Invariant Set and Controller Synthesis

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Overview

Robust Controlled Invariant Set

We consider Discrete Linear Time Invariant (DLTI) system:

$$x^+ = Ax + Bu + Dp,$$

where $x \in \mathbf{R}^n$, $p \in \mathcal{P} = \{p \in \mathbf{R}^d : Rp \le r\}$ and $u \in \mathcal{U} = \{u \in \mathbf{R}^m : Hu \le h\}$ are "specification" polytopes.

Controlled Robust Positively Invariant Set

A set $\mathcal{X}$ is called *controlled robust positively invariant* (CRPI) if:

$$\mathcal{X} = \{x \in \mathbf{R}^n : \exists u \in \mathcal{U} \text{ s.t. } Ax + Bu + Dp \in \mathcal{X},\ \forall p \in \mathcal{P}\}.$$

Robust Invariant Set

Robust Controlled Invariant Set

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Now consider that some control law exists and the system reduces to an autonomous one:

$$x^+ = Ax + Dp.$$

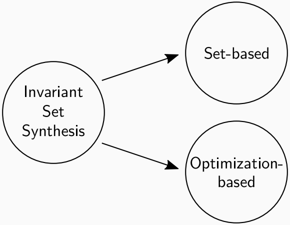
Robust Invariant Set

A set $\mathcal{X}$ is called *robust positively invariant* (RPI) if:

$$Ax + Dp \in \mathcal{X}, \quad \forall x \in \mathcal{X},\ p \in \mathcal{P}.$$

Goal: find an RPI $\mathcal{X}$.

Two Ways to Synthesize an Invariant Set



- Optimization-based methods rely on an explicit optimization problem (LP, LMI, etc.) to find $\mathcal{X}$
- Set-based methods rely on polytopic operations[1], i.e. computational geometry.

[1] These operations may implicitly involve an optimization, but what differentiates set-based methods is that people don't "talk" about it – they just assume that one can compute e.g. the Pontryagin difference.

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

Equivalent RPI Condition

$$\mathcal{X}(g) = \{x : Gx \leq g\} \text{ RPI} \Leftrightarrow \sigma(G_i \mid A\mathcal{X}(g)) + \sigma(G_i \mid D\mathcal{P}) \leq \sigma(G_i \mid \mathcal{X}(g)),$$

where $g \in \mathbf{R}^{n_g}$ and $\sigma(z \mid \mathcal{S}) \triangleq \sup\{y^T z : y \in \mathcal{S}\}$ is the support function of (some) set $\mathcal{S}$.

Note: $\sigma(G_i \mid \mathcal{X}(g)) \leq g_i$ with $<$ $\Leftrightarrow$ facet i is redundant.

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

Existence of an RPI Set

Fix G in $\mathcal{X}(g) = \{x : Gx \leq g\}$ (i.e. pick a "template"). Assumptions:

A1. $\mathcal{P}$ contains the origin

A2. $\lambda < 0 \ \forall \lambda \in \mathrm{spec}(A)$

A3. The interior of $\mathcal{X}$ contains the origin

A4. For the chosen G, a g exists such that $\mathcal{X}(g)$ is RPI

Then there exists a g^* such that

$$\sigma(G_i \mid A\mathcal{X}(g^*)) + \sigma(G_i \mid D\mathcal{P}) = \sigma(G_i \mid \mathcal{X}(g^*)) = g^* \quad \forall i = 1, \ldots, n_g.$$

$\mathcal{X}(g^*)$ is the min-volume RPI set, i.e. g^* achieves minimum $\|g^*\|_1$.

Fixed-Point Solution Uniqueness

Given assumptions A1-A4, the g^* in the above statement is unique.

One-Step Minimal RPI Computation

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Existence of an RPI Set

$$\sigma(G_i \mid A\mathcal{X}(g^*)) + \sigma(G_i \mid D\mathcal{P}) = \sigma(G_i \mid \mathcal{X}(g^*)) = g^* \quad \forall i = 1, \ldots, n_g.$$

$\mathcal{X}(g^*)$ is the min-volume RPI set, i.e. g^* achieves minimum $\|g^*\|_1$.

g^* can be computed iteratively:

Algorithm 1 Iterative computation of g^*.

