

Optimal trade-off analysis for efficiency and safety in the spacecraft rendezvous and docking problem

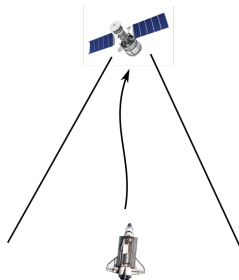
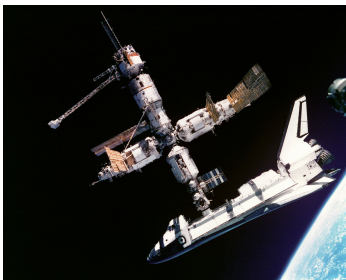
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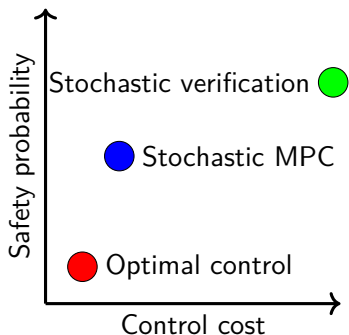
June 15, 2018

Motivation



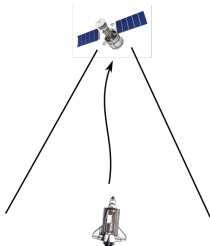
- ▶ Stochasticity ← disturbances and unmodeled phenomena
- ▶ Stochastic optimal control with requirements of
 - ▶ Safety (High probability of state constraints satisfaction)
 - ▶ Efficiency (Low fuel consumption)
- ▶ Can we maximize safety and efficiency **simultaneously**?

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Spacecraft rendezvous and docking problem



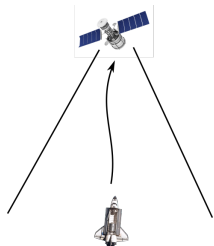
- ▶ Two spacecraft in same circular orbit
- ▶ Relative planar dynamics: Clohessy-Wiltshire-Hill

$$\left. \begin{aligned} \ddot{x} - 3\omega x - 2\omega \dot{y} &= \frac{u_1}{m_d} \\ \ddot{y} + 2\omega \dot{x} &= \frac{u_2}{m_d} \end{aligned} \right\} \Rightarrow T_s \begin{cases} \mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \mathbf{B}\bar{\mathbf{u}}_t + \mathbf{w}_t \\ \mathbf{x}_t = [x_t \ y_t \ \dot{x}_t \ \dot{y}_t]^\top \\ \mathbf{w}_t \sim \mathcal{N}(\bar{\mathbf{0}}, \Sigma_{\mathbf{w}}) \end{cases}$$

Parameter	Symbol	Value
Sampling time period	T_s	20 s
Orbital radius	R_0	7.2281×10^6 m ($R_e + 850$ km)
Gravitational constant times Earth's mass	$\mu = GM_e$	3.986×10^{14} m ³ s ⁻²
Orbital frequency	$\omega = \sqrt{\frac{\mu}{R_0^3}}$	1.027×10^{-3} rad s ⁻¹
Deputy spacecraft mass	m_d	300 kg
Noise covariance	$\Sigma_{\mathbf{w}}$	$\text{diag}([10^{-4} \ 10^{-4} \ \frac{10^{-9}}{2} \ \frac{10^{-9}}{2}])$

Lesser, Oishi, & Erwin, CDC 2013

Problem statements



- Q1 Maximize probability of staying in line-of-sight cone \mathcal{S} , reaching target \mathcal{T} at N ; and minimize fuel
- Q2 Characterize an empirical lower bound on thruster limits

$$\begin{aligned} & \underset{\bar{u}_0, \dots, \bar{u}_{N-1}}{\text{minimize}} && \begin{bmatrix} L(\bar{U}) \\ -\mathbb{P}_{\mathbf{X}}^{\bar{x}_0, \bar{U}} \{ \text{Reach } \mathcal{T} \text{ and stay within } \mathcal{S} \} \end{bmatrix} \\ & \text{subject to} && \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\bar{u}_k + \mathbf{w}_k, \\ & && \bar{u}_k \in \mathcal{U} = [-\bar{u}_{\text{bound}}, \bar{u}_{\text{bound}}]^2, \\ & && \mathbf{w}_k \sim \mathcal{N}(\bar{\mathbf{0}}, \Sigma_{\mathbf{w}}) \end{aligned}$$

where $\bar{U} = [\bar{u}_0 \dots \bar{u}_{N-1}]$, $L(\bar{U}) = \|\bar{U}\|_2$, $N = 5$ time steps (100 s),
 $\mathbf{X} = [\mathbf{x}_1^\top \dots \mathbf{x}_N^\top]$, $\mathbf{X} = \mathcal{A}\bar{x}_0 + \mathbf{H}\bar{U} + \mathbf{G}\mathbf{W}$, $\mathbf{X} \sim \mathcal{N}(\bar{\mu}_{\mathbf{X}}, \Sigma_{\mathbf{X}})$

