

LQG in Discrete Time (Cont'd and End)

Note Title

5/2/2021

Comments :

1. the sequence of matrices S_k is obtained from the same RICCATI backward equation as in the deterministic case with full-state feedback. Hence the optimal gains for the LQG problem with partial information and the LQR problem with full information are IDENTICAL: the Certainty Equivalence Principle holds.
2. the control law is a linear mapping of the state estimate $\hat{x}_{k|k}$: similar to the LQR controller with full information. this is a direct result from the assumptions underlying the LQG problem formulation: 1) Linearity of the Plant
2) Quadratic cost

3. The Kalman gains are calculated by a Forward RICCATI equation, which is independent of the Control input : the SEPARATION property between Estimation and Control holds for the LQG control.

4. Similarities / Differences between the solutions of the LQR/LQG problems

a. $\hat{x}_{R|K}$ instead of x_k , in the same control law

b. Random process noise \Rightarrow terms of the cost containing W covariance.

c. Estimation error \Rightarrow terms of the cost containing P covariance

5. The LQG algorithm will remain identical in the case where the matrices A, B, Q, R, W , and V are time-varying.

B.2 Continuous-time LQG.

a few words introduction ...

why continuous-time? ✓ simpler than discrete-time

✓ lower bound on the performances

✓ first principles usually yield continuous-time equations

✓ stochastic differential equations are novel to us

B.2.1. Deterministic Case

B.2.1.1. Dynamic Programming for Continuous-Time systems

- Consider the following non-linear differential equation

$$\frac{dx}{dt} = f(t, x) \quad t_0 \leq t \leq T \quad x(t_0) = x_0$$

$f(-, \cdot)$ is such

Growth condition i) $\exists K > 0 \mid f(t, x) \mid \leq K(1 + \mid x \mid) \quad t \in [t_0, T] \quad x \in \mathbb{R}^n$

Uniform Lipschitz condition ii) $\exists K > 0 \mid f(t, x) - f(t, y) \mid \leq K \mid x - y \mid \quad t \in [t_0, T] \quad x, y \in \mathbb{R}^n$

such that there is a Unique Solution to the diff. equation: $x(t)$

Integration Formula

For any function $\phi(t, x)$, where $\phi, \frac{\partial \phi}{\partial t}, \frac{\partial \phi}{\partial x}$ continuous

$$\phi[s, x(s)] = \phi[t, x(t)] + \int_t^s d\phi[\tau, x(\tau)] \quad s \geq t$$

$$\text{where } d\phi[\tau, x(\tau)] = \left\{ \frac{\partial \phi[\tau, x(\tau)]}{\partial \tau} + \frac{\partial \phi[\tau, x(\tau)]}{\partial x^T} \cdot f[\tau, x(\tau)] \right\} d\tau$$

- Problem formulation

Find a control law $u(x, t) \in \mathcal{U}$ that minimizes

$$J(x_0, t_0) = \int_{t_0}^{t_f} L(x, u, t) dt + g(x_f)$$

subject to

$$\frac{dx}{dt} = f(x, u, t); \quad x(t_0) = x_0$$

assumptions :

$$\left\{ \begin{array}{l} \bullet \mathcal{U} : \begin{array}{l} \text{a - Growth } \exists K_1 > 0 \quad |u(x, t)| \leq K_1 \sqrt{1 + |x|^2} \\ \text{b - Lipschitz } \exists K_2 > 0 \quad |u(x, t) - u(y, t)| \leq K_2 |x - y| \end{array} \\ \bullet \text{ bounded state and cost: } |x_f| < \infty \\ \quad |L(x, u, t)| < C(1 + |x| + |u|)^{\kappa} \end{array} \right.$$

Notation: $\gamma(t, t_f) = \{ u(x, \sigma); x \in \mathbb{R}^n, \sigma \in [t, t_f] \}$

• Optimal Return Function

$$\begin{aligned} J^0(x, t) &= \min_{\gamma(t, t_f) \in \mathcal{U}} \left[\int_t^{t_f} L(x_\tau, u_\tau, \tau) d\tau + g(x_{t_f}) \right] \\ &= J[\gamma^0(t, t_f); x, t] \end{aligned}$$

$$\Rightarrow J^0(x_{t_f}, t_f) = g(x_{t_f})$$

- Sufficient Condition of Optimality \equiv the Hamilton-Jacobi Equation

Consider $\gamma^1(t, t_f) = \begin{cases} u(x, \tau) & t \leq \tau \leq s \\ \text{optimal} & s \leq \tau \leq t_f \\ \gamma^0(s, t_f) \end{cases}$

$$\begin{cases} \bar{J}^0(x, t) = \int_t^s -\frac{d\bar{J}^0}{d\tau} d\tau + \bar{J}^0(x_s, s) \\ J[\gamma^1(t, t_f); x, t] = \int_t^{t_f} L + g(x, t) = \int_t^s L(x_\tau, u_\tau, \tau) d\tau + \underbrace{\int_s^{t_f} L(x_\tau, u_\tau^0, \tau) d\tau + g(x, t_f)}_{\equiv \bar{J}^0(x_s, s)} \end{cases}$$

