New fault tolerant control strategy for nonlinear systems with multiple model approach

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Motivations



Objective of diagnosis and fault tolerant control

Actuator fault tolerant control of nonlinear systems

- Fast fault estimation (diagnosis)
- Fault accommodation

Motivations .



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Difficulties

- Taking into account the system complexity in a large operating range
- Actuator faults



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Proposed strategy

- Takagi-Sugeno representation of nonlinear systems
- Observer-based fault tolerant control design
- Extension of the existing results on linear systems
- Relaxed design conditions with Polya's theorem



- Takagi-Sugeno approach for modeling
 - Takagi-Sugeno principle
 - Takagi-Sugeno model
- Pault tolerant control design
- Relaxed stability conditions: Polya's theorem
- Mumerical example
- Conclusions



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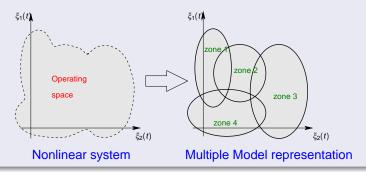


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- Operating range decomposition in several local zones.
- ▶ A local model represents the behavior of the system in a specific zone.
- The overall behavior of the system is obtained by the aggregation of the sub-models with adequate weighting functions.







The main idea of Takagi-Sugeno approach

- ▶ Define local models M_i , i = 1..r
- ▶ Define weighting functions $\mu_i(\xi)$, $0 \le \mu_i \le 1$
- ▶ Define an agregation procedure : $M = \sum \mu_i(\xi)M_i$

Takagi-Sugeno approach for modeling



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Interests of Takagi-Sugeno approach

- Simple structure for modeling complex nonlinear systems.
- The specific study of the nonlinearities is not required.
- Possible extension of the theoretical LTI tools for nonlinear systems.





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The difficulties

- How many local models?
- How to define the domain of influence of each local model?
- On what variables may depend the weighting functions μ_i?

Takagi-Sugeno approach for modeling



Obtaining a Takagi-Sugeno model

- Linearisation of an existing nonlinear model around operating points
 R. Murray-Smith, T. A. Johansen, Multiple model approaches to modelling and control. Taylor & Francis, 1997.
- Direct identification of the model parameters
 K. Gasso, Identification des système dynamiques non linéaires : Approche multimodèle, Ph.D., Institut
 National Polytechnique de Lorraine, France, 2000.
- Nonlinear transformations of an existing nonlinear model
 A.M. Nagy, G. Mourot, B. Marx, G. Schutz, J. Ragot, Model structure simplification of a biological reactor, 15th IFAC Symp. on System Identification, SYSID'09, 2009



Basic model

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

- Interpolation mechanism $\sum\limits_{i=1}^r \mu_i(\xi(t)) = 1$ and $0 \le \mu_i(\xi(t)) \le 1, \forall t, \forall i \in \{1,...,r\}$
- The premise variable $\xi(t)$ are measurable (like u(t), y(t)).



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A faulty system

$$\begin{cases} \dot{x}_f(t) = \sum_{i=1}^r \mu_i(\xi_f(t)) (A_i x_f(t) + B_i(u(t) + f(t))) \\ y_f(t) = C x_f(t) \end{cases}$$

• f(t) represents the fault vector (to be detected and accommodated).

Takagi-Sugeno model .



Two kinds of actuator faults are considered:

- External signal : $u_f(t) = u(t) + f(t)$
- ▶ Internal signal : $u_f(t) = (I_{n_u} \gamma)u(t)$ with $\gamma = diag(\gamma_1, \gamma_2, \dots, \gamma_{n_u})$

$$\left\{ \begin{array}{l} \gamma_i = 1 \Rightarrow \text{total failure of the } i^{th} \text{ actuator} \\ \gamma_i = 0 \Rightarrow \text{the } i^{th} \text{ actuator is healthy} \\ \gamma_i \in]0 \text{ , } 1 [\Rightarrow \text{loss of effectiveness of the } i^{th} \text{ actuator} \end{array} \right.$$



