



Robust Linear Quadratic Regulator for Uncertain Systems

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Outline



- 1 Introduction
- 2 Problem Formulation
- 3 Robust LQR
- 4 Numerical Example
- 5 Conclusions - Future Work



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Introduction

Motivation



- Optimal control design for linear dynamical systems appeared in many diverse applications (e.g., aerospace, communication, robotics, finance, biology)
- **Certainty Equivalence Principle:** same solution as for the deterministic problem as long as the disturbances present in the stochastic control system are zero mean
- **In realistic applications** the presence of (nonzero-mean) disturbances in stochastic control systems affect optimality of the controller and compromise their performance



Introduction I

Approach



- **Develop a LQR:** , which is robust to disturbance variability, by using the *total variation distance* as a metric

Total Variation Uncertainty Ball

Set of all possible noise distributions, center at a nominal distribution μ

$$\mathbb{B}_{R_{TV}}(\mu) \triangleq \left\{ \nu_{w_i}(\cdot) \in \mathcal{M}_1([p_1, p_2]), i = 1, \dots, N-1 : \sum_{i=0}^{N-1} \|\nu_{w_i}(\cdot) - \mu_{w_i}(\cdot)\|_{TV} \leq R_{TV} \right\}, \quad R_{TV} \in [0, 2]$$

- $\mathcal{M}_1([p_1, p_2])$: set of probability distributions on $[p_1, p_2]$
- $\mu(\cdot)$: “nominal” probability distribution of w_k
- $\nu(\cdot)$: “variation” probability distribution of w_k



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Problem Formulation I

Linear System



Consider a discrete-time system

$$x_{k+1} = A_k x_k + B_k u_k + w_k, \quad x_0 = x, \quad k = 0, \dots, N-1$$

- $x_k \in \mathbb{R}^n$, $u_k \in \mathbb{R}^m$: state and control vectors
- $A_k \in \mathbb{R}^{n \times n}$, $B_k \in \mathbb{R}^{n \times m}$: dynamics and input matrices
- $\{w_k : k = 0, \dots, N-1\}$ is independent sequence of RV's
 - unknown probability distribution $\{v_{w_k}(dw) : k = 0, \dots, N-1\}$
 - zero mean and $W_k = \mathbb{E}[w_k w_k^T] < \infty$



Problem Formulation I

Performance Criterion



Define the N-stage expected cost

$$J_N(\pi, \nu, x) \triangleq \mathbb{E}_x^\pi \left[\sum_{k=0}^{N-1} (x_k^T Q_k x_k + u_k^T R_k u_k) + x_N^T Q_N x_N \right]$$

- $Q_k \succeq 0$, $R_k \succ 0$: stage and input cost matrices
- $\mathbb{E}_x^\pi[\cdot]$: induced by the unknown distribution $\nu \triangleq \{\nu_{w_k}(\cdot)\}$ of the noise sequence w_k

Minimax Stochastic Problem

$$J_N^*(x) \triangleq \min_{u \in \mathcal{U}(x)} \max_{\nu(\cdot) \in \mathbb{B}_{R_{TV}}(\mu)} J_N(\pi, \nu, x), \quad \forall x \in \mathcal{X} \quad (1)$$

- **Minimization** is over the control laws $u \in \mathcal{U}(x)$
- **Maximization** is over the variation probability distribution $\nu(\cdot) \in \mathbb{B}_{R_{TV}}(\mu)$



Problem Formulation II

Performance Criterion



Remark

- For $R_{TV} = 0$ then (1) reduces to the standard LQR problem with a known solution¹
- The covariance of the noise W_k enters in the total cost, but not the control law, i.e.,

Control Law: $u_k = G_k x_k$ with $G_k = -(R_k + B_k^T P_{k+1} B_k)^{-1} B_k^T P_{k+1} A_k$

Total Cost: $J_0^*(x_0) = x_0^T P_0 x_0 + \sum_{k=0}^{N-1} \text{Tr}(P_{k+1} W_k)$

¹ B.D.O. Anderson and J.B. Moore, *Optimal Control: Linear Quadratic Methods*, Upper Saddle River, NJ, USA:Prentice-Hall, Inc., 1990.



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Solution of Robust LQR

Dynamic Programming



The dynamic programming algorithm gives²

$$J_N^*(x_N) = x_N^T Q_N x_N$$

$$J_k^*(x_k) = \min_{u_k} \left\{ x_k^T Q_k x_k + u_k^T R_k u_k \right. \\ \left. + \max_{v_{w_k}(\cdot) \in \mathbb{B}_{RTV}(\mu)} \mathbb{E}_{v_{w_k}(\cdot)} \left[J_{k+1}(A_k x_k + B_k u_k + w_k) \right] \right\}$$

Define

$$\begin{aligned} \ell_k(x_k, u_k, w_k) &\triangleq J_{k+1}(A_k x_k + B_k u_k + w_k) \\ &= (A_k x_k + B_k u_k + w_k)^T P_{k+1} (A_k x_k + B_k u_k + w_k) \\ &\quad + (A_k x_k + B_k u_k + w_k)^T F_{k+1} + r_{k+1}. \end{aligned} \quad (2)$$

² I.Tzortzis, C.D. Charalambous and T.Charalambous, *Dynamic Programming Subject to Total Variation Distance Ambiguity*, SICON, Volume 53(4), pp.2040–2075, 2015.



