

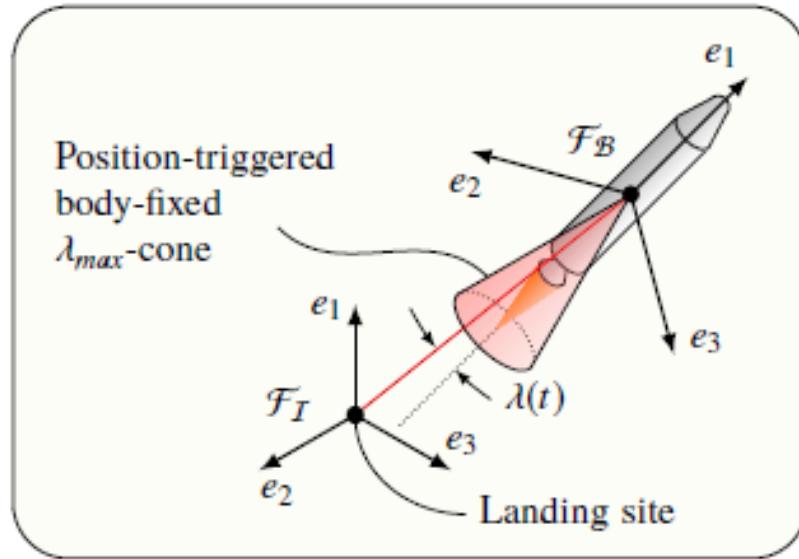
Dynamic Trajectories via Convex Optimization

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Autonomous Controls Lab
University of Washington

Problem Overview

Physics-based optimization...



Szmuk, Reynolds, Acikmese. (2020).
Successive Convexification for Real-Time 6-DOF Powered
Descent Guidance with State-Triggered Constraints. JGCD
2020.

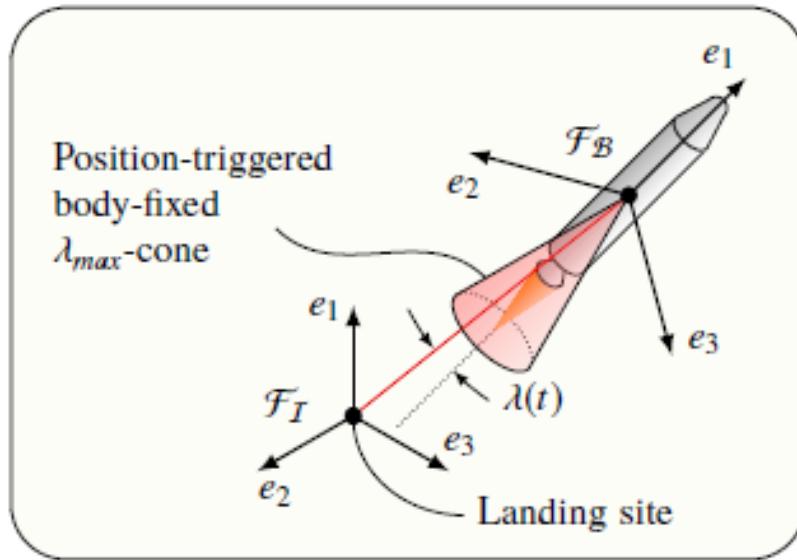
...results in dynamically feasible solutions



Scharf, Acikmese, Dueri et al. (2014).
ADAPT Demonstrations of Onboard Large-Diverge Guidance with a
VTOL Rocket. IEEE Aerospace Conference 2014.

Problem Overview

Optimal trajectory generated while satisfying necessary constraints



Szmuk, Reynolds, Acikmese. (2020).

Successive Convexification for Real-Time 6-DOF Powered Descent Guidance with State-Triggered Constraints. JGCD 2020.

Reynolds, Szmuk, Malyuta, Mesbahi, Acikmese (2020).

Dual Quaternion Based Powered Descent Guidance with State-Triggered Constraints. JGCD 2020.

Szmuk, Acikmese. (2018).

Successive Convexification for 6-DOF Mars Rocket Powered Landing with Free-Final-Time. AIAA GNC Conference 2018.

Problem 1. Minimum-fuel rocket-landing problem

Cost Function:

$$\underset{t_c, t_b, T_B(t)}{\text{minimize}} \quad -m(t_f)$$

$$\text{s.t.} \quad t_c \in [0, t_{c,max}]$$

Boundary Conditions:

$$m(t_{ig}) = m_{ig} \quad q_{B \leftarrow I}(t_f) = q_{id}$$

$$r_I(t_{ig}) = p_{r,ig}(t_c) \quad r_I(t_f) = 0$$

$$v_I(t_{ig}) = p_{v,ig}(t_c) \quad v_I(t_f) = -v_d e_1$$

$$\omega_B(t_{ig}) = 0 \quad \omega_B(t_f) = 0$$

Dynamics:

$$\dot{m}(t) = -\alpha_{\dot{m}} \|T_B(t)\|_2 - \beta_{\dot{m}}$$

$$\dot{r}_I(t) = v_I(t)$$

$$\dot{v}_I(t) = \frac{1}{m(t)} C_{I \leftarrow B}(t) (T_B(t) + A_B(t)) + g_I$$

$$\dot{q}_{B \leftarrow I}(t) = \frac{1}{2} \Omega(\omega_B(t)) q_{B \leftarrow I}(t)$$

$$J_B \dot{\omega}_B(t) = r_{T,B} \times T_B(t) + r_{cp,B} \times A_B(t) - \omega_B(t) \times J_B \omega_B(t)$$

$$m_{dry} \leq m(t)$$

$$\tan \gamma_{gs} \|H_\gamma r_I(t)\|_2 \leq e_1 \cdot r_I(t)$$

$$\cos \theta_{max} \leq 1 - 2 \|H_\theta q_{B \leftarrow I}(t)\|_2$$

$$\|\omega_B(t)\|_2 \leq \omega_{max}$$

Control Constraints:

$$0 < T_{min} \leq \|T_B(t)\|_2 \leq T_{max}$$

$$\cos \delta_{max} \|T_B(t)\|_2 \leq e_3 \cdot T_B(t)$$

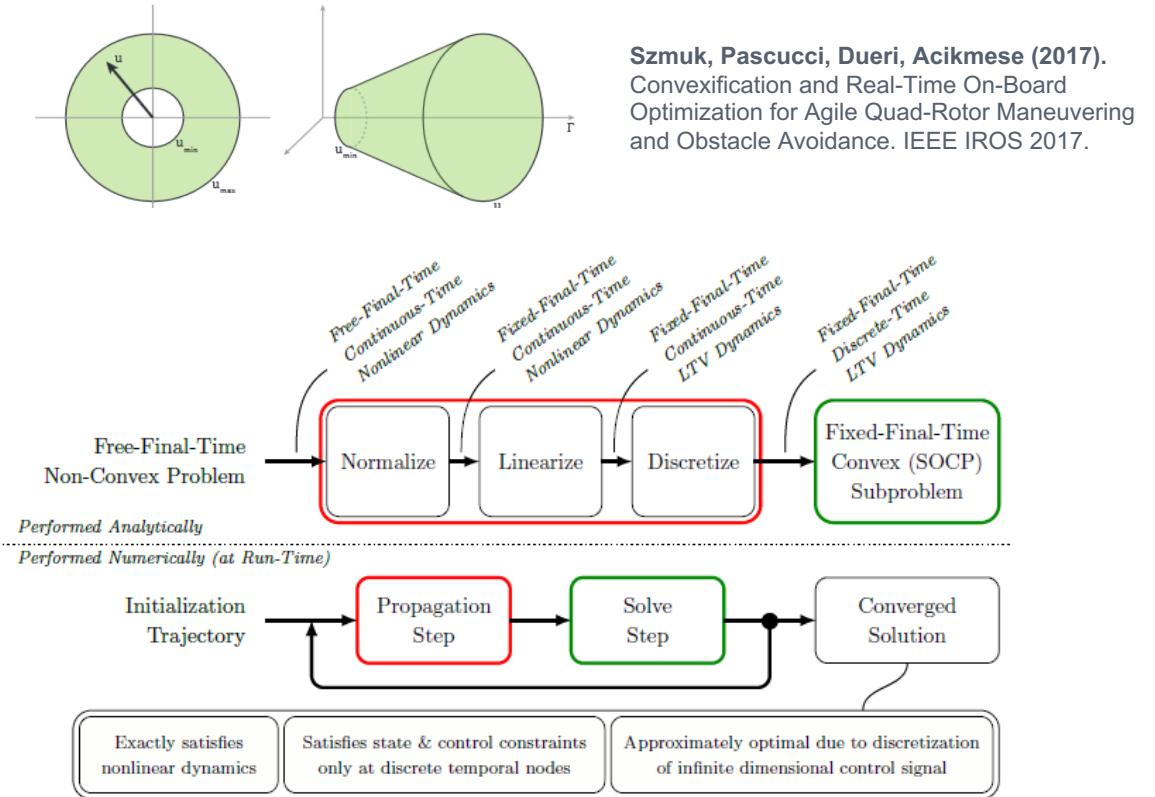
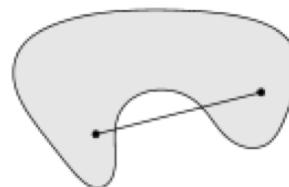
State-Triggered Constraints:

$$h_\alpha(v_I(t), q_{B \leftarrow I}(t)) \leq 0$$

Optimal Guidance Problem Overview

Why is it so fast?

