

PDE Backstepping: The First 25 Years

Miroslav Krstic

- CSS Control History Forum 2024 ●

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- Not a survey

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- **Community expansion only over the last ten years**

Feedback design for PDEs in the first four decades: 1960s-1990's

- LQ/optimal (operator Riccati eqns)
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Hard to imagine (general) extensions to **nonlinear** and **adaptive**.

Feedback linearization

(root of PDE bkst)

$$\begin{aligned}\dot{x} &= f(x) + g(x)u \\ y &= h(x)\end{aligned}$$

Output fbk linearization

$$\begin{aligned}\xi_1 &= h(x) \\ \xi_i &= L_f^{i-1}h(x), \quad i = 1, \dots, r-1 \quad \left(L_g L_f^{r-1} h(0) \neq 0 \right)\end{aligned}$$

Chain of integrators/Brunovsky

$$\boxed{\dot{\xi}_i = \xi_{i+1}} \quad \xi_r = L_f^{r-1}h(x) + L_g L_f^{r-1}h(x)u$$

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ODE backstepping

(adaptive and robust)

$$\dot{x}_i = x_{i+1} + f_i(x_1, \dots, x_i) \theta, \quad x_{n+1} = u$$

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Early lumping 1: PDE → Brunovsky

1997

$$u_t = u_{xx} + \lambda(x)u$$

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$$\begin{aligned} u_t &= u_{xx} + \lambda(x)u \\ &\downarrow \qquad \qquad \text{spatial discretiz.} \end{aligned}$$

$$\dot{u}_i = \frac{u_{i+1} - 2u_i + u_{i-1}}{h^2} + \lambda_i u_i$$

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↓ spatial discretiz.

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↓ transform: $u \rightarrow w = T(h)u$

$$\dot{w}_i = \frac{1}{h^2} w_{i+1} \quad \text{Brunovsky}$$

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elements of matrix $T(h)$ grow unbounded as $h \rightarrow 0$

Early lumping 2: Bkst. on space-discretized PDE

$$\dot{u}_i = \frac{u_{i+1} - 2u_i + u_{i-1}}{h^2} + \lambda_i u_i$$

↓

$$\dot{w}_i = \frac{w_{i+1} - 2w_i + w_{i-1}}{h^2} - cw_i$$

target sys. in same class

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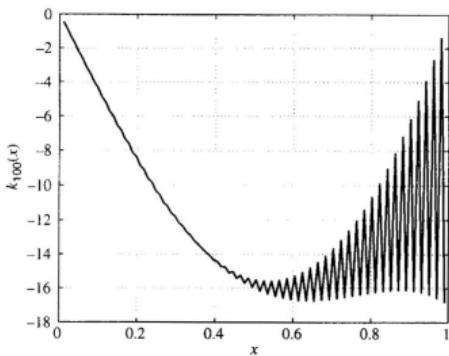
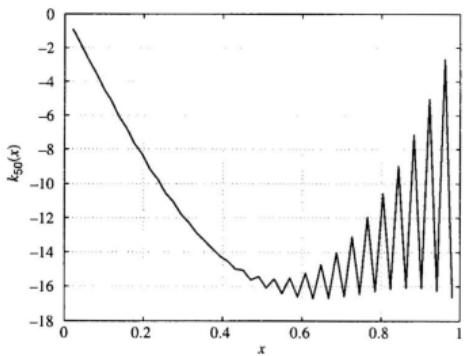
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Feedback **gain** converges only WEAKLY.



