

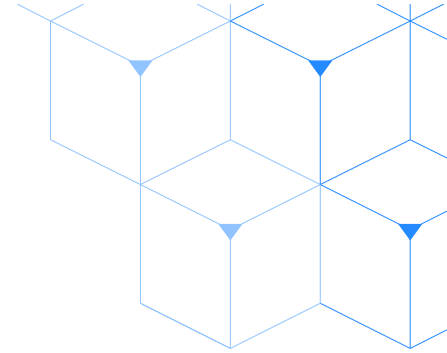
Time Optimal Robot Navigation with Navigation Functions

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Navigation with Artificial Potential Fields



Path Planning

- ▶ Find a path between the start and target.
- ▶ Path must be safe – avoid obstacle collision.

Control

- ▶ Tracking the planned path.
- ▶ Control inputs must comply with the system constraints.

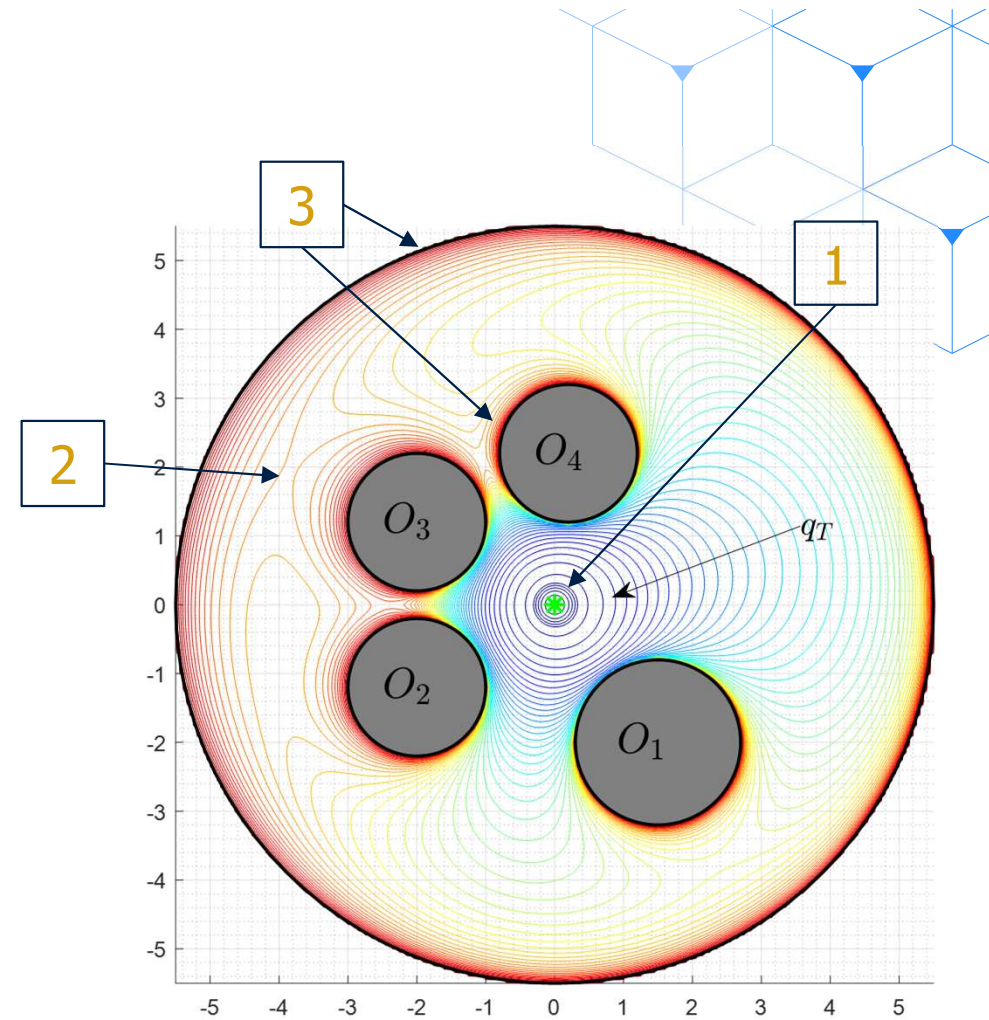
Artificial Potential Fields

- ▶ Encompasses complete information about the obstacle-free space.
- ▶ Used to form a feedback controller.

- ▶ Robot navigation using artificial potential fields unifies the path planning problem with the feedback controller design.

Navigation Functions

- ▶ Let q_T be a target point in the obstacle free space \mathcal{W} . A \mathcal{C}^2 -smooth function $\varphi : \mathcal{W} \rightarrow [0,1]$ *navigation function* if
 - φ polar with unique minimum at target
 - All other critical points of φ are non-degenerate saddle points
 - φ admissible with uniform maximal value on boundary of \mathcal{W}



