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Isolation and handling of sensor faults in nonlinear systems☆

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ABSTRACT

This work considers the problem of sensor fault isolation and fault-tolerant control for nonlinear systems subject to input constraints. The key idea is to design fault detection residuals and fault isolation logic by exploiting model-based sensor redundancy through a state observer. To this end, a high-gain observer is first presented, for which the convergence property is rigorously established, forming the basis of the residual design. A bank of residuals are then designed using a bank of observers, with each driven by a subset of measured outputs. A fault is isolated by checking which residuals breach their thresholds according to a logic rule. After the fault is isolated, the state estimate generated using measurements from the healthy sensors is used in closed-loop to maintain nominal operation. The implementation of the fault isolation and handling framework subject to uncertainty and measurement noise is illustrated using a chemical reactor example.

1. Introduction

Automatic control technologies have been widely used in industrial processes, leading to improved efficiency and profitability. The lasting benefits, however, are subject to faults in the key elements of a control system, such as actuators and sensors. This realization has led to increased emphasis on the development of automated fault detection and isolation (FDI) and fault-tolerant control (FTC) techniques that account for system complexities, such as nonlinear dynamics, to effectively mitigate or avoid the consequences of faults.

Existing results on model-based FDI utilize analytical redundancy in systems to generate residuals to detect the occurrence of faults and identify the failed equipment. This approach has been studied extensively for linear systems (see Frank (1990) for a survey) by using a bank of Luenberger observers (Clark, Fosth, & Walton, 1975), unknown input observers (Chen, Patton, & Zhang, 1996), sliding mode observers (Alwi, Edwards, & Tan, 2009; Tan & Edwards, 2002), and subspace identification models (Ding, Zhang, Naik, Ding, & Huang, 2009; Qin & Li, 2001; Yin, Ding, Haghani, Hao, & Zhang, 2012). Many practical systems, such as chemical reactors, however, exhibit strong nonlinear dynamics, which may invalidate the effectiveness of the methods developed for linear systems because of plant-model mismatch. Therefore, a reliable FDI system requires an explicit consideration of nonlinear dynamics in the generation of residuals. This problem has been studied for actuator faults by decoupling the effect of uncertainty from faults through a filter design (De Persis & Isidori, 2001), exploiting the system structure to generate dedicated residuals (Mhaskar, McFall, Gani, Christofides, & Davis, 2008), using adaptive estimation techniques to handle unstructured uncertainty (Zhang, Polycarpou, & Parisini, 2010), and driving the system to a region where the effect of faults can be differentiated from each other (Du & Mhaskar, 2013).

Compared to actuator FDI, relatively fewer results are available for sensor FDI of nonlinear systems. This problem has been studied for Lipschitz nonlinear systems (see, e.g., Rajamani and Ganguli (2004), Pertew, Marquez, and Zhao (2007), Zhang (2011)). In Rajamani and Ganguli (2004), a nonlinear state observer is designed to generate state estimates by using a single sensor, with the results requiring three or more outputs. The method developed in Zhang (2011) utilizes adaptive estimation techniques to account for unstructured (bounded) uncertainty, which requires knowledge of Lipschitz constants in the generation of the adaptive thresholds. The sensor fault estimation problem has been studied in Pertew et al. (2007), where linear matrix inequality techniques are used to identify the fault vector through an observer design. A

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bank of observers are used to generate residuals that are sensitive to faults in all the sensors except for one fault in Mattei, Paviglianiti, and Scordamaglia (2005), with the observer design, however, based on a linear approximation. In summary, there is a lack of results on sensor FDI that explicitly accounts for the system nonlinearity in the filter design.