1: Set $g \leftarrow 0$
2: **while** True **do**
3: $\quad g_i^* \leftarrow \sigma(G_i \mid A\mathcal{X}(g)) + \sigma(G_i \mid D\mathcal{P})\ i = 1, \ldots, n_g$
4: $\quad$ **if** $\|g - g^*\|_\infty < \epsilon_{\text{tol}}$ **then**
5: $\quad\quad$ **return** g^*
6: $\quad g \leftarrow g^*$

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

- g^* can also be computed as a one-shot LP (main contribution of [1])
- Let $c_i(g) = \sigma(G_i \mid A\mathcal{X}(g))$, $d_i = \sigma(G_i \mid D\mathcal{P})$, $b_i(g) = \sigma(G_i \mid \mathcal{X}(g))$. Core realization (thanks to uniqueness of g^*):

$$g^* = \arg\min_{g}\{\|g\|_1 : c(g)+d = b(g)\} = \arg\max_{g}\{\|g\|_1 : c(g)+d = b(g)\}$$

- Recalling that $b(g) \le g$, the above is readily converted to an LP:

$$\begin{aligned} g^* = c^* + d^*, \text{ where } (c^*, d^*) = \; & \underset{\substack{\{c_i, d_i, \xi^i, \omega^i\} \\ \forall i \in \{1,\dots,n_g\}}}{\arg\text{ maximize}} && \sum_{i=1}^{n_g} c_i + d_i \\ & \text{subject to} && c_i \le G_i A \xi^i \\ & && G\xi^i \le c + d \\ & && d_i \le G_i D \omega^i \\ & && F\omega^i \le g. \end{aligned}$$

One-Step Minimal RPI Computation

Trodden, “A One-Step Approach to Computing a Polytopic Robust Invariant Set”, 2016. [1]

$$\boxed{\text{Let } c_i(g) = \sigma(G_i \mid A\mathcal{X}(g)),\ d_i = \sigma(G_i \mid D\mathcal{P}),\ b_i(g) = \sigma(G_i \mid \mathcal{X}(g))}$$

$$
\begin{aligned}
g^* = c^* + d^*,\ \text{where } (c^*, d^*) = \arg \underset{\substack{\{c_i, d_i, \xi^i, \omega^i\} \\ \forall i \in \{1,\ldots,n_g\}}}{\text{maximize}} \quad & \sum_{i=1}^{n_g} c_i + d_i \\
\text{subject to} \quad & c_i \le G_i A \xi^i \\
& G\xi^i \le c + d \\
& d_i \le G_i D \omega^i \\
& F\omega^i \le g.
\end{aligned}
$$

The first two constraints evaluate $c_i(g)$ and the last two evaluate d_i. The first constraint holds with equality at optimality, since we want to maximize c_i. The RHS of the second constraint $= g^*$ at optimality, therefore the second constraint enforces $P\xi^i \le g^*$, i.e. the definition of $b(g^*)$.

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

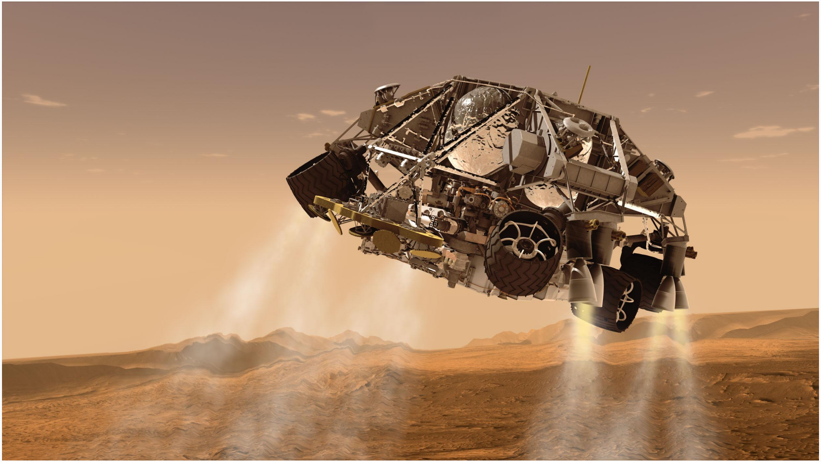
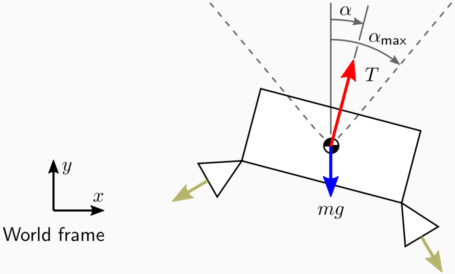


Image credit: NASA/JPL-Caltech

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]