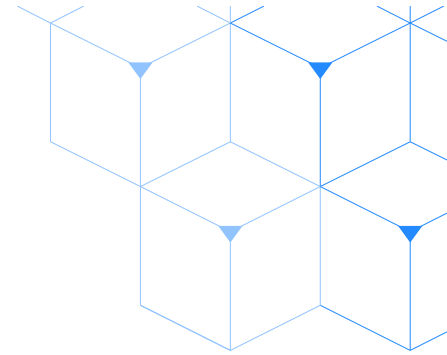
Navigation Function Construction

- ▶ Using *tuning parameter* k the navigation function is

$$\varphi(q) = \frac{\gamma(q)}{(\gamma^k(q) + \beta(q))^{\frac{1}{k}}}$$

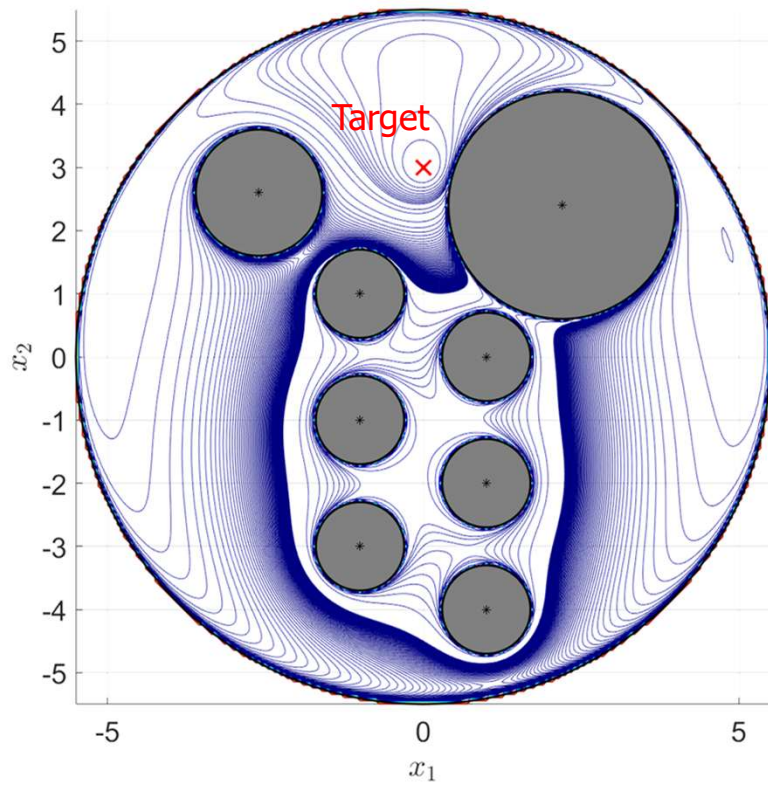
Distance to Target

Obstacle Product
 $\beta(q) = \prod \beta_i(q)$

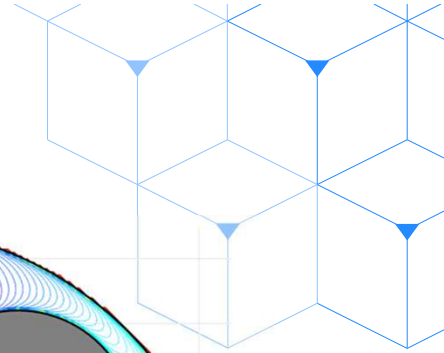
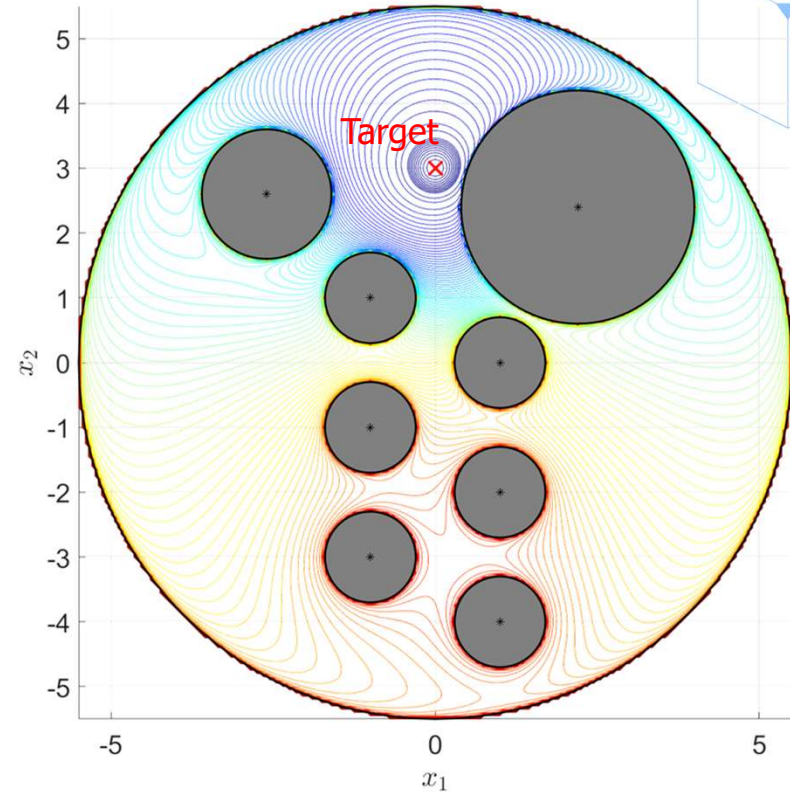


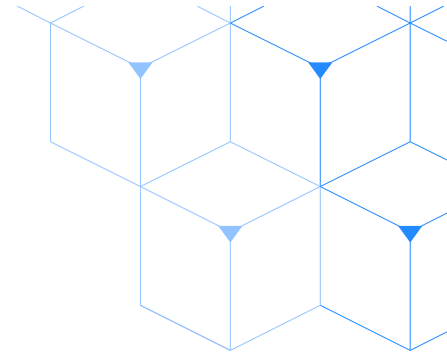
Tuned Navigation Functions

$k = 2$



$k = 8$





Navigation Function Classical Control Law

- ▶ Classical control law : $u(t) = -\nabla\varphi(x) - C\dot{x}$ $C > 0$
- ▶ Asymptotic convergence to target using total mechanical energy as a Lyapunov function $V(x, \dot{x})$:

$$V(x, \dot{x}) = \varphi(x) + \frac{1}{2}m\|\dot{x}\|^2$$

$$\frac{\partial V}{\partial t} = \nabla\varphi \cdot \dot{x} + m \cdot (\dot{x} \cdot \ddot{x}) = -\dot{x}^T C \dot{x} \leq 0$$

- ▶ LaSalle's invariance principle: robot trajectories converge to target from almost all initial points in \mathcal{W} (zero speed at target)



Bounded Control Input Problem

- ▶ Ensure **bounded control inputs** using *robot navigation functions*
- ▶ Preserve the navigation function **collision safety** and **arrival to target**
- ▶ Problem Statement :

Construct feedback control law that guides robot system $m\ddot{x}(t) = u(t)$ to the target while avoiding collision with known obstacles under **control input bound** $\|u\| \leq F_{max}$.

Bounded Control Law

- ▶ Bounded control navigation function law

$$u(t) = -h \cdot \nabla \varphi - F_T \cdot (\widehat{\nabla \varphi} \cdot \hat{v}) \widehat{\nabla \varphi} - F_N \cdot (\widehat{\nabla \varphi}^\perp \cdot \hat{v}) \widehat{\nabla \varphi}^\perp$$

- ▶ Based on a conservative rectangular bound $(2F_T)^2 + F_N \leq F_{max}$.
- ▶ \hat{v} denotes robot velocity direction - $\hat{v} = \frac{\dot{x}}{||\dot{x}||}$
- ▶ $h > 0$ is a scaling factor – used to enforce control input bound.
- ▶ Using the modified Lyapunov function