Motivated by the above considerations, this work addresses the problem of sensor fault isolation and fault-tolerant control for nonlinear systems subject to input constraints by first providing an alternate result for relaxing the system structure requirement for high-gain observer designs. This is then exploited to build sensor FDI filters that explicitly account for the system nonlinearity. The key idea is to design fault detection residuals and fault isolation logic by exploiting model-based sensor redundancy achieved through the use of multiple state observers. To this end, a high-gain observer is presented for a class of nonlinear systems (also shown via an alternative approach in Findeisen, Imsland, Allgöwer, and Foss (2003)), with a well defined convergence property. The convergence property of the observer is then utilized in the design of residuals, forming the basis of the fault detection mechanism. The isolation of faults relies on the use of a bank of state observers and a logic rule. The observer design also enables the use of healthy sensors in closed-loop to continue nominal operation after a fault is isolated. The stability of the closed-loop system using the high-gain observer is rigorously established for the fault-free system and also for the handling of faults.

The remainder of the manuscript is organized as follows. The system description, the objective of fault isolation, and the state observer design are first presented in Section 2. The convergence property of the observer and the stability of the closed-loop system are rigorously established in Section 3. Based on the results in Section 3, the design of fault detection residuals, fault isolation logic, and fault-handling mechanism is presented in Section 4. The implementation of the proposed method subject to uncertainty and measurement noise is illustrated using a chemical reactor example in Section 5. Finally, Section 6 gives some concluding remarks.

2. Preliminaries

Consider a multi-input multi-output nonlinear system described by

$$\begin{aligned}\dot{x} &= f(x) + g(x)u \\ y &= h(x) + v\end{aligned} \tag{1}$$

where $x \in \mathbb{R}^n$ denotes the vector of state variables, $u \in \mathbb{R}^m$ denotes the vector of constrained input variables, taking values in a nonempty compact convex set $\mathcal{U} \subseteq \mathbb{R}^m$ that contains 0, $y = [y_1, \dots, y_p]^{\mathrm{T}} \in \mathbb{R}^p$ denotes the vector of output variables, $v = [v_1, \dots, v_p]^{\mathrm{T}} \in \mathbb{R}^p$ denotes the fault vector for the sensors, and $g(x) = [g_1(x), \dots, g_m(x)]$. Throughout the manuscript, $L_f h(\cdot)$ denotes the standard Lie derivative of a scalar function $h(\cdot)$ with respect to a vector function $f(\cdot)$, and $\|\cdot\|$ denotes the Euclidean norm.

The specific problem we consider is that of sensor fault isolation via design of signals termed residuals and an appropriate logic rule. The key is to ensure that the residuals are below certain values termed thresholds in the absence of faults, and breach their thresholds selectively after the occurrence of faults. A fault can then be isolated by checking which residuals breach their thresholds according to the logic rule. In this work, the design of residuals relies on the ability to generate accurate enough state estimates exploiting the good convergence property of a high-gain observer (see, e.g., Atassi and Khalil (1999), El-Farra, Mhaskar, and Christofides (2005)).

In this section, we first present a high-gain observer design, with results on its convergence given in Section 3. To this end, we consider the system of equation (1) under fault-free conditions (i.e., $v \equiv 0$), which satisfies Assumption 1 below.

Assumption 1. The functions $f : \mathbb{R}^n \to \mathbb{R}^n$, $g_i : \mathbb{R}^n \to \mathbb{R}^n$, $i = 1, \dots, m$, and $h : \mathbb{R}^n \to \mathbb{R}^p$ are smooth on their domains of definition, and $f(0) = 0$.

Note that owing to the presence of system nonlinearity, the convergence of a state observer is analyzed in the closed-loop, with an associated control design, and we therefore consider a generic stabilizing control law, which satisfies Assumption 1 below.

Assumption 2. For the system of equations (1), there exists a positive definite $\mathcal{C}^2$ function $V : \mathbb{R}^n \to \mathbb{R}$ such that for any $x \in \Omega_c := \{x \in \mathbb{R}^n : V(x) \le c\}$, where c is a positive real number, the following inequality holds:

$$L_f V(x) + L_g V(x) u_c(x) \le -\alpha(V(x)) \tag{2}$$

where $L_g V(x) = [L_{g_1} V(x), \dots, L_{g_m} V(x)]$, $u_c : \Omega_c \to \mathcal{U}$ is a state feedback control law, and α is a class $\mathcal{K}$ function.

