

# Analysis of Systems with State-Dependent Delay

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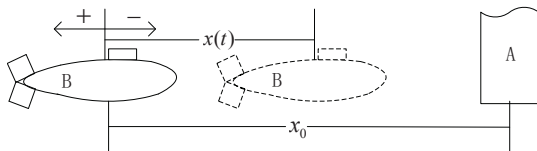


# Systems with State-Dependent Delay

State-Dependent Delay arises which communication distance changes with time.

- Any Moving System.
  - ▶ Sonar (Speed of Sound)
  - ▶ EM (Speed of Light)

**Example:** Position Measurement using Sonar



- Propagation Distance:  $2(\hat{x}(t) = x_0 + x(t))$
- Delay is  $\tau(t) = 2\frac{x_0 + x(t)}{c}$ .

**Feedback Dynamics:** neglecting inertia...

$$\dot{x}(t) = ax\left(t - \frac{2x_0}{c} - \frac{2}{c}x(t)\right)$$

# Stability of Systems with State-Dependent Delay

Consider the general class of systems with state-dependent delay:

$$\dot{x}(t) = f\left(x(t), x\left(t - g(x(t))\right)\right)$$

**Note:** State  $x(t)$  enters into the *independent argument*,  $t$ .

- Contrast to the fixed-delay case:  $\dot{x}(t) = f\left(x(t - \tau)\right)$

**Linear/Affine Form:**

$$\dot{x}(t) = A_0 x(t) + A_1 x(t - \tau_0) - b^T x(t)$$

**Question:** Given  $A \in \mathbb{R}^n$ ,  $\tau_0 > 0$  and  $-\tau \in \mathbb{R}^n$ ,

- Determine whether the system is stable.
- Estimate the rate of decay.

# Why State-Dependent Delay?

The most common source of delay is **Propagation Time**.

- A time-delay system is the interconnection of an ODE with a transport PDE in the feedback channel.

$$\dot{x}(t) = A_0x(t) + \sum A_i x(t - \tau_i)$$

**ODE:** The system  $G_1$

$$\dot{x}_1(t) = Ax_1(t) + Bu_1(t)$$

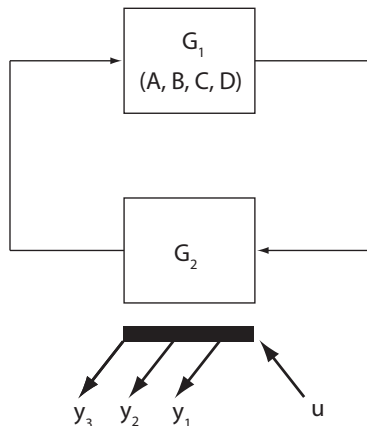
$$y_1(t) = Cx_1(t) + Du_1(t)$$

$$\left[ \begin{array}{c|c} A & B \\ \hline C & D \end{array} \right] \left[ \begin{array}{c|c} A_0 & [A_1 \ \cdots \ A_n] \\ \hline I & 0 \end{array} \right]$$

**PDE:** The system  $G_2$

$$\frac{\partial}{\partial t} x_2(t, s) = \frac{\partial}{\partial s} x_2(t, s) \quad x_2(t, 0) = u_2(t),$$

$$y_2(t) = [x_2(-\tau_1) \ \cdots \ x_2(-\tau_K)]^T$$



Of course, the solution is just  $x_2(t, s) = u_2(t - s)$ .

# Systems with State-Dependent Delay

Restrictions on the Model:

- For physical systems:
  - ▶ Delay is always positive
  - ▶ Delay is usually affine in the state
  - ▶ Lower and upper bounds for the delay
- Other types of systems are often ill-posed or otherwise pathological [Verriest, 2013]
  - ▶ Global Stability is not a well-defined problem for this model.

**Assumptions:** In this talk, we use scalar systems of the form

$$\dot{x}(t) = ax(t - b - cx(t))$$

where  $a, c \in \mathbb{R}$ ,  $b > 0$ .

- To ensure  $b + cx(t) > 0$ , we bound the state as  $\|x(t)\| \leq d$ .
  - ▶ Also leads to the bound  $b + cx(t) \leq \tau_m$ .