Solution of Robust LQR

Solution of Maximization (I)



Let

- $\ell_{\max,k}(x_k, u_k), \ell_{\min,k}(x_k, u_k)$: max. and min. values of (2) wrt w_k
- $\Sigma^o(k), \Sigma_o(k)$: corresponding support sets
- $\Sigma_j(k)$: set of indices for which (2) achieves $(j+1)$ th smallest value
- $\ell_{\Sigma_j,k}(x_k, u_k)$ the corresponding values of the sequence in $\Sigma_j(k)$

The maximization problem is given by³

$$\begin{aligned} & \max_{v_{w_k}(\cdot) \in \mathbb{B}_{RTV}(\mu)} \mathbb{E}_{v_{w_k}(\cdot)} \left[\ell_k(x_k, u_k, w_k) \right] \\ & = \ell_{\max,k} v_{w_k}^*(\Sigma^o(k)) + \ell_{\min,k} v_{w_k}^*(\Sigma_o(k)) + \sum_{j=1}^r \ell_{\Sigma_j,k} v_{w_k}^*(\Sigma_j(k)) \end{aligned}$$

³ C.D. Charalambous, I.Tzortzis, S.Loyka and T.Charalambous, *Extremum Problems with Total Variation Distance and their Applications*, IEEEETAC, Volume 59(9), pp.2353–2368, 2014.



Solution of Robust LQR

Solution of Maximization (II)



Optimal Distribution, $v^* \in \mathbb{B}_{R_{TV}}(\mu)$

The maximizing variation probability distribution of w_k is given by

$$v_{w_k}^*(\Sigma^o(k)) = \mu_{w_k}(\Sigma^o(k)) + \frac{\alpha}{2}$$

$$v_{w_k}^*(\Sigma_o(k)) = (\mu_{w_k}(\Sigma_o(k)) - \frac{\alpha}{2})^+$$

$$v_{w_k}^*(\Sigma_j(k)) = \left(\mu_{w_k}(\Sigma_j(k)) - \left(\frac{\alpha}{2} - \sum_{z=1}^j \sum_{i \in \Sigma_{z-1}(k)} \mu_{w_k}(\Sigma_i) \right)^+ \right)^+$$

$$\alpha = \min(R_{TV}, R_{\max}), \quad R_{\max} = 2(1 - \mu(\Sigma^0(k)))$$



Solution of Robust LQR

Solution of Maximization (III)



Equivalent Formulation

Assume that $v_{w_k}^*(\Sigma^o(k)) < 1$ and $v_{w_k}^*(\Sigma_o(k)) > 0$ and hence $v_{w_k}^*(\Sigma_j(k)) = \mu_{w_k}(\Sigma_j(k))$, then

$$\begin{aligned} & \max_{v_{w_k}(\cdot) \in \mathbb{B}_{R_{TV}}(\mu)} \mathbb{E}_{v_w(\cdot)} \left[\ell_k(x_k, u_k, w_k) \right] \\ &= \ell_{\max,k} v^*(\Sigma^o(k)) + \ell_{\min,k} v^*(\Sigma_o(k)) + \sum_{j=1}^r \ell_{\Sigma_j,k} v^*(\Sigma_j(k)) \\ &= \left(\ell_{\max,k} - \ell_{\min,k} \right) \frac{R_{TV}}{2} + \sum_{w_k \in \Sigma} \ell_k(w_k) \mu(w_k). \end{aligned}$$

- The first term in the right measures the difference between the max. and min. values of $\ell_k(x_k, u_k, w_k)$ wrt w_k scaled by the TV distance
- It has the interpretation of minimizing the disturbance variability



Solution of Robust LQR

Solution of Minimax Problem



Solution of Minimax Problem

- By the solution of the maximization

$$J_k^*(x_k) = \min_{u_k} \left\{ x_k^T Q_k x_k + u_k^T R_k u_k + \mathbb{E}_{v_{w_k}^*}(\cdot) \left[l_k(x_k, u_k, w_k) \right] \right\}$$