Remark 1. Note that the above assumption essentially draws from the stability of the closed-loop system and is readily satisfied for closed-loop systems that are stable (i.e., under the application of a stabilizing control law). In particular, the state feedback control law in Assumption 2 can be explicit, such as a bounded control law (see, e.g., Lin and Sontag (1991)), where a control Lyapunov function (CLF) is used to generate control input, or implicit, such as a model predictive control (MPC) law, where Eq. (2) is used as a constraint in the optimization problem (see, e.g., Mhaskar, El-Farra, and Christofides (2005), Mhaskar, El-Farra, and Christofides (2006), Mahmood and Mhaskar (2008)). Note also that the problem of determining a Lyapunov function for control design, while certainly involved, is an easier problem than that of finding a Lyapunov function to determine stability (see Mhaskar et al. (2005), Mhaskar et al. (2006), Mahmood and Mhaskar (2008) for further discussion).

Having assumed the presence of a stabilizing state feedback law, we now present a generalization of the assumption on the nonlinear state estimator design for closed-loop systems under discrete control implementation, which relies on the nonlinear system being observable from the measured outputs.

Assumption 3 (*Findeisen et al., 2003*)**.** There exist integers ω_i, $i = 1, \dots, p$, with $\sum_{i=1}^{p} \omega_i = n$, and a coordinate transformation $\zeta = T(x, u)$ such that if $u = \bar{u}$, where $\bar{u} \in \mathcal{U}$ is a constant vector, then the representation of the system of equations (1) in the ζ coordinate takes the following form:

$$\begin{aligned}\dot{\zeta} &= A\zeta + B\phi(x, \bar{u}) \\ y &= C\zeta\end{aligned} \tag{3}$$

where $\zeta = [\zeta_1, \dots, \zeta_p]^{\mathrm{T}} \in \mathbb{R}^n$, $A = \mathrm{blockdiag}[A_1, \dots, A_p]$, $B = \mathrm{blockdiag}[B_1, \dots, B_p]$, $C = \mathrm{blockdiag}[C_1, \dots, C_p]$, $\phi = [\phi_1, \dots, \phi_p]^{\mathrm{T}}$, $\zeta_i = [\zeta_{i,1}, \dots, \zeta_{i,\omega_i}]^{\mathrm{T}}$, $A_i = \begin{bmatrix} 0 & I_{\omega_i - 1} \\ 0 & 0 \end{bmatrix}$, with I_{ω_i-1} being an $(\omega_i - 1) \times (\omega_i - 1)$ identity matrix, $B_i = [0^{\mathrm{T}}_{\omega_i - 1}, 1]^{\mathrm{T}}$, with 0_{ω_i-1} being a vector of zeros of dimension $\omega_i - 1$, $C_i = [1, 0^{\mathrm{T}}_{\omega_i-1}]$, and $\phi_i(x, \bar{u}) = \phi_{i,\omega_i}(x, \bar{u})$, with $\phi_{i,\omega_i}(x, \bar{u})$ defined through the successive differentiation of $h_i(x)$: $\phi_{i,1}(x, \bar{u}) = h_i(x)$ and $\phi_{i,j}(x, \bar{u}) = \frac{\partial \phi_{i,j-1}}{\partial x}[f(x) + g(x)\bar{u}]$, $j = 2, \dots, \omega_i$. Furthermore, the functions $T : \mathbb{R}^n \times \mathcal{U} \to \mathbb{R}^n$ and $T^{-1} : \mathbb{R}^n \times \mathcal{U} \to \mathbb{R}^n$ are $\mathcal{C}^1$ functions on their domains of definition.