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Assumptions

A1. the faults are assumed to have norm bounded first time derivative

$$\|\dot{f}(t)\| \leq f_{1max}, \ \ 0 \leq f_{1max} < \infty$$

- ▶ A2. rank(CB_i) = n_u
- ▶ **A3.** Total actuator failures are not considered, i.e. $\gamma_i \in [0 \ 1[$

Fault tolerant control design

Fault tolerant control _



Faulty system

$$\begin{cases} \dot{x}_{f}(t) = \sum_{i=1}^{r} \mu_{i}(\xi(t)) (A_{i}x_{f}(t) + B_{i}(u(t) + f(t))) \\ y_{f}(t) = Cx_{f}(t) \end{cases}$$



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Objectives

- ▶ Simultaneous and fast estimation of the state $\dot{x}_f(t)$ and the fault f(t)
- ▶ Design of a control law based on a state feedback such as the state of the system converges asymptotically to zero if the fault is constant or to a small ball around the origin when f(t) is time varying with norm bounded first time-derivative



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Fault tolerant control law

$$u(t) = -\hat{f}(t) - \sum_{i=1}^{r} \mu_i(\xi_f(t)) K_i \hat{x}_f(t)$$

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$$u(t) = -\hat{f}(t) - \sum_{i=1}^{r} \mu_i(\xi_f(t)) K_i \hat{x}_f(t)$$

Structure of the proposed observer

$$\begin{cases} \dot{\hat{x}}_{f}(t) = \sum_{i=1}^{r} \mu_{i}(\xi_{f}(t))(A_{i}\hat{x}_{f}(t) + B_{i}(u(t) + \hat{f}(t)) + L_{i}e_{y}(t)) \\ \dot{\hat{y}}_{f}(t) = C\hat{x}_{f}(t) \\ \dot{\hat{f}}(t) = \Gamma \sum_{i=1}^{r} \mu_{i}(\xi_{f}(t))F_{i}(\dot{e}_{y}(t) + \sigma e_{y}(t)) \\ e_{y}(t) = y_{f}(t) - \hat{y}_{f}(t) \end{cases}$$



Fault tolerant control law

$$u(t) = -\hat{f}(t) - \sum_{i=1}^{r} \mu_i(\xi_f(t)) K_i \hat{x}_f(t)$$

Structure of the proposed observer

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This observer can be considered as an improvement of the classical PI observer : convergence is proved even in non constant fault situation.

K. Zhang, B. Jiang, and V. Cocquempot. Adaptive observer-based fast fault estimation. *International Journal of Control, Automation, and Systems*, 6(3):320-326, 2008.



$$\dot{\mathbf{e}}_{X}(t) = \sum_{i=1}^{r} \mu_{i}(\xi_{f}(t)) (\Phi_{i} \mathbf{e}_{X}(t) + B_{i} \mathbf{e}_{f}(t))
\dot{x}_{f}(t) = \sum_{i=1}^{r} \sum_{j=1}^{r} \mu_{i}(\xi_{f}(t)) \mu_{j}(\xi(t)) (\Xi_{ij} \mathbf{x}_{f}(t) + B_{i} \mathbf{e}_{f} + B_{i} \mathbf{K}_{j} \mathbf{e}_{X})$$

where

$$e_X(t) = x_f(t) - \hat{x}_f(t)$$

$$e_f(t) = f(t) - \hat{f}(t)$$

$$\Phi_i = A_i - L_i C$$

$$\Xi_{ij} = A_i - B_i K_j$$



$$\dot{\mathbf{e}}_{x}(t) = \sum_{i=1}^{r} \mu_{i}(\xi_{f}(t)) (\Phi_{i} \mathbf{e}_{x}(t) + B_{i} \mathbf{e}_{f}(t))
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The stability of the system with observer based actuator fault tolerant control is studied by Lyapunov theory using a quadratic function.

$$V(t) = x_f^T(t)P_1x_f(t) + e_x^T(t)P_2e_x(t) + \frac{1}{\sigma}e_f(t)\Gamma^{-1}e_f(t)$$

► The notion of ISS stability is also used in order to define the radius of the convergence ball around the origin in the case of time varying faults.