- Harness speed of convex optimization to solve complex, nonlinear problems
 - Take local convex approximation of nonlinear problem to achieve relevant run time
- Convexify an optimal control problem (lossless convexification)
- Create sequence of convexified subproblems (successive convexification)
 - In practice, number of iterations shown to be small

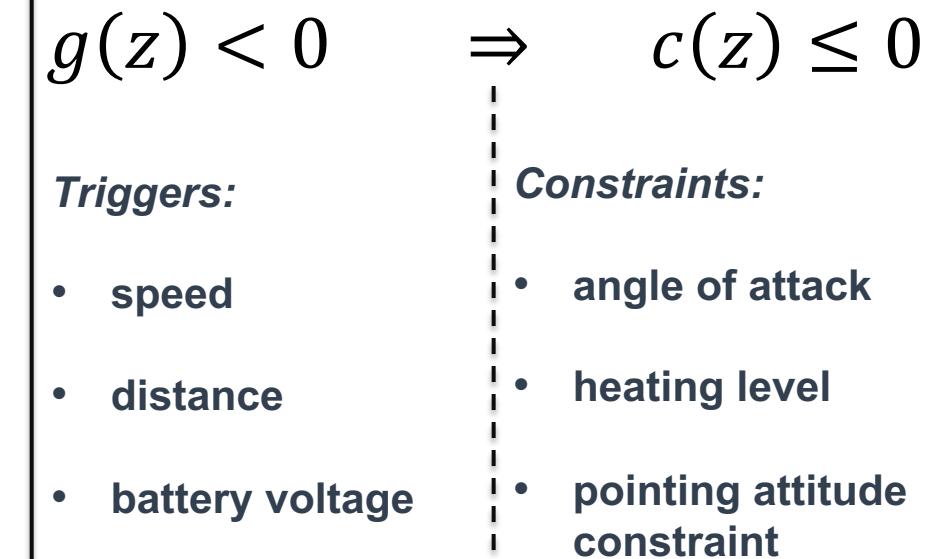


Szmuk, Reynolds, Acikmese, Mesbahi (2019).
Successive Convexification for 6-DOF Powered Descent Guidance
with Compound State-Triggered Constraints. AIAA SciTech 2019.

Optimal Guidance Problem Overview

How do we deal with conditional decision making?

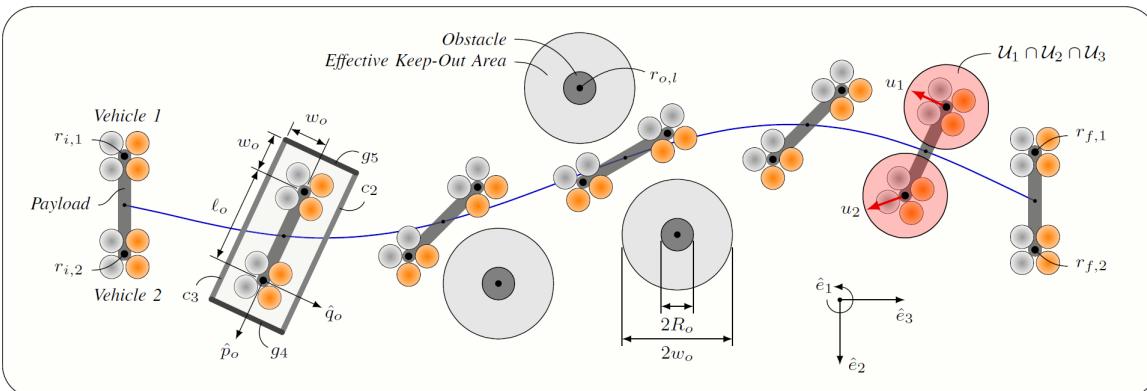
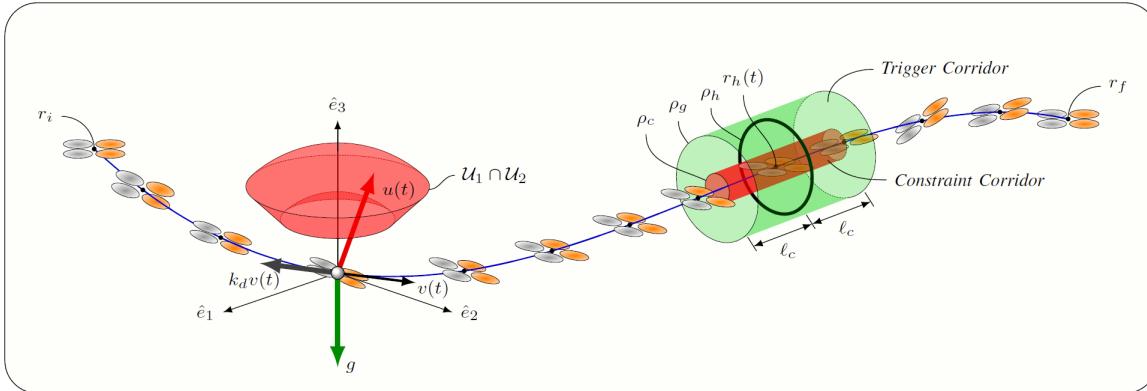
- **State-Triggered Constraints (STCs) model logical implications**
 - Constraints enforced when state-dependent criterion are met
 - Extension to optimization-based trajectory generation methods
- **Integrate conditional logic into a continuous optimization framework**
 - Embed a subset of discrete decision constraints into continuous problem
 - Formulated using continuous variables of the optimization problem
 - Nonlinear function models implications that trigger constraints
- **Composed of *trigger function* and *constraint function***
 - $g(z)$ – trigger function
 - $c(z)$ – constraint function
 - z – optimization variable
- ***Constraint function* is conditionally enforced based on the value of the *trigger function***
 - If the trigger function is non-negative, then optimization variable is not subject to the constraint condition
 - If trigger function becomes negative, then constraint is enforced



Szmuk, Malyuta, Reynolds, McEwen, Acikmese. (2019).
Real-Time Quad-Rotor Path Planning Using Convex
Optimization and Compound State-Triggered Constraints.
IEEE IROS 2019.

Optimal Guidance Problem Overview

Example 1: quadrotor with STCs



Szmuk, Malyuta, Reynolds, McEwen, Acikmese. (2019).
Real-Time Quad-Rotor Path Planning Using Convex
Optimization and Compound State-Triggered Constraints.
IEEE IROS 2019.

Problem 1: Non-Convex Formulation of Scenario 1

$$\underset{u}{\text{minimize}} \int_0^{t_f} \|u(t)\|_2 dt$$

subject to:

$$\begin{aligned} r(0) &= r_i, r(t_f) = r_f, \\ v(0) &= v(t_f) = 0_{3 \times 1}, \\ u(0) &= u(t_f) = mg\hat{e}_1, \\ \dot{x}(t) &= Ax(t) + Bu(t) + Ew, u(t) \in \mathcal{U}_1 \cap \mathcal{U}_2, \\ \|v(t)\|_2 &\leq v_{max}, h_1(r(t), r_h(t)) \leq 0. \end{aligned}$$

Objective: Min. fuel

Boundary conditions

Dynamics & control
State and safety

Problem 2: Non-Convex Formulation of Scenario 2

$$\underset{u}{\text{minimize}} \int_0^{t_f} (\|u_1(t)\|_2 + \|u_2(t)\|_2) dt$$

subject to:

$$\begin{aligned} r_1(0) &= r_{i,1}, r_1(t_f) = r_{f,1}, \\ r_2(0) &= r_{i,2}, r_2(t_f) = r_{f,2}, \\ v_1(0) &= v_2(0) = v_1(t_f) = v_2(t_f) = 0_{3 \times 1}, \\ u_1(0) &= u_2(0) = u_1(t_f) = u_2(t_f) = mg\hat{e}_1, \\ \dot{\tilde{x}}(t) &= \tilde{A}\tilde{x}(t) + \tilde{B}\tilde{u}(t) + \tilde{E}\tilde{w}, \\ u_1(t), u_2(t) &\in \mathcal{U}_1 \cap \mathcal{U}_2 \cap \mathcal{U}_3, \\ h_2(r_1(t), r_2(t), r_{o,l}) &= 0, \quad \forall j \in \mathcal{N}_o, \\ \|v_1(t)\|_2 &\leq v_{max}, \|v_2(t)\|_2 \leq v_{max}, \\ \|r_1(t) - r_2(t)\|_2 &= \ell_o. \end{aligned}$$

Objective: Min. fuel

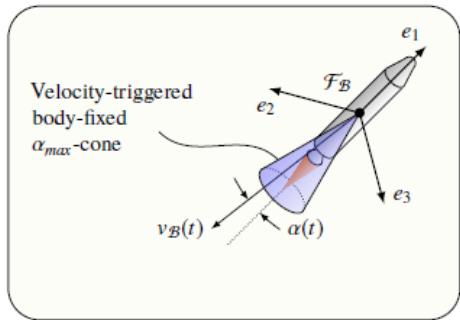
Boundary conditions

Dynamics, state and control

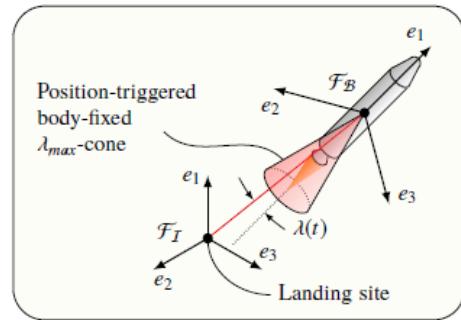
Safety constraints

Optimal Guidance Problem Overview

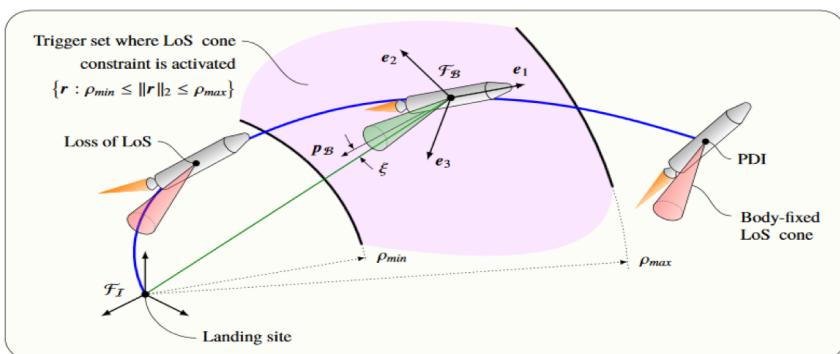
Example 2: rocket landing problem



(a) Angle of Attack State-Triggered Constraint



(b) Field of View State-Triggered Constraint



Szmuk, Reynolds, Acikmese. (2020). Successive Convexification for Real-Time 6-DOF Powered Descent Guidance with State-Triggered Constraints. JGCD 2020.

Reynolds, Szmuk, Malyuta, Mesbah, Acikmese (2020). Dual Quaternion Based Powered Descent Guidance with State-Triggered Constraints. JGCD 2020.

Reynolds, Malyuta, Mesbah, Acikmese. (2020). A Real-Time Algorithm for Non-Convex Powered Descent Guidance. AIAA SciTech 2020.