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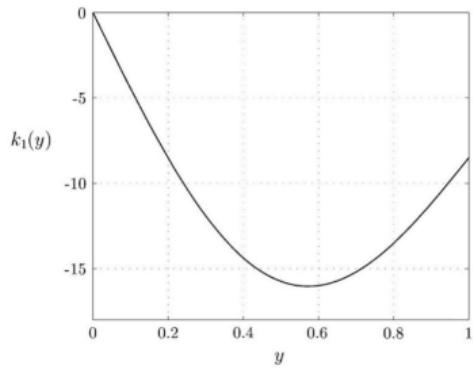
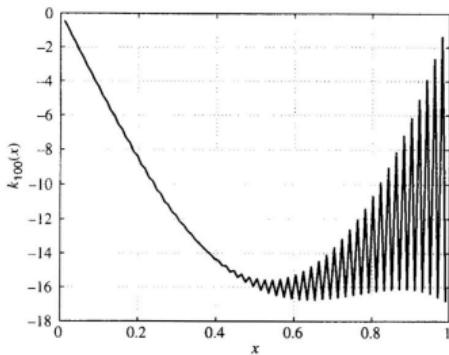
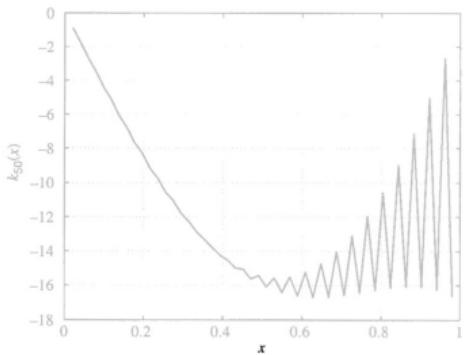
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Continuum backstepping for parabolic PIDEs

$$u_t = u_{xx} + \lambda(x)u + b(x)u_x + \int_0^x f(x,y)u(y,t)dy$$

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$$w(x, t) = u(x, t) - \int_0^{\boxed{x}} k(x, y)u(y, t)dy$$

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$$w_t = w_{xx} \quad (\text{exp. stable})$$

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under kernel PDE

$$\boxed{k_{xx} - k_{yy} = \lambda(x)k} + \text{more terms...}$$

Continuum backstepping for parabolic PIDEs

PDE $k_{xx} - k_{yy} = \lambda(x)k$ is equivalent to integral equation

$$4 G(\xi, \eta) = - \int_{\eta}^{\xi} \lambda\left(\frac{\tau}{2}\right) d\tau + \int_{\eta}^{\xi} \int_0^{\eta} \lambda\left(\frac{\tau-s}{2}\right) G(\tau, s) ds d\tau$$

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Smyshlyaev's (TAC, 2004) explicit solution for $\lambda = \text{const}$:

$$k(x, y) = -\lambda y \frac{I_1\left(\sqrt{\lambda(x^2 - y^2)}\right)}{\sqrt{\lambda(x^2 - y^2)}}$$

I_1 = Bessel function

Earlier (independent) encounters in mathematics

Transform $w(x, t) = u(x, t) - \int_0^x k(x, y, t)u(y, t)dy$

- Colton (JDE 1977): to solve $u_t = u_{xx} + \lambda(x, t)u$ by solving the heat equation $w_t = w_{xx}$

Analogous to using (in limited cases) a diffeomorphism only to solve a nonlinear ODE using a linear ODE.

- Seidman (Appl. Math. Optim. 1984):

Proves that cost of null controllability of $u_t = u_{xx} + \lambda(x, t)u$ in time T scales as $e^{O(1/T)}$.

No feedback of $u(x, t)$

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Transform $w(x, t) = u(x, t) - \int_0^{\textcolor{blue}{x}} k(x, y, \textcolor{red}{t})u(y, t)dy$

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Nonlinear bkst transform

(true $F\mathbf{L}$)

For nonlinear $u_t = u_{xx} + F[u]$, infinite nonlinear Volterra series:

$$w(x, t) = u(x, t) - \sum_{n=1}^{\infty} \int_0^x \int_0^{\xi_1} \cdots \int_0^{\xi_{n-1}} k_n(x, \xi_1, \dots, \xi_n) \left(\prod_{j=1}^n u(\xi_j, t) \right) d\xi_n \cdots d\xi_1$$

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Kernel PDEs on domains $\{0 \leq \xi_n \leq \dots \leq \xi_1 \leq x\}$ of increasing dimensions:

$$\partial_{xx} k_n = \partial_{\xi_1 \xi_1} k_n + \cdots + \partial_{\xi_n \xi_n} k_n + \text{lin. nonlocal terms in } k_1, \dots, k_n$$

Backstepping **observers**

Luenberger-type

$$\hat{u}_t = \underbrace{\hat{u}_{xx} + \lambda(x)\hat{u}}_{\text{copy of plant}} + p(x) \underbrace{\left[u(0, t) - \hat{u}(0, t) \right]}_{\text{output estim. error}}$$

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Bkst-transformable to error system

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Inspired by bkst observers of Krener-Kang (2003) and earlier Krener-Isidori (1983).