**Note:** The extension to  $\mathbb{R}^n$  is not hard.

# Lyapunov-Krasovskii Functionals

For linear fixed delay systems:

$$\dot{x}(t) = Ax(t) + Bx(t - \tau)$$

## Theorem 1.

*The discrete-delay system is stable if and only if there exist continuous functions  $M$  and  $N$  such that  $V(\phi) \geq \alpha\|\phi\|$  and  $\dot{V}(\phi) \leq 0$  where*

$$V(\phi) = \int_{-\tau}^0 \begin{bmatrix} \phi(0) \\ \phi(s) \end{bmatrix}^T M(s) \begin{bmatrix} \phi(0) \\ \phi(s) \end{bmatrix} ds + \int_{-\tau}^0 \int_{-\tau}^0 \phi(s)^T N(s, \theta) \phi(\theta) ds d\theta$$

**Note:** The functional is parameterized by unknown functions  $M$  and  $N$ .

**Problem:** How to numerically compute  $M$  and  $N$  such that

$$V(\phi) > \alpha\|\phi\|$$

$$\dot{V}(\phi) < 0$$

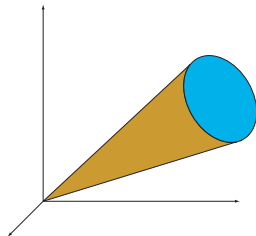
**Answer:** Convex Optimization

# Tractable or Intractable?

## Convex Optimization

### Problem:

$$\begin{aligned} & \max bx \\ & \text{subject to } Ax \in C \end{aligned}$$



The problem is *convex optimization* if

- $C$  is a convex cone.
- $b$  and  $A$  are affine.

**Computational Tractability:** Convex Optimization over  $C$  is, in general, tractable if

- The set membership test for  $y \in C$  is in P.
- $x$  is finite dimensional.

# Parametrization of Lyapunov-Krasovskii Functionals

**Problem 1:** Is the set of decision variables finite-dimensional?

- Decision variables are the functions  $M$  and  $N$

$$V(\phi) = \int_{-\tau(\phi(t))}^0 Z \left( \begin{bmatrix} \phi(0) \\ \phi(s) \end{bmatrix} \right)^T M(s) Z \left( \begin{bmatrix} \phi(0) \\ \phi(s) \end{bmatrix} \right) ds \\ + \int_{-\tau(\phi(t))}^0 \int_{-\tau(\phi(t))}^0 Z \left( \phi(s) \right)^T N(s, \theta) Z \left( \phi(\theta) \right) ds d\theta$$

**Solution:** Suppose  $M$  and  $N$  are polynomials of bounded degree.

$$M(s) = c_1^T Z(s), \quad N(s, \theta) = c_2^T Z(s, \theta)$$

**Problem 2:** How to enforce positivity of the L-K functional?

- Need constraints on  $c_1$  and  $c_2$ .



# Positivity Constraints for Polynomials

**Sum-of-Squares:**  $p(x) \geq 0$  if

$$p(x) = \sum_i g_i(x)^2, \quad \text{denoted } p \in \Sigma_s$$

## Lemma 2 (Parametrization of Sums-of-Squares).

Given multivariate polynomial  $p$  of degree  $2d$ ,  $p \in \Sigma_s$  ( $p(x) \geq 0$  for all  $x \in \mathbb{R}^n$ ) if and only if there exists a positive matrix  $M \in \mathbb{S}^q$  such that

$$p(x) = Z_d(x)^T M Z_d(x)$$

where  $z_d$  is the vector of monomials of degree  $d$  or less.

## Lemma 3 (Polynomial Positivity on a Subset of $\mathbb{R}^n$ ).

Given polynomial  $p$ ,  $p(x) \geq 0$  for all  $x \in \{x : g_i(x) \geq 0\}$  if there exist  $s_i \in \Sigma_s$  such that

