State and multiplicative sensor fault estimation for nonlinear systems

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Motivation and proposition

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Design a joint state and (multiplicative sensor) fault observer for nonlinear systems

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1. Rewrite the nonlinear system into a T-S model with unmeasurable premise variables
2. Describe the time-varying sensor fault using the sector nonlinearity approach
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Outline

1. Problem statement
2. Observer design
3. Illustrative example
4. Conclusions and perspectives

1. Problem statement

T-S approach for modeling

- The Takagi-Sugeno structure

$$\begin{cases} \dot{x}(t) & = & \sum_{i=1}^{n} \mu_i(\xi(t))(A_i x(t) + B_i u(t)) \\ y(t) & = & \sum_{i=1}^{n} \mu_i(\xi(t))(C_i x(t) + D_i u(t)) \end{cases}$$

$x(t) \in \mathbb{R}^{n_x}$ is the system state variable, $u(t) \in \mathbb{R}^{n_u}$ is the control input and $y(t) \in \mathbb{R}^{m}$ is the system output. $\xi(t) \in \mathbb{R}^{q}$ is the decision variable vector.

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- Nonlinear interpolation between linear submodels with adequate weighting functions $\mu_i(\xi(t))$ satisfying the convex sum property

$$\begin{cases} \sum_{i=1}^{n} \mu_i(\xi(t)) = 1 \\ 0 \leq \mu_i(\xi(t)) \leq 1, \quad i = 1, \ldots, n, \quad \forall t \end{cases}$$

How to systematically obtain a T-S model fom a given NL system?

- Sector nonlinearity transformation: a systematic procedure which guarantees an exact model construction for nonlinear systems with bounded nonlinearities.

1. Problem statement

How to systematically obtain a T-S model fom a given NL system?

- Sector nonlinearity transformation: a systematic procedure which guarantees an exact model construction for nonlinear systems with bounded nonlinearities.
- The nonlinear systems is rewritten as a quasi-LPV model. The T-S form is obtained by using the convex polytopic transformation.
  Each vertex defines a linear submodel and the nonlinearities are rejected into the weighting functions.

$$\text{NL} \begin{cases} \dot{x}(t) = f_x(x(t), u(t)) \\ y(t) = f_y(x(t), u(t)) \end{cases} \Rightarrow$$

$$\text{Quasi-LPV} \begin{cases} \dot{x}(t) & = & A(x(t), u(t))x(t) + B(x(t), u(t))u(t) \\ y(t) & = & C(x(t), u(t))x(t) + D(x(t), u(t))u(t) \end{cases} \Rightarrow$$

$$\text{T-S model} \begin{cases} \dot{x}(t) & = & \sum_{i=1}^{n} \mu_i(\xi(t))(A_i x(t) + B_i u(t)) \\ y(t) & = & \sum_{i=1}^{n} \mu_i(\xi(t))(C_i x(t) + D_i u(t)) \end{cases}$$

1. Problem statement

Takagi-Sugeno system with multiplicative time-varying sensor faults

$$\dot{x}(t) = \sum_{i=1}^{r} \mu_i(x(t))(A_i x(t) + B_i u(t)), \quad y(t) = C(t)x(t) = (I_m + F(t))Cx(t) \quad (1)$$

$F(t) = \sum_{j=1}^{m} f_j(t) F_j$ with F_j matrices of dimension $\mathbb{R}^{m \times m}$ and where the element of coordinate (j, j) is equal to 1 and 0 elsewhere.

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Polytopic decomposition of the sensor faults $f_j(t)$

$$f_j(t) = \widetilde{\mu}_j^1(f_j(t)) f_j^1 + \widetilde{\mu}_j^2(f_j(t)) f_j^2, \quad f_j(t) \in [f_j^2, f_j^1]$$

$$\begin{cases} \widetilde{\mu}_j^1(f_j(t)) = \dfrac{f_j(t) - f_j^2}{f_j^1 - f_j^2} \\ \widetilde{\mu}_j^2(f_j(t)) = \dfrac{f_j^1 - f_j(t)}{f_j^1 - f_j^2} \end{cases} \qquad \begin{cases} \widetilde{\mu}_j^1(f_j(t)) + \widetilde{\mu}_j^2(f_j(t)) = 1, \ \forall t \\ 0 \le \widetilde{\mu}_j^i(f_j(t)) \le 1, \quad i = 1, 2 \end{cases}$$