Related work

Stochastic verification

Abate, Amin, Prandini, Lygeros, & Sastry (2007); Abate, Prandini, Lygeros, & Sastry (2008); Summers, & Lygeros (2010); Lesser, Oishi, & Erwin (2013); Gleason, Vinod, & Oishi (2017); Kariotoglou, Kamgarpour, Summers, & Lygeros (2017); Vinod & Oishi (2017, 2018)

Bi-criterion optimization

Pareto (1971); Luenberger (1995); Boyd & Vanderberge (2004);

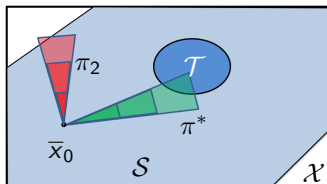
Stochastic MPC approaches

Park, Cairano, & Kolmanovsky (2011); Gavilan, Vazquez, & Camacho (2012); Hartley, Trodden, Richards, & Maciejowski (2012); Weiss, Baldwin, Erwin, & Kolmanovsky (2015); Starek, Schmerling, Maher, Barbee, & Pavone (2016)

Lexicographic approaches

Dueri, Leve, Açıkmeşe (2016); Lesser and Abate (2017)

Verification of LTI+Gaussian via convex optimization



- ▶ Reach-avoid objective: $\forall k \in \mathbb{N}_{[0, N-1]}, \mathbf{x}_k \in \mathcal{S} \wedge \mathbf{x}_N \in \mathcal{T}$
- ▶ Admissible feedback laws $\mathcal{M} = \{\pi : \mathcal{X} \rightarrow \mathcal{U} \mid \pi \text{ is measurable}\}$

maximize $\mathbb{P}_{\mathbf{x}}^{\bar{x}_0, \pi} \{\text{Reach-avoid}\}$

subject to $\pi_k(\cdot) \in \mathcal{M}$

\geq

maximize $\mathbb{P}_{\mathbf{x}}^{\bar{x}_0, \bar{U}} \{\text{Reach-avoid}\}$

subject to $\bar{U} \in \mathcal{U}^N$

Dynamic programming

Hard to compute!

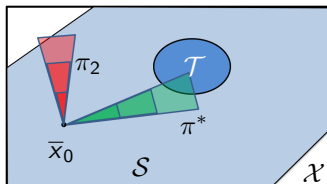
Log-concave optimization

Easy to compute!

Vinod & Oishi, LCSS 2017

Abate et. al., Automatica 2008; Summers & Lygeros, Automatica 2010

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maximize $\int_{\mathcal{S}^{N-1} \times \mathcal{T}} \mathcal{N}(\bar{\mu}_{\mathbf{x}}, \Sigma_{\mathbf{x}})$

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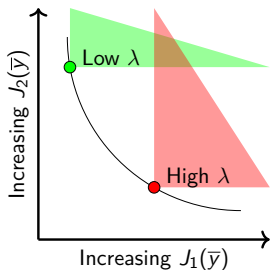
Abate et. al., Automatica 2008; Summers & Lygeros, Automatica 2010

Bi-criterion optimization

$$\begin{aligned} & \underset{\bar{y}}{\text{minimize}} \quad (\text{w.r.t. } \in \mathbb{R}_+^2) \begin{bmatrix} J_1(\bar{y}) \\ J_2(\bar{y}) \end{bmatrix} \\ & \text{subject to } \bar{y} \in \mathcal{Y} \end{aligned} \quad (1)$$

Scalarization: Choose $\lambda \in [0, \infty]$ to convert (1) into (2),

$$\begin{aligned} & \underset{\bar{y}}{\text{minimize}} \quad [1 \ \lambda] \begin{bmatrix} J_1(\bar{y}) \\ J_2(\bar{y}) \end{bmatrix} = J_1(\bar{y}) + \lambda J_2(\bar{y}) \\ & \text{subject to } \bar{y} \in \mathcal{Y} \end{aligned} \quad (2)$$



Pareto optimal curve by varying λ

$$\begin{bmatrix} 1 \\ 2 \end{bmatrix} \preceq \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad \text{but} \quad \begin{bmatrix} 1 \\ 2 \end{bmatrix} \not\preceq \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