Hyperbolic (1st-order) PDEs

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$$u_t = u_{\color{blue}x} + \int_0^x f(x, y)u(y, t)dy$$

transformed into transport PDE

$$w_t = w_x, \quad w(1, t) = 0$$

Settles in $T = 1$ sec.

Coupled (multiple) hyperbolic PDEs

$$\begin{aligned} u_t &= -\epsilon_1(x)u_x + \varphi_1(u, v, x)u_x + \psi_1(u, v, x)v_x + f_1(u, v, x) \\ v_t &= \epsilon_2(x)v_x + \varphi_2(u, v, x)u_x + \psi_2(u, v, x)v_x + f_2(u, v, x) \end{aligned}$$

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Local stabilization in H^2 .

$(n + m) \times (n + m)$ counterconvecting PDEs

- $u \in \mathbb{R}^n$ rightward, unactuated
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- $m, n > 1$: Hu, Di Meglio, Vazquez, Krstic (2016, 2019)
- hyp. with zero characteristic speeds: de Andrade, Vazquez, Karafyllis, Krstic (TAC)

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Applications: water canals, oil drilling, laser chambers, traffic

Academic application 1: Navier-Stokes

$$\begin{aligned} u_t &= \frac{1}{\text{Re}} \Delta u - uu_x - vu_y - wu_z - p_x \\ v_t &= \frac{1}{\text{Re}} \Delta v - uv_x - vv_y - wv_z - p_y \\ w_t &= \frac{1}{\text{Re}} \Delta w - uw_x - vw_y - ww_z - p_y \end{aligned}$$

Academic application 1: Navier-Stokes

$$u_t = \frac{1}{\text{Re}} \Delta u - uu_x - vu_y - wu_z - p_x$$

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$$w_t = \frac{1}{\text{Re}} \Delta w - uw_x - vw_y - ww_z - p_y$$

Convert to heat equation (with convection) for unstable wave numbers.

Academic application 2: unstable Timoshenko beam

$$\begin{aligned}(\varepsilon \partial_{tt} - \partial_{xx}) u &= -\alpha_x \\ (\mu \partial_{tt} - \partial_{xx}) \alpha &= \frac{a}{\varepsilon} (u_x - \alpha)\end{aligned}$$

with boundary anti-damping

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Converted to $n = m = 2$ coupled hyperbolic systems

Delays/predictors by (hyperbolic) backstepping

$$\dot{X} = AX + BU(t - D)$$

$$\dot{X} = f(X, U(t - D))$$

$$\dot{X} = f(X, U(t - D(\textcolor{blue}{X}, t))), \quad D \text{ depends on } \textcolor{blue}{\text{current } X}$$

$$\dot{X} = f\left(X, U\left((\text{Id} + D \circ X)^{-1}(t)\right)\right), \quad D \text{ depends on } \textcolor{red}{\text{past } X}$$

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Krstic, *Delay Compensation for Nonlinear, Adaptive, and PDE Systems*, 2009

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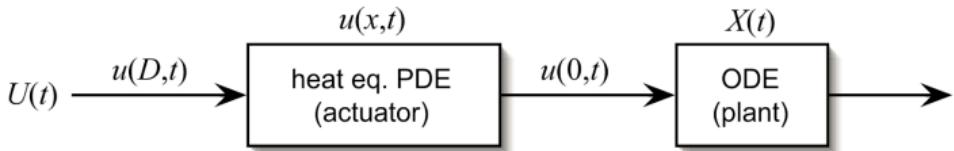
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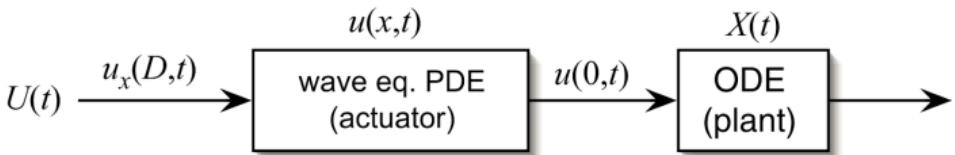
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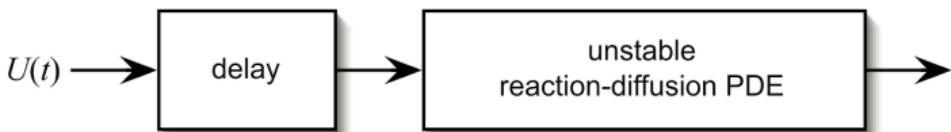
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Adaptive control of parabolic PDEs

