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Sensor fault diagnosis for nonlinear processes with parametric uncertainties☆

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Abstract

This paper addresses the problem of detecting, discriminating, and reconstructing sensor faults for nonlinear systems with known model structure but uncertainty in the parameters of the process. The convenience of the proposed technique lies in the fact that historical operational data and/or a priori fault information is not required to achieve accurate fault reconstruction except for fixed, short intervals. The overall fault diagnosis algorithm is composed of a series of nonlinear estimators, which estimates parameter and a fault isolation and identification filter. Parameter estimation and fault reconstruction cannot be performed accurately since faults and parametric uncertainty interact with each other. Therefore, these two tasks are performed at different time scales, where the fault diagnosis takes place at a more frequent rate than the parameter estimation. It is shown that the fault can be reconstructed under some realistic assumptions and the performance of the proposed methodology is evaluated on a simulated chemical process exhibiting nonlinear dynamic behavior.

Keywords: Fault detection; Fault isolation; Fault reconstruction; State and parameter estimation; Hurwitz stability; Kharitonov's theorem

1. Introduction

There is an impetus to reduce downtime, increase safety, product quality, minimize impact on the environment, and reduce manufacturing costs in modern chemical plants through early and accurate fault detection and diagnosis [1,2]. The need for accurately monitoring the process variables and interpreting their variations increases rapidly with the increase in level of instrumentation in chemical plants. These variations although mostly due to change in operating conditions can also be directly linked to faults. Gathering information about the state of a system and processing the data for detecting, isolating, and identifying abnormal readings are important tasks of a fault diagnosis system [3], where the individual goals are defined as:

- Fault detection: a Boolean decision about the existence of faults in a system.
- Fault isolation: determination of the location of a fault, e.g., which sensor or actuator is not operating within normal limits.
- Fault identification: estimation of the size and type of a fault.

Various techniques exist for performing fault diagnosis [4]. A major portion of these techniques are based upon data from past operations in which statistical methods are used to compare the current operating data to earlier conditions of the process where the state of the process was known. Although these techniques are easier to implement, they have shortcoming that the analysis relies on static models, which assumes that the process operates at a predefined steady-state condition. This is often not the case as the process may undergo throughput changes or exhibit highly nonlinear behavior [5]. Moreover, these methods cannot estimate the shape and size of the fault accurately. Utilizing first-principles-based models into the procedure allows for accurate diagnosis even when operating conditions have changed, while the online estimation of model parameters takes care of plant-model mismatch. The parameter estimation is performed using an augmented nonlinear observer [6,15], which is principally different from often used Extended Kalman filter or Extended Luenberger observer. The proposed fault diagnosis technique itself computes residuals (i.e., the mismatch between

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the measured output and estimated output using the model) for fault detection [3] and appropriate filters are derived to achieve fault isolation and identification as well. Since it is not possible to simultaneously perform parameter estimation and fault detection, due to the interactions of these two tasks, an approach where these computations are taking place at different time scales is implemented. It is shown that fault detection, isolation, and identification for nonlinear systems containing uncertain parameters can be performed under realistic assumptions with the presented approach.

2. Fault diagnosis for LTI systems

Consider a linear, time-invariant system with no input:

$$\begin{aligned}\dot{x} &= Ax\\ y &= Cx + f_s\end{aligned} \tag{1}$$

where $x \in R^n$ is a vector of state variables and $y \in R^m$ is a vector of output variables, n the number of states, and m refers to the number of output variables. A and C are matrices of appropriate dimensions and f_s is the sensor fault of unknown nature with the same dimensions as the output. Assuming the above system is observable, a Luenberger observer for the system can be designed.