Boyd & Vanderberge, 2004

Trade-off analysis between safety and efficiency

$$\begin{aligned} & \underset{\bar{U}}{\text{minimize}} \quad (\text{w.r.t. } \in \mathbb{R}_+^2) \left[\begin{array}{l} \|\bar{U}\|_2 \\ -\log(\mathbb{P}_{\mathbf{x}}^{\bar{x}_0, \bar{U}}\{\text{Reach-avoid}\}) \end{array} \right] \quad (3) \\ & \text{subject to } \quad \bar{U} \in \mathcal{U}^N \end{aligned}$$

► **Convex scalarized problem** for (3)

► Log-concave $\mathbb{P}_{\mathbf{x}}^{\bar{x}_0, \bar{U}}\{\text{Reach-avoid}\} = \int_{\mathcal{S}^{N-1} \times \mathcal{T}} \mathcal{N}(\bar{\mu}_{\mathbf{x}}, \Sigma_{\mathbf{x}})$

► Tractable for **polytopic** \mathcal{S}, \mathcal{T}

► Genz's algorithm \rightarrow noisy objective \rightarrow use patternsearch

► Initialize by mean trajectory optimization

$$\begin{aligned} & \underset{\bar{\mu}_{\mathbf{x}}, \bar{U}}{\text{minimize}} \quad \|\bar{U}\|_2 \\ & \text{subject to} \quad \bar{\mu}_{\mathbf{x}} = \mathcal{A}\bar{x}_0 + \mathcal{H}\bar{U} + \mathcal{G}\bar{\mu}_{\mathbf{w}}, \\ & \quad \bar{\mu}_{\mathbf{x}} \in \mathcal{S}^{N-1} \times \mathcal{T}, \\ & \quad \bar{U} \in \mathcal{U}^N \end{aligned}$$

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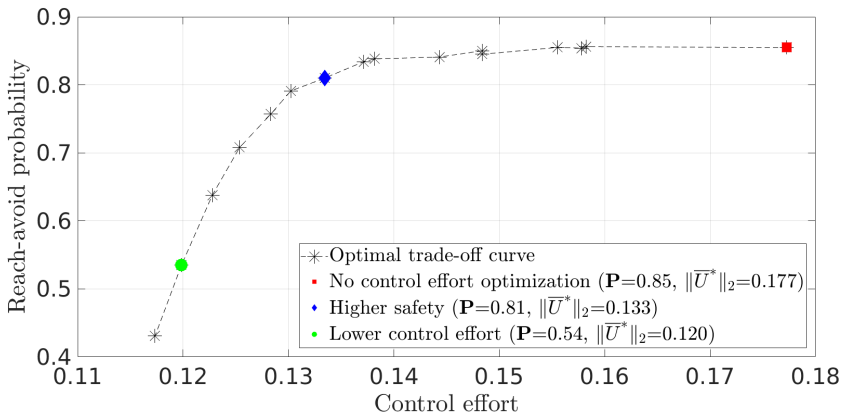
- ▶ **Convex scalarized problem** for (3)
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- ▶ Tractable for **polytopic** \mathcal{S}, \mathcal{T}
 - ▶ Genz's algorithm \rightarrow noisy objective \rightarrow use patternsearch
- ▶ Initialize by mean trajectory optimization (**Quadratic program**)

$$\begin{aligned} & \underset{\bar{\mu}_{\mathbf{x}}, \bar{U}}{\text{minimize}} \quad \|\bar{U}\|_2 \\ & \text{subject to} \quad \bar{\mu}_{\mathbf{x}} = \mathcal{A}\bar{x}_0 + \mathcal{H}\bar{U} + \mathcal{G}\bar{\mu}_{\mathbf{w}}, \\ & \quad \quad \quad P\bar{\mu}_{\mathbf{x}} \leq \bar{q}, \\ & \quad \quad \quad H\bar{U} \leq \bar{g} \end{aligned}$$

Trade-off analysis between safety and efficiency

Initial position (m) (0.75, -0.75) Input space (N) $[-0.1, 0.1]^2$
Initial velocity (0,0) Compute (min) ~ 59 (17 evals)