$$p(x) = s_0(x) + \sum_i g_i(x) s_i(x)$$

# Positivity Constraints for Lyapunov Functionals

## Lemma 4.

Suppose there exist  $S \in \Sigma_s$  and polynomial  $T$  such that

$$V(\phi(0), \phi(s), s) - \phi(0)^2 = S(\phi(0), \phi(s), s) + T(\phi(0), s)$$

with  $\int_{-\tau(x(t))}^0 T(\phi(0), s) ds = 0$ . Then

$$\int_{-\tau(\phi(t))}^0 V(\phi(0), \phi(s), s) ds \geq \alpha \phi(0)^2$$

for any  $\phi \in \mathcal{C}[-\tau_m, 0]$

We can tighten this a bit

- Restrict  $s \in [-\tau(\phi(s)), 0]$

$$\{s, \phi : g_1(s, \phi(s)) = -s(s + \tau(\phi(s))) \geq 0\}$$

- Restrict  $\|\phi(s)\| \leq d$

$$\{s, \phi : g_2(s, \phi(s)) = d - \phi(s)^2 \geq 0\}$$

# Positivity Constraints for Lyapunov Functionals

## Lemma 5.

Suppose there exist  $S, S_1, S_2, S_3 \in \Sigma_s$  and polynomial  $T$  such that

$$\begin{aligned} & V(\phi(0), \phi(s), s) - \phi(0)^2 \\ &= S + g_1(s, \phi(s))S_1 \\ &\quad + g_2(s, \phi(s))S_2 + g_2(s, \phi(0))S_3 + T(\phi(0), s) \end{aligned}$$

with  $\int_{-\tau(x(t))}^0 T(\phi(0), s) ds = 0$ . Then

$$\int_{-\tau(\phi(t))}^0 V(\phi(0), \phi(s), s) ds \geq \alpha \phi(0)^2$$

for any  $\|\phi\|_\infty \leq d$ .

## Where Recall

- $S, S_1, S_2, S_3, T$  and  $V$  are the decision variables
  - ▶ Represented using positive matrices.
- Constraints are equalities and matrix positivity (SDP).

# Positivity Constraints for Lyapunov Functionals

## Lemma 6.

Suppose there exists a positive matrix  $Q \geq 0$  such that

$$V_2(\phi(s), \phi(\theta), s, \theta) = Z(s, \phi(s))^T Q Z(\theta, \phi(\theta))$$

Then

$$\int_{-\tau}^0(\phi(t)) \int_{-\tau}^0(\phi(t)) V_2(\phi(s), \phi(\theta), s, \theta) ds d\theta \geq 0$$

for any  $\phi \in \mathcal{C}[-\tau_m, 0]$ .

## Positivity Constraints

- Constraints are equalities and matrix positivity (SDP).

## Convex Optimization

- Positive Lyapunov Functionals are represented using vectors and matrix positivity constraints.

# The Derivative

Now Recall the dynamics:

$$\dot{x}(t) = ax(t - \tau_0) + bx(t) \qquad \tau(x(t)) = \tau_0 + bx(t)$$

With Lyapunov Functional

$$V(t) = \int_{-\tau(x(t))}^0 V_1(x(0), x(s), s) ds + \int_{-\tau(x(t))}^0 \int_{-\tau(x(t))}^0 V_2(x(s), s, x(\theta), \theta) ds d\theta$$

The derivative is

$$\begin{aligned} \dot{V}(t) = & \int_{-\tau(x(t))}^0 V_3(x(t), x(t - \tau(x(t))), x(t + s), s) ds \\ & + \int_{-\tau(x(t))}^0 \int_{-\tau(x(t))}^0 V_4(x(t + s), x(t + \theta), s, \theta) ds d\theta \end{aligned}$$

where

$$V_4(x_\theta, x_\xi, \theta, \xi) = \frac{\partial}{\partial \theta} V_2(x_\theta, x_\xi, \theta, \xi) + \frac{\partial}{\partial \xi} V_2(x_\theta, x_\xi, \theta, \xi). \quad (1)$$

# The Derivative

$$\dot{x}(t) = ax(t - \tau_0 + bx(t)) \quad \tau(x(t)) = \tau_0 + bx(t)$$

$$\begin{aligned} \dot{V}(t) = & \int_{-\tau(x(t))}^0 V_3(x(t), x(t - \tau(x(t))), x(t + s), s) ds \\ & + \int_{-\tau(x(t))}^0 \int_{-\tau(x(t))}^0 V_4(x(t + s), x(t + \theta), s, \theta) ds d\theta \end{aligned}$$

$$\begin{aligned} V_3(x_t, x_\tau, x_s, s) = & \frac{1}{\tau(x_t)} (abx_\tau - 1) V_1(x_t, x_\tau, -\tau(x_\tau)) + \frac{1}{\tau(x_t)} V_1(x_t, x_t, 0) \\ & + ax_\tau \frac{\partial}{\partial x} V_1(x_t, x_s, s) - \frac{\partial}{\partial \theta} V_1(x_t, x_s, \theta) \\ & + (2abx_\tau - 2) V_2(x_\tau, x_s, -\tau(x_t), \theta) + 2V_2(x_t, x_s, 0, \theta) \end{aligned}$$