Problem statement

The time-varying matrice $F(t)$ is expressed as:

$$\begin{cases} F(t) & = \displaystyle\sum_{j=1}^{m}\sum_{k=1}^{2}\widetilde{\mu}_j^k(f_j(t))f_j^k F_j \\ & = \displaystyle\sum_{j=1}^{2^m}\widetilde{\mu}_j(f(t))\overline{F}_j \end{cases}$$

with

$$\begin{cases} \widetilde{\mu}_j(f(t)) = \displaystyle\prod_{k=1}^{m}\widetilde{\mu}_k^{\sigma_j^k}(f_k(t)) \\ \overline{F}_j = \displaystyle\sum_{k=1}^{m} f_k^{\sigma_j^k} F_j \end{cases}$$

where the $\widetilde{\mu}_j(f(t))$ satisfy the convex sum property.

1. Problem statement

Equivalent representation of the system

$$\left\{\begin{array}{rcl} \dot{x}(t) & = & g(x(t), u(t)) \\ y(t) & = & h(x(t), u(t), f(t)) \end{array}\right.$$

$$\equiv$$

$$\left\{\begin{array}{rcl} \dot{x}(t) & = & \sum_{i=1}^{r} \mu_i(x(t))(A_i x(t) + B_i u(t)) \\ y(t) & = & (I_m + F(t))Cx(t) \end{array}\right.$$

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$$\left\{\begin{array}{rcl} \dot{x}(t) & = & \sum_{i=1}^{r} \mu_i(x(t))(A_i x(t) + B_i u(t)) \\ y(t) & = & \sum_{j=1}^{2^m} \widetilde{\mu}_j(f(t))\widetilde{C}_j x(t) \end{array}\right.$$

Joint state and time-varying faults observer

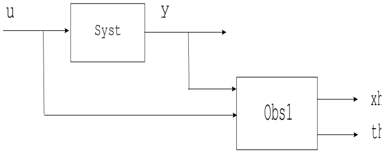

Figure: Joint state and time-varying fault observer

$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(A_i\hat{x}(t) + B_iu(t) \\ \qquad +L_i(y(t) - \hat{y}(t))) \\ \dot{\hat{f}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(-\alpha_i\hat{f}(t) \\ \qquad +K_i(y(t) - \hat{y}(t))) \\ \hat{y}(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(\hat{f}(t))\widetilde{C}_j\hat{x}(t) \end{cases}$$

Unknown gain matrices $L_i \in \mathbb{R}^{n_x \times m}$, $K_i \in \mathbb{R}^{m \times m}$ and $\alpha_i \in \mathbb{R}^{m \times m}$ must be computed to minimize the $\mathcal{L}_2$ gain from $f(t)$ to the state and fault estimation errors:

- $e_x(t) = x(t) - \hat{x}(t)$ the state estimation error
- $e_f(t) = f(t) - \hat{f}(t)$ the time-varying fault estimation error

2. Observer design

Difficulty

The estimation problem is not trivial since the weighting functions of the system depend on $f(t)$ and $x(t)$, while those of the observer depend on their estimate $\hat{f}(t)$ and $\hat{x}(t)$.

$$\text{system} \begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \mu_i(x(t))(A_i x(t) + B_i u(t)) \\ y(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(f(t))\widetilde{C}_j x(t) \end{cases}$$

$$\text{observer} \begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(A_i \hat{x}(t) + B_i u(t) + L_i(y(t) - \hat{y}(t))) \\ \dot{\hat{f}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(-\alpha_i \hat{f}(t) + K_i(y(t) - \hat{y}(t))) \\ \hat{y}(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(\hat{f}(t))\widetilde{C}_j \hat{x}(t) \end{cases}$$

Solution: rewritting of the state equation

Based on the convex sum property of the weighting functions, rewrite the system equation as an uncertain-like system:

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \left[\mu_i(\hat{x}(t))(A_i x(t) + B_i u(t)) + (\mu_i(x(t)) - \mu_i(\hat{x}(t)))\,(A_i x(t) + B_i u(t))\right] \\ y(t) = \sum_{j=1}^{2^m} \left[\widetilde{\mu}_j(\hat{f}(t))\widetilde{C}_j x(t) + \underbrace{(\widetilde{\mu}_j(f(t)) - \widetilde{\mu}_j(\hat{f}(t)))\widetilde{C}_j}_{\Delta C(t)}\, x(t)\right] \end{cases}$$

$$=$$

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))((A_i + \Delta A(t))x(t) + (B_i + \Delta B(t))u(t)) \\ y(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(\hat{f}(t))(\widetilde{C}_j + \Delta C(t))x(t) \end{cases}$$

$$\Delta A(t) = \sum_{i=1}^{r} (\mu_i(x(t)) - \mu_i(\hat{x}(t)))\,A_i \qquad \Delta B(t) = \sum_{i=1}^{r} (\mu_i(x(t)) - \mu_i(\hat{x}(t)))\,B_i$$

