Linear Quadratic Tracking Control with Sparsity-Promoting Regularization

Zhicheng Zhang[†] and Masaaki Nagahara[‡]

†Graduate School of Information Science and Technology
Osaka University

†The Institute Environmental Science and Technology
The University of Kitakyushu

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Linear Quadratic (LQ) Tracking

Master System: $\dot{z}_m(t) = Az_m(t), \ t \geq 0, \ z_m(0) = \xi_m \in \mathbb{R}^n$

Slave System: $\dot{z}_s(t) = Az_s(t) + Bu(t), \ t \geq 0, \ z_s(0) = \xi_s \in \mathbb{R}^n$

Tracking Goal:

$$\lim_{t\to\infty}\|z_s(t)-z_m(t)\|\doteq\lim_{t\to\infty}\|x(t)\|=0$$

Tracking Error System:

$$\dot{x}(t) = Ax(t) + Bu(t), \ x(0) = \xi_s - \xi_m = \xi \in \mathbb{R}^n, \ t \ge 0$$
 (1)

Performance Index (LQ Cost)

$$J_{LQ} = \frac{1}{2} \int_0^T \left\{ x(t)^\top Q x(t) + r u(t)^2 \right\} dt, \ Q = Q^T \ge 0, \ r > 0$$

Q: Is it possible to find a *feasible control* $\{u(t): 0 \le t \le T\}$ that

achieves tracking as well as minimizes the control effort?



Recall Control Signals

- ightharpoonup Minimum energy $\Leftrightarrow \mathcal{L}^2$ norm of control signal $\int_0^T u(t)^2 dt$
 - ightharpoonup Minimum fuel $\Leftrightarrow \mathcal{L}^1$ norm of control signal $\int_0^T |u(t)| dt$
 - ho ? $\Leftrightarrow \mathcal{L}^0$ norm of control signal $\int_0^T |u(t)|^0 dt$

where $|u|^0=1$ if $u \neq 0$ and 0 otherwise

- $\Longrightarrow \mathcal{L}^0$ norm of control signal is related to the *sparsity*. It can induce *more zero elements* compared to its dimension
- A: Sparsity-promoting method is a powerful technique!
 - Compressed Sensing
 - Maximum Hands-off Control



Sparse Optimization: LQ Hands-off Control

A novel LQ hands-off control problem via sparse optimization

min
$$\frac{1}{2} \int_{0}^{T} \left\{ x(t)^{\top} Q x(t) + r u(t)^{2} \right\} dt + \lambda \int_{0}^{T} |u(t)|^{0} dt$$

$$J_{0}: \text{ LQ hands-off control cost}$$
s.t.
$$\dot{x}(t) = A x(t) + B u(t)$$

$$x(0) = \xi, \quad x(T) = 0$$

$$|u(t)| \leq 1, \quad \forall t \in [0, T]$$

$$(P_{0})$$

Pros: Minimize the control inputs and achieve tracking

Cons: (P_0) is non-convex, non-smooth and discontinuous

Necessary Conditions: Non-smooth Maximum Principle

Lemma: Let (x^*, u^*) be a local minimizer for (P_0) . Then there exist the $\{p(t) \in \mathbb{R}^n : t \in [0, T]\}$ and Hamiltonian function

$$H^{\eta}(x,p,u) \triangleq p^{\top}(Ax + Bu) - \eta(\frac{1}{2}Ru^2 - \lambda|u|^0)$$
 (2)

with a scalar $\eta \in \{0,1\}$ satisfying the following properties:

1. the non-triviality condition for a.e. $t \in [0, T]$:

$$(\eta, p(t)) \neq 0$$

2. the adjoint equation for a.e. $t \in [0, T]$:

$$\dot{p}(t) = -A^{\top}p(t) + \eta Qx^{*}(t)$$

3. the maximum condition for a.e. $t \in [0, T]$:

$$u^*(t) = \arg\max_{u \in [-1,1]} p(t)^{\top} Bu - \eta(\frac{1}{2}ru^2 - \lambda|u|^0)$$

4. the constancy of the Hamiltonian for a.e. $t \in [0, T]$:

$$H^{\eta}(x^*(t), p(t), u^*(t)) = h \in \mathbb{R}$$



Optimal Solution

Theorem: The optimal control $u^*(t)$ (if it exists) satisfies

1. If $\eta = 1$, then

$$u^*(t) = \operatorname{sat}(\mathbf{H}_{\theta}(r^{-1}B^{\top}p(t))), \tag{3}$$

where $\theta = \sqrt{2\lambda/r}$, $\operatorname{sat}(\cdot)$ is the saturation function defined by

$$\operatorname{sat}(v) \triangleq egin{cases} -1, & \text{if } v < -1 \\ v, & \text{if } -1 \leq v \leq 1 \\ 1, & \text{if } v > 1. \end{cases}$$

and $\mathbf{H}_{\theta}(\cdot)$ is the hard-thresholding function defined by

$$\mathbf{H}_{\theta}(w) \triangleq egin{cases} 0, & \text{if } -\theta < w < \theta \\ w, & \text{if } w < -\theta \text{ or } \theta < w, \end{cases}$$

and $\mathbf{H}_{\theta}(w) \in \{0, w\}$, if $w = \pm \theta$.



