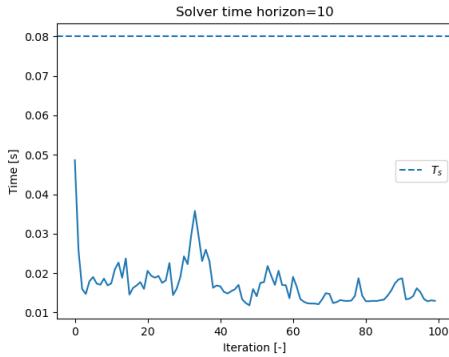
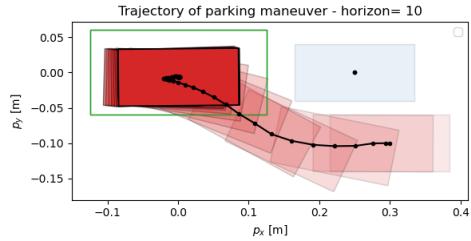


Figure 9: Analysis of the parking maneuver with a horizon of  $N = 30$ . (a) Solver time per iteration. (b) Optimal vehicle trajectory.

Decreasing the prediction horizon resolves this issue. The MPC controller is feasible in real-time and is still able to park fully enclosed in the parking spot.



(a) Solver Time vs. Iteration



(b) Trajectory of Parking Maneuver

Figure 10: Analysis of the parking maneuver with a horizon of  $N = 10$ . (a) Solver time per iteration. (b) Optimal vehicle trajectory.

## SESSION 5 STATE ESTIMATION

The goal of this assignment is to further improve the MHE you developed in the associated exercise session. Specifically right now we only use the data provided within the horizon of the MHE optimization problem. Instead we would like to use past information as well, which we can do using priors.

### Assignment 5.1

We will implement a prior update. Since you already have the EKF iterates available, these can be used to add the *filtering prior update* as described in the slides:

$$\Gamma_{T-N}(z) = \frac{1}{2} \|z - \hat{x}_{T-N}\|_{(P_{T-N}^-)^{-1}} .$$

1. Note that the prior can already be passed to the provided `build_mhe` method:

```
fs, hs = get_system_equations(symbolic=True, noise=True)
loss = lambda w, v: w.T @ w + v.T @ v
solver = build_mhe(loss, f, h, 10, lbx=0.0, ubx=10.0, use_prior=True)

# you can solve the optimization problem as follows:
x, w = solver(P=np.eye(3), x0=np.zeros(3), y=np.zeros((10, 1)))
```

2. Alter your MHE class to use EKF internally. Initialize your EKF with the same values as during the exercise session. Keep in mind that you should produce  $\hat{x}_{T-N}$  using only measurements available before time step  $T - N$  and the same is true for  $P_{T-N}^-$ . How many past estimates  $\hat{x}_{T-N}$  and  $P_{T-N}^-$  should you store internally?
3. Verify, both for longer horizons ( $N = 25$ ) and shorted ( $N = 10$ ) ones that the filtering prior improves the behavior. Plot the estimated trajectories.
4. Does clipping the state estimates in the EKF aid the performance? Plot the result.

## SESSION 6 OPTIMIZATION

The goal of this assignment is to get familiar with methods for solving nonlinear MPC problems. Due to the nonlinearity of the dynamics, the OCP will be nonconvex and therefore, the methods from during the session will no longer be applicable.

The given code (`problem.py`), defines a few test problems and some data-structures that you can use to build your nonlinear solver. Have a brief look at this file, and read the comments therein to get acquainted with the provided ingredients. You will not be required to make any changes in this file.

A scaffolding for your own implementation is given in `template.py`. Throughout this assignment, you will fill in the blanks in this file, to finally obtain a solver for nonlinear optimal control problems.

### 6.1 Building the solver

We will build a Newton-Lagrange method for multiple shooting (i.e., simultaneous approach).

#### Assignment 6.1

Implement the Newton-Lagrange method (SQP) by completing the auxiliary functions used by `newton_lagrange` in the provided template. Particularly, the functions `lqr_factor_step`, `lqr_solve_step` and `update_iterate` need to be implemented. The former two functions should implement Algorithms 2 and 3 in the related lecture slides. In `update_iterate`, you can for now assume that the option `linesearch` is `False`.

Run the function `test_linear_system` and present the output. This function calls your SQP solver on a problem involving a linear system. Is the output what you expect? Why?

<Paste the output of the program here.>

### 6.2 Nonlinear test case

Now that you have tested your implementation on a linear system, we will move on to a nonlinear example.

Consider the continuous time dynamics

$$\begin{aligned}\dot{x}_1 &= 10(x_2 - x_1) \\ \dot{x}_2 &= x_1(u - x_3) - x_2. \\ \dot{x}_3 &= x_1x_2 - 3x_3\end{aligned}$$

which are discretized using the forward Euler scheme. This system is already implemented in `problem.py` under `ToyDynamics`. The problem that you can pass to your SQP solver is described by `ToyProblem`.

#### Assignment 6.2

Construct an initial guess of all zeros for the inputs, the states and the costates. However, for the states, keep in mind that the first entry must be the provided initial state, i.e., `problem.x0`. Run your solver with this initial state. Give the cost and constraint violation of the last iterate (printed automatically using the `Logger` class in `given.problem`). Use the provided `animate_iterates` function to animate the states and inputs over the iterates and to export a figure of the final solution. Add this plot in your report. Does your solution look plausible?

### Assignment 6.3

Simulate the system and use this as an initial guess.

You may find that the solver now fails to converge. Why do you think this happens?

**Hint.** Plot the state trajectory you used as an initial guess. Does it look like the solution you just obtained in the previous exercise? Why is this important?

## 6.3 Adding Line Search

### Assignment 6.4

Implement line search and the experiment of Assignment 3. Use

$$\phi(z) = J_N(z) + c \|h(z)\|_1$$

as a merit function (see `problem.build_cost_and_constraint`).

**Hint.** Make sure to set `linesearch=True` in the `cfg` argument of the solver, which is expected to be an instance of `NewtonLagrangeCfg`.

Now does it converge? Give the output of the method at the final iterate and use this to argue that your method indeed converged to something meaningful. Do you notice any difference with respect to the solution in Assignment 2? How do you explain this?

### Assignment 6.5

Run it on the parking example. Use initial condition all zeros (except  $x_0 = \text{problem.x0}$ ).

Does it converge? Why?

**Hint.** During the Newton-Lagrange iterations, check whether the Hessian of the QP cost is positive definite.

## 6.4 Adding Regularization

### Assignment 6.6

Implement regularization in the function `regularize`. This method should check whether the QP is convex. If not, it should add  $\lambda I$  to the Hessian  $\bar{Q}$  of the cost function, where  $\lambda$  is (approximately) the smallest constant such that  $\bar{Q} + \lambda I$  is positive definite. To do so set  $\lambda = 10^{-6}$  and double it every time the result is not positive definite.

With this modification, run the method again on the Parking problem. Does it converge?

**Hint.** Make sure to set `cfg.regularize` to True!