2. Observer design

Rewritting of the state equation

System
$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))((A_i + \Delta A(t))x(t) + (B_i + \Delta B(t))u(t)) \\ y(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(\hat{f}(t))(\widetilde{C}_j + \Delta C(t))x(t) \end{cases}$$

Observer
$$\begin{cases} \dot{\hat{x}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(A_i\hat{x}(t) + B_i u(t) + L_i(y(t) - \hat{y}(t))) \\ \dot{\hat{f}}(t) = \sum_{i=1}^{r} \mu_i(\hat{x}(t))(-\alpha_i \hat{f}(t) + K_i(y(t) - \hat{y}(t))) \\ \hat{y}(t) = \sum_{j=1}^{2^m} \widetilde{\mu}_j(\hat{f}(t))\widetilde{C}_j \hat{x}(t) \end{cases}$$

Estimation errors dynamics

$$\dot{e}_x(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^m}\mu_i(\hat{x}(t))\widetilde{\mu}_j(\hat{f}(t))((A_i - L_i\widetilde{C}_j)e_x(t) + (\Delta A(t) - L_i\Delta C(t))x(t) + \Delta B(t)u(t))$$

$$\dot{e}_f(t) = \sum_{i=1}^{r}\sum_{j=1}^{2^m}\mu_i(\hat{x}(t))\widetilde{\mu}_j(\hat{f}(t))(-K_i\widetilde{C}_j e_x(t) - \alpha_i e_f(t) \dot{f}(t) - K_i\Delta C(t)x(t) + \alpha_i f(t))$$

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Estimation errors dynamics

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Let us consider the augmented vectors

$e_a(t) = \begin{pmatrix} e_x^T(t) & e_f^T(t) \end{pmatrix}^T$ and $\omega(t) = \begin{pmatrix} x^T(t) & f^T(t) & \dot{f}^T(t) & u^T(t) \end{pmatrix}^T$

$$\dot{e}_a(t) = \sum_{i=1}^{r} \sum_{j=1}^{2^m} \mu_i(\hat{x}(t))\widetilde{\mu}_j(\hat{f}(t)) \left(\Phi_{ij} e_a(t) + \Psi_i(t)\omega(t)\right) \quad (2)$$

2. Observer design

Augmented system dynamic

$$\dot{e}_a(t) = \sum_{i=1}^{r} \sum_{j=1}^{2^m} \mu_i(\hat{x}(t))\widetilde{\mu}_j(\hat{f}(t)) \left(\Phi_{ij} e_a(t) + \Psi_i(t)\omega(t)\right)$$

$$\Phi_{ij} = \begin{pmatrix} A_i - L_i\widetilde{C}_j & 0 \\ -K_i\widetilde{C}_j & -\alpha_i \end{pmatrix}$$

$$\Psi_i(t) = \begin{pmatrix} \Delta A(t) - L_i \Delta C(t) & 0 & 0 & \Delta B(t) \\ -K_i \Delta C(t) & \alpha_i & I & 0 \end{pmatrix}$$

The objective is to guarantee the stability of the augmented system and the boundedness of the transfer from the input $\omega(t)$ to $e_a(t)$ (to attenuate the effect of $\omega(t)$ on the estimation)

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The objective is to guarantee the stability of the augmented system and the boundedness of the transfer from the input $\omega(t)$ to $e_a(t)$ (to attenuate the effect of $\omega(t)$ on the estimation)

$\Delta A(t) = \mathcal{A}\Sigma_A(t)E_A$, $\Delta B(t) = \mathcal{B}\Sigma_B(t)E_B$ and $\Delta C(t) = \mathcal{C}\Sigma_C(t)E_C$ are time-varying matrices such that $\Sigma_A^T(t)\Sigma_A(t) \leq I$, $\Sigma_B^T(t)\Sigma_B(t) \leq I$ and $\Sigma_C^T(t)\Sigma_C(t) \leq I$