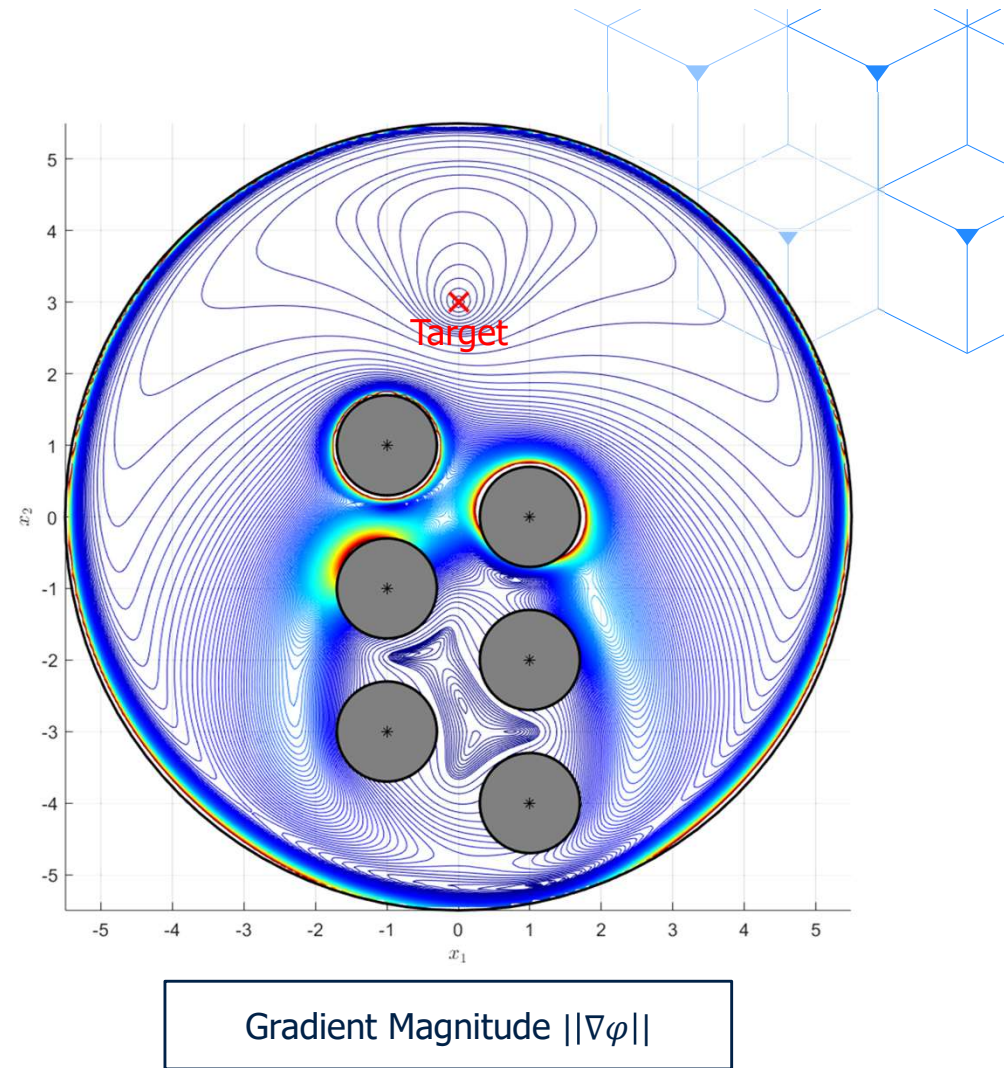
$$V(x, \dot{x}) = h \cdot \varphi(x) + \frac{1}{2} m ||\dot{x}||^2$$

Gradient Scaling Caveat

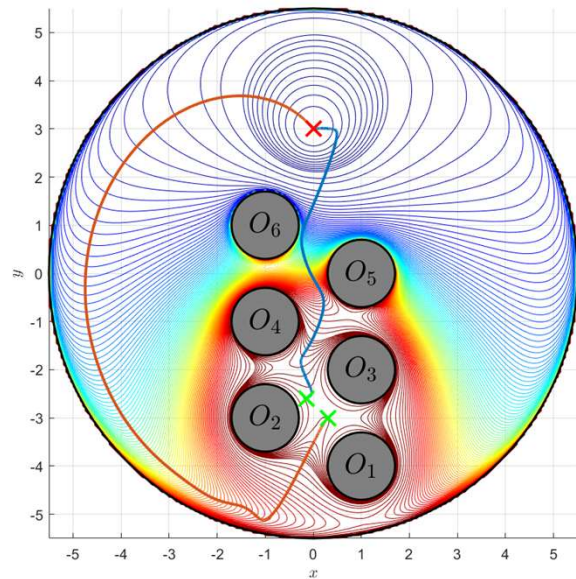
- ▶ Gradient scaling by h requires global information about the environment:

$$h = \frac{F_T}{\max_{x \in \mathcal{W}} ||\nabla \phi||}$$

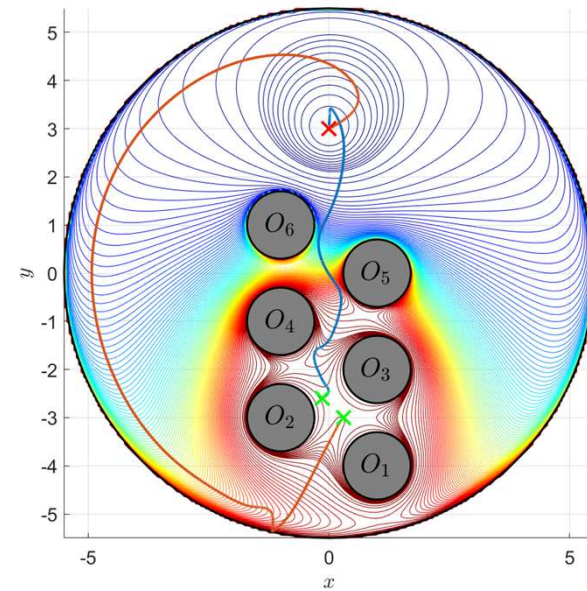
- ▶ Computation of h currently done numerically over the environment
- ▶ Adaptive on-line scaling law?



Simulation Results – Classical Law Vs Bounded Law



Classical law trajectory



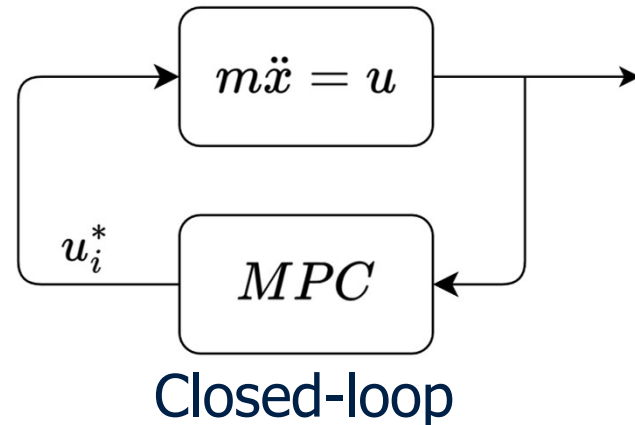
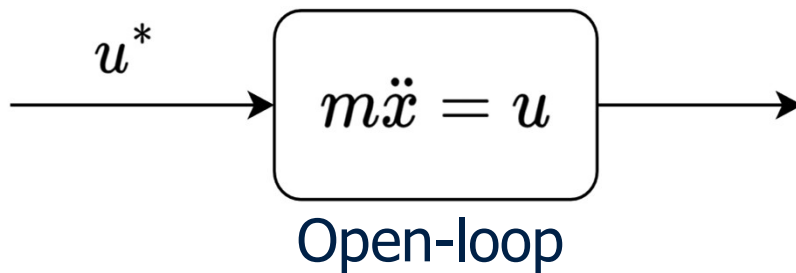
bounded control law trajectory

Navigation Function Based Time Optimal Control

► Problem Statement :

Construct feedback control law that guides robot system $m\ddot{x}(t) = u(t)$ to the target while avoiding collision with known obstacles under **control input bound** $\|u\| \leq F_{max}$ in minimal navigation time t_f .

