

Interval Observer Design for Uncertain Discrete-Time Linear Switched Systems with Unknown Inputs

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Introduction

A switched systems represent a class of hybrid systems:

- a finite number of continuous subsystems (modes).
- a logical rule operates switching between subsystems.

Physical systems with switching features can be regarded as switched systems:

- power and electronics systems
- automated highway systems
- flight control systems
- network control systems,...

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- The problem of state vector estimation is very challenging and can be encountered in many applications.
- Several cases are encountered:
 - Models without uncertainties.
 - Models with uncertain parameters.
 - Uncertain parameters and unknown inputs
- Possible Solutions
 - Adaptive approaches
 - Robust approaches
 - Set-membership estimation / Interval observers.

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Given a system described by:

$$\begin{cases} \dot{x}(t) = f(x, u) \\ y(t) = h(x) \end{cases} \quad (1)$$

Definition

The dynamical system

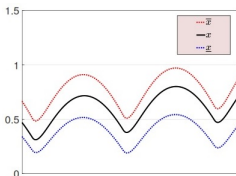
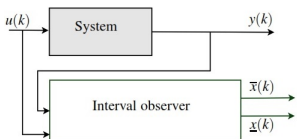
$$\begin{cases} \dot{z}(t) = \alpha(z, y, u) \\ [\underline{x}^T, \bar{x}^T]^T \end{cases} \quad (2)$$

is an *interval observer* for (2) if:

$$\underline{x}(0) \leq x(0) \leq \bar{x}(0) \Rightarrow -\infty < \underline{x}(t) \leq x(t) \leq \bar{x}(t) < +\infty; \forall t \geq 0. \quad (3)$$

An interval observer:

- compute the set of admissible values.
- provide the lower and upper bounds of state vector.



Two conditions have to be verified:

- ▶ Inclusion: $\underline{x}(t) \leq x(t) \leq \bar{x}(t), \forall t_0 \geq 0$
- ▶ Stability of estimation errors: $\underline{e} = x - \underline{x}$ and $\bar{e} = \bar{x} - x$

Consider the following discrete-time linear switched system:

$$\begin{cases} x(k+1) &= A_{\sigma_k}x(k) + B_{\sigma_k}u(k) + D_{\sigma_k}d(k) + \omega(k), \\ y_m(k) &= C_{\sigma_k}x(k) + v(k), \quad \sigma_k \in \overline{1, N}, \quad N \in \mathbb{N} \end{cases} \quad (4)$$

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- $x \in \mathbb{R}^n$: the state.
- $u \in \mathbb{R}^m$: the input.
- $y_m \in \mathbb{R}^p$: the output.
- $\omega \in \mathbb{R}^n$: the disturbances.
- $v \in \mathbb{R}^p$: the measurement noises.
- $d \in \mathbb{R}^l$: the unknown input.

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The objective is to design an interval observer:

- ① A potential candidates to cope with such uncertainties.
- ② a joint estimation of the state and the unknown input.
- ③ The given observer have to verify that:

$$\begin{aligned} \underline{x}(k) &\leq x(k) \leq \overline{x}(k) \\ \underline{d}(k) &\leq d(k) \leq \overline{d}(k) \end{aligned} \quad (5)$$

Two approaches are introduced:

- Classical approach based on decoupling the unknown input from the state vector:
 - Two changes of coordinates are used.
 - Estimate the bounds of the state vector x .
 - Computing two bounds for the unknown input vector d .

- New approach based on T-N-L method allowing the estimation of the state vector and the unknown input simultaneously.
 - new structure providing more design degrees of freedom.
 - relaxes the design conditions.

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Some assumptions are introduced

- 1 The state vector $x \in \mathbb{R}^n$ is bounded, i.e. $x \in \mathcal{L}_{\infty}^n$.
- 2 The switching signal $\sigma(k)$ is assumed to be known.
- 3 The state disturbance and the noise measurement are assumed to be bounded such that

$$-\bar{\omega} \leq \omega(k) \leq \bar{\omega}, \quad \forall k \geq 0, \quad (6)$$

$$-\bar{v} \leq v(k) \leq \bar{v}, \quad \forall k \geq 0, \quad (7)$$

with $\bar{\omega} \in \mathbb{R}^n$ and $\bar{v} \in \mathbb{R}^p$.

- 4 The matrices C_{σ_k} and D_{σ_k} verify:
 $rank(C_{\sigma_k} D_{\sigma_k}) = rank(D_{\sigma_k}) = l, \forall \sigma_k \in \overline{1, N}, l \leq p$

The stability is based on the following Lemma:

Lemma 1

Consider the discrete-time switched system

$x(k+1) = f_{\sigma(k)}(\xi(k), \eta(k))$, $\sigma(k) \in \overline{1, N}$. Suppose that there exists \mathcal{C}^1 functions $V_{\sigma(k)} : \mathbb{R}^n \rightarrow \mathbb{R}_+$, class \mathcal{K}_∞ functions $\alpha_1, \alpha_2, \gamma$ and constants $0 < \alpha < 1$, $\mu \geq 1$ such that $\forall \xi \in \mathbb{R}^n, \eta \in \mathbb{R}^l$, we have

$$\alpha_1(\|\xi\|) \leq V_{\sigma(k)}(\xi) \leq \alpha_2(\|\xi\|), \quad (8)$$

$$V_{\sigma(k)}(\xi(k+1)) - V_{\sigma(k)}(\xi(k)) \leq -\alpha V_{\sigma(k)}(\xi(k)) + \varrho(\|\eta\|), \quad (9)$$

and for each switching instant $k_l, l = 0, 1, 2, 3, \dots$,

$$V_{\sigma(k_l)}(\xi(k)) \leq \mu V_{\sigma(k_l-1)}(\xi(k)). \quad (10)$$

Then the system $x(k+1) = f_{\sigma(k)}(\xi(k), \eta(k))$, $\sigma(k) \in \overline{1, N}$ is

Input-to-State Stable (ISS) for any switching signal satisfying the average dwell time.

Step 1: Unknown input decoupling

Given the change of coordinates $z = T_{\sigma_k} x$, the system (4) becomes

$$\begin{cases} z(k+1) = \tilde{A}_{\sigma_k} z(k) + \tilde{B}_{\sigma_k} u(k) + \tilde{D}_{\sigma_k} d(k) + \tilde{w}_{\sigma_k}(k), \\ y_m(k) = \tilde{C}_{\sigma_k} z(k) + v(k), \quad \forall \sigma_k \in \overline{1, N}, \quad N \in \mathbb{N}, \end{cases} \quad (11)$$

where

$$T_{\sigma_k} = \begin{bmatrix} D_{\sigma_k}^* \\ (C_{\sigma_k} D_{\sigma_k})^{\oplus} C_{\sigma_k} \end{bmatrix} \quad (12)$$

$D_{\sigma_k}^* D_{\sigma_k} = 0$ and $(C_{\sigma_k} D_{\sigma_k})^{\oplus}$ is the left pseudo-inverse of $(C_{\sigma_k} D_{\sigma_k})$.

$$\tilde{A}_{\sigma_k} = T_{\sigma_k} A_{\sigma_k} T_{\sigma_k}^{-1} = \begin{bmatrix} \tilde{A}_{1\sigma_k} & \tilde{A}_{2\sigma_k} \\ \tilde{A}_{3\sigma_k} & \tilde{A}_{4\sigma_k} \end{bmatrix}, \quad \tilde{C}_{\sigma_k} = C_{\sigma_k} T_{\sigma_k}^{-1},$$

$$\tilde{B}_{\sigma_k} = T_{\sigma_k} B_{\sigma_k} = \begin{bmatrix} \tilde{B}_{1\sigma_k} \\ \tilde{B}_{2\sigma_k} \end{bmatrix}, \quad \tilde{D}_{\sigma_k} = T_{\sigma_k} D_{\sigma_k} = \begin{bmatrix} 0 \\ I_l \end{bmatrix},$$

$$\tilde{\omega}_{\sigma_k}(k) = T_{\sigma_k} \omega(k) = \begin{bmatrix} \tilde{\omega}_{1\sigma_k}(k), \\ \tilde{\omega}_{2\sigma_k} \end{bmatrix}, \quad z(k) = \begin{bmatrix} z_1(k) \\ z_2(k) \end{bmatrix}, \quad z_1 \in \mathbb{R}^{n-l}, \quad z_2 \in \mathbb{R}^l.$$

We get two subsystems:

$$\begin{cases} z_1(k+1) = \tilde{A}_{1\sigma_k} z_1(k) + \tilde{A}_{2\sigma_k} z_2(k) + \tilde{B}_{1\sigma_k} u(k) + \tilde{\omega}_{1\sigma_k}(k) \\ z_2(k+1) = \tilde{A}_{3\sigma_k} z_1(k) + \tilde{A}_{4\sigma_k} z_2(k) + \tilde{B}_{2\sigma_k} u(k) + d(k) + \tilde{\omega}_{2\sigma_k}(k) \\ \tilde{y}_1(k) = \check{C}_{\sigma_k} z_1(k) + U_{1\sigma_k} v(k) \\ \tilde{y}_2(k) = z_2(k) + U_{2\sigma_k} v(k) \end{cases}, \quad (13)$$

$$\tilde{y}(k) = U_{\sigma_k} y_m(k), \quad \tilde{y} = \begin{bmatrix} \tilde{y}_1 \\ \tilde{y}_2 \end{bmatrix}, \quad (14)$$

$$U_{\sigma_k} = \begin{bmatrix} U_{1\sigma_k} \\ U_{2\sigma_k} \end{bmatrix} = \begin{bmatrix} (C_{\sigma_k} D_{\sigma_k})^* \\ (C_{\sigma_k} D_{\sigma_k})^{\oplus} \end{bmatrix}, \quad \check{C}_{\sigma_k} = (C_{\sigma_k} D_{\sigma_k})^* C_{\sigma_k} (D_{\sigma_k}^*)^{\oplus}$$