- expectation performed wrt to maximizing p.d. of w_k
 - vectors w_k need not have zero mean under $v_{w_k}^*$
- By backward induction we show that

$$J_k^*(x_k) = x_k^T P_k x_k + x_k^T F_k + r_k$$



Solution of Robust LQR



Minimizer

The optimal control is given by

$$u_k^* = -H_{22}^{-1}(k) \left(H_{12}^T(k) x_k + B_k^T P_{k+1} \mathbb{E}_{v_{w_k}^*}(\cdot) [w_k] + \frac{1}{2} B_k^T F_{k+1} \right)$$

or, equivalently

$$u_k^* = -H_{22}^{-1}(k) \left(H_{12}^T(k) x_k + R_{TV} B_k^T P_{k+1} (w_k^+ - w_k^-) + \frac{1}{2} B_k^T F_{k+1} \right)$$

where

- $w_k^+ \triangleq \arg \max_{w_k \in [p_1, p_2]} J_{k+1}^*(A_k x_k + B_k u_k + w_k)$
- $w_k^- \triangleq \arg \min_{w_k \in [p_1, p_2]} J_{k+1}^*(A_k x_k + B_k u_k + w_k)$
- $H_{12}(k) \triangleq A_k^T P_{k+1} B_k$ and $H_{22}(k) \triangleq R_k + B_k^T P_{k+1} B_k$
- Feedback gain matrices and Riccati equations depend on the variation probability distribution of w_k



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Numerical Example

System description



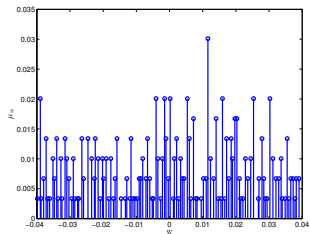
Example

Consider the linear discrete uncertain system, with the following dynamic and input matrices

$$A = \begin{bmatrix} 0.9974 & 0.0539 \\ -0.1078 & 1.1591 \end{bmatrix}, \quad B = \begin{bmatrix} 0.0013 \\ 0.0539 \end{bmatrix},$$

$$Q = \begin{bmatrix} 0.25 & 0 \\ 0 & 0.05 \end{bmatrix}, \quad Q_N = Q, \quad R = 0.5$$

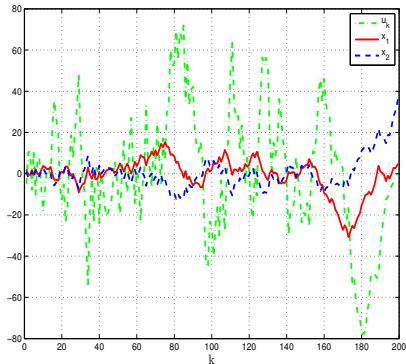
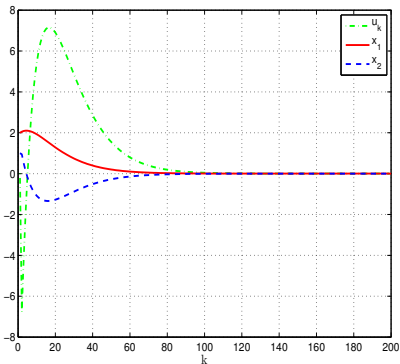
- Initial conditions
 $x_0 = [2 \ 1]^T$.
- w_k selected randomly with a known nominal probability distribution μ_w





Numerical Example

Standard LQR



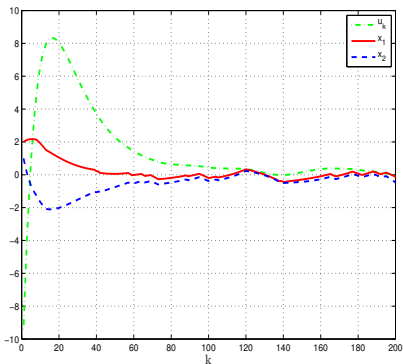
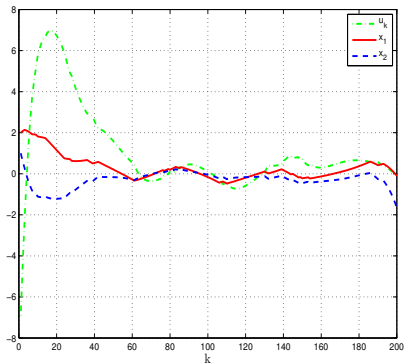
Optimal control and trajectories

- Left plot: standard LQR without noise
- Right plot: standard LQR with noise



Numerical Example

Robust LQR



Optimal control and trajectories

- Left plot: Robust LQR with $R_{TV} = 1$
- Right plot: Robust LQR with $R_{TV} = R_{\max}$



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Conclusions - Future Work



Conclusions

- Robust LQR with TV distance captures the disturbance variability, leading to an overall good performance
- Control laws which are more robust wrt disturbances, at the expense of additional costs
- Designer needs to balance the desire for low costs with undesirability of scenarios with high disturbance variability

Possible future direction:

Extension to the case of systems with parametric uncertainties

$$x_{k+1} = \left(A_k + \Delta A_k(w_k) \right) x_k + \left(B_k + \Delta B_k(w_k) \right) u_k$$



Thank you!



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