

*Inria*

## Interval Prediction for Continuous-Time Systems with Parametric Uncertainties

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# 01

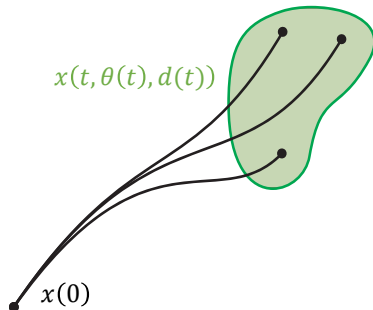
## Problem statement

### Linear Parameter-Varying systems

$$\dot{x}(t) = A(\theta(t))x(t) + Bd(t)$$

There are two sources of uncertainty:

- Parametric uncertainty  $\theta(t)$
- External perturbations  $d(t)$

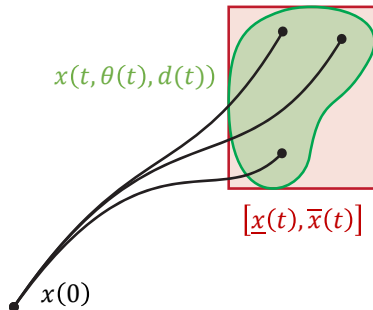


## Interval Prediction

Can we design an interval predictor  $[\underline{x}(t), \bar{x}(t)]$  that verifies:

- inclusion property:  $\forall t, \underline{x}(t) \leq x(t) \leq \bar{x}(t)$ ;
- stable dynamics?

We want the predictor to be as tight as possible.



### Assumption (Bounded trajectories)

- $\|x\|_\infty < \infty$
- $x(0) \in [\underline{x}_0, \bar{x}_0]$  for some *known*  $\underline{x}_0, \bar{x}_0 \in \mathbb{R}^n$

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- The matrix function  $A(\theta)$  is *known*

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### Assumption (Bounded perturbations)

- $d(t) \in [\underline{d}(t), \bar{d}(t)]$  for some *known* signals  $\underline{d}, \bar{d} \in \mathcal{L}_\infty^n$

How to proceed?



Assume that  $\underline{x}(t) \leq x(t) \leq \bar{x}(t)$ , for some  $t \geq 0$ .

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- ↳ To propagate the interval to  $x(t + dt)$ , we need to bound  $A(\theta(t))x(t)$ .

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- ↳ Why not use interval arithmetics?

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### Lemma (Image of an interval)

If  $A$  a *known* matrix, then

$$A^+ \underline{x} - A^- \bar{x} \leq Ax \leq A^+ \bar{x} - A^- \underline{x}.$$

where  $A^+ = \max(A, 0)$  and  $A^- = A - A^+$ .

Assume that  $\underline{x}(t) \leq x(t) \leq \bar{x}(t)$ , for some  $t \geq 0$ .

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- ↳ Why not use interval arithmetics?

### Lemma (Product of intervals)

If  $A$  is *unknown* but *bounded*  $\underline{A} \leq A \leq \bar{A}$ ,

$$\begin{aligned} \underline{A}^+ \underline{x}^+ - \bar{A}^+ \underline{x}^- - \underline{A}^- \bar{x}^+ + \bar{A}^- \bar{x}^- &\leq Ax \\ &\leq \bar{A}^+ \bar{x}^+ - \underline{A}^+ \bar{x}^- - \bar{A}^- \underline{x}^+ + \underline{A}^- \underline{x}^-. \end{aligned}$$

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- ✓ Since  $A(\theta)$  and the set  $\Theta$  are known, we can easily compute such bounds  $\underline{A} \leq A(\theta(t)) \leq \bar{A}$

Following this result, define the predictor:

$$\begin{aligned}
 \dot{\underline{x}}(t) &= \underline{A}^+ \underline{x}^+(t) - \overline{A}^+ \underline{x}^-(t) - \underline{A}^- \overline{x}^+(t) \\
 &\quad + \overline{A}^- \overline{x}^-(t) + B^+ \underline{d}(t) - B^- \overline{d}(t), \\
 \dot{\overline{x}}(t) &= \overline{A}^+ \overline{x}^+(t) - \underline{A}^+ \overline{x}^-(t) - \overline{A}^- \underline{x}^+(t) \\
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### Proposition (Inclusion property)

✓ The predictor (1) satisfies  $\underline{x}(t) \leq x(t) \leq \overline{x}(t)(t)$



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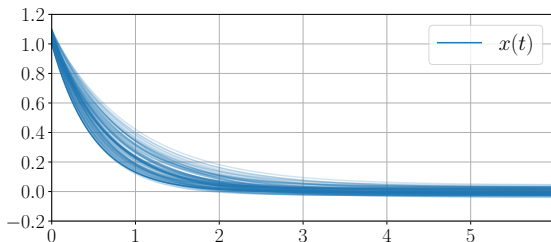
### Proposition (Inclusion property)

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? But is it stable?