Step 1: Unknown input decoupling

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We get two subsystems:

$$\begin{cases} z_1(k+1) = \tilde{A}_{1\sigma_k} z_1(k) + \tilde{A}_{2\sigma_k} z_2(k) + \tilde{B}_{1\sigma_k} u(k) + \tilde{\omega}_{1\sigma_k}(k) \\ \tilde{y}_1(k) = \check{C}_{\sigma_k} z_1(k) + U_{1\sigma_k} v(k) \end{cases}, \quad (13)$$

⇒ **Unknown input-free subsystem**

$$\tilde{y}(k) = U_{\sigma_k} y_m(k), \quad \tilde{y} = \begin{bmatrix} \tilde{y}_1 \\ \tilde{y}_2 \end{bmatrix}, \quad (14)$$

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We get two subsystems:

$$\begin{cases} z_2(k+1) = \tilde{A}_{3\sigma_k} z_1(k) + \tilde{A}_{4\sigma_k} z_2(k) + \tilde{B}_{2\sigma_k} u(k) + \mathbf{d}(k) + \tilde{\omega}_{2\sigma_k}(k) \\ \tilde{y}_2(k) = z_2(k) + U_{2\sigma_k} v(k) \end{cases}, \quad (13)$$

⇒ **Unknown input-dependent subsystem**

$$\tilde{y}(k) = U_{\sigma_k} y_m(k), \quad \tilde{y} = \begin{bmatrix} \tilde{y}_1 \\ \tilde{y}_2 \end{bmatrix}, \quad (14)$$

$$U_{\sigma_k} = \begin{bmatrix} U_{1\sigma_k} \\ U_{2\sigma_k} \end{bmatrix} = \begin{bmatrix} (C_{\sigma_k} D_{\sigma_k})^* \\ (C_{\sigma_k} D_{\sigma_k})^{\oplus} \end{bmatrix}, \quad \check{C}_{\sigma_k} = (C_{\sigma_k} D_{\sigma_k})^* C_{\sigma_k} (D_{\sigma_k}^*)^{\oplus}$$

The unknown free-subsystem can be written:

$$\begin{cases} z_1(k+1) &= \tilde{A}_{1\sigma_k} z_1(k) + \tilde{A}_{2\sigma_k} \tilde{y}_2(k) + \tilde{B}_{1\sigma_k} u(k) + \tilde{\omega}_{1\sigma_k}(k) \\ &- \tilde{A}_{2\sigma_k} U_{2\sigma_k} v(k) \\ \tilde{y}_1(k) &= \check{C}_{\sigma_k} z_1(k) + U_{1\sigma_k} v(k). \end{cases} \quad (16)$$

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$$\begin{cases} z_1(k+1) &= \tilde{A}_{1\sigma_k} z_1(k) + \tilde{A}_{2\sigma_k} \tilde{y}_2(k) + \tilde{B}_{1\sigma_k} u(k) + \tilde{\omega}_{1\sigma_k}(k) \\ &- \tilde{A}_{2\sigma_k} U_{2\sigma_k} v(k) \\ \tilde{y}_1(k) &= \check{C}_{\sigma_k} z_1(k) + U_{1\sigma_k} v(k). \end{cases} \quad (16)$$

To design an interval observer for (16), two properties have to be satisfied:

- **Framer property** which is the notion of providing intervals in which the state variables stay.
- **Stability property** which cares the length of estimated intervals

⇒ The observer gains L_{σ_k} need to be chosen such that:

- 1 $\tilde{A}_{1\sigma_k} - L_{\sigma_k} \check{C}_{\sigma_k}$ are nonnegative.
- 2 The estimation errors are stable.

The solution:

- A nonsingular transformation $\beta_1 = Pz_1$ such that the matrices $P(\tilde{A}_{1\sigma_k} - L_{\sigma_k}\check{C}_{\sigma_k})P^{-1}$ are nonnegative.
- The existence of a common transformation P for all $\sigma_k \in \overline{1, N}$ is not obvious, even impossible.
- The design, in the original coordinates of two conventional observers.