► Solution Approaches

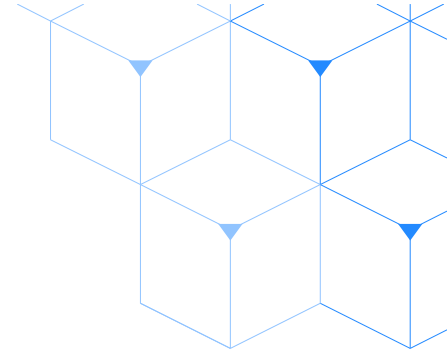


Time Optimal Navigation – Open Loop

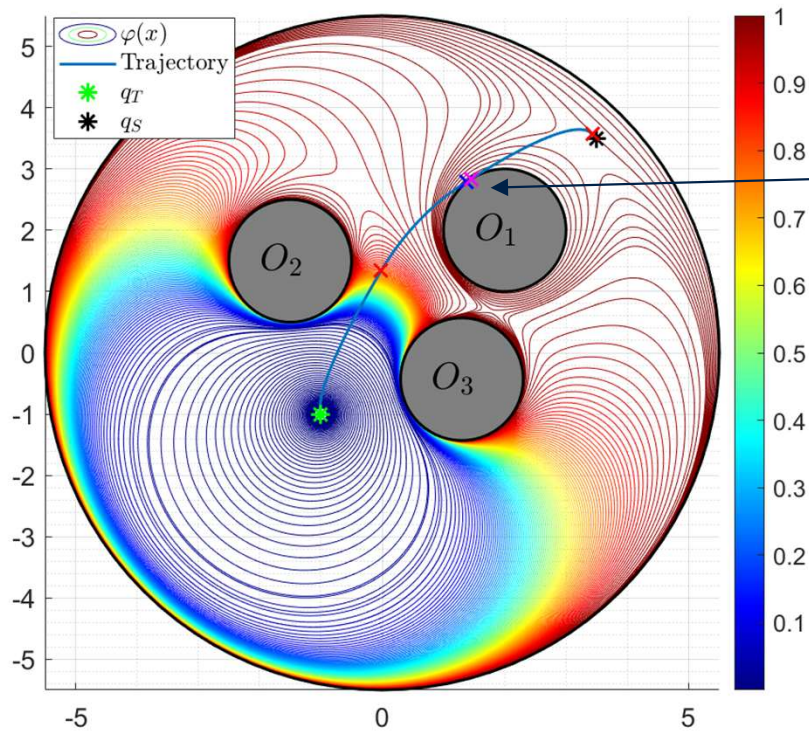
- Considers the optimal control problem

$$\left\{ \begin{array}{l} \min_{x,y,u,t_f} t_f \text{ subject to:} \\ \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \\ \varphi(x, y) < 1 \\ |u_1| \leq F_1, |u_2| \leq F_2 \\ \begin{bmatrix} x(0) \\ y(0) \end{bmatrix} = \begin{bmatrix} x_s \\ y_s \end{bmatrix} \quad \begin{bmatrix} x(t_f) \\ y(t_f) \end{bmatrix} = \begin{bmatrix} x_s \\ y_s \end{bmatrix} \end{array} \right.$$

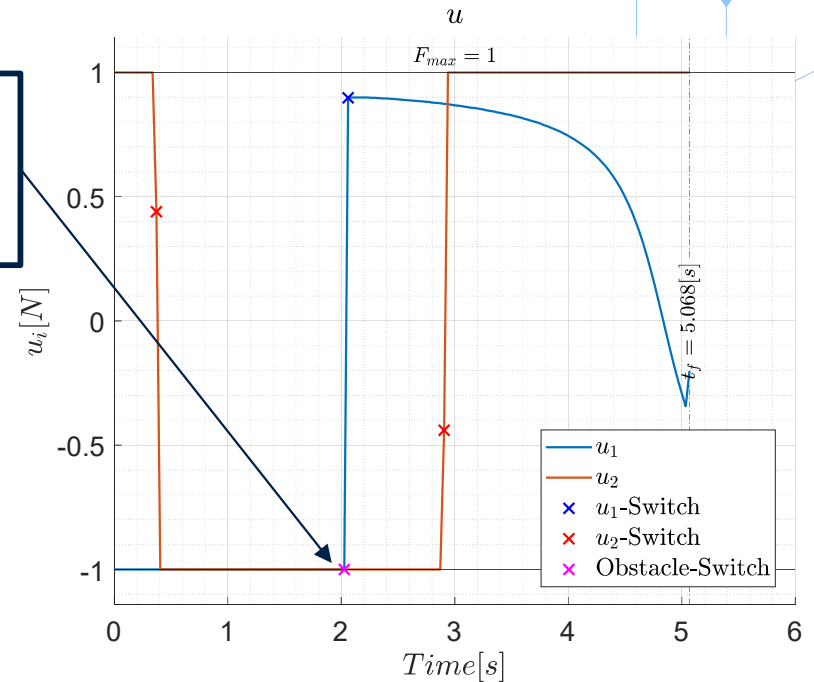
- The uniform maximal height of φ is used as a **single safety constraint**.



Simulation Results - Time Optimal Navigation

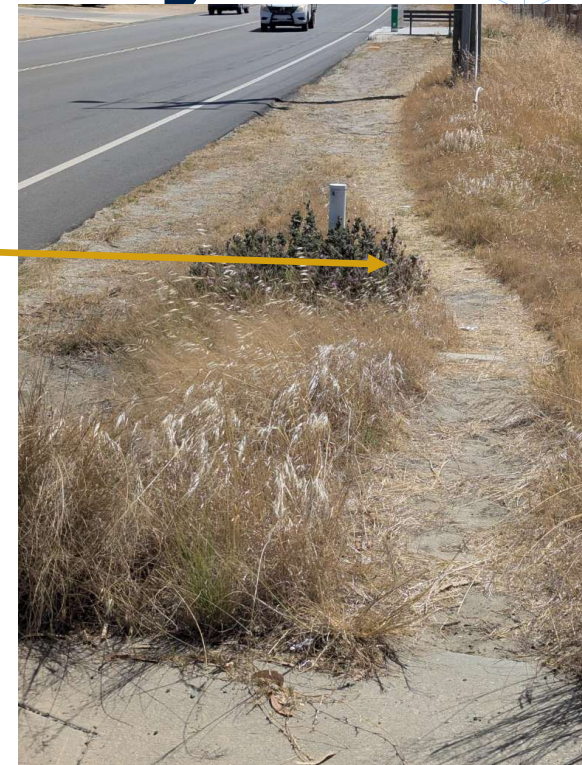
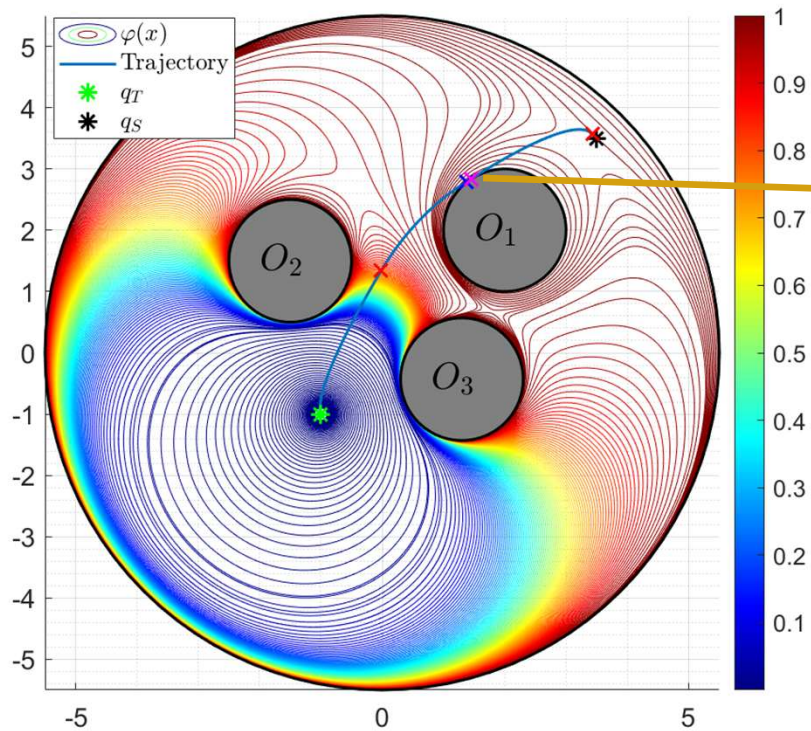


