## Delay Compensation in Control Systems

**Michael Malisoff** 

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M. Jankovic, M. Krstic, Z. Lin, SI. Niculescu, P. Pepe, A. Teel,...

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$$x'(t) = \mathcal{G}(t, x(t), x(t-\tau)), \ x(t) \in \mathcal{X}$$
 ( $\Sigma$ )

$$|x(t)| \le \gamma_1 \left( e^{t_0 - t} \gamma_2(|x|_{[t_0 - \tau, t_0]}) \right)$$
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$$\mathbf{x}'(t) = \mathcal{G}(t, \mathbf{x}(t), \mathbf{x}(t-\tau), \delta(t)), \ \mathbf{x}(t) \in \mathcal{X}$$
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Find  $\gamma_i$ 's by building Lyapunov-Krasovskii functionals (LKFs).

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}(t)) + g(t, \mathbf{x}(t))[u_{\mathbf{s}}(t, \mathbf{x}(t-\tau)) + \delta(t)].$$
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Assume: *f* and *g* are locally Lipschitz and grow linearly in *x*,  $u_s \in C^1$ ,  $|(\partial u_s/\partial x)(t, x)|$  bounded.

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**Definition:** A function  $U : [0, \infty) \times C_n([-\tau, 0]) \to [0, \infty)$  is an ISS-LKF for  $(\Sigma_d)$  provided there are  $\alpha_i \in \mathcal{K}_\infty$  such that for all solutions x(t) of  $(\Sigma_d)$ ,  $U(t, x_t)$  is absolutely continuous in t and

(i)  $\alpha_1(|\phi(0)|) \le U(t,\phi) \le \alpha_2(|\phi|_{[-\tau,0]})$  and (ii)  $\frac{d}{dt}(U(t,x_t)) \le -\alpha_3(U(t,x_t)) + \alpha_4(|\delta|_{[t_o,t]})$ 

hold for all  $\phi \in C_n([-\tau, 0])$  and almost all  $t \ge t_o$  and all  $t_0 \ge 0$ .

First Approach: Emulation

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Mazenc, F., M. Malisoff, and Z. Lin, "Further results on input-to-state stability for nonlinear systems with delayed feedbacks," *Automatica*, 44(9):2415-2421, 2008.

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Malisoff, M., and F. Zhang, "Robustness of adaptive control under time delays for three-dimensional curve tracking," *SIAM Journal on Control and Optimization*, 53(4):2203-2236, 2015.

Assumption L: There are  $\sigma \in \mathcal{K}_{\infty}$  such that  $\sigma(r) \leq r$  for all  $r \geq 0$ ; constants  $\mathcal{K}_1 \geq 1$  and  $\mathcal{K}_i \geq 0$  for i = 2, 3, 4; and a  $C^1$  uniformly proper and positive definite  $V : [0, \infty) \times \mathbb{R}^n \to [0, \infty)$  such that for all  $x \in \mathbb{R}^n$ ,  $q \in \mathbb{R}^n$ ,  $l \geq 0$ , and  $t \geq 0$ , we have

- H1  $V_t(t,x) + V_x(t,x)[f(t,x) + g(t,x)u_s(t,x)] \le -\sigma^2(|x|);$
- H2  $|V_x(t,x)g(t,x)| \leq K_1 \sigma(|x|), \left|\frac{\partial u_s}{\partial x}(t,x)f(l,x)\right|^2 \leq K_2 \sigma(|x|)^2;$
- H3  $\left|\frac{\partial u_s}{\partial x}(t,x)g(l,x)\right|^2 \leq K_3(\sigma(|x|)+1)$ ; and
- $\mathsf{H4} \left[ \left| \frac{\partial u_s}{\partial x}(t,x)g(l,x) \right| \left| u_s(l,q) \right| \right]^2 \leq \mathsf{K}_4[\sigma^2(|x|) + \sigma^2(|q|)].$

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- $\mathsf{H4} \left[ \left| \frac{\partial u_s}{\partial x}(t,x)g(l,x) \right| \left| u_s(l,q) \right| \right]^2 \leq \mathsf{K}_4[\sigma^2(|x|) + \sigma^2(|q|)].$

Exponentially stable  $\dot{x}(t) = (A(t) + B(t)K(t))x(t)$  with  $\sigma(s) = s$ 

Thm 1: (M-Mazenc-Lin, '08) If Assumption L holds, then

$$\dot{\mathbf{x}}(t) = f(t, \mathbf{x}(t)) + g(t, \mathbf{x}(t))[u_{s}(t, \mathbf{x}(t-\tau)) + \delta(t)] \qquad (\Sigma_{d})$$

with any constant feedback delay  $au \in (0, ar{ au}]$  where

$$\bar{\tau} = \frac{1}{4K_1\sqrt{3K_2+3K_4+1}}$$

admits the ISS-LKF

$$U(t, x_t) = V(t, x(t)) + \frac{1}{8\overline{\tau}} \int_{t-2\overline{\tau}}^t \left( \int_t^t \sigma^2(|x(p)|) \mathrm{d}p \right) \mathrm{d}r$$

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Delay need not be known. Can drop delay bound in many cases using reduction or prediction or scaling of controls.