$$\left\{ \begin{array}{l} \hat{z}_1^+(k+1) = (\tilde{A}_{1\sigma_k} - L_{\sigma_k}\check{C}_{\sigma_k})\hat{z}_1^+(k) + \tilde{B}_{1\sigma_k}u(k) + P_{\sigma_k}^{-1}|P_{\sigma_k}|\bar{\omega}_{1\sigma_k} \\ \quad + P_{\sigma_k}^{-1}\left[P_{\sigma_k}^+\left(\tilde{A}_{2\sigma_k}^+\bar{y}_2 - \tilde{A}_{2\sigma_k}^-\bar{y}_2\right) - P_{\sigma_k}^-\left(\tilde{A}_{2\sigma_k}^+\bar{y}_2 - \tilde{A}_{2\sigma_k}^-\bar{y}_2\right)\right] \\ \quad + P_{\sigma_k}^{-1}|P_{\sigma_k}|\tilde{A}_{2\sigma_k}U_{2\sigma_k}|\bar{v} + L_{\sigma_k}\bar{y}_1 + P_{\sigma_k}^{-1}|P_{\sigma_k}||L_{\sigma_k}U_{1\sigma_k}|\bar{v}, \\ \\ \hat{z}_1^-(k+1) = (\tilde{A}_{1\sigma_k} - L_{\sigma_k}\check{C}_{\sigma_k})\hat{z}_1^-(k) + \tilde{B}_{1\sigma_k}u(k) + P_{\sigma_k}^{-1}(-|P_{\sigma_k}|)\bar{\omega}_{1\sigma_k} \\ \quad + P_{\sigma_k}^{-1}\left[P_{\sigma_k}^+\left(\tilde{A}_{2\sigma_k}^+\bar{y}_2 - \tilde{A}_{2\sigma_k}^-\bar{y}_2\right) - P_{\sigma_k}^-\left(\tilde{A}_{2\sigma_k}^+\bar{y}_2 - \tilde{A}_{2\sigma_k}^-\bar{y}_2\right)\right] \\ \quad - P_{\sigma_k}^{-1}|P_{\sigma_k}|\tilde{A}_{2\sigma_k}U_{2\sigma_k}|\bar{v} + L_{\sigma_k}\bar{y}_1 - P_{\sigma_k}^{-1}|P_{\sigma_k}||L_{\sigma_k}U_{1\sigma_k}|\bar{v}, \end{array} \right. \quad (16)$$

- **Framer design**

Theorem 1

Let Assumptions 1-4 be satisfied and $\underline{x}(0) \leq x(0) \leq \bar{x}(0)$. Given the nonsingular transformation matrices $P_{\sigma_k} \in \mathbb{R}^{(n-l) \times (n-l)}$ such that $P_{\sigma_k} (\tilde{A}_{1\sigma_k} - L_{\sigma_k} \check{C}_{\sigma_k}) P_{\sigma_k}^{-1}$ are nonnegative and consider the suitably selected initial conditions

$$\begin{cases} \hat{z}_1^+(0) = P_{\sigma_k}^{-1} (P_{\sigma_k}^+ \bar{z}_1(0) - P_{\sigma_k}^- \underline{z}_1(0)), \\ \hat{z}_1^-(0) = P_{\sigma_k}^{-1} (P_{\sigma_k}^+ \underline{z}_1(0) - P_{\sigma_k}^- \bar{z}_1(0)), \end{cases} \quad (17)$$

where

$$\begin{cases} \bar{z}(0) = T_{\sigma_0}^+ \bar{x}(0) - T_{\sigma_0}^- \underline{x}(0), \\ \underline{z}(0) = T_{\sigma_0}^+ \underline{x}(0) - T_{\sigma_0}^- \bar{x}(0), \end{cases} \quad (18)$$

Theorem 1

Then, the bounds of the substate vector z_1 given by

$$\begin{cases} \bar{z}_1(k) = (P_{\sigma_k}^{-1})^+ P_{\sigma_k} \hat{z}_1^+(k) - (P_{\sigma_k}^{-1})^- P_{\sigma_k} \hat{z}_1^-(k), \\ \underline{z}_1(k) = (P_{\sigma_k}^{-1})^+ P_{\sigma_k} \hat{z}_1^-(k) - (P_{\sigma_k}^{-1})^- P_{\sigma_k} \hat{z}_1^+(k), \end{cases} \quad (19)$$

satisfy

$$\underline{z}_1(k) \leq z_1(k) \leq \bar{z}_1(k), \quad \forall k \geq 0. \quad (20)$$

- Stability conditions

Theorem 2

Assume that the conditions of Theorem 1 are satisfied. If there exist positive scalars $\alpha_2 > \alpha_1 > 0$, $\gamma > 0$, $0 < \alpha < 1$ and $0 \leq \beta \leq 1$, matrices W_{σ_l} , S_{σ_l} and diagonal positive definite matrices M_{σ_k} such that for $\sigma_{k,l} \in \overline{1, N}$ with $\sigma_k \neq \sigma_l$,

$$\begin{bmatrix} -(1-\alpha)M_{\sigma_k} & 0 & \tilde{A}_{1\sigma_k}^T M_{\sigma_k} - \check{C}_{\sigma_k}^T S_{\sigma_k} \\ 0 & -\gamma^2 I_n & M_{\sigma_k} \\ M_{\sigma_k} \tilde{A}_{1\sigma_k} - S_{\sigma_k} \check{C}_{\sigma_k} & M_{\sigma_k} & -M_{\sigma_k} \end{bmatrix} \preceq 0 \quad (21)$$

$$\alpha_1 I_n \leq M_{\sigma_k} \leq \alpha_2 I_n \quad (22)$$

Theorem 2

$$\begin{bmatrix} W_{\sigma_l} & M_{\sigma_k} \\ M_{\sigma_k} & M_{\sigma_k} \end{bmatrix} \preceq 0 \quad (23)$$

then, the lower and upper observer errors are ISS and the framer (17)-(19) is an interval observer. In addition, the gains L_{σ_k} , given by $L_{\sigma_k} = M_{\sigma_k}^{-1} S_{\sigma_k}$

Based on the estimation of the state in the coordinates z_1 , the bounds \underline{x} and \bar{x} are deduced in the following theorem.