2. Observer design

Procedure

1. Consider a quadratic Lyapunov function $V(e_a(t)) = e_a^T(t)Pe_a(t),\ P = P^T > 0$
2. Consider the $\mathcal{L}_2$ criterion

$$\dot{V}(e_a(t)) + e_a^T(t)e_a(t) - \omega^T(t)\Gamma_2\omega(t) < 0 \tag{3}$$

$$\Gamma_2 = \text{diag}(\Gamma_2^k),\ \Gamma_2^k < \beta I,\ \text{for } k = 0, 1, 2, 3$$

- guarantee the stability of $e_a(t)$ and a bounded transfer from $\omega(t)$ to $e_a(t)$.
- Γ_2 allows to attenuate the transfer of some $\omega(t)$ components to $e_a(t)$ components

Condition to solve

$$\sum_{i=1}^{r}\sum_{j=1}^{2^m}\mu_i(\hat{x}(t))\mu_j(\hat{f}(t))\begin{pmatrix} e_a(t) \\ \omega(t)\end{pmatrix}^T\left(\begin{array}{c|c} \Phi_{ij}^T P + P\Phi_{ij} + I_{2n_x} & P\Psi_i(t) \\ \hline \Psi_i^T(t)P & -\Gamma\end{array}\right)\begin{pmatrix} e_a(t) \\ \omega(t)\end{pmatrix} < 0$$

2. Observer design: theorem

There exists a joint robust state and multiplicative sensor fault observer for the considered TS model with an $\mathcal{L}_2$ gain from $\omega(t)$ to $e_a(t)$ bounded by β ($\beta > 0$) if there exists matrices $P_1 = P_1^T > 0$, $P_2 = P_2^T > 0$, $\Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4 > 0$, $\overline{\alpha}_i$, $\overline{K}_i$, R_i and scalars β, λ_1, $\lambda_{1C} > 0$, $\lambda_{2C} > 0$ and $\lambda_B > 0$ solutions of the optimization problem (4) under LMI constraints (5) and (6)

$$\min_{P_1,P_2,R_i,\overline{K}_i,\overline{\alpha}_i,\lambda_1,\lambda_{1C},\lambda_{2C},\lambda_B} \beta \tag{4}$$

$$\Gamma_k < \beta I \text{ for } k = 1,2,3,4 \tag{5}$$

$$\begin{pmatrix}
Q_{ij}^{11} & -\widetilde{C}_j^T \overline{K}_i^T & 0 & 0 & 0 & 0 & P_1\mathcal{A} & P_1\mathcal{B} & R_i\mathcal{C} & 0 \\
* & Q_i^{22} & 0 & \overline{\alpha}_i & P_2 & 0 & 0 & 0 & 0 & \overline{K}_i\mathcal{C} \\
* & * & Q^{33} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
* & * & * & -\Gamma_2 & 0 & 0 & 0 & 0 & 0 & 0 \\
* & * & * & * & -\Gamma_3 & 0 & 0 & 0 & 0 & 0 \\
* & * & * & * & * & Q_{ij}^{66} & 0 & 0 & 0 & 0 \\
* & * & * & * & * & * & -\lambda_1 I & 0 & 0 & 0 \\
* & * & * & * & * & * & 0 & -\lambda_B I & 0 & 0 \\
* & * & * & * & * & * & 0 & 0 & -\lambda_{1C} I & 0 \\
* & * & * & * & * & * & 0 & 0 & 0 & -\lambda_{2C} I
\end{pmatrix} < 0 \tag{6}$$

$$Q_{ij}^{11} = P_1 A_i + A_i^T P_1 - R_i \widetilde{C}_j - \widetilde{C}_j^T R_i^T + I_{n_x} \qquad Q_i^{22} = -\overline{\alpha}_i - \overline{\alpha}_i^T + I_m$$

$$Q^{33} = -\Gamma_1 + \lambda_1 E_A^T E_A + \lambda_{1C} E_C^T E_C + \lambda_{2C} E_C^T E_C \qquad Q^{66} = -\Gamma_4 + \lambda_B E_B^T E_B$$

3. Illustrative example

Process description

- A reduced form of an activated sludge reactor model with modelling errors is considered.
- The process consists in mixing used waters with a rich mixture of bacteria in order to degrade the organic matter.