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Thm 2: (MMN'14) If there is a bounded continuous K such that

$$\dot{z}(t) = \left[M(t) + \lambda(t, t+\tau)N(t+\tau)K(t)\right]z(t)$$
(2)

is UGAS, where  $\lambda$  is the fundamental matrix for *M*, then there are functions  $\gamma_i \in \mathcal{K}_{\infty}$  such that all trajectories of (1) with

$$\boldsymbol{u}(t) = \boldsymbol{K}(t) \left[ \boldsymbol{x}(t) + \int_{t-\tau}^{t} \lambda(t, r+\tau) \boldsymbol{N}(r+\tau) \boldsymbol{u}(r) \mathrm{d}r \right]$$
(3)

satisfy

$$|x(t)| + |u|_{[t-\tau,t]} \le \gamma_1 \Big( \gamma_2 \big( |x(t_0)| + |u|_{[t_0-\tau,t_0]} \big) e^{t_0-t} \Big) + \gamma_3 (|\delta|_{[t_0,t]})$$

for all initial times  $t_0 \ge 0$  and all  $t \ge t_0$ .

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Assumption 1: The functions *A* and *B* are bounded and continuous, and there is a known bounded continuous function  $K : [0, \infty) \to \mathbb{R}^{\ell \times n}$  such that  $\dot{x}(t) = [A(t) + B(t)K(t)]x(t)$  is uniformly globally exponentially stable to 0.

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Assumption 2: The function  $h : \mathbb{R} \to [0, \infty)$  is  $C^1$  and bounded from above by a constant  $c_h > 0$ . Also, its derivative  $\dot{h}$  is bounded from below, and  $\dot{h}$  is bounded from above by a constant  $l_h \in (0, 1)$ , and  $\dot{h}$  has a global Lipschitz constant  $n_h > 0$ .

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Assumption 2 holds with  $c_h = 0.924$ ,  $l_h = 0.98$ , and  $n_h = 592.72$ .

We use an *pn*-dimensional dynamic extension to build our delay compensating control for any number of predictors

$$p > \max\left\{2, 4\left(\frac{b_1}{\sqrt{2}} + b_2\right)\frac{c_h}{1 - l_h}
ight\},$$
 (LB)

where

$$b_{1} = \left[1 + \left(1 + \frac{u_{c}}{p}\right)^{p} |A|_{\infty}\right] \left(1 + \frac{u_{c}}{p}\right)^{p} |A|_{\infty},$$
  

$$b_{2} = \left[1 + \left(1 + \frac{u_{c}}{p}\right)^{p} |A|_{\infty}\right]^{2} \left(1 + \frac{u_{c}}{p}\right), \text{ and } u_{c} = \frac{c_{h}n_{h}}{(1 - l_{h})^{2}} + \frac{l_{h}}{1 - l_{h}}.$$

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 $\Omega_i(t) = t - (i/p)h(t) \text{ and } \theta_i(t) = \Omega_{p-i+1}^{-1}(\Omega_{p-i}(t)) \text{ for } i \in \{0, ..., p\}$ 

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$$\begin{split} b_1 &= \left[ 1 + \left( 1 + \frac{u_c}{\rho} \right)^{\rho} |A|_{\infty} \right] \left( 1 + \frac{u_c}{\rho} \right)^{\rho} |A|_{\infty}, \\ b_2 &= \left[ 1 + \left( 1 + \frac{u_c}{\rho} \right)^{\rho} |A|_{\infty} \right]^2 \left( 1 + \frac{u_c}{\rho} \right), \text{ and } u_c = \frac{c_h n_h}{(1 - l_h)^2} + \frac{l_h}{1 - l_h}. \end{split}$$

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 $\Omega_{i}(t) = t - (i/p)h(t) \text{ and } \theta_{i}(t) = \Omega_{p-i+1}^{-1}(\Omega_{p-i}(t)) \text{ for } i \in \{0, ..., p\}$  $R_{1}(t) = \dot{\theta}_{1}(t), R_{i}(t) = \dot{\theta}_{i}(t)R_{i-1}(\theta_{i}(t)) \text{ for } i > 1.$ 

Thm 3: (M-Mazenc, '17) Let Assumptions 1-2 hold and *p* satisfy (LB). Then if we use the control  $u(t) = K(\Omega_p^{-1}(t))z_p(t)$  in (LTV), where  $z_p$  is the last *n* components of the system

$$\dot{z}_{1}(t) = R_{1}(t)A(\theta_{1}(t))z_{1}(t) + R_{1}(t)B(\theta_{1}(t))u(\Omega_{p-1}(t)) + L_{1}(t)[z_{1}(\theta_{1}^{-1}(t)) - x(t)] \dot{z}_{i}(t) = R_{i}(t)A(G_{i}(t))z_{i}(t) + R_{i}(t)B(G_{i}(t))u(\Omega_{p-i}(t)) + L_{i}(t)[z_{i}(\theta_{i}^{-1}(t)) - z_{i-1}(t)], i \in \{2, \dots, p\}$$

$$(4)$$

where  $L_i(t) = -I_n - R_i(t)A(G_i(t))$  and  $G_i = \Omega_p^{-1} \circ \Omega_{p-i}$ , then the dynamics for  $(x, \mathcal{E})$  are globally exponentially stable to 0, where  $\mathcal{E}(t) = (z_1(t) - x(\theta_1(t)), z_2(t) - z_1(\theta_2(t)), \dots, z_p(t) - z_{p-1}(\theta_p(t))).$ 

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- ▷ We are developing analogs for ODE-PDE cascades.

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- > Distributed terms can produce implementation challenges.
- > They can sometimes be overcome by sequential predictors.
- > Sequential predictors allow outputs, sampling and uncertainty.
- $\triangleright$  We are developing analogs for ODE-PDE cascades.

Thank you for your attention!