Parameters [2]:

$$m_{\text{wet}} = 1905 \text{ kg}$$
$$g = -3.7114 \text{ m/s}^2$$
$$g_e = 9.81 \text{ m/s}^2$$
$$I_{sp} = 225 \text{ s} \quad T_{\max} = 3.1 \text{ kN}$$
$$\phi = 27 \text{ deg} \quad n = 6$$

Dynamics:

$$(\dot{x}, \dot{y}) = (v_x, v_y)$$
$$(\dot{v}_x, \dot{v}_y) = (T_x, T_y)/m + g$$
$$\dot{m} = -\frac{\|(T_x, T_y)\|_2}{I_{sp} g_e \cos\phi}$$

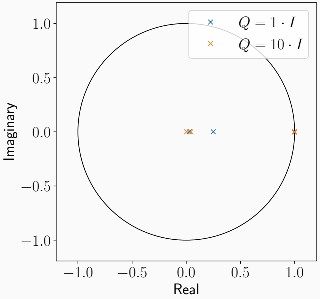
Letting $T \leftarrow T + mg$ be the gravity compensated control, the system is linearized about $(\bar{x}, \bar{y}, \bar{v}_x, \bar{v}_y, \bar{m}) = (0, 0, 0, 0, m_{\text{wet}})$ and $(\bar{T}_x, \bar{T}_y) = (0, 0)$.

One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

Synthesize an LQR stabilizing controller:

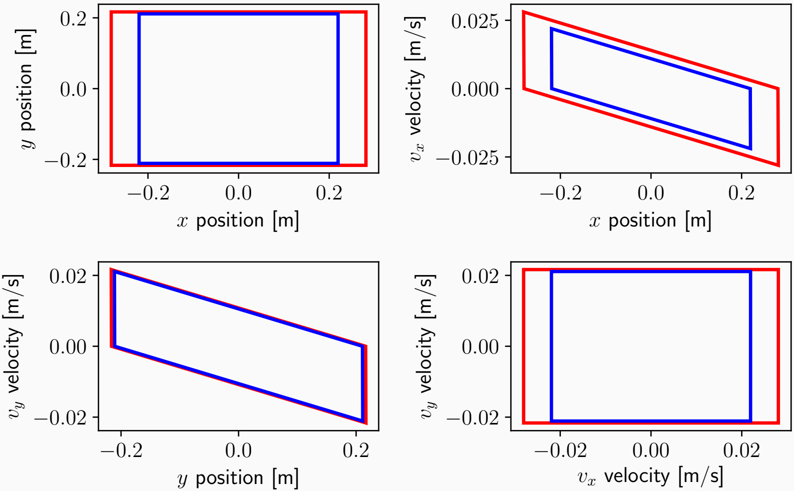
- State scaling: $D_x = \begin{bmatrix} 1 & 1 & 0.05 & 0.05 & 0.1 \end{bmatrix}$
- Input scaling: $D_u = \begin{bmatrix} nT_{\max} \cos\phi \sin\alpha_{\max} & nT_{\max} \cos\phi \end{bmatrix}$
- State penalty $Q = D_x^{-1} \hat{Q} D_x$ with $\hat{Q} \in \{I_5, 10I_5\}$
- Input penalty $R = D_x^{-1} \hat{R} D_x$ with $\hat{R} = I_2$



One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

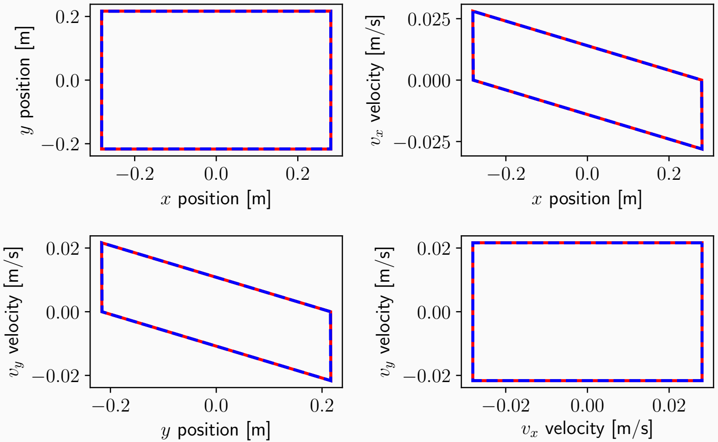
Direct application of LP on slide 10 ($\hat{Q} = I_5$, $\hat{Q} = 10I_5$):



One-Step Minimal RPI Computation

Trodden, "A One-Step Approach to Computing a Polytopic Robust Invariant Set", 2016. [1]

The one-shot LP of slide 10 and the iterative algorithm of slide 8 are identical...