Nonlinear system

$$\begin{aligned} \dot{x}_1(t) &= \frac{a(t)x_1(t)x_2(t)}{x_2(t)+b} - x_1(t)u(t) \\ \dot{x}_2(t) &= -\frac{ca(t)x_1(t)x_2(t)}{x_2(t)+b} + (d - x_2(t))u(t) \end{aligned} \tag{7}$$

$x_1(t)$ and $x_2(t)$ represent the biomass and the substrat concentration respectively.

$u(t)$ is the dwell-time in the treatment plant.

The biomass concentration is measured ($y(t) = x_1(t)$)

Modelling errors

- Parameters a, b, c, d have been identified and set to $a = 0.5$, $b = 0.07$, $c = 0.7$ et $d = 2.5$.
- It is assumed that a bounded multiplicative sensor fault $f_1(t)$ affects the output $y(t)$ such that:

$$y(t) = (1 + f_1(t))x_1(t)$$

with $\min(f_1(t)) = f_1^2 = 0.125$ and $\max(f_1(t)) = f_1^1 = 0.625$.

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T-S representation

Starting with the nonlinear system, a quasi-LPV state representation is established. The T-S form is obtained by using the sector nonlinearity transformation.

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T-S representation

Starting with the nonlinear system, a quasi-LPV state representation is established. The T-S form is obtained by using the sector nonlinearity transformation.

T-S model of the process

$$\dot{x}(t) = \sum_{i=1}^{4} \mu_i(x(t))(A_i x(t) + Bu(t)); \; y(t) = \sum_{j=1}^{2} \widetilde{\mu}_j(f_1(t))\widetilde{C}_j x(t)$$

6. Illustrative example

- Nominal output $y_n(t) : Cx(t)$
- Faulty system output : $y(t) : C(t)x(t)$

The output deviation caused by the time-varying parameter (multiplicative sensor fault)

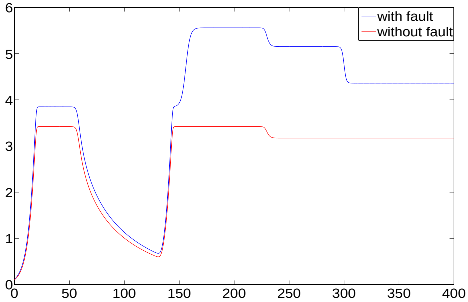

Figure: Output with and without $f_1(t)$

Initial conditions $x_0 = \begin{pmatrix} 0.1 & 1.5 \end{pmatrix}$, $\hat{x}_a(0) = \begin{pmatrix} 0.09 & 2.3 & 0 \end{pmatrix}$ for the joint state and fault observer

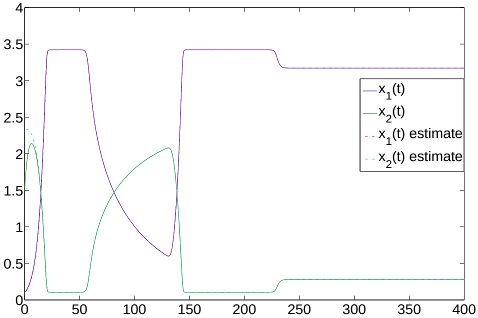

Figure: System states and their estimates

Actual and estimated time-varying parameter

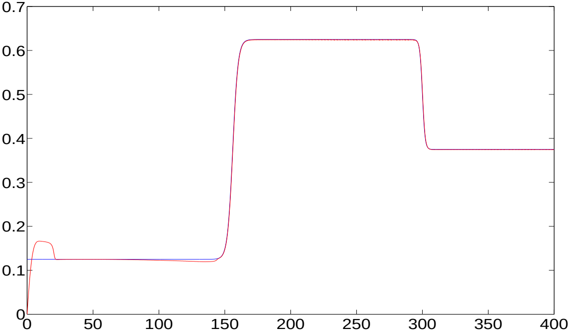

Figure: Time-varying fault $f_1(t)$ (blue) and its estimate (red)

Conclusions and perspectives

Conclusions

- A new systematic procedure was presented to deal with the state and multiplicative sensor fault estimation for nonlinear systems.
- Based on a T-S representation (by the sector nonlinearity approach).
- The estimation problem and observer synthesis are expressed in terms of LMI optimization.
- No assumption on the time-varying parameter and/or the system

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Perspectives

- Practical application (Benchmark of a Wastewater Treatment Plant)
- Use the results for Fault Tolerant Control (FTC)