Obstacle
Primitive
Switch



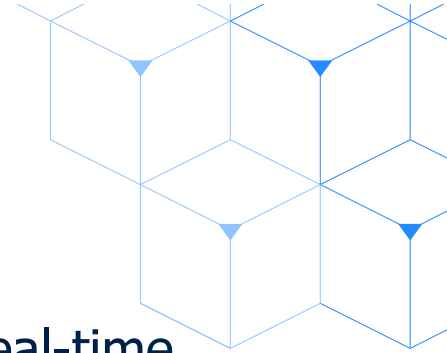
► Optimal control constructed by the primitives $\mathcal{B}^+ \mathcal{B}^- \mathcal{S}_2^- \mathcal{S}_2^+$.

Simulation Results - Time Optimal Navigation



► Resulting optimal trajectory reminds of desire paths!

Closed Loop Pseudo-Time Optimal Navigation



► Problem:

- Minimum time solution requires global solution – invalid for real-time.

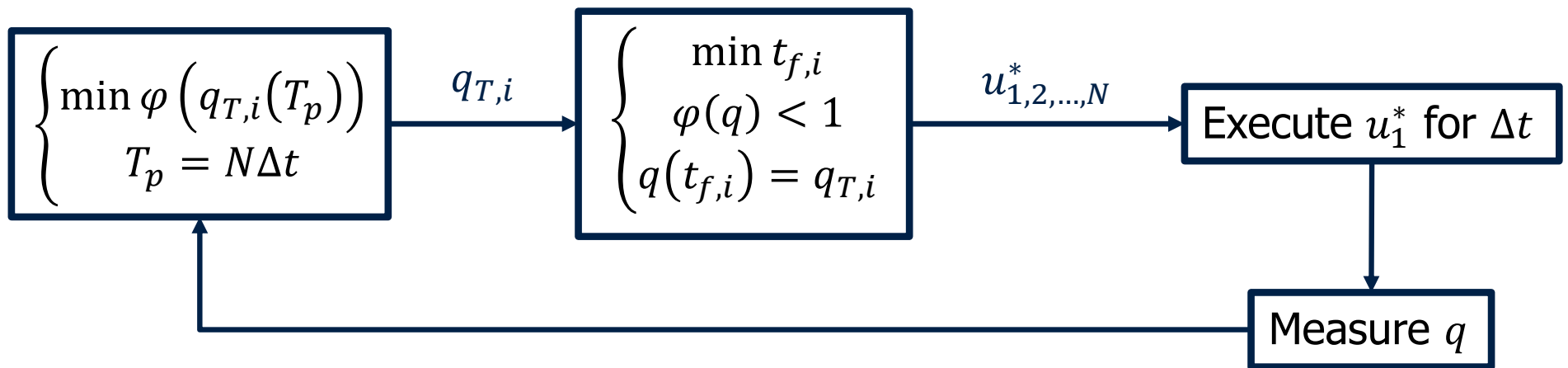
► Suggested Solution:

- Choose virtual target that **minimizes** the navigation function value at the end of the prediction time T_p .

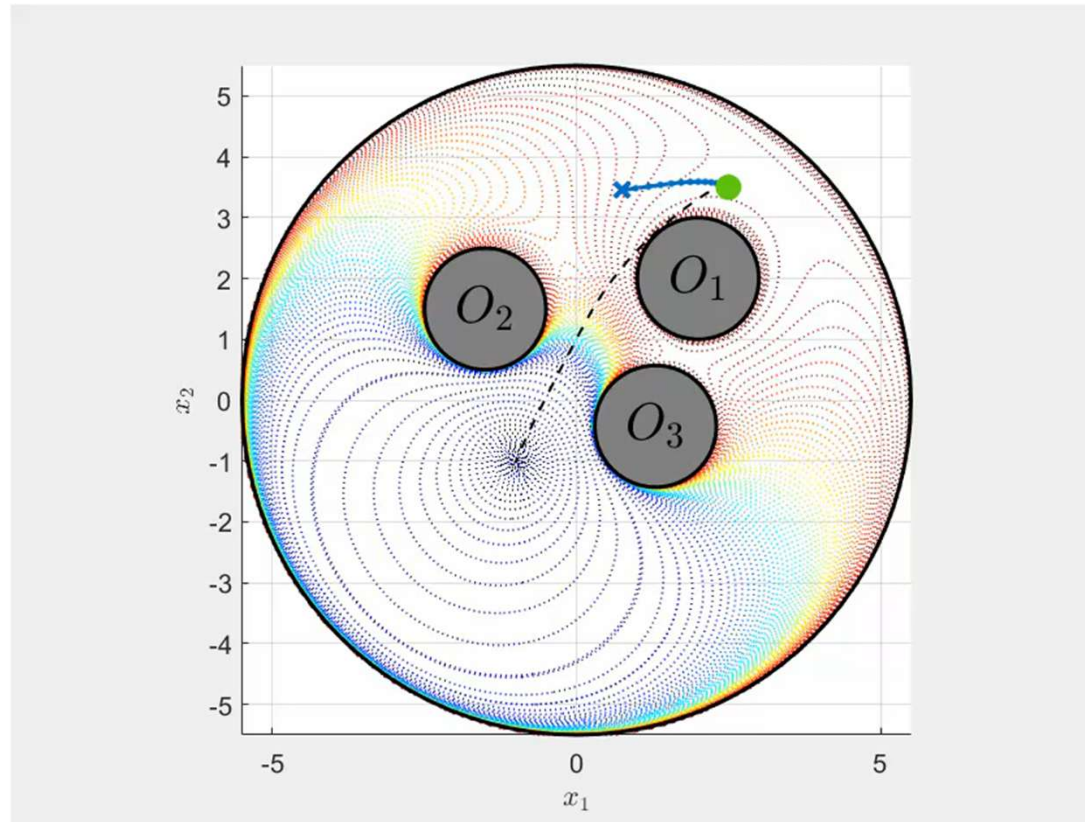
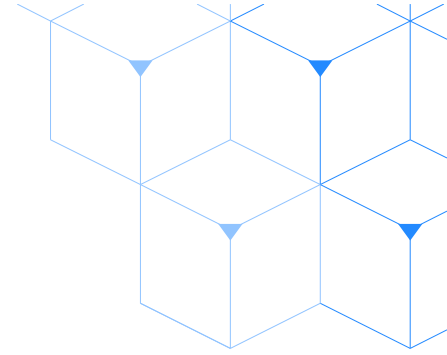
$$\left\{ \begin{array}{l} \min_{z_j, u_j} \varphi(x_N, y_N) \text{ subject to:} \\ z_{j+1} = (I + \Delta t A)z_j + \Delta t B u_j \quad 1 \leq j \leq N - 1 \\ \varphi(x_j, y_j) < 1 \\ |u_1| \leq F_1, |u_2| \leq F_2 \\ z_1 = z_{\text{measured}} \end{array} \right. \quad T_p = N\Delta t$$

Closed Loop Pseudo-Time Optimal Navigation

- ▶ Closed loop implementation of the solution of (1) using **MPC**.
- ▶ (1) requires global solution – an **intermediate** problem is solved.
- ▶ A virtual target $q_{T,i}$ is chosen to **minimize** $\varphi(q_{T,i})$.