$$u_t = u_{xx} + \lambda(x)u + \int_0^x f(x, \xi)u(\xi, t)d\xi$$

λ, f – unknown, u – unmeasured

Adaptive control of hyperbolic PDEs

$$\begin{aligned} u_t &= -\epsilon_1 u_x + c_1(x)v \\ v_t &= \epsilon_2 v_x + c_2(x)u \end{aligned}$$

c_1, c_2 – unknown, u, v – unmeasured

Delay-adaptive control

$$\dot{X} = AX + BU(t - D)$$

D – unknown, A, B – also unknown

Bresch-Pietri, Krstic (2009)

Delay-adaptive control

$$\dot{X} = AX + BU(t - D)$$

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Bresch-Pietri, Krstic (2009)

Extensions: unmeasured X , multiple inputs/delays, distributed delays

Output regulator by PDE bkst

Inspiration from Byrnes-Isidori.

Parabolic

$$u_t = u_{xx} + \lambda(x) + g(x)\delta(t), \quad \dot{\delta} = S\delta$$

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$$u_t = u_{xx} + \lambda(x) + g(x)\delta(t), \quad \dot{\delta} = S\delta$$

Regulator equation:

$$\begin{aligned} m'' &= S^T m + g(x) - \int_0^x k(x,y)g(y)dy \\ m(0) &= m'(0) = 0 \end{aligned}$$

Deutscher (Automatica, 2015) (parabolic)

Deutscher (Automatica, 2017) (hyperbolic)

Output regulator by PDE bkst

Inspiration from Byrnes-Isidori.

Parabolic

$$u_t = u_{xx} + \lambda(x) + g(x)\delta(t), \quad \dot{\delta} = S\delta$$

Regulator equation:

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Prescribed-time stabilization

$$u_t = u_{xx}$$

Coron, Nguyen (ARMA 2017)

Null-controllability by bkst time-varying fbk with PW-const gains that ↗ ∞ as $t \rightarrow T$.

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Continuous backstepping gain:

$$k(x, y, t) = -y\mu(t) e^{\sqrt{\mu(t)}(x^2 - y^2)/4} \frac{I_1\left(\sqrt{\mu(t)}(x^2 - y^2)\right)}{\sqrt{\mu(t)(x^2 - y^2)}}$$

$$\mu(0) = 1/T^2, \quad \lim_{t \rightarrow T} \mu(t) = \infty$$

Fredholm backstepping: Basic

$$w(x, t) = u(x, t) - \int_0^1 k(x, y)u(y, t)dy$$

Not automatically invertible.

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Korteweg-de Vries:

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Schrödinger (bilinear):

$$i\psi_t + \Delta\psi + u(t)\mu(x)\psi = 0$$

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Applications: 1 Additive manufacturing

Stefan model of phase change

$$T_t = \alpha T_{xx} \quad T(s, t) = T_m \quad \text{melting temp. at interface}$$

$$\dot{s} = -\beta T_x(s, t) \quad \text{nonlin. ODE for motion of liquid-solid interface}$$

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Applications: 2 Traffic flow

Stop-and-go instability:

$$\partial_t \rho + \partial_x (\rho v) = 0 \quad \text{LWR}$$

$$\partial_t (v + p(\rho)) + v \partial_x (v + p(\rho)) = \frac{V(\rho) - v}{\tau} \quad \text{Aw-Rascle}$$