Consider the scalar system, for all  $t \geq 0$ :

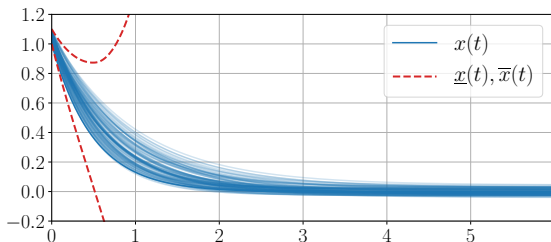
$$\dot{x}(t) = -\theta(t)x(t) + d(t), \text{ where } \begin{cases} x(0) \in [\underline{x}_0, \bar{x}_0] = [1.0, 1.1], \\ \theta(t) \in \Theta = [\underline{\theta}, \bar{\theta}] = [1, 2], \\ d(t) \in [\underline{d}, \bar{d}] = [-0.1, 0.1], \end{cases}$$



✓ The system is always **stable**

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✓ The system is always **stable**

✗ The predictor (1) is **unstable**

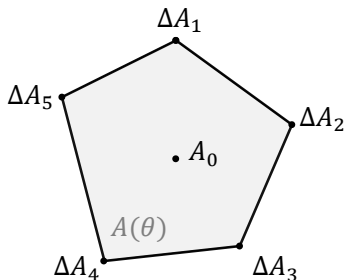
# 02

Our proposed  
predictor

## Assumption (Polytopic Structure)

There exist  $A_0$  Metzler and  $\Delta A_0, \dots, \Delta A_N$  such that:

$$A(\theta) = \underbrace{A_0}_{\text{Nominal dynamics}} + \sum_{i=1}^N \lambda_i(\theta) \Delta A_i, \quad \sum_{i=1}^N \underbrace{\lambda_i(\theta)}_{\geq 0} = 1; \quad \forall \theta \in \Theta$$



Denote

$$\Delta A_+ = \sum_{i=1}^N \Delta A_i^+, \quad \Delta A_- = \sum_{i=1}^N \Delta A_i^-,$$

We define the predictor

$$\begin{aligned} \underline{\dot{x}}(t) &= A_0 \underline{x}(t) - \Delta A_+ \underline{x}^-(t) - \Delta A_- \bar{x}^+(t) \\ &\quad + B^+ \underline{d}(t) - B^- \bar{d}(t), \\ \bar{\dot{x}}(t) &= A_0 \bar{x}(t) + \Delta A_+ \bar{x}^+(t) + \Delta A_- \underline{x}^-(t) \\ &\quad + B^+ \bar{d}(t) - B^- \underline{d}(t), \\ \underline{x}(0) &= \underline{x}_0, \quad \bar{x}(0) = \bar{x}_0 \end{aligned} \tag{2}$$

**Theorem (Inclusion property)**

*The predictor (2) ensures  $\underline{x}(t) \leq x(t) \leq \bar{x}(t)(t)$ .*

### Theorem (Stability)

If there exist diagonal matrices  $P, Q, Q_+, Q_-, Z_+, Z_-, \Psi_+, \Psi_-, \Upsilon, \Gamma \in \mathbb{R}^{2n \times 2n}$  such that the following LMIs are satisfied:

$$P + \min\{Z_+, Z_-\} > 0, \quad \Upsilon \preceq 0, \quad \Gamma > 0,$$
$$Q + \min\{Q_+, Q_-\} + 2 \min\{\Psi_+, \Psi_-\} > 0,$$

then the predictor (2) is input-to-state stable with respect to the inputs  $\underline{d}, \bar{d}$ .