# Stability Test

Suppose there exist  $S_i \in \Sigma_s$  for  $i = 1, 2, 3$ ,  $L_i \in \Sigma_s$  for  $i = 1, 2, 3, 4$ , some  $\epsilon_j > 0$  for  $j = 1, 2$ , polynomial  $R_1(x_0, \theta)$ ,  $R_2(x_0, x_1, \theta)$  and matrices  $M, N > 0$ , such that

$$1) V_1(x_0, x_2, \theta) + R_1(x_0, \theta) - \epsilon_1 x_0^2 - \sum_{i=1}^3 S_i(x_0, x_2, \theta) g_i(x_0, x_2, \theta) \in \Sigma_s,$$

$$2) -V_3(x_0, x_1, x_2, \theta) + R_2(x_0, x_1, \theta) - \epsilon_2 x_0^2 - \sum_{i=1}^4 L_i(x_0, x_1, x_2, \theta) g_i(x_0, x_1, x_2, \theta) \in \Sigma_s,$$

$$3) V_2(x_2, x_3, \theta, \xi) = Z_d^T(x_2, \theta) M Z_d(x_3, \xi),$$

$$4) V_4(x_2, x_3, \theta, \xi) = Z_d^T(x_2, \theta) N Z_d(x_3, \xi),$$

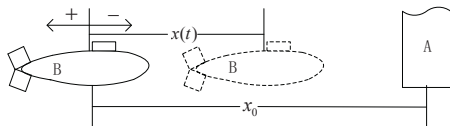
$$5) \int_{-\tau(x_0)}^0 R_1(x_0, \theta) d\theta = 0,$$

$$6) \int_{-\tau(x_0)}^0 R_2(x_0, x_1, \theta) d\theta = 0,$$

Then the system is asymptotically stable for all  $x_t \in \Omega$ , where  $\Omega$  is defined as

$$\Omega := \{x_t \in \mathbb{C} : \|x_t\| \leq \tau_0/(2b)\}.$$

# Numerical Validation



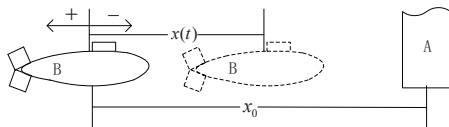
$$\dot{x}(t) = ax(t - \tau_0) + bx(t)$$

	$a = -0.1$	$a = -0.5$	$a = -1$
$\tau_0 = 0.1$	$b \in [4e-4, 1]$	$b \in [1e-4, 1]$	$b \in [2e-4, 1]$
$\tau_0 = 0.5$	$b \in [6e-4, 2]$	$b \in [3e-4, 2]$	$b \in [3e-3, 0.02]$
$\tau_0 = 1$	$b \in [7e-4, 3]$	$b \in [8e-4, 2]$	$b \in [3e-3, 0.02]$

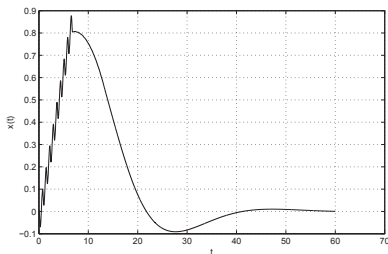
**Table:** The minimum and maximum stable values of  $b$  for a fixed  $a$  and  $\tau_0$ .



# Numerical Validation



$$\dot{x}(t) = ax(t - \tau_0) + bx(t)$$



**Figure:** Simulation Results using  $a = -0.1$ ,  $b = 1$ ,  $\tau_0 = 6$ , and initial condition  $\phi(\theta) = 0.5 \sin(\theta)$

# Conclusions:

## A Difficult Problem:

- Lyapunov Stability Test
  - ▶ Convexifies the problem
  - ▶ Relies on SDP.
  - ▶ Complexity depends on Accuracy.
- Practical Implications
  - ▶ The effect is small, but finite.

## Numerical Code Produced:

- Not currently posted
- Must generalize to multidimensional systems
- Future Work
  - ▶ Joint Positivity
  - ▶ Controller Synthesis

Will be Available for download at  
<http://control.asu.edu>