ISA Transactions 63 (2016) 49–59

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

# Sliding mode observer based incipient sensor fault detection with application to high-speed railway traction device

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ARTICLE INFO

*Article history:*
Received 25 December 2015
Received in revised form
28 February 2016
Accepted 8 April 2016
Available online 4 May 2016
This paper was recommended for publication by Dr. Steven Ding

*Keywords:*
Incipient sensor fault
Sliding mode observer
Adaptive threshold
Fault development detection

ABSTRACT

This paper considers incipient sensor fault detection issue for a class of nonlinear systems with "observer unmatched" uncertainties. A particular fault detection sliding mode observer is designed for the augmented system formed by the original system and incipient sensor faults. The designed parameters are obtained using LMI and line filter techniques to guarantee that the generated residuals are robust to uncertainties and that sliding motion is not destroyed by faults. Then, three levels of novel adaptive thresholds are proposed based on the reduced order sliding mode dynamics, which effectively improve incipient sensor faults detectability. Case study of on the traction system in China Railway High-speed is presented to demonstrate the effectiveness of the proposed incipient senor faults detection schemes.


## 1. Introduction

Modern control systems have become more complex in order to meet the increasing requirement for high levels of performance. Control engineers are faced with increasingly complex systems for which both the reliability and safety are very important. However, component incipient faults, such as electrolyte loss effectiveness of electrolytic capacitor, mechanical wears and bears etc., may induce drastically changes and result in undesirable performance degradation, even instability. These are life-critical for safety and actuate critical systems such as aircrafts, spacecrafts, nuclear power plants, chemical plants processing hazardous materials and high-speed railways. Therefore, incipient fault detection and development detection techniques are of practical significance. And, the most important issue of reliable system operation is to detect and isolate incipient faults as early as possible, which can give operators enough information and time to take proper measures to prevent any serious consequences on systems.

Typically, abrupt faults affect safety-relevant systems, which have to be detected early enough so that catastrophic consequences can be avoided by early system reconfiguration. Such faults normally have larger effect on detection residuals than that of modeling uncertainties, which can be detected by choosing appropriate thresholds. At the other end, incipient faults are closely related to maintenance problems and early detection of worn equipment is necessary. In this case, the amplitude of incipient faults are typically small. Thus the detection presents challenges to model-based FDI techniques due to the inseparable mixture between incipient fault and modeling uncertainty. Therefore, it is important to improve the residual robustness to system uncertainties and select more proper thresholds to improve the detectability of fault detection mechanism.

There are many methods proposed in last few decades to enhance the robustness in observer based fault detection, such as perfect unknown input decoupling [1–4], optimal $\mathcal{H}_2$, $\mathcal{H}_\infty$ schemes [5–8], total measurable fault information residual [9], and projection method [10]. Fault detection schemes for switching systems [11,12] and semiconductor manufacturing processes [13] have also been proposed. It has been recognized from general existence condition in [2] that, for a residual generator perfectly decoupled from unknown input, it is only possible when enough output signals are available. Different from perfect decoupling approach, the robust residual generators are designed in the context of a trade-off between robustness against disturbances and sensitivity to faults [5]. When perfect decoupling is not possible, the decision functions determined by residuals will be corrupted by unknown inputs. The common practice to evaluate the

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http://dx.doi.org/10.1016/j.isatra.2016.04.004
0019-0578/

decision functions is to define appropriate thresholds, with which the decision functions are compared [1]. Therefore, the robustness residuals and proper selected thresholds are two important factors to improve detectability of incipient fault detection mechanism.

During the past decades, sliding mode observers have been used for FDI extensively [14–22]. Ref. [14] uses a sliding mode observer to detect faults by disruption of sliding motion which is a difficult problem and motivate much research in the area. In [15–19], the “equivalent output injection” concept is used to explicitly construct fault signals to detect and isolate the faults, including sensor faults and actuator faults. In [18], uncertainties and disturbances are considered, which need the so called “matched uncertainty” in [23] assumption on the distribution matrices of the modeling uncertainties and disturbances. Also, [17] studies the so called “unmatched uncertainty” case based on the robust $\mathcal{H}_\infty$ to enhance the robustness. Based on different structures of distribution matrices of faults and uncertainties, [20,22] combine the Luenberger observer with sliding mode observer to detect faults, which needs perfect decoupling between faults and uncertainties. Therefore, sliding mode observer based FDI framework in [17,21] mainly focus on robust residual generator design to get a trade-off between robustness against disturbances and sensitivity to faults. In reality, fault detectability can also be improved by selecting proper thresholds and the adaptive threshold is intuitive (see, e.g. [24]). However, adaptive threshold design based on sliding mode observers has not been available.

In this paper, a nonlinear sliding mode observer with novel designed sliding surface is proposed for incipient sensor fault detection. The parameters of the observer are particular designed relying on $\mathcal{L}_2$ gain, guaranteeing residual robustness to uncertainties. At the same time, proper adaptive thresholds are obtained based on the reduced order sliding motion, which effectively improves incipient sensor fault detectability. Furthermore, different levels of detection decision schemes for incipient sensor fault development are proposed. The main contribution of this paper is as follows:

1. A novel FD sliding mode observer framework is proposed to get proper adaptive thresholds to improve incipient fault detectability.
2. Incipient sensor fault development detection schemes are studied and levels of detection decisions are proposed.