where

$$\Upsilon = \begin{bmatrix} \Upsilon_{11} & \Upsilon_{12} & \Upsilon_{13} & P \\ \Upsilon_{12}^\top & \Upsilon_{22} & \Upsilon_{23} & Z_+ \\ \Upsilon_{13}^\top & \Upsilon_{23}^\top & \Upsilon_{33} & Z_- \\ P & Z_+ & Z_- & -\Gamma \end{bmatrix},$$

$$\Upsilon_{11} = \mathcal{A}^\top P + P\mathcal{A} + Q, \quad \Upsilon_{12} = \mathcal{A}^\top Z_+ + PR_+ + \Psi_+,$$

$$\Upsilon_{13} = \mathcal{A}^\top Z_- + PR_- + \Psi_-, \quad \Upsilon_{22} = Z_+R_+ + R_+^\top Z_+ + Q_+,$$

$$\Upsilon_{23} = Z_+R_- + R_+^\top Z_- + \Psi, \quad \Upsilon_{33} = Z_-R_- + R_-^\top Z_- + Q_-,$$

$$\mathcal{A} = \begin{bmatrix} A_0 & 0 \\ 0 & A_0 \end{bmatrix}, \quad R_+ = \begin{bmatrix} 0 & -\Delta A_- \\ 0 & \Delta A_+ \end{bmatrix}, \quad R_- = \begin{bmatrix} \Delta A_+ & 0 \\ -\Delta A_- & 0 \end{bmatrix},$$



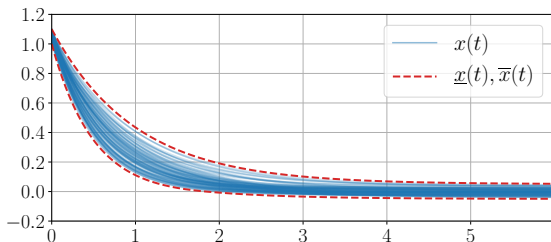
1. Define the extended state vector as  $X = [\underline{x}^\top \ \bar{x}^\top]^\top$
2. It follows the dynamics
$$\dot{X}(t) = \mathcal{A}X(t) + R_+X^+(t) - R_-X^-(t) + \delta(t)$$
3. Consider a candidate Lyapunov function:

$$V(X) = X^\top PX + X^\top Z_+X^+ - X^\top Z_-X^-$$

4.  $V(X)$  is positive definite provided that  $P + \min\{Z_+, Z_-\} > 0$ ,
5. Check on which condition we have  $\dot{V}(X) \leq 0$

Recall the scalar system, for all  $t \geq 0$ :

$$\dot{x}(t) = -\theta(t)x(t) + d(t), \text{ where } \begin{cases} x(0) \in [\underline{x}_0, \bar{x}_0] = [1.0, 1.1], \\ \theta(t) \in \Theta = [\underline{\theta}, \bar{\theta}] = [1, 2], \\ d(t) \in [\underline{d}, \bar{d}] = [-0.1, 0.1], \end{cases}$$



✓ The system is always **stable**

✓ The predictor (2) is **stable**

# 03

## Application to autonomous driving

$$\dot{z}_i = f_i(Z, \theta_i), \quad i = \overline{1, N},$$

where

- $z_i = [x_i, y_i, v_i, \psi_i]^T \in \mathbb{R}^4$  is the state of an agent
- $\theta_i \in \mathbb{R}^5$  is the corresponding unknown behavioural parameters
- $Z = [z_1, \dots, z_N]^T \in \mathbb{R}^{4N}$  is the joint state of the traffic
- $\theta = [\theta_1, \dots, \theta_N]^T \in \Pi \subset \mathbb{R}^{5N}$

Each vehicle follows the Kinematic Bicycle Model

$$\dot{x}_i = v_i \cos(\psi_i),$$

$$\dot{y}_i = v_i \sin(\psi_i),$$

$$\dot{v}_i = a_i,$$

$$\dot{\psi}_i = \frac{v_i}{l} \tan(\beta_i),$$

A linear controller using three features inspired from the intelligent driver model (IDM) [?].

$$a_i = [\theta_{i,1} \quad \theta_{i,2} \quad \theta_{i,3}] \begin{bmatrix} v_0 - v_i \\ -(v_{f_i} - v_i)^- \\ -(x_{f_i} - x_i - (d_0 + v_i T))^- \end{bmatrix},$$

where  $v_0$ ,  $d_0$  and  $T$  respectively denote the speed limit, jam distance and time gap given by traffic rules.

A cascade controller of lateral position  $y$  and heading  $\psi$ :

$$\begin{aligned}\dot{\psi}_i &= \theta_{i,5} \left( \psi_{L_i} + \sin^{-1} \left( \frac{\tilde{v}_{i,y}}{v_i} \right) - \psi_i \right), \\ \tilde{v}_{i,y} &= \theta_{i,4} (y_{L_i} - y_i).\end{aligned}\tag{3}$$

We assume that the drivers choose their steering command  $\beta_i$  such that (3) is always achieved:  $\beta_i = \tan^{-1} \left( \frac{1}{v_i} \dot{\psi}_i \right)$ .