Problem 1. Minimum-fuel rocket-landing problem

Cost Function:

$$\underset{t_c, t_b, T_B(t)}{\text{minimize}} \quad -m(t_f)$$

$$\text{s.t.} \quad t_c \in [0, t_{c,\max}]$$

Boundary Conditions:

$$m(t_{ig}) = m_{ig} \quad q_{B \leftarrow I}(t_f) = q_{id}$$

$$r_I(t_{ig}) = p_{r,ig}(t_c) \quad r_I(t_f) = 0$$

$$v_I(t_{ig}) = p_{v,ig}(t_c) \quad v_I(t_f) = -v_d e_1$$

$$\omega_B(t_{ig}) = 0 \quad \omega_B(t_f) = 0$$

Dynamics:

$$\dot{m}(t) = -\alpha \dot{m} \|T_B(t)\|_2 - \beta \dot{m}$$

$$\dot{r}_I(t) = v_I(t)$$

$$\dot{v}_I(t) = \frac{1}{m(t)} C_{I \leftarrow B}(t) (T_B(t) + A_B(t)) + g_I$$

$$\dot{q}_{B \leftarrow I}(t) = \frac{1}{2} \Omega(\omega_B(t)) q_{B \leftarrow I}(t)$$

$$J_B \dot{\omega}_B(t) = r_{T,B} \times T_B(t) + r_{cp,B} \times A_B(t) - \omega_B(t) \times J_B \omega_B(t)$$

State Constraints:

$$m_{dry} \leq m(t)$$

$$\tan \gamma_{gs} \|H_\gamma r_I(t)\|_2 \leq e_1 \cdot r_I(t)$$

$$\cos \theta_{max} \leq 1 - 2 \|H_\theta q_{B \leftarrow I}(t)\|_2$$

$$\|\omega_B(t)\|_2 \leq \omega_{max}$$

Control Constraints:

$$0 < T_{min} \leq \|T_B(t)\|_2 \leq T_{max}$$

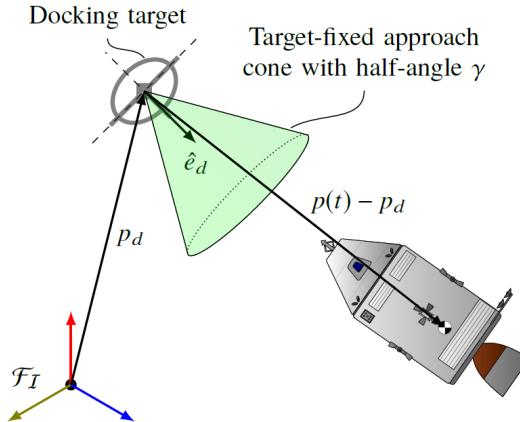
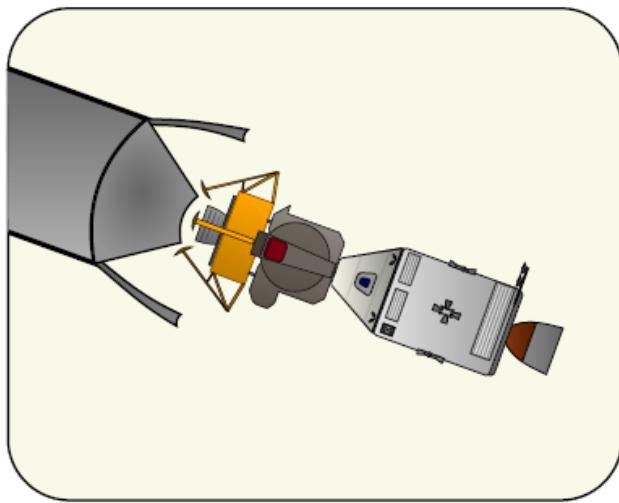
$$\cos \delta_{max} \|T_B(t)\|_2 \leq e_3 \cdot T_B(t)$$

State-Triggered Constraints:

$$h_\alpha(v_I(t), q_{B \leftarrow I}(t)) \leq 0$$

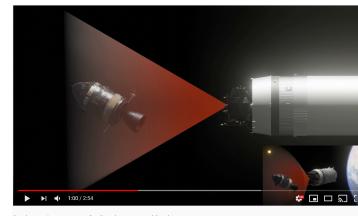
Optimal Guidance Problem Overview

Example 3: spacecraft rendezvous



Won: Best AIAA 2020 GNC Graduate Paper at SciTech
 Video Link: <https://www.youtube.com/watch?v=vU1nBL2cg04>

Malyuta, Reynolds, Szmuk, Acikmese, Mesbah. (2020).
 Fast Trajectory Optimization via Successive
 Convexification for Spacecraft Rendezvous with Integer
 Constraints. AIAA SciTech 2020.



$$\underset{\sigma_i(t)}{\text{minimize}} \ J_f$$

subject to : $\dot{p}(t) = v(t),$

$$\dot{v}(t) = \frac{1}{m} \sum_{i=1}^M q(t) \otimes f_i(t) \otimes q(t)^*,$$

$$\dot{q}(t) = \frac{1}{2} q(t) \otimes \omega(t),$$

$$\dot{\omega}(t) = J^{-1} \left[\sum_{i=1}^M r_i \times f_i(t) - \omega(t) \times (J\omega(t)) \right],$$

$$0 \leq \Delta t_k^i \leq \Delta t_{\max} \text{ for all } i = 1, \dots, M \text{ and } k \in \mathbb{Z}_{\geq 0},$$

$$\Delta t_k^i < \Delta t_{\min} \Rightarrow \Delta t_k^i = 0 \text{ for all } i = 1, \dots, M \text{ and } k \in \mathbb{Z}_{\geq 0},$$

$$\|p(t) - p_f\|_2 < r_a \Rightarrow e_1^\top [q_f] \otimes q(t)^* \geq \cos(\Delta\theta_{\max}/2),$$

$$\|p(t) - p_f\|_2 < r_a \Rightarrow \sigma_i(t) = 0 \text{ for all } i \in \mathcal{M},$$

$$\|p(t) - p_d\|_2 \cos(\gamma) \leq (p(t) - p_d)^\top \hat{e}_d,$$

$$p(0) = p_0, \ v(0) = v_0, \ q(0) = q_0, \ \omega(0) = \omega_0,$$

$$p(t_f) = p_f, \ v(t_f) = v_f, \ q(t_f) = q_f, \ \omega(t_f) = \omega_f.$$

Objective: min. fuel
 min Σ (thruster-fire duration)

Dynamics

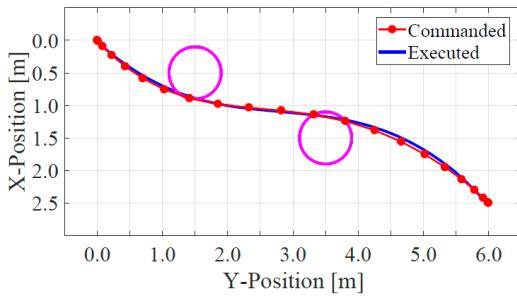
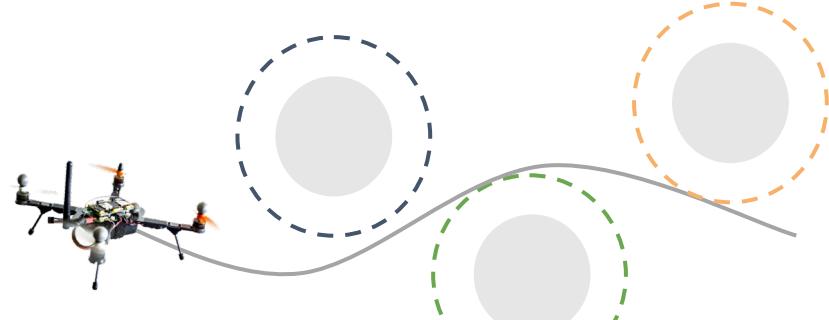
Thruster pulse duration

Safety constraints

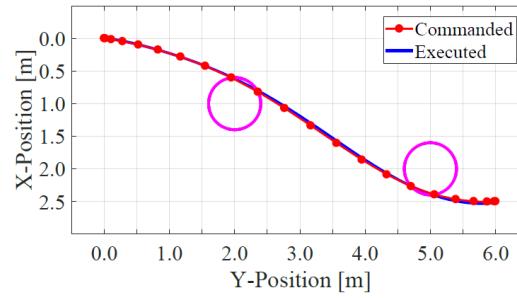
Boundary conditions

Optimal Guidance Problem Overview

Example 4: quadrotor obstacle avoidance



Szmuk, Pascucci, Dueri, Acikmese (2017). Convexification and Real-Time On-Board Optimization for Agile Quad-Rotor Maneuvering and Obstacle Avoidance. IEEE IROS 2017.



Dueri, Mao, Mian, Ding, Acikmese (2017). Trajectory Optimization with Inter-sample Obstacle Avoidance via Successive Convexification. IEEE CDC 2017.

Problem 2:

$$\underset{\mathbf{u}^k(t), \Gamma^k(t)}{\text{minimize}} \quad w \int_0^{t_f} (\Gamma^k(t))^2 dt + \sum_{j \in \mathbb{J}} \nu_j$$

subject to:

$$\begin{aligned} \mathbf{r}^k(0) &= \mathbf{r}_i & \mathbf{v}^k(0) &= \mathbf{v}_0 & \mathbf{u}^k(0) &= g\mathbf{e}_3 \\ \mathbf{r}^k(t_f) &= \mathbf{r}_f & \mathbf{v}^k(t_f) &= \mathbf{v}_f & \mathbf{u}^k(t_f) &= g\mathbf{e}_3 \end{aligned}$$

$$\begin{aligned} \dot{\mathbf{r}}^k(t) &= \mathbf{v}^k(t) \\ \dot{\mathbf{v}}^k(t) &= \mathbf{u}^k(t) - g\mathbf{e}_3 \end{aligned}$$

$$\begin{aligned} \|\mathbf{u}^k(t)\|_2 &\leq \Gamma^k(t) \\ 0 < u_{min} &\leq \Gamma^k(t) \leq u_{max} \\ \Gamma^k(t) \cos(\theta_{max}) &\leq \mathbf{e}_3^T \mathbf{u}^k(t) \end{aligned}$$

$$\begin{aligned} x_{min} &\leq \mathbf{e}_1^T \mathbf{x}^k(t) \leq x_{max} \\ y_{min} &\leq \mathbf{e}_2^T \mathbf{x}^k(t) \leq y_{max} \\ z_{min} &\leq \mathbf{e}_3^T \mathbf{x}^k(t) \leq z_{max} \end{aligned}$$