Theorem 3

Let the assumptions of Theorem 1 and Theorem 2 hold, then

$$\underline{x}(k) \leq x(k) \leq \bar{x}(k), \quad \forall k \geq 0 \quad (24)$$

Theorem 3

where:

$$\left\{ \begin{array}{l} \bar{x}_1 = T_{1\sigma_k}^+ \bar{z}_1 - T_{1\sigma_k}^- \underline{z}_1 + T_{2\sigma_k}^+ \bar{y}_2 - T_{2\sigma_k}^- \tilde{y}_2 \\ \quad + (-T_{2\sigma_k} U_{2\sigma_k})^+ \bar{v} + (-T_{2\sigma_k} U_{2\sigma_k})^- \bar{v} \\ \underline{x}_1 = T_{1\sigma_k}^+ \underline{z}_1 - T_{1\sigma_k}^1 \bar{z}_1 + T_{2\sigma_k}^+ \tilde{y}_2 - T_{2\sigma_k}^- \bar{y}_2 \\ \quad - (-T_{2\sigma_k} U_{2\sigma_k})^+ \bar{v} - (-T_{2\sigma_k} U_{2\sigma_k})^- \bar{v} \\ \bar{x}_2 = T_{3\sigma_k}^+ \bar{z}_1 - T_{3\sigma_k}^1 \underline{z}_1 + T_{4\sigma_k}^+ \bar{y}_2 - T_{4\sigma_k}^- \tilde{y}_2 \\ \quad + (-T_{4\sigma_k} U_{2\sigma_k})^+ \bar{v} + (-T_{4\sigma_k} U_{2\sigma_k})^- \bar{v} \\ \underline{x}_2 = T_{3\sigma_k}^+ \underline{z}_1 - T_{3\sigma_k}^1 \bar{z}_1 + T_{4\sigma_k}^+ \tilde{y}_2 - T_{4\sigma_k}^- \bar{y}_2 \\ \quad - (-T_{4\sigma_k} U_{2\sigma_k})^+ \bar{v} - (-T_{4\sigma_k} U_{2\sigma_k})^- \bar{v} \end{array} \right. \quad (25)$$

$$\underline{x}(k) = \begin{bmatrix} \underline{x}_1 \\ \underline{x}_2 \end{bmatrix}, \quad \bar{x}(k) = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}.$$

$$z_2(k+1) = U_{2\sigma_k} y_m(k+1) - U_{2\sigma_k} v(k+1) \quad (26)$$

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$$\begin{aligned} d(k) &= z_2(k+1) - \tilde{A}_{3\sigma_k} z_1(k) - \tilde{A}_{4\sigma_k} z_2(k) - \tilde{B}_{2\sigma_k} u(k) - \tilde{\omega}_{2\sigma_k}(k) \\ &= U_{2\sigma_k} [y_m(k+1) - v(k+1)] - \tilde{A}_{3\sigma_k} z_1(k) - A_{4\sigma_k} U_{2\sigma_k} y_m \\ &\quad + A_{4\sigma_k} U_{2\sigma_k} v(k) - \tilde{B}_{2\sigma_k} u(k) - \tilde{\omega}_{2\sigma_k}(k) \end{aligned} \quad (27)$$

The upper and lower bounds of d :

$$\left\{ \begin{array}{l} \bar{d}(k) = [U_{2\sigma_k}^+ \bar{\chi}(k+1) - U_{2\sigma_k}^- \underline{\chi}(k+1)] - \tilde{B}_{2\sigma_k} u(k) \\ \quad + [(-\tilde{A}_{3\sigma_k})^+ \bar{z}_1(k) - (-\tilde{A}_{3\sigma_k})^- \underline{z}_1(k)] + \tilde{\omega}_{2\sigma_k} \\ \quad + [(-A_{4\sigma_k} U_{2\sigma_k})^+ \bar{y}_m(k) - (-A_{4\sigma_k} U_{2\sigma_k})^- \underline{y}_m(k)] + |A_{4\sigma_k} U_{2\sigma_k}| \bar{v}, \\ \underline{d}(k) = [U_{2\sigma_k}^+ \underline{\chi}(k+1) - U_{2\sigma_k}^- \bar{\chi}(k+1)] - \tilde{B}_{2\sigma_k} u(k) \\ \quad + [(-\tilde{A}_{3\sigma_k}) \underline{z}_1(k) - (-\tilde{A}_{3\sigma_k})^- \bar{z}_1(k)] - \tilde{\omega}_{2\sigma_k} \\ \quad + [(-A_{4\sigma_k} U_{2\sigma_k})^+ \underline{y}_m(k) - (-A_{4\sigma_k} U_{2\sigma_k})^- \bar{y}_m(k)] - |A_{4\sigma_k} U_{2\sigma_k}| \bar{v}, \end{array} \right. \quad (28)$$

with $\chi(k) = y_m(k) - v(k)$. Where $\bar{\chi}(k)$ and $\underline{\chi}(k)$ are respectively upper and lower bound of $\chi(k)$

$$\left\{ \begin{array}{l} \bar{\chi}(k) = y_m(k) + \bar{v} \\ \underline{\chi}(k) = y_m(k) - \bar{v} \end{array} \right. \quad (29)$$