Numerical Computation

Convex relaxation:

min
$$J_{LQ} + \lambda ||u||_1$$
 s.t. (P_0) constraints (P_1)

Time-discretization:

 $(P_1) \rightarrow$ Finite-dimensional Optimization Problem (P_2)

min
$$\frac{1}{2} \sum_{k=0}^{m-1} \begin{bmatrix} x_d^k \\ u_d^k \end{bmatrix}^{\top} \begin{bmatrix} Q_d & S_d \\ S_d^{\top} & R_d \end{bmatrix} \begin{bmatrix} x_d^k \\ u_d^k \end{bmatrix} + \lambda \frac{T}{m} \sum_{k=0}^{m-1} |u_d^k|$$
s.t.
$$x_d^{k+1} = A_d x_d^k + B_d u_d^k$$

$$x_d^0 = \xi, \quad x_d^m = 0$$

$$|u_d^k| \le 1, \quad k = 0, 1, \dots, m-1$$

$$(P_2)$$

• Method: L¹ relaxation, Time-discretization, CVX



Robustness Analysis: Uncertainties in the initial states

We assume that the initial states are perturbed as

$$z_{\rm m}(0) = z_{\rm m} + \delta_{\rm m}, \quad z_{\rm s}(0) = z_{\rm s} + \delta_{\rm s},$$
 (4)

where $\delta_{\rm m}$ and $\delta_{\rm s}$ are uncertain vectors in \mathbb{R}^n . Define

$$\delta \triangleq \delta_{\rm s} - \delta_{\rm m}. \tag{5}$$

Then, the initial state x(0) in (1) is described as

$$x(0) = \xi + \delta. \tag{6}$$

Lemma: Let $u^*(t)$ be the LQ hands-off control that solves (P_1) with initial state $x(0) = \xi$. Let $x(t; \delta)$ denote the state variable of (1) with the optimal control u^* from the perturbed initial state in (6). Then we have

$$\|x(T;\delta)\|_{\ell^2} \le \|e^{AT}\|\|\delta\|_{\ell^2},$$
 (7)

where $\|e^{AT}\|$ is the maximum singular value of e^{AT} , and $\|\delta\|_{\ell^2}$ is the ℓ^2 norm of vector δ defined by $\|\delta\|_{\ell^2} \triangleq \sqrt{\delta^\top \delta}$.

Robustness Analysis: Gap between the A matrices

We consider the case when there is a gap between the A matrices in master-slave system. We denote the gap matrix by Δ , that is, we consider the following state-space equation instead of (1):

$$\dot{x}(t;\Delta) = (A+\Delta)x(t;\Delta) + Bu(t). \tag{8}$$

Lemma: Let $u^*(t)$ be the LQ hands-off control that solves (P_1) for the ideal plant (1). Then we have

$$||x(T;\Delta)||_{\ell^{2}} \leq \alpha(\Delta)(||\xi||_{\ell^{2}} + ||B||||u^{*}||_{1})$$

$$\leq \alpha(\Delta)(||\xi||_{\ell^{2}} + ||B||||u^{*}||_{0})$$
(9)

where

$$\alpha(\Delta) \triangleq e^{\min\{\|A\|,\|A+\Delta\|\}T} (e^{\|\Delta\|T} - 1). \tag{10}$$



Simulations

Consider a inverted pendulum-cart system without perturbations, which can be written as a linearized model

$$\begin{cases} \ddot{\epsilon} = \frac{(M_c + m_p)g}{M_c l_p} \epsilon - \frac{1}{M_c l_p} u, \\ \ddot{q} = -\frac{m_p g}{M_c} \epsilon + \frac{1}{M_c} u, \end{cases}$$
(11)

where parameters are: $M_c = 2.4$, $m_p = 0.23$, $I_p = 0.36$, g = 9.81, Q = 5I, R = 1, and $x(0) = [-\pi/120, \pi/12, 0, 0]^{\top}$.

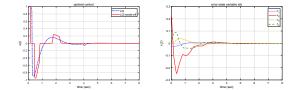


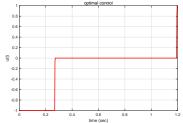
Fig. LQ and LQ hands-off control (left), tracking error states (middle), and different weights for LQ hands-off control (right)

Simulations

Consider a second-order linearized inverted pendulum system with a small disturbance

$$A = \begin{bmatrix} 0 & 1 \\ \frac{m_p l_p g}{L_p} & \frac{-b}{L_p} \end{bmatrix}, \ \Delta = \begin{bmatrix} 0 & 0 \\ 0 & 0.1 \end{bmatrix} \ \text{and} \ B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

The parameters are $m_p = 3$, $I_p = 1.5$, g = 9.81, $L_p = m_p I_p^2 / 2$, b = 0.06, $\lambda = 1$, Q = 3I, R = 1 and $x(0) = [0.02, 0.1]^{\top}$.



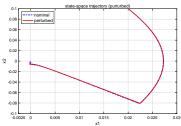


Fig. LQ hands-off control (Left) and Phase portraits (Right) of the perturbed system with gap Δ .

Conclusion

- Necessary conditions for LQ hands-off control
- LQ hands-off control may not be continuous
- Future work
 - ullet \mathcal{L}^p norm approximation, Majorization-mininization algorithms
 - Improve Robustness: Probabilistic Methods, Scenario approach

THANK YOU FOR YOUR ATTENTION!