For all $j \in \mathbb{J}$ and for $t \in [0, t_f]$:

$$\begin{aligned} \nu_j &\geq 0 \\ H_j &\succeq 0 \\ \Delta \mathbf{r}^{k,j}(t) &\triangleq (\mathbf{r}^{k-1}(t) - \mathbf{p}_j) \\ \delta \mathbf{r}^k(t) &\triangleq \mathbf{r}^k(t) - \mathbf{r}^{k-1}(t) \\ \xi^{k,j}(t) &\triangleq \|H_j \Delta \mathbf{r}^{k,j}(t)\|_2 \\ \zeta^{k,j}(t) &\triangleq \frac{H_j^T H_j \Delta \mathbf{r}^{k,j}(t)}{\|H_j \Delta \mathbf{r}^{k,j}(t)\|_2} \end{aligned}$$

$$\xi^{k,j} + [\zeta^{k,j}(t)]^T \delta \mathbf{r}^k(t) \geq R_j - \nu_j$$

Objective:
Min. fuel

Boundary conditions

Dynamics

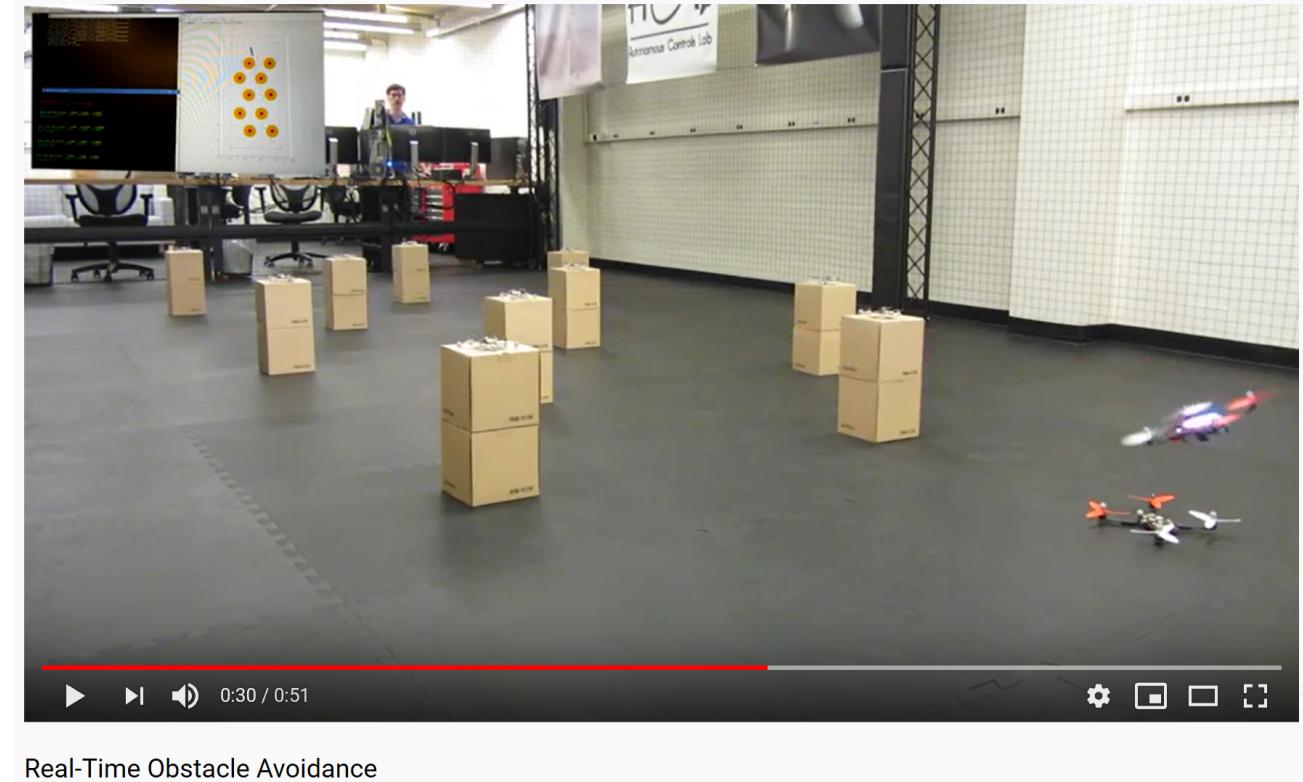
Control constraints

State constraints

Safety constraints

Video: Aggressive Obstacle Avoidance

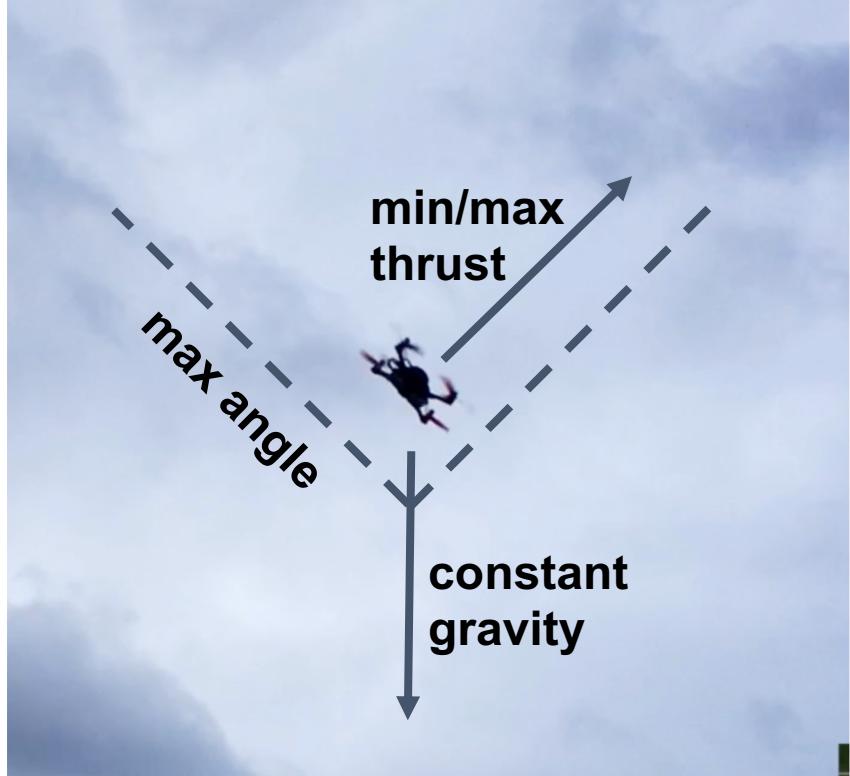
- Optimality based on sufficiently high-fidelity dynamic model allows us to push aggressive performance
- Dynamic feasibility allows us to exploit most of the systems operating envelope
- Links:
 - Aggressive Obstacle Avoidance:
<https://www.youtube.com/watch?v=EK-X3kiTnn8>
 - Mobile Obstacle Avoidance:
https://www.youtube.com/watch?v=0fP5kBx_rzE
 - Obstacle Avoidance:
<https://www.youtube.com/watch?v=ImZDifg91Ss>



Tablet Interface Overview & Progress

Optimization Interface

Physics-based vehicle dynamics



Problem 1: Non-Convex Formulation

$$\underset{\mathbf{T}(t)}{\text{minimize}} \quad \int_0^{t_f} \|\mathbf{T}(t)\|_2 dt$$

subject to:

$$\begin{aligned} \mathbf{r}(0) &= \mathbf{r}_i & \mathbf{v}(0) &= \mathbf{v}_i & \mathbf{T}(0) &= \mathbf{T}_i \\ \mathbf{r}(t_f) &= \mathbf{r}_f & \mathbf{v}(t_f) &= \mathbf{v}_f & \mathbf{T}(t_f) &= \mathbf{T}_f \end{aligned}$$

$$\dot{\mathbf{r}}(t) = \mathbf{v}(t)$$

$$\dot{\mathbf{v}}(t) = \frac{1}{m} \mathbf{T}(t) - g\mathbf{e}_1$$

$$0 < T_{min} \leq \|\mathbf{T}(t)\|_2 \leq T_{max} \quad (1)$$

$$\|\mathbf{T}(t)\|_2 \cos(\theta_{max}) \leq \mathbf{e}_1^T \mathbf{T}(t) \quad (2)$$

$$\|H_j(t)(\mathbf{r}(t) - \mathbf{r}_j(t))\|_2 \geq 1 \quad \forall j \in \mathbb{J}$$

Szmuk, Pascucci, Acikmese, B. (2018).
Real-Time Quad-Rotor Path Planning for Mobile Obstacle Avoidance Using Convex Optimization. IROS 2018

Interface: Task Specification

Task:

Goal

Waypoints

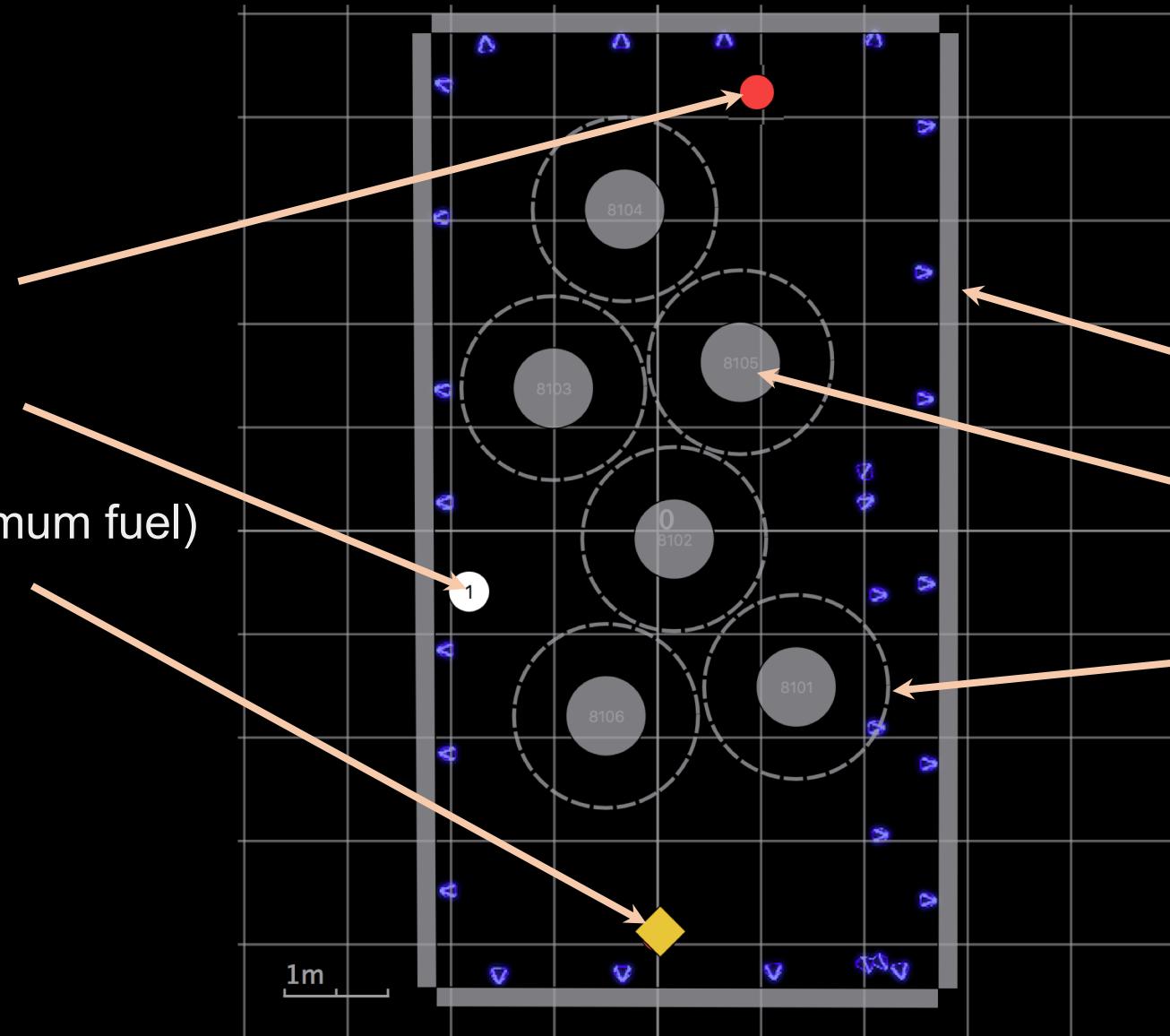
Vehicle (minimum fuel)