The remainder of this paper is organized as follows. In Section 2, preliminaries and assumptions are presented. In Section 3, the FDE sliding mode observer is proposed with parameters of observer being designed based on LMI and linear filter techniques. In Section 4, the sensor fault adaptive thresholds (for incipient fault, fault and failure) are designed and the continuous and piecewise continuous incipient sensor fault development detection decisions are made. In Section 5, case study of an application to the traction system in CRH (China Railway High-speed) is presented to demonstrate the obtained results. Section 6 concludes this paper.

## 2. Problems formulation

### 2.1. System description and incipient sensor fault modeling

Consider a class of linear systems with sensor faults described by

$$\begin{aligned} \dot{x} &= Ax + g(x,u) + \eta(x,u,\omega,t), \\ y &= Cx + Ff(x,u,t), \end{aligned} \tag{1}$$

where $x \in \mathcal{R}^n$ is state vector, $u \in \mathcal{R}^m$ is control, $\omega \in \mathcal{R}^h$ represents external disturbance vector, $f : \mathcal{R}^n \times \mathcal{R}^m \times \mathcal{R} \to \mathcal{R}^q$ is a nonlinear smooth vector representing the incipient sensor faults. $g(x,u) : \mathcal{R}^n \times \mathcal{R}^m \to \mathcal{R}^n$ is a known nonlinear smooth vector and $\eta(x,u,\omega,t) : \mathcal{R}^n \times \mathcal{R}^m \times \mathcal{R}^h \times \mathcal{R} \to \mathcal{R}^n$ is a nonlinear smooth vector representing the lumped disturbance, which is a generalized concept, possibly including external disturbances, un-modelled dynamics, parameter variations, and complex nonlinear dynamics. Matrices $A \in \mathcal{R}^{n\times n}$, $C \in \mathcal{R}^{p\times n}$ and $F \in \mathcal{R}^{p\times q}$ are known with $C$ being full row rank and $F$ full column rank.

Assuming that $n \ge p > q$. Without loss of generality, it is assumed that the outputs of the system (1) have been reordered (and scaled if necessary) so that the matrix $F$ has the structure

$$F = \begin{bmatrix} 0 \\ I_q \end{bmatrix}. \tag{2}$$

A lemma for piecewise continuous signals to establish differential dynamic model is given as follows:

**Lemma 1** (*Saif and Guan [29]*). *For any piecewise continuous vector function $f : \mathcal{R}^+ \to \mathcal{R}^q$, and a stable $q \times q$ matrix $A_f$, there exists an input vector $\xi \in \mathcal{R}^q$ such that $\dot{f} = A_f f + \xi$.*

Based on the continuous developing way of incipient faults analyzed in [26,28], this paper considers the incipient sensor fault $f(t)$ which is modeled by

$$\dot{f} = A_f f + \xi(x,u,t), \quad f(0) = 0, \tag{3}$$

where $A_f$ is a stable matrix with appropriate dimensions and $\xi = [\xi_1^T, \ldots, \xi_q^T]^T \in \mathcal{R}^q$ is an unknown vector. Taking the Laplace transformation of Eq. (3), it is clear to see that in the frequency domain, $f(s) = (sI - A_f)^{-1}\xi$, which shows that the fault signal $f$ is determined by $\xi(x,u,t)$ completely. It should be noted that $A_f$ is not a designed parameter. Such a class of incipient faults has been studied in [26,28].

Generally speaking, the amplitudes of the incipient faults are small. With time going on, the incipient faults may continuously develop to faults, and their amplitudes are bigger than that of incipient faults. If no actions is taken, incipient faults may continuously evolve into failures, which means that measured output signals are meaningless. The incipient sensor fault develops in a continuous way shown in Fig. 1.

For the considered continuous developing fault signals $f$ in system (1), it can be divided into three stages: incipient sensor fault, sensor fault and sensor failure. As seen from Fig. 1, the following terms can be given: $0 < \|\xi(x,u,t)\| < \overline{\xi}$, called “incipient sensor fault”; $\overline{\xi} \le \|\xi(x,u,t)\| < \overline{\overline{\xi}}$, called “sensor fault”; and $\overline{\overline{\xi}} \le \|\xi(x,u,t)\| < +\infty$ called “sensor failure”. The “sensor failure” can be further divided into “light sensor failure” and “severe sensor failure” by the bound $\overline{\overline{\overline{\xi}}}$, that is $\overline{\overline{\xi}} \le \|\xi(x,u,t)\| < \overline{\overline{\overline{\xi}}}$ called “light sensor failure” and $\overline{\overline{\overline{\xi}}} \le \|\xi(x,u,t)\| < +\infty$ called “light sensor failure”. In addition, four time instants $T_0$, $T_1$, $T_2$ and $T_3$ are defined, which represent incipient sensor fault occurrence time, incipient sensor fault developing to sensor fault time (i.e., the time when $\xi$

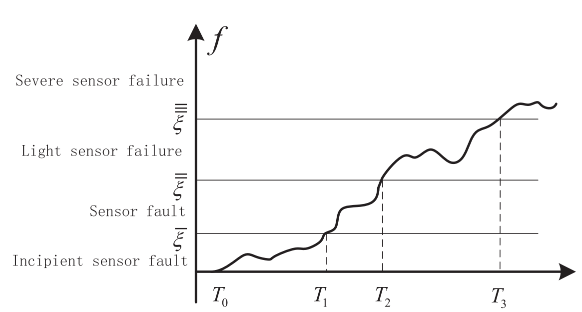


**Fig. 1.** Incipient sensor faults develop process.