Main result

Given positive scalars σ and β , if there exists symmetric and positive definite matrices $\mathscr{X} \in \mathbb{R}^{n \times n}$, $P_2 \in \mathbb{R}^{n \times n}$, $G \in \mathbb{R}^{n_f \times n_f}$ (with $n_f = n_u$) and matrices $M_i \in \mathbb{R}^{n_u \times n}$ and $N_i \in \mathbb{R}^{n \times n_y}$ and a positive scalar η solution to the optimization problem

min
$$\eta$$
 s.t.

$$\begin{pmatrix} \eta I & B_i^T P_2 - F_i C \\ (B_i^T P_2 - F_i C)^T & \eta I \end{pmatrix} > 0$$

$$\mathcal{Q}_{ij} = \begin{pmatrix} S_{ij} & B_i M_j & B_i & 0 & 0 \\ * & * & -2\beta \mathcal{X} & 0 & \beta I & 0 \\ * & * & & -2\beta I & 0 & \beta I \\ * & * & * & * & \Omega_j & \mathcal{R}_{ij} \\ * & * & * & * & \Psi_{ij} \end{pmatrix} < 0$$

$$S_{ij} = XA_i^T + XA_i - B_iM_i - M_i^TB_i^T, \ \Omega_j = A_i^TP_2 + P_2A_i - N_iC - C^TN_i^T$$

$$\mathcal{R}_{ij} = -\frac{1}{\sigma}(A_j^TP_2 - C^TN_j^T)B_i, \ \Psi_{ij} = -\frac{1}{\sigma}\left(B_i^TP_2B_j + B_j^TP_2B_i\right) + \frac{1}{\sigma}G$$

then the state of the system x(t), the state estimation error and the fault estimation error $e_f(t)$ are bounded. Furthermore, if $f_{1max} = 0$, these variables converge asymptotically to zero. The gains of the observer and the fault tolerant control are given by F_i , $L_i = P_2^{-1} N_i$ and $K_i = M_i \mathcal{X}^{-1}$.

Relaxed stability conditions: Polya's theorem ____



Objective

Reduce the conservativness of the LMI conditions by Polya's theorem

Principal

Let us consider the inequality

$$\Delta_{\xi\xi} = \sum_{i=1}^r \sum_{j=1}^r \mu_i(\xi(t)) \mu_j(\xi(t)) \Delta_{ij} < 0$$

Knowing that

$$\left(\sum_{i=1}^{r} \mu_{i}(\xi(t))\right)^{\rho} = \sum_{i=1}^{r} \mu_{i}(\xi(t)) = 1$$

where p is a positive integer, we obtain

$$\left(\sum_{i=1}^{r} \mu_{i}(\xi(t))\right)^{\rho} \sum_{i=1}^{r} \sum_{j=1}^{r} \mu_{i}(\xi(t)) \mu_{j}(\xi(t)) \Delta_{ij} < 0$$



Principal

For example, choosing p = 1 we obtain an equivalent inequality

$$\sum_{i_1=1}^2 \sum_{i_2=1}^2 \sum_{i_3=1}^2 \mu_{i_1} \mu_{i_2} \mu_{i_3} \Delta_{i_1 i_2} < 0$$

Consequently, the negativity of $\Delta_{\xi\xi}$ is ensured if

$$\begin{array}{ccccc} \Delta_{11} & < & 0 \\ \Delta_{22} & < & 0 \\ \Delta_{11} + \Delta_{12} + \Delta_{21} & < & 0 \\ \Delta_{22} + \Delta_{21} + \Delta_{12} & < & 0 \end{array}$$

• Remark that the negativity of Δ_{12} and Δ_{21} is not required.