Map:

Safety Zone (hard)

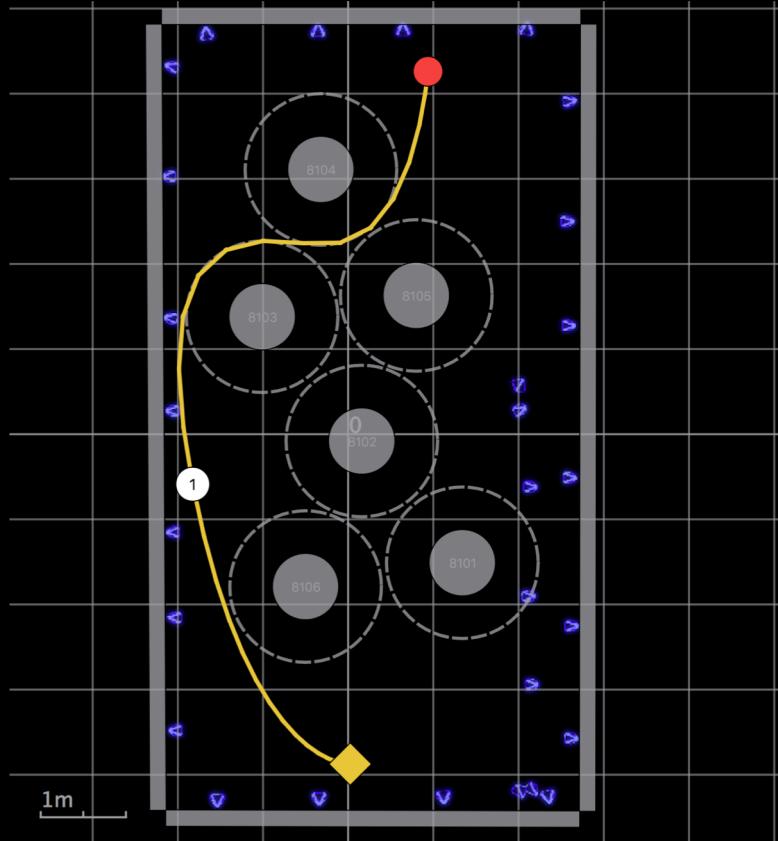
Live obstacles

Clearance (soft)