By augmenting unknown input $d(k)$ as a part of the state vector $\tilde{x}(k+1)$, the structural conditions for decoupling unknown input often used in literature are relaxed.

$$\begin{cases} E_{\sigma_k} \tilde{x}(k+1) &= \tilde{A}_{\sigma_k} \tilde{x}(k) + \tilde{B}_{\sigma_k} u(k) + \tilde{I} \omega(k), \\ y(k) &= \tilde{C}_{\sigma_k} \tilde{x}(k) + v(k), \end{cases} \quad (30)$$

$$\tilde{x}(k+1) = \begin{bmatrix} x(k+1) \\ d(k) \end{bmatrix}, \tilde{x}(0) = \begin{bmatrix} x(0) \\ 0 \end{bmatrix},$$

$$E_{\sigma_k} = \begin{bmatrix} I & -D_{\sigma_k} \\ 0 & 0 \end{bmatrix}, \tilde{I} = \begin{bmatrix} I \\ 0 \end{bmatrix}$$

$$\tilde{A}_{\sigma_k} = \begin{bmatrix} A_{\sigma_k} & 0 \\ 0 & 0 \end{bmatrix}, \tilde{B}_{\sigma_k} = \begin{bmatrix} B_{\sigma_k} \\ 0 \end{bmatrix}, \tilde{C}_{\sigma_k} = [C_{\sigma_k} \quad 0].$$

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The goal: The interval observer of the augmented state $\tilde{x}(k+1)$:

- $\underline{\tilde{x}}(k)$
- $\overline{\tilde{x}}(k)$

such that

$$\underline{\tilde{x}}(k) \leq \tilde{x}(k) \leq \overline{\tilde{x}}(k), \forall k \in \mathbb{Z}_+, \quad (31)$$

The following framer candidate is considered

$$\left\{ \begin{array}{l} \underline{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \underline{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \underline{\tilde{x}}(k)) + \Delta \\ \overline{\tilde{x}}(k) = \underline{\xi}(k) + N_{\sigma_k} y(k) \\ \underline{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \overline{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \overline{\tilde{x}}(k)) - \Delta \\ \overline{\tilde{x}}(k) = \underline{\xi}(k) + N_{\sigma_k} y(k) \end{array} \right. \quad (32)$$

$$\Delta = |T_{\sigma_k} \tilde{I}| \bar{\omega} + |L_{\sigma_k}| \bar{v} + |N_{\sigma_k}| \bar{v} \quad (33)$$

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The following framer candidate is considered

$$\left\{ \begin{array}{l} \bar{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \bar{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \bar{\tilde{x}}(k)) + \Delta \\ \bar{\tilde{x}}(k) = \bar{\xi}(k) + N_{\sigma_k} y(k) \\ \underline{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \underline{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \underline{\tilde{x}}(k)) - \Delta \\ \underline{\tilde{x}}(k) = \underline{\xi}(k) + N_{\sigma_k} y(k) \end{array} \right. \quad (32)$$

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$$\underline{\tilde{x}}(k) \leq \tilde{x}(k) \leq \bar{\tilde{x}}(k), \forall k \in \mathbb{Z}_+, \quad (31)$$

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$$\Delta = |T_{\sigma_k} \tilde{I}| \bar{\omega} + |L_{\sigma_k}| \bar{v} + |N_{\sigma_k}| \bar{v} \quad (33)$$

The goal: The interval observer of the augmented state $\tilde{x}(k+1)$:

- $\underline{\tilde{x}}(k)$
- $\overline{\tilde{x}}(k)$

such that

$$\underline{\tilde{x}}(k) \leq \tilde{x}(k) \leq \overline{\tilde{x}}(k), \forall k \in \mathbb{Z}_+, \quad (31)$$

The following framer candidate is considered

$$\left\{ \begin{array}{l} \overline{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \overline{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \overline{\tilde{x}}(k)) + \Delta \\ \overline{\tilde{x}}(k) = \overline{\xi}(k) + N_{\sigma_k} y(k) \\ \underline{\xi}(k+1) = T_{\sigma_k} \tilde{A}_{\sigma_k} \underline{\tilde{x}}(k) + T_{\sigma_k} \tilde{B}_{\sigma_k} u(k) \\ \quad + L_{\sigma_k} (y(k) - \tilde{C}_{\sigma_k} \underline{\tilde{x}}(k)) - \Delta \\ \underline{\tilde{x}}(k) = \underline{\xi}(k) + N_{\sigma_k} y(k) \end{array} \right. \quad (32)$$

$$\Delta = |T_{\sigma_k} \tilde{I}| \overline{\omega} + |L_{\sigma_k}| \overline{v} + |N_{\sigma_k}| \overline{v} \quad (33)$$