The candidate $J^0(x, t)$ is optimal if

$$J^0(x, t) \leq J[\sigma'(t, t); x, t] \quad \forall \sigma' \in \mathcal{U} \quad \forall t \in [t, t_f]$$

$$0 \leq J[\sigma'(t, t); x, t] - J^0(x, t)$$

$$0 \leq \underbrace{\int_t^s L(x_\tau, u_\tau, \tau) + \frac{dJ^0(x_\tau, \tau)}{d\tau} d\tau}_{\geq 0}$$

$$0 \leq L(x_\tau, u_\tau, \tau) + \frac{dJ^0(x_\tau, \tau)}{d\tau} \quad \forall u \in \mathcal{U} \quad \forall \tau \in [t, s]$$

$$-\frac{dJ^0}{dt}(x_t, \tau) \leq L(x_t, u_t, \tau)$$

rate of increase of the cost rate of increase of the cost
along the optimal Trj. along a nonoptimal trajectory

Reminding the Integration Formula; where $\Phi \longleftrightarrow J^0$

$$-\frac{\partial J^0}{\partial \tau}(x_t, \tau) \leq \frac{\partial J^0}{\partial x}(x_t, \tau) \cdot f(x_t, u_t^{\odot}, \tau) + L(x_t, u_t, \tau)$$

Equality takes place when $u_t = u_t^0 \Rightarrow$ H-J Equation

$$\begin{cases} -\frac{\partial J^0}{\partial \tau}(x_t, \tau) = \min_{u \in U} \left[\frac{\partial J^0}{\partial x}(x_t, \tau) f(x_t, u_t, \tau) + L(x_t, u_t, \tau) \right] ; t_0 \leq \tau \leq t_f \\ J^0(x_{t_f}, t_f) = g(x_{t_f}) \end{cases}$$

B.2.1.2 The LQR problem / algorithm

• Pb statement

Given $\frac{dx}{dt} = F_t x_t + B_t u_t \quad (1)$

$$J[r(0, t_f)] = \int_0^{t_f} \|x_t\|_{Q_t}^2 + \|u_t\|_{R_t}^2 dt + \|x_{t_f}\|_{S_f}^2$$
$$Q_t^T = Q_t \geq 0 \quad R_t^T = R_t > 0 \quad S_f^T = S_f \geq 0$$

Solve $\min_{r(0, t_f) \in U} J[r(0, t_f)]$ subject to (1)

• Solution

$$J^0(x, \tau) = \|x\|_{S_\tau}^2$$

a Guess ... $S_\tau^T = S_\tau \geq 0$

from this guess: $J^0(x_f, t_f) = \|x_f\|_{S_f}^2 = \|x_f\|_{S_f}^2 \Rightarrow S(\tau = t_f) = f$
↑ unknown
↑ given

by inserting $J^0(x, \tau) = \|x\|_{S_\tau}^2$ into the H-J equation:

$$0 = \frac{\partial J^0(x, \tau)}{\partial \tau} + \min_{u \in \mathcal{U}} \left[\frac{\partial J^0(x, \tau)}{\partial x} F(x, u, \tau) + L(x, u, \tau) \right]$$

$$= \dot{x}^T S x + \min_{u \in \mathcal{U}} \left[x^T (S_\tau + S_\tau^T) \cdot (F_\tau x_\tau + B_\tau u_\tau) + \|x\|_{Q_\tau}^2 + \|u\|_{R_\tau}^2 \right]$$

$$\min_u \left[2x^T S B u + \|u\|_R^2 \right] \longrightarrow \boxed{u^0(x, \tau) = -R^{-1} B^T S x_\tau}$$

Optimal Control Law

Back to the H-J equation:

$$\begin{aligned} 0 &= x^T \dot{S} x + x^T (S F + F^T S) x - x^T (S B R^{-1} B^T S) x + \|x\|_Q^2 \quad \forall(x, \tau) \\ &= x^T \left[\underbrace{\dot{S} + S F + F^T S - S B R^{-1} B^T S + Q}_{= 0 \quad \forall \tau} \right] x \quad \forall(x, \tau) \end{aligned}$$

A sufficient and necessary condition:

$$\dot{S} + S F + F^T S - S B R^{-1} B^T S + Q = 0$$

equivalently

LQR
in
Cont. time.

$$-\dot{S}_t = F_t^T S_t + S_t F_t - S_t B_t R_t^{-1} B_t^T S_t + Q_t; \quad S(t_f) = S_f$$

BACKWARD RICCATI DIFFERENTIAL EQ.

$$u^o = -R_t^{-1} B_t^T S_t x$$

OPTIMAL CONTROL LAW