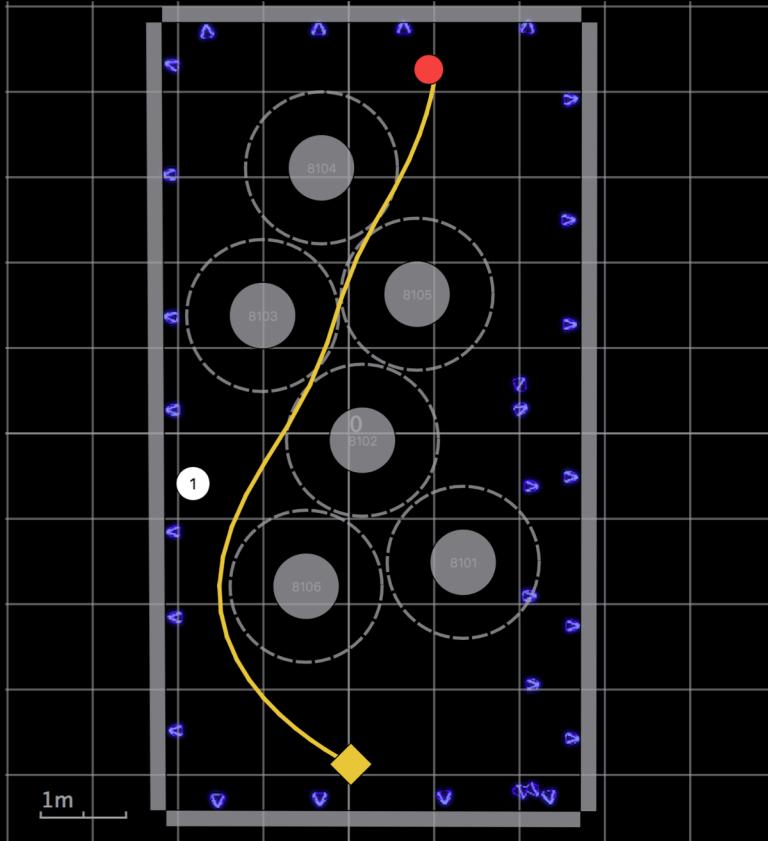


Interface: Constraint Types

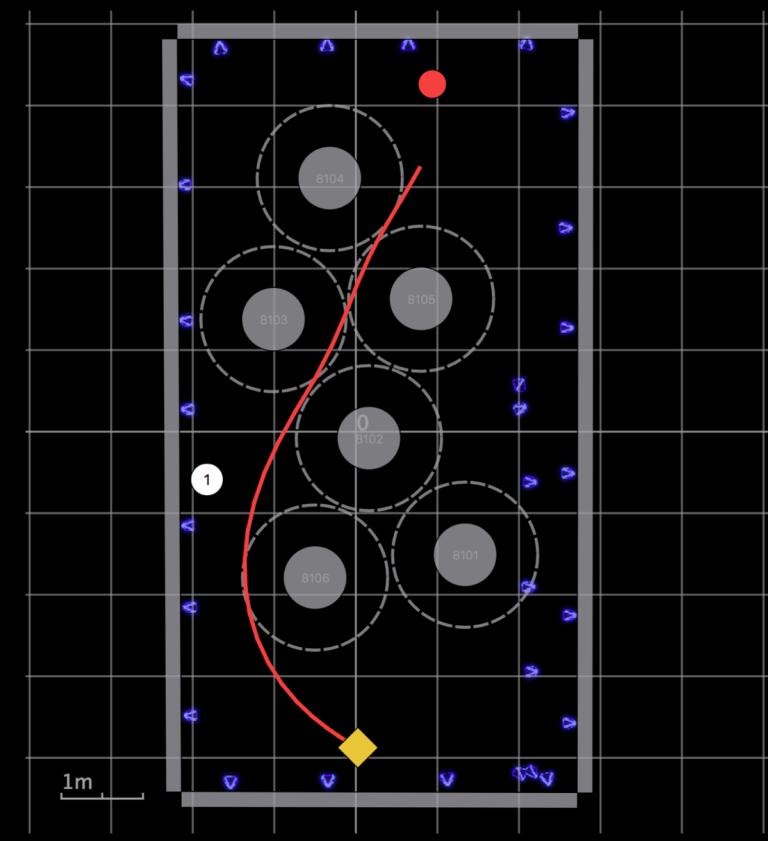
Soft and hard constraints



6.0 seconds

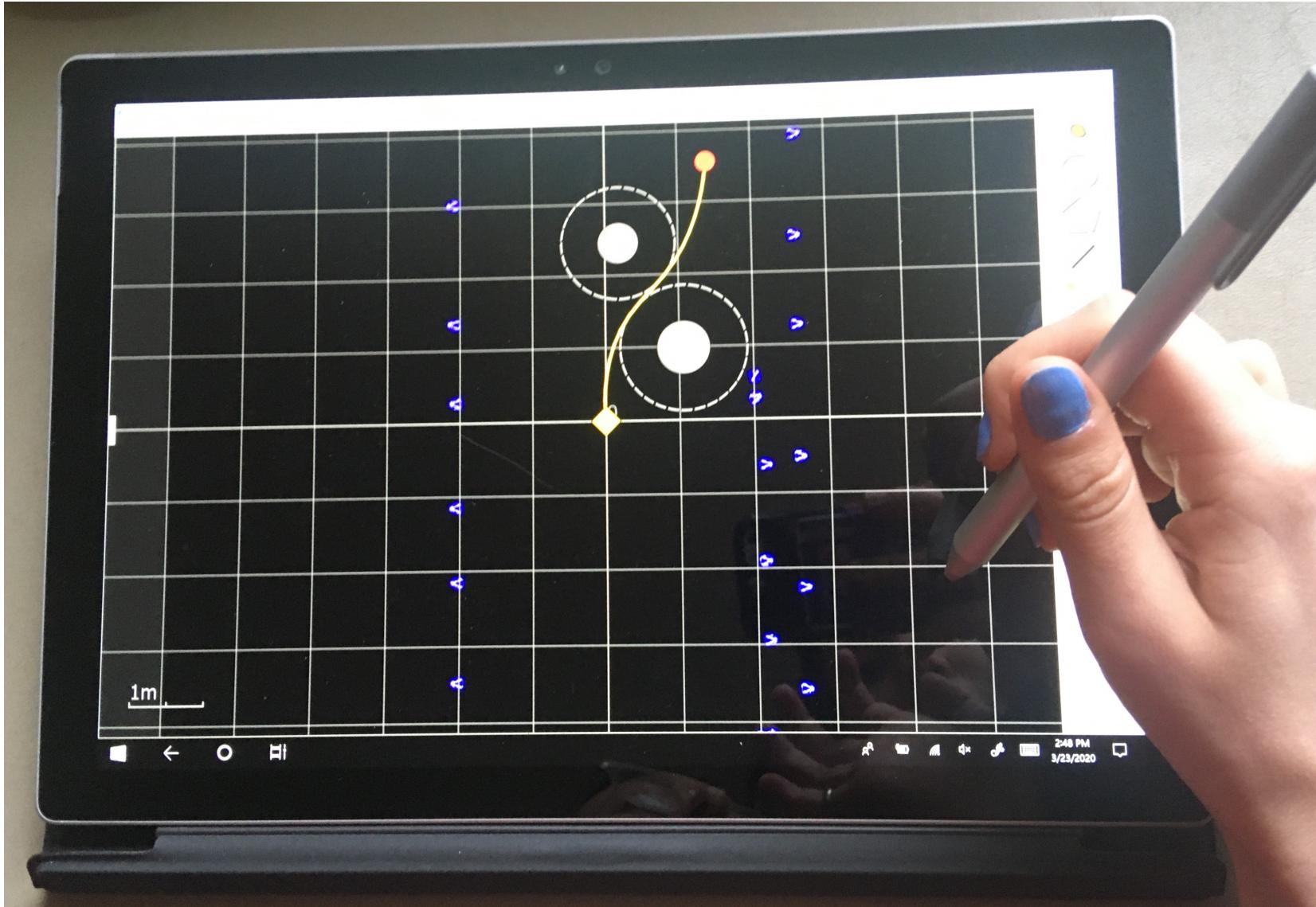


3.0 seconds



2.5 seconds

Interface: Handheld Tablet



Interface: Field Operations



Interface: Field Operations



K	25
dK	1
n_recalcs	14
a_min	5.00
a_max	12.00
theta_max	0.79
q_max	0.00
max_iter	10
delta_i	100.00
lambda	100.00
alpha	2.00
dL_tol	0.10
rho_0	-0.10
rho_1	0.25
rho_2	0.90
rrelax	1000.00
rfrelax	10.00



clearance	2.80
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Exec

Interface: Field Operations

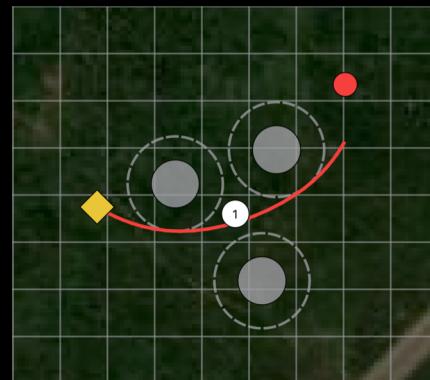
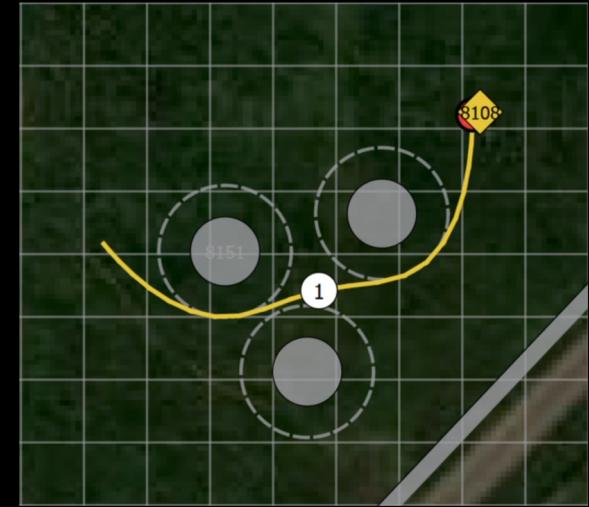
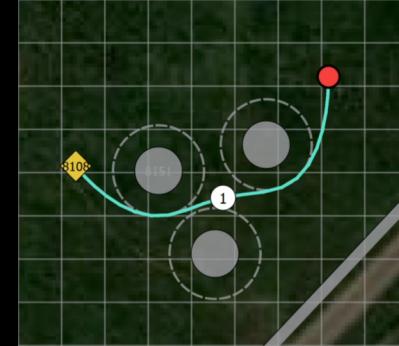
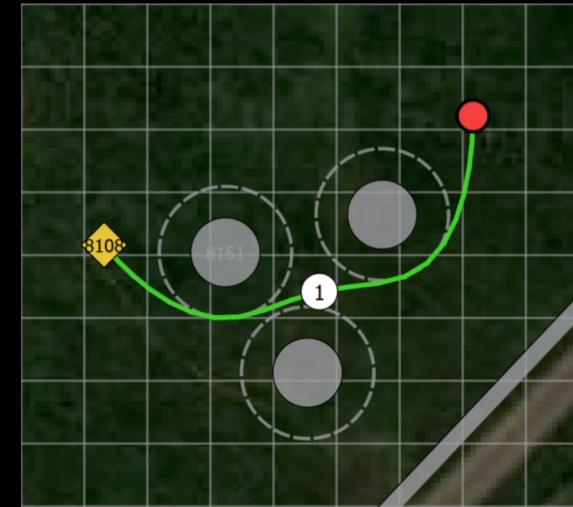
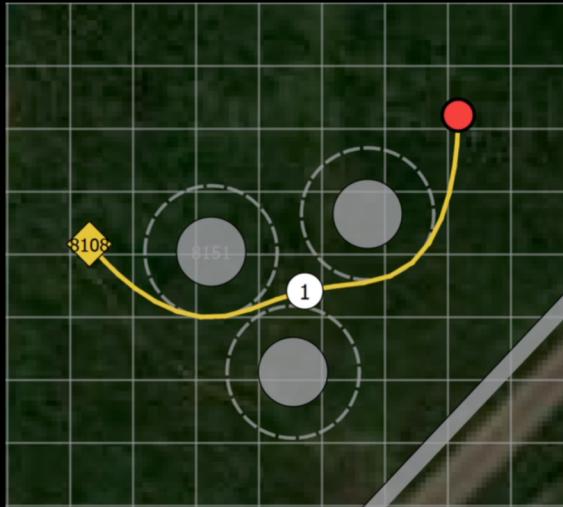


Nominal

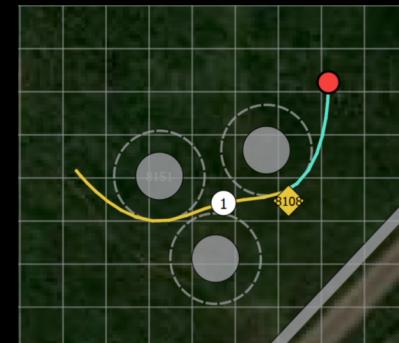
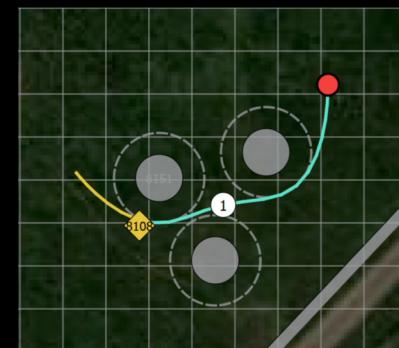
Staged

Executed

Task completed



Constraint violated



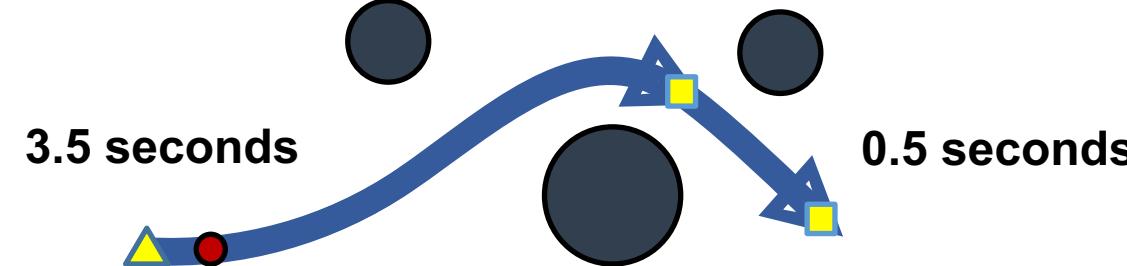
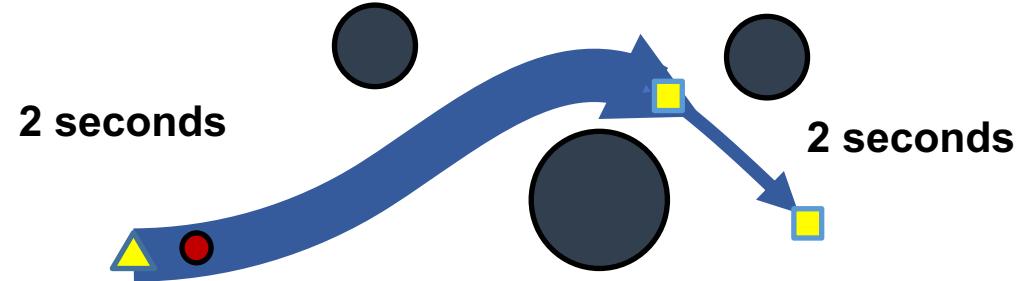
Current Work

Higher Fidelity Dynamics

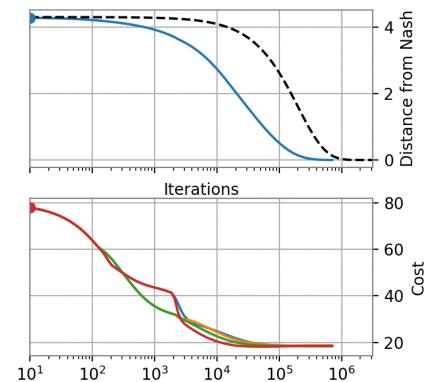


Variable Way Point Times

(In collaboration w/ P.S. Lysandrou)