- L_{σ_k} : the observer gain associated to the σ_k -subsystem.
- The matrices T_{σ_k} , N_{σ_k} are computed:

$$T_{\sigma_k} E_{\sigma_k} + N_{\sigma_k} \tilde{C}_{\sigma_{k+1}} = I \quad (34)$$

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$$T_{\sigma_k} E_{\sigma_k} + N_{\sigma_k} \tilde{C}_{\sigma_{k+1}} = I \quad (34)$$

The nonnegativity conditions: Framer design:

Theorem 4

Let Assumptions 1-4 hold, the lower bound $\underline{\tilde{x}}(k)$ and upper bound $\overline{\tilde{x}}(k)$ for the state $\tilde{x}(k)$ given by (32) satisfy (31), if (34) hold and $(T_{\sigma_k} \tilde{A}_{\sigma_k} - L_{\sigma_k} \tilde{C}_{\sigma_k}) \geq 0, \forall \sigma_k \in \overline{1, N}$ provided that

$$\tilde{\underline{x}}_0 := \begin{bmatrix} \underline{x}(0) \\ \underline{d}(0) \end{bmatrix} \leq \tilde{x}(0) \leq \tilde{\overline{x}}_0 := \begin{bmatrix} \overline{x}(0) \\ \overline{d}(0) \end{bmatrix}.$$

Proof.

- $\bar{e}(k) = \bar{\tilde{x}}(k) - \tilde{x}(k)$
- $\underline{e}(k) = \tilde{x}(k) - \underline{\tilde{x}}(k)$

The dynamic of the upper error follows

$$\begin{aligned} \bar{e}(k+1) &= (T_{\sigma_k} \tilde{A}_{\sigma_k} - L_{\sigma_k} \tilde{C}_{\sigma_k}) \bar{e}(k) + \Delta \\ &\quad - T_{\sigma_k} \tilde{I} \omega(k) + L_{\sigma_k} v(k) + N_{\sigma_k} v(k+1). \end{aligned} \quad (35)$$

$$\Delta - T_{\sigma_k} \tilde{I} \omega(k) + L_{\sigma_k} v(k) + N_{\sigma_k} v(k+1) \geq 0 \quad (36)$$

From the fact that $\bar{e}(0) = \bar{\tilde{x}}(0) - \tilde{x}(0) \geq 0$, it follows that, for all $k \in \mathbb{Z}_+$, $\bar{e}(k) \geq 0$ and for the same reasons $\underline{e}(k) \geq 0$.

Interval observer design using H_∞ performance

Let us define the estimation error as follows

$$e(k) = \bar{e}(k) - \underline{e}(k) \quad (37)$$

Thus,

$$e(k+1) = (T_{\sigma_k} \tilde{A}_{\sigma_k} - L_{\sigma_k} \tilde{C}_{\sigma_k})e(k) + \Phi_{\sigma_k} \delta(k) \quad (38)$$

with

$$\delta(k) = \begin{bmatrix} -T_{\sigma_k} \tilde{I} \omega(k) \\ v(k) \\ v(k+1) \end{bmatrix} \quad (39)$$

and

$$\Phi_{\sigma_k} = 2 \begin{bmatrix} I & L_{\sigma_k} & N_{\sigma_k} \end{bmatrix} \quad (40)$$

Interval observer design using H_∞ performance

Theorem 5

Assume that all assumptions of Theorem 4 hold. For given scalars $\gamma > 0$ and $0 < \alpha < 1$, if there exist positive scalars $\alpha_2 > \alpha_1 > 0$, a diagonal matrix $P_{\sigma_k} \in \mathbb{R}^{n \times n}$ such that $P_{\sigma_k} \succ 0$, $W_{\sigma_k} \in \mathbb{R}^{n \times n}$, $G_{\sigma_k} \in \mathbb{R}^{n \times p}$ and $H_{\sigma_k} \in \mathbb{R}^{n \times (n+p)}$ such that

$$P_{\sigma_k} \Theta_{\sigma_k}^\dagger \lambda_1 \tilde{A}_{\sigma_k} + H_{\sigma_k} \psi_{\sigma_k} \lambda_1 \tilde{A}_{\sigma_k} - G_{\sigma_k} \tilde{C}_{\sigma_k} \geq 0, \quad \forall \sigma_k \in \overline{1, N} \quad (41)$$

$$\alpha_1 I \leq P_{\sigma_k} \leq \alpha_2 I, \quad \forall \sigma_k \in \overline{1, N} \quad (42)$$

$$\begin{bmatrix} W_{\sigma_k} & P_{\sigma_k} \\ P_{\sigma_k} & P_{\sigma_k} \end{bmatrix} \succeq 0 \quad (43)$$