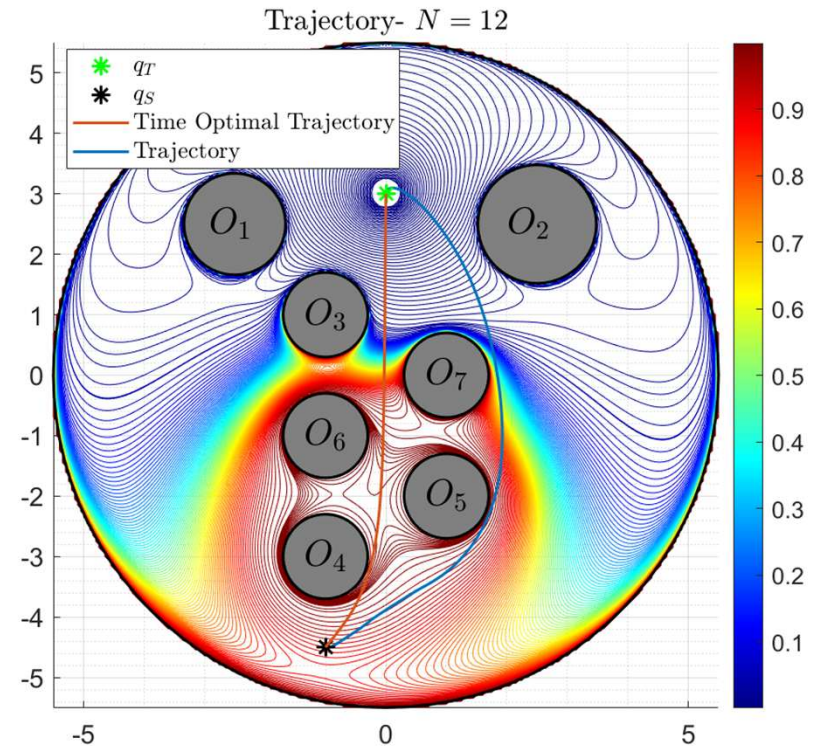


Closed Loop Pseudo-Time Optimal Navigation



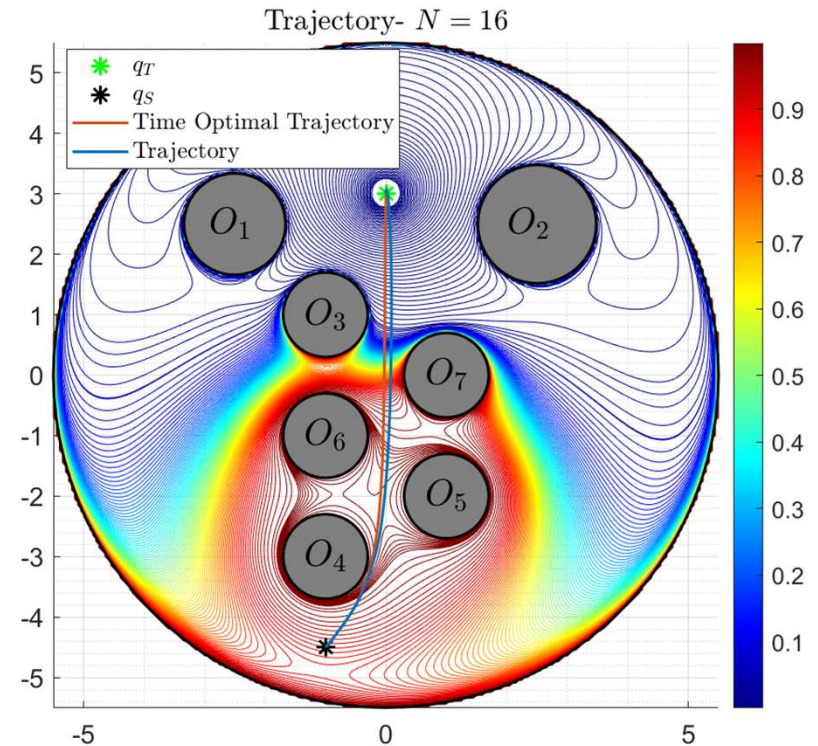
Simulation Results – MPC Navigation

Prediction Steps N	Navigation Time t_f [s]	Solve time \bar{t}_{solve} [s]
12	7.7	0.076
16	7.2	0.174
20	6.5	0.186
24	6.6	0.228
28	6.3	0.246
Time-optimal	5.4	-
Bounded	14.9	-