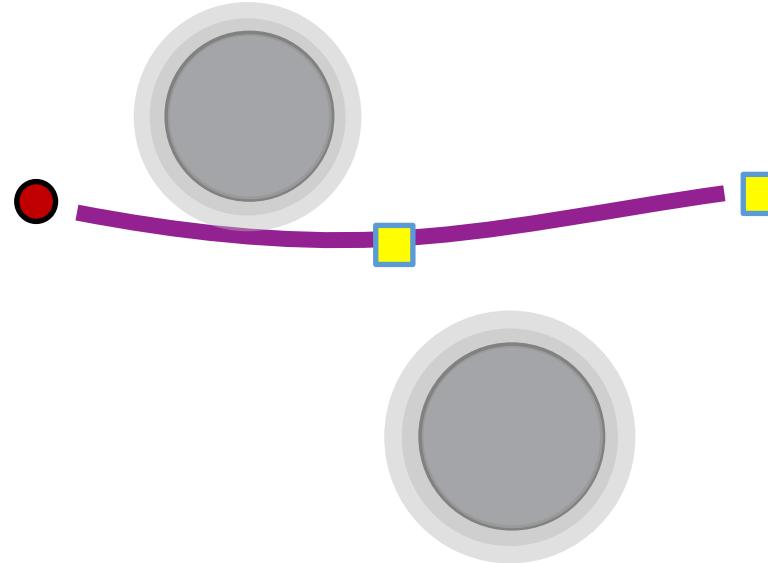
Game Theory Methods for Collision Avoidance



Future work:

Single Trajectory

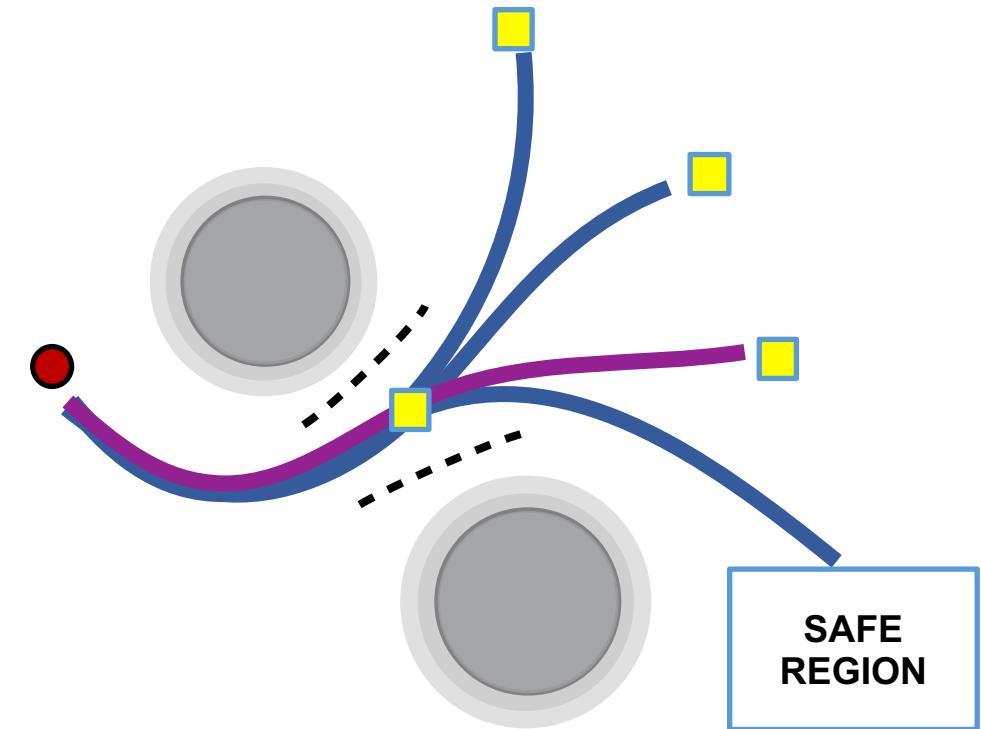
- Turn potential targets into constraints for other trajectories to maintain feasibility
- Warm-start capabilities for replanning after task change
- User interface with tablet for quick online reassignment



Trajectory Bundles

- Turn potential targets into constraints for other trajectories to maintain feasibility
- Warm-start capabilities for replanning after task change
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Single
Trajectory
Bundle



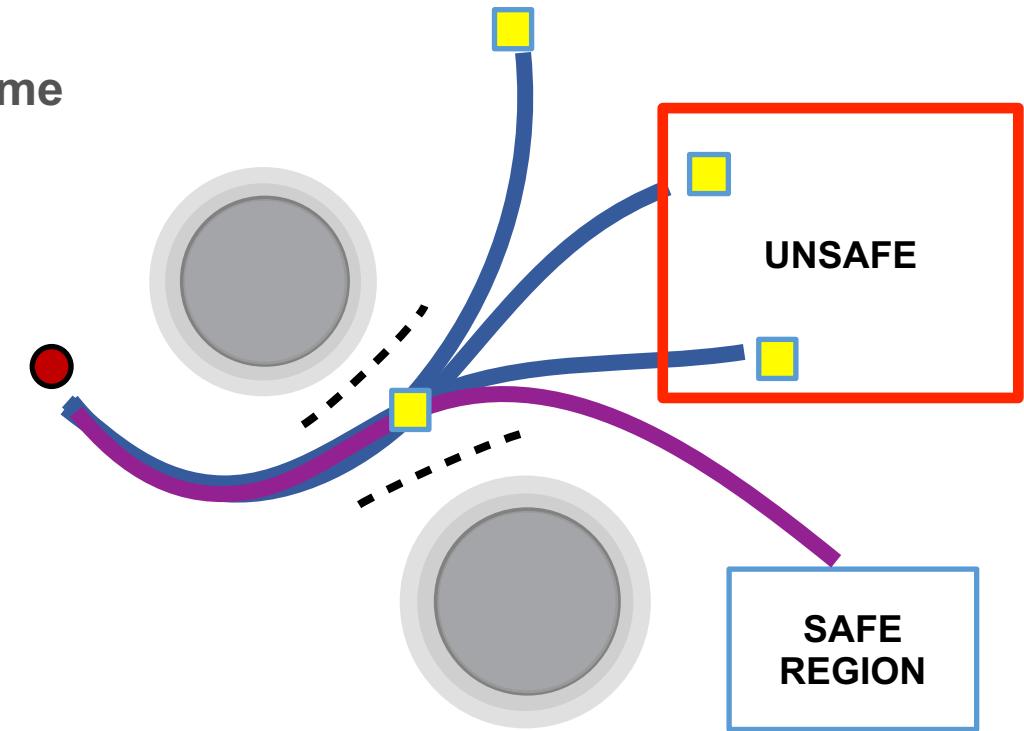
Trajectory Bundles

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Single
Trajectory

Trajectory
Bundle

Real Time
Update



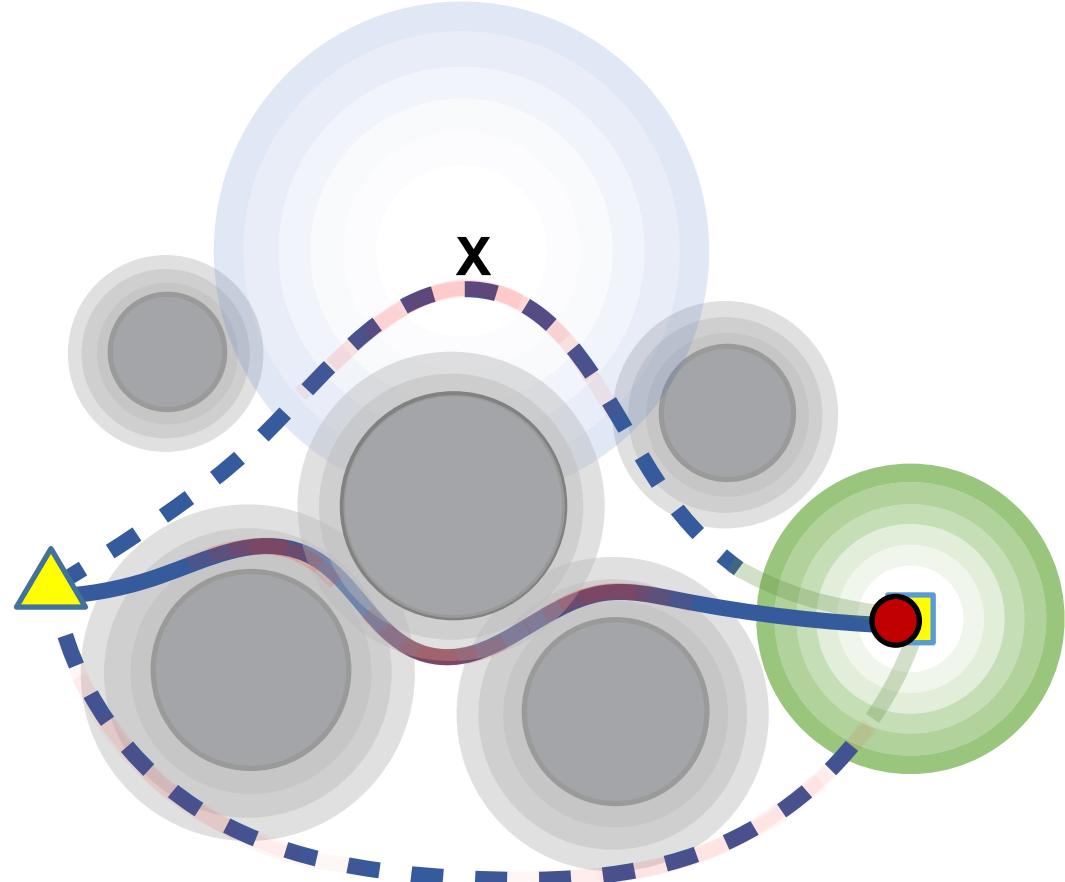
Multi-Objective Optimization

- Trade-offs in objective determine solution:

$$\begin{array}{ll} \min_x & w_f F(x) - w_T T(x) + w_w W(x) + w_p P(x) + w_b B(x) \\ \text{s.t.} & x \in \mathcal{X} \end{array}$$

- Multi-objective optimization
 - Sampling based techniques
 - Hierarchical optimization

- User feedback
 - Clearly display tradeoffs on tablet
 - User changes weights/enforces constraints/selects trajectories on screen