Interval observer design using H_∞ performance

Theorem 5

$$\begin{bmatrix} -(1-\alpha)P_{\sigma_k} & \star & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star & \star \\ 0 & 0 & -\gamma^2 I & \star & \star \\ 0 & 0 & 0 & -\gamma^2 I & \star \\ \kappa_{1\sigma_k} & 2P_{\sigma_k} & 2G_{\sigma_k} & 2\kappa_{2\sigma_k} & -P_{\sigma_k} \end{bmatrix} \preceq 0, \quad (44)$$

with

$$W_{\sigma_l} = \mu P_{\sigma_l}, \quad G_{\sigma_k} = P_{\sigma_k} L_{\sigma_k}, \quad H_{\sigma_k} = P_{\sigma_k} S_{\sigma_k}, \quad \forall \sigma_k, \sigma_l \in \overline{1, N}$$

$$\begin{aligned} \kappa_{1\sigma_k} &= P_{\sigma_k} \Theta_{\sigma_k}^\dagger \lambda_1 \tilde{A}_{\sigma_k} + H_{\sigma_k} \psi_{\sigma_k} \lambda_1 \tilde{A}_{\sigma_k} - G_{\sigma_k} \tilde{C}_{\sigma_k} \\ \kappa_{2\sigma_k} &= P_{\sigma_k} \Theta_{\sigma_k}^\dagger \lambda_2 + H_{\sigma_k} \psi_{\sigma_k} \lambda_2, \quad \forall \sigma_k \in \overline{1, N} \end{aligned}$$

Interval observer design using H_∞ performance

Theorem 5

Then, (32) is an interval observer for (4). Moreover, the optimal observer gain matrix

$$L_{\sigma_k} = P_{\sigma_k}^{-1} G_{\sigma_k}, \quad \forall \sigma_k \in \overline{1, N} \quad (45)$$

Given the system (4) with 3 modes ($N = 3$) where

$$A_1 = \begin{bmatrix} 0.55 & 0.5 & 0.7 \\ 0 & 0.8 & 0.5 \\ 0 & 0 & 0.4 \end{bmatrix}, B_1 = \begin{bmatrix} 0 \\ 0.5 \\ 0.7 \end{bmatrix}, C_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}, D_1 = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$

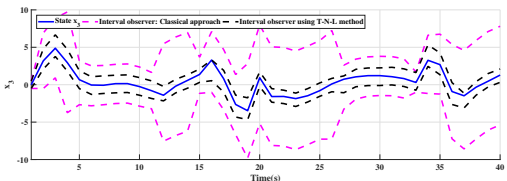
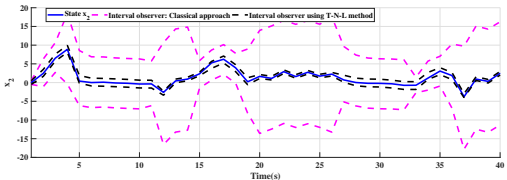
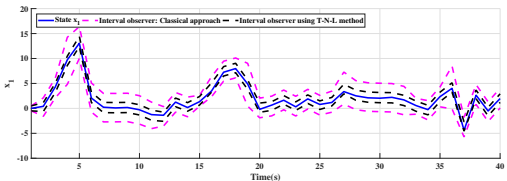
$$A_2 = \begin{bmatrix} -0.44 & -0.4 & -0.56 \\ 0 & -0.64 & -0.4 \\ 0 & 0 & -0.32 \end{bmatrix}, B_2 = \begin{bmatrix} 0.4 \\ 0.6 \\ 0 \end{bmatrix}, C_2 = \begin{bmatrix} 1.01 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix},$$

$$D_2 = \begin{bmatrix} 1 \\ 0 \\ 4.73 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 0.1 & 1 & 1 \\ 0 & .2 & -0.5 \\ 0 & 0 & 0.2 \end{bmatrix}, B_3 = \begin{bmatrix} 0.1 \\ 0.0 \\ 0.1 \end{bmatrix}, C_3 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}, D_3 = \begin{bmatrix} 1 \\ 0.5 \\ 1 \end{bmatrix}$$

We have as the following conditions $|w(k)| \leq \bar{w}$ with $\bar{w} = [0.06 \quad 0.06 \quad 0.06]$, and $|v(k)| \leq \bar{v}$ with $\bar{v} = [0.06 \quad 0.06]$.
The unknown input is given as $d(k) = 0.5 \sin(0.5k)$.

For the the state vector, we get:



For the unknown input, we have:

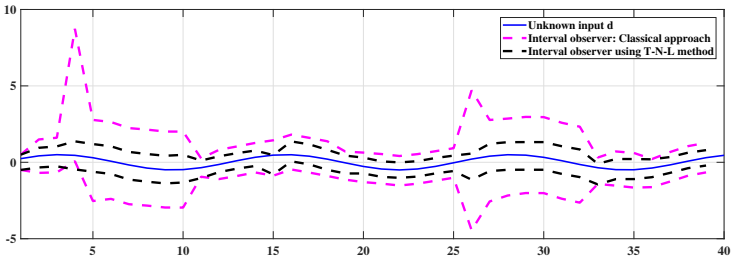


Figure 2: The unknown input

- Two methods to design interval observer for switched systems in presence of unknown input are presented.
- Sufficient conditions for the stability of the interval observer are derived in terms of LMIs.
- The effectiveness of the proposed approaches are shown on a numerical example.

The End