$$\begin{aligned}\dot{\hat{x}} &= A\hat{x} + L(y - \hat{y})\\ \hat{y} &= C\hat{x}\end{aligned} \tag{2}$$

where L is the observer gain chosen to make the closed loop observer stable and achieve a desired observer dynamics. A residual [3] is defined as:

$$r(t) = \int_0^t Q(t-\tau)(y(\tau) - \hat{y}(\tau))\,\mathrm{d}\tau \tag{3}$$

which represents the difference between the estimated output and the actual output passed through a filter $Q(t)$. Taking a Laplace transform of Eqs. (1)–(3) results in:

$$r(s) = Q(s)[I - C(sI - (A - LC))^{-1}L]f_s(s) \tag{4}$$

where $Q(t)$ is chosen such that $Q(s)$ is a RH_∞-matrix [7]. It can be shown that

(1) $r(t) = 0$ if $f_s(t) = 0$.
(2) $r(t) \neq 0$ if $f_s(t) \neq 0$.

indicating that the value of $r(t)$ predicts the existence of a fault in the system [7].

In addition, if one uses the dedicated observer scheme as shown for a system with three outputs in Fig. 1, then the fault detection system can also discriminate among various fault sources:

(3) $r_i(t) = 0$ if $f_{s,i}(t) = 0$, $i = 1, 2, 3, \ldots, m$.
(4) $r_i(t) \neq 0$ if $f_{s,i}(t) \neq 0$, $i = 1, 2, 3, \ldots, m$.

where i represents the ith measurement. A fault detection system that satisfies all of the above conditions is called as a fault detection and isolation filter (FDIF). A fault detection and isolation filter becomes a fault identification filter (FIDF) if additionally the following condition is satisfied [8]:

(5) $\lim_{t\to\infty}(r_i(t) - f_{s,i}(t)) = 0$, $i = 1, 2, 3, \ldots, m$.

In order to meet the above conditions, the following restrictions on the choice of $Q(s)$ are imposed:

(a) $Q(s) \neq 0$, $\forall s \in C$.
(b) $Q(s) = [I - C(sI - (A - LC))^{-1}L]^{-1} = C(sI - A)^{-1}L + I$.

Linear, observer-based fault detection, isolation, and identification schemes work well in the event when accurate fundamental model exists for the process over the whole operating region and if appropriate choices are made for L and Q.

3. Robust fault detection, isolation, and identification

3.1. Problem formulation

Consider a nonlinear system with possibly multiple outputs of the following form:

$$\begin{aligned}\dot{x} &= f(x, \theta)\\ y &= h(x, \theta) + f_s\end{aligned} \tag{5}$$

where $x \in R^n$ is a vector of state variables and $y \in R^m$ is a vector of output variables. It is assumed that $f(x, \theta)$ is an infinitely differentiable vector field in R^n and $h(x, \theta)$ is an infinitely differential vector field in R^m. Let $\theta \in R^k$ be a parameter vector assumed to be constant with time but a priori uncertain and f_s is the sensor fault of unknown nature with the same dimensions as the output. The goal of this paper is to estimate the state vector without accurate knowledge of the parameter values describing the process model and under the influence of output disturbances such that $\lim_{t\to\infty}(x - \hat{x}) = 0$, where $\hat{x}$ is the estimate of the state vector, x and to design a set of filters $Q(t)$ so that the residuals, given by the expression $r(t) = \int_0^t Q(t-\tau)(y(\tau) - \hat{y}(\tau))\,\mathrm{d}\tau$ have all the five properties discussed in Section 2.

The main challenge in this research is to overcome the effect of sensor faults and plant-model mismatch on the fault identification. In order to perform accurate state and parameter estimation, it is required to have reliable measurements, while at the same time, an accurate model of the process is desired to reconstruct the fault. This will be taken into account by performing the parameter estimation and the fault detection at different time scales. Whenever the parameters are estimated, it is assumed that there is either no fault or fault previously identified remains constant with time, while the values of the parameters are not adjusted during each individual fault detection. A variety of different techniques exist for designing nonlinear closed-loop observers [9–13]. However, since the class of problems under investigation includes parametric uncertainty it would be natural to address these issues through a parametric approach instead of the often used extended Kalman filter or extended Luenberger