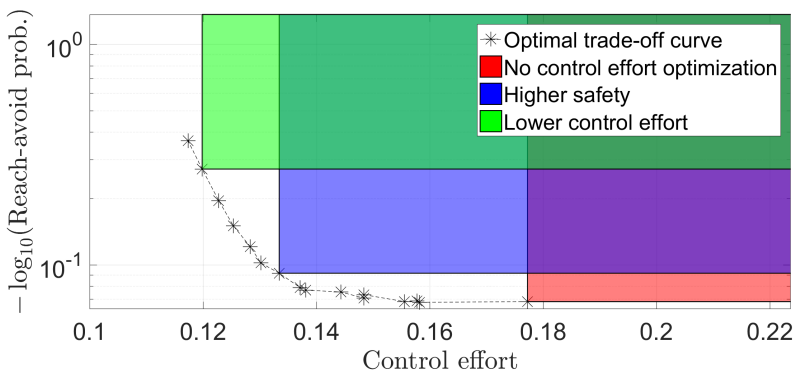
Scalarized cost $\lambda \|\bar{U}\|_2 - \log(\mathbb{P}_{\mathbf{x}^{\bar{x}_0}, \bar{U}} \{\text{Reach-avoid}\})$, $\lambda \in [0, \infty]$



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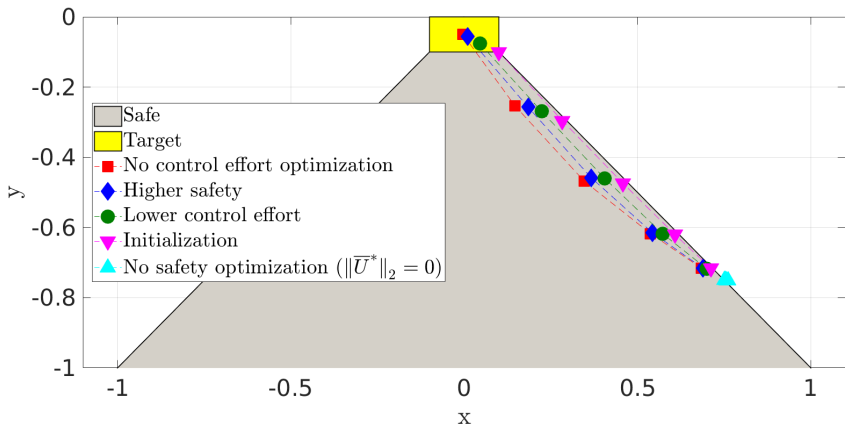
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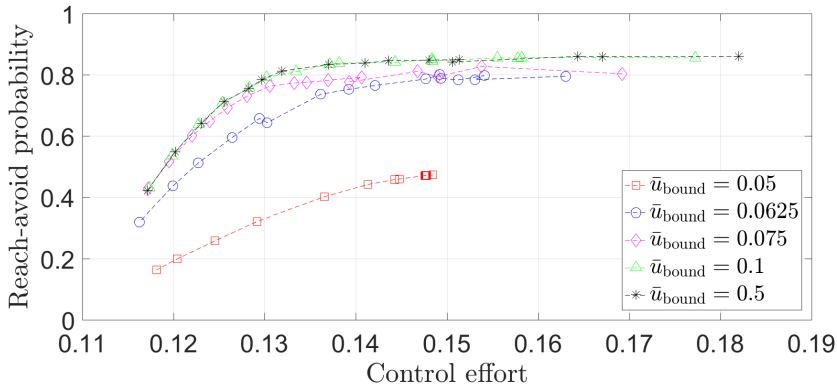


Influence of the control bounds on safety

Initial state $[0.75, -0.75, 0, 0]$

Scalarized cost $\lambda \|\bar{U}\|_2 - \log(\mathbb{P}_{\mathbf{X}}^{\bar{x}_0, \bar{U}}\{\text{Reach-avoid}\})$ with $\lambda \in [0, \infty]$

$\mathcal{U} = [-\bar{u}_{\text{bound}}, \bar{u}_{\text{bound}}]^2$ with $\bar{u}_{\text{bound}} \in \{0.05, 0.0625, 0.075, 0.1, 0.5\}$



Summary, future work, and acknowledgements

Summary

- ▶ Trade-off analysis b/n safety + efficiency
 - ▶ Convex bi-criterion optimization
- ▶ Influence of input bounds on safety

MATLAB code: github.com/unm-hscl/abyvinod-NAASS2018.

Future work

- ▶ Chance-constrained framework
- ▶ Analysis of closed-loop controllers
- ▶ Linear time-varying system dynamics

Work funded by

- ▶ NSF CMMI-1254990 (CAREER, Oishi),
- ▶ CNS-1329878, and
- ▶ AFRL Grant Number FA9453-17-C-0087 (for Oishi).