... but iterative takes ≈ 315 s while one-shot takes ≈ 0.2 s!

Maximal RCI Computation

Kvasnica et al., "Reachability Analysis and Control Synthesis for Uncertain Linear Systems...", 2015. [3]

First Way: Optimization

The control problem can be formulated as an optimization problem:

Control Policy Synthesis via Optimization

Let $\mathcal{I} \triangleq \{x \in \mathbf{R}^n \mid Gx \leq g\}$ be the maximal positively invariant set induced by the control policy $u[k] = \mu_k(z[k])$. Consider the following sequence of optimization problems (for $i = 1, \ldots, n_\mathrm{p}$):

$$\begin{aligned} g_i^+ = \underset{x,u,w,v,e,G,g,k}{\text{maximize}} \quad & G_i(A[k]x + B[k](u+e) + E[k]w) \\ \text{subject to} \quad & x \in \mathcal{I},\ u \in \mathcal{U},\ w \in \mathcal{W}(x,u),\ v \in \mathcal{V}(x),\ e \in \mathcal{L}(u) \\ & u = c_k(x+v) \\ & \mathcal{I} \subseteq \mathcal{X}, \quad k \in \mathbf{Z}_+. \end{aligned}$$

The control policy solves the control problem if and only if $g^+ \leq g$.

Authors employing optimization solve this problem via clever tricks for the particular structure that they consider (yields an LP, an SDP, etc.).

Second Way: Set-Based Iterative

Predecessor Set

Given a set $\mathcal{R} \subseteq \mathcal{X}$, the *predecessor set* $\text{Pre}(\mathcal{R})$ is:

$$\text{Pre}(\mathcal{R}) \triangleq \{x \in \mathbf{R}^n \mid \exists u \in \mathcal{U} \text{ s.t. } A[k]x + B[k](u+v) + E[k]w \in \mathcal{R} \\ \forall v \in \mathcal{V}(x), w \in \mathcal{W}(x,u)\},$$

i.e. $\mathcal{R}$ is 1-step robustly *reachable* from $\text{Pre}(\mathcal{R})$.

Consider the algorithm:

$$\mathcal{I}_0 = \mathcal{X}, \quad \mathcal{I}_{k+1} = \text{Pre}(\mathcal{I}_k).$$

Then $\mathcal{I}_{k+1} \subseteq \mathcal{I}_k \; \forall i \in \mathbf{Z}_+$ and the *maximal robust controlled invariant* set in $\mathcal{X}$ is $\mathcal{I}_\infty \subseteq \bigcap_{i \in \mathbf{Z}_+} \mathcal{I}_i$ and $\mathcal{I}_\infty = \mathcal{I}_j$ for some $j \in \mathbf{Z}_+ \Leftrightarrow \mathcal{I}_{j+1} = \mathcal{I}_j$.

The resulting control policy is set valued and is obtained a posteriori:

$$c_k(x) = \{u \in \mathcal{U} \mid A[k]x + B[k](u+v) + E[k]w \in \mathcal{I}_\infty \; \forall v \in \mathcal{V}(x), w \in \mathcal{W}(x,u)\}.$$

Can then use e.g. dynamic programming to obtain some optimal point-valued policy.

Comparison of Set-Based versus Optimization-Based

- Optimization-based methods are faster and compute point-valued controllers directly
- Set-based methods are slower but can potentially accommodate more features and can be *anytime* (i.e. aborted at any point and yield a valid albeit imprecise answer anyway)
- Set-based methods compute set-valued controllers $\Rightarrow$ post-processing (e.g. dynamic programming) required to obtain point-valued controllers.

Whether one or the other will solve all our problems remains to be seen as we *actually try to solve all our problems*.

Overview

Overview

- Present “the control problem”
- LQR, Linear From Spec, Bertsekas, perhaps other new ones...

Bibliography

[1] P. Trodden, “A one-step approach to computing a polytopic robust positively invariant set,” *IEEE Transactions on Automatic Control*, vol. 61, pp. 4100–4105, dec 2016.

[2] B. Acikmese and S. R. Ploen, “Convex programming approach to powered descent guidance for mars landing,” *Journal of Guidance, Control, and Dynamics*, vol. 30, pp. 1353–1366, sep 2007.

[3] M. Kvasnica, B. Takács, J. Holaza, and D. Ingole, “Reachability analysis and control synthesis for uncertain linear systems in MPT,” *IFAC-PapersOnLine*, vol. 48, no. 14, pp. 302–307, 2015.