Multi-Objective Optimization

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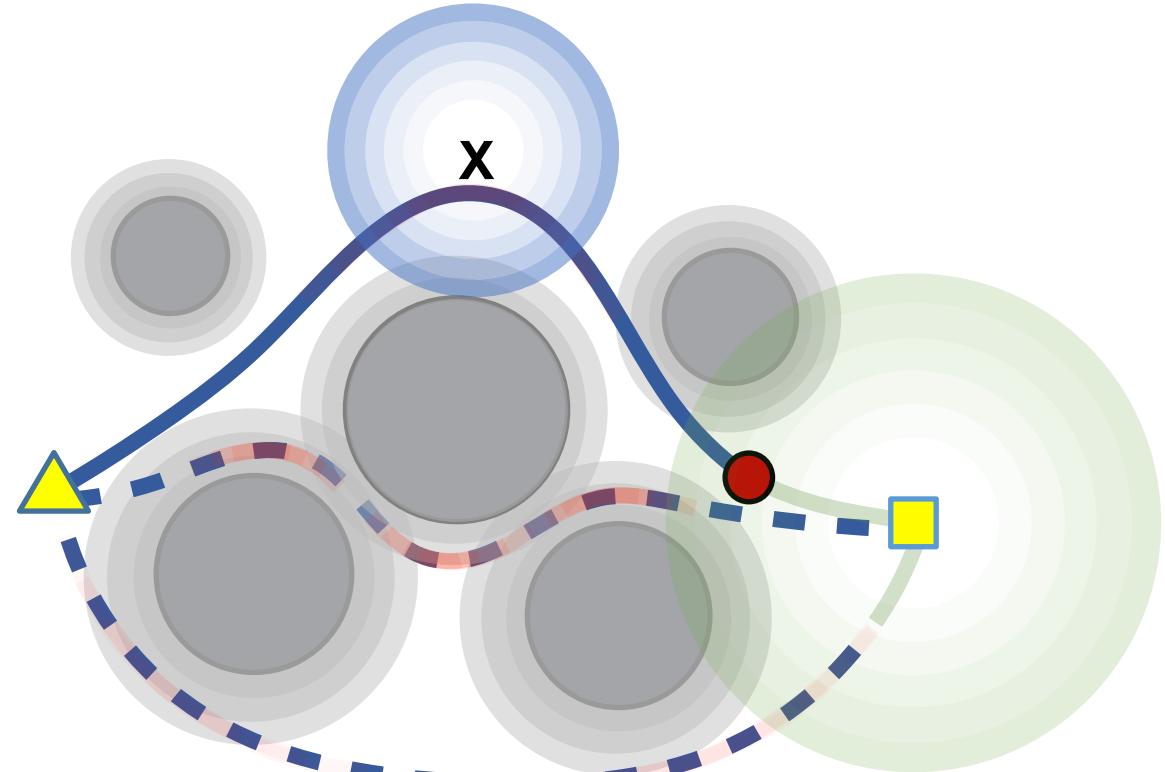
$$\begin{array}{llllll} & \text{Fuel} & \text{Time} & \text{Way Pts.} & \text{Perform} & \text{Boundary} \\ \min_x & w_f F(x) + w_T T(x) + w_w W(x) + w_p P(x) + w_b B(x) \\ \text{s.t.} & x \in \mathcal{X} \end{array}$$

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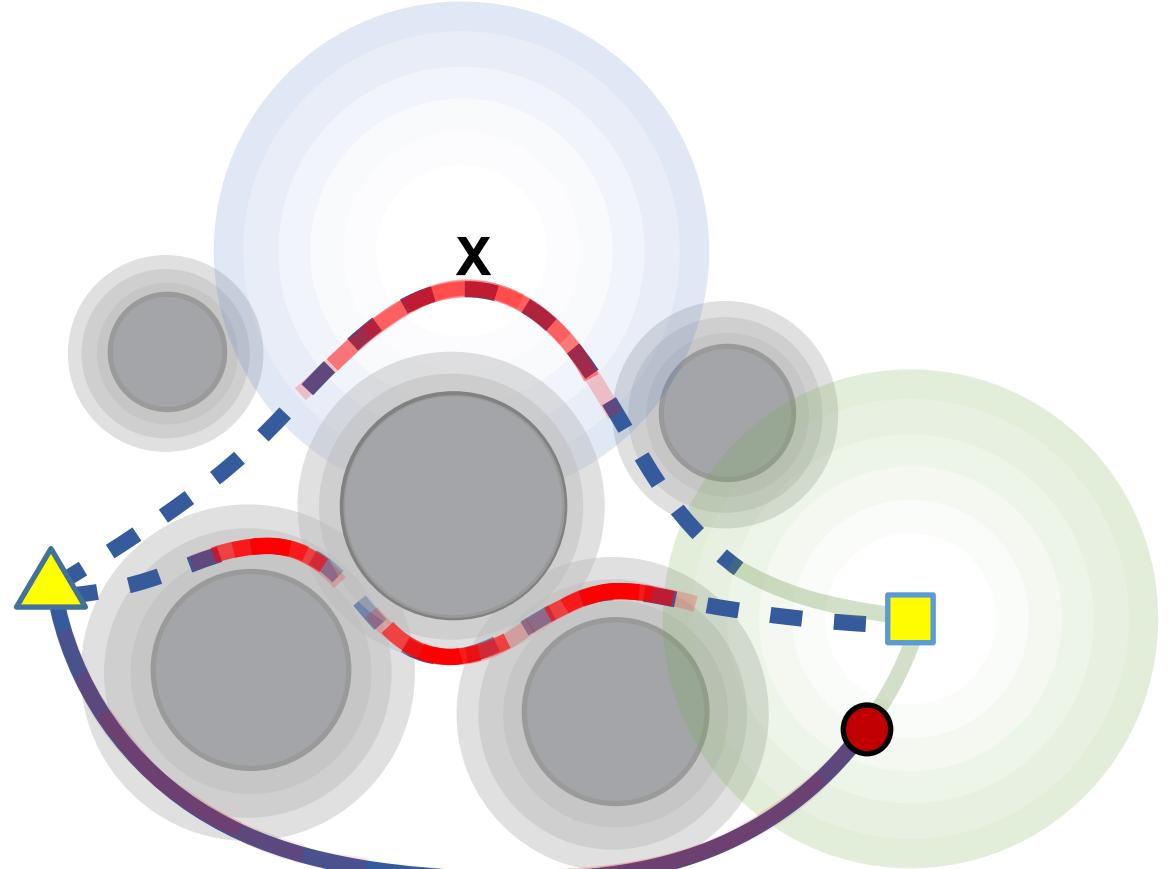
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Multi-Objective Optimization

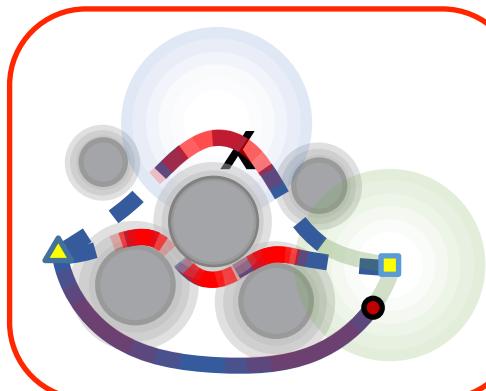
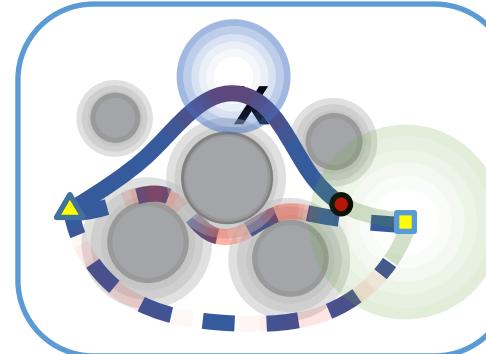
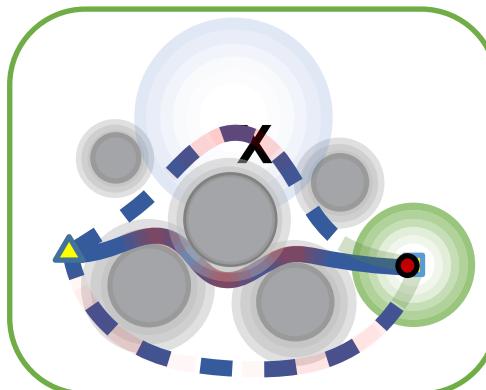
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Fuel Time Way Pts. Perform Boundary

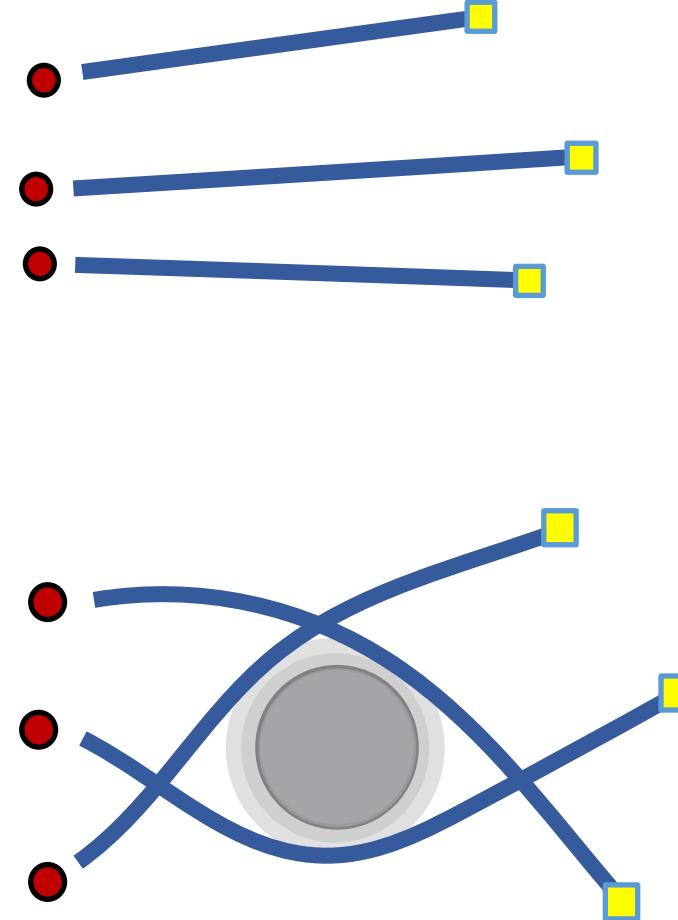
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Multi-Agent Optimization

- Multi-agent SCVX
 - Primal-dual methods for decentralization of trajectory planning - ADMM
- Task matching using trajectories
 - Assignment Algorithms
 - *Optimal transport – shortest path*
 - *Extensions*
 - Obstacle/collision avoidance
 - User assignment



Thank you!

Q&A