Linearize trigonometric operators around  $y_i = y_{L_i}$  and  $\psi_i = \psi_{L_i}$ .  
This yields the following longitudinal dynamics:

$$\dot{x}_i = v_i,$$

$$\dot{v}_i = \theta_{i,1}(v_0 - v_i) + \theta_{i,2}(v_{f_i} - v_i) + \theta_{i,3}(x_{f_i} - x_i - d_0 - v_i T),$$

where  $\theta_{i,2}$  and  $\theta_{i,3}$  are set to 0 whenever the corresponding features are not active.



$$\dot{Z} = A(\theta)(Z - Z_c) + d.$$

For example, in the case of two vehicles only:

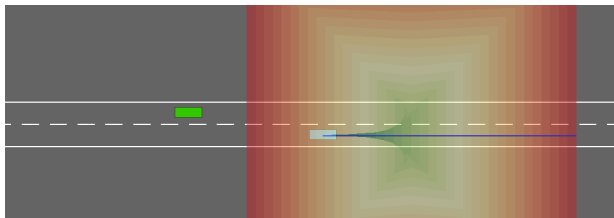
$$Z = \begin{bmatrix} x_i \\ x_{f_i} \\ v_i \\ v_{f_i} \end{bmatrix}, \quad Z_c = \begin{bmatrix} -d_0 - v_0 T \\ 0 \\ v_0 \\ v_0 \end{bmatrix}, \quad d = \begin{bmatrix} v_0 \\ v_0 \\ 0 \\ 0 \end{bmatrix}$$

$$A(\theta) = \begin{matrix} & i & f_i & i & f_i \\ \begin{matrix} i \\ f_i \\ i \\ f_i \end{matrix} & \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\theta_{i,3} & \theta_{i,3} & -\theta_{i,1} - \theta_{i,2} - \theta_{i,3} & \theta_{i,2} \\ 0 & 0 & 0 & -\theta_{f_i,1} \end{bmatrix} \end{matrix}$$

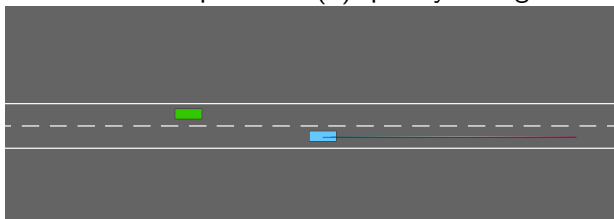
The lateral dynamics are in a similar form:

$$\begin{bmatrix} \dot{y}_i \\ \dot{\psi}_i \end{bmatrix} = \begin{bmatrix} 0 & v_i \\ -\frac{\theta_{i,4}\theta_{i,5}}{v_i} & -\theta_{i,5} \end{bmatrix} \begin{bmatrix} y_i - y_{L_i} \\ \psi_i - \psi_{L_i} \end{bmatrix} + \begin{bmatrix} v_i\psi_{L_i} \\ 0 \end{bmatrix}$$

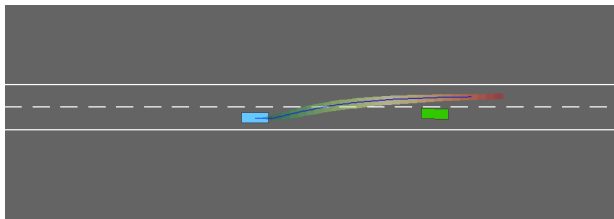
Here, the dependency in  $v_i$  is seen as an uncertain parametric dependency, *i.e.*  $\theta_{i,6} = v_i$ , with constant bounds assumed for  $v_i$  using an overset of the longitudinal interval predictor.



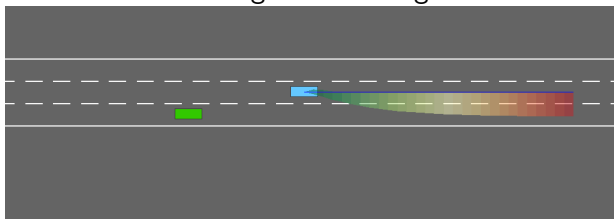
The naive predictor (1) quickly diverges



The proposed predictor (2) remains stable



Prediction during a lane change maneuver



Prediction with uncertainty in the followed lane  $L_i$