Applications: More

- **Water canals:** Coron, Bastin; Diagne
- **Oil drilling:** Di Meglio, Arsnès, Aamo, Hasan, Sagert, Auriol, Bresch-Pietri, Krstic
Experiments STATOIL, Total
- **Li-ion batteries:** Moura, Chaturvedi, Camacho, Koga, Krstic
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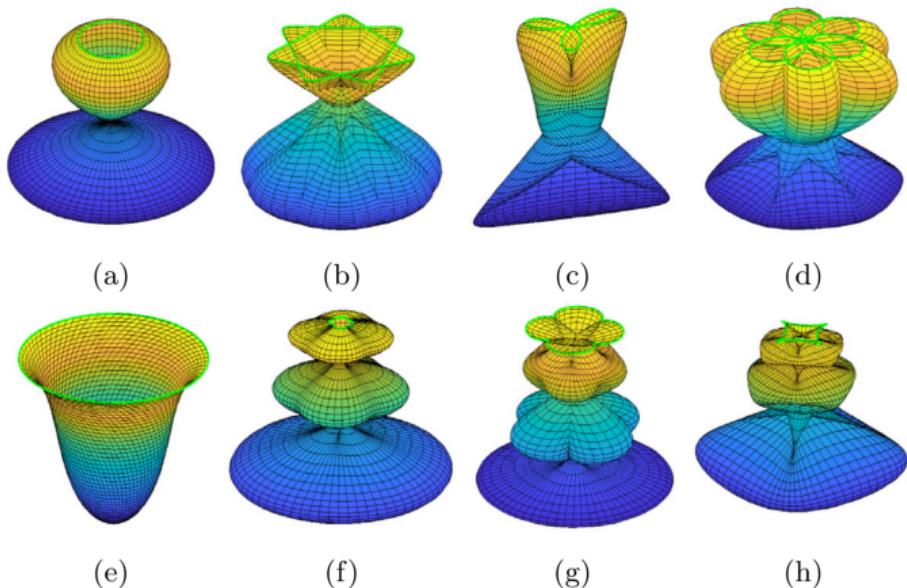
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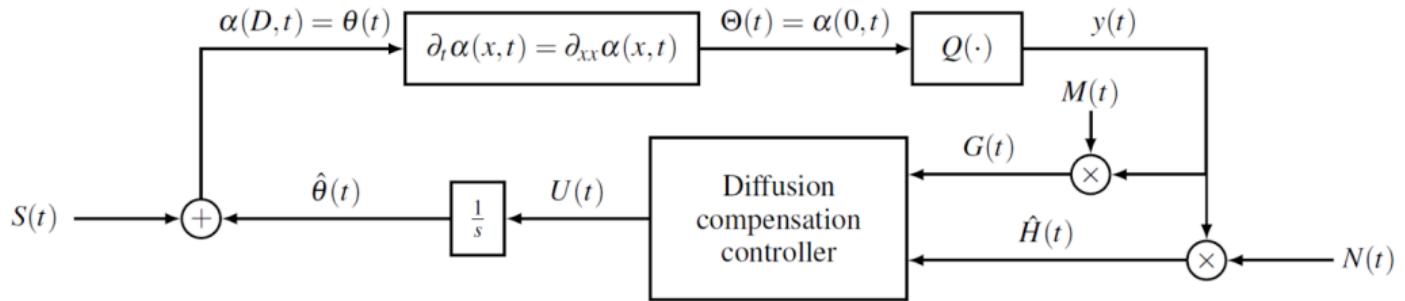
Vehicle swarm deployment by PDE bkst



Open-loop instability → rich deployment geometries

Extremum seeking for PDEs

Delays, parabolic, wave, games



Machine learning for PDE backstepping

Kernel operator

$$\mathcal{K} : \lambda(x) \mapsto k(x, y)$$

Neural operator approximation

$$\lambda \longrightarrow \boxed{\hat{\mathcal{K}}} \longrightarrow k$$

Learn the kernel mapping $\lambda \mapsto k$ “once-and-for-all,” for all λ .

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How to begin learning PDE backstepping?

*Boundary Control of PDEs:
A Course on Backstepping Designs*

SIAM 2008