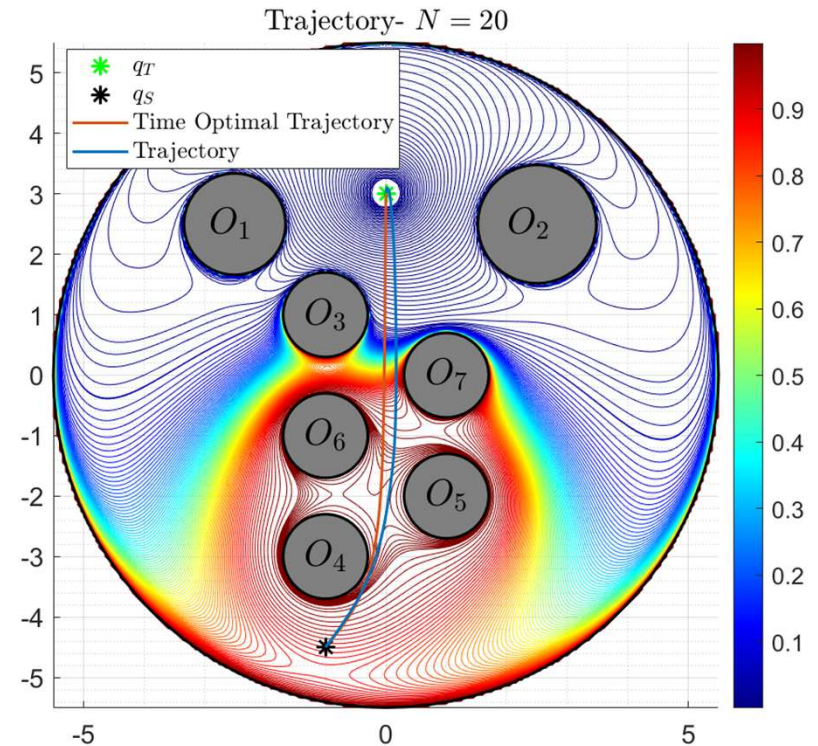
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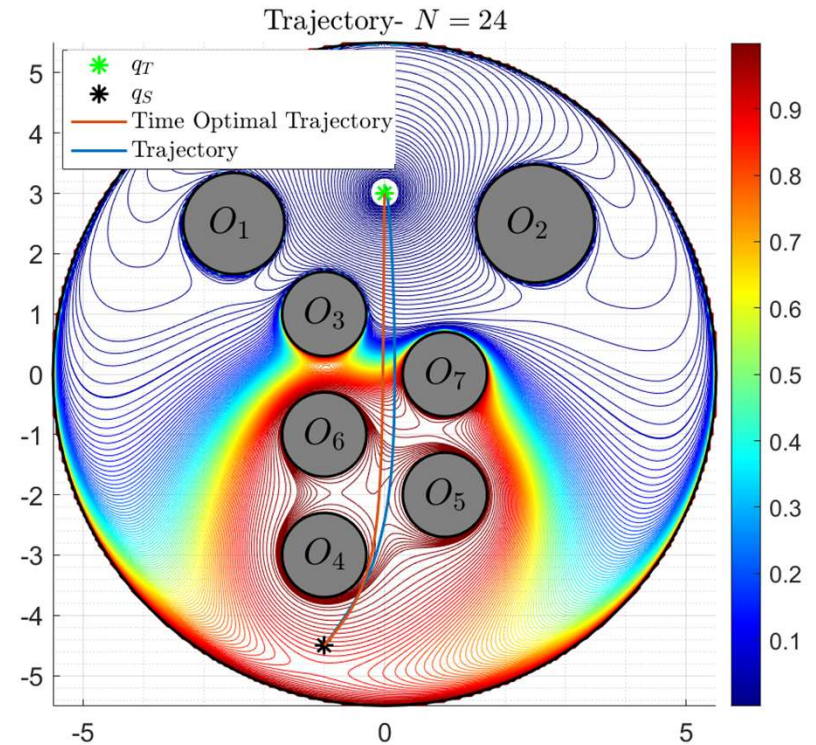
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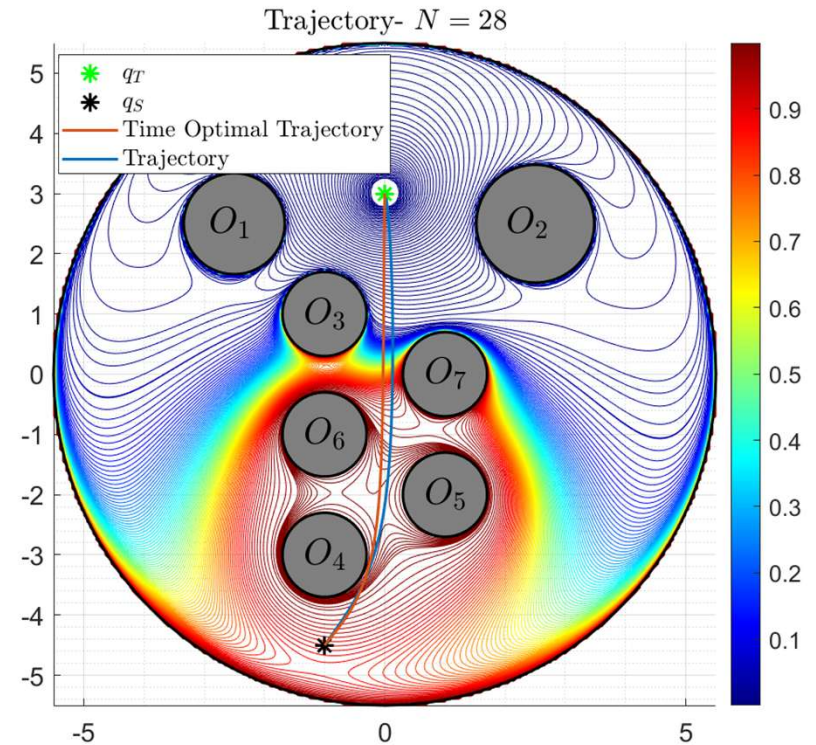
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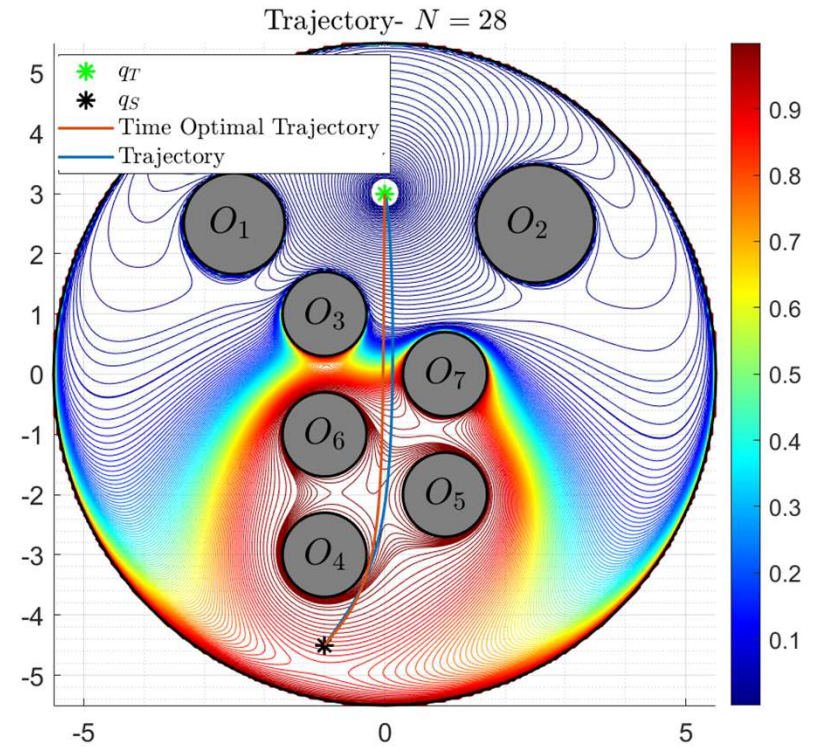
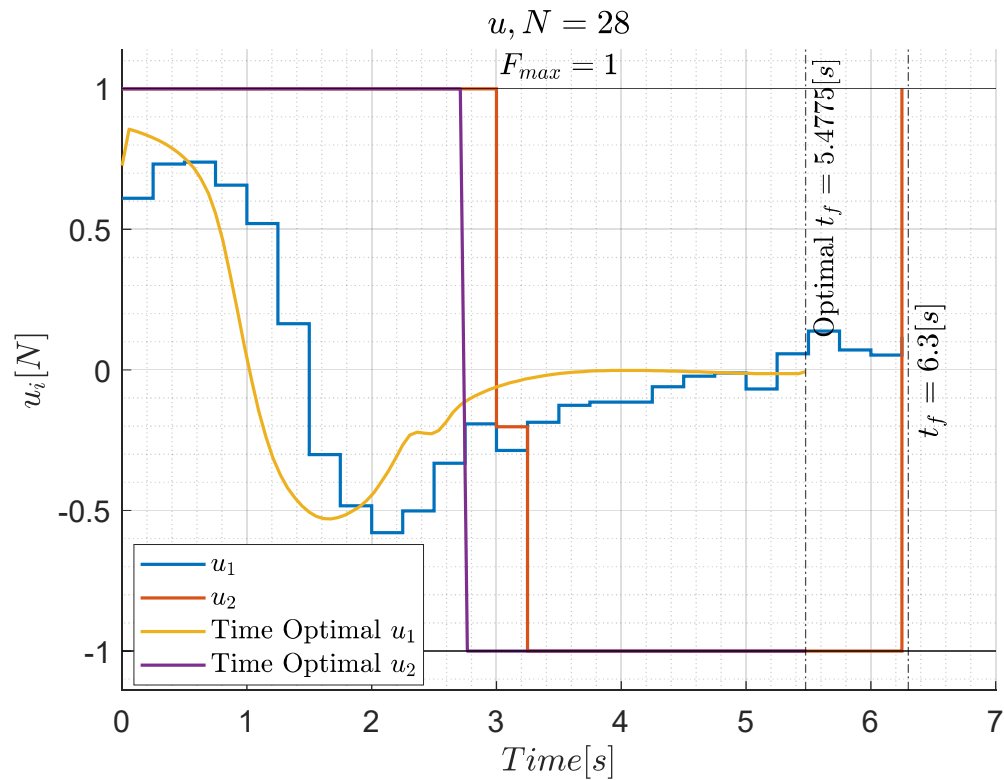