 \Rightarrow

- Less conservative conditions are obtained by increasing p
- ightharpoonup Asymptotic necessary and sufficient conditions can be obtained by chosing $p o \infty$
- ▶ In Sala *et al.*, 2007 an approach is proposed to evaluate a finite value of *p* which garantees the asymptotic necessary and sufficient conditions with a given accuracy.



Theorem with p = 3

Given positive scalars σ and β , if there exists symmetric and positive definite matrices $\mathscr{X} \in \mathbb{R}^{n \times n}$, $P_2 \in \mathbb{R}^{n \times n}$, $G \in \mathbb{R}^{n_f \times n_f}$ (with $n_f = n_u$) and matrices $M_i \in \mathbb{R}^{n_u \times n}$ and $N_i \in \mathbb{R}^{n \times n_y}$ and a positive scalar η solution to the optimization problem

the state of the system x(t), the state estimation error $e_x(t)$ and the fault estimation error $e_f(t)$ are bounded. The gains of the observer and the fault tolerant control are given by F_i , $L_i = P_2^{-1}N_i$ and $K_i = M_i \mathcal{X}^{-1}$.

i, j, k = 1, ..., r, i < j < k

Numerical example



Let us consider the nonlinear system defined by :

$$A_1 = \begin{pmatrix} 0 & 1 \\ 17.2941 & 0 \end{pmatrix}, A_2 = \begin{pmatrix} 0 & 1 \\ 3.5361 & 0 \end{pmatrix},$$

$$B_1 = \begin{pmatrix} 0 \\ -17.65 \end{pmatrix}, B_2 = \begin{pmatrix} 0 \\ -17.63 \end{pmatrix}, C = I_2$$

▶ The weighting functions μ_i are defined as follows

$$\begin{cases} \mu_1(\xi(t)) = 1 - \frac{2}{\pi} |x_1(t)| \\ \mu_2(\xi(t)) = 1 - \mu_1(\xi(t)) \end{cases}$$

The fault f(t) is time varying and defined by

$$f(t) = \begin{cases} 0 & t \le 20\\ 1.4\sin(t) + 21 & 20 \le t \le 50\\ 7.5\sin(2t) + 7.5 & 50 \le t \le 70\\ -0.88u(t) & 70 \le t \le 100 \end{cases}$$

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The first simulation is performed with a classic control law $u(t) = \sum_{i=1}^{r} \mu_i(\xi(t)) K_i \hat{x}(t)$.

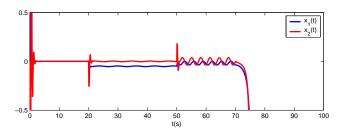


FIGURE: System states with classical control

Second case : proposed FTC law _



In the second simulation, the proposed FTC law $u(t) = -\hat{f}(t) - \sum_{i=1}^{r} \mu_i(\xi(t)) K_i \hat{x}_f(t)$ is used

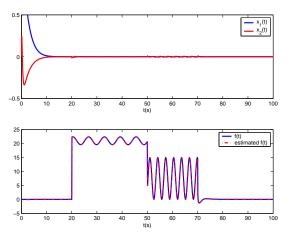


FIGURE: Fault tolerant control: states of the system (top) – fault and its estimation (bottom)



Conclusions

Active fault tolerant control law for nonlinear systems represented by a Takagi-Sugeno structure.



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Perspectives

▶ Study of the unmeasurable premise variable case $(\xi(t) = x(t))$.



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- Study of the case where both actuator and sensor faults affect the system



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- ▶ Study of the unmeasurable premise variable case ($\xi(t) = x(t)$).
- Study of the case where both actuator and sensor faults affect the system
- Extension to robust fault tolerant control (disturbances and modeling uncertainties).

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