Simulation Results – MPC Navigation

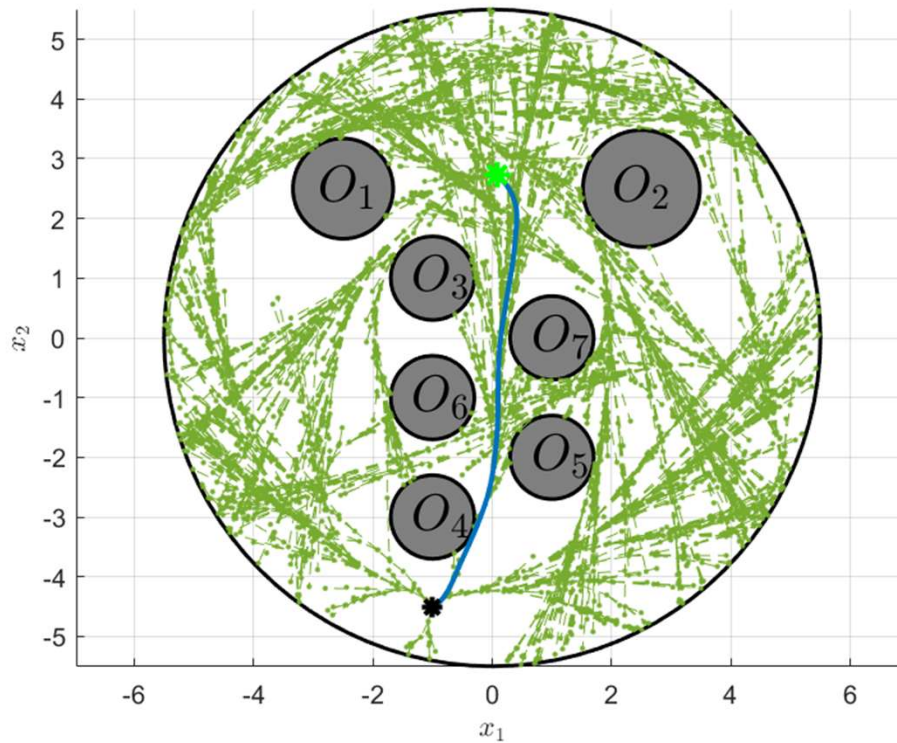
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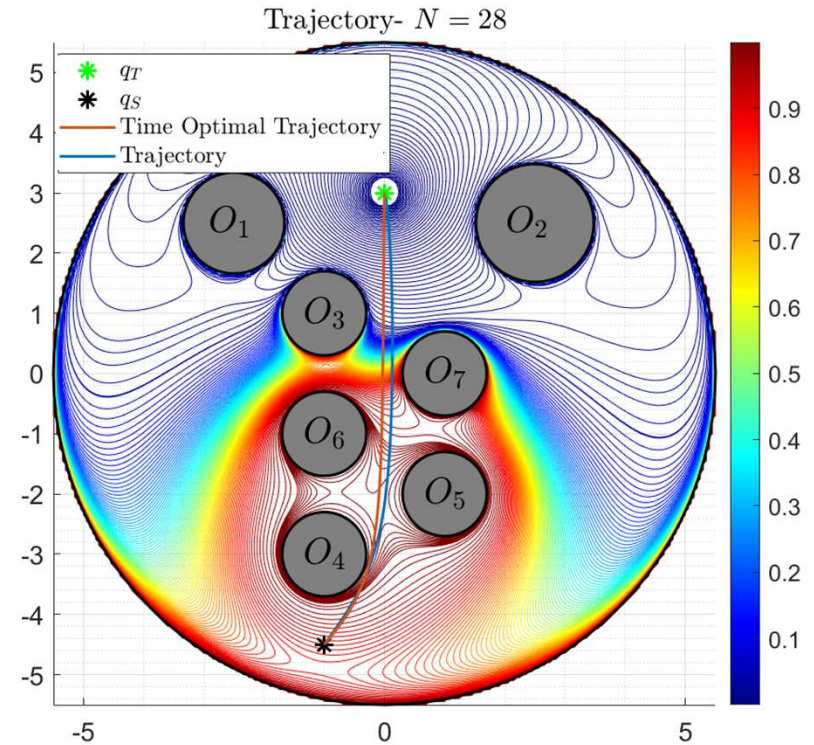
Simulation Results – MPC Navigation



MPC Navigation Vs. Kinodynamic Planner



$$t_f = 7.2[s]^1$$

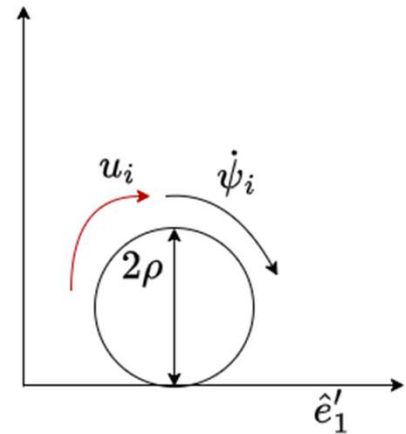
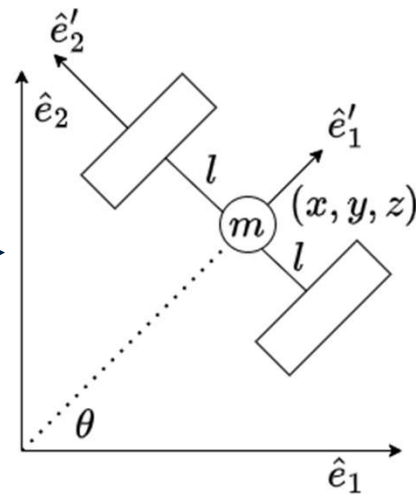


$$t_f = 6.3[s]$$

Future Research Goals

- ▶ Integrate newer and faster solvers to increase prediction horizon.
- ▶ Replace double-integrator model with non-holonomic vehicle models.

$$\begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$





Thank You! Questions?